Civil Engineering Infrastructures Journal 2023, 56(1): 137-157
DOI: 10.22059/CEIJ.2022.334953.1803

RESEARCH PAPER

Prediction of Shear Strength of Reinforced Concrete Deep Beams Using Neuro-Fuzzy Inference System and Meta-Heuristic Algorithms

Mohammadizadeh, M.R.[1*], Esfandnia, F.[2] and Khatibinia, M.[3]

[1] Associate Professor, Department of Civil Engineering, University of Hormozgan, Bandar Abbas, Iran.
[2] Ph.D. Student, Department of Civil Engineering, University of Hormozgan, Bandar Abbas, Iran.
[3] Associate Professor, Department of Civil Engineering, University of Birjand, Birjand, Iran.

Received: 03 Dec. 2021; Revised: 16 Mar. 2022; Accepted: 10 Apr. 2022

ABSTRACT: It is generally accepted that the shear strength of Reinforced Concrete (RC) deep beams depends on the mechanical and geometrical parameters of the beam. The accurate estimation of shear strength is a substantial problem in engineering design. However, the prediction of shear strength in this type of beams is not very accurate. One of the relatively accurate methods for estimating shear strength of beams is Artificial Intelligence (AI) methods. Adaptive Neuro-Fuzzy Inference System (ANFIS) was presented as an AI method. In this study, the efficiency of ANFIS incorporating meta-heuristic algorithms for predicting shear strength of RC beams was investigated. Meta-heuristic algorithms were used to determine the optimum parameters of ANFIS for providing the efficient models of the prediction of the RC beam shear strength. To evaluate the accuracy of the proposed method, its results were compared with those of other methods. For this purpose, the parameters of concrete compressive strength, cross-section width, effective depth, beam length, shear span-to-depth beam ratio (a/d), as well as percentage of longitudinal and transverse reinforcement were selected as input data, and the shear strength of reinforced concrete deep beam as the output data. Here, K-fold validation method with k = 10 was used to train and test the algorithms. The results showed that the proposed model with second root mean square error of 25.968 and correlation coefficient of 0.914 is more accurate than other methods. Therefore, neural fuzzy inference system with meta-heuristic algorithms can be adopted as an efficient tool in the prediction of the shear strength of deep beams.

Keywords: Meta-Heuristic Algorithms, Neuro-Fuzzy Inference System, Reinforced Concrete Deep Beam, Shear Strength.

1. Introduction

Deep beams are widely used in civil engineering including tall buildings, tanks, rectangular silos, floor diaphragms, shear walls, slabs and offshore structures (Gandomi et al., 2013; Prayogo et al., 2020). Due to complicated behavior of

[*] Corresponding author E-mail: mrzmohammadizadeh@yahoo.com

these beams, there is no consensus on the definition of the deep beams to which is approved by all researchers. A criterion for the definition of deep beams is the ratio of its span length (L) to its depth (D) which is less than 5. However, this criterion is less than 2.5, 5 and 4 in European, Canadian and American standards, respectively. Due to the complexity of the shear mechanism of deep concrete beams and the various parameters affecting it, it is difficult to develop a general model for accurate estimation of shear strength, and therefore the exact shear strength of these beams cannot be calculated using a closed-form solution. For pervious decades, few studies have examined the shear strength and analyzed the behavior of reinforced concrete deep beams. Many studies have also attempted to predict the shear capacity of reinforced concrete (RC) deep beams using various experimental relationships and analytical models (Liu and Mihaylov, 2016). Improving prediction performance is very important in the design of RC deep beams. Therefore, an efficient model is required to accurately predict the shear capacity prediction for different types of RC beams. In recent years, Artificial Intelligence (AI) methods have been used for this purpose. The use of AI methods has been attracted as extensive research in many fields of civil engineering (Moosazadeh et al., 2019; Taghi Dastorani et al., 2018; Baghban et al. 2020; Chitgar and Berenjian 2021). AI methods have been successfully used in complex problems, so that these methods can provide a powerful prediction method. The use of AI methods has shown that a complex nonlinear relationship could be established between the shear capacity of RC deep beams and all the effective parameters. Therefore, the use of AI methods has been proposed as efficient methods in the field of civil engineering. Artificial Neural Network (ANN) as an AI method is extensively proposed in order to model complex relationships between input and output data or to find a pattern for data. Although, ANNs are used in many problems and applications, their development can be time consuming. Adaptive fuzzy-neural inference (ANFIS) as an AI method combines the prominent features of a Fuzzy Inference System (FIS) with ANNs. In this type of method, the fuzzy rules of the samples are determined through ANN (Toghroli et al., 2014). This system has also shown good efficiency in recent years in comparison with older methods such as ANNs for classifying and estimating functions.

In recent years, the prediction of the shear strength of RC beams using the AI methods has attracted much attention of researchers. Nguyen et al. (2021) presented a model for the prediction of the shear strength of RC deep beams based on ANN and using four training algorithms. This study showed that ANN is a suitable method for predicting the shear strength of RC deep beams (Nguyen et al., 2021). In the study of Suguna et al. (2018), high-strength concrete beams were modeled based on ANN. Yield load, deflection at yield load, service load, deflection at service load, final load, deflection at final load, and flexibility were the target parameters and were predicted by ANN (Suguna et al., 2018). The capability of AI techniques for the prediction of the behavior of an innovative type of C-shaped shear connectors, called Tilted Angle Connectors was investigated by Shariati et al. (2021). Armaghani and Asteris (2021) studied the application of AI techniques for the prediction of the compressive strength of cement-based mortar materials with or without Metakaolin (Armaghani and Asteris, 2021). Keshavarz and Torkian (2018) also studied the application of ANN and ANFIS models in the prediction of the compressive strength of concrete. The results showed that ANN and ANFIS methods are successful models for predicting compressive strength of concrete. The results also showed that ANFIS has higher accuracy in predicting the compressive strength of concrete than that of ANN (Keshavarz and Torkian, 2018). Dao et al.

(2019) used ANN and ANFIS models to predict the compressive strength of Geopolymer concrete. The results of the study showed that ANN and ANFIS models have great potential for predicting the compressive strength of Geopolymer concrete (Dao et al., 2019). Naderpour and Mirrashid (2020) studied and predicted shear strength of RC beams using ANFIS. The results showed that the neural fuzzy network system, especially the ANFIS method, is highly capable of predicting shear strength of RC beams (Naderpour and Mirrashid, 2020). Some studies were used AI methods with meta-algorithms for the prediction of shear strength of RC beams. Khatibinia and Mohammadizadeh (2017) presented ANFIS with GA and PSO for determining the bonding of FRP polymer fibers and masonry elements. The results showed that the use of ANFIS model with PSO and GA can be significantly improving prediction accuracy (Khatibinia and Mohammadizadeh, 2017). Also, the study of Pham et al. (2018) can be mentioned as one of the most comprehensive researches for the use of AI methods and machine learning in the field of civil engineering. In this research, the shear capacity of soft soil was predicted using machine learning algorithms such as PSO-ANFIS (PANFIS), GA-ANFIS (GANFIS), Support Vector Regression (SVR) and ANN. The results of this study showed that the PANFIS has the highest predictability (Pham et al., 2018).

According to past studies, the importance of shear strength of RC deep beams in the design of structures is necessary. Therefore, the purpose of this study is to predict the shear strength of reinforced concrete beams using ANFIS with meta-heuristic algorithms. The prediction methods are proposed based on a hybrid of ANFIS with GA, PSO, Ant Colony Optimization (ACO) method and Differential Evolution (DE) algorithm. Furthermore, for comparing the prediction accuracy of the shear strength of RC deep beams based on ANFIS with the metaheuristic algorithms, the results obtained from these models were compared with shear strength calculated from ACI and CSA regulations as well as those of ANNs (ACI, 2011; CSA, 1994).

2. Shear Strength of RC Deep Beams

Numerous methods have been used to design of RC deep beams. The American Concrete Institute Standard code-318 (ACI, 2011) is based on a model called the truss model, in which the concrete contribution is presented based on experimental results. Based on ACI, the shear strength of RC deep beams is calculated as:

$$V_c = v_c b_w d = \left(3.5 - 2.5\frac{M_u}{V_u d}\right) \times \left(1.9\sqrt{f_c^{'}} + 2.5\rho_w \frac{V_u d}{M_u}\right) b_w d \quad (1)$$

where $f_c^{'}$: is the 28-day compressive strength of the 30 × 15 cylindrical concrete sample, and ρ_w: is the ratio of the longitudinal bars which is defined as follows:

$$\rho_w = A_S / b_w d \quad (2)$$

where V_u and M_u: are shear force and bending moment at the critical point, respectively. b_w and d: are width and effective depth of the beam, respectively. For beams reinforced in transverse direction, the nominal shear strength of the deep beam V_n shall include the shear strength obtained from V_c concrete share and the shear strength obtained from V_s bars share:

$$V_n = V_c + V_s \quad (3)$$

where V_s: is expressed as follows:

$$V_s = [\frac{A_v}{12s}(1 + \frac{L_n}{d}) + \frac{A_{vh}}{12s_2}(11 - \frac{L_n}{d})] f_y d \quad (4)$$

where A_v: is the area of shear bars, f_y: is the yield stress of the stirrups, s: is the distance of center to center of the stirrups, and ρ_v: is the ratio of the shear bars. In CSA (Canadian, 1994), the total shear strength of RC deep beam consists of two shear strengths obtained from the share strength of concrete and the shear strengths of bars. In CSA, the concrete shear share V_c, depends on the amount of transverse reinforcement and d of beam and defined as:

$$V_c = \frac{V_c}{b_w d} = 0.2\sqrt{f_c^{'}}\text{for}A_v \geq \frac{0.006\sqrt{f_c^{'}}b_w s}{f_{yv}}\text{or}d \leq 300\text{mm}$$
$$V_c = \frac{V_c}{b_w d} = \frac{260}{1000+d}\sqrt{f_c^{'}}\text{for}A_v < \frac{0.006\sqrt{f_c^{'}}b_w s}{f_{yv}}\text{or}d > 300\text{mm} \quad (5)$$

The shear strength of bars is similar to the equation provided for V_s in the ACI Regulations. Some researchers used the design method based on the Strut-and-Tiefor for RC deep beams. In the Strut-and-Tie method, it was assumed that compressive forces was are tolerated by concrete struts, while tensile forces were tolerated by steel bars (Pal and Deswal, 2011).

3. Experimental Database

In the present study, 106 laboratory data were used to predict the shear strength of RC deep beams using ANFIS method with meta-heuristic algorithms. Data sets of RC deep beams include 19 data obtained from experiments on high strength RC beams impelimented by Tan et al. (1995), 52 data obtained from the results of study-related tests by Smith and Vantsiotis (1982), 35 laboratory data obtained from the study of Kong et al. (1970). Hence, all the experimental database and the brief details database are presented in Tables 1 and 2, respectively.

Table 1. Experimental database of RC deep beam

V (kN)	ρ_v	ρ_h	$f_c^{'}(MPa)$	$\frac{d}{b_w}$	$\frac{L}{d}$	$\frac{a}{d}$
675	0.0048	0	58.80	4.2091	2.15	0.27
630	0.0048	0	51.60	4.2091	3.23	0.27
640	0.0048	0	53.90	4.2091	4.3	0.27
630	0.0048	0	57.30	4.2091	5.38	0.27
468	0.0048	0	56.00	4.2091	2.15	0.54
445	0.0048	0	47.00	4.2091	3.23	0.54
500	0.0048	0	53.90	4.2091	4.3	0.54
480	0.0048	0	53.00	4.2091	5.38	0.54
403	0.0048	0	51.02	4.2091	2.15	0.81
400	0.0048	0	44.00	4.2091	3.23	0.81
270	0.0048	0	48.20	4.2091	2.15	1.08
280	0.0048	0	44.10	4.2091	3.23	1.08
290	0.0048	0	46.80	4.2091	4.3	1.08
290	0.0048	0	48.00	4.2091	5.38	1.08
220	0.0048	0	50.80	4.2091	3.23	1.62
190	0.0048	0	44.50	4.2091	4.3	1.62
173	0.0048	0	45.30	4.2091	5.38	1.62
150	0.0048	0	41.10	4.2091	4.3	2.16
107	0.0048	0	42.08	4.2091	5.38	2.16
140	0	0	20.50	2.9902	2.67	1
136	0	0	20.90	2.9902	2.67	1
161	0.0028	0.0023	18.70	2.9902	2.67	1
149	0.0028	0.004	18.00	2.9902	2.67	1
141	0.0028	0.0068	16.10	2.9902	2.67	1

171	0.0028	0.0068	20.60	2.9902	2.67	1
184	0.0028	0.0091	21.10	2.9902	2.67	1
175	0.0063	0.0023	21.70	2.9902	2.67	1
171	0.0063	0.0045	19.80	2.9902	2.67	1
172	0.0063	0.0068	20.30	2.9902	2.67	1
162	0.0063	0.0091	19.10	2.9902	2.67	1
161	0.0125	0.0023	18.10	2.9902	2.67	1
173	0.0125	0.0045	19.20	2.9902	2.67	1
179	0.0125	0.0068	20.80	2.9902	2.67	1
168	0.0125	0.0091	19.90	2.9902	2.67	1
149	0	0	21.70	2.9902	3.08	1.21
148	0.0024	0.0023	22.10	2.9902	3.08	1.21
144	0.0024	0.0045	20.10	2.9902	3.08	1.21
141	0.0024	0.0068	20.80	2.9902	3.08	1.21
154	0.0024	0.0091	19.50	2.9902	3.08	1.21
129	0.0042	0.0023	19.20	2.9902	3.08	1.21
131	0.0042	0.0045	19.00	2.9902	3.08	1.21
126	0.0042	0.0068	17.50	2.9902	3.08	1.21
145	0.0042	0.0091	19.80	2.9902	3.08	1.21
131	0.0063	0.0023	16.20	2.9902	3.08	1.21
159	0.0077	0.0023	20.40	2.9902	3.08	1.21
159	0.0077	0.0045	19.00	2.9902	3.08	1.21
155	0.0077	0.068	19.20	2.9902	3.08	1.21
160	0.0077	0.0091	20.70	2.9902	3.08	1.21
154	0.0125	0.0023	17.10	2.9902	3.08	1.21
116	0	0	20.70	2.9902	3.67	1.5
119	0.0018	0.0023	19.20	2.9902	3.67	1.5
124	0.0018	0.045	21.90	2.9902	3.67	1.5
131	0.0018	0.0068	22.70	2.9902	3.67	1.5
123	0.0018	0.0091	21.80	2.9902	3.67	1.5
124	0.0031	0.0023	19.90	2.9902	3.67	1.5
104	0.0031	0.0045	19.20	2.9902	3.67	1.5
116	0.0031	0.0045	19.30	2.9902	3.67	1.5
125	0.0031	0.0068	20.40	2.9902	3.67	1.5
124	0.0031	0.0091	20.80	2.9902	3.67	1.5
141	0.0056	0.0023	21.00	2.9902	3.67	1.5
125	0.0056	0.0045	16.60	2.9902	3.67	1.5
128	0.0056	0.0068	18.30	2.9902	3.67	1.5
137	0.0056	0.0091	19.00	2.9902	3.67	1.5
147	0.0077	0.0023	19.60	2.9902	3.67	1.5
129	0.0063	0.0045	18.60	2.9902	3.67	1.5
153	0.0077	0.0045	19.20	2.9902	3.67	1.5
153	0.0077	0.0068	18.50	2.9902	3.67	1.5
160	0.0077	0.0091	21.20	2.9902	3.67	1.5
74	0	0	19.50	2.9902	4.83	2.08
88	0.0042	0.0023	16.10	2.9902	4.83	2.08
239	0.00245	0	21.50	9.5263	1.05	0.35
224	0.00245	0	24.60	7.8553	1.28	0.43
190	0.00245	0	21.20	6.1842	1.62	0.54
168	0.00245	0	21.20	4.5132	2.22	0.74
90	0.00245	0	21.70	2.8421	3.53	1.18
249	0.0086	0	19.20	9.5263	1.05	0.35
224	0.0086	0	18.60	7.8553	1.28	0.43
216	0.0086	0	19.90	6.1842	1.62	0.54
140	0.0086	0	22.80	4.5132	2.22	0.74
100	0.0086	0	20.10	2.8421	3.53	1.18
276	0	0.0245	22.60	9.5263	1.05	0.35
208	0	0.0245	19.20	6.1842	1.62	0.54
159	0	0.0245	21.90	4.5132	2.22	0.74
87	0	0.0245	22.60	2.8421	3.53	1.18

242	0	0.0086	22.00	9.5263	1.05	0.35
201	0	0.0086	21.00	7.8553	1.28	0.43
181	0	0.0086	20.10	6.1842	1.62	0.54
110	0	0.0086	22.00	4.5132	2.22	0.74
96	0	0.0086	22.60	2.8421	3.53	1.18
240	0.0061	0.0061	18.60	9.5263	1.05	0.35
208	0.0061	0.0061	19.20	7.8553	1.28	0.43
173	0.0061	0.0061	20.10	6.1842	1.62	0.54
127	0.0061	0.0061	21.90	4.5132	2.22	0.74
78	0.0061	0.0061	22.60	2.8421	3.53	1.18
308	0	0.005	26.10	9.5263	1.05	0.35
266	0	0.0061	25.10	7.8553	1.28	0.43
25	0	0.0077	26.10	6.1842	1.62	0.54
173	0	0.0102	26.10	4.5132	2.22	0.74
99	0	0.0153	25.10	2.8421	3.53	1.18
253	0	0	25.10	10.0263	1.05	0.5
300	0	0.0017	26.10	10.0263	1.05	0.35
260	0	0.0034	26.10	10.0263	1.05	0.35
264	0	0.0068	21.30	10.0263	1.05	0.35
297	0	0.0085	21.30	10.0263	1.05	0.35

Table 2. Brief of the experimental database of RC deep beams studied in the present study

Parameter	Minimum	Medium	Maximum	S.D
Width of the beam (*b*), (mm)	76	94.84	110	13.547
Effective depth (*d*), (mm)	216	401.57	762	108.465
The span-to-depth ratio (*a*/*d*)	0.27	1.006	2.16	0.468
Compressive stress of concrete (f_c'), (MPa)	16.20	25.80	58.80	15.93
Longitudinal reinforcement ratio (ρ_h)	0.00	0.0058	0.068	0.91
Shear Rebar Ratio (ρ_v)	0.00	0.004	0.0125	0.32
Ultimate shear strength (*V*), (kN)	25	201.48	675	2.15

Thus, the shear strength was considered as the output data. The 28-day compressive strength of 15 × 30 US cylinder specimen, cross-section width, effective depth, beam length, shear span-to-depth beam ratio, as well as the percentage of longitudinal and transverse reinforcement were adopted as the input data. The geometric dimensions and how the beam is loaded are shown in Figure 1.

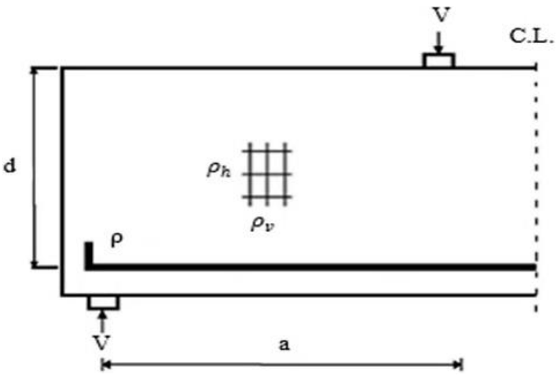


Fig. 1. Geometric dimensions of a reinforced concrete deep beam

4. Concept of ANFIS Model

A Fuzzy Inference System (FIS) was proposed as a nonlinear mapping approach from the input space to the output space (Jang, 1993; Jang et al., 1996). ANFIS uses a Sugeno type fuzzy system in a 5-layer network for two *x* and *y* inputs and one *f* output. ANFIS can optimize the performance of the fuzzy model by adjusting a parameter in the membership performance. This model combines the learning capabilities of a neural network with fuzzy logic inference to enhance predictability. This system has been so far used in a wide range of engineering fields and has shown considerable accuracy in estimating and predicting various engineering phenomena.

For simplicity a typical ANFIS shown in Figure 2 consists of two fuzzy if–then rules based on Takagi and Sugeno's type (Jang et al., 1996):

$$Rule1\text{:If}x\text{is}A_1\text{and}y\text{is}B_1\text{,then}f_1 = p_1x + q_1y + r_1$$
$$Rule2\text{:If}x\text{is}A_2\text{and}y\text{is}B_2\text{,then}f_2 = p_2x + q_2y + r_2 \quad (5)$$

where A_1, A_2, B_1, and B_2: stand for the labels of the representation of Membership Functions (MFs) for x and y inputs. Moreover, p_i, q_i, and r_i (i = 1, 2): refer to the variables of the output MFs (consequent variables).

As seen in Figure 2, an overall structure of ANFIS has 2 constant square nodes and adaptive circle nodes whose variables would be altered over the training procedure. A hybrid learning algorithm of ANFIS would be applied via the MFs parameters of input variables and linear parameters of the output variables. Gradient Descent (GD) strategies would be used to optimize the above parameters. The resulting output of the defined network with 1 output and 2 inputs with regard to these parameters may be computed in this way:

$$f = \sum_i \bar{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{\sum_{i=1}^{2} w_i}\text{,for}i = 1,2 \quad (7)$$

$$w_i = \mu A_i(x) \times \mu B_i(x)\text{for}i = 1,2 \quad (8)$$

where w_i: represents the firing strength of the rule i. $\mu A_i(x)$ and $\mu B_i(x)$: refer to the membership degrees of x and y in A_i and B_i.

In ANFIS, membership function can be expressed by a number of the shape functions consisting of trapezoidal, triangular, generalized bell shaped and Gaussian functions. Sihag et al. (2017) shown that Gaussian membership function-based ANFIS had better performance than the other membership function. Hence, Gaussian membership function is used in this study. Gaussian functions are defined as:

$$\mu A_i(x) = \frac{1}{1 + (\frac{x - c_i}{a_i})^2} \quad (9)$$

$$\mu B_i(y) = \frac{1}{1 + (\frac{y - d_i}{e_i})^2} \quad (10)$$

where $\{a_i, c_i\}$ and $\{d_i, e_i\}$: represent the premise variable set applied for adjusting the MF shape.

5. Meta-Heuristic Algorithms

5.1. Particle Swarm Optimization

Particle Swarm Optimization (PSO) algorithm has been designed on the basis of the inspiration provided by the social behaviors of animals, including insects swarming, fish schooling, and birds flocking (Kennedy et al., 2001). Kennedy and Eberhart (2001) proposed PSO technique for simulating the elegant motions of the bird swarms as a part of a social and cognitive research. The technique contains some particles which are randomly selected in the search spaces of optimization problem. All particles of the swarm represent one of the probable solutions for the problem of optimization. The i^{th} particle in the t^{th} iteration has a relationship to a velocity vector (V_i^t) and a position vector (X_i^t):

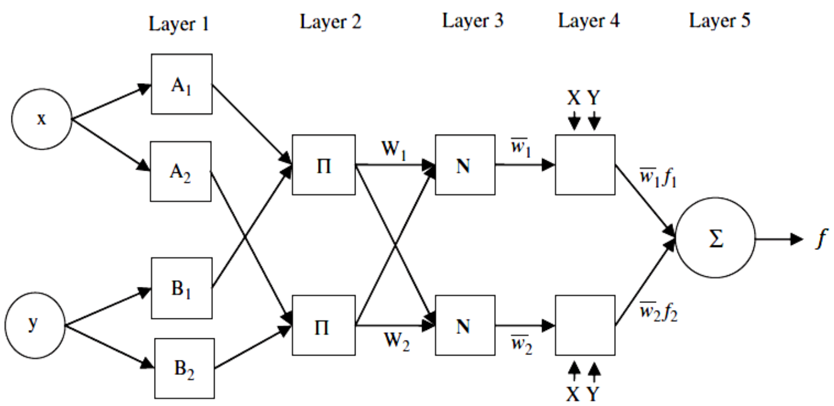


Fig. 2. The architecture of the ANFIS model

$$X_i^t = \{x_{i1}^t, x_{i2}^t, \ldots, x_{iD}^t\}$$
$$V_i^t = \{v_{i1}^t, v_{i2}^t, \ldots, v_{iD}^t\} \quad (11)$$

where D: refers to the volume of the solution space. As stated by researchers, the particles flying across the solution space, and its position would be updated with regard to the respective speed, global best position (***gbest***), and the best position particle (***pbest***) where swarms have met since the first iteration as:

$$V_i^{t+1} = \omega^t V_i^t + c_1 r_1(\text{pbest}_i^t - X_i^t) + c_2 r_2(\text{gbest}^t - X_i^t) \quad (12)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (13)$$

where r_1 and r_2: represent the uniform random sequences produced from intervals [0, 1]. C_1 and C_2: refer to the socio-cognitive scaling variables. ω: is the inertia weight that controls the influence of the previous velocity. Some researchers suggested that socio-cognitive scaling variables of c_1 and c_2 must be chosen as $c_1 = c_2 = 2$ for allowing the product c_1r_1 or c_2r_2 to be possessed a mean of 1. PSO is sensitivity to ω variable that possibly declines with the numbers of the iterations as follows (Shi et al., 2011):

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{t_{\max}} t \quad (14)$$

where ω_{max} and ω_{min}: represent the highest and least values of ω. t_{max}: refers to the limit numbers of optimization iteration. Table 3 represents the values of controlling parameters of PSO which is used in this study. The values of the parameters are selected based on a trial and error process.

Table 3. The value of controlling parameters for PSO algorithm

Parameter	Value
Number of population	40
Maximum number of iterations	1000
Ideal weight	1
Ideal slope to weight ratio	0.99
Private learning coefficient	1
Public learning coefficient	2

5.2. ACO for Continuous Domains (ACO_R)

First, Ant Colony Optimization (ACO) was proposed for solving the discrete problems of optimization (Socha and Dorigo, 2008). This algorithm has been proposed based on the inspiration via investigating the behaviours of the real ants for their food source. For finding an optimal solution for problem with continuous domains, ACO for continuous domains (ACO_R) is implemented based on the basis of two stages (Socha and Dorigo, 2008). At the first stage, a number of k artificial ants make solutions for problem via taking samples of a Probability Density Function (PDF) that is extracted from the pheromone data. At the second stage, the solutions would be applied for modifying the pheromone so that the construction probability of high-quality solutions would be enhanced. In the ACO_R procedure, the number of the solutions memorized in the archive P are adjusted at M; that is, $X^j = \{x_1^j, x_2^j, \ldots, x_d^j\}^T, j = 1, \ldots, M$. The solutions are consistently sorted with regard to their value of the objective function; that is:

$$f(X^1) \leq f(X^2) \leq \ldots \leq f(X^M) \quad (15)$$

For each variable $x_i (i = 1, \ldots, d)$, T: is used to derive the Gaussian kernel PDF as:

$$G_i(x) = \sum_{j=1}^{M} \zeta_j \frac{1}{\sigma_i^j \sqrt{2\pi}} exp(-\frac{(x - \mu_i^j)^2}{2\sigma_i^{j2}}), -\infty < x < +\infty \quad (16)$$

Furthermore, this kernel is used for guiding the ants in the respective search procedure. The weight ζ_j: is computed based on:

$$\zeta_j \propto \frac{1}{\gamma M \sqrt{2\pi}} exp(-\frac{(j-1)^2}{2\gamma^2 M^2}), j = 1, \ldots, M \quad (17)$$

where γ: is a parameter of the algorithm.

The small value of γ strongly causes the best solutions, and for its large value the probability becomes more uniform. The value of the *i*th variable in the *j*th solution is chosen as the mean, i.e. $\mu_i^j = x_i^j$. The standard deviation is obtained using the average distance of the other solutions from the *j*th solution which is multiplied by a parameter ρ:

$$\sigma_i^j = \frac{\rho}{M-1}\sum_{m=1}^{M}\left|x_i^m - x_i^j\right| \tag{18}$$

The lower the value of ρ the higher the convergence speed of the algorithm.

At each iteration of ACO_R, each artificial ant performs d steps from i = 1 to d. By sampling the PDF $G_i(x)$, the *k*th ant at step i is used for providing a partial solution of the optimization problem. By reaching the steps to the value d, a new solution, $X^k = \{x_1^k, x_2^k, \ldots, x_d^k\}$, is constructed. All k solutions are added to the archive T, and the same number of the worst solutions is removed from it. Table 4 represents the values of the parameters of the ACO_R algorithm. The values of the parameters were selected based on a trial and error process.

Table 4. The value of the parameters of the ACO_R algorithm

Parameter	Value
Number of population	20
Maximum number of iterations	200
Resonance coefficient	0.5
Deviation distance ratio	1

5.3. Real-Coded Ga with SBX Crossover

According to Gen and Cheng (2000), Genetic Algorithms (GAs) commonly contain 5 elements (Gen and Cheng, 2000):

- A genetic expression of the problem solutions;
- An operator to establish an early population of the solutions;
- A mechanism to evaluate the function rating solution with regard to its fitness;
- A mechanism to select parent and genetic operators altering the genetic compositions of the children over the reproduction process;
- The variables affecting GAs.

Real-coded GA (RCGA) was proposed as one of the acceptable methods for optimization problems with continuous variables. Real number encoding has more acceptable performance compared to the binary or gray encoding for such problems. Conventionally, the tournament selection in RCGA is used as a selection operator. Moreover, polynomial mutation and Simulated Binary Crossover (SBX) are chosen as other operators of RCGA.

In the SBX crossover operator, two children solutions is established from two parents (Subbaraj et al., 2011). Therefore, a random number, $u_i \in [0.1]$, is initially selected, and β_{qi}: is computed as follows:

$$\beta_{qi} = \begin{cases} (2u_i)^{\frac{1}{\eta_c+1}} u_i \le 0.5 \\ \left(\frac{1}{2(1-u_i)}\right)^{\frac{1}{\eta_c+1}} otherwise \end{cases} \tag{19}$$

where η_c: is the crossover index. Moreover, a spread factor β_{qi}: is described as the absolute difference ratio in the offspring values to that of the parents. Afterwards, two children solutions are achieved as:

$$\begin{aligned} X_i^{(1,t+1)} &= 0.5\left[\left(1+\beta_{qi}\right)X_i^{(1+t)} + \left(1-\beta_{qi}\right)X_i^{(2+t)}\right] \\ X_i^{(2,t+1)} &= 0.5\left[\left(1-\beta_{qi}\right)X_i^{(1+t)} + \left(1+\beta_{qi}\right)X_i^{(2+t)}\right] \end{aligned} \tag{20}$$

In the next stage of RCGA, new produced offspring experiences polynomial mutation operation. Moreover, instead of a normal distribution, the distribution of probability may be a polynomial function. This new offspring $Y_i^{(1,t+1)}$ would be estimated as follow (Deb, 2011):

$$Y_i^{(1,t+1)} = X_i^{(1,t+1)} + \left(X_i^U - X_i^L\right)\delta_i \tag{21}$$

where X_i^U and X_i^L: represent the upper and lower limit values. The parameter δ_i: is achieved from the polynomial probability distribution.

$$P(\delta) = 0.5(\eta_m + 1)(1 - |\delta|)^{\eta_m} \quad (22)$$

Table 5 represents the values of the parameters of RCGA. The value of the parameters was selected based on a trial and error process.

Table 5. Parameters related to GA algorithm

Parameter	Value
Number of population	100
Maximum number of iterations	500
Mutation percentage	0.5
Period percentage	0.7
Mutation rate	0.1
Selection pressure	8
Gamma	0.2

5.4. Differential Evolution Algorithm

Differential Evolution (DE) algorithm has been proposed by Storn and Price (1997). DE is considered as one of the stochastic optimization algorithms, which applies vector difference for perturbing the vector populations (Storn and Price, 1997). At initial stages, DE begins with a population containing N n-dimensional vectors as:

$$X_i(t) = \{x_i^1, x_i^2, \ldots, x_i^n\}, i = 1,2,\ldots,N \quad (23)$$

In this method, the vectors is randomly chosen on the intervals a $[X^{Li}, X^{Ui}], i = 1,2,\ldots,n$. Furthermore, e vectors are updated via mutation, crossover, and selection operations during the DE procedure.

Mutation operation: Based on the operation, three vectors $\boldsymbol{X}_{r1}(t)$, $\boldsymbol{X}_{r2}(t)$, and $\boldsymbol{X}_{r3}(t)$ are randomly selected for each certain $\boldsymbol{X}_i(t)$ vector at iteration t. However, $r1$, $r2$ and $r3$ indicators should be different. Consequently, the weighted differences of two vectors are added to the 3rd vector for forming a mutant vector $\bar{V}_i(t) = \{\bar{v}_i^1, \bar{v}_i^2, \ldots, \bar{v}_i^n\}$:

$$\bar{V}_i(t) = X_{r1}(t) + F(X_{r2}(t) - X_{r3}(t)) \quad (24)$$

Crossover operation: In this stage, the trial vector $\boldsymbol{U_i(t)}$ is designed through the components of the target vector, $\boldsymbol{X_i(t)}$ and components of the mutant vector $\bar{V}_i(t)$ through a binomial crossover operation:

$$u_i^j(t) = \begin{cases} \bar{v}_i^j(t)\ if\ rand_j \le C_r or j = j_{rand} \\ x_i^j(t) otherwise \end{cases} \quad (25)$$

where j_{rand}: represents a random integer in a range between 1 and n. $rand_j$: refer to the i^{th} assessment of an equal random number generator and $C_r \in (0,1)$. The $j = j_{rand}$ condition makes sure that the trial vector $\boldsymbol{U}_i(t)$ gets not less than 1 component from its mutant vector $\bar{V}_i(t)$.

Selection operation: By the comparison of the trial vector $\boldsymbol{U}_i(t)$ with the target vector $\boldsymbol{X}_i(t)$, the solution with the lowest objective function value is survived into the next generation:

$$X_i(t+1) = \begin{cases} U_i(t)\ if \quad fit(U_i(t)) \le fit(X_i(t)) \\ X_i(t) otherwise \end{cases} \quad (26)$$

It is noted that the DE method is implemented and continued using the mutation, crossover and selection operations until some criterion of the method stop is reached. In addition, the control parameters of the DE method contain the population size, N, the scaling factor, F, and the crossover constant, C_r. Table 6 represents the values of the parameters of the DE algorithm. The values of the parameters were selected based on a trial and error process.

Table 6. The value of the parameters of the DE algorithm

Parameter	Value
Number of population	20
Maximum number of iterations	200
Lowest scale coefficient	0.2
Highest scale coefficient	0.8
Crossover rate	0.1

6. The Proposed Intelligent ANFIS Technique

As presented in previous section, the ANFIS technique uses the advantages of both fuzzy systems and neural networks. Nonetheless, training the ANFIS model are considered as one of the major challenges for the real problems. Moreover, the GD strategies are used as the training techniques of ANFIS, which are known as local search strategies, and their functions commonly are contingent on the variables initial values. As it is possible to consider the optimum design of fuzzy systems (FSs) in the framework of an optimization problem, numerous authors suggested meta-heuristic strategies, including Genetic Algorithms (Jang, 1993; Savrun and İnci, 2021; Zhang, 2020) and PSO (Khoshbin et al., 2016; Lin et al., 2017) for designing optimum FSs. It is widely accepted that the accuracy and function of the ANFIS model is dependent on the premise variables and consequent variables that should be taught. For improving and increasing the ANFIS model accuracy in the present study, the PSO, ACO_R, RCGA and DE methods were used for finding the premise variables $\{a_i, b_i, c_i\}$. These parameters are adopted as the design variables of the optimization problem. In addition, the root mean squared error (*RMSE*) obtained based on actual output and desired outputs is considered as the objective function, which can be defined as follows.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - p_i)^2}{n}} \tag{27}$$

where y and p: stand for the measurement values and the predicted values. n: refers to the total numbers of the test data. Indeed, the errors variation in the suggested model may be calculated by *RMSE*, which would be too helpful in the case of undesirability of great errors.

In a conventional fuzzy inference system, the number of fuzzy rules is assigned by the user's experience. In ANFIS simulation, the number of MFs assigned to each input variable of problem is also selected by trial and error procedure. Therefore the Subtractive Algorithm (SA) (Chiu, 1997) is used for finding the optimum number of the fuzzy rules. The fuzzy inference system for the antecedents and consequents is also constructed by the fuzzy c-means (FCM) approach (Bezdek, 1981). The flowchart of the proposed ANFIS incorporating meta-heuristic algorithms is depicted in Figure 3.

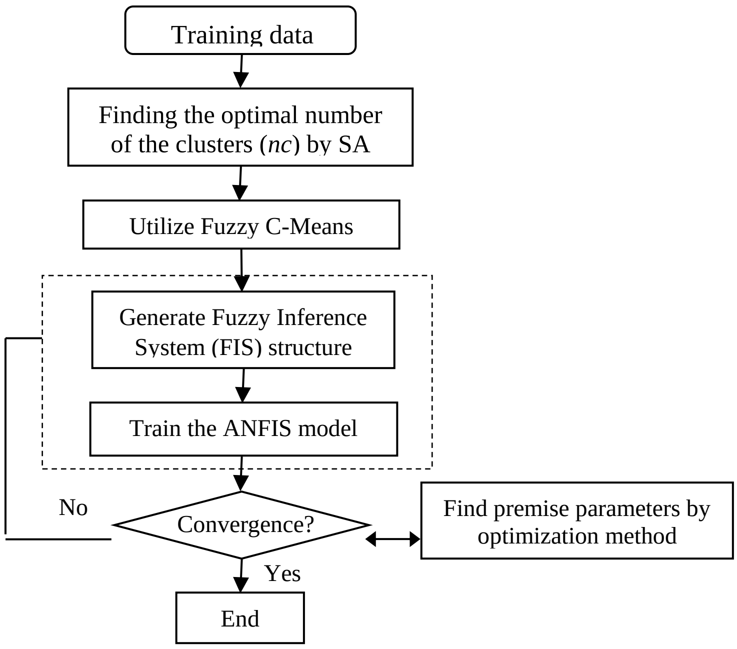


Fig. 3. Flowchart of the proposed ANFIS method with optimization methods

7. Numerical Results

In this study, a database containing 106 samples of RC deep beams were used to develop ANFIS with meta-heuristic algorithms (i.e. PSO, GA, ACO and DE) for the prediction of the shear strength of RC deep beams. For producing the prediction model, it is required that database is randomly divided into two sets of training and testing data. Simple procedures were proposed for splitting the data into training and testing data. These methods do not express the performance of the model well. Because each of them is highly dependent on data which is selected for training and testing data. This dependence sometimes results in higher model accuracy, and the other times in lower accuracy. To solve this problem and obtain the high accuracy of the proposed model, k-fold validation method was used. In this validation method, the number of partitions is usually proportional to the number of data points. By selecting k data points, it must be ensured that the number of data points in the training subset and the validation subset can contain proportional variation and show the same distribution. In this study, 90% of the data is used as the proportion of the training subsets and 10% for the validation subsets, which can be obtained by performing the ten-digit validation method to ensure that all subsets have the same distribution.

Using the cross-validation approach, the training data were randomly grouped into ten unique cross-subsets. In each iteration, one subset was used for the validation process and not another subset for the training process. Thus, each set of data is used at least once in both the training and validation phases. In the present study, the ten-fold cross-validation method (k = 10) was used, each set was trained ten times in the optimization process of parameters. Therefore, ten different values of the mean validation error for the objective function were obtained. Thus, the average of the results obtained from these ten subsets represents a useful method for predicting the overall performance of the ANFIS, ANFIS-GA, ANFIS-PSO, ANFIS-ACO and ANFIS-DE models.

It is noted that the values of the parameters presented in Tables 3 to 6 were selected based on a trial and error process. In fact, first, the different combinations of the values of the parameters were considered. Then, the optimization method was implemented for each combination. Thus, the combination with the minimum objective function is considered as the best combination of the values of the parameters.

7.1. Scaling and Dividing Database

For assessing the effectiveness and accuracy of the proposed ANFIS incorporating meta-heuristic algorithms, the values of the input variables were scaled. For this purpose, the values of the input variables were normalized between 0.2 and 0.8 and before dividing database as follows.

$$\bar{x}_i = b_1 \frac{x_i - x_{min}}{xmin_{max} + b_2} \tag{28}$$

where $\bar{x}_i$, $x_{\max}$ and $x_{\min}$: are the normalized, maximum and minimum values of the input variables, respectively. In this study, b_1 and b_2: were assumed to be equal to 0.6 and 0.2 based on the study of Khatibinia and Mohammadizadeh (2017), respectively. Then, the database was randomly divided into training and testing sets including 75 and 32 samples, respectively.

7.2. Results of the Proposed ANFIS Model

To explore and evaluate the accuracy of the proposed ANFIS with meta-heuristic in estimating the shear strength of RC beams, different statistical criterions were utilized. The second Root Mean Square Error (*RMSE*) (Eq. (27)), coefficient of determination (R^2) and Absolute Mean Error (*MAE*) were considered as the statistical criteria. These *MAE* and R^2 are defined as (Kaveh et al., 2017):

$$MAE = \frac{\sum_{i=1}^{n}[p_i - y_i]}{n} \quad (29)$$

$$R^2 = \frac{\left(\sum_{i=1}^{n}(y_i - y_{ave})\,(p_i - p_{ave})\right)^2}{\sum_{i=1}^{n}(y_i - y_{ave})^2\,\sum_{i=1}^{n}(p_i - p_{ave})^2} \quad (30)$$

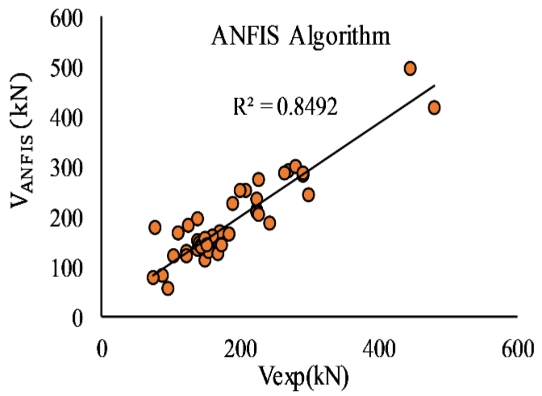
where p_i: is the predicted value and y_i: is the real value for n samples. y_{ave} and p_{ave}: are the mean of the measurement and predicted values in the data samples.

According to the statistical criteria, the statistical results ANFIS, ANFIS-GA, ANFIS-PSO, ANFIS-ACO and ANFIS-DE were presented in Table 7 for testing phase and were compared with those of ACI, CSA, ANN and GEP models.

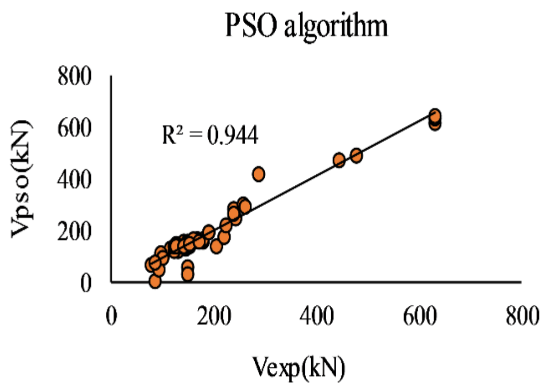
As can be seen from Table 7, the proposed ANFIS model with meta-heuristic methods predicts the shear strength parameter with much higher accuracy than other developed models. The predicted shear strength values obtained from ANFIS, ANFIS-GA, ANFIS-PSO, ANFIS-ACO and ANFIS-DE models are presented in Figures 4a to 4e, in terms of the shear strength obtained from the experimental results.

Table 7. Comparison of the statistical results using different models for testing phase

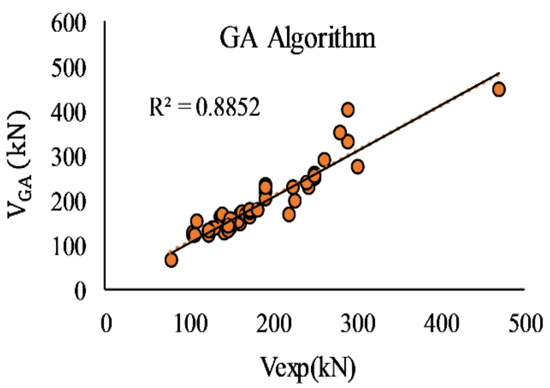
Model	**Reference**	***RMSE* (KN)**	***R*²**	***MAE* (KN)**
ACI	(Gandomi et al., 2013)	140.62	0.870	113.54
CSA	(Gandomi et al., 2013)	114.70	0.820	91.34
ANN	(Gandomi et al., 2013)	42.27	0.950	30.28
GEP	(Gandomi et al., 2013)	51.57	0.930	40.99
ANFIS	Present study	38.252	0.849	40.284
ANFIS-GA	Present study	31.357	0.944	23.931
ANFISA-ACO	Present study	37.095	0.925	26.429
ANFIS-PSO	Present study	36.058	0.885	20.540
ANFIS-DE	Present study	25.968	0.914	24.487



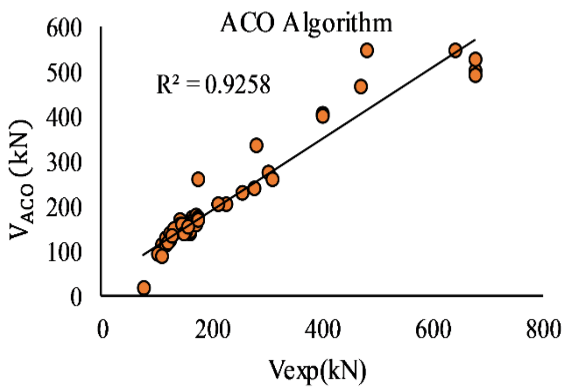
(a) ANFIS (*RMSE* = 40.35 kN)



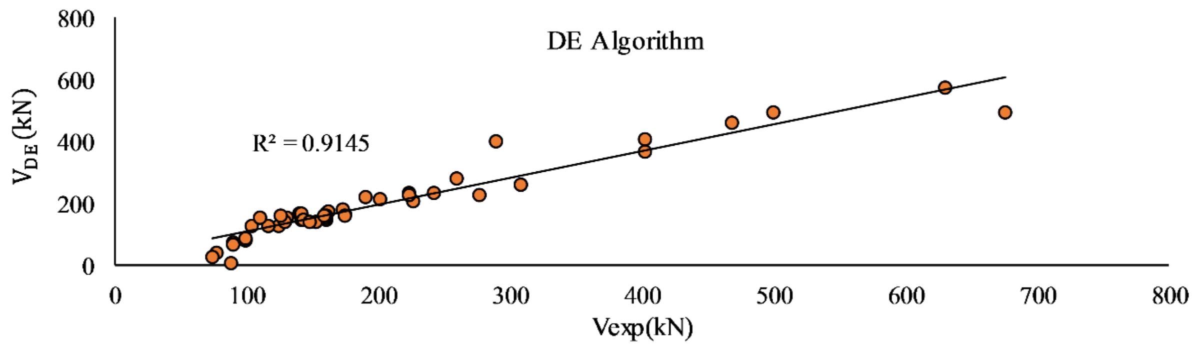
(b) ANFIS-PSO (*RMSE* = 36.06kN)



(c) ANFIS-GA (*RMSE* = 31.35 kN)



(d) ANFIS-ACO algorithm (*RMSE* = 37.095 kN)



(e) ANFIS-DE (*RMSE* = 25.96 kN)

Fig. 4. Experimental shear strength results in terms of predicted shear strength

The results show that the shear strength predicted by the proposed ANFIS with meta-heuristic algorithms is in good agreement with the shear strength obtained from the experimental results. In order to clarify an overall comparison, the statistical criteria used in testing phase were combined to create a normalized Reference Index (*RI*) as follows (Chou et al., 2011):

$$RI = \frac{\overline{RMSE} + \overline{MAE}}{2} \quad (31)$$

where $\overline{RMSE}$ and $\overline{MAE}$: are the normalized *RMSE* and *MAE*, respectively.

Table 8 shows the results based on *RI* for the proposed method, the original ANFIS, ANN, GEP, ACI and CSA techniques for comparison purposes. Based on the value *RI* obtained in the testing process, the proposed method outperforms the other techniques. It can also be observed from Table 8 that the ANFIS-DE model can be considered as an efficient technique with high accuracy in comparison with the other techniques.

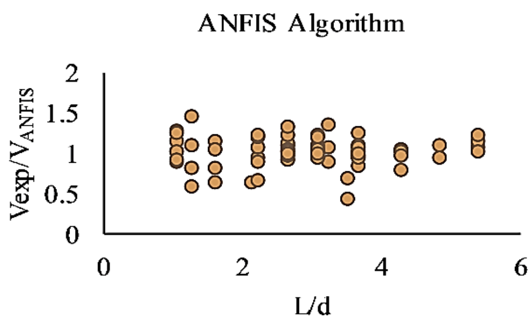
7.3. Influence of Parameters on the Ratio of Predicted to Experimental Shear Strength

7.3.1. Beam Span Length to Effective Depth (*L/d*)

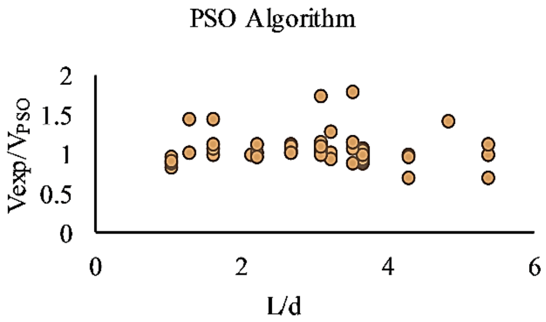
The changes of the ratio of the experimental shear strength to the predicted shear strength (V_{exp}/V_{pre}) using ANFIS, ANFIS-GA, ANFIS-PSO, ANFIS-ACO and ANFIS-DE models in terms of different ratios of L/d are shown in Figures 5a to 5e, respectively.

Table 8. Performance measurement results of various prediction techniques

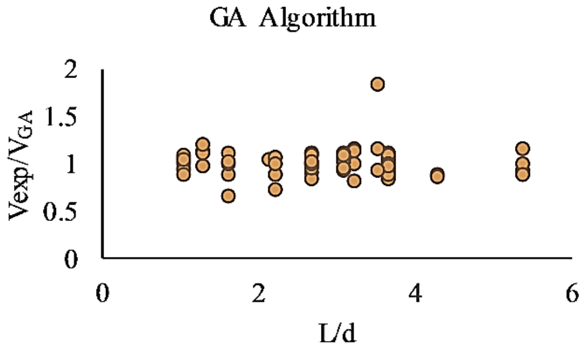
Model	Reference	$\overline{RMSE}$	$\overline{MAE}$	*RI*
ACI	(Gandomi et al., 2013)	0.00	0.00	0.00
CSA	(Gandomi et al., 2013)	0.24	0.23	0.15
ANN	(Gandomi et al., 2013)	0.90	0.86	0.58
GEP	(Gandomi et al., 2013)	0.78	0.78	0.52
ANFIS	Present study	0.79	0.89	0.56
ANFIS-GA	Present study	0.96	0.95	0.64
ANFISA-ACO	Present study	0.94	0.90	0.61
ANFIS-PSO	Present study	1.00	0.91	0.64
ANFIS-DE	Present study	0.96	1.00	0.65



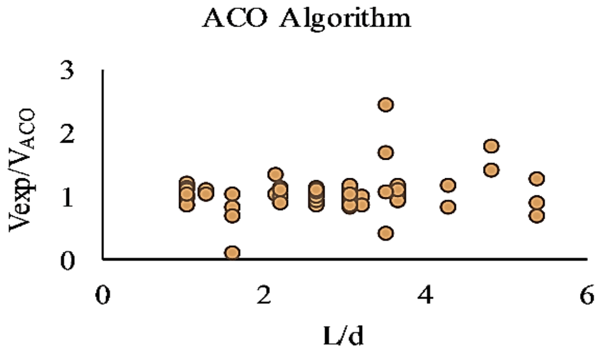
(a) ANFIS



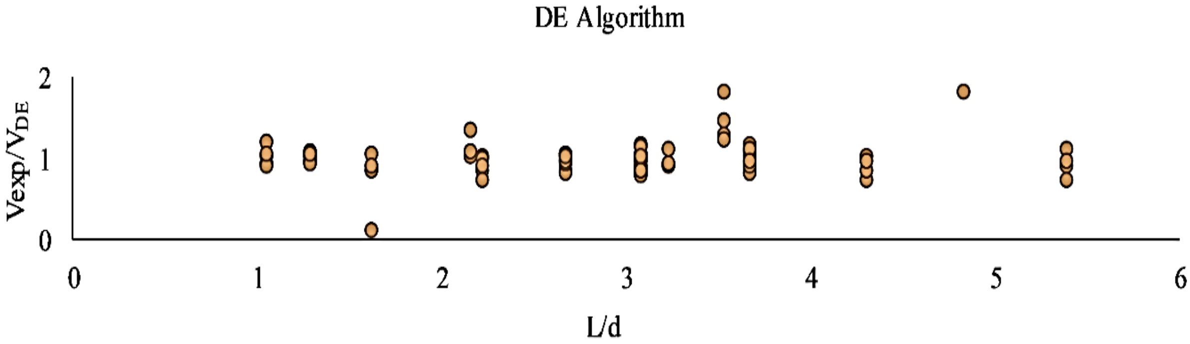
(b) ANFIS-PSO



(c) ANFIS-GA



(d) ANFIS-ACO



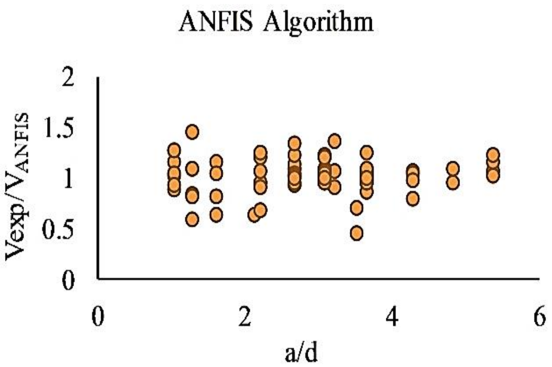
(e) ANFIS-DE

Fig. 5. The changes of the ratio of the experimental shear strength to the predicted shear strength in term of *L/d* parameter

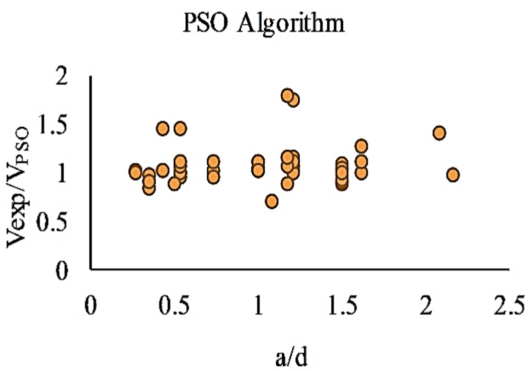
In other words, these figures show the accuracy of the proposed methods with respect to the geometrical properties of the examined beams. It can be seen from Figures 5c and 5e that the values of V_{exp}/V_{pre} for the ANFIS-GA and ANFIS-DE models have higher accuracy than that of the other models. It can also be concluded that the regardless of the geometrical type of the deep beam, the prediction of shear strength in these two models shows the high accurate for the different types of deep beams with arbitrary geometry. While ANFIS-PSO, and ANFIS-ACO models only have high accuracy in predicting shear strength of the beam in a range of $2 < L/d < 4$.

7.3.2. Shear Span to Effective Depth (*a/d*)

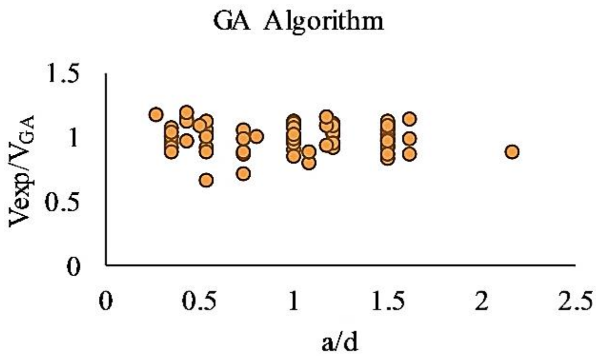
The changes of V_{exp}/V_{pre} obtained from ANFIS, ANFIS-PSO, ANFIS-GA, ANFIS-ACO and ANFIS-DE are shown in terms of different *a/d* ratios in Figures 6a to 6e, respectively. The results of these figures show that the values of V_{exp}/V_{pre} are more accurate in the ANFIS-GA and ANFIS-DE models and have less dispersion than those of the other examined models.



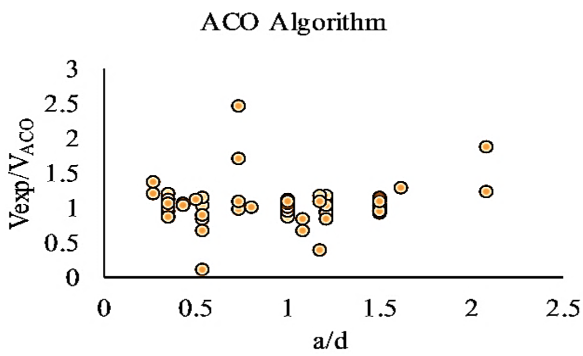
(a) ANFIS



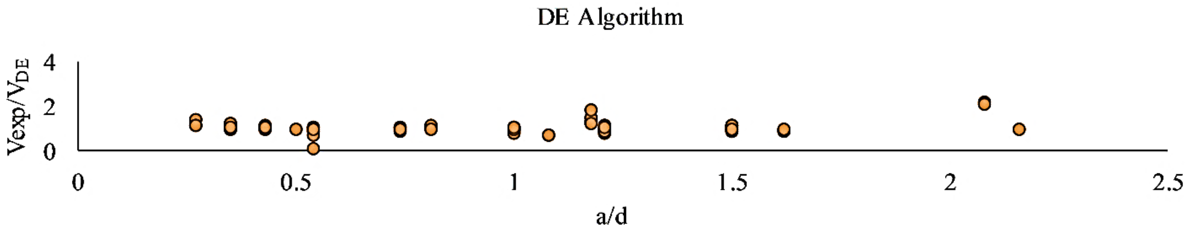
(b) ANFIS-PSO



(c) ANFIS-GA



(d) ANFIS-ACO

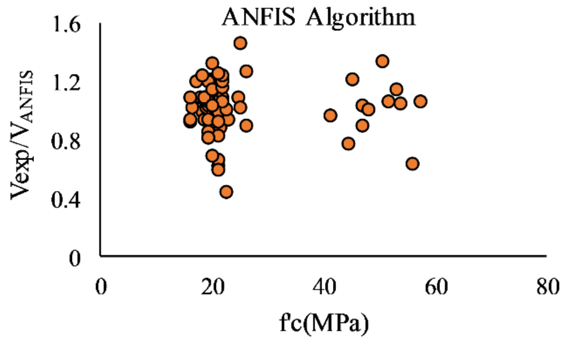


(e) ANFIS-DE

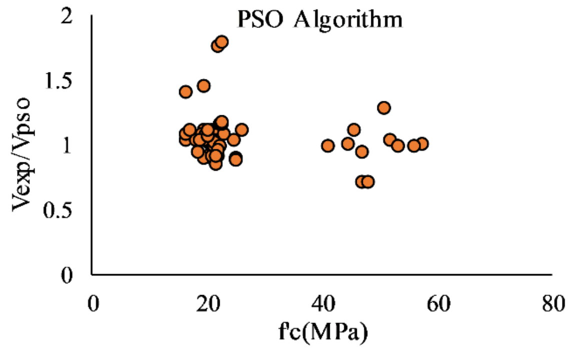
Fig. 6. The changes in the ratio of experimental shear strength to predicted shear strength in terms of a/d parameter

7.3.3. Compressive Strength of Concrete

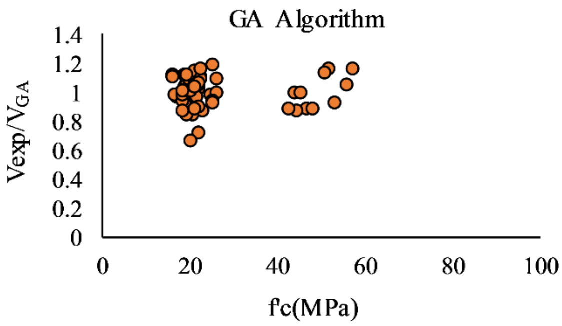
The changes of V_{exp}/V_{pre} in terms of the compressive strength values (28-day US Cylinder specimen) for different models of ANFIS, ANFIS-GA, ANFIS-PSO, ANFIS-ACO and ANFIS-DE are presented in Figures 7a to 7e, respectively. The compressive strength of concrete is considered as an import parameter in the design of RC beams. As can be seen from Figure 7e, the prediction of shear strength with the ANFIS-DE method is less affected by the changes in the compressive strength of concrete and has higher accuracy than the other methods. Thus, the ANFIS-DE method shows high accuracy for a wide range of concrete compressive strengths.



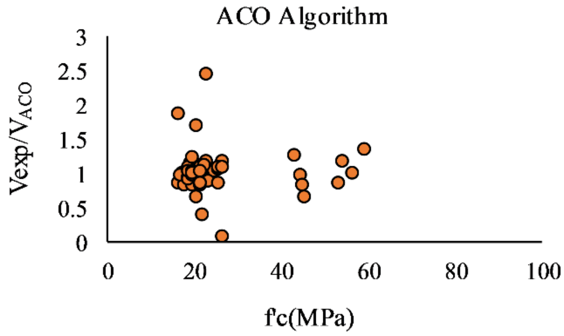
(a) ANFIS



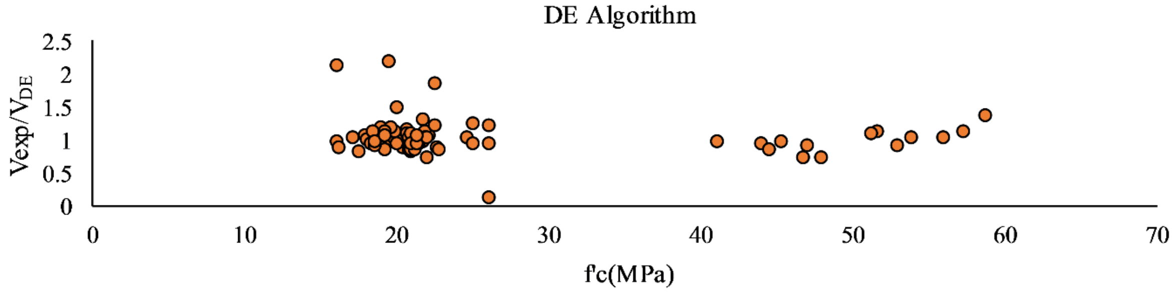
(b) ANFIS-PSO



(c) ANFIS-GA



(d) ANFIS-ACO

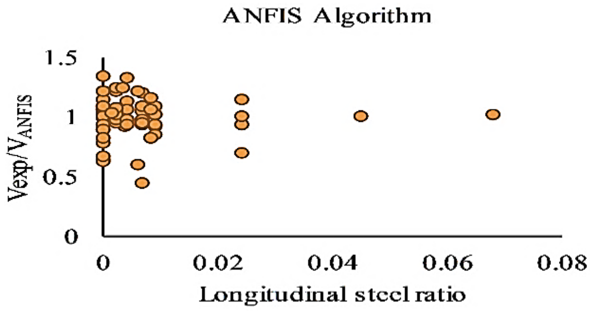


(e) ANFIS-DE

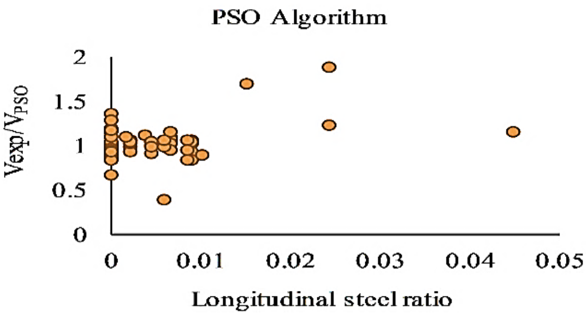
Fig. 7. The changes in the ratio of the experimental shear strength to the predicted shear strength in terms of f_c'

7.3.4. Longitudinal Reinforcement Percentage in Deep Beams

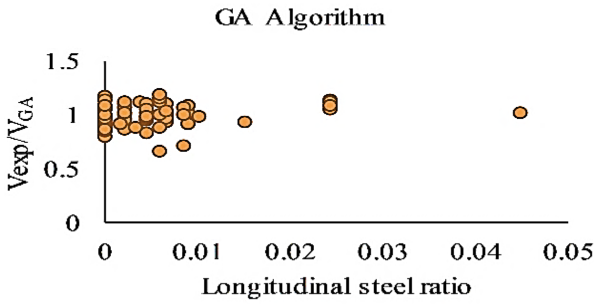
The changes of V_{exp}/V_{pre} for RC deep beams obtained from ANFIS, ANFIS-PSO, ANFIS-GA, ANFIS-ACO and ANFIS-DE models in term of the longitudinal reinforcement percentage are shown in Figures 8a to 8e, respectively. The results show that the values of V_{exp}/V_{pre} are closer to 1 in the ANFIS-GA and ANFIS-DE models. The higher accuracy is more pronounced in predicting the shear strength in term of longitudinal rebar percentage between 0.2 and 1%. These figures also show that ANFIS model has the highest data dispersion. Therefore, it can be seen from Figures 8c and 8e that for the prediction of the shear strength of deep beam, using ANFIS-GA, ANFIS-DE, ANFIS methods have more accurate.



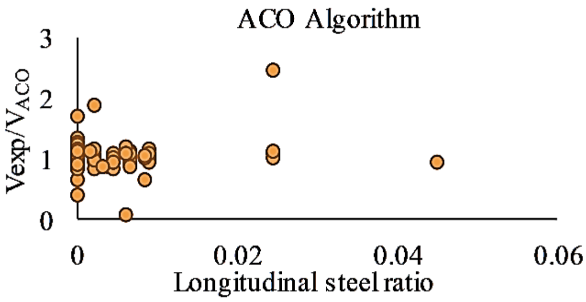
(a) ANFIS



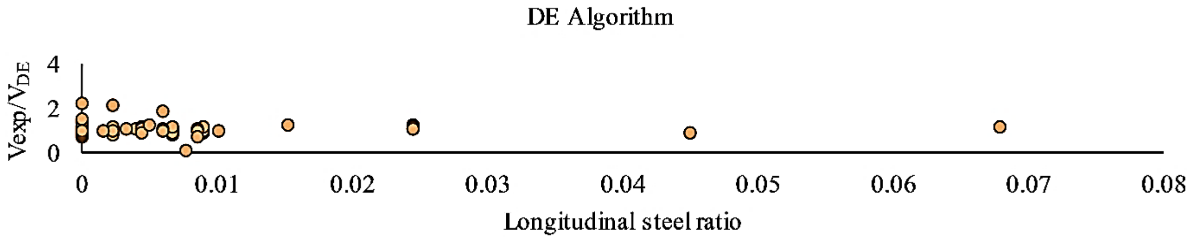
(b) ANFIS-PSO



(c) ANFIS-GA



(d) ANFIS-ACO

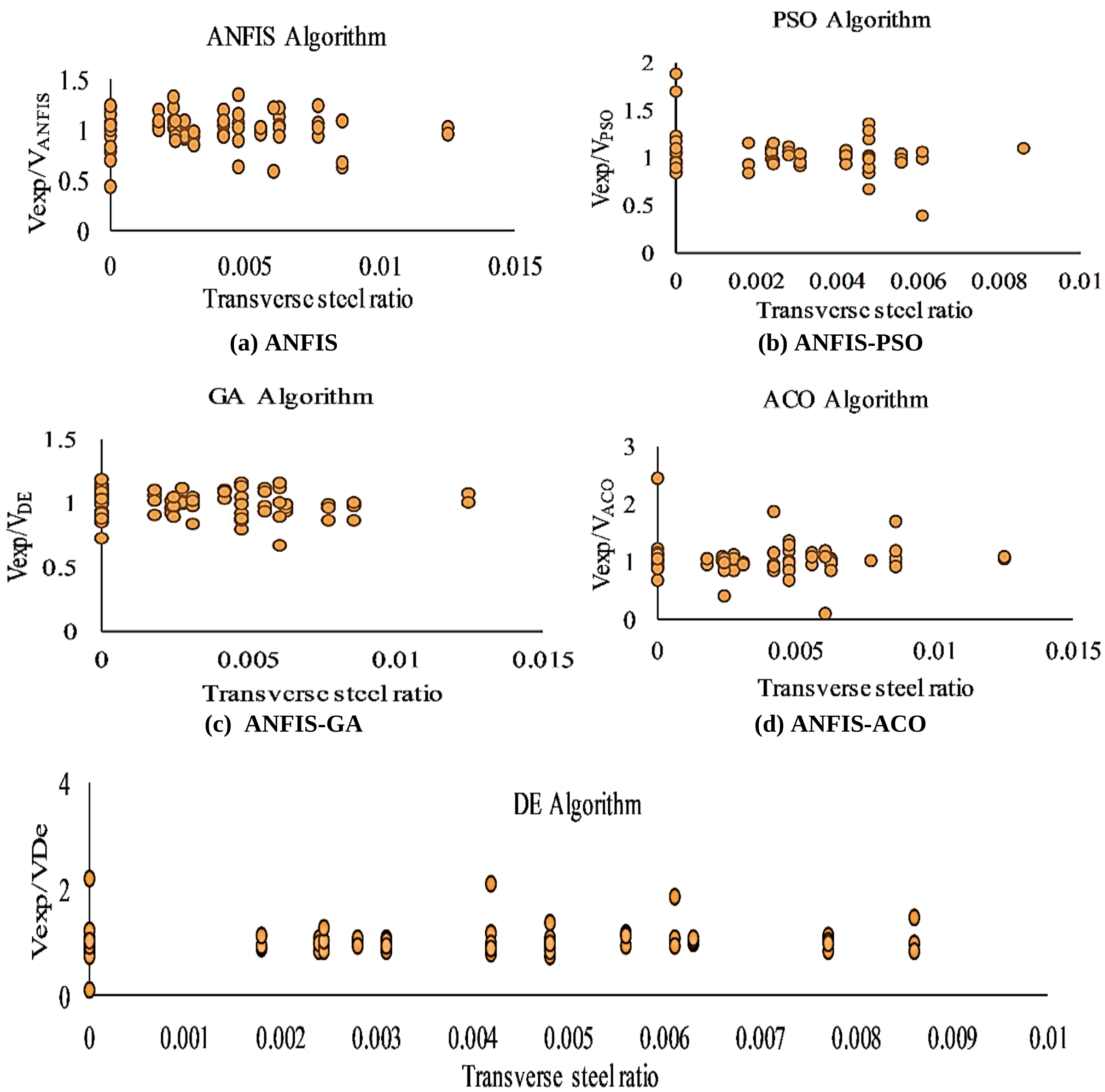


(e) ANFIS-DE

Fig. 8. The changes in the ratio of experimental shear strength to predicted shear strength in terms of the longitudinal rebar

7.3.5. Shear Reinforcement Percentage in Deep Beams

The changes of V_{exp}/V_{pre} obtained from ANFIS, ANFIS-PSO, ANFIS-GA, ANFIS-ACO and ANFIS-DE models in term of the shear reinforcement percentage of RC deep beams are shown in Figures 9a to 9e, respectively. The results show that the values of V_{exp}/V_{pre} in ANFIS-GA and ANFIS-DE models are closer to 1 than the other models, and have high accurate. The higher accuracy is more evident in the prediction of the shear strength in term of shear reinforcement percentage in a range of 0.3 to 0.6 percent. Figure 9a also shows that the ANFIS model has the highest data dispersion. Therefore, in the prediction of the shear strength of deep beam in the presence of the shear reinforcement percentage, ANFIS-GA, ANFIS-DE and ANFIS methods can lead to higher accuracy. As a general conclusion, it can be expressed that ANFIS-GA and ANFIS-DE models give the best results for estimating the shear strength of RC deep beam with shear reinforcement ratio of 0.3 to 1.2%.



(a) ANFIS (b) ANFIS-PSO

(c) ANFIS-GA (d) ANFIS-ACO

(e) ANFIS-DE

Fig. 9. The changes in the ratio of experimental shear strength to predicted shear strength in terms of the shear reinforcement percentage in deep beam

8. Conclusions

This study developed an ANFIS with meta-heuristic methods to predict the shear strength of RC deep beams. In the proposed approach, the meta-heuristic methods were employed to find the optimal parameters for membership functions and fuzzy rules in the ANFIS model which can generate a model for the shear strength of RC deep beams with high accuracy. The results reveals that the ANFIS method with meta-heuristic algorithms, as a powerful computational tool, can be used to analyze the complex relationships between different parameters in predicting shear strength of RC deep beams. The proposed ANFIS methods had better performance than the conventional ANFIS tuned based on the gradient decent approach. This efficient performance was obtained based on the stronger ability of the global search of the meta-heuristic algorithms. The comparison of these methods and the Strut-and-Tie method as well as the ACI approaches shows that the accuracy of the proposed ANFIS models is high. Furthermore, the results demonstrate that the ANFIS with meta-heuristic algorithms can be used as an alternative method to predict the shear strength of RC deep beams in comparison of ANN, GEP and other empirical approaches. The parametric studies show that shear strength of deep beams increases with the increase of concrete strength, and decreases with the increase of shear span to effective depth ratio. The results also show that among the different meta-heuristic methods, the DE method has the higher accuracy than other methods.

Although the computational cost of the proposed ANFIS method is higher than that for the conventional ANFIS. In future research, other optimization techniques may be developed to replace the GA, PSO, ACO and DE techniques used in this study for further comparison. It is also noted that the proposed ANFIS model considered in this study can certainly be used to accurately predict the shear strength of ordinary beams. However, due to the fact that the mechanism of ultimate fracture of ordinary beams is different from deep beams. Hence, for predicting the shear strength of ordinary beams, the database of the same beams should be used.

9. References

ACI. (2011). *Building code requirements for structural concrete (ACI 318-11)*, American Concrete Institute.

Armaghani, D.J. and Asteris, P.G. (2021). "A comparative study of ANN and ANFIS models for the prediction of cement-based mortar materials compressive strength", *Neural Computing and Applications*, 33(9), 4501-4532, https://doi.org/10.1007s00521-020-05244-4.

Baghban, A., Karamodin, A., and Haji Kazemi, H. (2020). "Fault-tolerant damage control of nonlinear structures using artificial intelligence", *Civil Engineering Infrastructures Journal*, 53(2), 395-406, https://doi.org/10.22059/CEIJ.2020.287804.1609.

Bezdek, J.C. (1981). *Pattern recognition with fuzzy objective function algorithms*, Plenum Press, New York, https://doi.org/10.1007/978-1-4757-0450-1.

CSA. (1994). *Building code, design of concrete structures: Structures (Design)-A National Standard of Canada (CAN-A23. 3-94), Clause 11.1. 2,* Canadian Standards Association, Toronto.

Gholamzadeh Chitgar, A. and Berenjian, J. (2021), "Performance evaluation of RBF networks with various variables to forecast the properties of SCCs", *Civil Engineering Infrastructures Journal*, 54(1), 59-73, https://doi.org/10.22059/CEIJ.2020.288257.1611.

Chiu, S. (1997). "Fuzzy model identification based on cluster estimation", *Journal of Intelligent and Fuzzy Systems*, 2(3), 267-278, https://doi.org/10.3233/ifs-1994-2306.

Chou, J.S., Chiu, C.K., Farfoura, M. and Al-Taharwa, I. (2011). "Optimizing the prediction accuracy of concrete compressive strength based on a comparison of data-mining techniques", *Journal of Computing in Civil Engineering*, 25(3), 242-253, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000088.

Dao, D.V., Ly, H.B., Trinh, S.H., Le, T.T. and Pham, B.T. (2019). "Artificial intelligence approaches for prediction of compressive strength of geopolymer concrete", *Materials*, 12(6), 983, https://doi.org/10.3390/ma12060983.

Deb, K. (2011). "Multi-objective optimisation using evolutionary algorithms: an introduction", In: Wang, L., Ng, A., Deb, K. (eds), *Multi-Objective Evolutionary Optimisation for Product Design and Manufacturing*, pp. 3-34, Springer: London.

Gandomi, A.H., Yun, G.J. and Alavi, A.H. (2013). "An evolutionary approach for modeling of shear strength of RC deep beams", *Materials and Structures*, 46(12), 2109-2119, https://doi.org/10.1007/978-0-85729-652-8_1.

Gen, M. and Cheng, R. (2000). *Genetic algorithms and engineering optimization*, John Wiley & Sons, Inc., USA, https://doi.org/10.1002/9780470172261.

Jang, J.S. (1993). "ANFIS: adaptive-network-based fuzzy inference system", *IEEE Transactions on Systems, Man, and Cybernetics*, 23(3), 665-685, https://doi.org/10.1109/21.256541.

Jang, J.S.R., Sun, C.T. and Mizulani, E. (1996). *Neuro–fuzzy and soft computing: a computational approach to learning and machine intelligence*, Prentice-Hall, https://doi.org/10.1109/tac.1997.633847.

Kaveh, A., Hamze-Ziabari, S.M. and Bakhshpoori, T. (2017). "M5'algorithm for shear strength prediction of hsc slender beams without web reinforcement", *International Journal of Modeling and Optimization*, 7(1), 48-53, https://doi.org/10.24200/sci.2017.4509.

Kennedy, J., Eberhart, R.C., and Shi, Y. (2001). *Swarm intelligence,* Morgan Kaufmann Publishers, San Francisco, https://doi.org/10.1007/s00897020553a.

Keshavarz, Z. and Torkian, H. (2018). "Application of ANN and ANFIS models in determining compressive strength of concrete", *Journal of Soft Computing in Civil Engineering*, 2(1), 62-70, https://doi.org/10.22115/SCCE.2018.51114.

Khatibinia, M. and Mohammadizadeh, M.R. (2017). "Intelligent fuzzy inference system approach for modeling of debonding strength in FRP retrofitted masonry elements", *Structural Engineering and Mechanics*, 6(2), 283-293, https://doi.org/10.12989/sem.2017.61.2.283.

Khoshbin, F., Bonakdari, H., Ashraf Talesh, S.H., Ebtehaj, I., Zaji, A.H. and Azimi, H. (2016). "Adaptive neuro-fuzzy inference system multi-objective optimization using the genetic algorithm/singular value decomposition method for modelling the discharge coefficient in rectangular sharp-crested side weirs", *Engineering Optimization*, 48(6), 933-948, https://doi.org/10.1080/0305215x.2015.1071807.

Kong, F.K., Robins, P.J. and Cole, D.F. (1970). "Web reinforcement effects on deep beams", *Journal Proceedings*, 67(12), 1010-1018, https://doi.org/10.14359/7336.

Lin, J.C.W., Yang, L., Fournier-Viger, P., Hong, T.P. and Voznak, M. (2017). "A binary PSO approach to mine high-utility itemsets", *Soft Computing*, 21(17), 5103-5121, https://doi.org/10.1007/s00500-016-2106-1.

Liu, J. and Mihaylov, B.I. (2016). "A comparative study of models for shear strength of reinforced concrete deep beams", *Engineering Structures*, 112, 81-89, https://doi.org/10.1016/j.engstruct.2016.01.012.

Moosazadeh, S., Namazi, E., Aghababaei, H., Marto, A., Mohamad, H. and Hajihassani, M. (2019). "Prediction of building damage induced by tunnelling through an optimized artificial neural network", *Engineering with Computers*, 35(2), 579-591, https://doi.org/10.1007/s00366-018-0615-5.

Naderpour, H. and Mirrashid, M. (2020). "Shear strength prediction of RC beams using adaptive neuro-fuzzy inference system", *Scientia Iranica*, 27(2), 657-670, https://doi.org/10.24200/sci.2018.50308.1624.

Nguyen, T.A., Ly, H.B., Mai, H.V.T., and Tran, V.Q. (2021). "On the training algorithms for artificial neural network in predicting the shear strength of deep beams", *Complexity*, 3(1), 1-18, https://doi.org/10.1155/2021/5548988.

Pal, M. and Deswal, S. (2011). "Support vector regression based shear strength modelling of deep beams", *Computers and Structures*, 89(13-14), 1430-1439, https://doi.org/10.1016/j.compstruc.2011.03.005.

Prayogo, D., Cheng, M.Y., Wu, Y.W. and Tran, D.H. (2020). "Combining machine learning models via adaptive ensemble weighting for prediction of shear capacity of reinforced-concrete deep beams", *Engineering with Computers*, 36(3), 1135-1153, https://doi.org/10.1007/s00366-019-00753-w.

Savrun, M.M. and İnci, M. (2021). "Adaptive neuro-fuzzy inference system combined with genetic algorithm to improve power extraction capability in fuel cell applications", *Journal of Cleaner Production*, 299(25 May), 126944, https://doi.org/10.1016/j.jclepro.2021.126944.

Shariati, M., Mafipour, M. S., Mehrabi, P., Shariati, A., Toghroli, A., Trung, N.T. and Salih, M.N.A. (2021). "A novel approach to predict shear strength of tilted angle connectors using artificial intelligence techniques", *Engineering with Computers*, 37(3), 2089-2109, https://doi.org/10.1007/s00366-019-00930-x.

Shi, Y., Liu, H., Gao, L. and Zhang, G. (2011). "Cellular particle swarm optimization", *Information Sciences*, 181(20), 4460-4493, https://doi.org/10.1016/j.ins.2010.05.025.

Sihag, P., Tiwari, N.K. and Ranjan, S. (2019). "Prediction of unsaturated hydraulic conductivity using adaptive neuro-fuzzy inference system (ANFIS)", *ISH Journal of Hydraulic Engineering*, 25(2), 132-142, https://doi.org/10.1080/09715010.2017.138186

1.
Smith, K.N. and Vantsiotis, A.S. (1982). "Shear strength of deep beams", *Journal Proceedings*, 79(3), 201-213, https://doi.org/10.14359/10899.
Socha, K. and Dorigo, M. (2008). "Ant colony optimization for continuous domains", *European Journal of Operational Research*, 185(3), 1155-1173, https://doi.org/10.1016/j.ejor.2006.06.046.
Storn, R. and Price, K. (1997). "Differential evolution, A simple and efficient heuristic for global optimization over continuous spaces", *Journal of Global Optimization*, 11(4), 341-359, https://doi.org/10.1023/a:1008202821328.
Subbaraj, P., Rengaraj, R. and Salivahanan, S. (2011). "Enhancement of self-adaptive real-coded genetic algorithm using Taguchi method for economic dispatch problem", *Applied Soft Computing*, 11(1), 83-92, https://doi.org/10.1016/j.asoc.2009.10.019.
Suguna, K., Raghunath, P.N., Karthick, J. and Uma Maheswari, R. (2018). "ANN based modeling for high strength concrete beams with surface mounted FRP laminates", *International Journal of Optimization in Civil Engineering*, 8(3), 453-467, http://ijoce.iust.ac.ir/article-1-355-en.htm.
Tan, K.H., Kong, F.K., Teng, S. and Guan, L. (1995). "High-strength concrete deep beams with effective span and shear span variations", *Structural Journal*, 92(4), 395-405, https://doi.org/10.14359/991.
Taghi Dastorani, M., Mahjoobi, J., Talebi, A. and Fakhar, F. (2018). "Application of machine learning approaches in rainfall-runoff modeling (Case Study: Zayandeh_Rood Basin in Iran)", *Civil Engineering Infrastructures Journal*, 51(2), 293-310, https://doi.org/10.7508/CEIJ.2018.02.004.
Toghroli, A., Mohammadhassani, M., Suhatril, M., Shariati, M. and Ibrahim, Z. (2014). "Prediction of shear capacity of channel shear connectors using the ANFIS model", *Steel and Composite Structures*, 17(5), 623-639, https://doi.org/10.12989/scs.2014.17.5.623.
Zhang, C. (2020). "Classification rule mining algorithm combining intuitionistic fuzzy rough sets and genetic algorithm", *International Journal of Fuzzy Systems*, 22, 1694-1715, https://doi.org/10.1007/s40815-020-00849-2.
Zhou, Q., Zhu, F., Yang, X., Wang, F., Chi, B. and Zhang, Z. (2017). "Shear capacity estimation of fully grouted reinforced concrete masonry walls using neural network and adaptive neuro-fuzzy inference system models", *Construction and Building Materials*, 153, 937-947, https://doi.org/10.1016/j.conbuildmat.2017.07.171.