Shear Strength Prediction of RC Beams Using Adaptive Neuro-Fuzzy Inference System

Hosein Naderpour¹ and Masoomeh Mirrashid²

1. Associate Professor, Faculty of Civil Engineering, Semnan University, Semnan, Iran.
2. Ph.D. Candidate, Faculty of Civil Engineering, Semnan University, Semnan, Iran.

Abstract

In complex engineering problems, there are some inexact conceptions or a lot of parameters which must be considered. Soft computing is an approach that successfully applied to solve such problems. Determination of fuzzy rules for many problems has not been quite possible by an expert human. In this case, a neuro-fuzzy system which is the combination of neural network (for its ability to learn by datasets) and fuzzy system (for solving the drawback of the neural network) can be enhancing the performance of the system with several parameters or complex conditions. This paper shows the capability of a neuro-fuzzy system namely ANFIS to predicting the shear strength of reinforced concrete beams with steel stirrups. For this propose, the collection of laboratory results which was published in literatures used to train and finally test the proposed system. For this purpose, the sub-clustering approach (SC) applied for generating ANFIS. The results indicated that the considered neuro-fuzzy system was able to predict the shear strength of the RC beams which have been reinforced with steel stirrups.

Keywords: Adaptive neuro-fuzzy inference system (ANFIS), sub-clustering, shear strength, reinforced concrete beams.

* Corresponding author: Telephone: +98 23 33533781; Fax: +98 23 33654121, E-mail address: naderpour@semnan.ac.ir (H. Naderpour)
1 Introduction

A reinforced concrete beam, resist the shear force using several mechanisms such as concrete shear strength (which is result shear compression force and aggregate interlock), vertical reinforcing steel and shear stirrups. The shear failure of a reinforced concrete beam is a dangerous brittle failure. Therefore, an exact analysis of shear must be considered for the RC element to prevent this type of failure. There are several experimental research which was investigation the performance of RC beams to improve the available relationships that presented in common codes such as (ACI 318-14) [1]. In many cases, there is a need for strengthening or retrofitting the reinforced concrete elements. Moreover, it sometimes needs to design the members with high shear strength. For this purpose, fibre reinforced polymer materials (FRP) have been widely used for reinforcing or strengthening the structural concrete elements such as RC beams [2, 3] especially for shear strengthening. There are several guidelines for determining the shear strength of an RC member which has FRP such as ACI 440.1 R-15 [4] and CIDAR [5].

The term of soft computing first defined by L.A Zadeh (1994) [6]. Wilamowski [7] investigated the advantages of soft computing in engineering. There are a lot of applications for this type of computational approach in civil engineering for prediction application such as for load forecasting [8] or earthquake magnitude prediction [9, 10]. In structural engineering, the published works for prediction the shear capacity of the reinforced concrete beams with or without strengthen material divided into two approaches which are described in the following section. The first one is based on traditional methods namely hard computing and the second one is based on soft computing.

1.1 Prediction based on hard computing

Hard computing as a computational approach which is used to solve problems with traditional ways such as statistical methods. With considering hard computing, shear strength in RC beams was investigated in last literature such as for size effect on the shear strength of RC beams [11]. Mungwa et al. (1999) developed a flexible shear connector possesses using modern fixing techniques based on an experimental study on composite wood–concrete beam with the aim of higher rigidity, ductility and ultimate strength [12]. Adhikary et al. (2000) predicted the ultimate shear strength in RC beams with epoxy-bonded continuous horizontal steel plates. Their results indicated that continuous steel plates bonded externally to beam webs are effective for the shear strengthening [13]. Finite element methods were also used for analysis headed stud shear connectors in the steel-concrete composite beam by Lam and El-Lobody (2001) [14].

Maro et al. (2003) showed that whereas differential vertical deflections between adjacent vertical members are small owing to high stiffness of beams, the load transfer between them can be significant [15]. Park et al. (2005) proposed the relationships to determine the shear strength of the connection between a steel coupling beam and a reinforced concrete shear wall in a hybrid wall system [16].
Eun et al. (2006) established the shear strength of a reinforced concrete deep beam with web opening based on experimental eighteen beams and showed that the load-carrying capacity of deep beams with openings can be largely improved by the increase in concrete strength [17]. Park and Yun (2006) presented the equations to predict the strength of steel coupling beam-reinforced concrete shear wall connections [18]. Park and Yun (2006) also investigated the analytical and experimental studies to develop the strength equations of steel coupling beams–concrete wall connections [19]. Kim and LaFave (2007) studied the most important influence parameters on joint shear behavior using an extensive database of reinforced concrete (RC) beam-column connection test specimens exhibiting joint shear failure. They were investigated the joint shear cracking stresses and strains by equations and examined the design checks recommended by codes [20]. Ranzi and Zona (2007) presented a model for the analysis of steel-concrete composite beams with partial shear interaction. The numerical solution was obtained by means of the finite element method and the numerical results obtained with the proposed model were compared to those of the composite beam model with partial shear interaction to determine under which conditions, shear deformations of the steel component need to be considered in the analysis and to evaluate how these were affected by the shear connection stiffness [21].

Gara et al. (2009) studied a beam finite element for the long-term analysis of the partial shear interaction at the slab–girder interface using the displacement approach [22]. Jurkiewicz (2009) tested a steel-concrete composite beam which built with a horizontal shear connector under cyclic loading and showed that the considered connector device allows satisfactory behavior under static and cyclic loading in accordance with structural modern codes requirements [23]. Buyukkaragoz and Arslan (2011) investigated the effect of steel plates with shear studs used in the weak column–strong beam connections based on five RC specimens which were tested under cyclic loading. The test results indicated that the shear studs improved the strength and stiffness of the specimens [24]. Muhsen and Umemura (2011) proposed a model for estimating the shear strength of RC interior beam-column connections. Their results showed that estimation of shear strength by the new model was good [25]. Ramadass and Thomas (2011) studied the details of the flexure-shear analysis of concrete beams reinforced with GFRP bars. Their prediction indicated that the longitudinally FRP reinforced concrete beams having no stirrups fail in shear [26]. Doh et al. (2012) developed a nonlinear layered finite element method with the aim of analyzing the punching shear strength of reinforced concrete flat palate with spandrel beams [27]. Setiawan and Satono (2012) investigated the capacity of RC beams with different cross-section types of lateral reinforcement [28]. Shi et al. (2012) analyzed the shear capacity and mechanical properties of deformation comparatively between GFRP reinforced concrete beams and steel reinforced concrete beams. They also investigated the influencing factors of shear capacity of GFRP-RC beam with circular cross-section and showed that the influencing coefficient of GFRP on concrete increases with shear span ratio reducing [29].

Gunasekaran et al. (2013) studied the structural shear behavior and shear capacity
of the reinforced concrete beam made with coconut shell and compared his results with the normal control concrete. It was observed that the shear behavior of coconut shell concrete was comparable to that of other lightweight concretes [30]. Houachine et al. (2013) proposed an analytical method and showed that by using the high order function of shear deformation, interfacial shear stresses and pull forces were suitably approximated [31]. Sung et al. (2013) presented a nonlinear pushover analysis procedures that consider shear failure at beam-column joints which can be used to estimate the structural behavior of RC frames [32]. Bui et al. (2014) proposed a stress-resultant model combines the descriptions of the diffuse plastic failure in the beam and the localized failure with the creation of the corresponding plastic hinges representing both bending and shear failure mechanisms [33]. Long et al. (2014) investigated models which were used to simulated beam-column members with a wide range of shear span-to-depth ratios and also proposed a method by comparing numerical predictions with experimental results [34].

Manos et al. (2014) studied validation of a numerical model which can approximate the shear behavior of reinforced concrete RC rectangular beams strengthened against shear with externally applied open hoop fibre reinforcing polymer (FRP) strips [35]. Yu et al. (2014) tested five pre-stressed steel ultra-high-strength reinforced concrete beams monotonically until shear failure to study the failure pattern, load-deflection behavior, shear capacity, shear crack width and shear ductility [36]. Alam et al. (2015) developed kenaf fibre reinforced polymer (KFRP) laminate for shear strengthening of reinforced concrete beams and proposed design and theoretical models [37]. Bompa and Elghazouli (2015) examined the shear transfer mechanisms and ultimate behavior of hybrid systems consisting of reinforced concrete beams connected to structural steel columns [38]. Shahbazpanahi and Kamgar (2015) developed a numerical method to model shear-strengthening of reinforced concrete beams by using fiber reinforced polymer (FRP) composites and observed that the load capacity increased with the number of CFRP sheets in the shear span [39]. Campione et al. (2015) presented a calculation method for the prediction of the shear resistance of precast composite beams and developed their model on the basis of the results of a reference experimental campaign of three-point bending tests [40]. Wang et al. (2015) proposed a joint connecting beam which widely used technologies of the mechanic sleeve and sleeve-mortar splicing connections to connect the reinforcement of precast concrete shear walls [41]. Zhang et al. (2015) studied a mechanics-based segmental approach which can analyze an RC beam with any type of concrete and reinforcement base on a segmental approach and also proposed simplified closed form solution for design [42].

1.2 Prediction based on soft computing

Soft computing is an approach which can be realized by experimental or analytical suitable data than hard computing. This computational method is used to solve problems with uncertain or complex conditions in multi-dimensional space. It has high accuracy. In concrete structures, there are more parameters which affect on analysis or design and recent studies indicated that soft computing was able to use in structural engineering applications such as for the shear strength of RC beams.
Adhikary and Mutsuyoshi (2004) investigated the ability of multilayer feedforward artificial neural network to predict the ultimate shear capacity of RC beams with web-bonded steel plates and showed that ANN predicted the ultimate shear capacity of RC beams as well as cross-validating the results from other models such as a finite element model and analytically empirical models [43]. Adhikary and Mutsuyoshi (2006) predicted the ultimate shear strength of steel fibre RC beams based on a multilayer feed forward neural network with the back propagation learning algorithm. They showed that ANN was able to consider prediction [44]. The shear resistance of RC beams using neural networks was estimated by Abdalla et al. (2007). This study confirmed that ANN can be used for prediction [45]. Nehdi et al. (2007) used Zsutty equation [46] for optimization the equations of calculating the shear capacity of FRP-reinforced concrete beams with and without shear reinforcement based on the genetic algorithm [47].

Ahn et al. (2007) investigated the shear force characteristics of steel fiber reinforced concrete with varying shapes and mixture ratios using artificial neural networks with backpropagation algorithm and showed that ANN was a suitable approach for the prediction [48]. Perera et al. (2010) applied neural networks to predict the ultimate shear strength of FRP-strengthened RC beams by a database which included shear strengthened RC beams with FRP using U-jacketing and full wrapping configurations. They also presented design equations to calculate the shear capacity of RC beams FRP-strengthened in shear [49]. Tanarslan (2011) investigated the performance of ANN to predict the shear capacity of the reinforced concrete beams retrofitted in shear by means of side-bonded FRP and his results indicated more accuracy with the values which were obtained based on ANN [50]. Tanarslan et al. (2012) were also used the back propagation network to determine the shear strength contribution of RC beams strengthened in shear by retrofitting externally bonded wrapped and U-jacketed FRP reinforcement and showed that ANN was a good tool for predicting [51]. Lee and Lee (2014) studied a theoretical approach which predicted the shear strength of slender FRP reinforced concrete flexural members without stirrups [52]. Nasrollahzadeh and basiri (2014) presented a fuzzy system with Gaussian membership functions and with the Takagi–Sugeno inference system using the subtractive clustering algorithm to predict the shear strength of FRP-reinforced concrete beams. Their fuzzy system was able to predict the shear strength of FRP-RC beams [53]. Perera et al. (2014) proposed formulations of design equations for RC beams shear strengthened with NSM-FRP rods using artificial neural networks which created by backpropagation and the training algorithm of Levenberg-Marquardt to predict the capacity of the shear strengthened RC beams with NSM-FRP and their results indicated that ANN can be used for evaluating the shear capacity of RC members strengthened with NSM-FRP [54]. A shear design approach to predict the contribution of the anchorage FRP reinforcement to the ultimate shear capacity using feed-forward back-propagation algorithm also proposed by Tanarslan et al. (2015) [55]. Furthermore, there are some other investigations based on soft computing methods for estimating the response of concrete structures [56-70]

1.3 The aim of the study
Failure under shear of a reinforced beam with longitudinal bars and stirrups in the web may occur by diagonal tension which is resisted by beam action in the shear span without web reinforcement and also truss mechanism of web reinforcement that is generates an additional resisting mechanism to shear for the beam [71]. The shear resistance in a usual RC beams is governed by shear strength of the compression zone (which is depends on concrete strength), aggregate interlock, dowel effect of tensile longitudinal bars and also shear reinforcements such as stirrups. Shear forces cause shear stresses [72] and a high shear stress generally cause cracks in RC beams. The failure in shear for a reinforced concrete beam is a mode of failure due its brittleness. Because of the importance of this failure, it is necessary to consider more investigations and the current study followed this purpose based on neuro-fuzzy system as a soft computing approach which is not applied before.

2 Adaptive neuro-fuzzy inference system (ANFIS)

2.1 Structure of ANFIS

Adaptive neuro-fuzzy inference system (ANFIS) is a fuzzy inference system for function approximation based on hybrid neuro-fuzzy systems was introduced by Jang [73]. ANFIS used a Sugeno-type fuzzy system in the five-layer network (the input layer not counted by Jang) which illustrate in Fig.1. For two inputs $x$ and $y$ and one output $z$.

Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno’s type:

Rule 1: If $x$ is $A_1$ and $y$ is $B_1$, then $f_1 = p_1 x + q_1 y + r_1$

Rule 2: If $x$ is $A_2$ and $y$ is $B_2$, then $f_2 = p_2 x + q_2 y + r_2$

Then the corresponding equivalent ANFIS architecture is shown in Fig.1.

The node functions in the same layer are of the same function family as described below [74]:

**Layer 1**: Every node $i$ in this layer is a square node with a node function as Eq.1:

$$O_i^1 = \mu_{A_i}(x) \tag{1}$$

Where $x$ is the input to node $i$, and $A_i$ is the linguistic label (such as “small” or “large”) associated with this node function. In other words, $O_i^1$ is the membership function of $A_i$ and it specifies the degree to which the given $x$ satisfies the quantifier $A_i$. Any continuous and piecewise differentiable function, such as commonly used bell-shaped, trapezoidal or triangular-shaped membership functions are qualified candidates for node function in this layer.
Layer 2: Every node in this layer is a circle node labeled $\Pi$ which multiples the incoming signals and sends the product out. For instance (Eq.2),

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \ i = 1,2.$$  \hspace{1cm} (2)

Each node output represents the T-norm operators that combine the possible input membership grades in order to compute the firing strength of a rule.

Layer 3: Every node in this layer is a circle node labeled $N$. The $i$th node calculates the ratio of the $i$th rule’s firing strength to the sum of all rules’ firing strengths (Eq.3):

$$\bar{w}_i = \frac{w_i}{w_1 + w_2}, \ i = 1,2.$$  \hspace{1cm} (3)

For convenience, outputs of this layer will be called normalized firing strengths.

Layer 4: Every node $i$ in this layer is a square node with a node function (Eq.4):

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i)$$

Where $\bar{w}_i$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as consequent parameters that are adjustable.

Layer 5: The single node in this layer is a circle node (adaptive node) labeled $\sum$ that computes the overall output as the summation of all incoming signals (Eq.5):

$$O_i^5 = \text{overall output} = \sum_i \bar{w}_i f_i = \frac{\sum \bar{w}_i f_i}{\sum \bar{w}_i}$$

2.2 Sub-clustering approach

Clustering is a task of assigning a set of data into groups called clusters to discover structures and patterns in a dataset and the radius of a cluster is the maximum distance between all the points and the centroid. Sub-clustering (SC) is based on classifying each point of the dataset just to one cluster and was proposed by Chiu [75]. The SC method assumes that each data point is a potential cluster center and calculates the potential for each data point based on the density of surrounding data points [9]. The measure of the potential for a data point is a function of its distances to all other data points. A data point with many neighboring data points will have a high potential value. The data point with the highest potential is selected as the first cluster center, and the potential of data points near the first cluster center is destroyed. Then data points with the highest remaining potential as the next cluster center and the potential of data points near the new cluster center are destroyed [9]. It is notable that the influential radius of the cluster is critical for determining the
number of clusters and data points outside this radius has little influence on the potential. Also, a smaller radius leads to many smaller clusters in the data space, which results in more rules [75].

3 Database

ANFIS needs a dataset for training. It is mentioned that the ability of a system such as ANN or ANFIS is depended on the data which is used in train or validation phase. In this paper, the collection of 194 experimental results which were published in literature applied to train and tests the ANFIS [76-93]. A summary of dataset presents in Table.1. The parameters in this table including: width of the member (b), effective depth of the member (d), concrete compressive strength ($f_{co}$), the yielding strength of transverse reinforcement ($f_{ty}$), the yielding strength of longitudinal reinforcement ($f_{ty}$), web cross-sectional area of the reinforcement as a proportion of the cross-sectional area of the beam ($\rho_{st}$), the transverse reinforcement ratio ($\rho_{tr}$) and the experimental shear strength ($V$).

To classify the interval of values that are different to the same scale, the normalizing procedure was used. A simple normalization relationship within the value of 0.1 to 0.9 which is used for normalization in this paper is the Eq.6:

$$x_i = 0.8 \frac{x-x_{\text{min}}}{x_{\text{max}}-x_{\text{min}}} + 0.1$$  \hspace{1cm} (6)

Where $x_i$ is the normalized value of a certain parameter, $x$ is the measured value for this parameter, $x_{\text{min}}$ and $x_{\text{max}}$ are the minimum and maximum values in the database for this parameter, respectively. In order to use the proposed ANFIS in this paper and accordance with the Eq.6, the minimum and maximum values of each variable are needed to calculate its normal value (0.1 to 0.9 in this paper). These amounts can be extracted from the Table.1 and can be used in the determination process of the ANFIS. The other details such as mean or average also presented to have an acknowledge about the applied database.

4 The proposed ANFIS model

4.1 Properties of the model

First, the datasets divided to train data consist of 160 pairs of inputs and outputs; and test data with 34 pairs. In this study, ANFIS with seven parameters including: width of the member, effective depth of the member, concrete compressive strength, the yielding strength of transverse reinforcement, the yielding strength of longitudinal reinforcement, web cross-sectional area of the reinforcement as a proportion of the cross-sectional area of the beam and also the transverse reinforcement ratio used to prediction the shear strength of RC beams with steel stirrups. The range of influence considered 0.6 (to specify a cluster center’ range of influence in each of the data dimension) and the squash factor (the factor to multiply the range of influence that
determines the neighborhood of a cluster) applied 1.25. The accept ratio (the factor which sets the potential, as a fraction of the potential of the first cluster center, above which another data point is accepted as a cluster center) and reject ratio (the factor which sets the potential, as a fraction of the potential of the first cluster center, below which another data point is accepted as a cluster center) was 0.5 and 0.15 respectively.

4.2 Membership functions and clusters

ANFIS based on sub-clustering approach, used a Gaussian membership function (Fig.2) for input parameters which are shown in Figs. 3-9 as follows (Eq.7):

$$
\mu (x; \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}}
$$

(7)

Where c is the mean and \( \sigma \) is the variance for \( x \).

It is mentioned that this type of membership function needs two parameters to define (includes \( \sigma \) and \( c \)). For each input, six Gaussian membership functions used and their details presented in Table.2. The parameters of clusters (CL) also showed in Table.3. These parameters refer to the output’s equations (Eq.8) which are used to calculate the shear strength based on Eq.4. The final ANFIS structure is illustrated in Fig.10.

$$
CL_j = a_1x_1 + a_2x_2 + a_3x_3 + C \quad j=1,...,6
$$

(8)

The parameters \( a_1, ..., a_7 \) are coefficients of the input \( x_1, ..., x_7 \). The parameter \( C \) is deal with a constant value. The amounts of these parameters presented in Table 3.

4.3 Rules

In this study, first, several ANFIS models with different approach and parameters created and finally, the best of them were considered. The selected model which generated based on the subtractive clustering method used six simple rules including:

**Rule 1:** If “\( b \)” is C1 and “\( d \)” is C1 and “\( f_{co} \)” is C1 and “\( \rho_{rt} \)” is C1 and “\( f_{sy} \)” is C1 and “\( \rho_{st} \)” is C1, then “\( V \)” is in cluster1.

**Rule 2:** If “\( b \)” is C2 and “\( d \)” is C2 and “\( f_{co} \)” is C2 and “\( \rho_{rt} \)” is C2 and “\( f_{sy} \)” is C2 and “\( \rho_{st} \)” is C2, then “\( V \)” is in cluster2.

**Rule 3:** If “\( b \)” is C3 and “\( d \)” is C3 and “\( f_{co} \)” is C3 and “\( \rho_{rt} \)” is C3 and “\( f_{sy} \)” is C3 and “\( \rho_{st} \)” is C3 and “\( f_{sy} \)” is C3, then “\( V \)” is in cluster3.
Rule 4: If “b” is C4 and “d” is C4 and “fc” is C4 and “ρt” is C4 and “fy” is C4 and “ρst” is C4 and “fxy” is C4, then “V” is in cluster4.

Rule 5: If “b” is C5 and “d” is C5 and “fc” is C5 and “ρt” is C5 and “fy” is C5 and “ρst” is C5 and “fxy” is C5, then “V” is in cluster5.

Rule 6: If “b” is C6 and “d” is C6 and “fc” is C6 and “ρt” is C6 and “fy” is C6 and “ρst” is C6 and “fxy” is C6, then “V” is in cluster6.

4.4 Final ANFIS output

Based on the rule base which is presented in the previous section, the rule’s weight W for each of six rules can be calculated as follows:

\[ W_1 = (c_{11})(c_{12})(c_{13})(c_{14})(c_{15})(c_{16}) \]
\[ W_2 = (c_{21})(c_{22})(c_{23})(c_{24})(c_{25})(c_{26}) \]
\[ W_3 = (c_{31})(c_{32})(c_{33})(c_{34})(c_{35})(c_{36}) \]
\[ W_4 = (c_{41})(c_{42})(c_{43})(c_{44})(c_{45})(c_{46}) \]
\[ W_5 = (c_{51})(c_{52})(c_{53})(c_{54})(c_{55})(c_{56}) \]
\[ W_6 = (c_{61})(c_{62})(c_{63})(c_{64})(c_{65})(c_{66}) \]

The normal value of the shear strength \( V_n \) based on the ANFIS model can be determined by Eq.9. It is worth noting that the output of the Eq.9 can be easily converted to the real value based on Eq.6 and the amount values of Table.1 (the minimum and maximum of the output parameter).

\[ V_n = \frac{\sum_{j=1}^{6} w_{Rule,j} C_{L,j}}{\sum_{j=1}^{6} w_{Rule,j}} \]  

(9)

5 Results

5.1 ANFIS results

After generating ANFIS, it was trained with considered 160 pairs of inputs-output based on selected conditions which presented in previous sections. Fig.11 showed the training process which indicated that the ANFIS reached to its minimum error at less than 50 epochs. The outputs of the ANFIS against experimental data (normalized values between 0.1 to 0.9) presented in Fig.12. It is clear from the figure that ANFIS has a good performance in the training phase. The selected neuro-fuzzy also predicted the shear strength of RC beams with steel stirrups as well (Fig.13).

The proposed ANFIS in this paper has a correlation coefficient \( R^2 \) equal to 0.98 and 0.94 in training and the test phase respectively. This values was clear from Fig.14 and also Fig.15. It was important that the selected data for training must be
covered all of the range of shear values. This is because of increasing the accuracy of the ANFIS.

5.2. Error calculations and correlation coefficient values

The details of results for the ANFIS have been included one point in the train (0.097) and also two points in test (0.074, 0.076) which have values less than 0.1. These amounts lead to negative values after converting them to real values (based on Eq.6). To avoid this, we assume that they correspond with 0.1. Because these amounts are so close to 0.1, the considered assumption can be suitable. Table.4 presented the final results after converting to whole 160 training data and 34 test data. A comparison between the results of the proposed ANFIS and other codes for $\frac{V_{\text{test}}}{V_{\text{ANFIS}}}$ ratio showed a value equal to 0.998 for ANFIS, while it is equal to 1.88, 1.48, 1.37 for ACI 318-08, CSA A23.3-04 and CEN 2004 respectively.

6 Conclusion

In this paper, a neuro-fuzzy system namely ANFIS proposed to predict the shear strength of reinforced concrete beams with steel stirrups using seven parameters including the width of the member, effective depth of the member, concrete compressive strength, the yielding strength of transverse reinforcement, the yielding strength of longitudinal reinforcement, web cross-sectional area of the reinforcement as a proportion of the cross-sectional area of the beam and also the transverse reinforcement ratio. ANFIS needs to a database to determine its value. It is mention that a collection of more data can be a direct affect on results of ANFIS and leads to a model with high accuracy. In this paper, ANFIS generated by the subtractive clustering method and trained with 160 data which collected from the literature based on experimental data. Afterward, the neuro-fuzzy model was examined to specify the capability of ANFIS and for this purpose, 34 data was considered. The final results indicated that ANFIS can be used to predict the shear strength of RC beams with a suitable accuracy. ANFIS is a powerfull tool for determining the values of parameters in multi-dimensional space with uncertain conditions. Because of these, there are many types of research in civil engineering which were done by it and the current paper, presents another application of this neuro-fuzzy system.

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Figure 1. Structure of ANFIS with 2 inputs and 2 rules. A square node (adaptive node) has parameters while a circle node (fixed node) has none [24].

Figure 2. Gaussian membership function with parameters 5 and 2 as the mean and the variance respectively.

Figure 3. Membership functions for “b”.

Figure 4. Membership functions for “d”.

Figure 5. Membership functions for “f_co”.

Figure 6. Membership functions for “ρ_tr”.

Figure 7. Membership functions for “f_ry”.

Figure 8. Membership functions for “ρ_st”.

Figure 9. Membership functions for “f_sy”.

Figure 10. The proposed ANFIS structure

Figure 11. The training process

Figure 12. The train results of ANFIS

Figure 13. The test results of ANFIS

Figure 14. The results of ANFIS for training phase

Figure 15. The results of ANFIS for test data
Table 1. Range of experimental data

Table 2. Parameters of the membership functions for each of the inputs

Table 3. Parameters of the output’s clusters.

Table 4. Distribution of error for the proposed ANFIS based on experimental data.

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Figure 15. The results of ANFIS for test data
Table 1. Range of experimental data

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<td>300.00</td>
<td>707.00</td>
<td>131.10</td>
</tr>
<tr>
<td>$\rho_{rt}$</td>
<td>2.70</td>
<td>2.72</td>
<td>1.00</td>
<td>4.80</td>
<td>0.91</td>
</tr>
<tr>
<td>$\rho_{st}$</td>
<td>0.30</td>
<td>0.36</td>
<td>0.10</td>
<td>1.90</td>
<td>0.26</td>
</tr>
<tr>
<td>$V$ (kN)</td>
<td>214.00</td>
<td>252.96</td>
<td>13.60</td>
<td>836.10</td>
<td>163.96</td>
</tr>
</tbody>
</table>

Table 2. Parameters of the membership functions for each of the inputs

<table>
<thead>
<tr>
<th>Input</th>
<th>Membership functions</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
<th>C6</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b$</td>
<td></td>
<td>0.21</td>
<td>0.38</td>
<td>0.14</td>
<td>0.57</td>
<td>0.15</td>
<td>0.36</td>
</tr>
<tr>
<td>$d$</td>
<td></td>
<td>0.21</td>
<td>0.40</td>
<td>0.12</td>
<td>0.49</td>
<td>0.12</td>
<td>0.45</td>
</tr>
<tr>
<td>$f_{co}$</td>
<td></td>
<td>0.17</td>
<td>0.37</td>
<td>0.17</td>
<td>0.40</td>
<td>0.16</td>
<td>0.37</td>
</tr>
<tr>
<td>$\rho_{rt}$</td>
<td></td>
<td>0.19</td>
<td>0.55</td>
<td>0.16</td>
<td>0.32</td>
<td>0.20</td>
<td>0.25</td>
</tr>
<tr>
<td>$f_{ry}$</td>
<td></td>
<td>0.15</td>
<td>0.15</td>
<td>0.20</td>
<td>0.79</td>
<td>0.15</td>
<td>0.13</td>
</tr>
<tr>
<td>$\rho_{st}$</td>
<td></td>
<td>0.18</td>
<td>0.22</td>
<td>0.15</td>
<td>0.10</td>
<td>0.21</td>
<td>0.26</td>
</tr>
<tr>
<td>$f_{sy}$</td>
<td></td>
<td>0.17</td>
<td>0.34</td>
<td>0.20</td>
<td>0.33</td>
<td>0.17</td>
<td>0.29</td>
</tr>
</tbody>
</table>

Table 3. Parameters of the output’s clusters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_1$: Coefficient of $b$</td>
<td>1.0960</td>
<td>0.9559</td>
<td>0.4386</td>
<td>0.7244</td>
<td>2.3590</td>
<td>1.9460</td>
</tr>
<tr>
<td>$a_2$: Coefficient of $d$</td>
<td>0.4803</td>
<td>1.3460</td>
<td>-4.4590</td>
<td>0.2059</td>
<td>1.3620</td>
<td>-1.3860</td>
</tr>
<tr>
<td>$a_3$: Coefficient of $f_{co}$</td>
<td>-0.0359</td>
<td>-0.1656</td>
<td>0.3612</td>
<td>0.0348</td>
<td>0.3841</td>
<td>0.0550</td>
</tr>
<tr>
<td>$a_4$: Coefficient of $\rho_{rt}$</td>
<td>1.6890</td>
<td>0.4570</td>
<td>1.6600</td>
<td>0.1079</td>
<td>0.2317</td>
<td>-0.7271</td>
</tr>
<tr>
<td>$a_5$: Coefficient of $f_{ry}$</td>
<td>-0.8179</td>
<td>-0.0567</td>
<td>2.2690</td>
<td>0.1138</td>
<td>-1.1040</td>
<td>-0.1055</td>
</tr>
<tr>
<td>$a_6$: Coefficient of $\rho_{st}$</td>
<td>0.3102</td>
<td>1.6790</td>
<td>-0.3096</td>
<td>0.1445</td>
<td>0.6772</td>
<td>0.1339</td>
</tr>
<tr>
<td>$a_7$: Coefficient of $f_{sy}$</td>
<td>0.2422</td>
<td>-0.3519</td>
<td>0.1526</td>
<td>0.4228</td>
<td>0.0046</td>
<td>0.0437</td>
</tr>
<tr>
<td>c: Coefficient of constant</td>
<td>-1.4060</td>
<td>-1.003</td>
<td>1.4790</td>
<td>-0.3252</td>
<td>-1.0520</td>
<td>0.6370</td>
</tr>
</tbody>
</table>
Table 4. Distribution of error for the proposed ANFIS based on experimental data.

<table>
<thead>
<tr>
<th>Range of error (%)</th>
<th>Number of data in the range of ANFIS</th>
<th>Percentage of whole data for ANFIS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Train data</td>
<td>Test data</td>
</tr>
<tr>
<td>&lt; ±5</td>
<td>65</td>
<td>12</td>
</tr>
<tr>
<td>&lt; ±10</td>
<td>112</td>
<td>22</td>
</tr>
<tr>
<td>&lt; ±15</td>
<td>133</td>
<td>26</td>
</tr>
<tr>
<td>&lt; ±20</td>
<td>143</td>
<td>27</td>
</tr>
<tr>
<td>&lt; ±25</td>
<td>153</td>
<td>28</td>
</tr>
<tr>
<td>&lt; ±30</td>
<td>156</td>
<td>28</td>
</tr>
<tr>
<td>&lt; ±35</td>
<td>157</td>
<td>29</td>
</tr>
<tr>
<td>&lt; ±40</td>
<td>158</td>
<td>30</td>
</tr>
<tr>
<td>&lt; ±45</td>
<td>160</td>
<td>31</td>
</tr>
<tr>
<td>&gt; ±45</td>
<td>0</td>
<td>3</td>
</tr>
</tbody>
</table>

Hosein Naderpour received his Ph.D. degree with high honors in structural engineering. He then joined Semnan University where he is presently Associate Professor of Structural Engineering. Since joining the faculty of Civil Engineering at Semnan University, Dr. Naderpour has taught a variety of undergraduate and graduate courses in the areas of structural engineering, numerical methods, mechanics of materials, structural stability, concrete structures, structural reliability, as well as soft computing. Dr. Naderpour is author of 60 papers published in journals and about 100 papers presented at national and international conferences. He has given several speeches in Switzerland, China, Australia, South Korea, Romania, Turkey, Canada, Hong Kong, Belgium, Portugal, Spain, Japan, Germany, Italy, Czech Republic and France. He is currently a chief member of Iranian Earthquake Engineering Association, Iran Concrete Institute (ICI), Iranian Society for Light Steel Framing (LSF), Iran's National Elites Foundation, Safe School Committee, Organization for Development, Renovation and Equipping Schools of Iran (DRES). Furthermore, he is currently the editor-in-chief of two international journals in the area of civil and mechanical engineering including Journal of Soft Computing in Civil Engineering (SCCE) and Journal of Computational Engineering and Physical Modeling (CEPM). His major research interests include: application of soft computing in structural engineering, seismic resilience, structural reliability, structural optimization and damage detection of structures.

Masoomeh Mirrashid is currently Ph.D candidate in structural engineering at the Semnan University, Iran. She earned third rank and the highest rank in Civil and Structural Engineering among all graduates from Islamic Azad University, Iran, in B.Sc and M.Sc degrees respectively. She has taught several courses of higher education including Theory of Elasticity and Plasticity, Dynamic of Structures, Advanced Concrete and Steel Structures. She was a technical committee member in 3rd Annual International Conference on Computer Science and Mechanical
Automation in China, 2017. Masoomeh Mirrashid is a technical reviewer for the journal of Frontiers of Structural and Civil Engineering published by Springer and also is author and co-author of several research publications including journal articles, international conference articles and also a book chapter in Saxe-Coburge publications -Stirlingshire, UK. Her fields are Structural engineering, Earthquake, vulnerability, neural networks, Fuzzy and Neuro-Fuzzy systems, machine learning methods and also optimization algorithms.