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RESEARCH PAPER

ARTIFICIAL NEURAL NETWORK MODEL FOR LOW STRENGTH RC BEAM SHEAR CAPACITY

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ABSTRACT
This research was to investigate how the shear strength prediction of low strength reinforced concrete beams will improve under an ANN model. An existing database of 310 reinforced concrete beams without web reinforcement was divided into three sets of training, validation and testing. A total of 224 different architectural networks were tried, considering networks with one hidden layer as well as two hidden layers. Error measures of strength ratios were used to select the best ANN model which was then compared with 3 conventional design code equations in predicting the shear strength of 26 low strength RC beams. Even though the ANN was the most accurate, it was less conservative compared with the design code equations. A model reduction factor based on the characteristic strength concept is derived in this research and used to modify the ANN output. The modified ANN model is conservative in terms of safety and economy but not overly conservative as the conventional design equations. The procedure has been automated such that when new experimental sets are added to the database, the model can be updated and a new model could be developed.

Keywords: *Shear strength, reinforced concrete, Artificial Neural Network, design equations*

INTRODUCTION

Structural behavior of reinforced concrete members in terms of bending is well understood. This is because various procedures for design and code provisions for bending strength capacity are reasonably consistent. However, shear behavior of such concrete elements is still not fully explained. Provisions made by different international building codes reveal great variation from code to code in the fundamental principles of shear prediction. This has led to research over the last century, with increased research activity over the last 20 years. The understanding of shear behavior in reinforced concrete is limited as a result of a complex transfer mechanism and varying influencing parameters. The major challenge in this research area is that of an analytical direction which constitutes a basic approach to understanding shear behavior with respect to material properties and structural analysis (Shah and Ahmad, 2007, Regan, 1993, Oreta, 2004, Jung and Kim, 2008).Analytical models such as compression field models (Zsutty, 1968,Vecchio and Collins, 1986) have been corrected over the years through testing and have become part of structural concrete codes of practice. Development of theoretical models has seen advancement with the development of numerical methods (mostly finite element methods) and computation systems capable of solving a great number simultaneous equations derived from component testing results (Dopico *et al*., 2008). An approximation of the theoretical shear behavior of structural concrete has therefore been obtained through experimental and empirical means. It is also believed by others (Zsutty, 1968) that regression analysis of database of experimental tests may not adequately capture the complex interdependence between influencing variables and the uncertainties introduced into the results.

To improve on shear prediction capabilities, database of experimental results have been compiled by some researchers. Yang and Ashour (2008) organized a database of deep beams with varying parameters of length, concrete strength, amount of reinforcement and cross-sectional properties. Reinack *et al*. (2003) including others (Bohigas, 2000; Chung, 2000) have compiled comprehensive database of both slender beams and deep beams individually. To maximize the use of this database of experimental results, researchers have recognized the use of computerization procedures. This has helped to improve efficiency, culminating in better models and predictions. The state of the art approach to computation procedures is the use of artificial intelligence to imitate problem-solving strategy of humans (Cladera and Mari, 2004, Kim *et al*., 2005; El-Chabbib *et al*., 2006).

The retrieval mechanism in this procedure is the Artificial Neural Networks (ANN). Shear behavior in concrete is an adequate field for the development of analysis techniques based on the neural networks(Nandi, 2001).Cladera and Mari (2004) proposed a new design equation for shear strength based on information retrieved with ANN. Sanad and Saka (2001) predicted the ultimate shear strength based on 111 experimental data processed by ANN. El-Chabib et al. (2006) also developed ANN models using 398 experimental data to study the effect of stirrups on shear.

The major contribution of coarse aggregates to the strength of a reinforced concrete beam is in shear. Therefore, reasonable predictions as well as conservative shear designs are necessary in reinforced concrete engineering. Experience from previous works (Adom-Asamoah and Afrifa, 2011; Adom-Asamoah *et al*., 2009, Kankam and Adom-Asamoah, 2002; Kankam and Adom-Asamoah, 2006) have shown that concrete beams produced in Ghana by artisans and small scale contractors using both conventional and non-conventional aggregates result in low strength concrete. Shear failure is the most predominant failure mode even for such beams when designed with adequate shear reinforcement. The implication of this observation is that existing structural codes of practice may not be adequate in predicting the shear capacity of such concrete members. Work by other researchers using artificial intelligence to improve on theoretical shear modeling did not consider low strength concrete beams made from both conventional and non-conventional aggregates. Such beams are mostly slender with effective depths up to 600mm and percent longitudinal reinforcement up to 3%.

This research was to investigate how the shear strength prediction of low strength reinforced concrete beams will improve under an ANN model. An existing database of 310 reinforced concrete beams without web reinforcement were trained, validated and tested using a wide range of concrete parameters including low strength, medium strength and high strength concrete. Performance evaluation of the best ANN model was then undertaken to obtain an accurate and reasonably conservative prediction model. The evaluation was undertaken by use of a novel data of 26 beams obtained from the laboratory tests of low strength concrete RC beams made from granite, phyllite, weathered granite and recycled concrete aggregates.

SHEAR TRANSFER MECHANISM OF RC BEAMS WITHOUT WEB REINFORCEMENT

The complex redistribution of stresses after cracking in a concrete beam without web reinforcement contributes to the various factors that affect shear transfer mechanisms. The basic mechanisms of shear transfer reported elsewhere (ASCE, 1973, ASCE, 1998) and adopted by researchers involved in the investigation of the shear models used in ASCE-ACI codes of practice is simplified as presented in Fig. 1. It illustrates the most important contributions to the transfer mechanisms as shear in compression zone, V_{cc} interface shear transfer due to aggregate interlock V_{ca}, dowel action of longitudinal reinforcement, V_d and residual tensile stresses across the cracks, V_{cr}. On the advent of a flexural crack, tensile stresses build-up in the longitudinal reinforcement until dowel action reaches its capacity. With a further increase in shear load, shear cracks cause concrete in-between the flexural cracks to isolate, leading to termination of the tensile flow in the longitudinal reinforcement. Aggregate interlock effect reduces as the crack width increases with shear load increment. This allows a large shear force to be induced in the concrete compression zone after which an abrupt failure occurs, indicating shear failure. Some of the factors that influence shear capacity of RC beams other than compressive strength are; beam depth or size (Bazant and Kim, 1984, Shioya *et al*., 1989), span to effective depth (Taylor, 1972, Mphone and Frantz, 1984), longitudinal reinforcement or dowel action (Collins *et al*., 1996) and yield strength (MacGregor, 1992).

Cracks in concrete can transmit shear forces by virtue of the roughness of their interfaces. With regard to this roughness, the aggregate particles protruding from the crack faces play an important role. Low strength concrete has much more micro cracking at all stress levels than high strength concrete (Carrasquillo *et al*., 1981) and therefore fails with more planes of failure. Fenwick and Paulay (1958) also found out that there is substantial reduction in shear transmitted by aggregate interlock action in low strength concrete since crack widths are increased.

ARTIFICIAL NEURAL NETWORK

The Artificial Neural Networks (ANNs) appro–

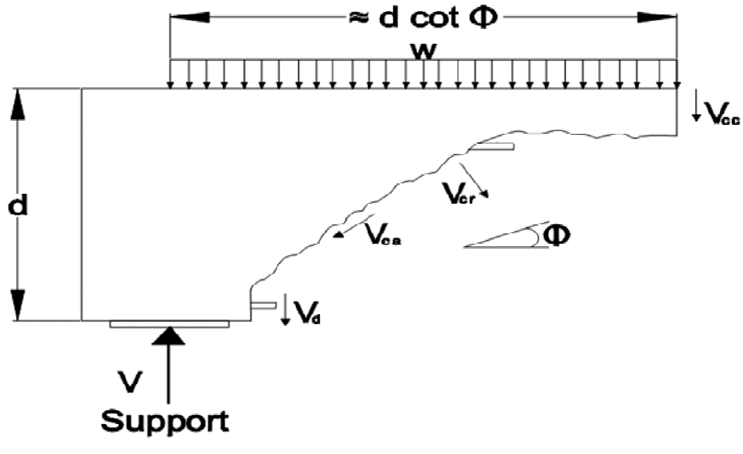


Fig.1: Shear transfer mechanism

ach is used to predict the shear stress of the concrete in this study. An ANN is a mathematical model that emulates biological neural networks. It consists of interconnected groups of artificial neurons that process information using connectionist approach to computation (Singh and Chauhan, 2005). It has the ability to learn relationship between input and output provided that sufficient data are available for its training. It does not require an explicit understanding of the mechanism underlying the process, which is the main advantage.

The ANN makes use of simple processing units connected by links. The processing unit may be grouped into three main layers namely input layer, hidden layer(s) and output layer. A general Topology or Architecture is presented schematically in Fig.2.

There may be one or more hidden layers before the output layer. Each hidden layer will possess an activation function to compute output to the proceeding layer.

The strength of any connection between any two nodes or neurons is provided by weights. Each hidden and output layer processes its input by multiplying each input by its weight and sum the product. Weight may be negative implying that the signal is inhibited by the weight. The sum is further processed using a non-linear transfer function to produce results. The output of each intermediate hidden layer turns to be input to the following layer. Each processing unit can send out only one output although it normally receives various inputs. The final output produced is compared to the target (actual or desired) output.

The weights used for the feed-forward process are adjusted by training the network through data set of inputs and outputs. Training the neural involves an iterative adjustment of the connection weights so that the network produces the desired output in response to every input signal. Back-propagation network is the most common and powerful technique for training (Howard, 2002, Sarle, 1994), the error produced is systematically distributed backwards into the network. Figure 3 illustrate summary of the forward-feed and back-propagation technique of learning /training.

EXPERIMENTAL DATABASE

Existing database that is easily accessible is very limited even though many researchers have compiled a number of them. This study made use of 310 shear test results from different sources (Shah and Ahmad, 2007, Hassan *et al*., 2008, Angelakos, 1999, Kwak *et al*., 2002, Cladera and Mari, 2007, Imram and Saeed, 2007, Russo *et al*., 2004). Most of the beams were rectangular and loading was simply supported, under four-point and three-point bending systems. All the beams did not have web reinforcement. The major parameters that were considered in selecting these beams included concrete strength, span to effective depth ratio, beam width and depth and amount of longitudinal reinforcement. Moreover, the database of test results available provides mainly these five parameters. The statistical distributions of these influencing parameters are shown in Table1. The total number of data was grouped into three subsets; a training set of 250 data, a validation set of 15 data and a testing set of 45 representing approximately 80%, 5% and 15% of data respectively. The statistics of training, validation and testing sets are in good agreement meaning they represent almost the same population and influencing parameters are well distributed among the three data sets. The training set captures the extreme values of the parameter since it has the least minimum value and the largest maximum value for each parameter.

BUILDING THE ARTIFICIAL NEURAL NETWORK

The ANN for this study contained 5 input variables of concrete compressive strength, f_{cu}(N/mm^2), beam depth, d(mm), beam width b(mm), span to depth ratio, a/d and amount of reinforcement p(%). One (1) output of shear stress, v_u (N/mm^2)was desired. A neural network dev-

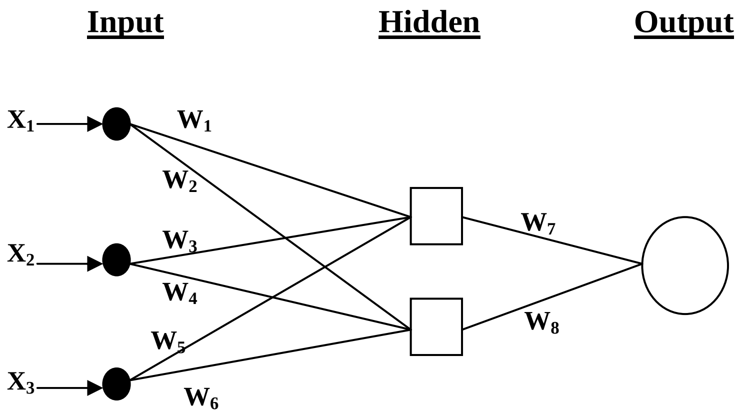


Fig. 2: Schematic drawing of the topology of ANN

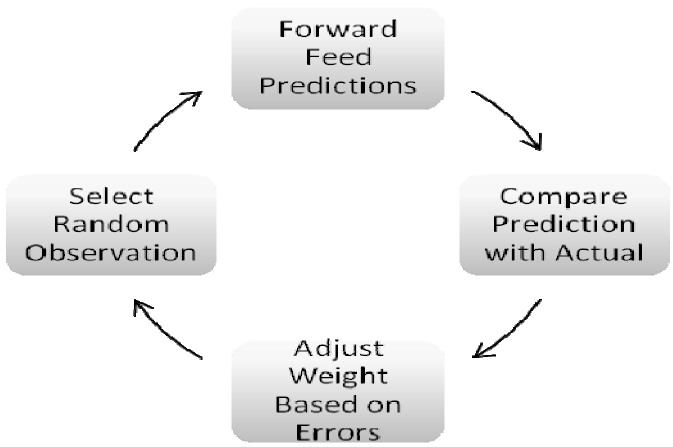


Fig. 3: Summary of the training of data set

eloping software called NeuroSolutions (2009) was used as the core computational tool for the ANN. A multilayer neural network having a back-propagation algorithm with a nonlinear function was employed. Since nonlinear transform functions can result in a well-trained process with back-propagation algorithms, the log-sigmoid function was used in both hidden and output layers. The activation function of the log -sigmoid and its derivative are asymptotic to value 0 and 1.Therefore each input for the ANN was divided by a scalar that is slightly larger than the largest component in the database so that a normalized input is smaller than 1.0.This is very important since the ANN is very sensitive to absolute magnitudes (Oreta,

Table 1: Statistical distribution of influencing parameters

	(ρ)% %	**a/d**	**f_{cu} (Mpa)**	**d (mm)**	**b (mm)**	***v_u (N/mm^2)***
Training set						
No. of data	**250**	**250**	**250**	**250**	**250**	**250**
Mean	1.19	3.00	49.95	269.73	206.30	1.84
Stdv	0.60	1.44	9.03	77.33	134.12	1.24
Cov	0.50	0.43	0.18	0.29	0.65	0.68
Min. V	0.35	1.00	22.50	51.00	90.00	0.21
Max.V	3.06	6.95	74.80	667.50	839.00	9.66
Validation set						
No. of data	**15**	**15**	**15**	**15**	**15**	**15**
Mean	1.29	2.64	26.18	261.00	215.00	2.31
Stdv	0.60	1.20	4.42	111.45	288.96	0.61
Cov	0.47	0.45	0.17	0.43	1.34	0.26
Min. V	0.44	1.90	23.00	126.00	90.00	1.43
Max.V	2.00	2.48	38.00	460.00	839.00	3.53
Testing set						
No. of data	**45**	**45**	**45**	**45**	**45**	**45**
Mean	1.23	3.06	39.55	236.40	174.41	1.90
Stdv	0.58	1.29	15.01	48.88	89.84	1.12
Cov	0.47	0.42	0.38	0.21	0.52	0.59
Min. V	0.35	1.00	19.80	126.00	90.00	0.32
Max.V	2.74	6.90	66.10	307.00	466.00	4.89

2005).

Training of ANN

To prevent over-fitting (Sarle, 1994), ANN architecture of 1 hidden layer and 2 hidden layers are investigated in this study. The number of nodes/neurons for each layer is varied from 2 to 15. Through trial and error, 14 different models are created for ANN with 1 hidden layer and 210 different models for 2 hidden layers. The different ANN topologies or architectures are identified as ANN followed by the number of neurons in each layer. The first and last figures of each ANN indicate the number of neurons in input and output layers respectively, and others refer to the number of neurons in hidden layers. Each network is trained and validated using 10,000 iterations while saving the network architecture every100 iterations. The networks at various iterations are evaluated for testing cases.

Selection of best ANN Model

In determining the best ANN model, error measure of the strength ratios (ratio of experimental to predicted shear) of all the models were monitored at each stage of training, validation and testing. Initial selection is made with the mean measure that was close to 1.0. Five of these models that showed the smallest maximum error are selected, based on the testing data sets. Since error measures of standard deviation and the minimum error for the selected models were very similar, the criterion of maximum error measure was employed as it showed notable scatter. The five best models selected with their corresponding error measures are shown in Table 2. The strength of the overall best model, ANN (5791) was measured using the least mean and the Pearson product moment correlation (R). An R measure of 0.92 indicates that the model can explain about 92% of the variability in the prediction capability. This shows a good generalization of the ANN model to predict concrete shear strength.

COMPARISON OF THE ANN SHEAR MODEL WITH CONVENTIONAL CODE EQUATIONS

The mechanisms of shear transfer in concrete are complex and difficult to model. Therefore different researchers employ varying levels of modeling ranging from simple empirical equations to complex nonlinear finite element considerations. The three most common design code approaches used by designers in Ghana for shear strength of reinforced concrete members and adopted for this research are shown in Table 3.

The concrete shear strength obtained from the 3 conventional code equations are compared with that of the best ANN model using some error measures. Table 4 provides the mean, standard deviation (Stdev), coefficient of variation (cov), maximum and minimum strength ratio for the experimental to theoretical shear strengths (V_{exp}/V_{code}) for the 4 different approaches to

Table 2: Error measures of five best models

	MIN	MEAN	MAX	STD	R
(1)ANN (551)	0.52	1.006	1.82	0.28	0.88
(2)ANN (571)	0.54	0.989	1.61	0.27	0.90
(3)ANN (5651)	0.43	0.999	2.39	0.32	0.91
(4)ANN (5531)	0.42	0.987	1.70	0.30	0.89
(5)ANN (5791)	0.45	0.995	1.90	0.34	0.92

Table 3: Summary of some current codes of practice

Code	Predicted failure shear strength
ACI 318 (2005)	$v_c = 0.16\sqrt{f_{cu}} + 17\rho\frac{V_u d}{M_u}$
BS 8110 (1997)	$v_c = 0.79(\rho)^{\frac{1}{3}}\left(\frac{400}{d}\right)^{\frac{1}{4}}\left(\frac{f_{cu}}{25}\right)^{\frac{1}{3}}(\frac{1}{1.25})$
EC 2 (2003)	$v_c = 0.12k(100\rho(f_{ck})^{\frac{1}{3}} - 0.15\frac{N_u}{A_c}; k = 1 + \sqrt{\frac{200}{d}} \leq 2.0;\ f_{ck} = f_{cu} - 1.6$

v_c: Shear strength provided by concrete; f_{cu}: Concrete compressive strength; d: Effective depth;
a: Shear span; ρ: Longitudinal reinforcement ratio ($A_s/b_w d$); A_s: Amount of longitudinal reinforcement; b_w: Web width,
Vu: Shear force; M_u: External moment; N_u: Axial force; A_c: Cross section of concrete

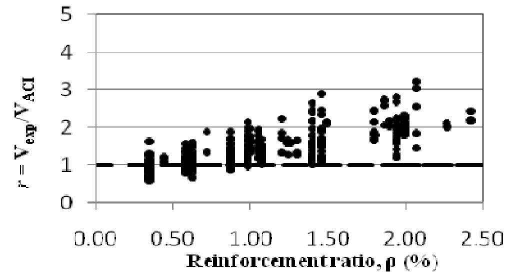
shear prediction using 310 tests results in the database. As reported by others (Dopico et al., 2008, Yang et al., 2008, Russo et al., 2004), the mean can be used as a rough measure of conservative or unconservative bias of the approaches on the safety, and the cov can be used as an indication of accuracy. The simplified ACI 318-05 shear formula gives a mean of 1.51 and cov of 0.34. ACI which considers only the effect of concrete strength on shear strength tends to be unconservative as percent longitudinal reinforcement decrease but underestimates the shear strength as percent longitudinal reinforcement increase as shown in Fig 2a. ACI generally provides conservative estimates of concrete shear strength for beam depths less than 700mm (Fig 2b).

Earlier work (Jung and Kim, 2008) on ACI shear prediction of deep beams of depths ranging from 1000-2000mm indicated overestimated predictions. BS 8110 (1997) provides slightly better predictions than ACI in terms of accuracy of strength ratio with a mean of 1.51 and cov of 0.23. Figs 2c and 2d indicate that BS 8110 is conservative in the prediction of concrete shear strength for percent longitudinal reinforcements up to 2.5 and effective beam depths up to 700mm. EC 2 (2003) prediction (Table 4) which has a mean of 1.36 and cov of 0.31 is generally less biased as compared to ACI and BS 8110. Figs 2e and 2f show very conservative results in percent longitudinal reinforcements less than 2.5 and beam depths up to 300mm. In the best ANN model, a strength ratio mean of 1.15 and a cov of 0.18 obtained indicate the best performance of shear strength. Contrary to the conventional code expressions (BS8110, ACI and EC 2), the ANN model leads to a point distribution almost horizontal, close to the ordinate value 1, and within a very narrow band (Figs 2g and 2h). Therefore the prediction of the experimental shear strength value is almost uniformly approximate for the 310 beam specimens and quantitatively accurate for the ANN code. It can clearly be seen from Fig 2g-h that there is no biased trend in strength ratios as compared to other approaches in Fig 2a-f.

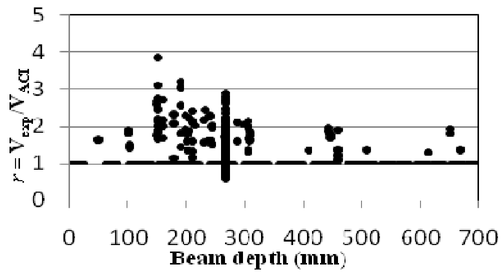
EVALUATION OF SHEAR MODELS USING EXPERIMENTAL RESULTS OF LOW STRENGTH CONCRETE BEAMS

In order to evaluate the implications of the various models on the prediction of shear strength of low strength class concrete, a different data set of 26 reinforced concrete beams was used. Beams made from different coarse aggregate types were selected to cover the various aggregates that may contribute to low shear capacity of concrete beams in developing countries. All the beams were without web reinforcement selected from previous research works (Afrifa, 2011, Adom-Asamoah et al., 2009) conducted at the Department of Civil Engineering, University of Science and Technology, Ghana. Ten (10) of the beams were made from phyllite aggregates (P1-P10), twelve (12) of the beams were made from normal granite aggregates (G1 -G10, B1-B2), two (2) beams were made from weathered granite aggregates (W1-W2) and two (2) beams made from recycled concrete aggregates (R1-R2) to make up the novel data set. The beam design values of the variables used to generate the novel data (case study beams) cover a reasonable domain of reinforced concrete beams span, dimensions, compressive strength, reinforcing steel ratio and span to depth ratios. Table 5 presents the description of beam geometrical properties, material properties and experimental failure shear strengths. All the beams failed in shear under four point bending test.

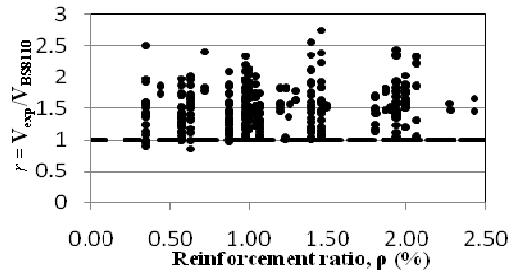
A comparison of the experimental shear strengths of the beams has been made with that of the predictions by the 4 models (ANN, ACI 318-05, BS 8110, 1997 and EC 2, 2003) as shown in Fig 3. The ACI shear predictions of all the beams were the most conservative of all the codes. This is because the ACI shear formula is dependent mainly on concrete compressive strength and therefore tends to produce fairly constant shear strength so long as compressive strength remained constant as observed in beams P1-P10 and G1-G10.



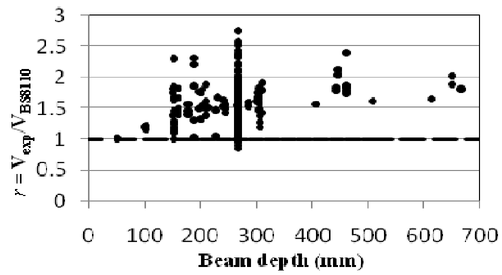
(a) ACI code strength ratio vs reinforcement ratio



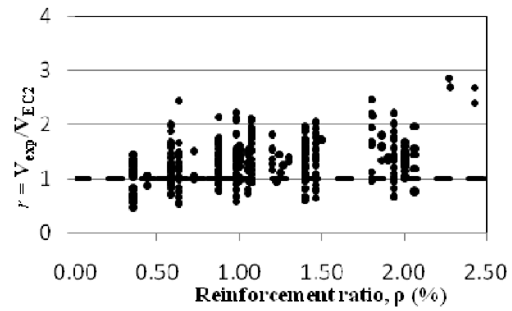
(b) ACI code strength ratio vs beam depth



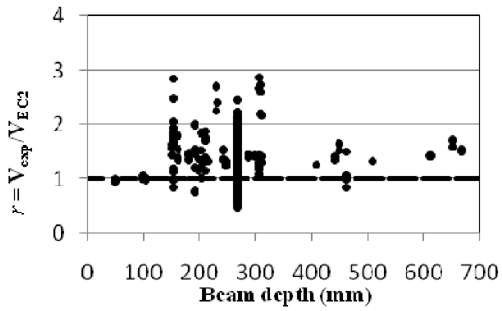
(c) BS8110 code strength ratio vs reinforcement ratio



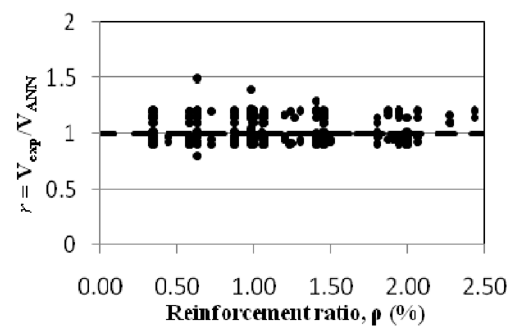
(d) BS8110 code strength ratio vs beam depth



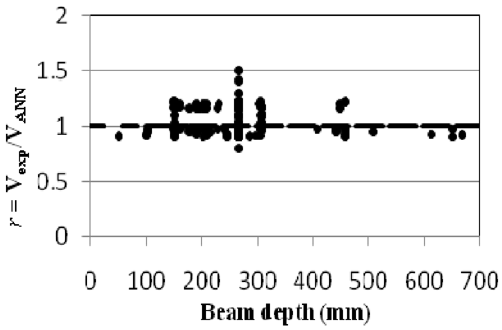
(e) EC2 code strength ratio vs reinforcement ratio



(f) EC2 code strength ratio vs beam depth



(g) ANN code strength ratio vs reinforcement ratio



(h) ANN code strength ratio vs beam depth

Fig. 2: Strength ratios of 4 code approaches using 310 beams

Table 4: Error measures of strength ratios

	Max	Min	Mean	StDev	Cov
BS8110	2.75	0.85	1.40	0.31	0.23
ACI	3.88	0.59	1.50	0.51	0.34
EC2	2.86	0.47	1.36	0.43	0.31
ANN	1.50	0.80	1.03	0.11	0.11

Table 5: Description of Beams of Novel data

BEAM No.	BXD (mm xmm)	Length (mm)	Shear span/ eff.depth (a_v/d)	Long. Reinf. ρ (%)	Concrete comp. f_{cu} (N/ mm^2)	Concrete tensile. f_{cr} (N/ mm^2)	Exptal Shear Strength (N/mm^2)
P1	140 X 310	2400	2.45	1	23.5	3.4	1.70
P2	140 X 310	2400	2.45	2	23.5	3.4	1.95
P3	140 X 265	2000	2.45	1	23.5	3.4	1.96
P4	140 X 265	2000	2.45	2	23.5	3.4	2.37
P5	110 X 225	1700	2.48	1	23	3.38	2.26
P6	110 X 225	1700	2.48	2	23	3.38	2.26
P7	110 X 184	1500	2.46	1	23	3.38	2.27
P8	110 X 184	1500	2.46	2	23	3.38	2.61
P9	90 X 150	1000	2.35	1	23	3.38	2.47
P10	90 X 150	1000	2.35	2	23	3.38	3.53
G1	140 X 310	2400	2.45	1	27.1	2.7	1.85
G2	140 X 310	2400	2.45	2	27.1	2.7	2.15
G3	140 X 265	2000	2.45	1	27.1	2.7	1.96
G4	140 X 265	2000	2.45	2	27.1	2.7	2.90
G5	110 X 225	1700	2.48	1	26.4	3.4	2.35
G6	110 X 225	1700	2.48	2	26.4	3.4	2.35
G7	110 X 184	1500	2.46	1	26.4	3.4	2.61
G8	110 X 184	1500	2.46	2	26.4	3.4	3.07
G9	90 X 150	1000	2.35	1	26.4	3.4	3.70
G10	90 X 150	1000	2.35	2	26.4	3.4	4.23
W1	140 X 230	2000	2.5	1.2	14	3	1.19
W2	140 X 230	2000	2.5	1.2	14	3	1.75
B1	140 X 230	2000	2.5	1.2	19.8	3.75	1.75
B2	140 X 230	2000	2.5	1.2	19.8	3.75	1.82
R1	140 X 230	2000	2.5	1.2	14.6	3	1.19
R2	140 X 230	2000	2.5	1.2	14.6	3	1.26

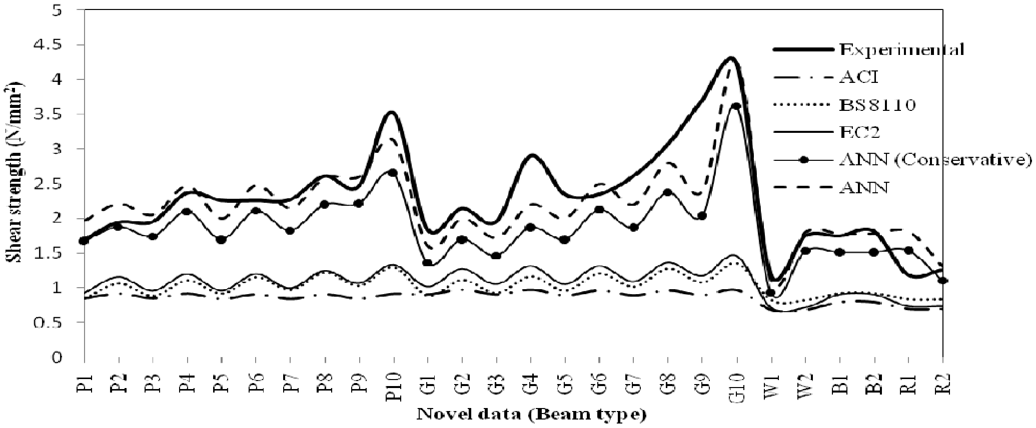


Fig. 3: Evaluation of shear codes using novel data of low strength RC beams

As the number of dependent variables increased from BS 8110 (3 variables) to EC 2 (4 variables), the provision of a larger margin of safety reduced as shown in Fig 3. The ANN model which is the least conservative of all the models however gives the most accurate estimate of shear strength. As a result of the high uncertainty in concrete shear strength prediction, it is advisable to obtain a conservative prediction rather than an accurate but less- conservative prediction. The non-conservative nature of the ANN model prediction implies that it may not be suitable for conventional design. This observation has also been made by other researchers (Jung et al., 2008) on ANN shear prediction who employed a reduction factor to correct the error of non-conservative prediction. In that research, the reduction factor was obtained by randomly dividing the non-conservative prediction into testing and training sets via the ANN building procedure.

In this research work, a conservative ANN model adequate for design is obtained by imposing that the probability of the computed strength (ANN model) to exceed the test results (provided in Table 4) must be less than 5% (ie deriving a characteristic expression). Therefore the design (characteristic) shear strengths are obtained by multiplying the ANN results by a reduction coefficient r, which is the 0.05 fractile of the corresponding statistical distribution. The r coefficient is computed as:

$$r = AVG\text{-}\alpha STD \qquad (1)$$

where AVG = mean strength ratio, STD=standard deviation of strength ratio and the acceptance constant α=1.645 for a normally distributed population of more than 30. Substituting AVG=1.03 and STD=0.11 from Table 4 into equation 1, a reduction coefficient r=0.85 was used to multiply the ANN values. This resulted in a conservative ANN curve which shows a great improvement in the conservatism as compared to the ANN, ACI 318-05, BS 8110 (1997) and EC 2 (2003) as shown in Fig 3. Therefore subsequent predictions of concrete shear strength must be made using the ANN model multiplied by the reduction coefficient to obtain the conservative ANN model.

CONCLUSION

This paper employs artificial neural networks which emulates biological neural networks. A database of concrete shear strength for beams is used to generate ANN models that predict concrete shear strength. Error measures of strength ratios were used to select the best ANN model which is then compared with 3 conventional code expressions. The best ANN model produced the lowest mean, standard deviation and coefficient of variation for test/computed strength ratios for 310 beam shear failures implying high accuracy and precision in prediction. When the 4 models were evaluated using low strength RC beam data, although the ANN was the most accurate, it was less conservative compared with the design code equations. When conservative prediction is preferred as is a requirement for safety in design, the existing code equations outperform the ANN model. A model reduction factor based on the characteristic strength concept was used to modify the ANN output. The modified ANN model is conservative in terms of safety and economy but not overly conservative as the conventional design equations. The procedure has been automated such that when new experimental sets are added to the database, the model can be updated and a new model could be developed.

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