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Investigation of Ultimate Shear Capacity of RC Deep Beams with Opening using Artificial Neural Networks

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Abstract

Deep beams are structural elements loaded as beams in which a significant amount of the load is transferred to the supports by a compression strut joining the load and the reaction. According to ACI 318-08 ration of free span to height in deep beams are less than 4. The ratio of shear span (the distance between the concentrated load to support in deep beam) is less than 2. Loading transmission mechanism in these beams is loads to reaction. The model takes into account the effects of the effective depth, shear span-to-depth ratio, modulus of elasticity, ratio of the FRP, flexural reinforcement and compressive concrete strength on shear strength. It is also goal to extend an effectual and applied neural network model. So, mechanical attribute and dimensional properties of strengthening beams are chosen as input data. A developed harmony search (HS) algorithm in ANN models is trained, validated and tested by 30 deep beams with opening. Afterward ANN results are estimated with ABAQUS results and theoretical prediction computed from ACI 318-08. Comparisons between the predicted values and 30 test data showed that the developed ANN model resulted in improved statistical parameters with better accuracy than other existing equations. Performed analysis showed that the neural network model is more accurate than the guideline equations with respect to the experimental results and can be applied satisfactorily within the range of parameters covered in this study.
Keywords: *Deep beam, Shear strength, Neural networks, Opening*

1. Introduction

Reinforced concrete (RC) deep beams are used for load distribution in a wide range of structures; for example in tall buildings, offshore gravity structures, as transfer girders, pile caps, folded plates, and foundation walls, also shear walls are considered as cantilever deep beam[1]. Deep beams are often located on the perimeter of framed structures where they provide stiffness against horizontal loads[2].

A deep beam is a beam in which a significant amount of the load is transferred to the supports by a compression thrust joining the load and the reaction[3].

Deep beams can be classified according to their concrete compressive strength as normal or high. The high strength concrete is a type of high performance concrete.

The structural behavior of deep beams differs from that of shallow beams because of the small ratio between shear span and the depth. In contrast to shallow beams, the response is characterized by
nonlinear strain distribution even in the elastic range[4].

The ultimate shear strength of deep beams can be predicted using various methods. These methods comprise the ACI code and Strut-and-Tie model which is also included on the ACI 318-02 Code.

The basic problem of deep beams appears from the reality that a number of parameters affecting shear behavior have led to a limited conception of shear failure mechanism and forecasting of exact shear capacity. Although there were a large number of researches carried out, there is no agreed rational procedure to investigate the strength of reinforced concrete deep beams with opening. This is mainly due to the highly nonlinear behavior associated with the failure of the RC deep beams.

Artificial neural networks (ANNs) are computational modeling instruments that are defined as structures comprised of densely interconnected adaptive simple processing elements. They are able to accomplish massive parallel computations for data processing and knowledge representation. The last few decades have witnessed the growth of artificial neural networks (NNs) practical to different structural engineering problems. They are applied in several civil engineering problems such as structural, geotechnical, management etc. Due to their unique characteristics, NNs can be used to solve problems which are complicated, problems that cannot be handled by analytical methods and even problems whose underlying numerical and physical models may not be well-known. In this respect, NNs may be suitable for predicting the shear resistance of concrete members longitudinally reinforced with FRP bars. The overall research objective is to develop a neural network model to predicting he ultimate shear strength of deep beams.

Training neural networks (NNs) is a complex task of great importance in the supervised learning area. However, performance of the NNs is mostly dependent on the achievement of training procedure, and therefore the training algorithm. To cope the complexity of AAN training problem, metaheuristic optimization algorithms such as genetic algorithm (GA) [5], particle swarm optimization (PSO) [6] and ant colony optimization (ACO) [7] have been highly proposed to search for the optimal weights of the network.

Harmony search is a meta-heuristic algorithm inspired from the initiative process of musicians [8]. Harmony search (HS) algorithm, which is originated from the improvisation process of musicians not from biological or physical processes, is also affiliate for the training of NNs.

To the best of our knowledge, this is the first paper to apply the integration of neural network and harmony search algorithms for estimating shear strength of deep beam with opening.

The rest of the paper is organized as follows: Section 2 gives a brief review of previous works. Section 3 presents the preliminary concepts of neural network-based proposed method. Section 4 reports the experimental results on well-known engineering dataset. Finally, Section 5 presents the conclusion.

2. Currently available shear design guidelines

In deep beams a remarkable value of load is carried to bearing by a compression thrust joining the load and the reaction [9]. This compression in the diagonal direction composed with the tension along the beam bars form the basis for the strut-and-tie model [10].

In general, deep beams are prevailed by shear, rather than flexural. A large amount of compressive forces are directly transferred to supports by “Arch action". A linear elastic analysis is only valid while the deep beam stay Uncracked [11]. However in practice tensile cracks develop in most deep beams between one-third and one-half of the ultimate loads. Therefore, tension reinforcement governs the design of the deep beams. Since the main loads and reactions act in the level of the member, a state of plane stress in the concrete can be computed approximately

Several codes and design guidelines addressing FRP bars as primary reinforcement for structural concrete have been recently published worldwide[12-14]. Most of these design provisions follow the traditional approach of V_C+ V_S+ V_{FRP} for shear design, V_C where is the concrete contribution and V_{FRP} is the FRP stirrup contribution. Nevertheless, the concrete contribution V_C is different in the manner that it has been calculated in these guidelines. Most of the shear design provisions in these guides are based on the design formulas for standard steel reinforced concrete. Many published provisions and methods for shear resistance of FRP reinforced concrete members have been considered in this study i.e. the latest versions and those which are currently performed around the world. However, for the sake of brevity, only three methods are assessed and presented here, namely provisions developed by ACI-440.1R-06, CNR DT 203/2006 and ISIS-M03-07. It is also to be noted that in these design provisions, all safety factors were ignored, i.e. assigned to 1.0. In reality safety factors would be applied to make shear capacity predictions more conservative and acceptable for design aims.

Siao [15] used the strut-and-tie approach, to examine the ability of it in the analysis of shear strength of deep beams with web openings. The results showed that this approach could be used.

Goh [16] used the artificial neural network ANN to predict the ultimate shear strength of deep beams. The neural network predictions were more reliable than predictions using other conventional methods such as ACI and Strut-and-Tie model.

Tan et al [17] studied the variations of the effective span and shear span on the high strength concrete deep beams. Foster and Gilbert [18] studied the crack patterns and failure mechanisms of high strength concrete deep beams by the aid of experimental data.

Tan and Lu [19] investigated the shear behavior of large reinforced concrete deep beams experimentally and a comparison with different codes of practice was made. Aguilar et al [59] evaluated experimentally the design procedure for the shear strength of deep reinforced concrete beams, the behavior of the beep beams was described in terms of cracking pattern, load-versus-deflection response, failure mode, and strain in steel reinforcement and concrete .

Ashour et al [20] performed an empirical modeling of shear strength of reinforced concrete deep beam by genetic programming (GP), which is a new form of artificial intelligence, good agreement between the model predictions and experiments has been achieved.

Sanad and Saka [21] used the artificial neural network in predicting the ultimate shear strength of reinforced-concrete deep beams and the results obtained were compared with the experimental values and with those determined from the ACI code method, strut –and-tie method, and Mau-Hsu method.

3. Neural network

Feed-forward NNs, which are also known as Multi-Layer Perceptrons (MLP), are one of the most popular and most widely used models in many practical applications due to their high capability to forecasting and classification. various NN architectures can be used for assortment purposes such as Self-Organizing Maps (SOM) and Learning Vector Quantization (LVQ)[22]. But it should be indicated that if the class memberships of the training data are known, supervised classification methods such as MLP and LVQ should be used in such cases[23].
Feed-forward NNs have an input layer of source nodes and an output layer of neurons. In addition to these two layers feed-forward NNs generally have one or more hidden layers with hidden neurons, which extract important features embedded in the input data. A sample feed-forward NN with two hidden layers is shown in Fig. 1.

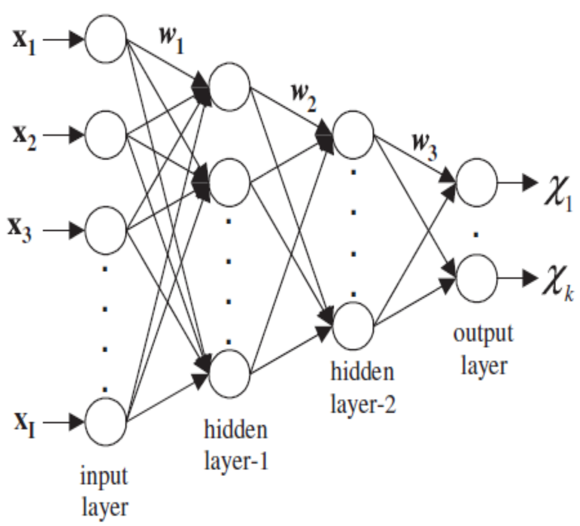

Fig 1: Feed-forward NNs with two hidden layers

In feed-forward NNs signals flow from the input layer through the output layer by unidirectional connections, the neurons being connected from one layer to the next, but not within the same layer. Information flow from input layer to output layer is achieved by hidden layers using weights and activation functions. Each weight specify the influence of an input on the neuron and activation function controls the amplitude of the output of the neuron. In this study, sigmoid function given by Eq.(1) is used as activation function. Here NET_j is the weighted sum of all inputs and O_j is the output of neuron j:

$$O_j=1/1+e^{-NET_j} \quad (1)$$

Feed-forward NNs are usually trained with the BP algorithm. The application of BP basically involves two phases: during the first phase inputs are presented and propagated forward through the NN to compute the output values for each output neuron. Then this output is compared with its desired value and error of each output is calculated. The second phase involves back-propagation of error to each unit in the NN and appropriate weight changes are calculated to make the output values at the output neurons closer to desired outputs. purpose of the BP algorithm is to minimize the error. A widely used error function is the Sum of Squared Error (SSE).
Based on the characteristics of ANNs and EA, we propose ECPA to develop ANNs based on an evolutionary constructive and pruning manner.
Harmony search [24] is a meta-heuristic algorithm inspired from the improvisation process of musicians. In music, harmony at a time is analogous to a solution vector; each musical instrument is analogous to each decision variable; musical instrument’s pitch range is analogous to decision variable’s value range; audience’s esthetics are analogous to objective function and musician’s improvisations are analogous to local and global search schemes in optimization.
The ANN tuned by our HS algorithm is a three-layer feed forward network. The nodes of the input layer are inactive, meaning that they do not modify the features, they only receive them. The inputs are join to all the hidden units, which in turn all connected to all the outputs. All neurons are connected to a bias unit, with stable output of 1. Hidden units employ hyperbolic tangent as their activation function, while output units make use of step function.
Connection weights are regulated by our HS algorithm as represented in Fig. 2.

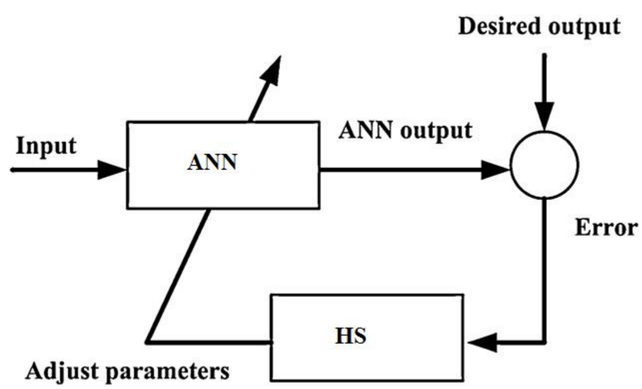

Fig 2: Schematic diagram of HS-based ANN

In the other word, in this paper and artificial neural network algorithm which effectively compounds the local searching ability of the back propagation (BP) method with the global searching ability of HS was implemented for estimating shear strength of deep beam. In this research, we have expressed an Imperialist Competitive algorithm evolved artificial neural network. In Our methodology, HS algorithm was implemented to optimized connection weights of proposed neural network, while combines the local searching ability of the imperialist competitive algorithm and global searching ability of neural network.

4. Proposed Harmony Search (HS) Algorithm

In this study harmony search algorithm is using for finding the best answer to the problem. At first a value for each input variable of possible values is considered. Then collection of the values such as opening size, concrete compression strength, FRP thickness, percentage of longitudinal reinforcement and … constitute a response vector for the variables, amounts of these variables is stored in memory and the possibility of making a better response would increase in the next iterations. The benefits of HS algorithm are insensitive to the initial values, replacing the random searches instead of gradients and less use of mathematics. This algorithm also be used in optimization and data classification and combinatorial optimization. HS can also be used to lower the original random variables and obtained the best answer with less mathematical equations. For the best convergence is achieved, it should compared merit of a new harmony in every category to the worst harmony of those class. For converging solutions if harmony is better than the previous one was replaced by the worst harmony. The equation of proposed algorithm that used to obtain ultimate shear strength is shown in mathematical equation (2):

$$V_i (t+1)= v_i(t) + (R_{cloud} * Rand) \qquad (2)$$

$-1< Rand < 1$, R= class convergence radius,
v_i = harmony vector
V_i = shear strength in deep beam

```
// initialize swarms
for each swarm i
     for each ahrmony j
          initialize vi,j
          pbest i,j = vi,j
    end
    Gbest= arg min f(pbesti,j)
end
// initialize swarm finder
for each harmony finder
     initialize vi,j
end
repeat:
for each swarm i
     for each harmony j
          update vi,j based on equation 2
     end
          call HS Algorithm
end
call HS Algorithm for finder
if finder convergence to peak
   replace worst swarm with finder
end
Execute exclusion and anti-convergence
for each swarm i
      if swarm i convergence to peak
           swarm i is sleep
      end
end
until stopping criterion is met
```

Fig 3:Code of proposed algorithm

5. Experimental and ABAQUS results

In order to measure the proposed method several experiments were conducted for estimating shear strength of deep beam. In this section, the results are reviewed. The experiments have been run on a machine with a 3.2 GHz CPU and 2 GB of RAM. Moreover, the proposed method was compared on experimental shear deep beam. An experimental database of 138 FRP reinforced concrete members failed in shear was initially created to compare experimentally determined shear capacities with the predictions of the three shear design methods presented above, and also to train and test NNs to be developed for shear capacity prediction.
A few of the specimens collected from the same investigation had the same material and geometrical properties, however, their experimentally obtained shear capacities were different. Therefore, the shear capacities of

specimens with identical geometrical and material properties have been averaged to reduce the noise in the training samples and consequently achieve successful training and generalization of NNs created.

Fig4: Cantor tension in strengthening deep beam with opening

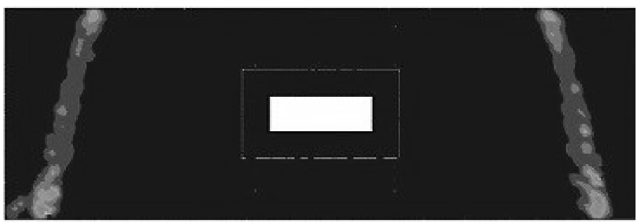

Fig5: Crack pattern in strengthening deep beam with opening

5.1. Dataset Definition

Experimental data used in present study includes data on 310 deep beams collected by Roowusu Afrifa (2012). All of deep beams are rectangular and loading by two point loads under shear systems. All of beams have vertical and horizontal longitudinal reinforcement. The used parameters in this study are Concrete Compressive Strength, shear span, opening size, span to efective depth ratio, beam width and depth, thickness of FRP layers and amount of longitudinal reinfocement. Furthermore, the database of test results available provides these parameters. The fact distribution of these influencing parameters that is mentioned are shown in table 1. The total number of data was classified into three subset, a training set of 26 data, a validation set of 13 data and a testing set of 8 representing approximately 50%, 35%, 15% data respectively. The facts of training, validation and testing sets are in good settlement meaning. They represent almost the same population and impressing parameters are well repartition among the three data sets. The test data values are obtained from modeling deep beams in ABAQUS. These data are compatible with regulations of ACI-318.

6. Training of ANN

By performing certain pre-processing steps on the network inputs and targets, NN training can be made more efficient, commonly referred to as normalization. As upper and lower bounds of the tan-sigmoid function output are +1 and -1, respectively, inputs and targets in the database were normalized so that they fall in the interval [-1, 1]. The network output is then reverse transformed back into the units of the original target data when the created network is simulated.

After the normalization process, samples were given of nine datasets, each of which was partitioned into three subsets: a training set (50 percent of all sample), a validating set (35 percent of all samples) and a testing set (15 percent of all samples). These sets are randomly selected and used for train and test process. The training set is used to train the algorithm for good learning capability, while the testing set is applied to evaluate the generalization capability of the proposed algorithm.

At early stages of trial and error network creation and testing, data corresponding to a high error for the test set were moved into the training set and replaced in the test set with another random combination to achieve better results and learning.

In the training process of the multi-layer feed-forward NNs developed, the error between the prediction of the output layer and experimental shear strength was then back propagated from the output layer to the input layer in which the connection weights and biases were adjusted. The training process was repeated until the maximum epochs were reached, the SSE converged or the performance gradient fell below a minimum value. However, the SSE converged in most trials. A total of 5 different NNs with different architectures were created and tested i.e. networks with varying number of hidden layers and corresponding neurons as listed in Table 3. Each created network weights and biases were randomly re initialized nine times thus the results shown are the most favorable of the ten trials for each NN architecture. SSE was used to monitor the network performance. For each NN four statistical observations; mean, standard deviation, COV% and MAE% of V_{exp}/V_{pred} are used to assess predicted to experimentally observed shear capacities for all specimens as presented in Table 2. It should be noted The NN has a mean value closer to 1, indicating its superior average accuracy as compared to the design methods. Moreover, much less value for the NN standard deviation, COV% and MAE% represents a better functionality for that NN architecture. Although the mean and standard deviation of the ratio of predicted and measured shear capacities of FRP reinforced concrete members presented in Table 1 were similar for different NN architectures, the 14 × 10 × 1 NN was finally selected for predicting shear capacity. The predicted ANN results are primarily compared with experimental FRP contribution of strengthened beams and then with those 'theoretical' predictions calculated directly from the FRP guidelines. It has been from this figure, neural network model successfully build up a relation between the input parameters and the output (contribution of FRP) and predicted efficiently.

Table 1: actuarial distribution of influencing parameters

Training data	**h(mm)**	**b(mm)**	**a(mm)**	**opening Height (mm)**	**opening Length (mm)**	**a/d**	**FRP Thickness (mm)**	**f_c(Mpa)**	**ρ**	**V_u(shear strength) KN**	**P_C (cracking load) KN**
	306	150	300	25	60	2	1.2	40.2	0.44	814	312
	310	155	280	27	60	1.8	1.2	45.4	0.67	471	187
	310	155	295	27	60	1.9	1.2	41.3	0.82	243	143
	310	155	295	27	60	1.9	1.2	64.6	1.098	192	163
	400	200	380	38	75	1.9	1.3	50	0.88	890	280
	608	300	570	55	110	1.9	1.35	40.5	0.387	1273	387
	606	300	570	55	105	1.9	1.35	39.9	0.388	799	287
	607	300	570	55	106	1.9	1.35	41.2	0.387	431	237
	606	300	580	55	100	1.95	1.35	40.7	0.388	830	412
	607	300	600	55	100	2	1.4	66.4	0.387	1062	387
	610	300	600	55	105	2	1.4	68.5	0.386	376	212
	1003	301	700	56	190	2.33	1.5	51.6	0.234	2269	613
	1005	304	760	60	190	2.5	1.5	50.7	0.231	1324	413
Test data											
	350	100	300	18	45	3	1.6	20	0.57	496	139
	450	250	420	35	90	1.68	1.5	30	0.18	550	170
	482	110	410	20	50	3.8	1.5	37	0.38	565	175
	500	120	417	27	65	3.5	1.6	25	0.33	452	127
	510	150	415	27	67	2.8	1.6	25	0.29	480	134.4
	510	104	416	27	67	4	1.6	25	0.38	474	133
	670	200	515	35	83	2.7	1.8	30	0.15	703	197
	5500	2000	5000	350	1000	2.5	2	30	0.02	2301	700

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Table 2: Statistical results for 30 NNs created

architecture	Mean	MAE %	COV %	Standard Deviation
14 × 5 × 1	1.0074	14.76	24.87	2.78
14 × 10 × 1	1.0028	14.32	21.68	2.14
14 × 20 × 1	1.0071	14.86	22.19	3.19
14 × 5 × 5 × 1	1.0038	14.65	22.95	3.78
14 × 10 × 5 × 1	1.0065	14.71	23.65	3.07

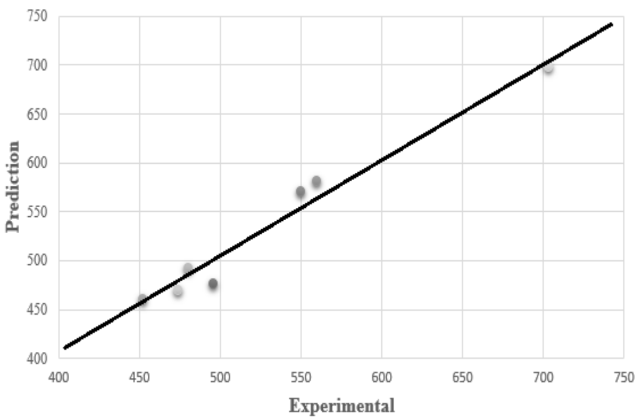

Fig 6: Comparison of ANN predictions with experimental

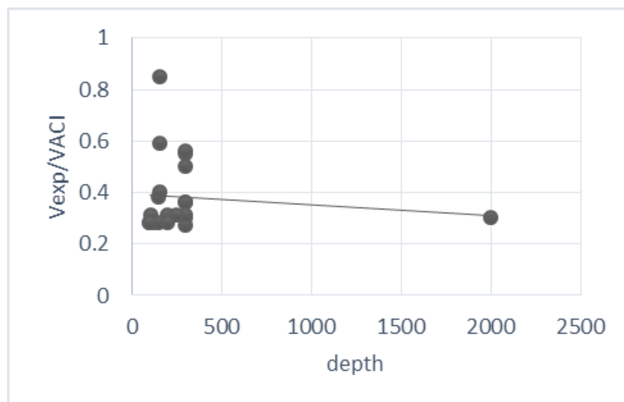

Fig 8: ACI code strength ratio vs beam depth

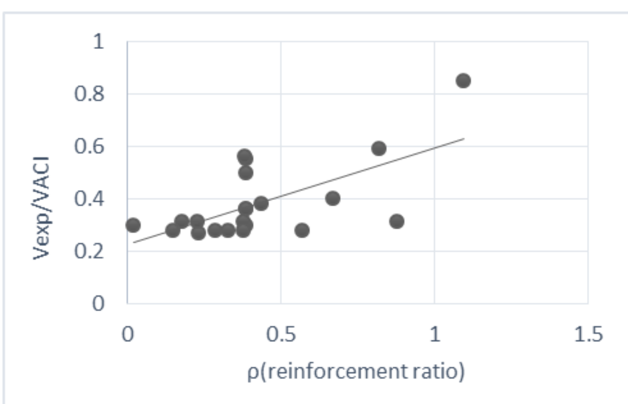

Fig 7: ACI code strength ratio vs reinforcement ratio

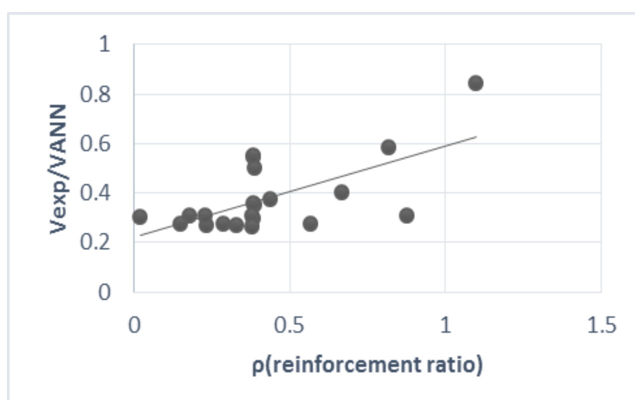

Fig 9: ANN code strength ratio vs reinforcement ratio

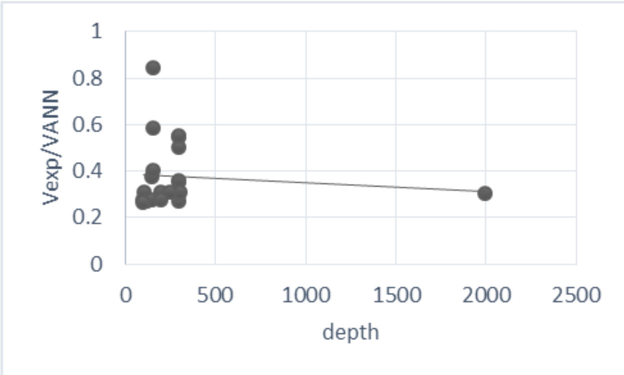

Fig 10: ANN code strength ratio vs beam depth

7. Conclusions

The application of Artificial Neural Networks (ANN) to predict the ultimate shear strength and ultimate cracking load of strengthened deep reinforced concrete (RC) beams with normal and high compressive strength has been investigated in this thesis. The ANN shear strength predicted results were also compared to those obtained using the American Concrete Institute (ACI) code 318-08. ANN model was created trained and tested by using harmony search (HS) algorithm. The outreached model was used to carry out a parametric research, in order to measure the effect of the variables of strengthened deep beams on ultimate shear strength and cracking loads. The half-value ratio of the experimental shear strength and cracking load to the predicted shear strength and cracking load using developed ANN is 1.00552 for strengthened deep beam with opening whereas the average ratio of experimental shear strength and cracking load to predicted shear strength and cracking load in ACI 318-08 is 2.992 and these average of laboratory results to ABAQUS models outcome is 1.8876. By comparing the results of neural networks and finite element methods and ACI 318-08 with experimental results found that HA algorithm in neural network has it more adaptation with shear strength values in laboratory. The next selection that can use for prediction of shear strength in deep beams is the results of finite element analysis (ABAQUS). The values obtained were of ACI 318-08 has the most errors in the calculations. Therefore, we can say ACI is conservative in determining the shear strength of Strengthened deep beams with opening. So the results show that ANN have strong potential as a feasible tool for predicting the ultimate shear strength and cracking load of strength RC deep beams within the range of input parameters.

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