

Prediction of Shear Strength of Ultra High Performance Reinforced Concrete Deep Beams without Stirrups by Neural Network

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Received: June 9 , 2017

Accepted: August 28, 2017

Online Published: September 1, 2017

doi: 10.23918/eajse.v3i1sip142

Abstract: Shear strength of ultra high performance reinforced concrete deep beams without stirrups predicted by neural network models. The neural network model based on 233 beams from literatures considering different parameters such as span to depth ratio, shear span to depth ratio, concrete compressive strength, amount of longitudinal reinforcement,...etc. Neural network can be used as an effective tool for predicting the shear capacity of normal & high strength concrete deep beams. Prediction shear strength by neural network very close to the experimental results with correlation coefficient of 0.836, while for ACI design eq., proposed eq. by Aziz & Zsutty where 0.394, 0.5624, and 0.488 respectively. The predicted shear strength model by neural network compared with ACI Code, Aziz and Zsutty equations, the results show that the Neural Network approach adequately captured the influence of concrete compressive strength on the shear capacity of reinforced concrete deep beams without shear reinforcement.

Keywords: Deep Beam, Neural Network, Shear Strength, Ultra High Performance

1. Introduction

UHPC (Ultra-High Performance Concrete) is a relatively new type of concrete that exhibits mechanical properties that are far superior to those of conventional concrete and in some cases rival those of steel, the main characteristics that distinguish UHPC from conventional reinforced concrete are the improved compressive strength, the tensile strength, improved ductility by addition of steel fibers, and the resistance to corrosion and degradation (Aziz & Ghafur, 2012). ACI CT – 13(ACI, 2013) define HPC as “A concrete meeting special combinations of performance and uniformity requirements that cannot always be achieved routinely using conventional constituent and normal mixing, placing, and curing practices”. Deep beams are defined as members loaded on one face and supported on the opposite face, so that compression struts can develop between the loads and the supports (ACI, 2014). Moreover, deep beams have either $(\frac{l_n}{h}) \leq 4.0$ (for distributed load case) or $(\frac{a}{d}) \leq 2.0$ (for points load case). A typical sketch of a deep beam is shown in Fig. (1)(Gaetano Russo, 2005)

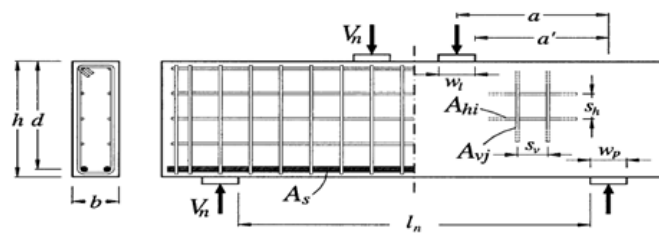


Figure 1: Typical sketch of a deep beam (Ref.4)

Reinforced concrete deep beams appear as common structural elements in many structures from tall buildings to offshore gravity structures. They are used as panel beams and, more recently, as deep grid walls in offshore gravity-type concrete structures. The term deep beam is applied to any beam which has a depth to span ratio great enough to cause non-linearity in the elastic flexural stresses over the beam depth and the distribution of shear stress to be non-parabolic (Kong & Rangan, 1998). The combination of stresses (bending and shear) in the shear span results inclined cracks which transform the beam into a tied-arch (Sarsam & Janan, 1992).

The strength of deep beams is usually controlled by shear, rather than flexural, provided that normal amount of longitudinal reinforcement is used. On the other hand, shear strength of deep beams is significantly greater than that predicted using expression developed for slender beams, because of their capacity to distribute internal forces before failure and develop mechanisms of force transfer quite different from beams of normal proportions (Smith & Vantsiatis, 1982). Elzanaty, Nilson, and Slate (1986) found that the ACI code provision were conservative in predicting the shear strength of short beams without stirrups for all values of f_c' .

Neural networks are an information processing techniques based on the biological nervous systems, such as the brain (Cheung, 1997). It is a powerful modeling tool can be used in a lot of scientific and engineering sectors, consists of three main parts, an input layer, hidden layers and an output layer this called as feed-forward neural. The input consists of 7 nodes, the first hidden layer consists of 4 and one node in the output layer. The schematic of the feed-forward neural network with an input layer, an output layer, and one hidden layer is shown in Fig.(2).

In a multi-layer feed-forward neural network, the artificial neurons are arranged in layers, and all the neurons in each layer have connections to all the neurons in the next layer. Associated with each connection between these artificial neurons, a weight value is defined to represent the connection weight. The operation of the network consists of a forward pass through the network. A number of learning rules are available. The back propagation learning algorithm is used in this study (Salim & Majid, 2010).

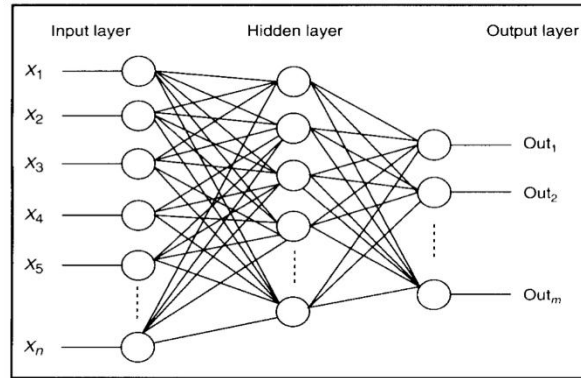


Figure 2: feed forward neural network with two layers

In is a simplest type of neural networks, A single node in the neural network model is called perceptron, a model consist of a number of these perceptrons arranged in layers that is why sometimes called multi-layer perceptron or MLP, starting from input nodes to the hidden layer nodes and finally to the output layer nodes, The cyclic path of the data is only one direction (forward), it is not going back to the input nodes or hidden layer nodes, that is why called by (feed-forward). A multi-layer perceptron or feed-forward network may consist of a single-layer or more than one layer. In such networks number of hidden layers is optional. Notice that the word “layer” hasn’t been appended to the word “input”, input is not a real layer (no summation, no bias, and no transfer function). For explaining how the network used in this investigation works, it’s necessary to understand how a simple perceptron or a neuron works, Fig.(3).

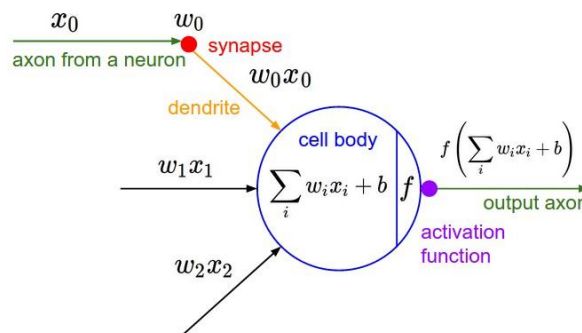


Figure 3: A simple neuron from hidden layer

The information (X_i) that fed to the neuron from input layer are multiplied by their connection weights (W_i) then summed together, also summed with the bias value (b_i). The resultant value is fed to the transfer function or sometimes called activation function, the result of this function is the output of the neuron or perceptron. Range of the output will be according to the type of the transfer function. The resultant value is fed to the transfer function either it’s a simple pure line function, Fig. (4-a) the result of this function is the output of the neuron or perceptron will be between (-1 and 1) Equation (1), or a logsig function (the study case) Fig. (4-b), the result of this function is the output of the neuron or perceptron will be between (0 and 1), because of the range of logsig function which lies in this period. Equation (2) gives the feed-forward mathematical process in the hidden layer:

$$g(x) = \text{purelin} \left\{ \left[\sum_{j=1}^n X(i) * W(j) \right] + [b] \right\} \quad \text{----- (1)}$$

$g(x) = \text{transfer function}$

Where, $g(x)$ is the output of the single neuron, $X(i)$ is the input data, $W(i)$ is the connection weight for input i . b_i is the bias value for this neuron.

The input are fed to all neurons in a layer, after calculating results for all neurons this output will fed as input to next layer the same process is repeated again. Neural network is very good regressions tool also its used widely in classification and clustering problems.

$$d(j) = \text{logsig} \left\{ \left[\sum_{i=1}^n X(i) * W(i) \right] + [b(j)] \right\} \quad \text{----- (2)}$$

Where, $d(j)$ is the output of a neuron in the hidden layer, $X(i)$ is the input value from input neuron i , $W(i)$ is the weight of connection between input neuron i and the neuron j , and $b(j)$ is the bias value of the neuron j . The feed-forward mathematical process in the neuron can be simplified in the mathematical equation (1) or (2):

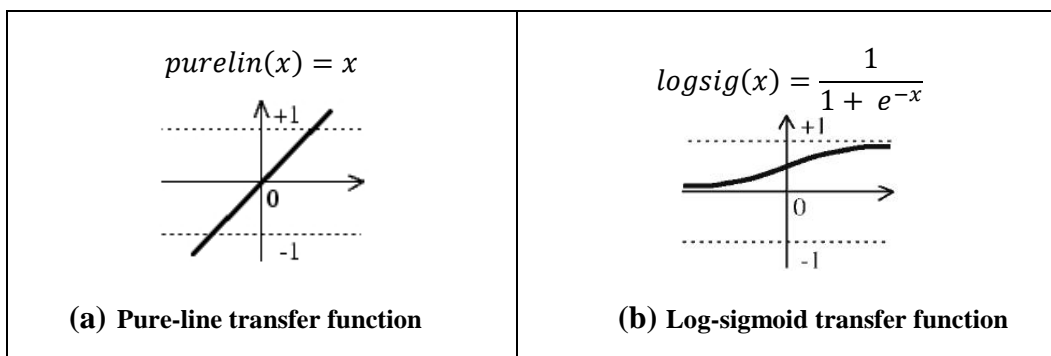


Figure 4: Transfer functions used in the neural model

2. Research Significance

Prediction of shear strength of ultra high performance concrete deep beams, by Neural Network models based on data from previous works (233 beams), considering different parameters. The predicted model compared with design equations given by ACI Code and predicted equations by Aziz & Zsutty.

3. Shear in Deep Beams

Prediction of shear strength of deep beams by codes of practice, and by researches all over the world has been specified different formulae considering different parameters into consideration. Leading to disagreement between researchers, making it difficult to choose an appropriate model or code for predicting shear resistance of reinforced concrete (Sudheer et al., 2010). The usual arrangement for investigating shear failure is that of a beam subjected to symmetrically placed two equal concentrated loads ‘P’ at distance ‘a’ (shear span) from the supports. It has the advantage of combining two different test conditions, viz, pure bending, that is, no shear force is present between

the two loads P, and constant shear force in the two end regions or shear spans (Msheer, 2012). According to ACI318M-14, the shear strength of normal weight concrete beams without shear reinforcement subjected to shear and flexure is given as follows;

$$V_c = (0.16\lambda\sqrt{f'_c} + 17\rho_w \frac{V_u d}{M_u})b_w d \quad \text{----- (3)}$$

where; λ is the modification factor, $\lambda=1.0$ for normal weight concrete.

For normal weight concrete deep beams, the code has limited nominal strength (V_n) as;

$$V_n = 0.83\sqrt{f'_c} * b_w d \quad \text{----- (4)}$$

Foster and Gilbert tested 16 high-strength concrete deep beams (Stephen & Gilbert, 1998). Variables considered in the investigation were shear-span to depth ratio, concrete strength (50 to 120MPa), and the provision of shear reinforcement. The investigation examines deep beam behavior and compares the experimental results with the ACI 318 code method and other methods. The results of the investigation show that ACI 318 prediction generally conservative for deep beams with high-strength concrete. Ashour (2000) proposed a numerical method of estimating the shear capacity of RC deep beams. Deep beams were considered to be in a state of plane stress. The concrete and steel reinforcement assumed to be rigid perfectly plastic. Shear failure mechanisms idealized as assemblage of moving rigid blocks separated by yield lines. Good agreement observed between the predicted shear capacity and experimental results.

Aziz (1999) tested twelve high strength fibrous reinforced concrete deep beams (HSFRCDB) under two point loading. All the specimens were reinforced with main steel reinforcement ratio of about (2.4%) to avoid flexural failure of beams, Shear span to depth ratio (a/d) ranging from 1.25 to 2.4 and volume fraction of steel fiber from 0.0 to 1.0% . The results showed that the ultimate shear stress decreases by increasing a/d and increases by increasing the amount of steel fiber and proposed empirical equations for estimating the shear strength of reinforced concrete deep beams and compared with several codes of practice and works of other investigators, the result of comparison of 233 high and normal strength concrete deep beams without stirrups showed lowest standard deviation, COV and conservative predictions for the proposed equations. The proposed equations were;

$$V_u = 0.85(V_c + V_s) \quad \text{----- (5)}$$

$$V_c = 1.51 \left[\frac{(f'_c \rho_w (1+F) b d)}{l a} \right]^{0.46} \quad \text{----- (6)}$$

$$V_s = \rho_v f_y + \rho_h f_y \quad \text{----- (7)}$$

Where;

f'_c = Compressive strength of concrete at 28 days in MPa

F = Fiber factor equal to $(l_f / d_f V_f \beta)$, $\beta=0.75$ for deformed steel fibers.

Wu and Han (2009) tested eleven girders to predict the first diagonal cracking and ultimate shear load of reinforced girder made of ultra-high performance fiber reinforced concrete (UHPFRC) in which eight girders failed in shear. Yaseen (2016) tested 12 deep beams made of ultra-high performance fiber reinforced concrete (UHPFRC) by taking several variable in the consideration. The same studies is carried out by A simplified formulation for the first diagonal cracking load was proposed. An analytical model to predict the ultimate shear load was formulated based on the two bounds theory (upper and lower). The predicted values were compared with the conventional predictions and the test results. The proposed equation can be used for the first cracking status analysis.

$$V_c = \frac{\xi}{\sqrt{\lambda(1+\lambda)}} \left(\frac{b_w}{d}\right)^{0.5} f_{ck} b_w d \quad \text{----- (8)}$$

Where;

ξ is the fiber volume fraction effective coefficient and $\xi = 5.08V_f^{0.2}$

λ is the shear span ratio and $\lambda = a / d$ in which a is the half shear span and d is the depth.

f_{ck} is the normal compressive strength of UHPFRC. b_w is the girder web width. V_f is the fiber volume fraction.

3.1. Data gathering for Neural Network Mode

The experimental data collected from the literature covering the shear strength of the deep beams with different parameters. The basic parameters that control the ultimate shear stress of deep beams are listed in Table (1), these parameters are feed to the neural model as input features. The experimental data include 233 beam results, which are taken from the present study and tests carried out in references in the appendix of this paper, the data are rearranged in such a way that 8 basic parameters are listed as input values and the ultimate shear stress is included as the corresponding target values. The data collected contain the ranges is listed in Table (1).

Table 1: Ranges of Data of Input Parameters

Parameter	Symbol	Minimum	Maximum
Length to depth ratio	l/d	1.00	11.6
Shear span to depth ratio	a/d	0.1	3.46
Cylindrical concrete compressive strength	f_c' (MPa)	6.7	122
Tension reinforcement ratio	ρ_w %	0.22 %	7.57%
Beams depth to width ratio	d/b	0.90	9.5
Tension bar diameter	d_b (mm)	12	32
Maximum aggregate size	d_{agg} (mm)	9.5	25

These parameters are collected in a Microsoft- Excel sheet (file with csv extension) to be processed by a neural model. Table (2) shows a sample of the features collected from articles to be used in model evaluation. For regression purposes and training a supervised model target values are necessary. The target values which are shear strength of specimens are collected in a last column.

Table 2: The features collected in an MS-Excel sheet

A	B	C	D	E	F	G	H
l/d	a/d	fc'	roh w%	d/b	db	dagg	Vc exp
4.53	1.51	25.36	3.05	2	32	25	4.75
4.53	1.51	22.94	3.05	2	32	25	4.53
4.53	1.51	21.84	1.88	2	25	25	3.72
4.53	1.51	26.4	1.88	2	25	25	4.42
4.53	1.51	25.7	1.88	2	25	25	4.1
4.53	1.51	25.6	1.88	2	25	25	4.1
4.53	1.51	24.1	1.88	2	25	25	4.1
4.53	1.51	24.9	1.88	2	25	25	4.27
4.53	1.51	23.1	1.88	2	26	25	3.1
4.53	1.51	26.9	1.16	2	22	25	3.71
4.53	1.51	25.4	1.16	2	22	25	3.1
4.53	1.51	25.6	1.16	2	22	25	3.73
4.53	1.51	22.4	1.16	2	22	25	3
4.53	1.51	26.7	1.75	2	16	25	3

The data collected from similar researches for deep beams with related variables, 233 instant were

the total used data. For better simulation to find the best model, the data set split to training set and test set. According to this, the data examined from five groups into five, each group split to four different ratios of training set and test set. The groups and sets are shown in Table (3). This process to determine the best model that converges to the real data, the correlation coefficient, mean absolute error, root mean squared error, relative absolute error %, root relative squared error% were the comparative criteria that used as a base for selection the nearest set.

Table 3: Group Variables and set divisions for model creation

Group	Training set 60%	Test Set 40%	Training set 70%	Test Set 30%	Training set 80%	Test Set 20%	Training set 90%	Test Set 10%
	Hidden Layer		Learning Rate		Momentum		Training Time	
First	2		0.3		0.2		500	
Second	3		0.3		0.2		1000	
Third	4		0.3		0.2		2000	
Fourth	Auto selection		0.2		0.2		500	
Fifth	Auto selection		0.3		0.1		500	

3.2. The Software Used for Training

Weka 3.6 is used as modeling software, Weka is a workbench that contains a collection of visualization tools and algorithms for data analysis and predictive modeling . Weka together with graphical user interfaces for easy access to these functions. Weka supports several standard data mining tasks, more specifically, data preprocessing, clustering, classification, regression, visualization, feature selection. And ease of use due to its graphical user interfaces. An important note here is that the software initializes all weights and bias values required to start learning process in the first step Fig.(5), users are only asked to specify the structure of the model like number of hidden layers and number of nodes inside each layer, also type of the transfer functions for each layer should be specified. The parameters and the target shear values, which are already saved in the Excel sheets, are fed to the model.

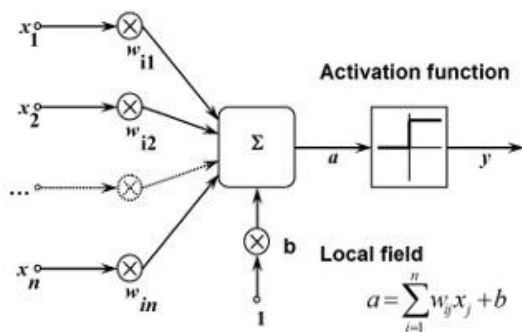


Figure 5: The learning process done by Weka 3.6

3.3. Data Normalization

Data normalization is not necessary in Multi layer Perceptron (MLP) models because input variables are combined linearly, then it is not necessary to standardize the inputs. For making sure the input set is normalized and given to the model, there was no sensible difference between results. The reason normalization is needed is because if you look at how an adaptive step proceeds in one place in the domain of the function, and you just simply transport the problem to the equivalent of the same step

translated by some large value in some direction in the domain, then you get different results. It boils down to the question of adapting a linear piece to a data point. How much should the piece move without turning and how much should it turn in response to that one training point? It makes no sense to have a changed adaptation procedure in different parts of the domain, so normalization is required to reduce the difference in the training result. There are a variety of practical reasons why standardizing the inputs can make training faster and reduce the chances of getting stuck in local optima. If the input variables are combined linearly, as in an MLP, then it is rarely strictly necessary to standardize the inputs, at least in theory. The reason is that any rescaling of an input vector can be effectively undone by changing the corresponding weights and biases, leaving you with the exact same outputs as you had before. However, there are a variety of practical reasons why standardizing the inputs can make training faster and reduce the chances of getting stuck in local optima. Also, weight decay and Bayesian estimation can be done more conveniently with standardized inputs.

3.4. The Regression Model

The technique used in this paper is a Multi-layer Perceptron (MLP) Neural Network regression model, this model is a very efficient regression model for continues data (in the present investigation, shear strength). The MLP model consists of three layers: an input, a hidden layer and an output layer. The number of nodes in the input is 7; each node is specialized for inputting a parameter. The number of nodes in the hidden layer is 4, and there is only one node in the output layer Fig.(6). The structure can be summarized as 7-4-1.

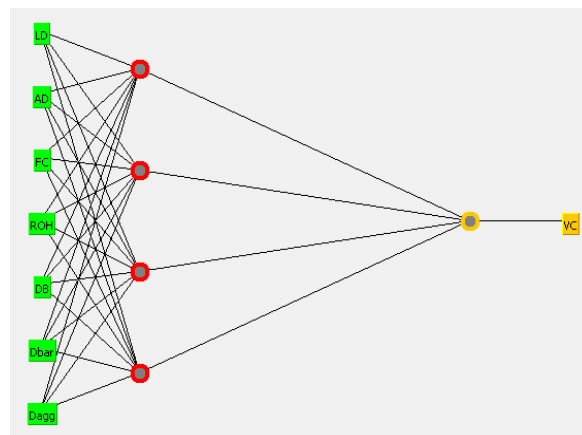


Figure 6: The three layer in MLP model

The information that fed to the neuron from 7 input neurons are multiplied by their connection weights then summed together, also summed with the bias value.

The same process is repeated in all 4 neurons of the hidden layer, then this 4 information are fed to the output layer and the same process is repeated. Number of nodes in the output layer is only one node. The transfer function here is different, pure line function was used as in Fig. (4-a), where the range of the results are from (-ve) infinity to (+ve) infinity. The feed-forward mathematical process in the output layer is declared in Equation (1).

3.5. Learning Process

Back-propagation is a common method used for supervised learning. In this method an artificial

network learns from comparing an output with desired outputs, then propagating the error occur in a backward direction by justifying the weights of the connections between nodes. This backward propagation needs the transfer functions used in the nodes to be differentiable to ensure smooth back-distribution of errors on the weights.

In the supervised learning, desired or target results is compared with the obtained results and the squared error is calculated according to Equation (9).

$$Er = (T - D)^2 \quad (3) \quad \text{-----} (8)$$

Where: Er is a squared error, T is the target value, and D is the desired value

Optimization methods are used to minimize this error value Er . There are lots of methods that can be used for this issue. In this paper a Levenberg-Marquardt optimization is used for optimizing errors. The LM is one of the best and most efficient methods for optimizing back propagation of errors which designed to approach second-order training speed not like other back propagation algorithms, LM is very fast and doesn't have a problem of local minimums.

3.6. Results of the model

During the study, 163 of the beam specimens (70%) were used for training the neural network model, and the other 70 beam specimens (30%) were used for evaluation process. The model tested 20 times over different sets, randomly separated to training and evaluation sets (i.e each time the training and test set ratio varies). The best model among 20 trials was taken in consideration as accuracy of the model. The correlation coefficient was 0.943, the mean absolute error was 0.822, the root mean squared error was 1.14, the relative absolute error ratio was 35.35%, and the root relative squared error ratio was 36.78%. Now the model is ready to predict the shear strength for other unseen beams. Weka provides the ability to save the complete structure of any neural network with weights and bias.

4. Evaluation of Results by Neural Network, ACI Code, Aziz and Zsutty Equation

Fig.(7) Shows a plot of actual tested parameters against corresponding ANN predictions. A linear correlation observed and the correlation coefficient was found to be (0.836), thus it can be concluded that the ANN can successfully modeled the shear strength of reinforced concrete deep beams. To compare the neural network results with the ACI code formula and Aziz and Zsutty equations, the same test data were used to calculate the predicted ultimate shear stress using the ACI 318 formula, proposed equation by Aziz and Zsutty. As shown in Figures (7 to 10), the correlation coefficient is 0.836 for ANN against 0.394 for ACI code , 0.562 for Aziz equation and 0.488 for Zsutty equation. It is obvious that the ANN values are very comparable with experimental results within the range of applicable data.

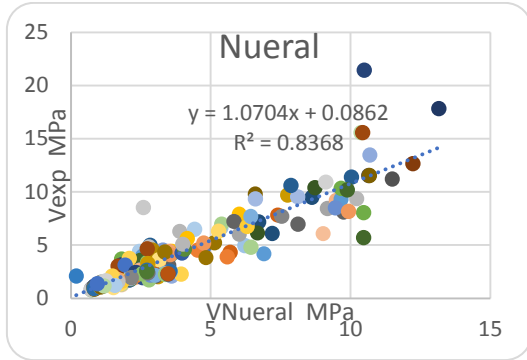


Figure 7: Experimental versus predicted shear stress by ANN

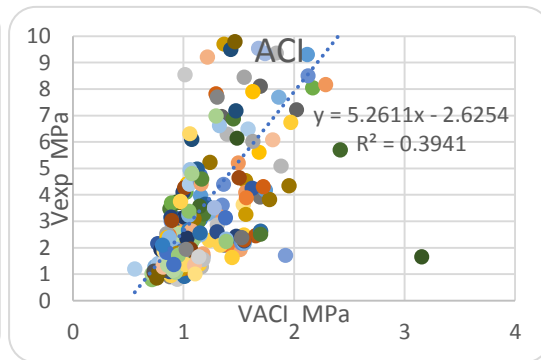


Figure 8: Experimental versus predicted shear stress by ACI

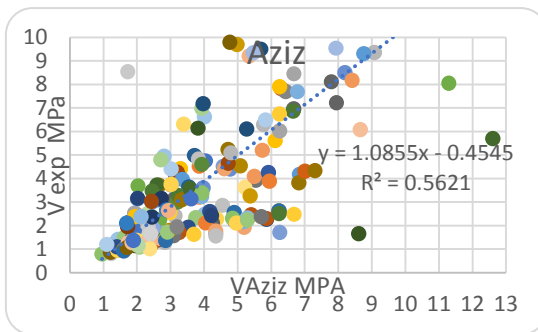


Fig. (9) Experimental versus predicted shear stress by Aziz

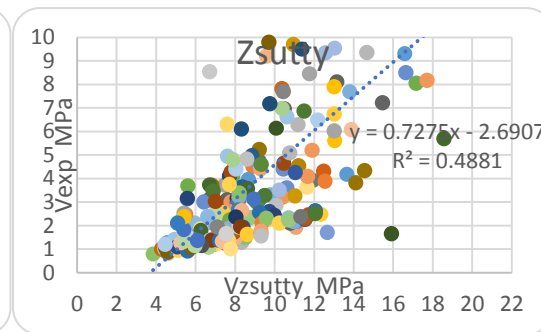


Fig. (10) Experimental versus predicted by shear stress Zsutty

5. Influence of Major Parameters

Different relationships have been proposed by codes of practice and researches for predicting the shear capacity of concrete deep beams. Unfortunately, the relationships differ considerably in their selected parameters since there is no generally accepted model for the load transfer and the ultimate shear capacity of reinforced concrete deep beams. A large database of experimental work conducted on deep beams was collected. This database contained a total of 233 tests. The database covered a very wide range of beam parameters including their dimensions, concrete strengths, reinforcement ratios and yield stresses, and shear span to depth ratios, maximum size of aggregate & bar diameter. The database utilized in the present study to evaluate neural network model, ACI 318 codes design eq., Aziz and Zsutty predicted equations for the shear capacity of deep beams. The predictions of the neural network and those of the ACI 318 code and other equations were compared. It was found that, among all the existing models, the results obtained from the neural network are the most accurate results, giving values of maximum shear capacity very close to the experimental values. Moreover, the results obtained using the neural network were very consistent and covered a very wide range of variation of any of the input parameters as shown in Figs. (11, 12, 13 and 14). This accuracy suggests that the most critical variables that control the shear capacity of concrete beams have been used as input data to the neural network model.

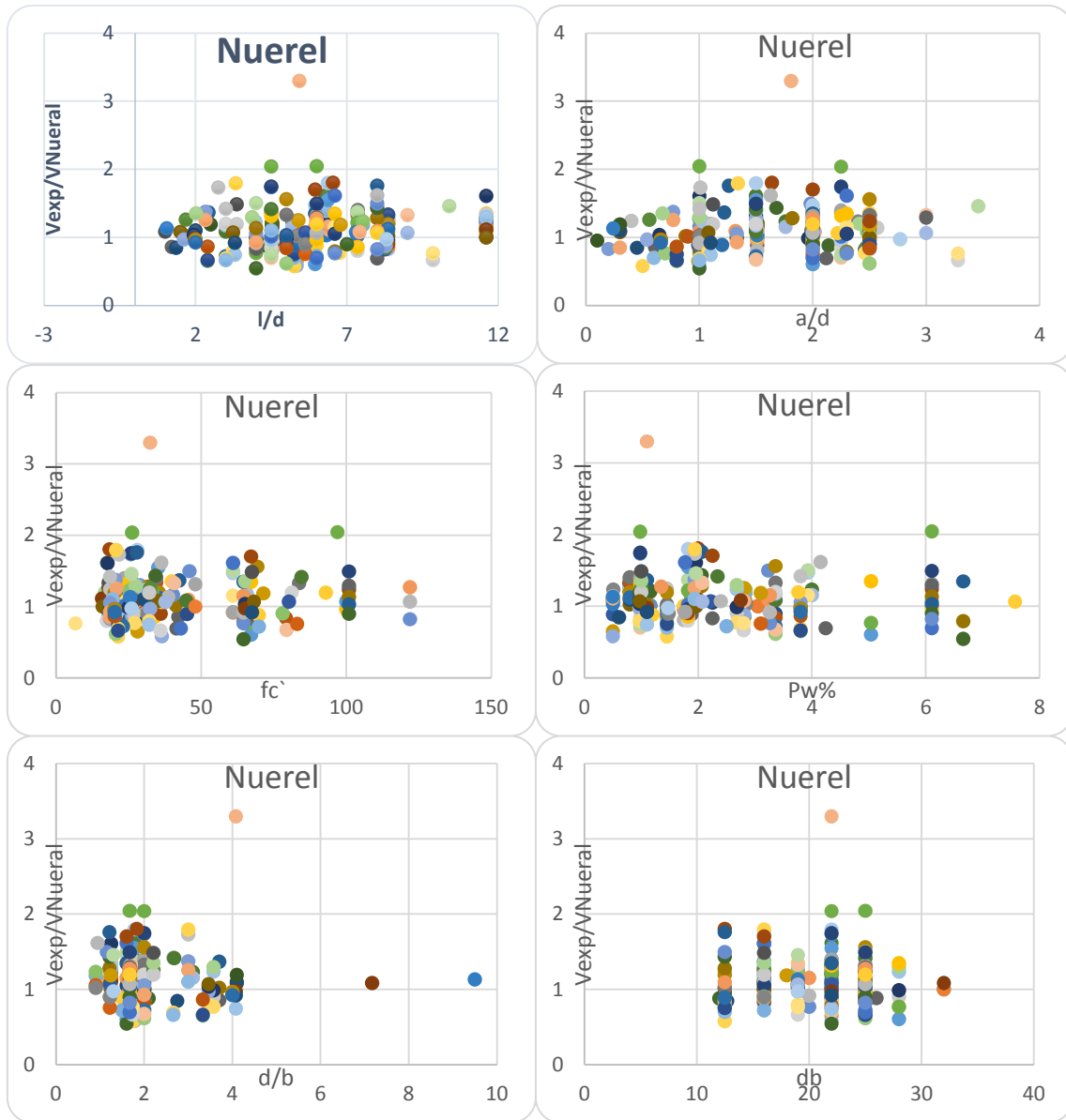


Figure 11: $V_{exp}/V_{predict}$ by Neural versus l/d , a/d , f_c , ρ_w , d/b , and d_b

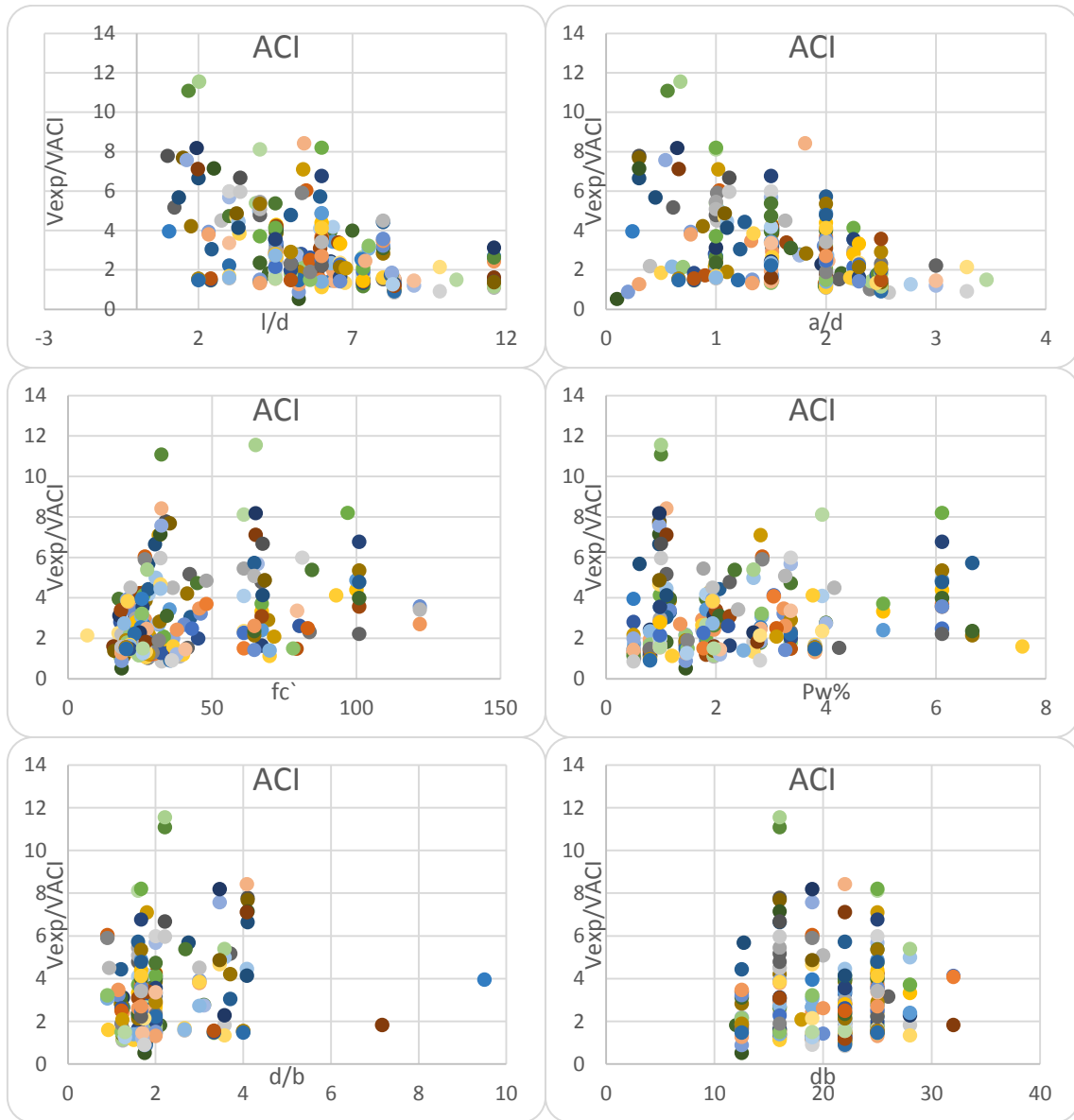


Figure 12: $V_{exp}/V_{predict}$ by ACI 318 versus l/d , a/d , f_c , ρ_w , d/b , and d_b

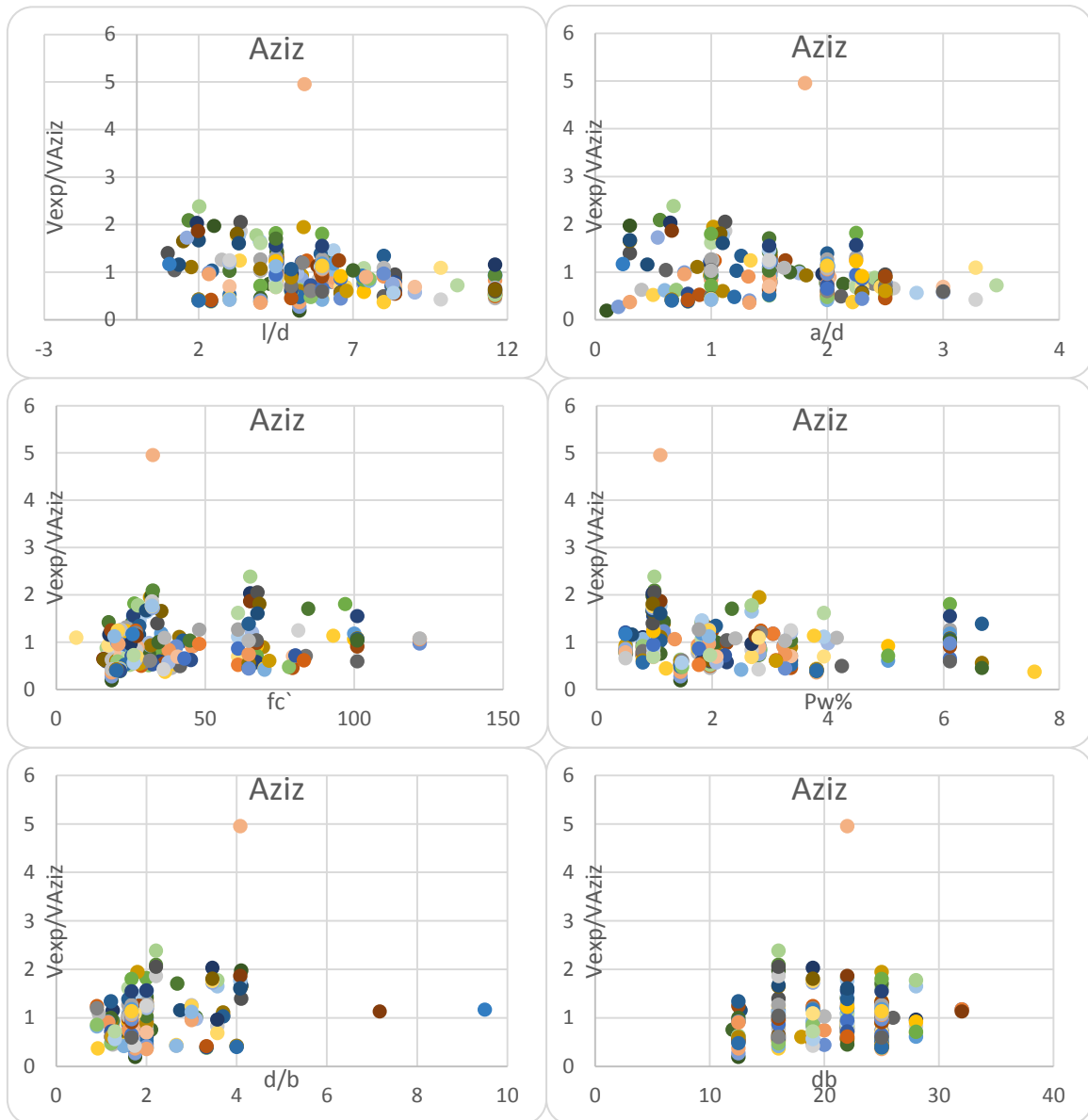


Figure 13: $V_{exp}/V_{predict}$ by Aziz equation versus l/d , a/d , f_c , ρ_w , d/b , and d_b

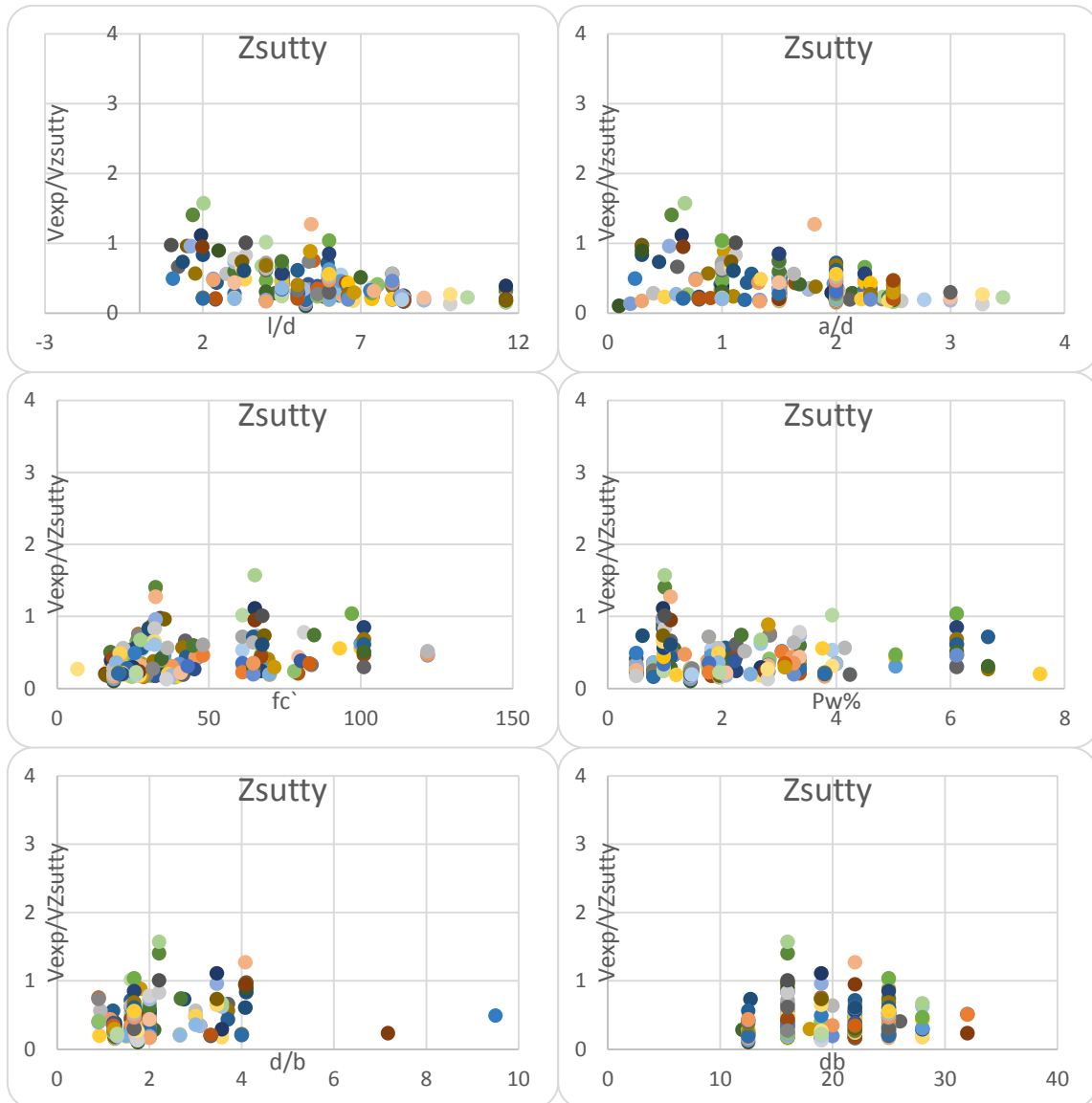


Figure 14: $V_{exp}/V_{predict}$ by Zsutty equation versus l/d , a/d , f_c' , ρ_w , d/b , and db

6. Evaluation of Results by Neural Network

The shear capacity of the reinforcement concrete deep beams in the testing database, which is used to evaluate the performance of the Neural Network model, was also calculated using the shear strength calculation procedures. Most current shear design codes generally assume that adding shear reinforcement to a reinforced concrete beam will only enhance its shear strength by the shear capacity of stirrups. Such a practice ignores the influence of stirrups on the contribution of other shear design parameters and assumes that the presence of stirrups does not interfere with other shear-resisting mechanisms, which presumes a linear relationship between the amount of shear reinforcement and the nominal shear strength. A sensitivity analysis was conducted in this study to investigate the effect of stirrups on the shear strength of reinforced concrete beams using the various shear calculation procedures. It is generally accepted that an increase in the compressive strength of concrete increases the shear strength of reinforced concrete. Furthermore, most current shear design techniques either do not acknowledge such a variation in the effect of concrete compressive strength on the shear capacity of beams or simply do not account for the influence of adding shear

reinforcement to other shear transfer mechanisms. Table (4) shows the ANN, ACI, Aziz and Zsutty in prediction of load capacity and selected parameters for a rectangular deep beams.

Table 4: The ANN, ACI, Aziz and Zsutty prediction of load capacity and selected parameters

		Vexp/Vaziz	Vexp/Vzsutty	Vexp/VACI	Vexp/VNeural
Mean		0.943	0.396	2.919	1.114
Standard Dev		0.488	0.243	1.898	0.311
COV%		0.517	0.614	0.650	0.279
Range	High	4.955	1.573	11.553	3.297
	Low	0.193	0.104	0.526	0.544
Number < 1*		142	233	1	77

7. Conclusions

The main conclusions obtained from the numerical analysis of deep beams and compared with the results predicted by Neural Network are listed below briefly:

- 1- A successfully trained Neural Network model can be used as an effective tool for predicting the shear capacity of normal and high strength reinforced concrete deep beams. The Neural Network model proved to be reliable, accurate, and easy to use.
- 2- ANN shear strength capacity prediction covered wide range of parameters such as span to depth ratio, shear span to depth ratio, concrete compressive strength, ...etc.
- 3- ANN predictions are close to the experimental results, the correlation coefficient was 0.836, while for ACI, Aziz & Zsutty were 0.394, 0.562 & 0.488 respectively.
- 4- The Neural Network approach adequately captured the influence of compressive strength on the shear capacity of reinforced concrete deep beams without shear reinforcement. It showed that shear strength increases with an increase in concrete compressive strength.
- 5- Results from ACI code for calculating the shear strength of reinforced concrete deep beams without shear reinforcement is very conservative.

References

- Achavy D. N. (1965). Significance of Dowel Forces on the Shear Failure of Rectangular Reinforced Concrete Beams. *ACI Journal Proceeding*, 62, 1265-1279.
- ACI. (2013). CT-13, ACI Concrete Terminology. An ACI STANDARD *An ACI STANDARD*, .
- ACI. (2014). 318M-14, Building Code Requirements for Structural Concrete and Commentary *Reported by ACI Committee 318*.
- Ahmed, S.H., Khaloo, A.R., & Poveda, A. (1986). Shear Capacity of Reinforced High-Strength Concrete Beams. *ACI Journal Proceeding*, 83(2), 297-305.
- Andrew, G., M., & Gregory, C. (1984). Shear Tests of High and Low Strength Concrete Beams without Stirrups. *ACI Journal Proceeding*, 81(4), 350-357.
- Ashour, A. F. (2000). Shear Capacity of Reinforced Concrete Deep Beams. *Journal of Structural Engineering*, 126(9), 1045-1052.
- Aziz, O.Q. (1997). *Shear Strength Prediction of Crushed Stone Reinforced Concrete Deep Beams*. (Ph.D. Thesis), University of Technology, Baghdad, Iraq.
- Aziz, O.Q. (1999). Shear Strength Behavior of High Strength Fibrous R.C. Deep Beams

- (HSFRCDB) Without Stirrups. *Mu'tah Journal, University of Mu'tah, Jordan*, 14(1).
- Aziz, O.Q., & Ghafur, H.A. (2012). *Mechanical Properties of Ultra High Performance Concrete (UHPC)*. Paper presented at the Twelfth International Conference on Recent Advances in Concrete Technology and Sustainability Issues, Prague, Czech Republic.
- Boris, B., & James, M. (1967). Review of Concrete Beams Failing in Shear. *ASCE Journal, ST1*, 343-372.
- Cheung, W. H. (1997). *Neural Network Aided Aviation Fuel Consumption Modeling*. (M. Sc. Thesis), Blacksburg.
- Clark, A.P. (1951). Diagonal Tension in Reinforced Concrete Beams. *ACI Journal*, 48, 145-156.
- De Paiva, H.A., & Chester, P. S. (1965). Strength and Behavior of Deep Beams in Shear. *ASCE Journal*, 91(5), 19-41.
- Elzanaty, A. H., Nilson, A.H., & Slate, F.O. (1986). Shear Capacity of Reinforced Concrete Beams Using High Strength Concrete. *ACI Journal Proceeding*, 83(2), 290-296.
- Gaetano Russo, R., Margherita, P. (2005). Reinforced Concrete Deep Beams-Shear Strength Model and Design Formula. *ACI Structural Journal*, 102(3), 429-437.
- Kang-Hai, T., Fung-Kew, K., Susanto, T., & Lingwei, G. (1995). High Strength Concrete Deep Beams With Effective Span and Shear Span Variations. *ACI Structural Journal Proceedings*, 92, 395-405.
- Kani, G.N.J. (1967). How Safe are Our Large Reinforced Concrete Beams ? *ACI Journal Proceeding*, 64(3), 128-141.
- Kani, G.N.J. (1964). The Riddle of Shear Failure and its Solution. *ACI Journal*, 61, 441-467.
- Kong, Y.L.K., & Rangan B.V. (1998). Shear strength of high-performance concrete beams. *ACI Structural Journal*, 95, 677-688.
- Kony, F., Robins P.J., & Cole, D.F. (1970). Web Reinforcement Effects on Deep Beams. *ACI Journal Proceeding*, 67(12), 1010-1017.
- Krefeld, W.J., & Thurston, C.W. (1966). Studies of The Shear and Diagonal Tension Strength of Simply Supported Reinforced Concrete Beams. *ACI Journal Proceeding*, 63(4), 451-476.
- Mansur, M.A., & Ong, K. C. G. (1991). Behavior of Reinforced Fiber Concrete Deep Beams in Shear. *ACI Structural Journal Proceedings*, 88, 98-105.
- Msheer, H.A. (2012). *Shear Strength and Behavior of UHPC Deep Beams without Web Reinforcement*. (M.Sc. Thesis), Salahaddin University, Erbil, Iraq.
- Narayanan, R., & Darwish Y.S. (1988). Fiber Concrete Deep Beams in Shear. *ACI Structure Journal Proceedings*, 85(2), 141-149.
- Oresle, M. (1945). An Investigation of the Strength of Welded Stirrups in Reinforced Concrete Beams. *ACI Journal Proceeding*, 42(11), 141-162.
- Prackash, D. (1986). A Method for Determining the Shear Strength of Reinforced Concrete Beams with Small a/d *Magazine of Concrete Research*, 26(86), 29-38.
- Robert, F.M. (1971). Deep Beam Behaviour Affected by Length and Shear Span Variation. *ACI Journal Proceeding*, 68(12), 954-958.
- Salim, T.Y., & Majid, A. (2010). Modeling of Ultimate Load for R.C. Beams Strengthened with Carbon FRP using Artificial Neural Networks. *Al-Rafidain Engineering Journal*, 18(6), 28-41.
- Santha, K. A. R. (1972). Strength and Behavior of Single-Span, Deep Reinforced Concrete Beams. *Indian Concrete Journal*, 46(11), 459-465.
- Sarsam, K. F., & Abdulla, A. M. (1989). Shear Strength of High Strength Concrete Beams. *Al-Muhandis Magazine*, 2, 15-24.
- Sarsam, K.F., & Janan, M. S. (1992). Shear Design of High-and-Normal Strength Concrete Beams with Web Reinforcement. *ACI Structural Journal, Proceeding*, 89(6), 658-664.
- Siao, W. B. (1995). Deep Beams Revisited. *ACI Structural Journal Proceedings*, 92(1), 95-102.
- Smith, K. N., & Vantsiatis A.S. (1982). Shear Strength of Deep Beams. *ACI Journal Proceeding*, 79(3), 201-213.
- Stephen, J.F., & Gilbert, R. I. (1998). Experimental Studies on High-Strength Concrete Deep Beams. *ACI Structural Journal*, 95(4), 382-390.

- Sudheer, R.L., Ramana Rao. N.V., & Gunneswara Rao T.D. (2010). Shear Resistance of High Strength Concrete Beams without Shear Reinforcement. *International Journal of Civil and Structural Engineering*, 1(1), 101-113.
- Swamy, R. N.& Bahia, H. M. (1985). The Effectiveness of Steel Fibers as Shear Reinforcement. *Magazine of Concrete International*, 35-40.
- Taylor, R. (1960). Some Shear Tests on Reinforced Concrete Beams Without Shear Reinforcement. *Magazine of Concrete Research*, 12(36), 145-154.
- WEKA. Waikato Environment for Knowledge Analysis (Weka) (Version 3.9). New Zealand.: developed at the University of Waikato.
- Wu, X., & Han, M. (2009). First Diagonal Cracking and Ultimate Shear of I-Shaped Reinforced Girders of Ultra High Performance Fiber Reinforced Concrete without Stirrup. *International Journal of Concrete Structures and Materials*, 3(1), 47-56.
- Yagendra, P. (1976). Serviceability Considerations for Reinforced Concrete Deep Beams. *Journal of Structural Engineering*, 4(1), 33-38.
- Yaseen, S.A. (2016). An Experimental Study on the Shear Strength of High-performance Reinforced Concrete Deep Beams without Stirrups. *Eng.&Tech.Journal*, 34(10).
- Ziad, K.B. (1994). *The Effect of Shear Span to Depth Ratio on the Shear Strength of High Strength Concrete Beams*. (M.Sc. Thesis), University of Technology, Baghdad, Iraq.
- Zsutty, T. C. (1968). Beam Shear Strength Prediction by Analysis of Existing Data. *ACI Journal Proceeding*, 65(11), 943-951.

Appendices:

A. References for data's used in neural model(in addition to references)

B. Table of Experimental and predicted shear strengths of deep beams from literatures

Vc exp	Vc neural	Vexp./Vn	Vc ACI	Vexp./Vaci	Vc aziz	Vexp./Vaziz	Vc zsutty	Vexp./Vzsutty
4.750	4.740	1.002	1.149	4.134	4.037	1.177	9.200	0.516
4.530	4.530	1.000	1.110	4.082	3.855	1.175	8.901	0.509
3.720	3.370	1.104	0.959	3.877	3.017	1.233	7.465	0.498
4.420	3.600	1.228	1.034	4.276	3.292	1.343	7.947	0.556
4.100	3.580	1.145	1.023	4.009	3.251	1.261	7.877	0.521
4.100	3.570	1.148	1.021	4.015	3.245	1.263	7.867	0.521
4.100	3.510	1.168	0.997	4.112	3.157	1.299	7.712	0.532
4.270	3.550	1.203	1.010	4.227	3.204	1.333	7.795	0.548
3.100	3.500	0.886	0.981	3.161	3.096	1.001	7.605	0.408
3.710	3.090	1.201	0.960	3.863	2.659	1.395	6.819	0.544
3.100	3.070	1.010	0.937	3.309	2.590	1.197	6.691	0.463
3.730	3.070	1.215	0.940	3.967	2.599	1.435	6.708	0.556
3.000	2.970	1.010	0.888	3.379	2.444	1.227	6.419	0.467
3.000	3.140	0.955	1.024	2.930	3.202	0.937	7.790	0.385
2.420	2.990	0.809	1.005	2.408	3.135	0.772	7.673	0.315
2.550	2.530	1.008	0.961	2.653	2.977	0.856	7.395	0.345
1.280	1.210	1.058	0.740	1.730	1.368	0.936	4.570	0.280
0.790	0.730	1.082	0.716	1.104	0.954	0.828	3.850	0.205
2.160	2.440	0.885	0.768	2.811	1.792	1.206	5.219	0.414
1.000	0.920	1.087	0.761	1.314	1.175	0.851	4.286	0.233
0.900	0.730	1.233	0.878	1.025	1.188	0.758	4.505	0.200
2.030	3.120	0.651	0.934	2.173	2.188	0.928	6.023	0.337
1.330	1.290	1.031	0.904	1.471	1.667	0.798	5.240	0.254
1.020	0.920	1.109	0.863	1.182	1.329	0.767	4.681	0.218
2.100	3.600	0.583	1.052	1.997	2.456	0.855	6.545	0.321
1.430	1.290	1.109	0.997	1.434	1.822	0.785	5.613	0.255
0.810	0.710	1.141	0.945	0.857	1.227	0.660	4.613	0.176
1.180	1.080	1.093	0.773	1.527	1.431	0.825	4.935	0.239
1.410	1.080	1.306	0.773	1.825	1.431	0.985	4.935	0.286
1.020	0.850	1.200	0.714	1.428	1.162	0.878	4.434	0.230
1.930	1.470	1.313	0.795	2.426	1.753	1.101	5.427	0.356
1.060	0.840	1.262	0.735	1.442	1.179	0.899	4.481	0.237
1.120	0.840	1.333	0.735	1.524	1.179	0.950	4.481	0.250
0.860	0.840	1.024	0.759	1.133	1.217	0.707	4.585	0.188
1.180	1.080	1.093	0.874	1.350	1.620	0.728	5.394	0.219
1.000	0.830	1.205	0.875	1.143	1.400	0.714	5.069	0.197
1.080	0.830	1.301	0.915	1.181	1.462	0.739	5.230	0.207
1.740	1.500	1.160	0.892	1.950	1.963	0.887	5.908	0.294
1.050	0.830	1.265	0.887	1.183	1.419	0.740	5.120	0.205

0.950	0.830	1.145	0.887	1.071	1.419	0.669	5.120	0.186
2.110	1.520	1.388	0.900	2.344	1.991	1.060	5.947	0.355
1.490	1.080	1.380	0.878	1.698	1.626	0.917	5.408	0.275
1.100	0.830	1.325	0.875	1.257	1.400	0.786	5.069	0.217
1.430	1.070	1.336	1.008	1.419	1.864	0.767	5.968	0.240
1.500	1.070	1.402	1.008	1.488	1.864	0.805	5.968	0.251
0.980	0.820	1.195	1.008	0.973	1.607	0.610	5.597	0.175
0.920	0.820	1.122	1.008	0.913	1.607	0.572	5.597	0.164
3.470	2.150	1.614	0.878	3.954	2.449	1.417	6.893	0.503
1.200	1.450	0.828	0.924	1.299	1.996	0.601	6.539	0.184
1.260	1.460	0.863	0.812	1.552	1.738	0.725	5.920	0.213
1.450	1.810	0.801	0.824	1.760	1.992	0.728	6.257	0.232
1.860	1.810	1.028	0.824	2.257	1.992	0.934	6.257	0.297
4.400	2.450	1.796	1.053	4.179	3.014	1.460	8.034	0.548
2.520	1.840	1.370	0.948	2.657	2.330	1.082	7.001	0.360
1.890	1.850	1.022	0.989	1.911	2.440	0.775	7.237	0.261
1.240	1.440	0.861	0.999	1.242	2.168	0.572	6.937	0.179
1.320	1.440	0.917	0.990	1.334	2.147	0.615	6.890	0.192
1.580	1.840	0.859	1.088	1.452	2.705	0.584	7.794	0.203
3.960	2.560	1.547	1.156	3.426	3.350	1.182	8.666	0.457
2.240	1.840	1.217	1.077	2.081	2.674	0.838	7.729	0.290
1.370	1.430	0.958	1.066	1.285	2.321	0.590	7.286	0.188
1.290	1.430	0.902	1.085	1.189	2.364	0.546	7.382	0.175
6.960	8.120	0.857	1.346	5.171	6.673	1.043	10.484	0.664
5.230	5.130	1.019	1.241	4.215	4.716	1.109	9.224	0.567
3.650	2.670	1.367	1.196	3.051	3.545	1.030	8.360	0.437
1.790	2.030	0.882	0.980	1.827	2.369	0.756	6.265	0.286
3.610	3.100	1.165	1.349	2.676	3.969	0.910	10.614	0.340
3.200	2.950	1.085	1.317	2.430	3.853	0.830	10.392	0.308
1.280	1.130	1.133	1.162	1.102	2.832	0.452	8.331	0.154
1.380	1.020	1.353	1.144	1.206	2.592	0.532	7.818	0.177
3.300	2.600	1.269	1.230	2.683	3.538	0.933	9.775	0.338
1.490	1.330	1.120	1.113	1.339	2.919	0.510	8.514	0.175
1.380	1.130	1.221	1.076	1.282	2.607	0.529	7.851	0.176
1.230	1.140	1.079	1.021	1.205	2.460	0.500	7.531	0.163
1.300	1.050	1.238	0.999	1.301	2.249	0.578	7.061	0.184
1.200	1.050	1.143	0.978	1.226	2.198	0.546	6.948	0.173
3.080	2.390	1.289	1.152	2.673	3.255	0.946	9.208	0.334
3.000	2.340	1.282	1.136	2.640	3.198	0.938	9.090	0.330
1.690	1.330	1.271	1.049	1.611	2.725	0.620	8.105	0.209
1.460	1.320	1.106	1.032	1.415	2.673	0.546	7.993	0.183
1.540	1.150	1.339	0.960	1.604	2.299	0.670	7.174	0.215
1.230	1.150	1.070	0.944	1.303	2.256	0.545	7.077	0.174

1.380	1.060	1.302	0.936	1.474	2.098	0.658	6.718	0.205
1.080	1.060	1.019	0.927	1.165	2.075	0.521	6.665	0.162
3.150	1.960	1.607	1.008	3.124	2.725	1.156	8.105	0.389
1.380	1.240	1.113	0.858	1.608	2.141	0.645	6.817	0.202
1.150	1.150	1.000	0.820	1.402	1.924	0.598	6.314	0.182
1.070	1.070	1.000	0.775	1.380	1.707	0.627	5.795	0.185
6.100	7.200	0.847	1.074	5.679	5.266	1.158	8.314	0.734
1.660	1.740	0.954	3.155	0.526	8.605	0.193	15.917	0.104
1.710	2.060	0.830	1.923	0.889	6.255	0.273	12.663	0.135
1.930	2.270	0.850	1.512	1.277	5.191	0.372	11.077	0.174
2.860	2.300	1.243	1.306	2.189	4.548	0.629	10.074	0.284
2.280	3.940	0.579	1.233	1.849	4.377	0.521	9.802	0.233
2.490	3.550	0.701	1.151	2.163	4.025	0.619	9.229	0.270
2.340	3.050	0.767	1.092	2.142	3.750	0.624	8.772	0.267
1.930	2.560	0.754	1.048	1.841	3.526	0.547	8.393	0.230
1.710	1.690	1.012	0.993	1.722	3.253	0.526	7.921	0.216
1.570	1.530	1.026	0.966	1.626	3.099	0.507	7.651	0.205
1.790	1.500	1.193	0.943	1.898	2.966	0.603	7.414	0.241
1.370	1.540	0.890	0.925	1.482	2.850	0.481	7.204	0.190
3.280	2.660	1.233	1.183	2.772	3.237	1.013	9.496	0.345
3.510	3.040	1.155	1.279	2.745	3.591	0.977	10.232	0.343
1.270	1.810	0.702	0.816	1.556	1.853	0.685	5.251	0.242
1.530	1.810	0.845	0.890	1.719	2.022	0.757	5.591	0.274
1.700	1.810	0.939	0.853	1.993	1.938	0.877	5.423	0.313
1.720	1.810	0.950	0.851	2.020	1.934	0.889	5.415	0.318
1.340	1.810	0.740	0.856	1.565	1.946	0.689	5.438	0.246
1.830	1.810	1.011	0.850	2.154	1.931	0.948	5.408	0.338
2.480	1.810	1.370	0.869	2.853	1.975	1.256	5.497	0.451
2.530	1.810	1.398	0.850	2.978	1.931	1.311	5.408	0.468
2.380	1.810	1.315	0.851	2.796	1.934	1.230	5.415	0.439
3.140	1.810	1.735	0.887	3.541	2.015	1.558	5.577	0.563
3.690	1.810	2.039	0.893	4.132	2.030	1.818	5.605	0.658
3.160	1.810	1.746	0.888	3.557	2.019	1.565	5.584	0.566
3.030	1.680	1.804	0.894	3.391	2.430	1.247	7.007	0.432
2.100	3.030	0.693	1.371	1.532	4.251	0.494	10.789	0.195
3.100	2.420	1.281	1.095	2.832	3.329	0.931	8.189	0.379
4.980	2.830	1.760	1.123	4.434	3.712	1.341	8.855	0.562
3.570	2.490	1.434	1.146	3.117	3.576	0.998	8.621	0.414
4.400	2.940	1.497	1.362	3.229	4.778	0.921	10.436	0.422
5.200	4.750	1.095	1.496	3.475	5.735	0.907	11.895	0.437
6.290	3.890	1.617	1.397	4.503	5.770	1.090	11.178	0.563
2.480	2.330	1.064	1.546	1.604	6.682	0.371	12.332	0.201
3.230	2.740	1.179	1.049	3.081	3.927	0.823	8.196	0.394

3.380	2.740	1.234	1.050	3.219	3.934	0.859	8.206	0.412
1.730	2.100	0.824	0.995	1.739	2.447	0.707	7.563	0.229
7.820	7.400	1.057	1.295	6.036	6.299	1.241	10.370	0.754
7.700	7.540	1.021	1.305	5.901	6.432	1.197	10.437	0.738
9.700	7.750	1.252	1.366	7.099	4.981	1.947	10.948	0.886
2.660	2.470	1.077	1.045	2.546	2.883	0.923	8.169	0.326
1.820	2.140	0.850	1.012	1.798	2.503	0.727	7.695	0.237
1.870	2.130	0.878	1.010	1.851	2.489	0.751	7.664	0.244
2.640	2.450	1.078	1.072	2.462	2.943	0.897	8.335	0.317
1.940	2.150	0.902	1.057	1.836	2.331	0.832	8.188	0.237
1.370	1.780	0.770	1.018	1.346	1.995	0.687	7.667	0.179
6.620	5.360	1.235	1.325	4.995	4.011	1.650	10.624	0.623
6.980	5.390	1.295	1.294	5.393	3.928	1.777	10.370	0.673
2.360	2.390	0.987	1.031	2.289	2.447	0.964	8.041	0.293
1.950	1.800	1.083	1.065	1.831	1.720	1.134	8.273	0.236
11.530	10.650	1.083	1.481	7.784	8.250	1.398	11.826	0.975
11.530	10.670	1.081	1.500	7.685	6.974	1.653	11.985	0.962
9.500	8.620	1.102	1.429	6.648	5.687	1.671	11.383	0.835
10.400	8.730	1.191	1.455	7.149	5.271	1.973	11.603	0.896
4.520	3.290	1.374	1.153	3.921	4.566	0.990	9.225	0.490
4.410	3.510	1.256	1.160	3.802	4.607	0.957	9.284	0.475
4.830	2.790	1.731	1.072	4.506	3.833	1.260	8.595	0.562
3.750	2.090	1.794	0.974	3.850	3.016	1.243	7.709	0.486
2.380	2.160	1.102	0.871	2.734	2.120	1.123	6.612	0.360
1.720	2.790	0.616	0.955	1.802	2.907	0.592	7.510	0.229
2.600	2.900	0.897	1.304	1.994	4.171	0.623	9.730	0.267
2.460	2.930	0.840	1.653	1.488	5.404	0.455	11.717	0.210
3.920	2.950	1.329	1.693	2.316	5.542	0.707	11.930	0.329
4.540	2.910	1.560	1.561	2.908	5.082	0.893	11.212	0.405
2.560	3.540	0.723	1.149	2.227	4.899	0.523	9.227	0.277
6.870	6.340	1.084	1.452	4.731	6.651	1.033	11.489	0.598
9.540	8.110	1.176	1.678	5.685	7.931	1.203	13.036	0.732
6.080	9.020	0.674	1.807	3.365	8.654	0.703	13.877	0.438
10.920	9.120	1.197	1.823	5.990	8.744	1.249	13.980	0.781
3.630	3.150	1.152	1.540	2.357	5.216	0.696	11.631	0.312
6.490	4.420	1.468	1.584	4.098	5.835	1.112	12.180	0.533
15.570	10.370	1.501	1.918	8.119	9.634	1.616	15.310	1.017
3.130	1.940	1.613	1.380	2.267	3.614	0.866	8.939	0.350
2.110	2.300	0.917	1.400	1.507	4.043	0.522	9.361	0.225
8.450	9.170	0.921	1.551	5.450	6.675	1.266	11.767	0.718
5.610	4.160	1.349	1.684	3.331	6.115	0.917	13.036	0.430
4.180	6.900	0.606	1.740	2.402	6.840	0.611	13.651	0.306
8.050	10.470	0.769	2.168	3.712	11.294	0.713	17.160	0.469

2.430	2.310	1.052	1.478	1.644	4.220	0.576	9.990	0.243
4.650	2.730	1.703	1.503	3.094	4.720	0.985	10.461	0.444
8.110	9.750	0.832	1.694	4.787	7.793	1.041	13.150	0.617
3.820	4.830	0.791	1.778	2.148	6.827	0.560	14.107	0.271
10.600	7.870	1.347	1.852	5.723	7.635	1.388	14.773	0.718
5.700	10.470	0.544	2.418	2.357	12.608	0.452	18.569	0.307
2.180	2.840	0.768	1.527	1.428	4.915	0.444	11.144	0.196
4.090	3.550	1.152	1.563	2.617	5.497	0.744	11.670	0.350
9.360	10.220	0.916	1.840	5.086	9.077	1.031	14.669	0.638
1.630	1.850	0.881	1.440	1.132	3.694	0.441	8.614	0.189
2.170	3.010	0.721	1.550	1.400	5.178	0.419	10.974	0.198
2.310	2.550	0.906	1.540	1.500	4.847	0.477	9.574	0.241
4.250	3.970	1.071	1.622	2.619	5.916	0.718	11.046	0.385
4.310	5.690	0.757	1.722	2.503	7.008	0.615	12.472	0.346
1.940	2.160	0.898	1.024	1.895	3.192	0.608	7.095	0.273
3.260	2.750	1.185	1.564	2.085	5.374	0.607	11.026	0.296
4.600	4.060	1.133	1.164	3.953	3.935	1.169	9.324	0.493
13.460	10.690	1.259	1.214	11.085	6.436	2.091	9.577	1.405
9.210	9.490	0.970	1.216	7.573	5.339	1.725	9.596	0.960
8.540	2.590	3.297	1.014	8.422	1.724	4.955	6.711	1.273
6.310	5.280	1.195	1.058	5.962	3.387	1.863	7.596	0.831
4.950	6.220	0.796	1.059	4.673	2.810	1.762	7.611	0.650
4.800	6.440	0.745	1.077	4.459	2.714	1.769	7.885	0.609
17.820	13.160	1.354	1.542	11.553	7.474	2.384	11.331	1.573
12.650	12.230	1.034	1.545	8.185	6.224	2.033	11.375	1.112
11.200	11.490	0.975	1.574	7.116	6.002	1.866	11.780	0.951
9.790	6.590	1.486	1.466	6.677	4.767	2.054	9.707	1.009
7.180	6.710	1.070	1.474	4.871	3.974	1.807	9.759	0.736
6.140	6.670	0.921	1.485	4.136	3.820	1.607	10.077	0.609
1.670	1.680	0.994	1.176	1.420	4.348	0.384	9.313	0.179
1.770	1.680	1.054	1.176	1.505	4.348	0.407	9.313	0.190
1.560	1.680	0.929	1.176	1.327	4.348	0.359	9.313	0.168
2.100	1.480	1.419	1.336	1.572	4.963	0.423	10.232	0.205
2.330	3.380	0.689	1.386	1.681	5.294	0.440	10.716	0.217
2.240	3.380	0.663	1.386	1.616	5.294	0.423	10.716	0.209
2.260	3.470	0.651	1.548	1.460	5.862	0.386	11.535	0.196
2.300	3.470	0.663	1.548	1.486	5.862	0.392	11.535	0.199
2.380	2.750	0.865	1.527	1.559	5.708	0.417	11.317	0.210
2.620	2.720	0.963	1.698	1.543	6.233	0.420	12.059	0.217
2.630	2.720	0.967	1.698	1.549	6.233	0.422	12.059	0.218
2.510	2.720	0.923	1.698	1.478	6.233	0.403	12.059	0.208
9.340	6.600	1.415	1.737	5.378	5.470	1.707	12.573	0.743
1.330	1.250	1.064	1.100	1.209	2.323	0.573	7.357	0.181

1.660	1.250	1.328	1.138	1.459	2.406	0.690	7.545	0.220
1.010	1.520	0.664	1.105	0.914	2.381	0.424	7.773	0.130
1.200	1.570	0.764	0.559	2.146	1.099	1.092	4.463	0.269
1.150	1.180	0.975	0.906	1.269	2.036	0.565	5.968	0.193
1.370	0.940	1.457	0.912	1.502	1.894	0.723	6.098	0.225
3.890	5.590	0.696	1.568	2.480	5.943	0.655	12.552	0.310
6.020	6.020	1.000	1.628	3.698	6.252	0.963	13.016	0.462
7.900	6.020	1.312	1.628	4.853	6.252	1.264	13.016	0.607
9.310	9.660	0.964	2.119	4.393	8.762	1.063	16.584	0.561
10.330	9.660	1.069	2.119	4.875	8.762	1.179	16.584	0.623
21.440	10.490	2.044	2.614	8.201	11.885	1.804	20.637	1.039
15.570	10.430	1.493	2.300	6.769	10.048	1.550	18.295	0.851
7.220	5.830	1.238	2.023	3.568	7.944	0.909	15.457	0.467
4.340	3.360	1.292	1.954	2.221	7.305	0.594	14.554	0.298
11.380	10.030	1.135	2.127	5.350	10.607	1.073	16.638	0.684
10.180	9.880	1.030	2.127	4.786	9.573	1.063	16.638	0.612
8.500	9.460	0.899	2.127	3.996	8.200	1.037	16.638	0.511
8.170	9.930	0.823	2.286	3.573	8.411	0.971	17.708	0.461
5.090	4.000	1.273	1.882	2.705	4.795	1.062	10.761	0.473
6.740	6.300	1.070	1.971	3.419	6.248	1.079	13.011	0.518