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Prediction of bond strength of spliced steel bars in concrete using artificial neural network and fuzzy logic

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HIGHLIGHTS

- ▶ Application of artificial intelligence for prediction of material behavior.
- ▶ Prediction of the bond strength of steel bars in concrete using ANN and fuzzy logic.
- ▶ ANN and fuzzy logic save time, reduce waste materials and decrease the design costs.
- ▶ ANN and fuzzy logic can predict in a quite short period of time with tiny error rate.
- ▶ ANN and fuzzy logic can effectively predict in spite of the complexity and incompleteness of the available data.

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ABSTRACT

Artificial neural networks (ANNs) and fuzzy logic (FL) models have been used in many areas of civil engineering applications in recent years. The main purpose of this study is to develop an ANN and FL models to predict the bond strength of steel bars in concrete. For this purpose, the experimental data of 179 different splice beam tests were used for training, validating and testing of the models. The models have six inputs including the splice length, the relative rib area, the minimum concrete cover, ratio of the area of longitudinal tension bars to the effective cross section in the splice region, ratio of the cross-sectional area of stirrups to their spacing in the splice region and concrete compressive strength. The bond strength of steel bars in concrete was the output data for both models. The mean absolute percentage error was found to be less than 6.60% for ANN and 6.65% for FL and R^2 values to be about 99.50% and 99.45% for ANN and FL for the test sets respectively. The results revealed that the proposed models have good prediction and generalization capacity with acceptable errors. Meanwhile, in this study the proposed ANN is a slightly more accurate than FL.

1. Introduction

Adequate bond between concrete and reinforcing bars in a splice is an essential requirement in the design of reinforced concrete structures. In general, the resistance to slippage of bars is defined as bond strength. A simple method of splicing a bar in reinforced concrete beams is lap splice. The behavior of splice region depends on both flexural and splitting cracks and they are related strictly to bond strength. For this reason, calculation of bond strength through splice beam tests becomes more popular and some national codes such as ACI408R-03 [1] represent a design-oriented formula for determining the splice length based on several experimental tests.

The bond strength of reinforcing bars (τ_b) is a function of the geometric and material properties of the concrete member and the reinforcing bars. As mentioned above, several factors influence the bond strength of spliced beams. The most important of them are concrete compressive strength ($\acute{f}_c$), splice length (l_S), the relative rib area (R_r, the ratio of projected rib area normal to bar axis to the product of the nominal bar perimeter and the center-to-center rib spacing), minimum concrete cover (C_{min}) defined as the smallest of clear concrete covers in bottom and/or sides or $\frac{1}{2}$ of the clear spacing between bars, the amount of transverse steel area to spacing ratio $(\frac{A_v}{S})$, and the splice bar size illustrated as ratio of the area of the splice bar to the effective cross section of the beam (ρ) [1].

Azizinamini et al. [2] in their experimental studies on the bond strength of bars in high-strength concrete revealed that in this type of concrete, the average normalized bond strength respect to root of concrete compressive strength at failure decreases with an

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increase in compressive strength, and this rate of reduction increases as splice length increases.

El-Hacha et al. [3] investigated the effect of splice length and showed that increasing the splice length of a reinforcing bar increases its bond capacity. The relationship between bond force and the splice length to bar diameter ratio is nearly linearly, not proportionally, related to the stress in the steel bar up to yield strength. Beyond the yield strength, the relationship becomes nonlinear and significant splice length is required to achieve higher stress level.

Darwin et al. [4] described the analysis of 83 beam-splice specimens containing steel bars with relative rib areas ranging from 0.065 to 0.140. In this range, the splice strength of steel bars increased with the increase in the stress of stirrups, and resulting in an increase in the confining force.

Tepfers [5] illustrated that the bond strength increases as cover and bar spacing increase. The mode of failure also depends on cover and bar spacing. For large cover and bar spacing, it is possible to obtain a pull-out failure, but for smaller ones, a splitting tensile failure occurs resulting in lower bond strength.

Orangun et al. [6] expressed the effect of transverse reinforcement by confining spliced bars and limiting the progression of splitting cracks and showed that confinement increase the bond strength. They also searched on the relationship between bar size and bond strength. The results showed that a longer development or splice length is required as bar size increases, and for a given splice length, larger bars achieve higher total bond forces than smaller bars for the same degree of confinement. This is true until bar spacing are reduced to the point that bond strength is decreased.

Generally, theses parameters have noticeable effects on the bond strength of steel bars in the splice region. But the individual contributions of these factors are difficult to separate, and sometimes they will be coupled. Although coupling effects are common such as the relation between the splice length and the relative bar area, several studies have revealed that compressive strength has the most significant contribution to the splice strength.

Nowadays, for reducing the amount of experiment costs, modeling methods based on artificial neural networks (ANNs) and fuzzy logic (FL) systems have become more popular and have been used by many researchers for many civil engineering applications such as drying shrinkage [7], concrete durability [8], ready mixed concrete delivery [9], mechanical behavior of concrete at high temperatures [10], concrete structures [11–14], and the behavior of bonding of bars in concrete [15,16].

Dahou et al. [15] investigated the bond strength by conducting pull-out tests on ribbed bars and developed an Artificial Neural Network (ANN) based on same experimental data to predict the ultimate bond strength. The results showed that ANN can be implemented to model the pull-out test accurately. Tanyildizi [16] presented a fuzzy logic model to predict bond strength of light-weight concrete under different curing condition accompanied with an experimental study. The obtained results from bond strength tests were compared with fuzzy logic results and showed that with a very low average error (6.6%), the proposed fuzzy logic model predicted successfully the bond strength of concrete.

The ANN and fuzzy logic models are two well-known branches of artificial intelligence and have been broadly and successfully used to simulate input–output systems. The basic strategy for developing ANN and FL systems is to train them on the results of a series of experiments. If the experimental results contain the relevant information about the problem, then the trained ANN and FL systems will contain sufficient information about the problem's response to qualify as a model.

Table 1
The range of parameters in database.

Variables	Minimum	Maximum	Mean	Standard deviation
L_s (mm)	254.0	5969.0	784.9	865.3
R_r	0.0590	0.1800	0.1059	0.0331
C_{min} (mm)	10.02	76.20	34.46	16.15
ρ (mm^2/mm^2)	0.7269	3.9705	2.4252	0.7310
$\frac{A_{tr}}{S}$ (mm^2/mm)	0	3.8943	1.4439	1.0020
$\acute{f}_c$ (MPa)	26.25	110.26	55.14	28.73
τ_b (MPa)	1.521	8.994	5.506	1.533

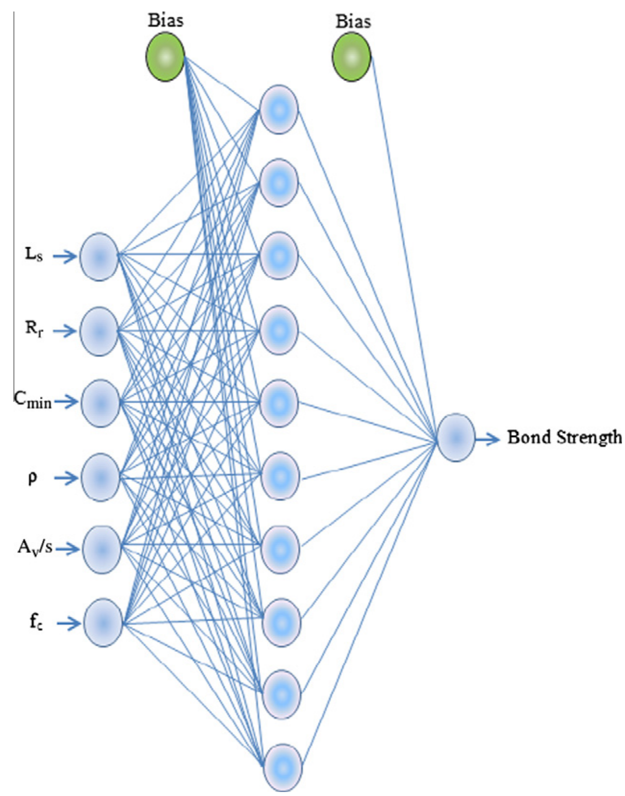

Fig. 1. The system used in the ANN model.

The main purpose of this study is to establish an artificial neural network and fuzzy logic model to predict the bond strength of steel bars in concrete. A total of 179 records from experimental studies were used as input for these models with six parameters each. Comparison of the models' outputs with the target bond strength revealed that the models' results have a good agreement with the experimental data.

2. Data collection

The main objective of this research is to develop ANN and fuzzy logic models to predict the bond strength of concrete. For this aim, at first it is needed to collect sufficient data and build a database for training, validating, and testing samples. The data used in this research was obtained from different sources [4,17–23].

Totally 179 records were gathered from the above-mentioned sources. Of these, 125 records were used for training, 27 records for validating, and 27 records for testing of the system. These selections are done by a random process to prevent any man-selection effects on the training process. Table 1 summarizes the range of input and output records.

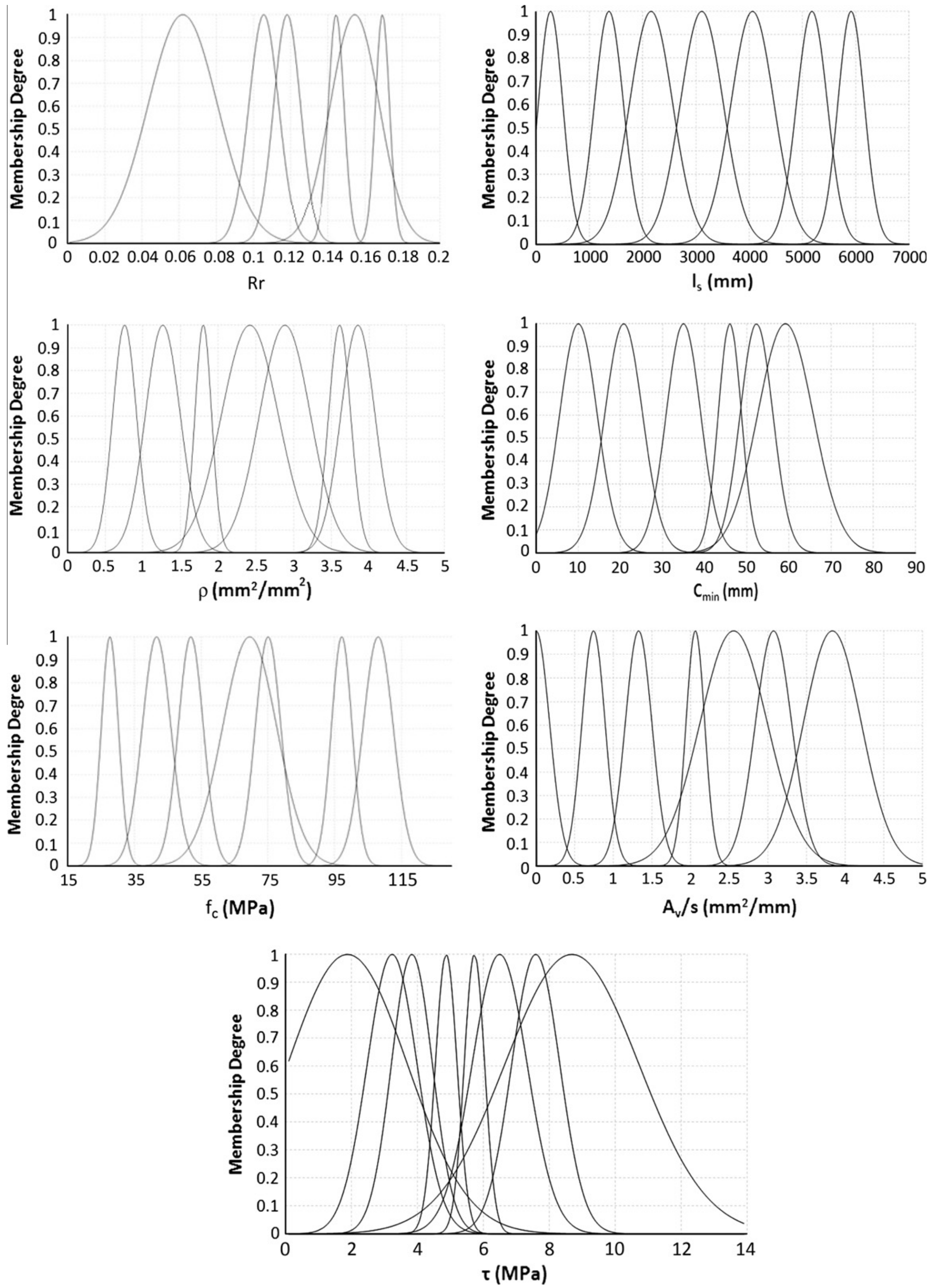

Fig. 2. Membership functions of input and output variables.

3. Artificial neural networks

The ANN modeling approach is a computer-based methodology that attempts to simulate some important features of the human nervous system. In other words, the ability to solve problems by applying information obtained from past experiences to new problems or case scenarios. In this section, a brief description of ANN modeling is given to help the reader's understanding [24].

3.1. Description of ANN

ANN architectures are formed by three or more layers including an input layer, an output layer, and a number of hidden layers in which neurons are connected to each other with modifiable weighted interconnections. The ANN architecture is commonly referred to as a fully interconnected feed forward multilayer perception. In addition, there is a bias, which is only connected to neurons in the hidden and output layers with modifiable weighted connections. The number of neurons in each layer may vary depending on the problem [25].

The most widely used training algorithm for multi-layered feed-forward networks is the back-propagation (BP) algorithm. The BP algorithm is a gradient descent technique that minimizes errors for a particular training pattern in which it adjusts the weighting by a small amount each time. The BP algorithm basically involves two phases. The first one is the forward phase where the activations are propagated from the input to the output layer. The second one is the backward phase where the error between the observed actual value and the desired nominal value in the output layer is propagated backwards in order to modify the weights and bias values. The inputs and outputs of training and testing sets must be initialized before the training of the feed work network. In the forward phase, the weighted sum of input components is calculated through the following equation [25]:

$$\mathrm{net}_j = \sum_{i=1}^{n} W_{ij} X_i + \mathrm{bias}_j \tag{1}$$

where net_j is the weighted sum of the jth neuron for the input received from the preceding layer with n neurons, W_{ij} is the weight between the jth neuron and the ith neuron in the preceding layer, X_i is the output of the ith neuron in the preceding layer. The output of the jth neuron out_j is calculated with a sigmoid function as follows [25]:

$$\mathrm{out}_j = f(\mathrm{net}_j) = \frac{1}{1 + e^{-(\mathrm{net}_j)}} \tag{2}$$

The training of the network is achieved by adjusting the weights and is carried out through a large number of training sets and cycles. The goal of the training procedure is to find the optimum set of weights, which would produce the right output for any input in the ideal case. Training the weights of the networks iteratively adjusted to capture the relationship between the input and output patterns [25].

Table 2
The τ statistical values of proposed models.

Data set	Model type	MAE	MAPE	RMSE	R^2	COR
Training	ANN	0.2363	4.7859	0.3029	0.9972	0.9832
	FL	0.1940	3.7860	0.2742	0.9976	0.9831
Validating	ANN	0.3444	6.3915	0.4101	0.9951	0.9724
	FL	0.2423	4.7039	0.2907	0.9974	0.9856
Testing	ANN	0.3185	6.5986	0.4065	0.9950	0.9778
	FL	0.3444	6.6488	0.4324	0.9945	0.9652

3.2. Network selection

Previous studies have related the number of neurons of each layer to the number of input and output variables and the number of training patterns [26,27]. However, these rules cannot be generalized [28]. Other researchers have proposed that the upper bound for the required number of neurons in the hidden layer should be one more than twice the number of input points. But, again this rule does not guarantee generalization of the network [29].

Choosing the number of hidden layers and neurons of each layer must be based on experiences, and a few numbers of trials are usually necessary to determine the best configuration of the network [30]. The number of neurons in an ANN must be sufficient for correct modeling of the problem of interest, but it should be sufficiently low to ensure generalization of the network [29].

Generally, a neural network is created for three phases commonly referred to as ‘training’, ‘validation’ and ‘testing’. Training is presented to the network during training, and the network is adjusted according to the obtained errors. Sample data (both inputs and desired outputs) are processed to optimize the network’s output and thereby minimize deviation. Validation is used to measure network generalization, and to halt training

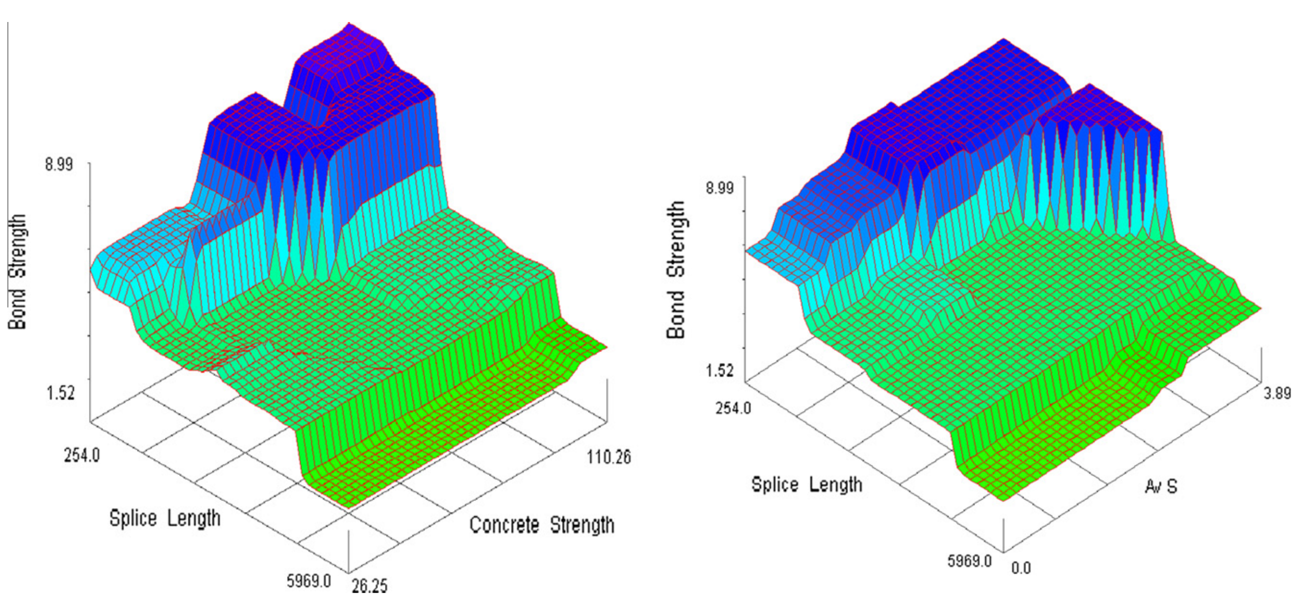

Fig. 3. Some inputs with τ_b surface, (a) combined effects L_s and $\acute{f}_c$ on τ, (b) combined effects L_s and $\frac{A_V}{S}$ on τ_b .

when generalization ceases improving and testing has no effect on training [29].

In this study, the ANN toolbox (nftool) in MATLAB was used to perform the necessary computations. A back-propagation training algorithm was utilized in a three-layer feed-forward network trained using the Levenberg–Marquardt algorithm [31,32].

In this paper, Levenberg–Marquardt back-propagation (LMBP) algorithm is utilized as the training algorithm instead of commonly used standard BP method for its robustness in computing process. LMBP is often the fastest available back-propagation algorithm, and is highly recommended as a first-choice supervised algorithm although it requires more memory than other algorithms [33]. Also in the present study, a nonlinear hyperbolic tangent sigmoid transfer function was used in the hidden layer and a linear transfer function in the output layer. The momentum rate and learning rate were determined and the model was trained through multiple iterations.

3.3. Neural network model and parameters

The ANN model developed in this research has six neurons (variables) in the input layer and one neuron in the output layer as illustrated in Fig. 1. The neurons of the input layer receive information from the outside environment and transmit them to the neurons of the hidden layers without performing any calculation. The hidden layer neurons then process the incoming information and extract useful features to reconstruct the mapping from the input space. The neighboring layers are fully interconnected by weights. Finally, the output layer neurons produce the network predictions to the outside world. As mentioned earlier, there is no general rule for selecting the number of neurons in a hidden layer. The choice of hidden layer size is mainly a problem and to some extent depends on the number and quality of the training pattern. After trying various networks, the numbers of neurons in hidden layer was matched to ten as illustrated in Fig. 1. The input layer weights (ILWs), the input layer biases (ILBs), the hidden layer weights (HLWs) and the hidden layer bias (HLB) of the optimum ANN model are given by:

$$\mathrm{ILW}=\begin{pmatrix} -0.2182 & -3.1757 & 0.7517 & -4.2051 & -0.4162 & 1.9857 & -0.2182 & -3.1757 & 0.7517 & -4.2051 \\ -3.3384 & -2.4569 & 0.1739 & 3.4254 & -1.0688 & -2.6017 & -3.3384 & -2.4569 & 0.1739 & 3.4254 \\ -2.2521 & 3.8483 & 4.4615 & 3.7986 & 5.5175 & 6.4529 & -2.2521 & 3.8483 & 4.4615 & 3.7986 \\ 2.8756 & 1.7623 & -2.3748 & -4.8030 & -1.5775 & 2.8231 & 2.8756 & 1.7623 & -2.3748 & -4.8030 \\ 1.4889 & -0.3499 & -0.0511 & 0.6598 & -0.3295 & 0.0774 & 1.4889 & -0.3499 & -0.0511 & 0.6598 \\ -7.3264 & 0.0696 & -0.6062 & -0.1044 & 0.7012 & 0.3519 & -7.3264 & 0.0696 & -0.6062 & -0.1044 \end{pmatrix} \tag{3}$$

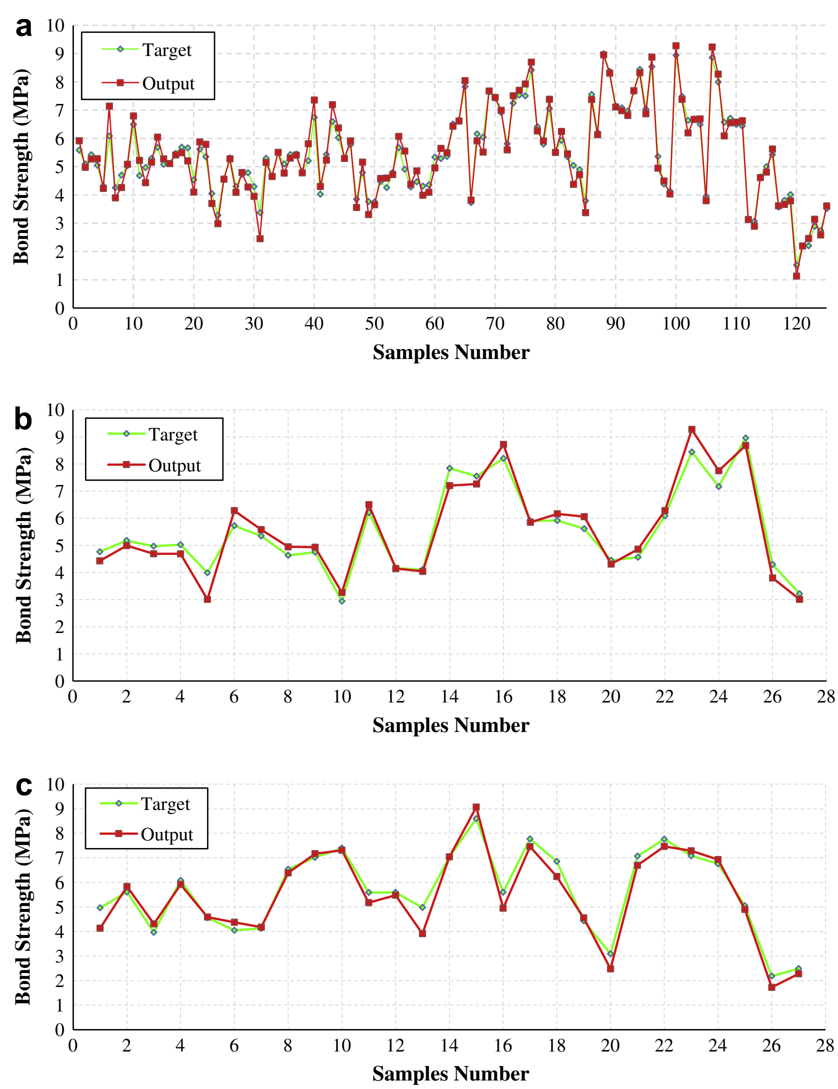

Fig. 4. Comparison of the ANN model output and actual data for (a) training, (b) validating and (c) testing sets.

$$\mathrm{ILB}^{\mathrm{T}} = (\,4.5726 \quad 4.7803 \quad 0.0782 \quad 1.0023 \quad 0.7184 \quad -6.5925 \quad 3.3504 \quad 4.9590 \quad -0.6443 \quad -0.4237\,) \tag{4}$$

$$\mathrm{HLW} = (\,0.0084 \quad 1.6553 \quad 0.0385 \quad -0.1979 \quad -0.7150 \quad 0.4448 \quad -0.1558 \quad 0.3850 \quad -0.3404 \quad -0.0482\,) \tag{5}$$

$$\mathrm{HLB} = (\,-1.8831\,) \tag{6}$$

4. Fuzzy logic model development

Fuzzy theory represents the uncertain state of the real world as it is, and consists of fuzzy set and fuzzy measure theories. Fuzzy set theory, proposed by Zadeh [34], sets up problems expressed as linguistic notions with unclear boundaries and uncertain concepts into useful concepts with the notion of membership functions and a definition of fuzzy sets. The fuzzy measure expresses the degree of fuzziness, which exists strongly in multi-subjective information, and solves problems using degrees of belief based on uncertain information [35].

The knowledge in fuzzy systems is often presented in fuzzy rule bases. Fuzzy rule base contains rules including all possible fuzzy relations between inputs and outputs. These rules are expressed in the IF–THEN format and obtained as in the following equation:

$$R_i : (l_s \text{ is } l_i) \text{ and } (R_r \text{ is } R_j) \text{ and } (C_{min} \text{ is } C_j) \text{ and } (\rho \text{ is } \rho_i) \text{ and } \left(\frac{A_v}{s} \text{ is } A_i\right) \text{ and } (f_c \text{ is } f_i) \tag{7}$$

Then $(\tau_b \text{ is } \tau_k)$ $i = 1, \ldots, 7, j = 1, \ldots, 6, k = 1, \ldots, 8$

The simplest structure of a fuzzy inference system consists of a unique and simple rule base relating input and output variables with linguistic concepts. The universe of discourse of the variables is covered by fuzzy sets associated with those linguistic concepts. The inference system is based on three stages: fuzzification, inference mechanism, and defuzzification.

Fuzzification converts each piece of input data to degrees of membership by a look up in one or more membership functions. The fuzzy inference mechanism is performed with three steps: firstly, the activation degree of each rule is calculated by applying conjunctive or disjunctive operators between the antecedents; secondly, an implication function is used to obtain the conclusion of

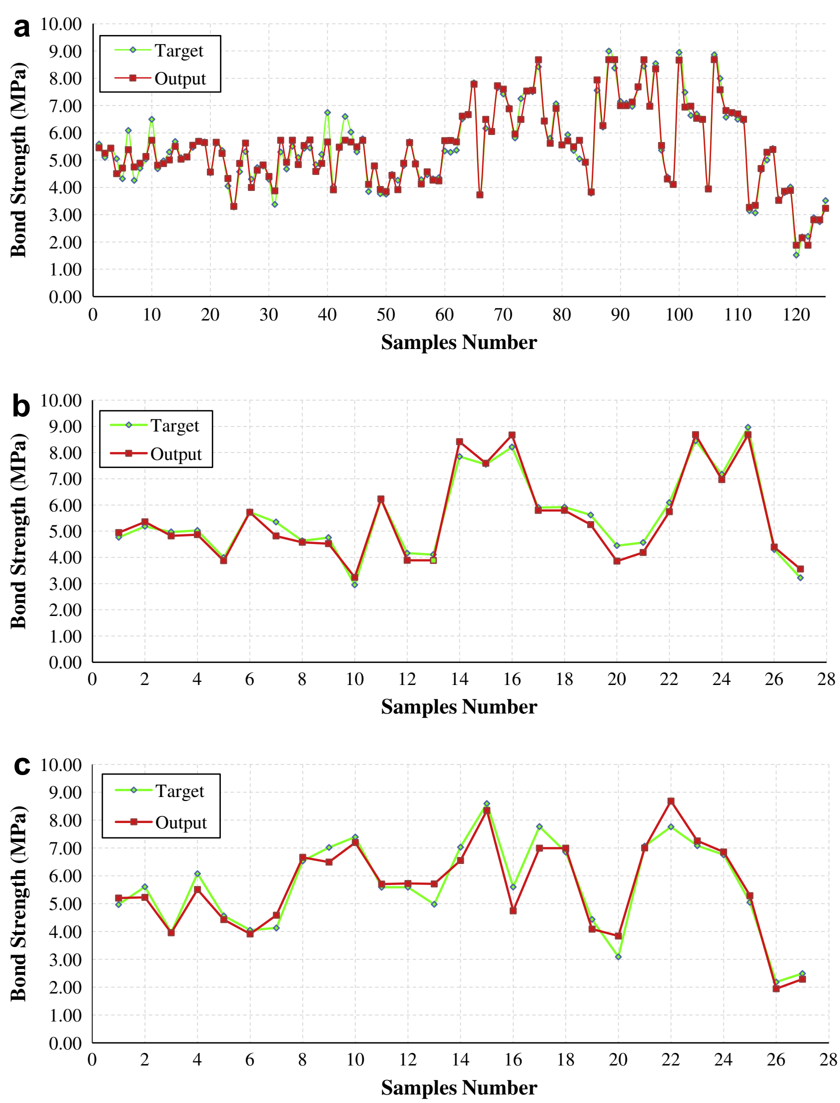

Fig. 5. Comparison of the FL model output and actual data for (a) training, (b) validating and (c) testing sets.

each rule; and, finally, the global conclusion is calculated by an aggregation operator. Defuzzification converts the resulting fuzzy outputs from the fuzzy inference engine to a number. There are many defuzzification methods such as weighted average (wtaver) or weighted sum (wtsum). Mamdani and Assilian [36] type fuzzy inference is the most common fuzzy inference mechanisms in practice and in the literature. In this study a max–min Mamdani inference was used on the rules and the centroid method was used for defuzzification.

In this study, the tool xfdm that can be carried out with the Xfuzzy3 [37] environment was used since it could extract the fuzzy rule from numerical data and allowed the user to apply supervised learning algorithms to complex fuzzy systems. The fixed Grid-based algorithm (Wang and Mendel algorithm [38]) was employed to extract the fuzzy rule base and back propagation with momentum and simplification methods were applied for tuning, verifying and simplification of fuzzy modeling. Membership functions of input and output variables for fuzzy logic model are given in Fig. 2 based on the results of predicting runs of the model. Also Fig. 3 shows the effects of two factors at a time on each surface plot of the bond strength.

5. Model assessment

To examine how close the predicted to the bond strength of steel bars in concrete, five indices, mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), absolute fraction of variance (R^2) and correlation coefficient (COR) were employed to evaluate the performance of models. These norms are according to the following equations:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|O_i - t_i| \tag{8}$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|O_i - t_i|}{t_i} \times 100 \tag{9}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_i - t_i)^2} \tag{10}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N}(O_i - t_i)^2}{\sum_{i=1}^{N}(O_i)^2}\right) \tag{11}$$

$$\mathrm{COR} = \frac{\sum_{i=1}^{N}(O_i - \overline{O}_i)(t_i - \bar{t}_i)}{\sqrt{\sum_{i=1}^{N}(O_i - \overline{O}_i)^2\sum_{i=1}^{N}(t_i - \bar{t}_i)^2}} \tag{12}$$

where t_i is the bond strength of steel bars in concrete, O_i is the predicted value, N is the total number of data points in each set of data,

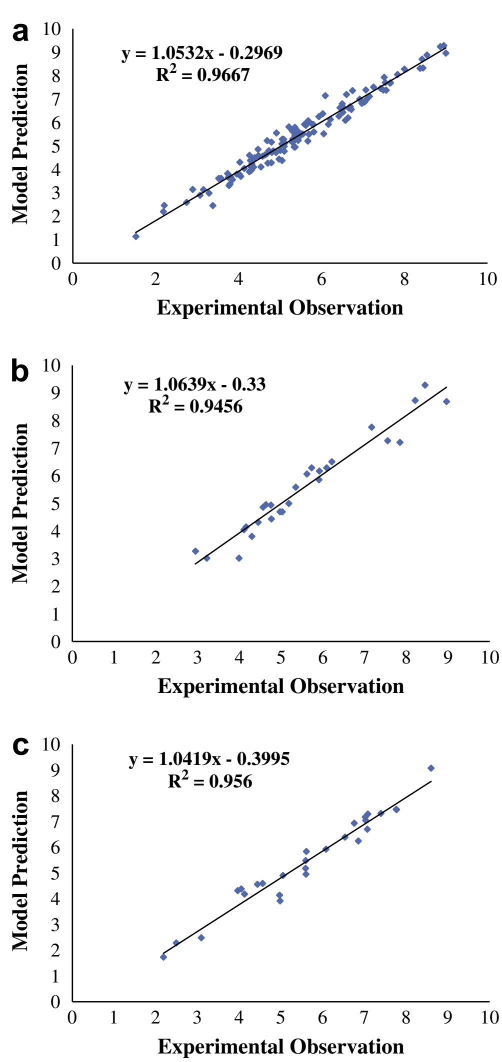

Fig. 6. Comparison of the ANN model prediction and experimental observation for (a) training, (b) validating and (c) testing sets.

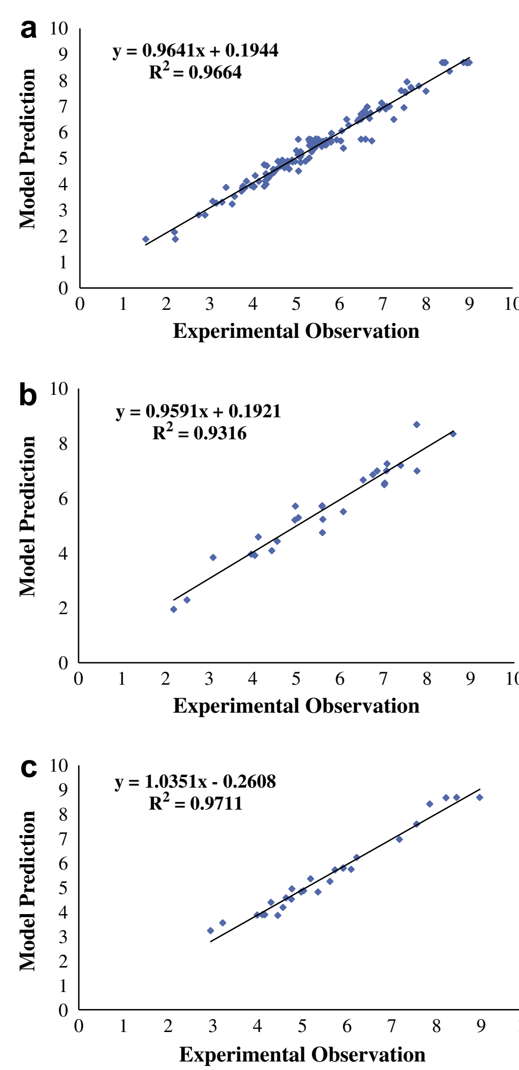

Fig. 7. Comparison of the FL model prediction and experimental observation for (a) training, (b) validating and (c) testing sets.

$\overline{O}$ is the mean value of predictions, and $\bar{t}$ is the mean value of observations.

6. Evaluation of results

The ANN and fuzzy logic models developed in this study are used to predict the bond strength of concrete. As mentioned earlier, 125 samples were used for training, 27 samples for validating, and 27 samples for testing of the models. The statistical values with training, validating, and testing data obtained from ANN and FL models were given in Table 2.

The performance of ANN and FL models for training, validating, and testing data can be seen in Figs. 4 and 5 respectively. In these figures, the results of various model's output are compared with actual experimental data. Horizontal axis of these figures are the sample numbers in training, validating, and testing records and vertical ones are their corresponding bonding strength in MPa. The results of these figures indicate that the ANN and fuzzy logic models were successful in learning the relationship between the different input parameters and outputs. The results of validating phase show that ANN and fuzzy logic models were capable of generalizing between input variables and the output and finally the results of testing phase show that these models had good potential for predicting the bond strength of steel bars in concrete.

Figs. 6 and 7 illustrate a comparison between these models' predictions and actual outputs for each of training, validating, and testing records. In these figures, horizontal axis is the representative of experiment's results and vertical one is related to the results of models' prediction for the bond strength of samples. The linear least square fit line, its equation and the R^2 values are shown in these figures for training, validating, and testing sets. As it is visible in Figs. 6 and 7 the value obtained from the training, validating, and testing sets in ANN and FL models are very closer to the experimental results. This case proves that the experimental results with ANN and FL models results show a close match.

7. Conclusions

The bond of steel bars in concrete is an important problem and modeling of its behavior is a difficult task. For this reason, the ANN and FL are good tools to model these complicated systems. In this study, an attempt is made to apply artificial neural network and fuzzy logic models in predicting the bond strength of steel bars in concrete. The predicted values are very close to the experimental results obtained from training, validating, and testing for artificial neural network and fuzzy logic models. Mean absolute error, mean absolute percentage error, root mean square error, absolute fraction of variance and correlation coefficient are statistical values that access the accuracy of the models. Meanwhile, Comparison with lower case showed that ANN provided slightly better results than FL.

This study showed that the ANN and FL can effectively predict the bond strength of steel bars in concrete in spite of the complexity and incompleteness of the available data without attempting any experiments in a quite short period of time with low error rates. The proposed models will save time, reduce waste materials and decrease the design costs.

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