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Forecasting the Shear Strength of Binary Blended Concrete Containing Hydrated Lime Using Artificial Intelligence

C.T.G. Awodiji[1*], D.O. Onwuka[2], S. Sule[1]

1. Senior Lecturer, Department of Civil and Environmental Engineering, University of Port-Harcourt, Nigeria
2. Professor, Department of Civil Engineering, Federal University of Technology, Owerri, Nigeria

Corresponding author: *chimbaegbu@yahoo.com*

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ABSTRACT

In this exploratory study, the shear strength of blended cement concrete made using the hydrated lime (HL) as an admixture was studied. 120 shear strength values were experimentally obtained for several mix ratios at 7, 14, 21, and 28 days. This concrete was put together from water, portland cement (PC), HL, river sand (RS), and granite chippings (GC). 96 of the results were utilized to formulate a Levenberg-Marquardt backpropagation artificial neural network (ANN) for determining the shear strength of the concrete. The effectiveness of the forecast was tested using the unused 24 results. The model had 6 input variables namely; proportions of PC, HL, RS, GC, water, and curing age. While the output variable was the shear strength value. 1 hidden layer of 20 neurons was adopted. Uppermost 28 days shear strength value of 1.257N/mm2 was observed at 13.75% replacement of PC with HL for 0.58 water-cement ratio. The performance of the ANN proved that the model was acceptably executed. Root mean square errors (RMSE) obtained between network forecast and experimental values ranged from 0.0278 to 0.06536. These are close to 0. In addition, the factor of agreement (IA) determined were within the limits of 0.0475 and 0.1747. These are between the stipulated range of 0 to 1 for consistency between variables. The highest average percentage error recorded between model predictions and experimental values was 2.5066%. Lastly, the ANN created can be convincingly used to predict the shear strength of hydrated lime cement concrete and eliminate the need for try-out laboratory research.

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1. Introduction

In order to improve the properties of ordinary portland cement for various applications especially concerning environmentally friendliness, blended cement is adopted [1]. This is cement made by mixing ordinary portland cement (OPC) with mineral admixtures such as silica, slag, and fly ash. Some advantages of using this type of cement are that it provides a finer texture than OPC in concrete. It is less permeable than OPC thereby assist in improving the life span of concrete or mortar. The inclusion of admixtures to OPC drops the risk associated with thermal stresses that develop within concrete. These stressed usually result in the formation of cracks and consequently, reduce the strength of concrete.

Blended types of cement boost the absorptivity and workability of concrete, manage pollution that is connected with the production of cement, and are energy-efficient [2]. In this study, hydrated lime as an admixture is incorporated into OPC in making the concrete of interest. This lime is seen as a white powder that is made by heating limestone to get quicklime and then slaking with water. It has been shown that its addition in OPC aids in producing concrete that is long-lasting and fuel-efficient [3].

Concrete shear force is interpreted by [4][4], as an inner force that is digressive to the plane of action. This force makes two adjoining parts of the concrete flow proportionately to each other in a route parallel to their plane of contact. Shear strength of concrete can also be said to be the opposition a concrete produce against the yield or structural breakdown that happens when concrete malfunctions as a result of shear stresses [5]. It is the strength of concrete subjected to shearing load and encountered just before it breaks.

Concrete is weak in resisting shear stresses due to its fragile nature. Shear failure in concrete is one of the most crucial and unwanted manners of failure. It can be very dangerous, unpredictable, and often explosive [6]. Its occurrence in a structure must be avoided as much as possible. Therefore, a knowledge of the shear strength property of any type of concrete (including blended concrete) used for structural purposes is of utmost importance.

Concrete shear strength is a key attribute in research and structural design. It plays a critical part in the appraisal of failure models used in estimating the mechanics of concrete and structural analysis [7]. In structural engineering, the shear strength of an element is cardinal for designing the sizes and substance to be used for its creation/erection. But, the extent customary approach for the assessment of this property is not accessible. Accordingly, the prediction of the shear strength of lime cement concrete is conducted using the ANN model in this study.

Cement production has a massive carbon footprint on the earth. It is the third largest emitter of CO_2 in the world. In order to reach the Paris Agreement on climate change, annual emissions from cement production must fall by at least 16% by 2030 [8]. The effect of increasing CO_2 in the atmosphere has caused the world to be hotter than it used to be. This increase in atmospheric temperature has resulted to global warming leading to climate change. More glacier in the North Pole is melting leading to sea level rise. The natural habitats of man and animals are distorted and very extreme weather conditions are seen in different parts of the earth [8].

90% of the CO_2 emission from the cement industry comes from the production of clinker. This means that altering the composition of materials for making clinker with admixtures or agricultural waste, will go a long way in reducing the amount of CO_2 generation since the energy needed for making clinker will grossly reduce. This will cause a decline in the negative effects of global warming and make the earth more conducive for humans to live in. Therefore, the shear strength of concrete made using HL a partial substitute for PC, is investigated in this work.

Due to the non-linear characteristic of concrete, the use of empirical formula in estimating the shear strength of concrete is usually associated with errors. However, the ANN uses its powerful technique known as “Pattern recognition” to teach itself the patterns within any given data. This frees the analyst from carrying out tedious computations unlike in mathematical modeling. Therefore, accurate forecasting can still be made even when input data is incomplete or non-linear [9]. In the event of a very drastic change, the ANN can comfortably adapt to the constantly changing information although it may take some time. This property makes it a very flexible modeling tool.

Artificial neural networks (ANNs) are estimation tools that can be applied in the form of a computer piece or replicated on standard computers [10]. They comprise many easy processors that are extremely interrelated. Each processor in the network keeps only one piece of active fact i.e., it current level of activation, and is capable of only a few simple calculations (adding inputs, computing a new activation level, or comparing inputs to a portal value). The pattern of incitement at the input processing units represents the issue being introduced to the network and the pattern of activation at the output units are regarded as the result of the estimations carried out by the neural network. A neural network executes calculations by spreading changes in activation (i.e. level of simulation) between the processors. This computation by the network is greatly influenced by the strength and topology of the relationship between the processors.

According to [11], ANNs have a lot of advantages over other types of modeling techniques. They have the ability to learn and model nonlinear and complex relationships. These kinds of relationships are synonymous with real-life situations. They can infer relationships on unseen data after learning from the initial inputs and their relationships. ANNs are non-parametric models and do not require a higher background in statistics. So, they are easy to learn and understand when compared to statistical or mathematical models. They are adequate in solving different types of forecasting and classification problems.

Unlike the ANN, the Genetic programming (GP) is used for classification and function finding. There are no anticipated relationship connecting dependent and independent variables. But, proper parameters, objective function and its coefficient could be obtained for any given data set. In GP, output from a training set is known as a solution. It is usually in the form of a mathematical expression and its never constant [12]. The model tree algorithm is another soft computing technique that is used to determine the values of numerical response variable. It offers two main advantages which are; provision and insight of mathematical equations, and very convenient to develop and implement [13].

Some researchers in the field of concrete technology have come up with various ways of evaluating the shear strength of concrete using artificial intelligence. [14] studied the adaptive neuro-fuzzy interference system (ANIFS) and ANN to predict the shear strength of the reinforced concrete beam. They observed that the ANN model with multilayer perception and backpropagation algorithm provides a better prediction for shear strength. They also stated that the ANN and ANIFS gave more accurate results than the Iranian and ACI models. [15], used the ANN to predict the compressive strength of Metakaolin mortar. Ratio of metakaolin replacement, water-binder ratio, ratio of superplasticizer, ratio of sand to binder and age of sample were the predictive parameters used. Their results revealed that the ANN had good accuracy since the r values of 0.9754, 0.9830, and 0.9865 were obtained for the testing, validating, and training data accordingly. They further reported that the sand to binder ratio contributes the most, to the development of the compressive strength of the mortar.

[16] developed a better dynamic modulus regression model for asphalt mixtures in Costa Rica using the ANN. They worked on ten different kinds of asphalt mixtures and observed a 69% improvement in the R^2 values when compared to those of the Witezak model. [17] determined the unconfined compressive strength (UCS) of kaolin clay mixed with pond ash (PA) and rice husk ash (RHA) using the ANN. The model inputs were; clay content, cement content, pond ash, RHA and curing age. They reported that the best topology for estimating the UCS of the Kaolin clay mixture was 5-10-1 i.e. 5 inputs parameters, 10 neurons in the hidden layer and 1 output variable. Optimal performance was obtained at the 27^{th} epoch. From the sensitivity analysis carried out, they observed that the RHA content provided about 26% of the UCS while 24% of the UCS was generated by the pod ash content. All the other parameters provided about 10%. The ANN model performed better than the multilinear regression models applied. R^2 and R-values for the ANN model were 0.97 and 0.98 accordingly. While those for the regression models were 0.88 and 0.94 for the testing phase.

In this study, a Levenberg-Marquardt backpropagation artificial neural network was developed and used in predicting the shear strength of lime cement concrete. Some advantages of using the Levernberg-Maquardt algorithm are that it is less sensitive to local convergence. Therefore, it provides a better learning-training approach and has a shorter training time as a result of accelerated training speed.

2. Research significance

It is important to note that the deficiency in the shear design of concrete structures is interestingly more dangerous than that of flexural design. This is so since shear failure can occur with no prior warning and no possibility for redistribution of internal forces. Therefore, results obtained from this study will enable concrete designers to adequately quantify the type of shear reinforcements that will be required to link together the two sides of concrete members made from HL-PC concrete, as well as determine how much of the reinforcement is needed to prevent premature shear failure [18]. Furthermore, the developed ANN will help to make the process of the mix design of this type of concrete less laborious and time consuming.

3. Materials and methods

3.1. Materials

Water, Portland cement (PC), hydrated lime, (HL) rivers sand (RS) and granite chippings (GC) were the materials used for the experimental tests. The water was potable in nature and acquired from the Federal Polytechnic, Nekede, Imo State. HL was procured from Oyo State, Nigeria. Dangote brand of Portland cement 42.5R was bought from the local market in Owerri West, Nigeria. River sand was mined from Otamiri River and the chippings were obtained from Okigwe, Nigeria.

3.2. Methods

3.2.1. Experimental program

The experimental work was performed in order to obtain from the laboratory, values of shear strength of lime cement concrete that was used to formulate an ANN model for predicting the shear strength of the concrete. The shear strength was estimated using the formula given by [19] as shown in Equation 1. This formula states that the shear strength of concrete is the measure of the shear load divided by the cross-sectional area of the specimen.

$$\tau = F/A \tag{1}$$

Where, τ is the shear strength in N/mm^2, F is the shear load in Newton and A is the cross-sectional area of the specimen in mm^2.

The shear load was obtained by recording the values of the forces that caused the concrete beams of sizes 150x150x600mm to experience shear failure. This procedure was conducted according to [20]. Three specimens were tested for each mix proportion after being cured for 7, 14, 21, and 28 days in water tanks at ambient temperature respectively. The values of the shear loads obtained were divided by the cross-sectional area of the specimen in order to get the shear strengths of the concrete samples. A total of 120 shear strength values were generated from the 30 mix ratios and 4 curing ages reviewed.

The mix proportions adopted are presented in Table 1. While, the shear strength values obtained are seen in Table 2.

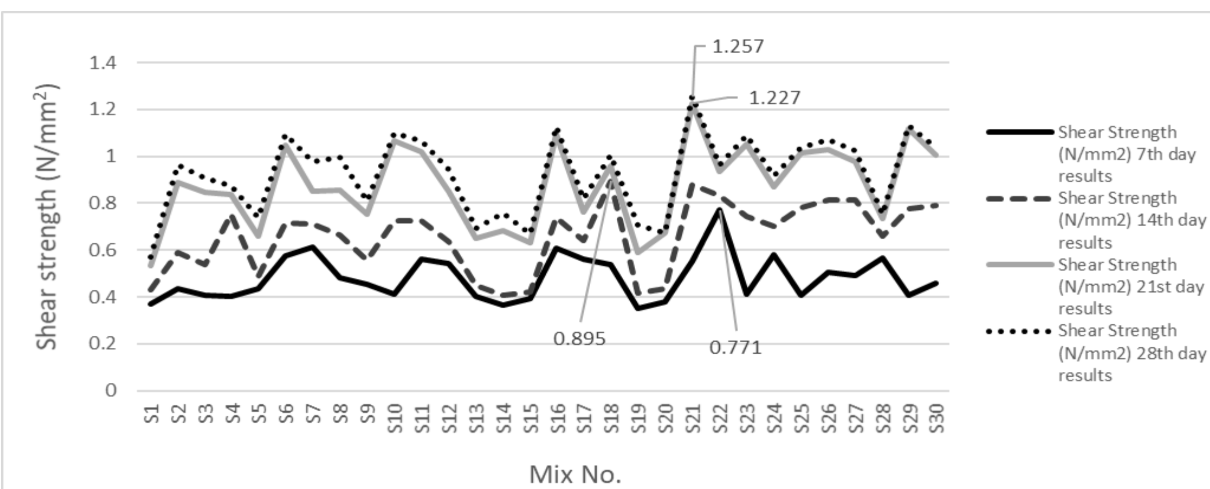

Fig. 1. Relationship between the shear strength and Mix No. for the various curing age.

Table 1
Proportion of mix for concrete beam samples.

S/NO	Mix No.	Mix ratio					The proportional of mix for one beam sample (Kg)				
		Lime	PC	W/C	RS	GC	Lime	PC	WATER	RS	GC
1	S1	0.100	0.900	0.600	3.000	6.000	0.380	3.380	2.250	11.250	22.500
2	S2	0.150	0.850	0.570	2.000	4.000	0.800	4.550	3.060	10.720	21.440
3	S3	0.200	0.800	0.550	2.500	5.000	0.880	3.530	2.430	11.030	22.060
4	S4	0.300	0.700	0.530	1.500	3.000	2.050	4.770	3.230	10.230	20.460
5	S5	0.400	0.600	0.500	1.000	2.000	3.750	5.630	4.690	9.380	10.750
6	S6	0.125	0.875	0.585	2.500	5.000	0.550	3.860	2.580	11.030	22.060
7	S7	0.150	0.850	0.575	2.750	5.500	0.610	3.450	2.330	11.150	22.300
8	S8	0.200	0.800	0.565	2.250	4.500	0.970	3.870	2.730	10.890	21.770
9	S9	0.250	0.750	0.550	2.000	4.000	1.340	4.020	2.950	10.710	21.430
10	S10	0.175	0.825	0.560	2.250	4.500	0.850	3.990	2.710	10.890	21.770
11	S11	0.225	0.775	0.550	1.750	3.500	1.360	4.690	3.330	10.580	21.170
12	S12	0.275	0.725	0.535	1.500	3.000	1.880	4.940	3.650	10.230	20.450
13	S13	0.250	0.750	0.540	2.000	4.000	1.340	4.020	2.890	10.710	21.430
14	S14	0.300	0.700	0.525	1.750	3.500	1.800	4.200	3.150	10.500	21.000
15	S15	0.350	0.650	0.515	1.250	2.500	2.760	5.130	4.070	9.870	19.740
16	S16	0.125	0.875	0.586	2.500	5.000	0.550	3.870	2.600	5.520	22.100
17	S17	0.150	0.850	0.575	2.750	5.550	0.610	3.430	2.320	11.100	22.410
18	S18	0.225	0.775	0.550	1.750	3.550	1.340	4.620	3.280	10.430	21.160
19	S19	0.300	0.700	0.525	1.750	3.550	1.790	4.170	3.130	10.430	21.160
20	S20	0.350	0.650	0.517	1.250	2.500	2.760	5.130	4.070	9.870	19.740
21	S21	0.138	0.863	0.580	2.625	5.500	0.580	3.680	2.450	11.060	22.180
22	S22	0.238	0.763	0.550	1.875	3.750	1.350	4.320	3.120	10.620	21.460
23	S23	0.188	0.813	0.563	2.250	4.500	0.620	2.710	2.720	7.510	15.020
24	S24	0.268	0.732	0.543	1.825	3.650	1.550	4.240	3.140	10.570	21.140
25	S25	0.201	0.799	0.560	2.325	4.650	1.260	3.440	2.550	8.580	17.160
26	S26	0.183	0.817	0.567	2.165	4.330	1.050	4.690	3.250	12.420	24.840
27	S27	0.210	0.790	0.557	2.150	4.300	1.060	4.530	2.800	10.820	21.610
28	S28	0.225	0.775	0.553	2.100	4.200	1.160	4.530	2.840	10.790	21.760
29	S29	0.188	0.813	0.562	2.225	4.450	0.920	3.970	2.750	10.870	21.740
30	S30	0.210	0.790	0.560	2.100	4.200	1.080	4.040	2.880	10.790	21.560

Table 2
Shear strength of HL-PC concrete for different curing ages.

S/No	Mix No.	Shear Strength (N/mm^2)			
		7th day results	**14th day results**	**21st day results**	**28th day results**
1	S1	0.369	0.430	0.535	0.569
2	S2	0.437	0.587	0.889	0.965
3	S3	0.408	0.540	0.848	0.906
4	S4	0.400	0.751	0.837	0.873
5	S5	0.434	0.488	0.657	0.741
6	S6	0.575	0.715	1.049	1.093
7	S7	0.613	0.710	0.852	0.978
8	S8	0.483	0.663	0.855	0.996
9	S9	0.455	0.555	0.754	0.807
10	S10	0.412	0.723	1.068	1.098
11	S11	0.563	0.723	1.021	1.065
12	S12	0.543	0.635	0.850	0.946
13	S13	0.404	0.450	0.650	0.693
14	S14	0.367	0.408	0.684	0.759
15	S15	0.394	0.420	0.629	0.668
16	S16	0.608	0.741	1.095	1.128
17	S17	0.562	0.640	0.760	0.818
18	S18	0.536	0.895	0.959	1.006
19	S19	0.349	0.416	0.590	0.704
20	S20	0.377	0.435	0.674	0.674
21	S21	0.554	0.877	1.227	1.257
22	S22	0.771	0.833	0.933	0.963
23	S23	0.410	0.744	1.050	1.090
24	S24	0.579	0.703	0.870	0.917
25	S25	0.409	0.779	1.015	1.037
26	S26	0.507	0.812	1.030	1.070
27	S27	0.490	0.814	0.975	1.026
28	S28	0.568	0.657	0.733	0.755
29	S29	0.409	0.775	1.115	1.130
30	S30	0.457	0.790	1.005	1.040

3.2.2. Artificial neural network (ANN)

The artificial neural network toolbox found in Matlab R2014a software was used to develop an ANN model for predicting the shear strength of lime cement concrete. Fig 2 presents the flowchart used for creating the network.

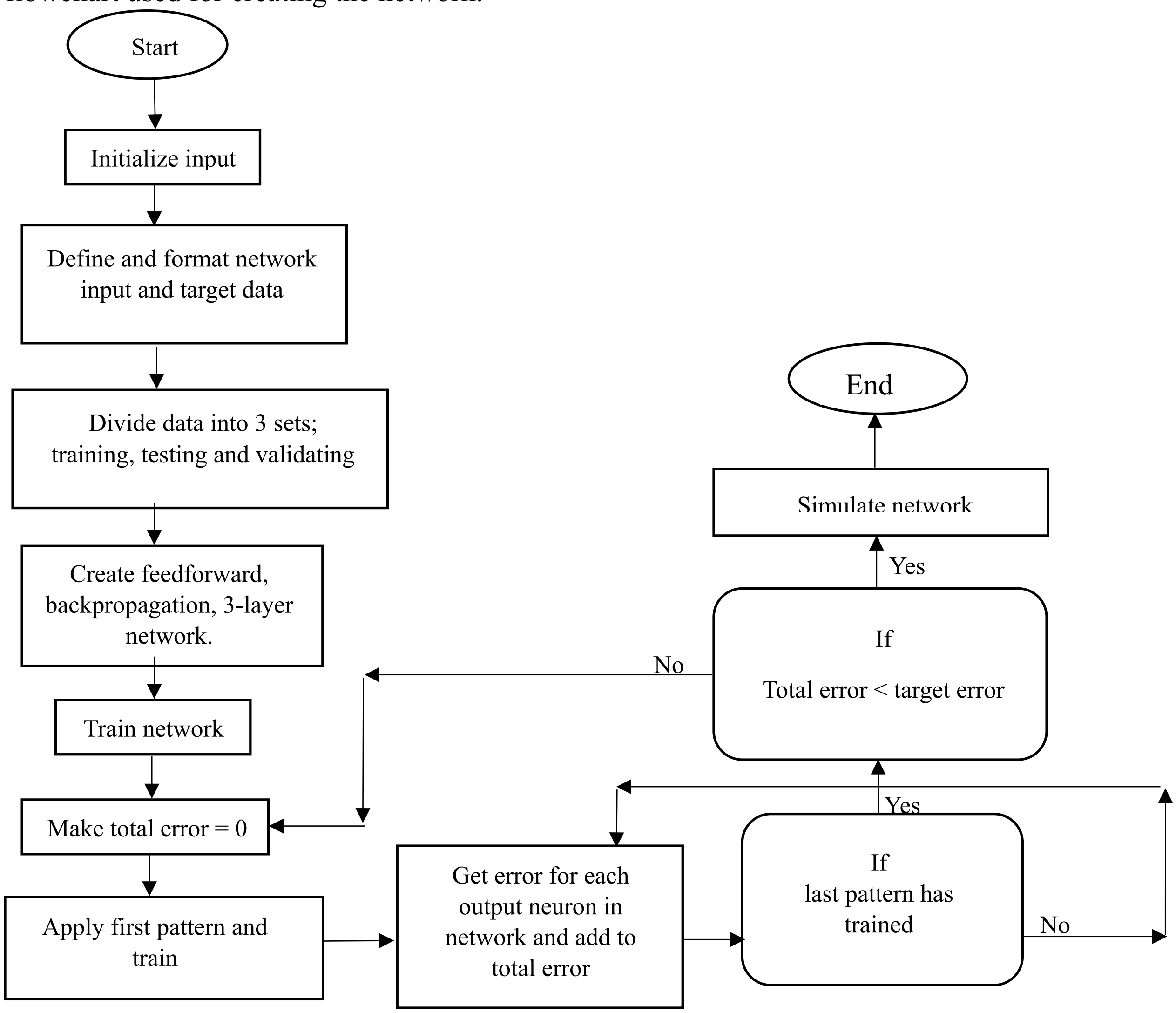

Fig. 2. Flow chart for the development of the back propagation neural network.

3.2.3. Structure of the ANN

The structure of the ANN developed in this study is as follows;

A. Architecture

The developed network is a three-layer feed-forward back propagation neural network. These layers are the input, hidden, and outer layers. The input variables in the input layer are the proportion of PC, hydrated lime, RS, GC, water, and curing age of the composite. Whereas, the output variable in the input layer is the shear strength of the concrete. The hidden layer is made up of 20 information processors known as neurons. They are able to capture nonlinear relationships between variables as well as complex phenomena.

All of the neurons in the different layers are connected. Within these connections are weights and biases that enable the network to learn the pattern between the input and the output variables. The learning process is achieved through an iterative procedure where the weights and biases are adjusted such that the error within the system is reduced greatly [21].

B. The learning algorithm (Teacher)

The Levernberg-Marquadt algorithm was used to teach the ANN the relationship between the input and output variables. It achieves this task by calculating the error correction factor and feeds it back into the network. This error factor then modifies the weights in the network connections in such a way that the next output will be closer to the expected value. The Levernberg-Marquardt algorithm is shown in Equation 2 and its development can be seen in the work of [9].

$$[J^T J + \lambda_{diag}(J^T J)]\ \delta = J^T\ [t - f(\beta)] \tag{2}$$

Where;

J = Jacobian matrix whose kth row equals J; J^T = Transpose of the Jacobian matrix;

f and t = vectors with k^{th} components $f(o_k, \beta)$ and t_k respectively;

λ_{diag} = damping factor for the diagonal elements;

δ = error correction factor.

The mix ratios and their corresponding shear strength values were applied in training the ANN model to understand the connection between the input and output variables. These ratios plus the curing ages represented the input variables. While their corresponding shear strength values were the output variable. A total of 96 data sets were used for this procedure

The last 6 mix proportions and their correlating shear strength values were not used in the learning process. They were left out and later utilized to investigate the performance of the trained network. A total of 24 data sets were employed.

C. Activation function

The activation function also known as the transfer function is used to determine the output of neurons in the ANN [22]. The Tan-sigmoid (tan-sig) function as indicated in Equation 3 was adopted in this study. It has the ability to help the network adapt to the various data presented to it and differentiate between the outputs.

$$F(x) = \tan(x) = 2/(1 + e^{-2x}) - 1 \tag{3}$$

3.2.4. Model performance

In order to further check how well the model was performing, the percentage error, root mean square error (RMSE), and the factor of agreement (IA) were used. Their formulas are expressed in Equation 4 to 5 respectively;

$$\% \text{ Error} = \left[\frac{ti - yi}{ti}\right] * 100\% \tag{4}$$

$$\text{RMSE} = \sqrt{\left[\frac{1}{n}\sum_{i=1}^{n}(ti - yi)^2\right]} \tag{5}$$

$$\text{IA} = \left[\sum_{i=1}^{n}(ti - yi)^2\right] \div \left[\sum_{i=1}^{n}(ti - t)^2 * \sum_{i=1}^{n}(yi - y)^2\right] \tag{6}$$

Where, t_i is the measured values; y_i is the predicted sample values; t is the mean of all measured values; y is the mean of predicted sample values and n is the number of samples.

The input and output data sets not applied during the training session were put to use in determining these measurements.

4. Results

The results of the experimental work, neural network prediction, and the performance of the network are presented here;

4.1. Shear strength of lime-cement concrete

Table 2 shows the experimental results of the shear strength of lime cement concrete as obtained from the laboratory. The highest shear strength value obtained was 1.257N/mm^2. This was derived at a mix ratio of 0.863:0.138:2.625:5.250 (i.e. Portland cement-hydrated lime-river sand-granite chippings mixture) at a water-cement ratio of 0.58 for a curing age of 28 days. Optimum PC replacement with an HL of 13.8% was observed. The lowest shear strength value at 28 days of 0.57N/mm^2 happened at a mix ratio of 0.9:0.1:3:6. Highest values obtained at 7, 14 and 21 days are 0.77N/mm^2, 0.895N/mm^2 and 1.227N/mm^2 respectively. As the curing age rose, the shear strength of the lime-cement concrete increased. This means that the more the concrete is left to cure, the better its resistance against shear forces that may act on it. However, shear force values generated in this study were low.

4.2. Shear strength neural network model

A neural network model to forecast the shear strength of lime cement concrete was achieved in this work. Its performance is discussed in this section. Fig 3, which is the graph of the mean square error (MSE) against the number of epochs, revealed that the best output from the network was obtained after the 8th epoch (iteration) at an MSE value of 0.0046744. This result is close to zero and is therefore sufficient. A total of 14 epochs were conducted.

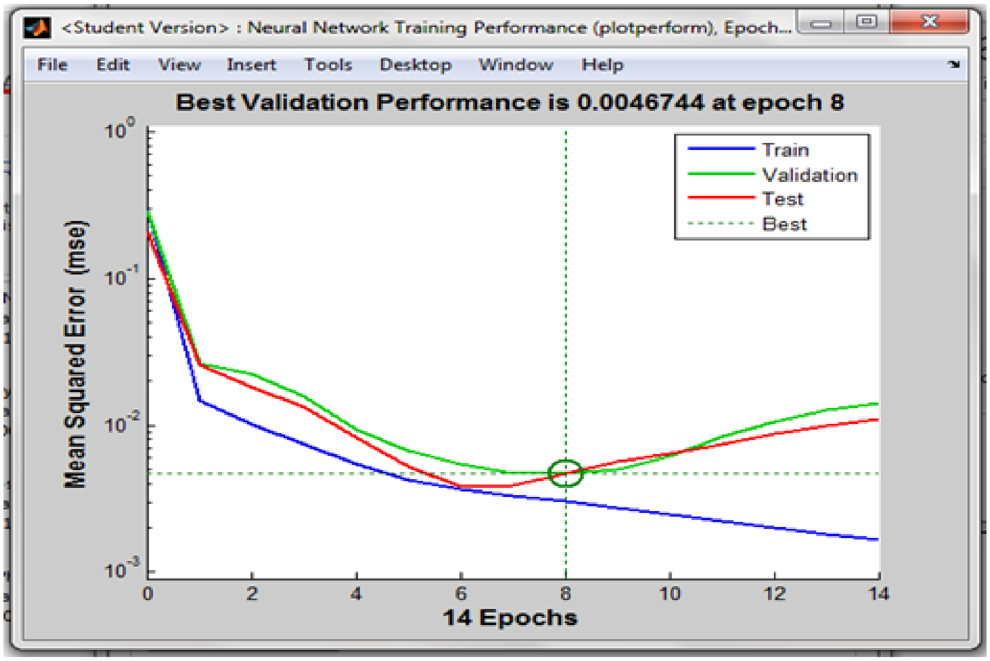

Fig. 3. Relationship between MSE and no. of epoch.

The error gradient as presented in Fig 4 gives an insight into the direction and magnitude of the error calculated while training the neural network. It was used to updates the weights within the network. The adjustment of weights enabled the network to learn the pattern between the input and output data. The gradient recorded was 0.0027272. This value is close to zero. So, it is acceptable. At zero gradient, functions are at their maximum values and cannot be better.

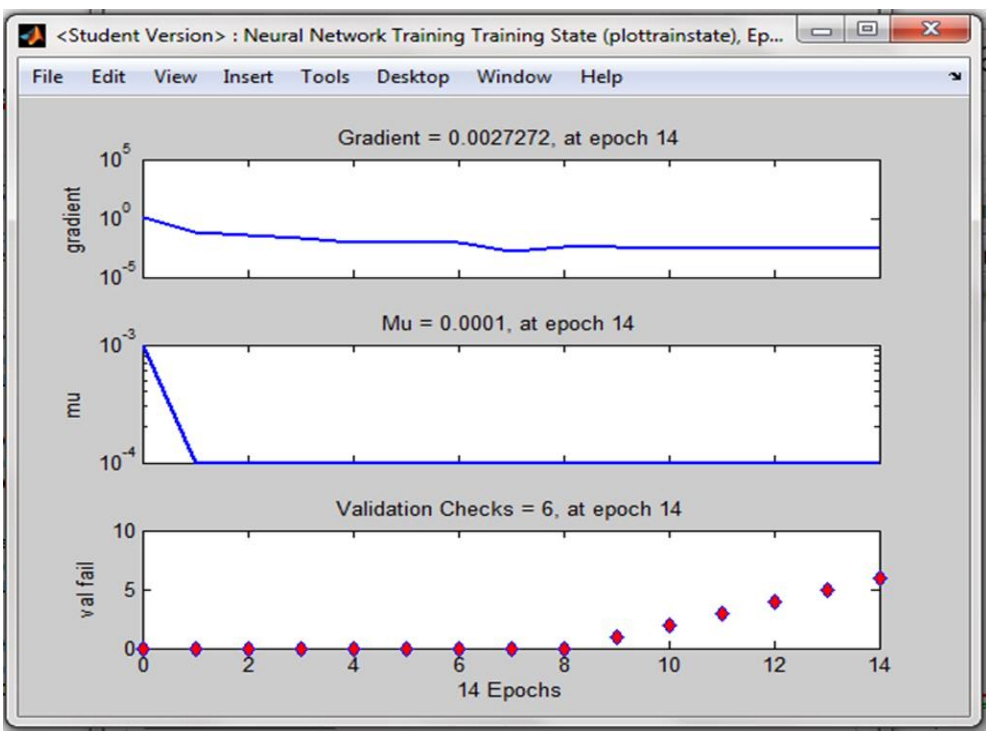

Fig. 4. Graph of the training state of the neural network.

A validation check of six (6) and a Mu value of 0.0001 were adopted. The duty of the validation check is to tell any ANN to stop its training process when the error rates keep increasing for more than 6 iterations. Similarly, the Mu value is used to control the rate at which the updating process of neurons occur during training. If the training stops when maximum Mu is reached, any further training will not better the process of learning. In this study, training stopped when the validation check was up to 6.

The error histogram shown in Fig. 5 gives an illustration of how the predicted values were differing from the target values after the training session. The 20 bins mean that there are 20 vertical bars observed from the graphs. The total error ranged from -0.1395 to 0.1535. Each vertical bar represents the number of samples from the data set which lie in a particular bin.

Considering the midpoint of Fig 5, it can be seen that 8 data sets were used for training. While 1 data set was used for validation. They all had errors that lie in the range of -0.01473 and -0.0007. These values are close to zero. Therefore, the results obtained are acceptable.

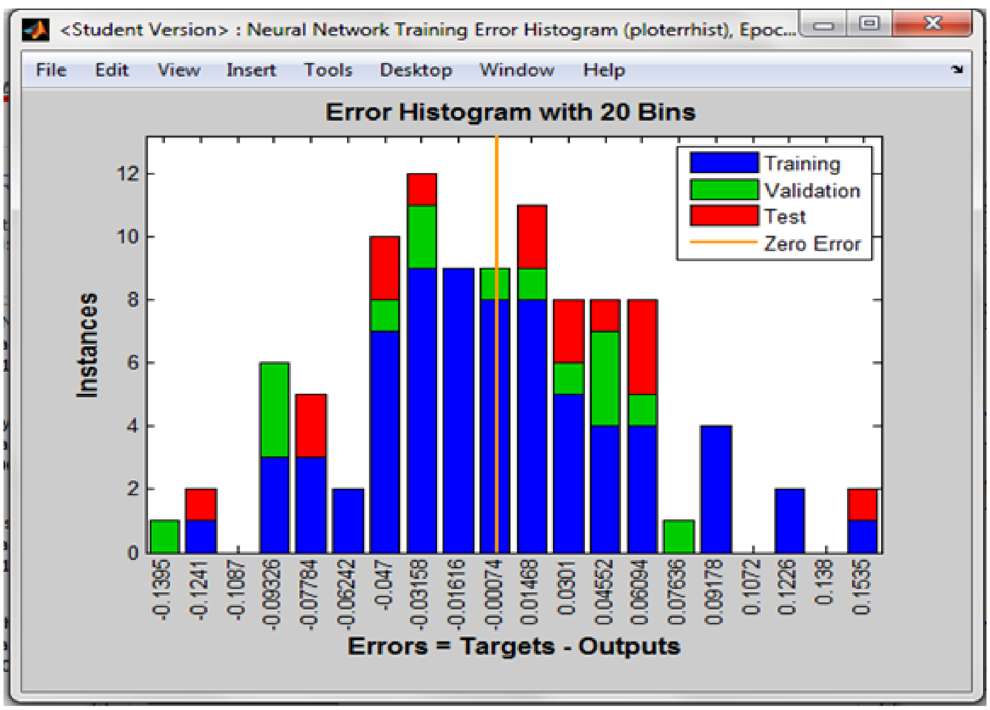

Fig. 5. Error histogram of the data sets.

The regression curve of Fig 6 shows how well the model fits the data set. If the R-value is close to 1, it means that the model predictions are very close to the actual dataset. But, if the R-value is 0, then the predictions are bad. All the R-values obtained during the development of the network are greater than 0.95. This means that the model fits adequately with the data set.

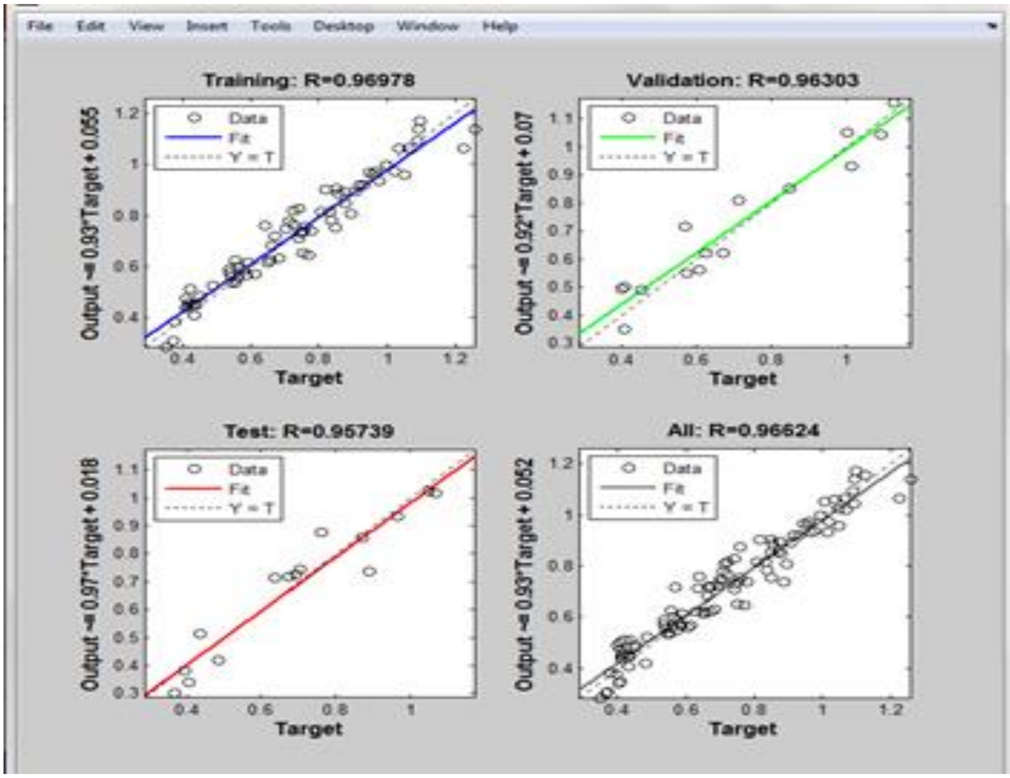

Fig. 6. Relationship between the output and target values for data sets used for training, validation and testing respectively.

4.3. Performance measurement

The relationship between the experimental values and the ANN predictions for the 7, 14, 21 and 28 days samples are illustrated in Fig 7. Likewise, the performance measurement of the network model using percentage error, RMSE, and IA are presented in Table 3.

Table 3
Performance measurement of shear strength ANN model.

Age of specimens	Av % Error	Av. RMSE	IA
7	0.6311	0.0278	0.0890836
14	2.5066	0.0284900	0.1746973
21	2.3585150	0.0463300	0.0474664
28	-0.5225100	0.0653600	0.1210473

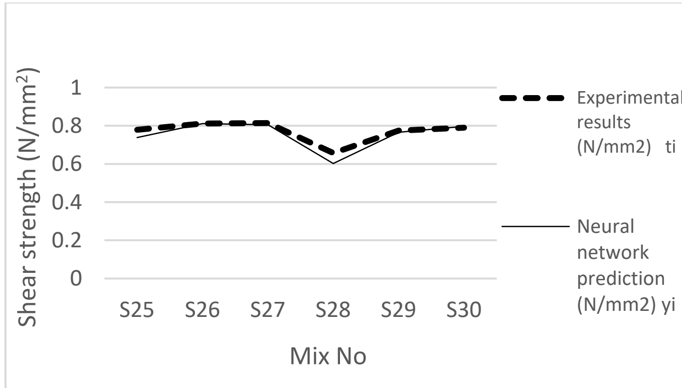

Fig. 7(a). 7 days samples.

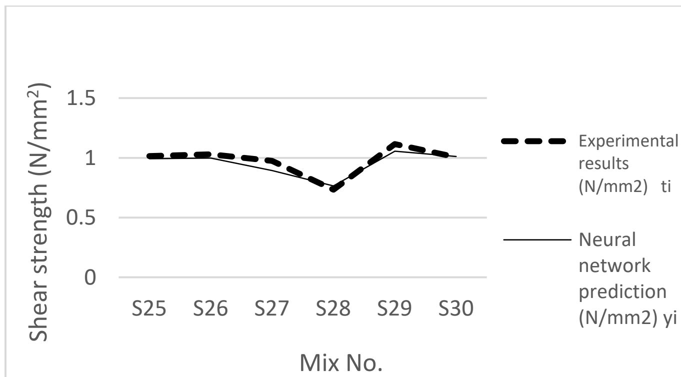

Fig. 7(b). 14 days samples.

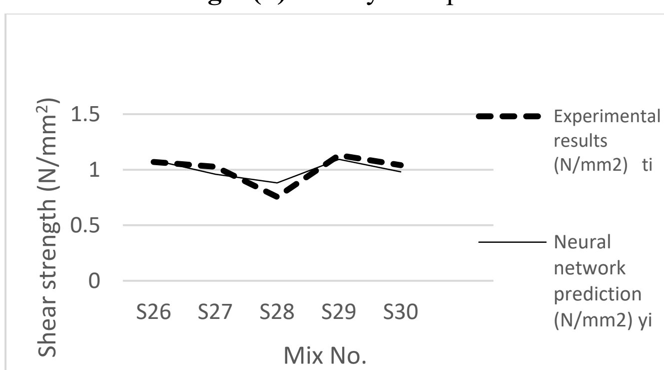

Fig. 7(c). 21 days samples.

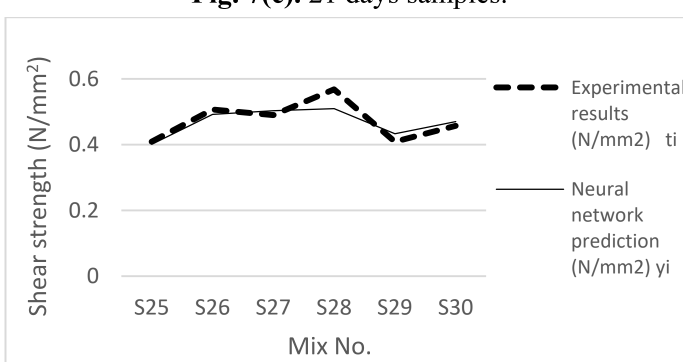

Fig. 7(d). 28 days samples.

Fig. 7. Relationship between experimental results (ti) and neural network predictions (yi).

Figure 7 shows that there is little variation between experimental data and ANN predictions for all the specimens considered. The values for average RMSE ranged from 0.0278 at 7 days to 0.0653600 at 28 days. As the curing age increased, the RMSE values also increased. Since these values are close to 0, then the network can be said to be predicting satisfactorily. Similarly, the average values of the factor of agreement (IA) were from 0.0474664 at 7 days to 0.1746973 at 28 days. The IA is restricted from 0 to 1. Readings obtained are within the specified range. Consequently, there is good consistency between values. A 2.5066 highest average percentage error was recorded for samples cured for 14 days. While a minimum of 0.5225% happened for the 28 days sample

5. Conclusions

The 7, 14, 21 and 28 days shear strength values of binary blended cement composed of HL and PC were obtained in this research. It was observed that as the curing age increased, the shear strength value increased. The most shear strength values at 21 and 28 days are 1.227N/mm^2 and 1.25N/mm^2 respectively. This happened for Mix No. S21, having a 13.75% replacement of PC with HL and 0.58 water-cement ratio. Also, highest readings for the 7 and 14 days specimen were 0.771N/mm^2 and 0.895N/mm^2 at mix no. S22 and S18 accordingly.

The results obtained from the formulated ANN were satisfactory and compare favorably to experimental readings. The MSE determined by the ANN for all data samples used for training the network was 0.0046744 and this value is very close to 0. Moreover, the utmost correlation coefficients (R) values obtained by the network for all data sets (training, testing, and validation data sets) were greater than 0.95. This means that there is a good fit between the predictions and outputs, made by the network since the values are very close to 1.

The performance measurements using data sets not used during the training session revealed that the RMSE readings with respect to the curing ages are in the ranges of 0.0278 and 0.06536. These values are close to zero. Besides, the factors of agreement (IA) obtained are within the limits, 0 and 1. This result also suggests an adequate predicting ability of the network. The highest average % error of 2.506% was observed for samples cured for 14 days. 28 days samples experienced a minimum of -0.5225 average % error. In conclusion, the ANN created can be convincingly used to predict the shear strength of hydrated lime cement concrete and eliminates the need for try-out laboratory research.

Finally, it can be seen that the shear strength of concrete produced from hydrated lime and Portland cement as binders have very low values. Hence, it is required that for this concrete to be used for structural purposes, it must be provided with shear reinforcements.

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Conflicts of interest

The authors declare no conflict of interest.

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