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Bond strength prediction of steel bars in low strength concrete by using ANN

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Abstract. This paper presents Artificial Neural Network (ANN) models for evaluating bond strength of deformed, plain and cold formed bars in low strength concrete. The ANN models were implemented using the experimental database developed by conducting experiments in three different universities on total of 138 pullout and 108 splitting specimens under monotonic loading. The key parameters examined in the experiments are low strength concrete, bar development length, concrete cover, re-bar type (deformed, cold-formed, plain) and diameter. These deficient parameters are typically found in non-engineered reinforced concrete structures of developing countries. To develop ANN bond model for each bar type, four inputs (the low strength concrete, development length, concrete cover and bar diameter) are used for training the neurons in the network. Multi-Layer-Perceptron was trained according to a back-propagation algorithm. The ANN bond model for deformed bar consists of a single hidden layer and the 9 neurons. For Tor bar and plain bars the ANN models consist of 5 and 6 neurons and a single hidden layer, respectively. The developed ANN models are capable of predicting bond strength for both pull and splitting bond failure modes. The developed ANN models have higher coefficient of determination in training, validation and testing with good prediction and generalization capacity. The comparison of experimental bond strength values with the outcomes of ANN models showed good agreement. Moreover, the ANN model predictions by varying different parameters are also presented for all bar types.

Keywords: low strength concrete (LSC); Artificial Neural Network (ANN); non-engineered reinforced concrete (NERC); Reinforced Concrete (RC); bond-strength, deformed bar; cold-formed bar; plain bar

1. Introduction

One of the important aspect in the behaviour of RC elements is the transfer of forces between concrete and steel reinforcement bar interface through bond stresses. There are two main situations when bond stresses need to develop. Due to anchorage or bar development, where bars are terminated, and when there is a change in bending moment along the member which results in change of force along the bar. However, bond is also needed to keep the steel and concrete together in between cracks and that contributes to "tension stiffening" of RC. Under monotonic loading, there are two types of bond failure modes. One is pullout of the bar, which usually occurs in elements with enough confinement. This type of failure depends on the pattern and geometry of the deformations of the bar and concrete strength. Pullout failure occurs due to shearing of concrete between the lugs which immediately surrounds the bar. When confinement or cover is insufficient to obtain pullout failure, then splitting failure occurs. Splitting is due to tensile radial stresses, which develop from lug bearing forces. When the bar moves with respect to concrete, splitting failure initiates due to the wedging action of ribs. Cover and bond is lost when splitting reaches the edges of the member. Splitting failure usually occurs in bars having cover equal to three bar diameters or less but it may occur for bars having cover more than three bar diameter.

Post earthquake surveys and reports (Naseer *et al*. 2006, Duranni *et al.* 2005, Nisikawa *et al*. 2005, Naseer *et al*. 2006, Peiris *et al*. 2005, Bal *et al*. 2008) have shown that the use of inferior quality materials, inadequate detailing and poor construction practices are responsible for most of the brittle failure modes of Non-Engineered Reinforced Concrete (NERC) structures in developing countries. Bond failures in NERC elements due to short anchorages or low concrete cover result in large slip deformations prevent the development of plastic deformations and reduce energy dissipation capacity. Low Strength Concrete (LSC) is also one of key parameter that governs poor performance of detail deficient NERC structures. This is observed particularly after the Kashmir earthquake 2005, Pakistan and many RC structures were found to have pullout failure or large slip deformations. The parameters such as low strength concrete, low concrete cover, low development length, bar diameter need to be accounted for the evaluation of bond strength of different bar types in LSC. This is very important for seismic performance evaluation of NERC structures and no such study exist so far that describe the bond-slip (τ-s) behaviour of various bar types in low strength concrete along with typical deficiencies as mentioned above.

Different relationships can be found in the literature for

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the determination of the bond strength of reinforcing bars both in unconfined normal strength concrete (NSC) and in the high strength concrete (HSC) (Orangun *et al.* 1975, Zuo and Darwin 2000, Eligehausen *et al.* 1983). These equations are based on either summation or product functions and accounts for various important variables as well as bond failure modes. Various analysis techniques can be used to predict the bond strength for different bar types by including multiple parameters. A powerful technique for determining multi-parameter influence is known as Artificial Neural Network (ANN) and can be used to evaluate τ_{max} of different bar types in concrete. ANN involves learning of relationship between input and output data using mathematical training processes. ANN has been implemented recently to solve a variety of civil engineering problems. Few studies can be found in literature which uses ANN for evaluating maximum bond strength. Dahoua *et al.* (2009) evaluated the bond strength of deformed steel ribbed bars by considering the concrete mix constituents as the input parameters in one ANN bond model and also using concrete strength and bar diameter as input parameters in another ANN bond model. Emre (2009) also developed the ANN bond strength model for reinforcing bars in light weight concrete. Fan and Hu (2007) developed ANN model for evaluating bond strength of corroded bars in concrete.

The main aim of the current study is to develop ANN bond strength models for different bar types by considering the deficient parameters which have large influence on the poor seismic performance of NERC structural components during earthquakes which generally fails in brittle manner due to bond failures. These deficient parameters are low concrete compressive strength, short development length, small cover, diameter which are included in developing ANN bond strength models in current study. The performance of different developed ANN models is assessed for each parameter by using experimental data. The proposed bond strength models can be used in a seismic fragility assessment framework for NERC structures for the inelastic analysis of the low strength reinforced concrete structures.

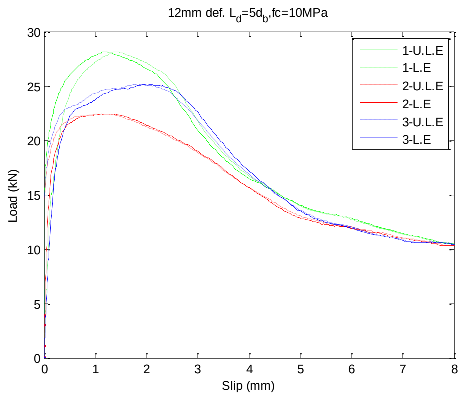
This paper briefly describes initially various applications of ANN in civil engineering. Experimental programme conducted in different universities to study the bond-slip characteristics of different bar types in LSC is briefly discussed. The statistical data of the bond strength for both pullout and splitting specimens are presented. ANN modelling which is more sophisticated approach as compare to multi-variable nonlinear regression is adopted and the basics of ANN modelling are discussed. ANN models for evaluating bond strength of deformed, plain and cold formed bars in low strength concrete are developed by training the neurons in the hidden layers using the experimental data. Experimental bond strength values are compared with the outcomes of ANN models. Moreover, the ANN model predictions by varying different parameters are also presented for all bar types.

2. Application of ANN in civil engineering

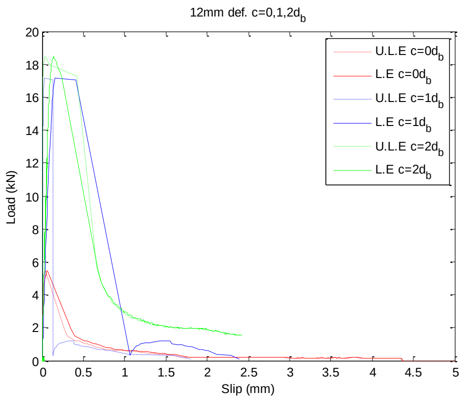
ANN has been implemented recently to solve a variety of civil engineering problems such as evaluating modulus of elasticity of concrete (Demir 2008), predicting shear capacity (Adhikary and Mutsuyoshi 2004), and assessing the seismic induced structural damage (DeLautour and Omenzetter 2009). Yeh (1998), Kasperkiewics (1995), Lai and Serra (1997) and Lee (2003) used ANN technique for predicting properties of conventional concrete and high performance concretes. Duan and Poon (2014) studied factors affecting the properties of recycled concrete using ANN. Dias and Pooliyadda (2001) used ANN back propagation approach to predict the slump and strength of ready mixed concrete and high strength concrete with chemical admixtures and/or mineral additives. Kong *et al.* (2016) studied effect of aggregate on concrete permeability by using ANN. Oztas *et al.* (2006) used ANN model for predicting compressive strength of high strength concrete (HSC) with suitable workability. Bilgham and Turgut (2010), Lingama and Karthikeyan (2014) used ANN for predicting the concrete compressive strength. For predicting the concrete strength development, Lee (2003) developed ANN model. Pala *et al.* (2005) studied the effects of silica fume and fly ash replacement content on the strength of concrete cured for a long term period of time by using ANN. The developed ANN model consisted of eight input parameters and an output parameter that is compressive strength. In another study performed as the experimental analysis (Sahin and Shenoi 2003), two steel beams with eight surface-bonded electrical strain gauges and an accelerometer mounted at the tip were used to obtain modal parameters. The authors applied the feed-forward back propagation ANNs by using the data obtained from the experimental damage case. In the study performed by Kelesoglu *et al.* (2005), feed forward and back propagation trained ANN was used for analysing the requirement of insulation for brick wall and to evaluate minimum required thickness of this insulating material. The results obtained from the ANN model were compared with the numerical results and it was found the results are sensitive enough. Joshi *et al.* (2014) used ANN for dynamic analysis of structures, Kao and Yeh (2014) used ANN for structural design of RC plane frame. In a study by Ozsoy and Firat (2004) conducted the horizontal displacement values were estimated from the ANN model. Riza (2017) predicted the shear strength of SFRC slender beams without stirrups. Similarly there are different studies, which evaluated the bond strength considering different parameters and are already discussed in introduction. In literature, authors have presented ANN as a feasible tool for solving various civil engineering problems.

3. Experimental programme

In the experimental programme (Ahmad 2011), an investigation was undertaken to study *τ-s* characteristics of different types of steel reinforcing bars typically used in past and in recent years for the construction of RC structures (especially in Pakistan). This includes three different types of steel bars which vary in their deformations and diameter. These bars are 1-deformed (def.), 2-cold twisted (Tor) and 3-plain. The main focus was

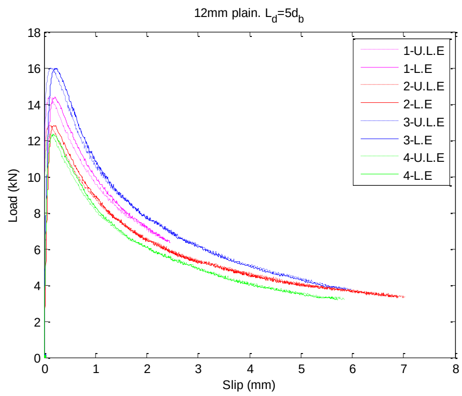


(a)

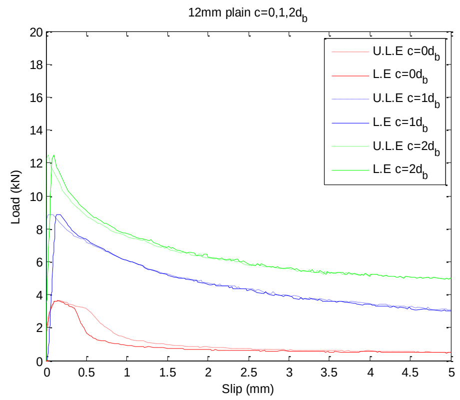


(b)

Fig. 1 Typical bond-slip curves from tests at UoS (a) 12 mm deformed (pullout) (b) 12 mm deformed (splitting)



(a)



(b)

Fig. 2 Typical bond-slip curves from tests at UoS (a) 12 mm plain (pullout) (b) 12 mm plain (splitting)

to study pullout and splitting bond failure modes in LSC under monotonic loading. All the tested specimens were unconfined and made from plain concrete. The main parameters included LSC (~15 MPa), bar development length (L_d), concrete cover (c), rebar type and diameter (d_b). This experimental work has been done at three different Universities including the University of Sheffield (UoS), and at two universities in Pakistan; UET, (Taxila) and NED, Karachi which included 138 pullout and 108 splitting tests. Using the statistical data from these experiments, the bond strength models were developed. The bond-slip curves of deformed cold formed, and plain bar specimens are used in current study to develop ANN bond strength model for LSC.

3.1 Representative experimental bond-slip curves

Representative results for the deformed and plain bars pullout and splitting specimens tested at UoS, having d_b=12 mm, L_d=5d_b are shown in Figs. 1 and 2, respectively. Cold formed (Tor) bars pullout specimens tested at NED, having d_b=12 mm, L_d=5d_b are shown in Figs. 3(a) and 3(b), respectively. The U.L.E. and L.E. in these figures represents the un-loaded and loaded end bond-slip curves, respectively.

The bond-slip curves of deformed bars pullout specimens having concrete compressive strength <10 MPa in general showed low bond strength as shown in Fig. 1(a). A plataeu in the bond-slip curve can be seen prior to decay. The slip value at maximum bond strength is close to 1mm. As expected plain bars pullout specimens showed lower bond strength than deformed bar specimens and the slip corresponding to bond strength in plain bars is very low as shown in Fig. 2(a). The load-slip curve decay is not as gradually as deformed bars. The bond slip behavior of cold formed pullout specimens in Fig. 3(a) is almost similar to deformed bars.

Deformed bars splitting specimens (d_b=12 mm, L_d= 5d_b and c=0-2d_b) in Fig. 1(b) showed abrupt failure of all deformed bar splitting specimens. The value of c=0 represents extremely small concrete cover and practically represents exposed reinforcement condition in beams or columns typically observed in developing countries due to poor construction practices. Deformed bar split specimens with extremely small cover showed a very low $\tau_{\max}$ at a small slip value. The bond strength increased by almost four times for curves c=1 and 2d_b (Fig. 1(b)). In plain bar split specimens (d_b=12 mm, L_d=5d_b and c=0-2d_b)) in Fig. 2(b), splitting did not occur in all cases. A few specimens with c=0 and c=1d_b showed brittle behavior, but most of the specimens especially with cover 1d_b and 2d_b showed a gradual decay of the load-slip curve, as shown in Fig.2(b). In cold formed bars splitting specimens (d_b=12 mm, L_d= 5d_b) in Fig. 3(b), abrupt failure was observed in all specimens similar to deformed bar splitting specimens. The splitting bond strength of cold formed bars in low strength concrete can be observed to be lower than deformed bars.

Table 1 Summary of the pullout tests using averages for each set of variables

d_b	Bar type	L_d	n	f_c'	τ_{max}	$\tau_{max}/\sqrt{f_c'}$	$\tau_{max}/\sqrt{f_c'}$	$\tau_{max}/\sqrt{f_c'}$
					μ	μ	σ	COV
mm		mm		MPa	MPa	MPa	MPa	
				UoS				
12.75	*Def.*	64	5	14.7	14.3	3.72	0.324	0.087
12.75	*Def.*	64	3	9.2	7.8	2.55	0.397	0.155
12.75	*Def.*	64	3	12.5	9.9	2.79	0.247	0.088
12.75	*Def.*	128	4	15.0	7.7	1.99	0.667	0.335
12.75	*Def.*	128	3	10.0	6.3	1.98	0.283	0.142
12.75	*Def.*	191	3	15.0	7.8	2.01	0.009	0.004
17	*Def.*	85	3	15.0	11.3	2.91	0.480	0.160
17	*Def.*	170	3	15.0	11.9	3.08	0.072	0.023
17	*Def.*	255	3	15.0	8.9	2.30	0.106	0.046
12	*plain*	60	4	15.5	6.0	1.52	0.147	0.097
12	*plain*	120	5	16.2	6.4	1.59	0.143	0.090
12	*plain*	180	3	15.0	4.7	1.22	0.192	0.157
16	*plain*	80	5	14.8	6.7	1.74	0.166	0.095
16	*plain*	160	3	15.0	5.9	1.52	0.013	0.009
16	*plain*	240	3	15.0	5.1	1.33	0.027	0.020
				UET				
13	*Def.*	65	3	15.0	15.5	4.00	0.267	0.067
13	*Def.*	130	3	15.0	11.4	2.94	0.207	0.071
13	*Def.*	195	3	15.0	8.0	2.07	0.018	0.009
13	*Cold-formed*	65	3	15.0	12.1	3.13	0.346	0.111
13	*Cold-formed*	130	3	15.0	11.2	2.90	0.028	0.010
13	*Cold-formed*	195	3	15.0	6.5	1.67	0.068	0.041
19	*Def.*	95	2	15.0	12.8	3.30	0.365	0.110
19	*Def.*	190	3	15.0	7.9	2.04	0.243	0.119
19	*Def.*	285	3	15.0	4.9	1.26	0.093	0.074
				NED University				
13	*Def.-3*	65	4	16.4	12.4	3.07	0.577	0.188
16	*Def.-3*	80	6	16.2	10.6	2.63	0.388	0.147
20	*Def.-3*	100	4	15.4	12.7	3.24	0.327	0.101
13	*Tor-1*	65	6	12.6	11.4	3.20	0.608	0.190
16	*cold-1*	80	6	12.7	12.6	3.10	0.610	0.200
20	*cold-1*	100	4	12.7	11.5	3.22	0.680	0.211
13	*cold-2*	65	6	15.0	12.9	3.34	0.569	0.170
16	*cold-2*	80	6	15.7	13.9	3.50	0.369	0.106
20	*cold-2*	100	6	16.1	13.1	3.28	0.343	0.105

Where d_b= bar diameter; L_d=development length; n=number of tested specimens , f'_c =concrete compressive strength; τ_{max}= bond strength; μ=mean; σ=standard deviation; COV= covariance

3.2 Direct comparison and statistical analysis (pullout specimen)

A summary of results of pullout tests conducted at each University along with the average results for each set of variables is presented in Table 1.

3.3 Direct comparison and satistical analysis (Splitting specimen)

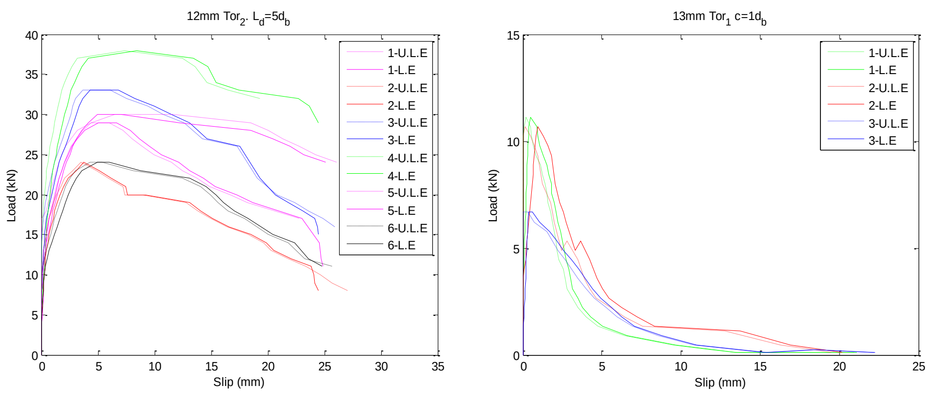
Table 2 presents a summary of results of splitting tests conducted at the three universities.

4. Artificial Neural Network (ANN) for evaluating bond strength in LSC

4.1 Introduction

Artificial Neural Network (ANN) involves learning of relationship between input and output data using mathematical training processes. The basic functionality of ANN is described in the following flow chart in Fig. 4.

The ANN function is based on the human brain biological function and consist of networks of many parallel operating processors. These processing components in a network are highly inter-linked and are termed as artificial neurons which are the basic elements of this method and are also termed as perceptrons and represent the mathematical model of the biological neuron. The main functionality of the perceptron is to evaluate the output by doing weighted sum of all the inputs. In order to solve a problem, a single neuron with multiple inputs may not be sufficient. Multiple neurons can be interlinked to develop an ANN which is also called Multi layer perceptron (MLP). The use of MLP increases the accuracy of the model. Typically the structure of ANN (MLP) contains an input layer with input parameters, a hidden layer with neurons and an output layer with a single or multiple parameters as shown in Fig. 5. An optimisation of the model parameters occur which reduces



(a) (b)

Fig. 3 Typical load-slip curves from tests at NED (a) 12 mm cold formed (pullout) (b) 12 mm cold formed (splitting)

Table 2 Summary of the splitting tests using averages for each set of variables

d_b	Bar type	cover	c/d_b	n	f'_c	τ_{max}	$\tau_{max}/\sqrt{f'_c}$	$\tau_{max}/\sqrt{f'_c}$	$\tau_{max}/\sqrt{f'_c}$
		c					μ	σ	COV
mm		mm			MPa	MPa	MPa$^{1/2}$	MPa$^{1/2}$	
				UoS					
12.75	*Def.*	26	2.0	3	15.0	6.3	1.64	0.201	0.123
12.75	*Def.*	13	1.0	3	15.0	6.3	1.62	0.139	0.086
12.75	*Def.*	0	0.0	5	15.0	1.9	0.48	0.118	0.244
17	*Def.*	34	2.0	3	15.0	3.9	1.00	0.138	0.138
17	*Def.*	17	1.0	3	15.0	3.8	0.98	0.058	0.059
17	*Def.*	0	0.0	3	15.0	2.8	0.72	0.044	0.062
12.75	*plain*	26	2.0	3	15.0	5.7	1.47	0.077	0.052
12.75	*plain*	13	1.0	3	15.0	3.9	1.01	0.105	0.104
12.75	*plain*	0	0.0	3	15.0	1.8	0.46	0.081	0.175
17	*plain*	34	2.0	3	15.0	4.9	1.26	0.199	0.158
17	*plain*	17	1.0	3	15.0	3.2	0.83	0.054	0.066
17	*plain*	0	0.0	3	15.0	1.8	0.46	0.055	0.119
				UET					
13	*Def.*	32	2.5	3	15.0	9.5	2.30	0.310	0.135
13	*Def.*	45	3.5	3	15.0	12.8	3.11	0.290	0.092
13	*Cold-formed*	32	2.5	3	15.0	8.7	2.10	0.233	0.111
13	*Cold-formed*	45	3.5	3	15.0	10.4	2.52	0.178	0.071
19	*Def.*	29	1.5	3	15.0	4.7	1.15	0.117	0.102
19	*Def.*	41	2.2	3	15.0	8.8	2.14	0.310	0.145
				NED University					
13	*Def.-2*	26	2.0	3	9.8	4.6	1.49	0.366	0.246
16	*Def.-2*	32	2.0	3	9.8	3.4	1.07	0.216	0.202
20	*Def.-2*	40	2.0	3	9.8	3.2	1.06	0.466	0.438
13	*Def.-2*	13	1.0	3	10.6	4.6	1.41	0.333	0.236
16	*Def.-2*	16	1.0	3	10.6	1.7	0.52	0.120	0.231
20	*Def.-2*	20	1.0	3	10.6	3.9	1.20	0.146	0.122
13	*Def.-3*	26	2.0	3	10.4	2.9	0.91	0.209	0.229
16	*Def.-3*	32	2.0	3	10.4	3.5	1.08	0.327	0.303
20	*Def.-3*	40	2.0	3	10.4	3.0	0.94	0.281	0.300
13	*Def.-3*	13	1.0	3	10.6	2.8	0.86	0.333	0.385
16	*Def.-3*	16	1.0	3	10.6	3.2	0.97	0.486	0.499
20	*Def.-3*	20	1.0	3	10.6	2.8	0.87	0.194	0.224
13	*Cold-1*	26	2.0	3	9.8	3.6	1.15	0.254	0.220
16	*Cold-1*	32	2.0	3	9.8	3.7	1.17	0.196	0.168
20	*Cold-1*	40	2.0	3	9.8	3.1	1.00	0.287	0.286
13	*Cold-1*	13	1.0	3	9.5	4.3	1.38	0.432	0.312
16	*Cold-1*	16	1.0	3	12.1	3.4	0.97	0.338	0.350
20	*Cold-1*	20	1.0	3	12.1	2.3	0.67	0.235	0.351

Where d_b=bar diameter; c=concrete cover; n=number of tested specimens, f'_c =concrete compressive strength; τ_{max}=bond strength; μ=mean; σ=standard deviation; COV=covariance

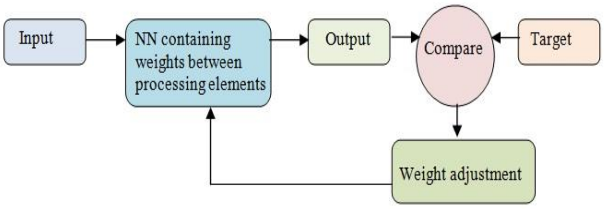


Fig. 4 ANN basic functionality for training

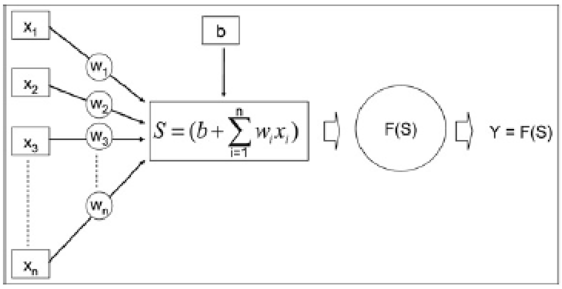


Fig. 5 A neuron (perceptron) with multiple inputs

the error between the predicted outcomes and the target values (from experiments) by adjusting the weights of the internal links. The detailed description of ANN and the processes involved are discussed in section 4.2. The ANN application for evaluating the bond strength from the experimental data is given in the following section.

4.2 Processes involved in ANN

The ANN function is based on the human brain biological function and consist of the network of many parallel operating processors. These processing components in a network are highly inter-linked and are termed as artificial neurons which are the basic elements of this method and are also termed as perceptrons which represents the mathematical model of the biological neuron. A perceptron in the network is shown in Fig. 5. The main functionality of the perceptron is to evaluate the output by doing weighted sum of all the inputs.

Inputs are received by neurons from various adjoining components but delivers only single output. The above figure shows that the input (x_1, x_2, x_3, x_n) is weighted by the weight elements (w_1, w_2, w_3, w_n) along with bias to reach the summation operator. The product of inputs and weights is added with the bias by the summation operator to generate the result '*s*' (Eq. (1)) which is further transmitted to the transfer function F(s) which processes that results and generate the output '*y*'(Eq. (2)) depending on whether the threshold is attained in the computational results. The information rate transmitted between input and output is also governed by the weight and bias.

$$s=\sum_{i=1}^{n} w_i x_i + b \tag{1}$$

$$y=F(s)=F\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{2}$$

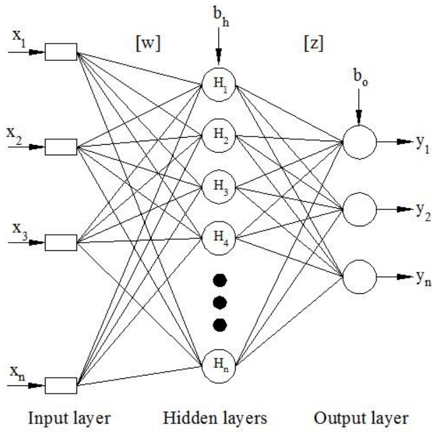


Fig. 6 Sample architecture of Artificial Neural Network (ANN)

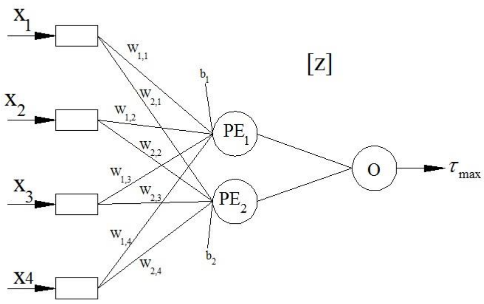


Fig. 7 Weighted assignment to the inputs connected to neurons in a hidden layer in processing elements

Where;
x_i=input data ; w_i=weight corresponding to each input, b=bias, s=summation result Y=predicted outcome, F=transfer function

In order to solve a problem, a single neuron with multiple inputs may not be sufficient. To resolve this issue multiple neurons can be interlinked to develop an ANN which is also called as Multi layer perceptron (MLP). The use of MLP increases this accuracy of the model. Typically, the structure of ANN (MLP) contains an input layer with input parameters, Hidden layer with neurons and an output layers with a single or multiple parameters as shown in Fig. 6. An optimisation of the model parameters occur which reduces the error between the predicted outcomes and the target values (from experiments) by adjusting the weights of the internal links. Matrices are formed for the weights whose columns are equal to the number of input parameters and rows are equal to the number of neurons. The weight matrices linking input layer to the hidden layer is represented by [*w*] and the weight matrix [*z*] links hidden layer to the output layer as shown in Fig. 7. The learning process continues in ANN even if the data are insufficient or inaccurate, which is considered to be one of the strength of ANN.

ANN can be trained using a variety of algorithms but back propagation (BP) provides satisfactory results for the engineering problems. The network parameters (weights and bias) changes in accordance with the negative of error function and BP algorithm is also termed as gradient descent algorithm. Eqs. (3)-(4) represents the new weights and bias, respectively. This is an iterative process and new weights and bias are assigned until the error of network is minimized. The network is also tested at each iteration with a new dataset which was not used previously in the training purpose and is usually 20% of the whole dataset. This is a cross validation method and to enhance the generalization capacity of the ANN model.

$$w_{i+1} = w_i - \eta \nabla E_{i/w} \tag{3}$$

$$b_{i+1} = b_i - \eta \nabla E_{i/b} \tag{4}$$

Where ;

w_i+1 and b_i+1 are the new corrected values of weights and bias

w_i is the weight at iteration i

η= learning rate

∇_i= error gradient computed at iteration i

$$\nabla E_{i/w} = \frac{\partial E_i}{\partial w_i} \tag{5}$$

E_i is the Root Mean Square Error (RSME) for iteration i, and is given by

$$E_i = \sqrt{\frac{1}{N}\sum_{n=1}^{N}|e_n|^2} \tag{6}$$

Where e_n is the error between target and the predicted outcome and N is the total number of data in the dataset used for training.

Different transfer function exists which are supported by different ANN tools and they can either be linear or nonlinear which depends on the dataset. The purpose of the transfer function is to induce nonlinearity in ANN model. Log-sigmoid and Tan-Sigmoid transfer functions are most commonly used in solving the engineering problems. The outcome from the summation operator is transformed in to -1, 0 or 1 by the transfer function.

The number of neurons in the input layer depends on the variables considered in the test data. The training procedure can be slowed down significantly if large number of variables are considered. A trial and error method is used to decide the number of neurons in the hidden layer. The learning and the generalization (network response to unseen data) capacity of the ANN model is reduced if very few neurons are taken into account in the hidden layer. On the other hand over-fitting can result if too many neurons are considered in the hidden layer. It is suggested by some researchers that a single layer with reasonable number of neurons are required for a continuous function but for a discontinuous functions a second hidden layer is required.

5. Application of ANN for bond modelling

In this study an ANN model has been made for evaluating the bond strength of three different bar types in LSC. The sample architecture of the ANN bond model is shown in Fig. 8. The input parameters in the input layers of ANN bond strength model are f_c', L_d, c, d_b and bar type.

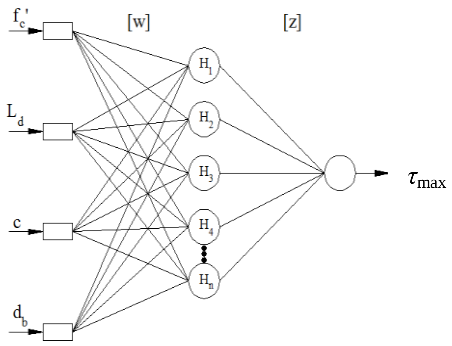


Fig. 8 ANN model for predicting bond strength of different type of bars in LSC

Table 3 ANN bond models R^2 value for training, validation and testing

ANN model	R^2		
	Training	Validation	Testing
Deformed bar	0.96	0.94	0.94
Tor bar	0.94	0.9	0.82
Plain bar	0.99	0.98	0.92

A trial and error method is used in selecting the number of neurons for a hidden layer until best fit results are achieved. Using the mentioned input parameters (Fig. 8) and the target values the output is calculated. The evaluated error between the target and predicted output is propagated from the output layer to the preceding layer in a process called back propagation. Lavenberg-Marquardt algorithm is used in this study to minimise error. From the available dataset 80% of the data is used for training the ANN model and the remaining 20% dataset is used to carry out validation and testing. The R^2 for the training, validation and testing is given in Table 3. The ANN bond model for deformed bar consists of a single hidden layer and the 9 neurons. For Tor bar and plain bars the ANN models consist of 5 and 6 neurons and a single hidden layer, respectively.

The developed ANN models are capable of predicting τ_{max} for both bond failure modes. First of all the ANN bond models developed for different bar types are assessed and τ_{max} predictions from the ANN models using the same inputs parameters as used in experiments are plotted against the actual experimental τ_{max} and the scatter is shown in Figs. 9(a)-(c). The three lines are plotted in Figs. 9 (a)-(c) to show deviation of bond strength predictions by ANN model from experimental bond strength values. If a point lies on or close to this line it means there is no or very less error, respectively in the finding from the model. The upper and lower lines corresponds to $\pm 1\sigma$ of error in predicting the bond strength using ANN model by using experimental parameters. It can be seen that most of the data lies within $\pm 1\sigma$ bounds with little deviation showing good performance of model. Moreover, the frequency distribution of the predicted τ_{max} normalized to the experimental τ_{max} is shown in Fig. 9 (d)-(f) for the test sample data, validation sample data and the complete input data. As mentioned in section 5

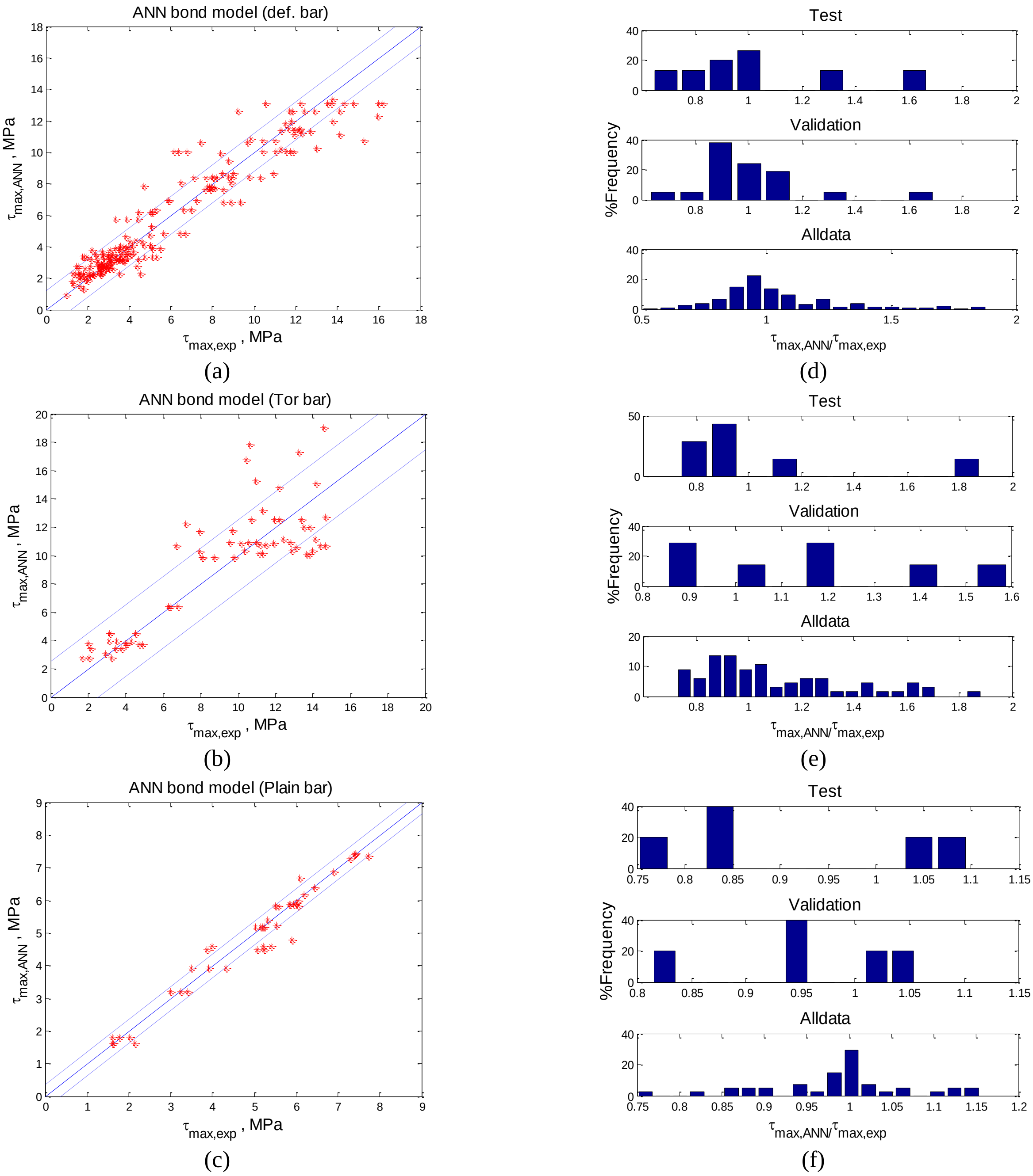


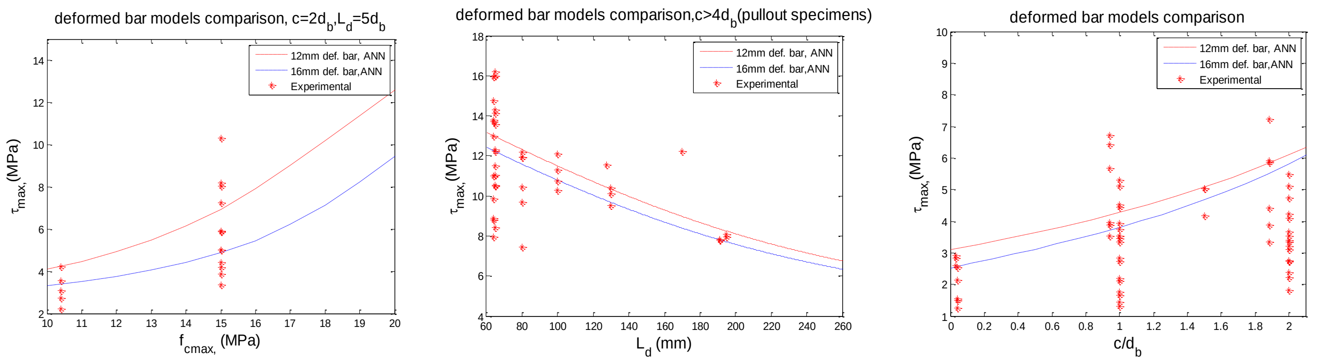
Fig. 9 Comparison between ANN bond model predictions and experimental outcomes. (a) Def. bar (b) Tor bar (c) Plain bar, % Frequency distribution of $\tau_{max,ANN}/\tau_{max,exp}$ (d) Def. bar (e) Tor. bar f) Plain bar

that 20% of the experimental dataset was allocated for validation and testing while developing ANN bond strength models. The validation data set is used to compare the performances of the prediction algorithms that were created based on the training set and decide to select a model among different models (In ANN, comparison of ANN models with different number of hidden layers for instance). In order to avoid overfitting, it is necessary to have a validation set in addition to the training and test sets. Finally, the test set is used to obtain the performance characteristics such as accuracy (RMSE) of our chosen algorithm. The test data set is not used in model building process. The validation and testing results of the models in Fig. 9 indicates good performance of model with majority of dataset having predicted to experimental bond strength ratio range of 0.8 to 1.2. These results show a good performance for the ANN predictions, and this is further assessed by doing parametric study and by evaluating τ_{max}.

By varying different parameters (f_{cmax}, L_d and c/d_b), the ANN model predictions are compared with the experimental data and is discussed as follow for three bar types.

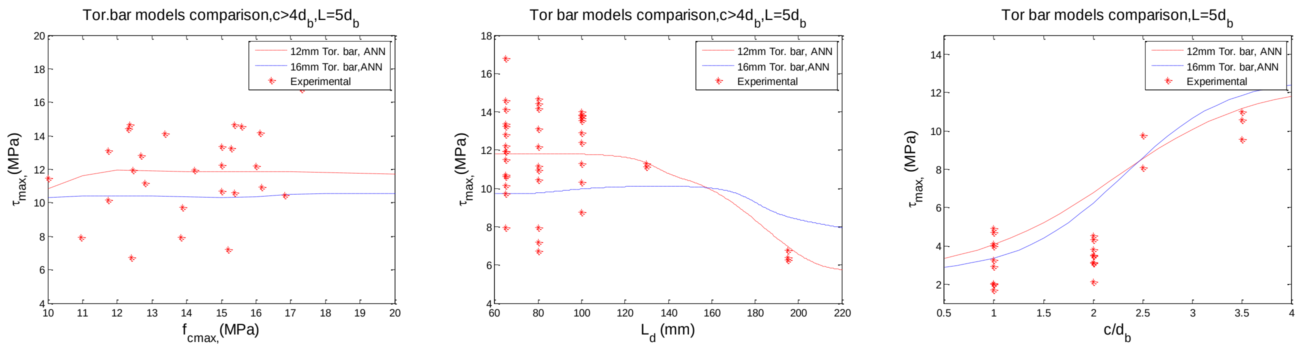
5.1 Deformed bars

τ_{max} versus f_{cmax}, L_d and c/d_b ratio are given in Fig. 10



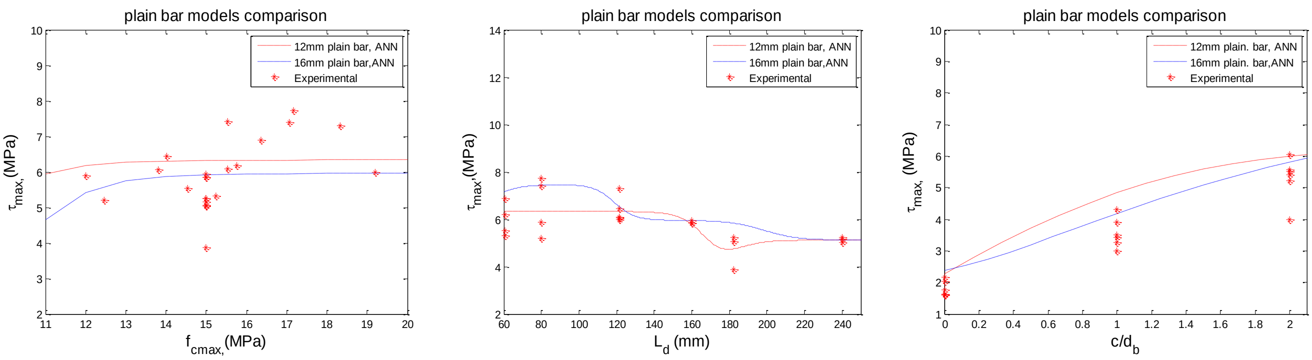
(a) (b) (c)

Fig. 10 Comparison of ANN model for deformed bar with experimental data for different parameters (a) f_{cmax} (b) L_d (c) c/d_b



(a) (b) (c)

Fig. 11 Comparison of ANN model for Tor bar with experimental data for different parameters (a) f_{cmax} (b) L_d (c) c/d_b



(a) (b) (c)

Fig. 12 Comparison of ANN model for plain bar with the experimental data for different parameters (a) f_{cmax} (b) L_d (c) c/d_b

(a)-(c) for deformed bars. Despite the variability, the ANN predictions for the deformed bars show good overall capability in predicting the bond strength corresponding to different parameters for both failure modes. The reason for this improved performance is due to use of a small number of neurons in a single hidden layer to avoid over-fitting.

5.2 Tor bars

τ_{max} versus f_{cmax}, L_d and c/d_b ratio are given in Fig. 11(a)-(c) for Tor bars. The ANN bond model predictions for Tor bars are quite reasonable. 11(b) and (c) shows that the ANN model followed the pattern of experimental data at longer embedment lengths (>5d_b) and larger concrete cover (>2d), respectively.

5.3 Plain bars

The Variation of τ_{max} with the increase of f_{cmax}, L_d and varying c/d_b ratio is given in Fig. 12 (a)-(c) for plain bars. This model has the highest training and validation correlation coefficients due to less variability. Prediction of bond strength for pullout and splitting modes showed satisfactory predictions with slight over fitting of the 16mm bar prediction over the development length.

6. Conclusions

ANN bond strength models are developed for different bar types in this study.

• The ANN bond models developed for different bar types (i.e., deformed, tor, plain) can be used for evaluating bond strength in low strength concrete.
• Besides the low strength concrete other deficient parameters typical of Non Engineered Reinforced Concrete structures (NERC), such as low concrete cover and short embedment length are also accounted for in the ANN model. The effect of bar diameter on bond strength is also accounted in ANN models.
• The developed ANN bond models have higher coefficient of determination for training, validation and testing with good prediction and generalization capacity.
• The comparison of the ANN model predictions with the experimental data shows good agreement for all bar types.
• The developed ANN models can be used in the seismic performance evaluation of sub-standard NERC structures by modelling bond-slip behaviour.
• More sophisticated algorithm such as Bayesian updating or other may be used to improve the generalization capability of the current ANN models for the data having variability.

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