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NEURAL NETWORK MODEL TO PREDICT SHEAR STRENGTH OF RC BEAM

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Abstract

In recent years, application of Artificial Neural Networks (ANN) in civil engineering has drawn lot of attention. The potential of ANN as an analytical substitute for conventional methodologies, which are usually bound by inflexible assumptions, is recognized and accepted widely. Artificial neurons, which are a set of interconnected units or nodes that loosely resemble the neurons in a biological brain, are the foundation of ANN. Like the synapses in a human brain, each link has the ability to send a signal to neighboring neurons. After receiving inputs, an artificial neuron processes them and the output of each neuron is computed by a function of the sum of its inputs. The present work focuses on the use of ANN to predict the shear strength of reinforced concrete beams without shear reinforcement. The conventional stress analysis criteria are neither adequate to anticipate the shear strength of reinforced concrete beams nor competent to characterize the failure mechanism in beams. The neural network is trained using google colaboratory platform considering experimental data gathered from previous research studies. The results are compared with experimentally measured shear strength as well as those computed from various codes of practice. It is inferred that with adequate training ANN can predict the shear strength of RC beam satisfactorily.

Keywords: Artificial Neural Network (ANN), Shear strength, Reinforced concrete beam (RC beam)

1. INTRODUCTION

Real-world issues call for a system that combines information, technique and methodologies from several sources to arrive at feasible solution. This system should be able to adapt, figure out how to get better in changing circumstances and justify the decisions or actions they do. Engineers have been working consistently to increase the effectiveness of classical problem-solving techniques for challenging situations in various technical domains. The recent past has seen a growth in soft computing in fields related to civil engineering, giving rise to numerous exciting and creative applications. Soft computing approaches are used as problem-solving interfaces to find approximate to precise solutions to challenging problems. Humans utilize natural language to think and reach conclusions. Human intelligent behaviour is expressed in the language of symbolic rules in traditional Artificial Intelligence (AI). It manipulates the symbols on the postulation that such behaviour can be stored in a symbolically organized knowledge base known as the physical symbol system hypothesis. The majority of natural phenomena and the solutions that nature develops to challenges serve as inspiration for soft computing techniques.

The objective of the present work is to develop an ANN model to forecast the shear strength of RC beam. Shear transfer mechanism in beams is a complex phenomenon and is still an active area of research. The study involves identifying important parameters which influence the shear strength of RC beam. Shear strength test results of RC beams available in literature are used to train, validate and test the ANN model. The shear strength results predicted from the developed ANN model for test beams are also compared with those computed from various codes of practice.

2. METHODOLOGY

The methodology adopted in the development of ANN model to achieve the objectives of the present work is described below,

- Carry out analytical study on shear strength of RC beam through literature review and various codes of practice and identify the parameters influencing the shear strength of RC beams.
- Develop an ANN model to predict the shear strength of RC beam without shear reinforcement using google colaboratory platform with appropriate number of neurons in the input, hidden and output layers.
- Train the ANN model with the available test data on shear strength of RC beam without shear reinforcement and validate the model for its efficacy.
- Compare the shear strength results of RC beams without shear reinforcement predicted from the developed ANN model with available test results and those obtained from standard codes of practice.

Fig.1 depicts the methodology adopted in the present work.

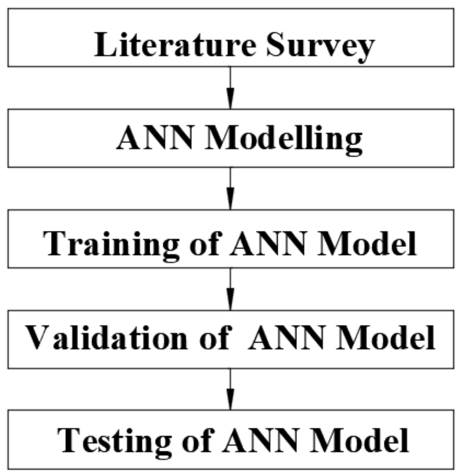

Fig. 1 Methodology adopted in developing ANN model

3. DEVELOPMENT OF ANN MODEL

The experimental shear strength data of RC beams without shear reinforcement is compiled from a thorough literature review. A total of 584 RC shear strength test results compiled from research studies are shown in Table 1. A multi-layer perceptron model is created using python programming language. The input layer, single hidden layer and output layer make up the perceptron. The number of dependent factors that influence the shear strength of RC beam determines the number of neurons in the input layer. The literature review suggests that six parameters influence the shear strength of RC beams without shear reinforcement and are considered as the variables in the input layer of ANN model (Table 2). Only one neuron is considered in the output layer since the work aims to predict shear strength of RC beam (τ_c). A single hidden layer with eleven hidden neurons is adopted based on trial-and-error method as it yielded more accurate outcome. The arrangement of neurons and layers adopted in the ANN model is pictorially represented in Fig.2.

Table 1 Details of RC beams tested for shear strength by investigator

Sl. No.	Investigators	Sl. No.	Investigators
1	Ahmad et al. (1986) (2)	31	Kulkarni and Shah (1998) (4)
2	Angelakos et al. (2001) (5)	32	Laupa et al. (1953) (2)
3	Aster and Koch (1974) (5)	33	Leonhardt and Walther (1962) (6)
4	Bernander (1957) (6)	34	Lubell et al. (2004) (9)
5	Bentz and Buckley (2005) (9)	35	Lubell (2006) (7)
6	Bhal (1968) (8)	36	Marti et al. (1977) (2)
7	Bresler and Scordelis (1963) (3)	37	Mathey and Watstein (1963)(9)
8	Birgisson (2011) (11)	38	Moody et al. (1954) (20)
9	Chidananda (2016) (40)	39	Morrow and Viest (1957) (9)
10	Cladera and Mari (2002) (3)	40	Mphonde and Frantz (1984) (1)
11	Chana (1981) (25)	41	Niwa et al. (1987) (3)
12	Chang and Kesler (1958) (15)	42	Podgorniak-Stanik (1998)(3)
13	Collins and Kuchma (1999) (5)	43	Rajagopalan and Ferguson (1968) (5)
14	Diaz de Cossio and Siess (1960) (2)	44	Regan (1971) (4)
15	Elzanaty et al. (1986) (6)	45	Rehm et al. (1978) (1)
16	Ferguson (1956) (1)	46	Rosenbusch and Teutsch (2002) (3)
17	Fujita et al. (2003) (34)	47	Rusch et al. (1962) (3)
18	Ghannoum (1998) (1)	48	Sarkhosh (2014) (42)
19	Hallgren (1994) (10)	49	Salandra and Ahmad (1989) (2)
20	Hamadi (1976) (4)	50	Sherwood (2008) (8)
21	Hanson (1958) (6)	51	Shioya (1989) (3)
22	Hanson (1961) (4)	52	Slowik (2014) (9)
23	Hedmann and Losberg(1978) (4)	53	Taylor (1968) (7)
24	Iguro et al. (1985) (5)	54	Taylor (1972) (5)
25	Kani (1967) (41)	55	Thiele (2010) (5)
26	Kani et al. (1979) (63)	56	Tureyen and Frosch (2002) (3)
27	Kawano and Watanabe (1998) (2)	57	Winkler (2011) (5)
28	Kim and Park (1994) (14)	58	Walraven (1978) (3)
29	Krefeld and Thurston (1966) (39)	59	Xie et al. (1994) (1)
30	Kung (1985) (5)		

*Figures in parathesis indicate the number of RC beams tested for shear strength

Table 2 Parameters influencing shear strength of RC beam

Sl No	Influencing parameters	Notations (Units)
1	Width of beam	b (mm)
2	Effective depth of beam	d (mm)
3	Shear span to depth ratio	a/d
4	Percentage reinforcement	Pt (%)
5	Yield strength of steel	f_sy(N/mm^2)
6	Compressive strength of concrete	f_lc(N/mm^2)

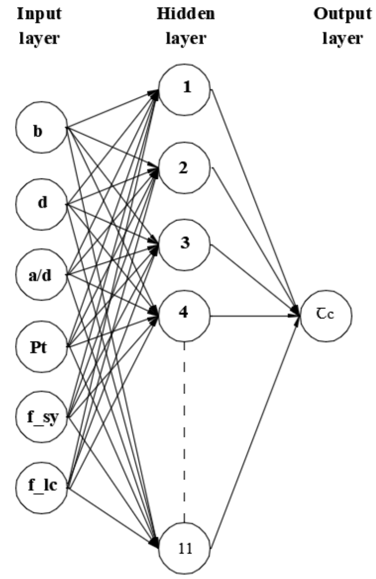

Fig. 2 ANN model adopted in the present work

3.1 Training of ANN model

The 584-dataset compiled in the study is randomly reserved as training dataset, validation dataset and testing dataset. About 70% of the data is set aside for training phase of the neural network. Feed forward-back propagation type of network architecture is adopted for training the neural network model. Mean absolute error is used as the measuring criteria of training accuracy. Training is carried until the global minima is achieved i.e., until the network possesses the generalization ability over the training set.

ReLu activation function is used between the input layer and the hidden layer. It is a non-linear activation function that is generally used in multilayer neural networks which is given by,

$$f(x) = \max(0, x) = \begin{cases} 0, \text{if } x < 0 \\ x, \text{if } x \geq 0 \end{cases}$$

The output of ReLu is the maximum of zero and the input value, x.

Linear activation function is used between hidden layer and output layer during training process. It is a simple linear function which is directly proportional to the input i.e., the weighted sum of neurons and the function is represented as,

$$f(x) = k * (\sum W_{ij} * X_j)$$

where k = Constant, W_{ij}= Weight associated with the link, X_j= Input neuron.

3.2 Validation of ANN model

After training, about 10% of the total dataset (not used in training) is used to validate the ANN model. The shear strength predicted for the validation dataset provides an unbiased evaluation of the model fit on the training dataset while tuning the model's hyperparameters such as number of hidden layers, number of hidden neurons, learning rate and number of epochs.

3.3 Testing of ANN model

The ANN model is put to test by considering about 20% of the total dataset (not used in training and validation). The shear strength predicted from the fresh dataset, also called as holdout dataset, provides an unbiased evaluation of the final model fit on training dataset.

4. RESULTs AND DISCUSSION

4.1 Correlation between the influencing parameters and the shear strength of RC beams without shear reinforcement

Fig.3 represents the feature correlation map developed between the shear strength of RC beam and the influencing parameters from the colaboratory platform. Correlation coefficients indicate the influence of the variables on the shear strength of RC beam. The positive correlation of 0.53 is identified between percentage of steel and shear strength of RC beam which means that shear carrying capacity increases with increase in amount of longitudinal reinforcement. The negative correlation of 0.54 between effective depth of RC beam and the shear strength of beam indicate that shear strength decreases with the increase in effective depth of RC beam. The correlation map indicates that grade of steel has least influence on the shear strength of RC beam.

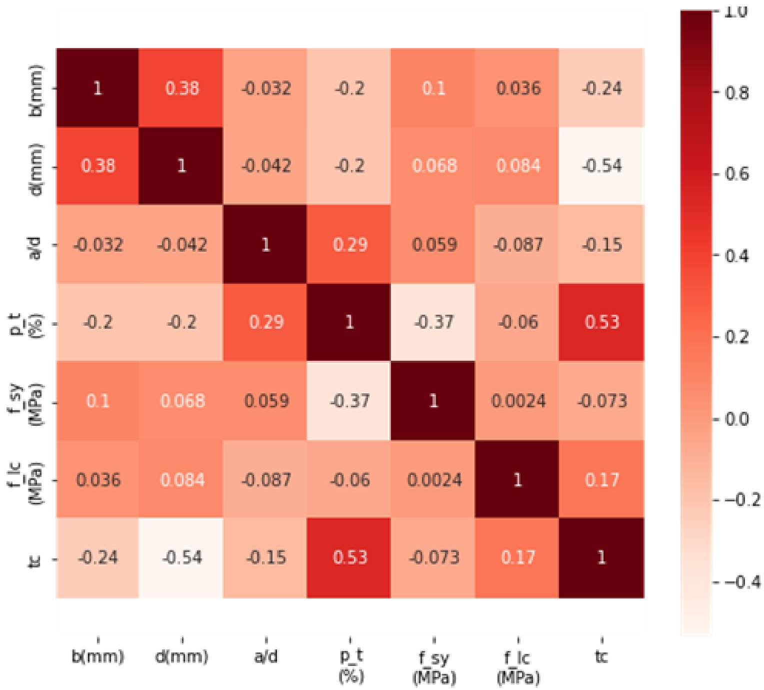

Fig. 3 Feature correlation map between the influencing parameters and shear strength of RC beam

4.2 Comparison between shear strength results predicted from ANN model with experimental results

The holdout dataset of 116 RC beams without shear reinforcement reserved randomly for the testing purpose is used to check the prediction accuracy of the ANN model. The shear strength predicted for the holdout dataset from ANN is compared with experimental test results and is shown in Fig.4. The average ratio of experimental shear strength to shear strength predicted from ANN {τ_c (Test))/ τ_c (ANN)} is found to be 0.98. The results indicate that the developed ANN model satisfactorily predicts the shear strength RC beam without shear reinforcement.

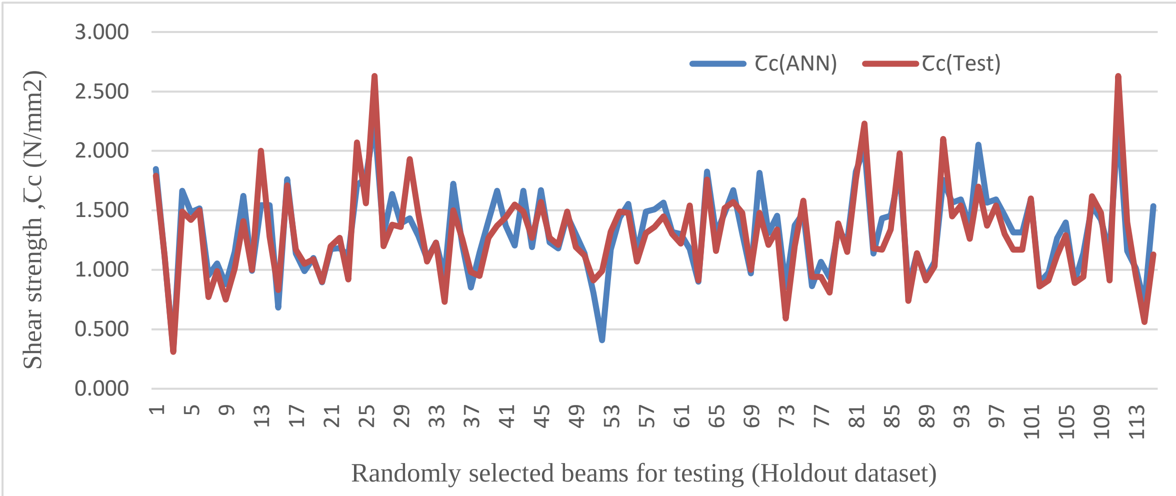

Fig. 4 Comparison of shear strength predicted from ANN with test results

4.3 Comparison between shear strength predicted from ANN model with various codes of practice

The shear strength predicted from ANN is also compared with those computed from various codes of practice for the holdout dataset and are presented in Figs.5 to 8. Table 3 shows the average ratio of the shear strength computed from standard codes of practice to the shear strength predicted from the ANN model for the holdout dataset.

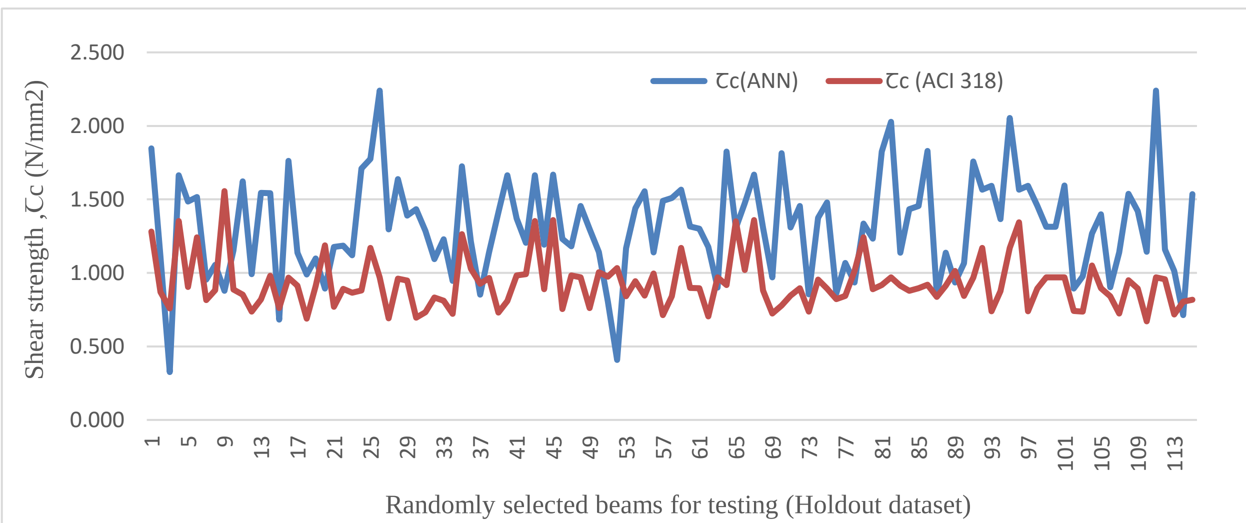

Fig. 5 Comparison of shear strength of RC beams results predicted from ANN and ACI 318

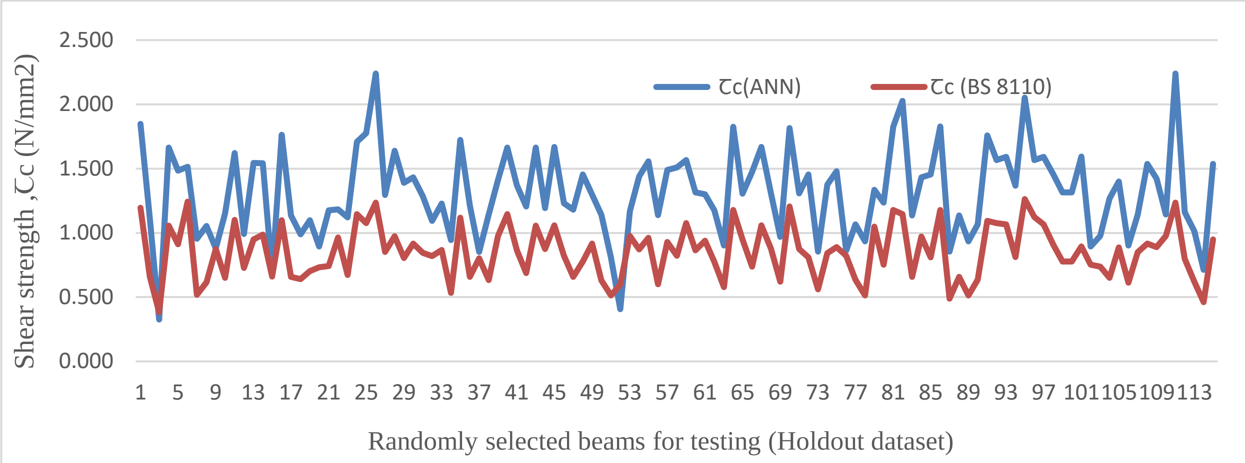

Fig. 6 Comparison of shear strength of RC beams results predicted from ANN and BS 8110

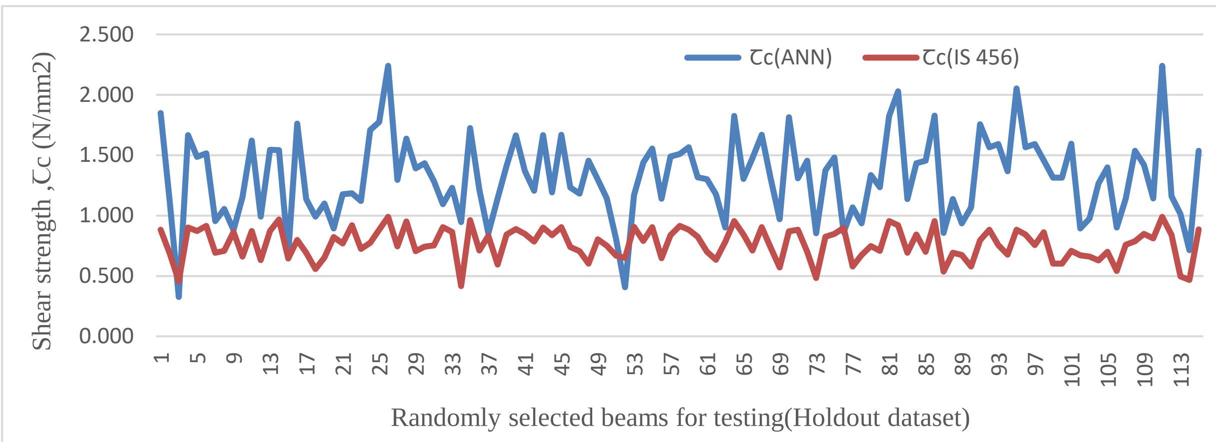

Fig. 7 Comparison of shear strength of RC beams results predicted from ANN and IS 456

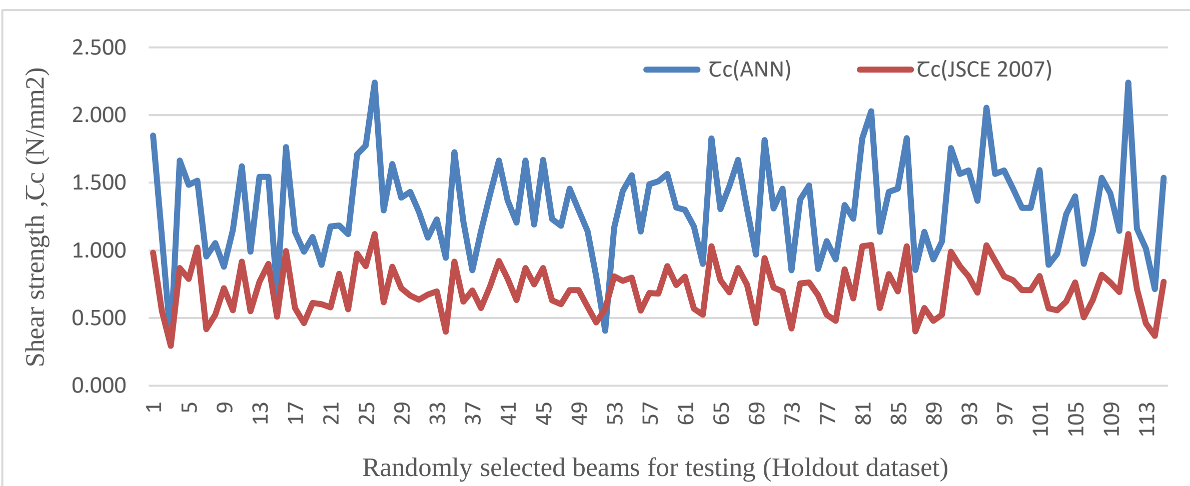

Fig. 8 Comparison of shear strength of RC beams results predicted from ANN and JSCE 2007

Table 3 Average ratio of Ʈc (Code)/Ʈc (ANN)

Sl.no	Standard codes	Ʈc (Code)/Ʈc (ANN)
1	ACI 318 (2014)	0.75
2	BS 8110 (1997)	0.66
3	IS 456 (2000)	0.61
4	JSCE 2007 (2010)	0.55

The results presented in Figs.5 to 8 and Table 3 indicates that the shear strength results of RC beam computed for the holdout dataset from the standard codes of practice underestimate the shear strength predicted from ANN model.

5. CONCLUSIONS

The important conclusions drawn from the present work are.

1. The ANN model developed with the python programming language can predict the experimental shear strength of RC beams without transverse reinforcement satisfactorily.
2. The feature correlation map suggests that percentage of reinforcement and effective depth of member have larger influence on shear strength of RC beam. However, grade of steel has little influence on shear strength of the RC beam.
3. The shear strength of RC beams predicted using ANN model are in good agreement with the experimental results. The shear strength computed from various codes of practice is found to underestimate the shear strength predicted from ANN model.
4. The present study indicates that the ANN model having six variables in input layer and single hidden layer with 11 hidden neurons is sufficient to predict the shear strength of RC beam satisfactorily.

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