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Full Length Research Paper

Using feed-forward back propagation (FFBP) neural networks for compressive strength prediction of lightweight concrete made with different percentage of scoria instead of sand

Razavi S. V.[1]*, Jumaat M. Z.[1] and Ahmed H. El-Shafie[2]

[1]Civil Engineering Department, University Malaya (UM), Malaysia.
[2]Civil Engineering Department, Universiti Kebangsaan Malaysia (UKM), Malaysia.

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Artificial neural networks (ANNs) are the result of academic investigations that use mathematical formulations to model nervous system operations. Neural networks (NNs) represent a meaningfully different approach to using computers in the workplace, and have been used to recognize patterns and relationships in data. In this paper, the compressive strength (CS) of lightweight material with 0, 20, 30, and 50% of scoria instead of sand, and different water-cement ratios and cement content for 288 cylindrical samples were studied. Out of these, 36 samples were randomly selected for use in this research. The CS of these samples was used to teach ANNs CS prediction to achieve the optimal value. The ANNs were formed by MATLAB software so that the minimum error in information training and maximum correlation coefficient in data were the ultimate goals. For this purpose, feed-forward back propagation (FFBP) with TRAINBR training function, LEARNGD adaption learning function, and SSE performance function were the last networks tried. The end result of the FFBP was 3-10-1 (3 inputs, 10 neurons in the hidden layer, and 1 output) with the minimum error below 1% and maximum correlation coefficient close to 1.

Key words: Compressive strength (CS), scoria, artificial neural networks (ANNs), feed-forward back propagation (FFBP).

INTRODUCTION

The master unit of the human brain is the neuron with each neuron working similar to numerical processing. Brains are a series of many millions of neurons that have been connected together that are hugely complex and operate in parallel. Neurons in the brain normally receive inputs from other neurons and through their transmission function make their output to other layers of neurons. These neurons also send the output to other layers. Similarly, ANN consists of many thousands of sample processing units that have a parallel connection and are following together in multi layers.

The effect of a local connection is called the weight of the connection. ANN gets random amounts of the weight of internal connections. These neurons have reclaimed in the teaching operation between input and output link. The structure of a multi input neuron is shown in Figure 1 where (P) and (a) are the input and output, respectively.

$$W = [W(1,1)W(1,2)\dots W(1,R)]$$

The effectiveness of (P) on (a) is defined by the weight (W). The other information is 1 (the constant amount) that is multiplied in bios (b) and with WP added. The conclusion is defined by theoretical data (n) for a function (f) that is calculated by Equations 1 and 2

$$n = \sum_{i=1}^{R} P_i W(1,i) + b = WP + b \quad (1)$$

$$a = f(WP+b). \quad (2)$$

In recent years, ANN has been effectively applied in

*Corresponding author. E-mail: Vahidrazavy@yahoo.com.

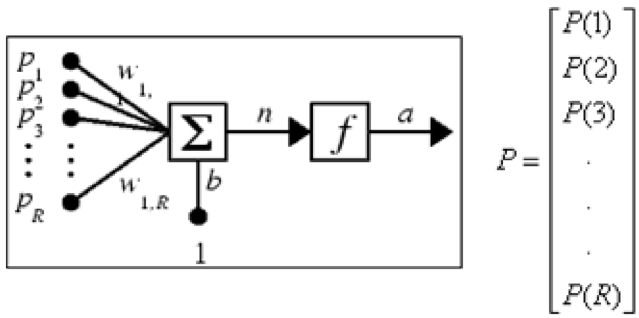

Figure 1. The neuron model with R-element in input.

different engineering divisions (Bishop, 1995; Davies, 2000; Laurene, 1994; Kulkarni 1994) and, ANN seems to be highly satisfactory. Fatih et al. (2008) used ANN to predict the compressive strength of lightweight concrete by adding steel fibre. The parameters considered for the ANN inputs were the amounts of steel fibre, water, water-cement ratio, cement, pumice sand, pumice gravel, and super plasticizer. The test results obtained from the ANN were compared with the multi linear regression (MLR) technique based on mean square error, mean absolute error, and correlation coefficient criteria. The ANN predicted the compressive strength of steel fibre added lightweight concrete with a relative absolute mean error of 6.75%. Raghu et al. (2001) studied the compressive strength prediction of self compacting concrete (SCC) high performance concrete (HPC), high value ash concrete using ANN. Two hidden layers were selected in the neural network in which the network structures were 10-10-5-1 and 9-9-5-1 for SCC and HPC, respectively. The selected neural networks showed satisfactory results at 30 to 60 Mpa at the end of the project. Manish and Rajiv (2006) used ANN to predict the compressive strength of normal concrete using ultrasonic pulse velocity (UPV) data results. They compared the results of ANN with the effect of multiple regeneration (MR) system and it was determined that the results of ANN were more exact than MR. Ilker and Mustafa (2007) studied the use of ANN to predict the properties of waste autoclaved aerated concrete (ACC). They used 45 data results for neural network processing, 23 were selected for training and 22 for testing. The applied ANN had seven input layers, with 7 neurons in the first hidden layer, 8 neurons in the second hidden layer, and 4 parameters in the output layer. The results after training and testing only showed a 6% difference between ANN and the experimental testing results. Indeed, within the area of research, civil engineering, the ANN appears to demonstrate the brilliant success of computing. In the present study, ANN was used to determine the compressive strength of lightweight concrete made with different percentage of scoria instead of sand. There are many ways to make lightweight concrete such as increasing of mixture volume (Short and Kinniburgh, 1978), using natural lightweight aggregates (Short and Kinniburgh, 1978), and using artificial aggregates (Merikallio and Mannonen, 1996). Unal et al. (2007) made block elements by using different size of diatomite and cement contents. According to the result of mechanical and physical properties, using diatomite in lightweight concretes can be applied to decrease the service load and achieve high insulation in buildings. Gadea et al. (2010) produce lightweight mortar by using rigid polyurethane foam instead of sand. The results of the experimental study show a decrease in the density and mechanical properties and an increase in the workability. According to the referred study, the experimental work needs to take time for sampling, testing, and analyzing. Whereas, ANN can predicts the results with minimum error and maximum correlation coefficient.

The major objective in current experimental work is making lightweight concrete by replacing scoria instead of fine aggregate and generates ANN for compressive strength prediction. This scoria has a white to light grey colour with varying openings, closed pores, rough surface, and angular particles. It is created from the accumulation of volcanic ash; upon cooling bubbles are formed by the vapour and existing gases. The specific gravity of the aggregate with respect to the porosity is less than 1 g/cm^3.

METHODOLOGY OF TESTING AND ANALYSIS

Lightweight concrete (testing)

The first part of this project was the laboratory testing of 288 lightweight samples in the shapes of 15×15×15 (cm) and cylinders 15×30 (cm) that were made to determine the compressive strength. Subsequently, the data for the selected results were applied in the ANN method. The used parameters are shown in Table 1.

Research method (analysis)

One way of predicting the properties of concrete is by using ANN. This process uses (nntool) case in MATLAB software to train, verify, and test the neural network. EXCEL software was used for input data processing. The ANN information is shown in Table 2.

Table 1. The schedule of construction of lightweight concrete.

Parameter	Concrete sample
Scoria instead of sand in lightweight concrete (%)	0, 20, 30 and 40
Water-cement ratio	0.5, 0.55 and 0.6
Cement content in compressive sample (kg/m^3)	300, 350, 400
Cement content in tensile sample (kg/m^3)	300
Curing time (days)	7 and 28

Table 2. ANN information.

No.	ANN information		Database
1	The number of used data in network		36 data were selected from 288 results
2	Data number used for training		27
3	Data number used for verifying		5
4	Data number used for testing		4
5	Input data	Cement content	300, 350 and 400 kg/m^3
		Water-cement ratio	0.5, 0.55 and 0.6
		Scoria percent	0, 20, 30 and 40%
6	Output		Density

Table 3. ANN modelling.

Training algorithm	Function	Network architecture	Training	verifying	Testing
Back propagation	LOGSIG	3-10-1	27 Data	5 Data	4 Data

Network modelling

Modelling of the network consists of some parameters seen in Table 3 and the six parameters as follows:

Training algorithms: The back propagation was used for network training. Back-propagation neural networks (BPNN) are the common network architecture (Rumelhart et al., 1968). BPNNs are training algorithms in a supervised style. The input-output pairs are used to train a network until the network can approximate a function (Haykin, 1999).

The best function*:* Different functions with constant architecture (3-10-1) were investigated using the LOGSIG function in the input and output layer for the end results.

The best network architecture: The best architecture was calculated by testing a different number of neurons in the hidden layer. Normally, one or two hidden layers within random large number of neurons may be sufficient to estimate any function (Haykin, 1999). The minimum number of neurons in the hidden layer is defined by Equation 3. (Carpenter and Barthelemy, 1994):

$$HN = IN + 1 \quad (3)$$

Where, HN is the number of nodes in the hidden layers and IN is the number of nodes in the input layer.

According to three input layer, the minimum number of neurons in hidden layer are 4 neurons. The minimum and maximum number of neurons in current study is 9 and 18. In this order, SSE and MSE methods were used to determine minimum error. The 3-10-1 architecture was selected at the end of the calculation (3-10-1: 3 input, 10 hidden layer, and 1 output).

Training: In this part, 27 data comprising three kinds of information, cement content, water-cement ratio, and percent of scoria, were applied to normalized in [0,1].

Verifying: In this programme, the time stop of calculation was applied with five data to determine the network structure work that was not used in training. Verifying data have checked in a different sequence of training and continued when the number of error reduced in the verifying.

Testing: Four data were applied for the testing process after training and verifying.

RESULTS AND DISCUSSION

As can be seen, the process of experimental work needs considerable time for the concreting, curing, and testing. Therefore, creating an ANN based on experimental

Table 4. Properties of applied ANN.

Neural network ID	Training function	Adaption learning function	Performance function	Number of Neurons in Hidden layer	Transfer function in hidden layer	Transfer function in output layer	Data arrangement in figure
N1	TRAINLM	LEARNGD	MSE	18	TANSIG	TANSIG	DIAG.1
N2	TRAINLM	LEARNGD	MSE	17	TANSIG	TANSIG	DIAG.1
N3	TRAINBR	LEARNGD	SSE	10	TANSIG	LOGSIG	DIAG.1
N4	TRAINBR	LEARNGDM	SSE	9	TANSIG	LOGSIG	DIAG.1
N5	TRAINBR	LEARNGD	SSE	10	LOGSIG	LOGSIG	DIAG.1
N6	TRAINBR	LEARNGD	SSE	9	LOGSIG	LOGSIG	DIAG.1

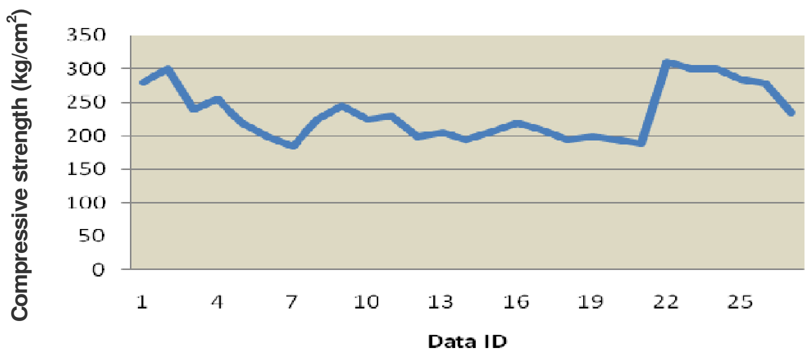

Figure 2. Data arrangement for AAN ID = 1 – 6.

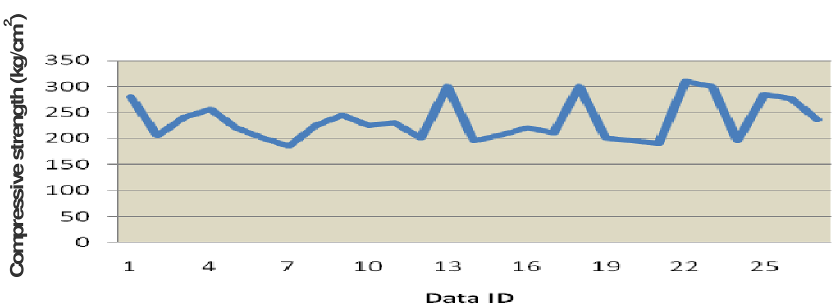

Figure 3. Data arrangement for AAN ID = 7.

results helps in predicting the compressive strength of lightweight concrete without the need for any practical operation. The output of the selected network is compared with the experimental output to justify the created network. In this case, eight networks with different structures (Table 4) were studied to identify the optimal result. The different data layout in Figures 2 to 4 was applied as a first parameter to test different networks. The second parameter was the network type, and feed-forward back propagation (FFBP) was the final design for ANN. The other parameters shown in Table 4 such as training function, adaption learning function, performance function, number of hidden layer, transfer function in hidden layer, and transfer function in output layer, were considered to find the best network.

The best network was selected based on the following two conditions:

1. The minimum error in training data.
2. The high correlation coefficient of data.

The minimum error was extracted using the MSE method for eight networks, as shown in Figure 5. The correlation coefficient is shown in Table 5. Network N8, with 10

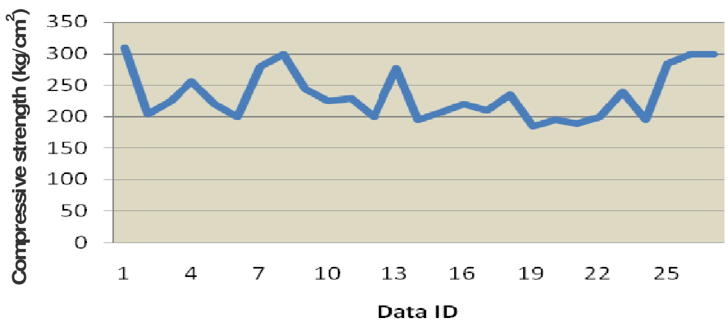

Figure 4. Data arrangement for AAN ID = 8.

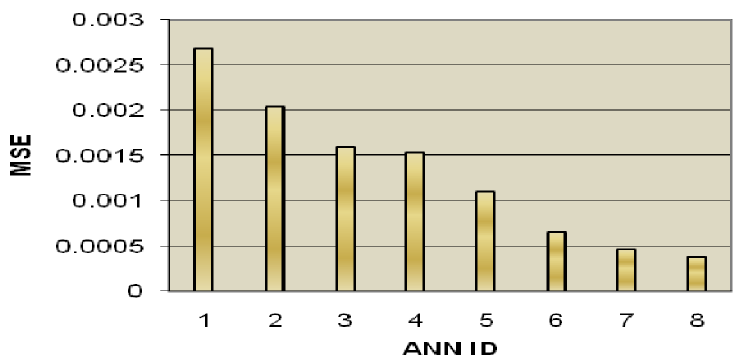

Figure 5. Classified neural network.

Table 5. The best neural network.

Neural network ID	R^2	MSE
N1	0.6848	0.002682
N2	0.9846	0.002038
N3	0.9486	0.001591
N4	0.9694	0.001529
N5	0.9261	0.001102
N6	0.9612	0.000652
N7	0.9551	0.000464
N8	0.9639	0.00038

neurons in the hidden layer, is considered to have the minimum error (Figure 5) and maximum correlation coefficient, close to 1 (Table 5).

For this network, the input data arrangement, as indicated in Figure 4, was the important parameter in comparing with the networks N7 and N5. In networks N7 and N5 all other parameters are similar to network N8. However, the created network N8 is more knowledgeable than either N7 or N5.

Concerning the calculated MSE and R2 in Table 5, neural network 8, with a means squared error of 0.00038 and correlation coefficient of 0.9639, was the best network. The network architecture is shown in Figure 6.

The correlation coefficient of testing data in optimal network and physical data for network N8 is shown in Figure 7. In Figure 8, the network output data and laboratory results for the compressive strength are compared.

Based on the outcome indicated in Figure 8, the output results of the created network N8 are close to the results of the experimental effort. It is concluded that the generated network with the properties exposed in Table 4 can be applied to predict the compressive strength of

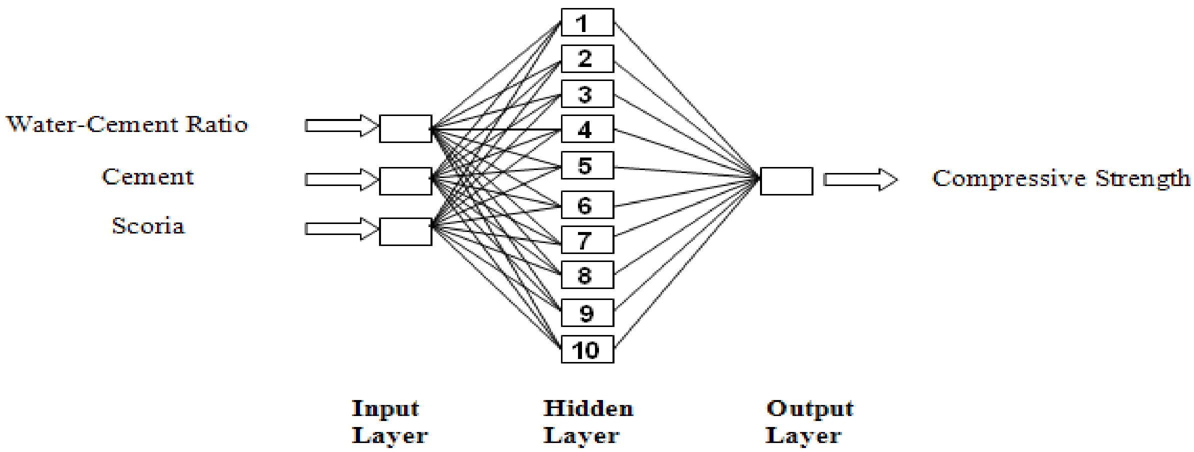

Figure 6. Layer architecture of ANN.

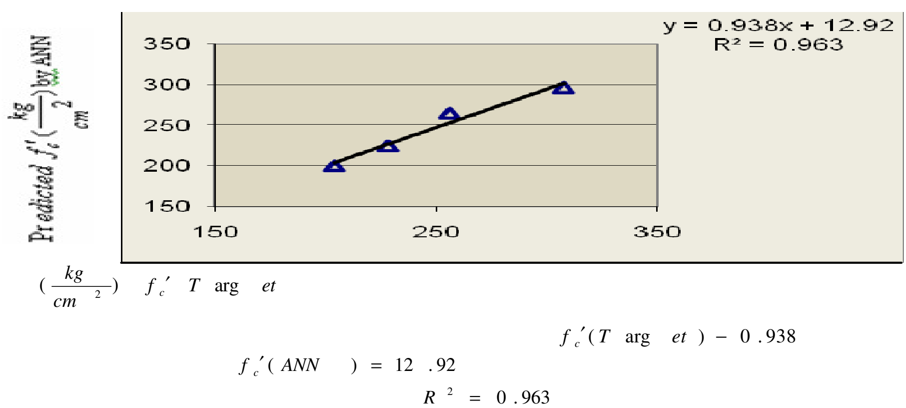

Figure 7. ANN response for prediction of compressive.

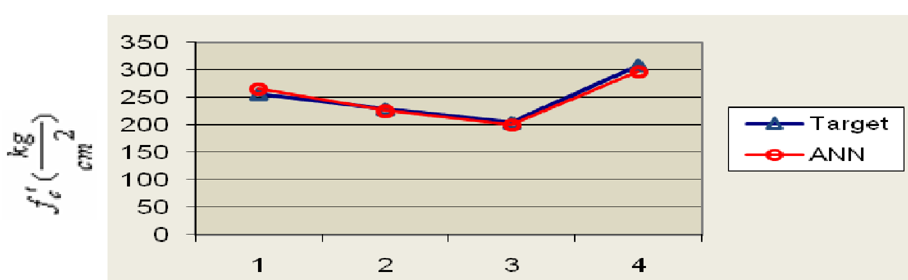

Figure 8. Evaluation of target and predicted compressive strength by ANN.

lightweight concrete.

Conclusion

In the current study, the experimental results of 36 samples were applied to generate an artificial neural network to predict the compressive strength of lightweight concrete. The lightweight concrete is made of different percentages of scoria instead of sand. The outcome of the created ANN was compared with the results of the experimental work. The selected network and its parameters were:

1. The water-cement ratio, cement, and scoria percentage were the input, and the compressive strength of lightweight concrete was the output of the network.
2. The architecture of the selected network was 3-10-1.
3. A total of 27 data were used for training and 5 and 4 data were used for verifying and testing, respectively.
4. The ultimate network to predict the compressive strength was feed-forward back propagation in which the training and transmission functions were TRAINBR and LOGSIG, respectively.
5. This research used three different data arrangements, as shown in Figures 2 to 4. The best outcome data presentation was Figure 4, which was used for network N8 in Table 4.
6. The output results of the created network N8 are close to the results of the experimental effort.
7. The selected ANN can be used to predict the compressive strength with minimum error, below 1%, and a maximum correlation coefficient close to 1.

Using different type of neural network such as generalized regression, radial basis, self-organizing, and probabilistic is recommended by authors.

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