Research Article
Application of Artificial Neural Network in Predicting Compressive Strength of Vege Block

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Abstract: Vege block is a building or construction block manufactured from the mixture of sand aggregates and waste cooking oil as a sustainable binder. This study explores the use of Artificial Neural Network (ANN) in the prediction of the compressive strength. Nine ANN models were developed with different hidden neurons ranges from 7-15 and it performances were tested after properly trained using the Root Mean Square Error (RMSE) and coefficient of determination(R-square) and correlation coefficient (r). The result shows that model with 8 hidden neurons show a better performance.

Keywords: Artificial neural network, compressive strength, linear regression, waste cooking oil

INTRODUCTION

The reliability of any model to correctly predict the concrete behavior depends on how good the model is. In this study, two different techniques were used in developing reliable models for the prediction of Vege blocks; they are Regression and Artificial Neural Network.

Artificial Neural Networks (ANN) are universal models that can be used by any linear or nonlinear function. They are prevailing tool for modeling, as a result of the flexibility of function approximation, especially when the underlying data relationship is unknown. ANN networks are powerful methods in tasks involving classification models, as well as assessment and prediction of continuous variables (Lande and Gadewar, 2012).

Qasrawi (2000) reported that ANNs network is a viable tool for prediction of compressive strength of concrete. Tapkin et al. (2006) developed ANN for the prediction of concrete compressive strength using ultrasonic pulse velocity values and some other factors. The neural network toolbox of MATLAB has been utilized in order to estimate the compressive strength of concrete specimens. Erdal (2009) explored the use of regression equations and an ANN in predicting compressive strength of vacuum processed concrete, he reported that that ANN is more effective in the prediction of the compressive strength.

Deshpande et al. (2014) explored the use of ANN, Model tree (MT) and Non-linear regression (NLR) models to predict 28 days compressive strength of recycle aggregates concrete (RAC), they reported that the compressive strength was predicted better by ANN than MT and NLR, ANN has the best performance prediction. Kewalramani and Gupta (2006) reports the use of multiple regression analysis and ANN for prediction of compressive strength of concrete based on weight and UPV for two different concrete mixtures, they concluded that ANN is more effective in the prediction of the compressive strength.

Deshpande et al. (2014) explored the use of ANN, Model tree (MT) and Non-Linear Regression (NLR) models to predict 28 days compressive strength of Recycle Aggregates Concrete (RAC), they reported that the compressive strength was predicted better by ANN than MT and NLR. Duan et al. (2013) reported that ANN has a fairly high accuracy on predicting the strength of Recycle Aggregate Concrete (RAC) and that the performance of ANN model may be improved with more parameters considered. The objective of this study is to develop ANN model for the prediction of compressive strength of Vege block.

MATERIALS AND METHODOLOGY

Block units of 210×110×65 mm were prepared manually in the laboratory, for each sample, weighed quantity of two type sand (river and crushed) was mixed together at ratio 1:1 and cylindrical samples were also prepared using mould sizes of 100 mm×50 mm and were compacted to ensure sufficient degree of compaction. The liquid binder used in the production of all blocks was 10%. After thorough manual mixing, the
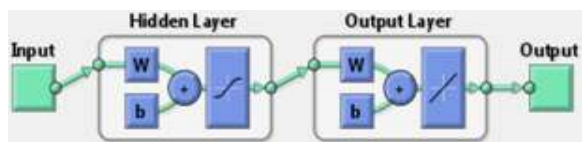
Fig. 1: ANN network

freshly prepared mixes were placed in moulds and compacted in 3 layers on one face. The compacted specimens were extruded from their moulds and then thermally cured in a conventional oven at 170-200°C for 2.5-15 days.

Regression technique: Regression approach is used to develop relationships between two or more variables (dependent and independent) by fitting linear equation across the measured data while minimizing the square deviation of the measured values. MATLAB Toolbox was used for the regression analysis of the experimental data using a curve fitting.

Predicting compressive strength of vege block using ANN: A model was developed using Artificial Neural Network (ANN) in the prediction of compressive strength of Wastvege block specimens. ANN contains a set of well-arranged elements known as "neurons" that generate output from a series of inputs. Inputs are combined linearly and each input is multiplied by a coefficient known as the "weight" and is then added to

an independent term called "bias". The result of this linear combination is applied to a function that is often non-linear, called the "activation function", by which the neuron's output is calculated (Pezo *et al.*, 2014).

The ANN model is divided into three layers; Input layer, Hidden layer and Output layer as shown in Fig. 1. The input consist curing temperatures and curing ages, the hidden layers varied from n = 7 to 15, whilst the output is the compressive strength. Neural network fitting tools (nftool) were used in the data selection, to create and train network and evaluate its performance using mean square error and regression analysis. The detailed data for various neurons tested is attached in the appendices B.

RESULTS AND DISCUSSION

The experimental data from 73 samples with compressive strength in the ranges of 4-37 MPa with curing temperatures of 170-200°C and curing age of 4-10 days were collected and used to develop predictive models using MATLAB. The model will be able to predict the compressive strength of the sample within the selected temperatures and ages. The compressive strength values used are average of at least 4 samples from each curing temperature and ages. Table 1 shows the data for the experimental sample with their respective curing ages and temperatures and the

Table 1: Compressive strength, curing age and temperature of experimental data

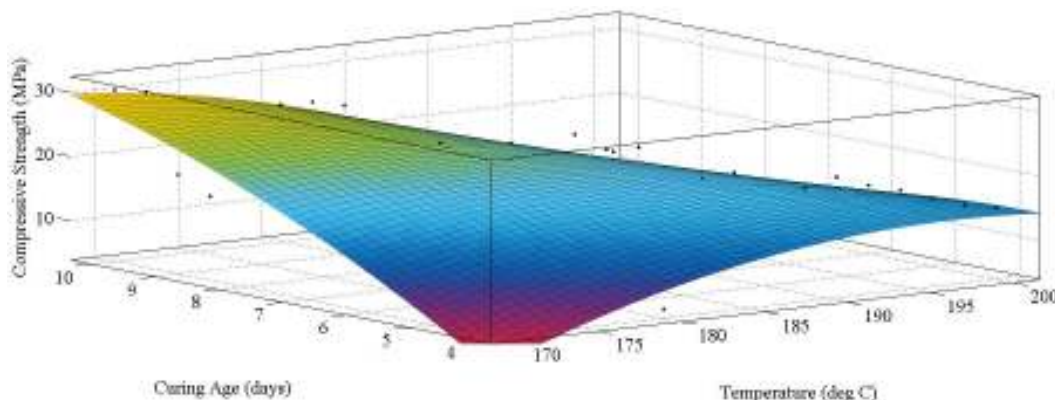| °C	Compressive strength (MPa)	°C	Compressive strength (MPa)	°C	Compressive strength (MPa)	°C	Compressive strength (MPa)
170	6.54	180	5.06	190	15.10	200	14.80
170	7.57	180	8.82	190	16.65	200	14.19
170	7.92	180	11.32	190	17.28	200	14.27
170	13.52	180	14.70	190	20.34	200	14.57
170	13.13	180	18.95	190	18.44	200	14.33
170	14.61	180	20.69	190	16.97	200	14.60
170	22.52	180	19.58	190	21.31	200	11.89
170	22.18	180	24.06	190	19.95	200	9.16
170	22.89	180	23.05	190	21.31	200	8.36
170	16.79	180	19.44	190	14.93	200	6.25
170	19.17	180	26.92	190	17.97	200	5.84
170	31.02	180	26.46	190	15.34	200	5.74
170	30.36	180	25.04	190	15.21	200	11.65

Fig. 2: Relationship between compressive strength, curing age and temperature

resultant compressive strength. The relationship is shown in Fig. 2, showing the best fit results with 95% confidence bound, for which values of Root Mean Square Error (RMSE) and coefficient of determination (R-squared) values are 2.889 and 0.8126 respectively. Using the curve fitting toolbox of MATLAB a regression analysis equation is generated, using temperature and age as the independent variables. The generated equation is shown in Eq. (1):

$$\text{Compressive strength} = A \times x^2 + B \times x \times y + C \times y^2 + D \times x + E \times y + F1$$

where,
A = -0.281
B = -0.1917
C = -0.01943
D = 40.75
E = 8.331
F = -879.6

x is the curing age in days and y is the corresponding curing temperature at that level; A, B, C, D, E, F are the constants.

Table 2: Compressive strength, curing age and temperature of model data

Day	170°C	180°C	190°C	200°C
4	3.291	10.928	14.679	14.544
4.5	6.17725	12.85575	15.64825	14.55475
5	8.923	14.643	16.477	14.425
5.5	11.52825	16.28975	17.16525	14.15475
6	13.993	17.796	17.713	13.744
6.5	16.31725	19.16175	18.12025	13.19275
7	18.501	20.387	18.387	12.501
7.5	20.54425	21.47175	18.51325	11.66875
8	22.447	22.416	18.499	10.696
8.5	24.20925	23.21975	18.34425	9.58275
9	25.831	23.883	18.049	8.329
9.5	27.31225	24.40575	17.61325	6.93475
10	28.653	24.788	17.037	5.4

Table 3: Performance of the regression model for compressive strength

Temperature (°)	RMSE	R²	R
170	1.750419	0.815279	0.902928
180	1.410832	0.915215	0.956669
190	1.004174	0.237962	0.487814
200	1.181875	0.563794	0.750862

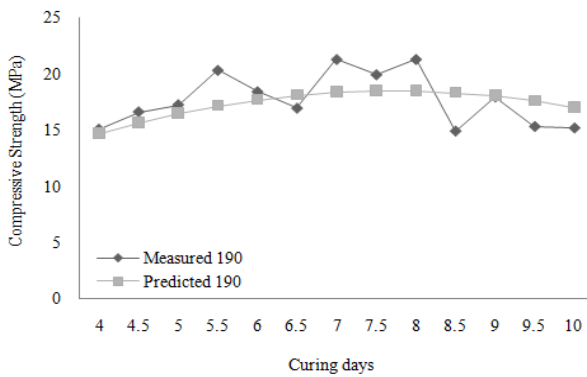Table 2 shows the compressive strength values from the predictive model.

The predictive equation was tested and its performance was determined, as shown in Table 3, using Root Mean Squared Error (RMSE), coefficient
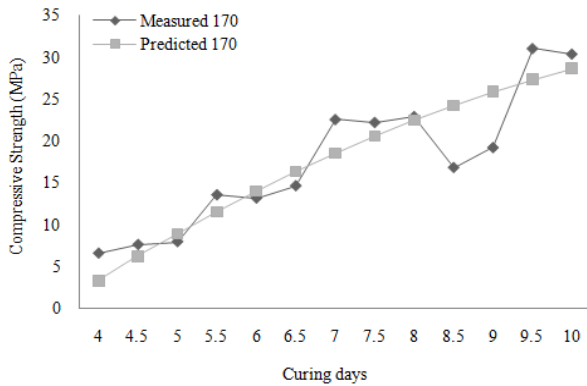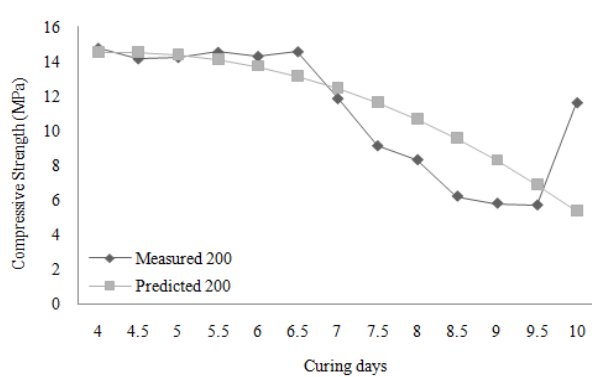

(a)
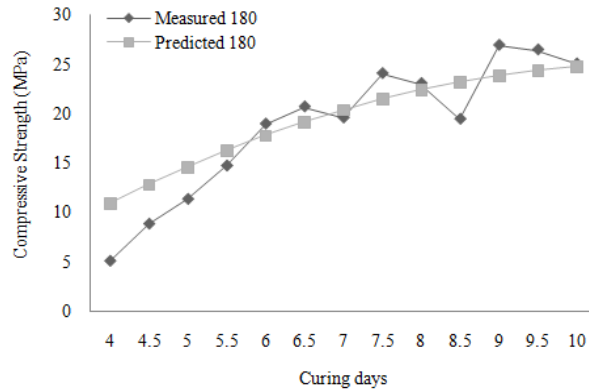
(b)

(c)

(d)

Fig. 3: Compressive strength of measured experimental data compared with the Model data, at different curing temperature; (a): At 170°C; (b): At 180°C; (c): At 190°C; (d): At 200°C

of determination (R²) and correlation coefficient (r). Considering the values of RMSE, R² and r for all the temperatures, it can be deduced that the predicted values at 170°C and 180°C are more reliable than at 190°C and 200°C. However the variance recorded may be as a result of the inconsistency in the production of the samples which is shown in the varying values of the porosity, due to compaction. Figure 3 shows the relationship between the actual experimental values and the predicted values, it can be observed that at 170°C and 180°C curing temperatures there is a good relationship between the measured values and the predicted values and the R-square show a good reliability of the predictive equation. However, at 190 and 200°C curing temperatures, the value of R-square shows that the predictive equation is less reliable, this

implies that the predictive model may not be able to predict accurately for samples cured at 190°C and 200°C.

The experimental data were used as input data in the development of the model. The data was divided into three sets called training (70%), testing (15%) and validation (15%). The training set is the largest set which is used by neural network to learn to identify the compressive strength of the data. The network was trained with Levenberg-Marquardt back propagation algorithm (trainlm). The Levenberg-Marquardt algorithm was adopted because it has proved to be the fastest for network convergence and particularly adapted for networks of moderate size (Pezo *et al.*, 2014). The testing set is used to evaluate the ability of trained network; the ANN model was retrained until the
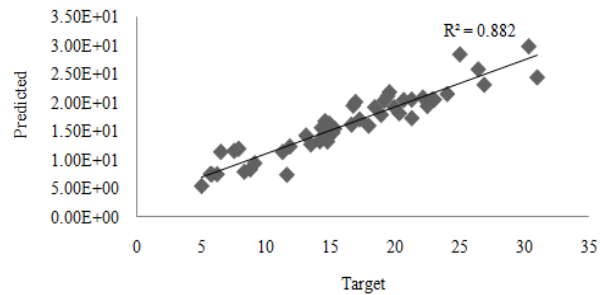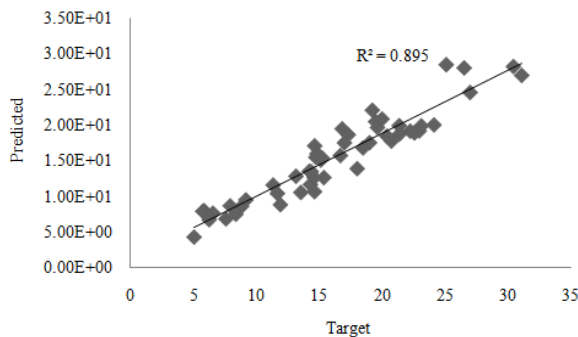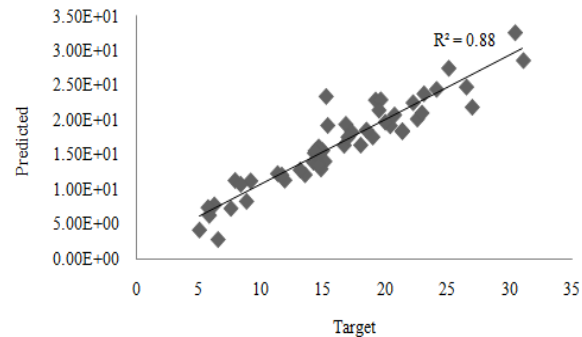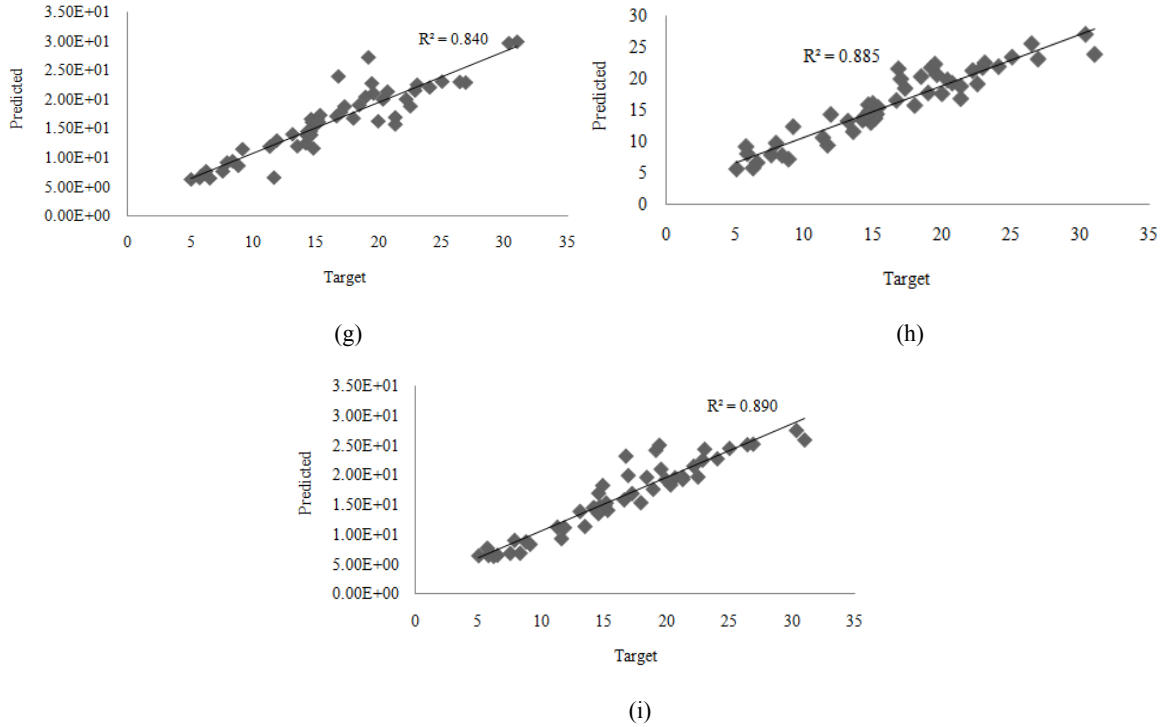
(a)

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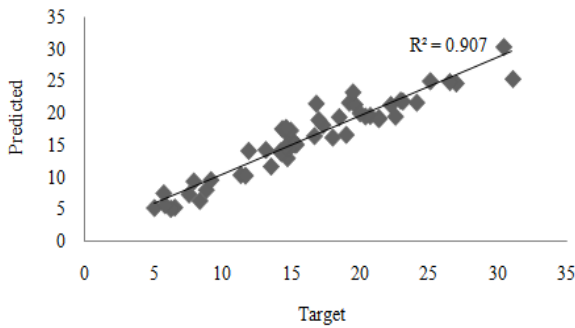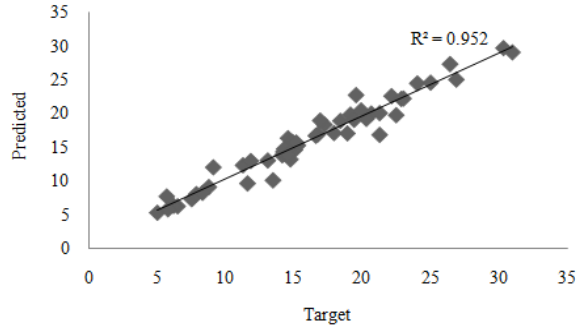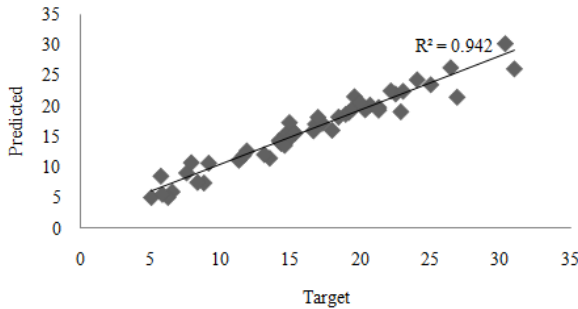
Fig. 4: Relationship between the predicted and the actual values of Compressive strength at; (a): 7; (b): 8; (c): 9; (d): 10; (e): 11; (f): 12; (g): 13; (h): 14; (i): 15 hidden neuron
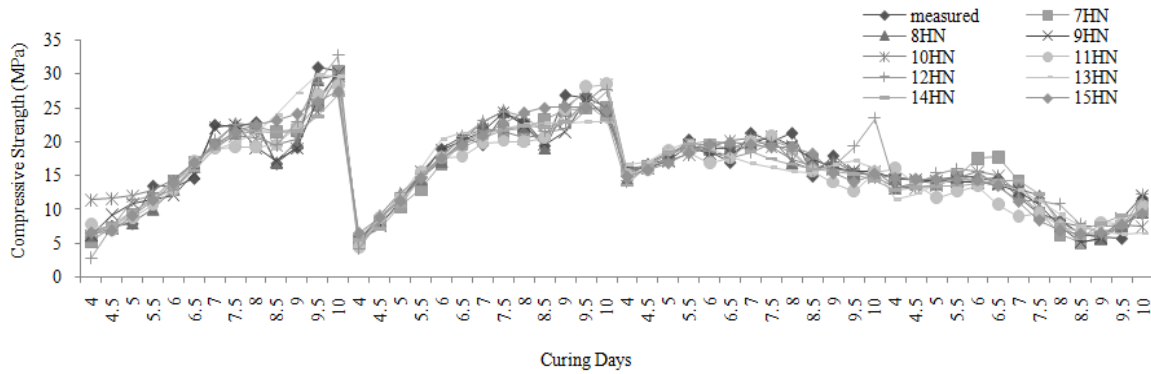

Fig. 5: Error! No text of specified style in document: Actual compressive strength compared with the predicted values by the ANN models with different Hidden Neurons (HN)

Table 4: Performance values of RMSE, r and R-square of compressive strength

No of Hidden Neuron	RMSE	Correlation coefficient (r)	Coefficient of determination (R^2)
7	1.910189	0.952660	0.907561
8	1.382140	0.975848	0.952280
9	1.571757	0.970764	0.942383
10	2.201776	0.939126	0.881958
11	2.145800	0.946448	0.895764
12	2.220815	0.938082	0.879997
13	2.522104	0.916586	0.840130
14	2.214629	0.941228	0.885910
15	2.076645	0.943867	0.890884

variation of error is reasonably small. A final check on the performance of trained network is carried out using the validation dataset. The results are compared by means of root mean squared error and coefficient of determination. The variation in the predicted compressive strength values compared to the actual values was also used to make the final decision on the adoption of the model. Figure 4 shows the relationship between the actual values measured and the predicted values at the different number of hidden neurons.

Nine ANN models were developed in this study with hidden neuron ranges from 7-15 in numbers. The models were tested for their performance using RMSE, R-square and r. Table 4 shows the values of RMSE, R-square and r, for all the models. The performance was compared and relatively, the ANN with 8 hidden neurons shows a better performance than other ANN.

Figure 5 shows the actual compressive strength compared with the predicted values by the ANN models with different hidden neurons. It can be observed that all the models show a similar trend in predicting the measured compressive strength. An ANN model with 8 hidden neurons proved to be the best that is capable of predicting the compressive strength values that are very close to the measured values.

CONCLUSION

This study presents findings from the use of linear regression and ANN in the prediction of compressive strength of Vege blocks and the following conclusions were drawn:

- Linear regression can be used to develop models in the prediction of compressive strength of vege block, however, its accuracy may not be reliable at some curing temperatures.
- Artificial Neural Network (ANN) can reliably be used in the development of predicting models for vege blocks with higher accuracy at any curing temperature.
- Artificial Neural Network (ANN) models are more reliable in the prediction of compressive strength of vege block compared to linear regression.
- An ANN model with 8-hidden neurons provides the best prediction with higher performance values.

ACKNOWLEDGMENT

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