The International Journal of Soft Computing and Software Engineering [JSCSE], Vol. 3, No. 3, Special Issue:
The Proceeding of International Conference on Soft Computing and Software Engineering 2013 [SCSE'13],
San Francisco State University, CA, U.S.A., March 2013
Doi: 10.7321/jscse.v3.n3.101 e-ISSN: 2251-7545

Prediction of Compressive Strength of Plain Concrete Confined with Ferrocement using Artificial Neural Network (ANN)

T. Ayub
* Universiti Teknologi PETRONAS
tehminaa@hotmail.com

S.U. Khan
Universiti Teknologi PETRONAS
sadaquat78@hotmail.com

M.F. Nuruddin
Universiti Teknologi PETRONAS
fadhilnuruddin@petronas.com.my

F.A. Memon
Universiti Teknologi PETRONAS
engrfam@gmail.com

***Abstract*—This paper focuses on the development of a predictive model for compressive strength of concrete confined with Ferrocement using MATLAB Artificial Neural Network (ANN) approach. Data of fifty five (55) plain concrete cylinders confined with Ferrocement in three (03) ways, has been gathered from existing literature, out of which basic parameters of randomly selected nineteen (19) specimens have been used in the multilayer feed forward neural network model to develop a predictive model through training. Basic eight input parameters included cylinder and core dimension, no. of wire-mesh layers, wire diameter and spacing, yield strength of the wire of wire-mesh and unconfined compressive strength. After training, predictive model had been tested using overall data of fifty five (55) specimens which showed excellent agreement between the results generated by the ANN predictive model and experimental results. Regression value (R), root mean square error (RMS) and absolute fraction of variance (V) were also calculated to compare experimental and ANN predictive model results which also showed better performance of the ANN predictive model.**

Keywords-compressive strength; confinement; ferrocement; wire-mesh layers; artificial neural network

I. INTRODUCTION

Since last decade, Artificial Neural Network (ANN), a sub-domain of artificial intelligence system, is being widely used in the Civil Engineering to solve various problems. In 1994, J. Garrett described engineering definition of ANN as a computational mechanism which is capable of acquiring and working out mapping from a multivariate space of information to another by giving a set of data representing that mapping [1]. ANN, now a days, is a preferable tool due to its ability of learning directly from examples; therefore, in the absence of laws to solve a problem or when conventional computing techniques like regression analysis are very hard to apply, then ANN may be very helpful to sort out a problem [2] due to its ability of adaptation according to new data and retraining. Other remarkable features of ANN include its accurate or nearly accurate approach to the unfinished tasks and extraction of information from strident or poor records; henceforth ANN may be applied to an inadequate, uncertain or noisy data due to its learning capability [2]; however, it requires adequate input-output records to include the effects of all parameters [3]. In Civil Engineering, ANN tool has been used in numerous domains; for example tidal level forecasting [3], earthquake-induced liquefaction [4], wave-induced seabed instability [5], ultimate bearing capacity of soil [6], prediction of compressive strength [7-12], slump [13] and workability of concrete [14] etc., and has been found very promising tool. Moreover, a neural network model has also been developed using the ANN approach to predict the workability of concrete containing Metakaolin (MK) and fly ash (FA) [15] and about 98% accurate compressive strength of concrete containing Metakaolin and silica fume has been predicted [10]. These diverse applications of ANN lead authors to apply this approach to predict the compressive strength of concrete confined with Ferrocement. Therefore, already used data of plain concrete confined with Ferrocement [16] has been selected to develop predictive models using MATLAB ANN approach.

II. DETAILS OF THE PLAIN CONCRETE CYLINDERS CONFINED WITH FERROCEMENT

Authors of current paper gathered detailed information about the parameters of plain concrete confined with Ferrocement after referring four (04) studies [17-20] which showed that till date, confinement to plain concrete cylinders has been done in three ways as mentioned underneath:

The International Journal of Soft Computing and Software Engineering [JSCSE], Vol. 3, No. 3, Special Issue:
The Proceeding of International Conference on Soft Computing and Software Engineering 2013 [SCSE'13],
San Francisco State University, CA, U.S.A., March 2013
Doi: 10.7321/jscse.v3.n3.101 e-ISSN: 2251-7545

- By integrally casting wire-mesh in layers [17-19]
- By initially casting pre-cast shell with Wire-mesh layers [17] and
- By wrapping wire-mesh layer on the pre-cast core of [17-19].

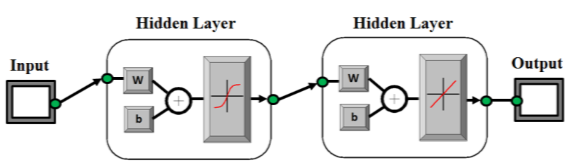
Details of the parameters of the data used to develop ANN predictive model is given in Table 1.

III. Development Procedure of the Predictive Model for the Compressive Strength of Concrete Confined with Ferrocement using Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is generally comprised of the input layer of neurons, one or more hidden layer of neurons and the output layer of neurons. Hidden layer exists between input and output layers and contains a bulk number of hidden processing units [21]. Outside atmosphere provides information to the input layer of neurons from where this input layer transmits information to the hidden layer(s) of neurons without computation [22, 23].

A. *Details of Input, Hidden and Output Neurons*

In this paper, eight (08) input parameters and experimental results of nineteen (19) specimens out of total fifty five (55) has been used to develop a predictive model for compressive strength of plain concrete confined with Ferrocement. Details of eight (08) parameters used as external input neurons, has been highlighted in Table I; however detailed procedure to train these eight (08) inputs using the MATLAB ANN system is shown in Fig. 1.



Algorithms

Training:	Levenberg-Marquardt (trainlm)
Performance:	Mean Squared Error (mse)
Data Division:	Random (dividerand)

Fig. 1. Architecture of the ANN model used

Two hidden layers have been used to develop the predictive model to which sixteen (16) neurons have been assigned initially in order to compute linear combination of the output taking information from input layer neurons. Moreover, these hidden layer neurons have also been used to calculate bias whose coefficients are called "weights" (i.e. Coefficients of the linear combination plus bias). After computing linear combination output, neurons in the hidden layer computed nonlinear function called "sigmoid function" [24] of the input. It is important to mention that these neurons gather information from other neurons through multiplication of the output of connected neuron depending on the synaptic strength of the connection between them and the output of the neurons is connected to the network input through a transformation function called activation function [25].

Information of the Parameters used to develop ANN Predictive Model

Parameters	Values Used
Number of input layer neurons	8
Number of hidden layer neurons	16
Number of output layer neuron	1
Max. Number of epochs	300
Mu	1×10^{-8}
Mu decrease factor	0.1
Mu increase factor	10
Performance goal	1×10^{-5}
Gradient	7×10^{-11}

B. *Architecture of the Artificial Neural Network (ANN)*

The architecture of ANN used is comprised of multilayer feed forward and back propagation algorithm. Two-layer tansig/purelin network has been used to construct the model as shown in Fig. 1 and tan-sigmoid tansig function has been used as transfer function. After initializing the network weights and biases, network has been trained for the pattern recognition using Levenberg-Marquardt (trainlm) training function. Network inputs and target outputs have been provided for training process. During training, network weights and biases have been iteratively adjusted in order to minimize the network performance function net.performFcn. The default performance function for feed forward networks is mean square error (mse) which is the average squared error between network outputs and the target outputs [21]. The parametric values used in the ANN model are summarized in Table II. After several trials, input parameters (i.e. Input neurons) have been observed to influence the compressive strength of plain concrete confined with Ferrocement. After training the model with nineteen (19) experimental results, overall data of fifty five (55) specimens have been used as an experimental input for simulation which produced similar results to the experimental results.

The International Journal of Soft Computing and Software Engineering [JSCSE], Vol. 3, No. 3, Special Issue:
The Proceeding of International Conference on Soft Computing and Software Engineering 2013 [SCSE'13],
San Francisco State University, CA, U.S.A., March 2013
Doi: 10.7321/jscse.v3.n3.101 e-ISSN: 2251-7545

TABLE I. COMPARISON OF THE RESULTS OF THE ANN PREDICTIVE MODEL AND THEORETICAL MODELS [17-20] WITH EXPERIMENTAL RESULTS

Specimen Label	Cylinder Dimension (mm)		Core Dimension H_c (mm)	No. of mesh layers N	Yield Strength f_y (MPa)	Wire Diameter d_w (mm)	Wire Spacing S (mm)	Unconfined Compressive Strength f_{cu} (MPa)	Experimental Confined Compressive Strength f_{ct} (MPa)	Method of Attach-ment of Ferrocement Layers	References for the Expermental Data	Predicted Confined Compressive Strength f_{ct} by ANN Model (MPa)
	H	**D**										
Aa-ii-1*	152	305	114	1	345	0.96	6	27.62	30.8	Integrally cast mesh layers	[17]	30.25
Aa-ii-2	152	305	114	2	345	0.96	6	27.62	34.24			33.54
Aa-ii-3*	152	305	114	3	345	0.96	6	27.62	37.52			34.98
Aa-iii-1	152	305	114	1	345	0.96	6	26.37	29.6			28.71
Aa-iii-2*	152	305	114	2	345	0.96	6	26.37	33			32.43
Aa-iii-3	152	305	114	3	345	0.96	6	26.37	36.22			34.42
Ab-i-1*	152	305	114	1	345	0.96	6	32.14	35.37			33.66
Ab-i-2	152	305	114	2	345	0.96	6	32.14	38.37			34.86
Ab-i-3*	152	305	114	3	345	0.96	6	32.14	41.42			34.43
Ab-ii-1	152	305	114	1	345	0.96	6	30.73	33.84			33.01
Ab-ii-2	152	305	114	2	345	0.96	6	30.73	36.95			34.88
Ab-ii-3	152	305	114	3	345	0.96	6	30.73	40			34.96
Ba-ii-1	152	305	114	1	345	0.96	6	27.62	30.45	Mesh layer in precast shell		30.25
Ba-ii-2	152	305	114	2	345	0.96	6	27.62	33.1			33.54
Ba-ii-3	152	305	114	3	345	0.96	6	27.62	35.82			34.98
Ba-iii-1	152	305	114	1	345	0.96	6	26.37	29.03			28.71
Ba-iii-2	152	305	114	2	345	0.96	6	26.37	31.86			32.43
Ba-iii-3	152	305	114	3	345	0.96	6	26.37	34.41			34.42
Bb-i-1	152	305	114	1	345	0.96	6	32.14	34.8			33.66
Bb-i-2	152	305	114	2	345	0.96	6	32.14	37.35			34.86
Bb-i-3	152	305	114	3	345	0.96	6	32.14	39.73			34.43
Bb-ii-1	152	305	114	1	345	0.96	6	30.73	33.39			33.01
Bb-ii-2	152	305	114	2	345	0.96	6	30.73	35.93			34.88
Bb-ii-3	152	305	114	3	345	0.96	6	30.73	38.48			34.96
Ca-ii-1	152	305	114	1	345	0.96	6	27.62	30.45	Wrapped mesh layer on precast core		30.25
Ca-ii-2	152	305	114	2	345	0.96	6	27.62	33.27			33.54
Ca-ii-3	152	305	114	3	345	0.96	6	27.62	36.39			34.98
Ca-iii-1*	152	305	114	1	345	0.96	6	26.37	29.31			28.71
Ca-iii-2	152	305	114	2	345	0.96	6	26.37	32.14			32.43
Ca-iii-3*	152	305	114	3	345	0.96	6	26.37	34.97	Wrapped mesh layer on precast core	[17]	34.42
Cb-i-1	152	305	114	1	345	0.96	6	32.14	37.63			33.66
Cb-i-2*	152	305	114	2	345	0.96	6	32.14	40.29			34.86
Cb-i-3	152	305	114	3	345	0.96	6	32.14	28.75			34.43
Cb-ii-1*	152	305	114	1	345	0.96	6	30.73	33.56			33.01
Cb-ii-2	152	305	114	2	345	0.96	6	30.73	36.22			34.88
Cb-ii-3*	152	305	114	3	345	0.96	6	30.73	38.93			34.96
PB-1*	150	300	120	1	585	1.09	12.5	37.895	42.37	Integrally cast mesh layers	[18]	41.99
PB-2	150	300	120	2	585	1.09	12.5	37.895	49.61			45.24
PB-3*	150	300	120	3	585	1.09	12.5	37.895	52.364			48.44
PB-4	150	300	120	4	585	1.09	12.5	37.895	54.78			51.64
SKSP-1*	150	300	120	1	340	0.7	6	26.65	46.5		[19]	46.16
SKSP-2	150	300	120	2	340	0.7	6	26.65	50			56.43
SKSP-3	150	300	120	3	340	0.7	6	26.65	53.5			66.34
A1-2	150	300	126	2	530	0.94	11.6	41.13	51.38	Wrapped mesh on pre-cast core by special fasten-ers	[20]	51.76
A1-4	150	300	114	4	530	0.94	11.6	41.13	52.71			59.64
A1-8	150	300	105	8	530	0.94	11.6	41.13	50.74			62.50
A2-2*	150	300	126	2	530	0.94	11.6	41.13	50.76			51.76
A2-4*	150	300	114	4	530	0.94	11.6	41.13	48.82			59.64
A2-8*	150	300	105	8	530	0.94	11.6	41.13	55.99			62.50
B2-2*	150	300	126	2	530	0.94	11.6	41.13	53.3	Wrapped mesh on precast core bonded on edges		51.76
B1-8*	150	300	105	8	530	0.94	11.6	41.13	60.3			62.50
B1-2	150	300	126	2	530	0.94	11.6	41.13	48.8			51.76
B1-4	150	300	114	4	530	0.94	11.6	41.13	49.57			59.64
C1-4	150	300	114	4	530	0.94	11.6	41.13	59.87	Mesh wrapped on precast core by bonding first two layers		59.64
C1-8*	150	300	105	8	530	0.94	11.6	41.13	71.78			62.50

*Data of these 19 randomly selected specimens has been used for the development of the ANN predictive model through training

The International Journal of Soft Computing and Software Engineering [JSCSE], Vol. 3, No. 3, Special Issue:
The Proceeding of International Conference on Soft Computing and Software Engineering 2013 [SCSE'13],
San Francisco State University, CA, U.S.A., March 2013
Doi: 10.7321/jscse.v3.n3.101 e-ISSN: 2251-7545

IV. Results and Discussion

Results of compressive strength of plain concrete confined with Ferrocement predicted by ANN model are summarized in Table 1. To compare predictive model results with experimental, regression values (R), root mean square (RMS) errors and absolute fraction of variances (V) have also been calculated as shown in Figure 2. For linear regression "R", a command used in MATLAB is underneath:

$$[m, b, r] = \text{postreg}(t_i, o_i) \quad (1)$$

Where, "m" is the slope of the linear regression, "b" is the Y-intercept of the linear regression, *r* is the regression i.e. "R" (R=1 indicates perfect correlation), "t_i" is the experimental result (used as target) and "o_i" is the theoretical results (used as output).Root mean square (RMS) errors and absolute fraction of variance (V) have been manually calculated using following formulation:

$$RMS = \sqrt{(\sum|t_i - o_i|^2) / n} \quad (2)$$

(Where, n = number of observations)

$$V = 1 - (\sum|t_i - o_i|^2) / \sum o_i^2) \quad (3)$$

As mentioned [16], theoretical model proposed by *Waliuddin and Rafeeqi* [17] estimates compressive strength of plain concrete confined with Ferrocement very efficiently and more accurately than experimental results and other existing theoretical models for different methods of the attachment of Wire-mesh i.e. *integrally cast Wire-mesh*, *precast Wire-mesh* and *wrapped Wire-mesh*. However in this paper, in spite of using input parameters of 19 specimens, the ANN predictive model exhibited more promising results than all theoretical models [17-19].

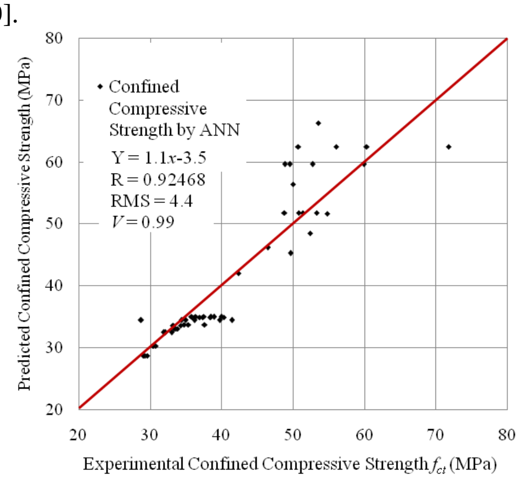


Fig. 2. Experimental *vs.* Predictive Results

V. Conclusion

Successful development of the predictive model for the compressive strength of concrete confined with the Ferrocement leads to a conclusion that Artificial Neural Network (ANN) is a proficient tool due to its self-learning and generalizing capability from experimental results; as only providing raw information (i.e. cylinder and core dimension, no. of wire-mesh layers, wire diameter and spacing, yield strength of the wire of wire-mesh and unconfined compressive strength)to the training model, compressive strength of plain concrete confined with Ferrocement has been predicted closed accurately. Regression value "R", root mean square error (RMS) and absolute fraction of variance (*V*) calculated to compare ANN predictive model results with experimental results [17-20] alsoshowed better performance of ANN predictive model. Beside this, compressive strength of plain concretes confined with Ferrocement has been predicted in a fairly small period of time with minute errors using multilayer feed forward ANN model without performing hectic experimental work. This indicates that multilayer feed forward ANN is a feasible method. Moreover, it may be inferred that ANN model as a predictive model is capable to predict more correctly the compressive strength of plain concrete confined by different methods such as integrally cast Wire-mesh layers, or precast Wire-mesh layers or wrapped Wire-mesh layers.

References

[1] J. Garrett, "Where and why artificial neural networks are applicable in civil engineering," *Journal of Computing in Civil Engineering, ASCE,* vol. 8, pp. 129-130, 1994.

[2] M. Rafiq, *et al.*, "Neural network design for engineering applications," *Computers & Structures,* vol. 79, pp. 1541-1552, 2001.

[3] C. P. Tsai and T. L. Lee, "Back-propagation neural network in tidal-level forecasting," *Journal of waterway, port, coastal, and ocean engineering,* vol. 125, p. 195, 1999.

[4] J. Wang and M. Rahman, "A neural network model for liquefaction-induced horizontal ground displacement," *Soil Dynamics and Earthquake Engineering,* vol. 18, pp. 555-568, 1999.

[5] D. S. Jeng, *et al.*, "Neural network model for the prediction of wave-induced liquefaction potential," *Ocean engineering,* vol. 31, pp. 2073-2086, 2004.

[6] S. Hakim and S. Jamalaldin, "Development and Applications of Artificial Neural Network for Prediction of Ultimate Bearing Capacity of Soil and Compressive Strength of Concrete," *Masters thesis, Universiti Putra Malaysia*, 2006.

[7] I. B. Topcu and M. Saridemir, "Prediction of compressive strength of concrete containing fly ash using artificial neural networks and fuzzy logic," *Computational Materials Science,* vol. 41, pp. 305-311, 2008.

[8] S. J. S. Hakim, *et al.*, "Application of artificial neural networks to predict compressive strength of high strength concrete," *Int. J. Phys. Sci,* vol. 6, pp. 975-981, 2011.

[9] F. Altun, *et al.*, "Predicting the compressive strength of steel fiber added lightweight concrete using neural network," *Computational Materials Science,* vol. 42, pp. 259-265, 2008.

[10] M. SarIdemir, "Prediction of compressive strength of concretes containing metakaolin and silica fume by artificial neural networks," *Advances in Engineering Software,* vol. 40, pp. 350-355, 2009.

[11] J. Noorzaei, *et al.*, "An optimal architecture of artificial neural network for predicting compressive strength of concrete," *Indian Concrete Journal,* vol. 81, p. 17, 2007.

Doi: 10.7321/jscse.v3.n3.101 e-ISSN: 2251-7545

[12] N. Hong-Guang and W. Ji-Zong, "Prediction of compressive strength of concrete by neural networks," *Cement and Concrete Research*, vol. 30, pp. 1245-1250, 2000.

[13] A. Öztaş, *et al.*, "Predicting the compressive strength and slump of high strength concrete using neural network," *Construction and Building Materials,* vol. 20, pp. 769-775, 2006.

[14] W. Dias and S. Pooliyadda, "Neural networks for predicting properties of concretes with admixtures," *Construction and Building Materials,* vol. 15, pp. 371-379, 2001.

[15] J. Bai, *et al.*, "Using neural networks to predict workability of concrete incorporating metakaolin and fly ash," *Advances in Engineering Software,* vol. 34, pp. 663-669, 2003.

[16] S. Rafeeqi and T. Ayub, "Investigation of versatility of theoretical prediction models for plain concrete confined with Ferrocement," *Asian Journal Of Civil Engineering (Building And Housing),* vol. 12, pp. 337-352, 2011.

[17] A. Waliuddin and S. Rafeeqi, "Study of the behavior of plain concrete confined with ferrocement," *Journal of ferrocement,* vol. 24, pp. 139-151, 1994.

[18] P. Balaguru, "Use of ferrocement for confinement of concrete," *Journal of ferrocement,* vol. 19, pp. 135-140, 1989.

[19] S. Kaushik and S. Singh, "Behavior of Ferrocement Composite Columns in Compression," *ACI Special Publications,* vol. 172, pp. 669-682, 1997.

[20] S. E. M. Mourad, "Performance of Plain Concrete Specimens Externally Confined with Welded Wire Fabric," *Final Research Report No. 47 / 426, King Saud University,* 2006.

[21] H. Demuth and M. Beale, "Neural network toolbox for use with MATLAB," 1993.

[22] F. Demir, "Prediction of elastic modulus of normal and high strength concrete by artificial neural networks," *Construction and Building Materials,* vol. 22, pp. 1428-1435, 2008.

[23] M. Y. Mansour, *et al.*, "Predicting the shear strength of reinforced concrete beams using artificial neural networks," *Engineering Structures,* vol. 26, pp. 781-799, 2004.

[24] B. B. Adhikary and H. Mutsuyoshi, "Prediction of shear strength of steel fiber RC beams using neural networks," *Construction and Building Materials,* vol. 20, pp. 801-811, 2006.

[25] A. Mukherjee and S. Nag Biswas, "Artificial neural networks in prediction of mechanical behavior of concrete at high temperature," *Nuclear engineering and design,* vol. 178, pp. 1-11, 1997.