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Anticipating the Compressive Strength of Hydrated Lime Cement Concrete Using Artificial Neural Network Model

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Abstract

In this research work, the levernberg Marquardt back propagation neural network was adequately trained to understand the relationship between the 28th day compressive strength values of hydrated lime cement concrete and their corresponding mix ratios with respect to curing age. Data used for the study were generated experimentally. A total of a hundred and fourteen (114) training data set were presented to the network. Eighty (80) of these were used for training the network, seventeen (17) were used for validation, and another seventeen (17) were used for testing the network's performance. Six (6) data set were left out and later used to test the adequacy of the network predictions. The outcome of results of the created network was close to that of the experimental efforts. The lowest and highest correlation coefficient recorded for all data samples used for developing the network were 0.901 and 0.984 for the test and training samples respectively. These values were close to 1. T-value obtained from the adequacy test carried out between experimental and model generated data was 1.437. This is less than 2.064, which is the T values from statistical table at 95% confidence limit. These results proved that the network made reliable predictions. Maximum compressive strength achieved from experimental works was 30.83N/mm^2 at a water-cement ratio of 0.562 and a percentage replacement of ordinary portland cement with hydrated lime of 18.75%. Generally, for hydrated lime to be used in making structural concrete, ordinary portland cement percentage replacement with hydrated lime must not be up to 30%. With the use of the developed artificial neural network model, mix design procedure for hydrated lime cement concrete can be carried out with lesser time and energy requirements, when compared to the traditional method. This is because, the need to prepare trial mixes that will be cured, and tested in the laboratory, will no longer be required.

Keywords: Hydrated Lime; Compressive Strength; Artificial Neural Network; Ordinary Portland Cement.

1. Introduction

Concrete is one of the primary and salient material used in building and construction. It is generally defined as a composite material comprising mainly of fine aggregates, coarse aggregates, cement and water in predefined mix proportions. The binding material in concrete is cement. When concrete of special qualities are needed, chemical admixtures or cementitious materials are added to the mix.

As time went by, there has been a sweep in the request for concrete in erecting structures, due to increase in infrastructural growth of most countries of the world. This has evolved to a swell in the demand for the making of

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cement, which is a notable origin of worldwide carbon dioxide (CO_2) emission [1]. This green-house gas is expending the isothermal layer of the earth, resulting in increased heating of the globe. The increasing climatic warmth, has led to climatic changes with unfortunate effects such as flooding, earthquakes, hurricanes, and emergence of new viruses. The large amount of energy required for ordinary portland cement (OPC) production has also emanated to high production cost leading to the monopolization of the cement industry by few investors who can afford the very high production cost of the cement. This high cost in manufacturing cement has led to the exorbitant cost of the product itself, thereby making it difficult for low and average income earners to own houses. Finally, the traditional method of mix design of concrete is time consuming and energy demanding since trial mixes will have to be cast, cured for days, and tested in laboratory before they can be adopted for use. These challenges has deemed it necessary to seek out alternative cementing materials that are green. Hence, the need to investigate the compressive strength of lime cement concrete (since it has been discovered that lime leaves a lesser carbon footprint than OPC) and to develop artificial neural networks that will make the mix design process, less laborious and faster.

The cement industry is a critical part of the international climate management strategy because globally, this sector produces nearly 1.4 billion tons of CO_2 or nearly 6% of all man-made CO_2 emission [2]. But, in 2017 global emission of CO_2 from fossil fuels and industry rose to about 37 billion metric tons [3]. This is quite alarming and possible ways to save the globe from destruction caused by man-made activities are of great importance.

Hydrated lime (HL) is calcium hydroxide in powdered form, produced by the heating of limestone. It is an inorganic compound with the chemical formula $Ca(OH)_2$. It is a colourless crystal or white powder and is obtained from the slaking of quick lime. HL is defined by [4] as lime produced by burning argillaceous or siliceous limestone and reducing them to powder by slaking with water (with or without grinding). It can also be defined as a dry powder manufactured by treating quicklime (CaO) with sufficient water to satisfy its chemical affinity for water, thereby converting the oxides to hydroxides. Other names for this type of lime are slaked lime, builder lime and pickling lime. To produce dry powdered hydrated lime, just enough water is added for the quicklime lumps to breakdown to a fine powder. This material will have a ‘shelf life’ of only a number of weeks, depending on the storage conditions. Old hydrated lime would have partially carbonated and become a less effective binder. There are four types of hydrated lime according to [5]. They are type-S, type-SA, type-N, and type-NA. The hydrated lime is the type of lime used in the construction industry and is studied in this research work.

The inclusion of hydrated lime as a partial replacement of portland cement, will assist in reducing the emission of the green-house gases to the atmosphere. This is possible since a reduction in the amount of the clinker content in cement production by hydrated lime, will reduce the amount of CO_2 released into the atmosphere during the calcination of the clinker [2]. Also, the addition of hydrated lime as a partial replacement of clinker, will evolve to lower calcination temperature, thereby reducing CO_2 emissions from the fossil fuel used to heat up the cement kilns [6]. Further, hydrated lime in concrete has the ability to re-absorb CO_2 gases from the atmosphere [7]. The use of HL as a construction material in concrete production reduces the risk of trapped moisture and consequent damage of the building fabric, reduces the permeability of concrete by filling the pores in concrete, improves cohesion, achieves economy through cement replacement, increases the bond strength of concrete, improves resistance against efflorescence in concrete, provide autogenous healing of mortar and assists concrete in accommodating stresses caused by building movement and cyclic changes without excessive cracking [8, 9].

Compressive strength of concrete is the maximum compressive stress that, under a gradually applied load, a given concrete volume can sustain without fracture. It is defined as the capacity of a material or structure to withstand load tending to reduce its size. It can also be seen as the resistance of a material to breaking (rupture), under compression [10]**.** For structural design, the compressive strength is taken as the criterion of the quality of concrete [11]. It is the most common test on hardened concrete. This is partly because it is an easy test to perform, and partly due to the fact that many desirable characteristics of concrete are qualitatively related to its strength. They are the most common performance measure, used by engineers in designing buildings and other structures.

Concrete is designed by past experience acquired from previous mixes or by making trial batches in the laboratory and testing the concrete. Results obtained from the laboratory test, usually, require some modification to meet with the site requirement. All these traditional procedures are time consuming and laborious, making mix design more difficult and complicated [12]. Most times, mathematical models are used to understand the relationship between components and material behavior. The models are usually made up of expressions and rules that covers the different complex behavior [13]. Since concrete is a non-linear material, it can be very difficult to model its behavior mathematically. Therefore, the use of the artificial neural network model becomes a very convenient approach for modelling concrete.

An artificial neural network (ANN) is an information paradigm that is inspired by the way biological nervous systems, such as the brain, process information [14]. It is from the artificial intelligence family, and is a type of information processing system based on modeling the neural system of the human brain [15]. It is an information processing system that has certain performance characteristics in common with biological neural networks [16].The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons), working in unison to solve specific problems. Artificial neural networks like people, learn by examples. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well. Commonly, neural networks are adjusted or trained, so that a particular input leads to a specific target output. The network is adjusted based on a comparison of the output and the target, until the network output marches the target. When compared to mathematical models, they have the advantage of solving very complex non-linear problems with very high accuracy and have been implemented in resolving many cogent areas in concrete technology.

Many researchers have successfully used artificial intelligence to model the relationship between parameters in concrete. ANN have been used in predicting the compressive strength of Ultra high performance concrete containing fly ash and silica fume [17]. [18], applied it in predicting the compressive strength of cement based materials exposed to sulphate attacks. [19], used it in predicting the 28 days compressive strength of recycled aggregate concrete. While [20] applied the ANN in the analysis of the ultrasonic testing of concrete. [21], modeled the steel-concrete bond using ANN models. [22], predicted the self-compacting properties of concrete using ANN. While, [23] used the ANN to predict the compressive strength and durability of high performance concrete.

Many researchers have reported their findings on the use of lime in the making of concrete. A thorough and comprehensive review of research into the use of blended or inter-ground limestone in Portland cement was carried out by [24]. They looked into the effects of limestone use on particle size distribution, grinding, workability, hydration and setting of the cement, reaction chemistry and kinetics, heat generation, microstructure, setting time and durability. From the studies of [25], it was reported that there was only a minor difference in the performance between ordinary Portland cement and 15% Portland limestone cement concretes of the same cement content and water cement ratio. They observed an adverse effect with increasing limestone content beyond 15% of the cement content for many of the properties studied. Incorporation of limestone powder in cement enhanced the compressive strength of the mortar when compared to the mortar containing marble powder [26]. The best lime replacement with normal concrete in order to produce structural concrete is less than 25% of cement volume in concrete mixture as stated by [27]. [28], in his study on building green with blended cement, reported that cement and concrete strengths are normally not reduced by using five percent (5%) to ten percent (10%) limestone. [6], observed that at fifteen percent (15%) replacement of marble powder containing lime, with cement, the compressive strength was reduced. However, the strength reduction did not restrict the applicability of the marble powder in the field when the grade of concrete, is designed for M30. The compressive strength of concrete decreased with an increase in percentage of lime. At age 56 days and beyond, [8] observed that the difference between the compressive strength of normal and the modified concrete, was lesser than the difference at the age of 7 days.

A 7% replacement of cement with hydraulic lime was observed to increase the compressive and flexural strength of concrete made using portland slag cement (PSC) and portland pozzolana cement (PPC) [29]. The workability of the concrete reduced with the addition of lime. Acid and sulphate resistance increased slightly up to 7% addition. The lime addition up to 10% did not affect the soundness of the blended cements like PSC and PPC. [30], concluded from their work that lime concrete reinforced with Glass Fibre Reinforced (GFRP) is a viable alternative to replace the reinforced concrete design in the repairs of historical eating. Highest compressive obtained was 14MPa. The influence of the 7, 28 and 56 days compressive and splitting tensile strength was investigated by [31]. The concrete was perceived to show an unbroken strength gain. Lime cement concrete showed a 70% rise in strength over lime concrete at 28 days curing age and had good workability and plasticity properties. They also reported that using lime in making concrete was cheaper and locally available.

Thus, the purpose of this study is to determine experimentally the compressive strength of hydrated lime-cement concrete without the inclusion of any pozzolanic material using some selected mix ratios and formulate an artificial neural network model that can be used to predict the compressive strength of the hydrated lime cement concrete.

2. Materials and Methods

2.1 Materials

The materials used for this research work include; portland cement of grade 32.5 and conformed with the requirement of [32]; hydrated lime that satisfied the requirement of [5] and [33]; river sand obtained from Otamiri River in Owerri West Local Government area of Imo State, Nigeria, having bulk density of 1656.022 kg/m^3; granite chippings of maximum size 19mm of bulk density 1706.225 kg/m^{3}and was obtained from Okigwe in Imo State, Nigeria; water used for the concrete production was potable and obtained at the Federal Polytechnic, Nekede, Owerri, Nigeria. The river sand and granite chippings were poorly graded. Figure 1 depicts the hydrated lime used for the study. While, Table 1 shows its chemical composition.

Figure 1. Hydrated lime

Table 1. Chemical property test of hydrated lime [1]

S/NO	Chemical properties	Percentage composition
1	Calcium Oxide (CaO)	93.0%
2	Moisture (H_2O)	0.58%
4	Silicon Oxide(SiO_2)	2.38%
5	Aluminum Oxide(AL_2O_3)	2.04%
6	Magnesium Oxide(MgO)	2.0%
7	pH	8.6

2.2 Methods

Three methods were used in the conduct of this research and they are; experimental, prediction and statistical methods.

- Experimental method (Compressive strength test)
- Prediction method (Artificial neural network model)
- Statistical methods (Percentage error, student t-test)

2.2.1 Compressive Strength Test

Compressive strength of concrete is the maximum compressive stress a given concrete volume can sustain without fracture. The following procedure was carried out in order to determine the compressive strengths of hydrated lime cement concrete:

(a) Concrete cube specimen

The specimen produced for the compressive strength test, was the concrete cube of size$150 \times 150 \times 150\ mm$. This was prescribed according to [34]. Three concrete specimens were prepared for each mix proportion at curing ages of 7, 14, 21, and 28 days in open water tanks. 30 mix rations were investigated resulting to a total of 360 concrete cubes.

(b) Test procedure

The compressive strength test was conducted on the $150 \times 150 \times 150\ mm$ concrete cubes using the universal testing machine according to [34], to determine their failure loads. Figure 2 illustrates the test procedure.

Figure 2. Specimen testing in compression

(c) Calculation

The crushing loads obtained from the investigation were used to calculate the compressive strength of the lime cement concrete using the formula:

$$F_c = \frac{P}{A} \tag{1}$$

Where,

F_c: Compressive strength of concrete (N/mm^2), P: Crushing load (N), A: cross sectional area of the specimen (mm^2).

2.2.2 Artificial Neural Network Model

Data for this study were generated experimentally. The concrete under study is a five component mixture; so, five starting set of mix ratios (N1 to N5) were used to generate extra twenty five mix ratios using the Henry Scheffes simplex lattice [35].This gave a total of thirty mix ratios. These mixes were then used to experimentally generate results of the compressive strengths of hydrated lime cement concrete. Table 2 shows the mix proportions of concrete specimens used for the study. The experimental values of the compressive strengths of lime cement concrete, were then used to formulate an artificial neural network model for predicting this property. This was implemented using the neural network toolbox found in the Matlab R2014a software.

Table 2. Mix proportion of concrete cubes

S/No	Mix No.	Mix ratio					Mix proportions in weight for one cube (Kg)				
		W/C	Cement	Lime	Sand	Granite	Water	Cement	Lime	Sand	Granite
1	N1	0.600	0.900	0.100	3.000	6.000	0.510	0.765	0.085	2.550	5.100
2	N2	0.570	0.850	0.150	2.000	4.000	0.692	1.032	0.182	2.429	4.857
3	N3	0.550	0.800	0.200	2.500	5.000	0.550	0.800	0.200	2.500	5.000
4	N4	0.530	0.700	0.300	1.500	3.000	0.819	1.082	0.464	2.318	4.637
5	N5	0.500	0.600	0.400	1.000	2.000	1.063	1.275	0.850	2.125	4.250
6	N12	0.585	0.875	0.125	2.500	5.000	0.585	0.875	0.125	2.500	5.000
7	N13	0.575	0.850	0.150	2.750	5.500	0.538	0.781	0.138	2.527	5.054
8	N14	0.565	0.800	0.200	2.250	4.500	0.620	0.878	0.220	2.468	4.936
9	N15	0.550	0.750	0.250	2.000	4.000	0.668	0.911	0.304	2.429	4.857
10	N23	0.560	0.825	0.175	2.250	4.500	0.614	0.905	0.192	2.468	4.936
11	N24	0.550	0.775	0.225	1.750	3.500	0.748	1.054	0.306	2.380	4.760
12	N25	0.535	0.725	0.275	1.500	3.000	0.827	1.121	0.425	2.318	4.637
13	N34	0.540	0.750	0.250	2.000	4.000	0.656	0.911	0.304	2.479	4.857
14	N35	0.525	0.700	0.300	1.750	3.500	0.714	0.922	0.408	2.380	4.760
15	N45	0.515	0.650	0.350	1.250	2.500	0.922	1.163	0.627	2.237	4.474
16	C1	0.585	0.875	0.125	2.500	5.000	0.590	0.880	0.130	2.500	5.000

17	C2	0.575	0.850	0.150	2.750	5.550	0.526	0.777	0.137	2.513	5.073
18	C3	0.550	0.775	0.225	1.750	3.550	0.743	1.046	0.304	2.361	4.790
19	C4	0.525	0.700	0.300	1.750	3.550	0.708	0.944	0.405	2.361	4.790
20	C5	0.517	0.650	0.350	1.250	2.500	0.922	1.163	0.627	2.237	4.474
21	C6	0.580	0.863	0.138	2.625	5.500	0.556	0.826	0.132	2.514	5.027
22	C7	0.550	0.763	0.238	1.875	3.750	0.706	0.978	0.305	2.406	4.812
23	C8	0.563	0.813	0.188	2.250	4.500	0.617	0.891	0.257	2.469	4.937
24	C9	0.543	0.732	0.268	1.825	3.650	0.713	0.961	0.352	2.395	4.791
25	C10	0.560	0.799	0.201	2.325	4.650	0.597	0.852	0.215	2.479	4.957
26	C11	0.567	0.817	0.183	2.165	4.330	0.643	0.927	0.278	2.455	4.910
27	C12	0.557	0.790	0.210	2.150	4.300	0.636	0.902	0.240	2.453	4.907
28	C13	0.553	0.775	0.225	2.100	4.200	0.644	0.903	0.262	2.446	4.891
29	C14	0.562	0.813	0.188	2.225	4.450	0.623	0.899	0.208	2.464	4.929
30	C15	0.560	0.790	0.210	2.100	4.200	0.652	0.920	0.245	2.446	4.891

(a) Formulation of the artificial neural network model.

The result of the compressive strengths of lime cement concrete shown on Table 2, was used to develop an artificial neural network for predicting the compressive strength of hydrated lime cement concrete. The mix proportions of water-cement ratio, portland cement, hydrated lime, river sand, granite chippings and curing age represented the input vectors used for the training of the networks, while their corresponding compressive strength values represented their output vector. A total of a hundred and fourteen (114) training data set were presented to the network. Eighty (80) of these were used for training the network, seventeen (17) were used for validation, and another seventeen (17) were used for testing the network's performance. This division was achieved by the use of the 'dividerand' function and the network objects. The training function used was the "trainlm" (i.e. the Levernberg-Marquardt back propagation training function), while the activation function used was the "Tansig" i.e. the tangent sigmoid function. Input and output data for the last six (6) mix ratios were left out and used to test how well the network was predicting after training.

Figure 3 shows the architecture (arrangement of neurons) within the neural network developed. It has 6 input neurons, 20 hidden layer neurons and one output neuron. This was selected by trial and error, in order to minimize the error and obtain speedy convergence of the network (i.e. the training of the network).

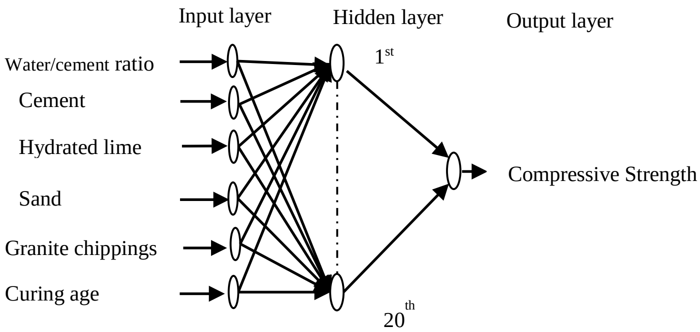

Figure 3. Architecture of the neural network model formulated

(b) Back propagation of error using the Levenberg-Marquardt algorithm

For back propagation algorithm, an error measure known as the mean square error is used [36]. The mean square error is defined as;

$$\mathrm{E}_p = \sum_{k=1}^{p} ½ \, (t_k \; - \; o_k)^2 \tag{2}$$

Where,

t_k= Target (desired) value of O_k output unit;

o_k= Actual output obtained from O_k output unit;

E_p= Mean square error.

In the training phase of back propagation learning algorithm, the total error of the network is minimized by adjusting the weights within the network connections. The Levernberg-Marquardt (LM) algorithm is used for this. Each weight is thought to be in an N – dimensional error space and they act as independent variables. The shape of the corresponding error surface is obtained by the error function in combination with the training set. Applying the LM algorithm, Equation 2 can be re-written as:

$$E_p(\beta) = \sum_{k=1}^{p} [t_k - f(o_k, \beta)]^2 \tag{3}$$

Where,

t_k= Target (desired) value of O_k output unit. ; $f(o_k, \beta)$= Actual output obtained from O_k output unit.
$E_p(\beta)$= Mean square error; β= Parameter vector; o_k= Measured vector; f= Functional relationship.

To solve Equation 3, an initial value must be assumed for β.
For every iteration, β is substituted by 'β + δ', where δ is the error correction or error function. Therefore, (3) becomes;

$$E_p(\beta + \delta) = [t_k - \sum_{k=1}^{p} f(o_k, \beta + \delta)]^2 \tag{4}$$

Approximating the function $f(o_k, \beta + \delta)$ by their linearization (Taylor series), will give;

$$f(o_k, \beta + \delta) \approx f(o_k, \beta) + \left[\left(\frac{\partial f}{\partial \beta}\right)(o_k, \beta)\right]\delta \tag{5}$$

But $\left[\left(\frac{\partial f}{\partial \beta}\right)(o_k, \beta)\right] = J_k$; where J_k is the Jacobian matrix from output O_k.

Equation 5 can then be re-written as;

$$f(o_k, \beta + \delta) \approx f(o_k, \beta) + J_k\delta \tag{6}$$

Substituting (6) into (4) will give

$$E_p(\beta + \delta) = [t_k - \sum_{k=1}^{p} f(o_k, \beta) + J_k\delta)]^2 \tag{7}$$

Note that at the minimum of the sum of squares $E_p(\beta)$, the gradient of E_p w.r.t 'β' will be zero.

Re-writing (7) in vector form gives;

$$E_p(\beta + \delta) = |t - f(\beta) - J\delta|^2 \tag{8}$$

Differentiating (8) w.r.t. 'δ' and setting the results to zero gives;

$$J\delta = t - f(\beta) \tag{9}$$

Multiplying both sides by the transpose of the Jacobian matrix gives;

$$(J^T J)\delta = J^T[t - f(\beta)] \tag{10}$$

Where,

J = Jacobian matrix whose k^{th} 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

Levenberg's contribution was to replace the (10) with a "damped version" as shown in Equation 11;

$$(J^T J + \lambda I)\delta = J^T[t - f(\beta)] \tag{11}$$

Where,

I = Identity matrix given as the increment δ to the estimated parameter vector β.

λ= Non negative damping factor. This is adjusted in each iteration.

Marquardt made a new addition to the Levenberg algorithm by replacing the identity matrix 'I' with a diagonal elements of J^TJ, resulting to larger movement along the directions where the gradient is smaller and avoided slow convergence. The Levenberg-Marquardt algorithm is given in (12) as:

$$[J^TJ + \lambda_{diag}(J^TJ)]\,\delta \;=\; J^T[t - f(\beta)] \tag{12}$$

Solving (12) generated the error correction/function 'δ' which was then used to compute the weight changes accordingly. The value of 'δ' that best minimizes the Equation 12 was the solution to the non-linear least square problem [37]. The Levenberg-Marqaurdt training algorithm was implemented in the neural network toolbox of Matlab by typing the function 'trainlm'.

2.2.3 Test of Adequacy of the Neural Network Model

The adequacy of the network predictions against the experimental values were tested using the student's t-test as presented in Equation 13;

$$T = \frac{(DA \times N^{0.5})}{S} \tag{13}$$

Where;

$$DA = \sum \frac{D_i}{N}; \quad S = \sqrt{S^2}; \quad S^2 = \sum \frac{(DA - Di)^2}{(N-1)}; \quad D_i = YM - YE$$

N -Represent the number of responses; YM = Model results; YE = Experimental results.

3. Results and Discussions

Chemical analysis carried out on the HL showed it satisfied the ASTM C207 requirement that the CaO content must not be less than 75.56%. A CaO content of 93% was recorded as shown in Table 1. The compressive strength test results obtained from the experimental work carried out on the hardened hydrated lime cement concrete are presented in Table 3.

Table 3. Summary of compressive strength result of hydrated lime cement concrete

S/No	Mix no.	Density kg/m^3	Compressive Strength (N/mm^2) 7th day	14th day	21st day	28th day
1	N1	2449	5.60	11.24	14.72	15.12
2	N2	2514	8.68	16.24	18.30	18.50
3	N3	2489	7.37	14.61	16.06	17.86
4	N4	2499	5.67	19.34	21.68	22.00
5	N5	2558	4.55	14.35	15.78	19.56
6	N12	2521	9.78	19.18	20.02	20.85
7	N13	2539	10.29	19.17	22.30	22.70
8	N14	2558	7.59	18.72	22.30	22.17
9	N15	2504	7.76	15.87	21.43	21.56
10	N23	2616	7.03	19.32	25.26	23.81
11	N24	2568	8.63	18.76	22.56	23.34
12	N25	2464	7.48	18.32	20.65	21.33
13	N34	2499	8.71	11.93	16.00	16.22
14	N35	2499	9.08	10.78	15.35	16.16
15	N45	2449	6.61	10.90	17.23	19.00
16	C1	2578	9.62	19.15	20.10	20.85
17	C2	2578	10.47	19.21	22.27	22.45
18	C3	2509	11.09	20.67	26.37	26.68
19	C4	2469	8.92	10.72	16.11	16.20
20	C5	2471	6.80	10.43	17.48	19.15
21	C6	2607	10.97	14.90	23.11	23.56
22	C7	2528	8.81	20.01	23.55	23.87

23	C8	2529	12.31	22.02	28.00	28.50
24	C9	2548	8.65	20.03	23.56	23.94
25	C10	2517	9.10	24.91	29.33	29.85
26	C11	2528	13.24	20.92	27.33	27.80
27	C12	2509	11.06	19.13	24.22	24.58
28	C13	2509	12.26	18.91	28.42	28.90
29	C14	2548	6.68	24.01	30.23	30.83
30	C15	2460	12.90	19.34	21.00	21.45

The wet densities of the concrete cubes were determined. These values ranged from 2449 to 2616 kg/m^2, showing that the concrete studied is a normal weight concrete [11]. The greater the density of hardened concrete, the stronger and more durable it will be.

The highest compressive strength values obtained at 7 days, 14 days, 21 days and 28 days of curing were 13.24N/mm^2, 24.01N/mm^2, 30.23N/mm^2 and 30.83N/mm^2 respectively. These strength values corresponded to mix no. C12 for the 7 days strength, and C14 for the 14 days, 21 days, and 28 days strength respectively. Lowest values obtained for 7 days, 14 days, 21 days, and 28 days were, 5.60N/mm^2, 11.24N/mm^2, 14.72N/mm^2, and 15.12N/mm^2 respectively. These strengths corresponded to mix label N1.

Optimum mix proportion at the 28th day was 0.8125:0.1875:2.225:4.450 at a water-cement ratio of 0.562. The compressive strength values of the hydrated lime cement concrete increased with increasing curing age, which means that all things being equal, the concrete does not deteriorate with time. Optimum percentage replacement of portland cement with hydrated lime was 18.75% as against 15% portland cement replacement with limestone by [25]; 10% portland cement replacement with limestone by [28]; and 20% replacement of portland cement with lime by [8]. From the works of [38], it can be deduced that compressive strength values for concrete produced by partially replacing Portland cement with lime content in marble powder, are higher than those with hydrated lime replacement. The higher values showed greater resistance to crushing. Generally, it can be seen from Table 2 and 3, that the mix ratios that gave compressive strength values above 20N/mm^2 had their percentage replacement of portland cement with hydrated lime ranging from 12.5% to 26.8%. Performance validations conducted on the formulated neural network model are presented in Figures 4 to 7.

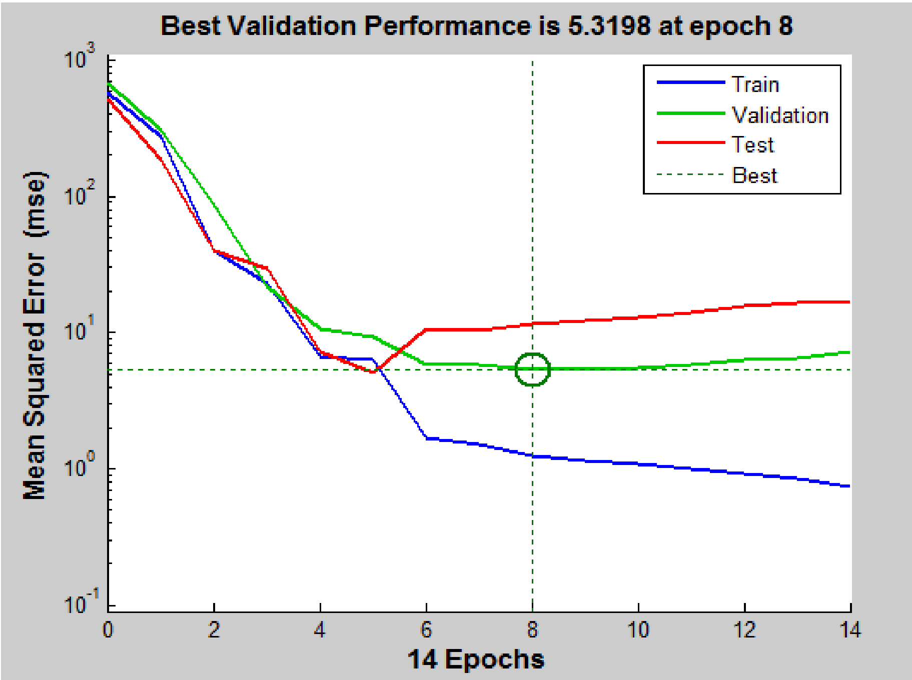

Figure 4. Training performance graph for compressive Strength neural network (NN)

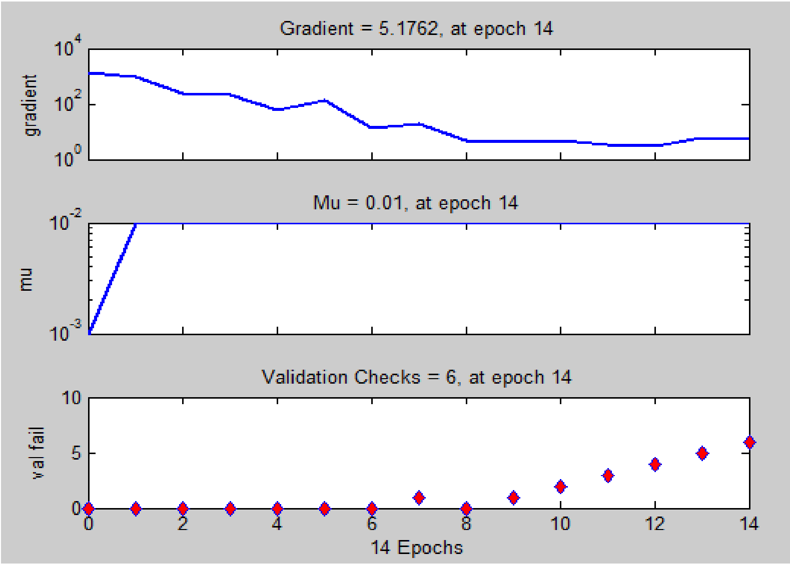

Figure 5. Compressive strength neural network training state

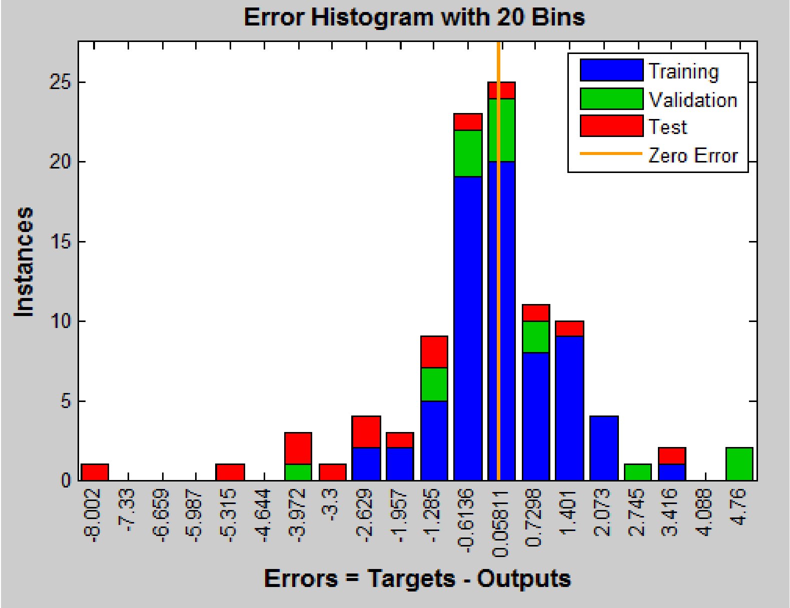

Figure 6. Error Histograph

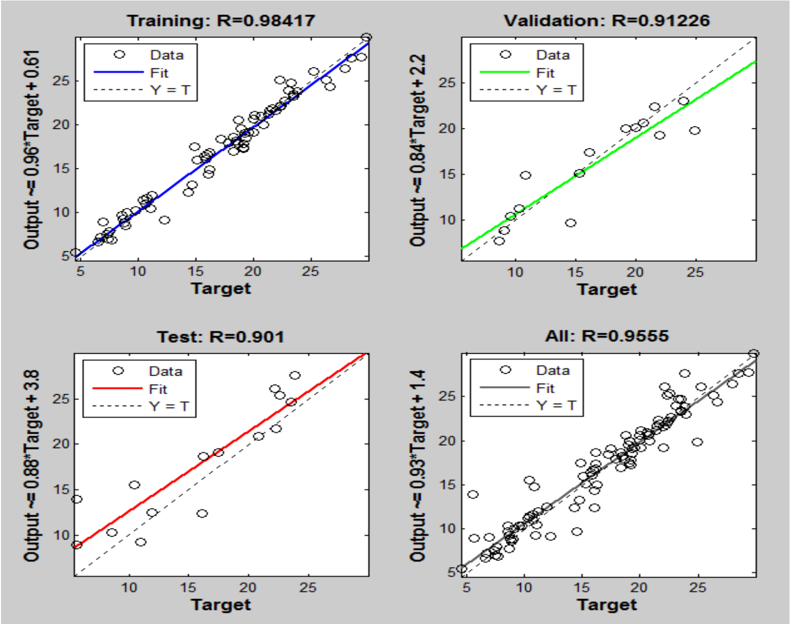

Figure 7. Regression curve

In Figure 4, the compressive strength NN training had 14 epochs (rounds of training) to meet the best training state. A gradient of 5.18 targeting $1.0e^{-07}$ was achieved at this point after performing 6 validation checks before convergence as shown in Figure 5. It was also observed that the best validation check occurred at the 8th epoch at a mean square error of 10^0 and best performance at 5.3198. The gradient at the very last epoch (Mu) was 0.01. The error histogram of Figure 6 depicts that the 9th bin has zero error at 0.05811 and produced the best performance for the network. Figure 7 illustrates the regression values (R) for the training, validation, and testing data set. The R value is an indication of the relationship between the outputs and targets. If R = 1, then there is a linear relationship between the output and the targets [39]. R = 0.98417 for training; 0.91226 for validation; 0.901 for testing and finally 0.9555 for the combination of the three. These values are very close to 1, showing that the artificial neural network model formulated for predicting compressive strength of hydrated lime cement concrete has good predicting ability. Table 4 shows the comparison of experimental results against neural network prediction for the compressive strength of hydrated lime cement concrete using percentage error method.

Figure 4. Comparison of the experimental results against neural network predictions against percentage error of the compressive strength of lime cement concrete.

Mix label	Curing age	Experimental results (N/mm^2)	Neural network prediction (N/mm^2)	Error	% Error
C10	7	9.10	10.0704	-0.9704	-10.663736
C11	7	13.24	13.2549	-0.0149	-0.1125378
C12	7	11.06	11.0248	0.0352	0.31826401
C13	7	12.26	12.1836	0.0764	0.62316476
C14	7	6.68	6.6690	0.0110	0.16467066
C15	7	12.90	11.9903	0.9097	7.05193798
C10	14	24.91	24.9732	-0.0632	-0.2537134
C11	14	20.92	19.9601	0.9599	4.58843212
C12	14	19.13	18.5780	0.5520	2.88552013
C13	14	18.91	17.8796	1.0304	5.4489688
C14	14	24.01	24.7682	-0.7582	-3.1578509
C15	14	19.34	19.2900	0.0500	0.25853154
C10	21	29.33	29.1770	0.1530	0.52165019
C11	21	27.33	27.2665	0.0635	0.23234541
C12	21	24.22	24.1784	0.0416	0.17175888
C13	21	28.42	28.6914	-0.2714	-0.9549613
C14	21	30.23	29.6406	0.5894	1.94971882
C15	21	21.00	21.4936	-0.4936	-2.3504762
C10	28	29.85	29.4931	0.3569	1.19564489
C11	28	27.80	27.2217	0.5783	2.08021583
C12	28	24.58	23.9001	0.6799	2.76606998
C13	28	28.90	28.8671	0.0329	0.11384083
C14	28	30.83	31.0664	-0.2364	-0.7667856
C15	28	21.45	21.2109	0.2391	1.11468531

The modelling and simulation of the neural network with the data obtained experimentally has produced considerable encouraging results. Overview, it can be seen from Table 4 that the highest percentage error obtained was not up to 11%. This result further confirms that the neural network have been satisfactorily trained, as all outputs given by the network are close to the values of the experimental results.

Predictions from the model formulated were further tested for adequacy against their experimental values using the student's t-test. Table 5 presents the result obtained from this test.

Table 5. Student's t-test of neural network compressive strength

S/no.	Mix label	Curing age	YE	YM	Di = YE - YM	$D_A = (\sum Di)/N$	DA - Di	$(D_A - Di)^2$
1	C10	7	9.10	10.0704	-0.9704	0.1479625	1.1184	1.250735
2	C11	7	13.24	13.2549	-0.0149	0.1479625	0.1629	0.026524
3	C12	7	11.06	11.0248	0.0352	0.1479625	0.1128	0.012715
4	C13	7	12.26	12.1836	0.0764	0.1479625	0.0716	0.005121
5	C14	7	6.68	6.6690	0.0110	0.1479625	0.1370	0.018759
6	C15	7	12.90	11.9903	0.9097	0.1479625	-0.7617	0.580244
7	C10	14	24.91	24.9732	-0.0632	0.1479625	0.2112	0.04459
8	C11	14	20.92	19.9601	0.9599	0.1479625	-0.8119	0.659243
9	C12	14	19.13	18.5780	0.5520	0.1479625	-0.4040	0.163246
10	C13	14	18.91	17.8796	1.0304	0.1479625	-0.8824	0.778696
11	C14	14	24.01	24.7682	-0.7582	0.1479625	0.9062	0.82113
12	C15	14	19.34	19.2900	0.0500	0.1479625	0.0980	0.009597
13	C10	21	29.33	29.1770	0.1530	0.1479625	-0.0050	2.54E-05
14	C11	21	27.33	27.2665	0.0635	0.1479625	0.0845	0.007134
15	C12	21	24.22	24.1784	0.0416	0.1479625	0.1064	0.011313
16	C13	21	28.42	28.6914	-0.2714	0.1479625	0.4194	0.175865
17	C14	21	30.23	29.6406	0.5894	0.1479625	-0.4414	0.194867
18	C15	21	21.00	21.4936	-0.4936	0.1479625	0.6416	0.411602
19	C10	28	29.85	29.4931	0.3569	0.1479625	-0.2089	0.043655
20	C11	28	27.80	27.2217	0.5783	0.1479625	-0.4303	0.18519
21	C12	28	24.58	23.9001	0.6799	0.1479625	-0.5319	0.282958
22	C13	28	28.90	28.8671	0.0329	0.1479625	0.1151	0.013239
23	C14	28	30.83	31.0664	-0.2364	0.1479625	0.3844	0.147735
24	C15	28	21.45	21.2109	0.2391	0.1479625	-0.0911	0.008306
				$\sum Di$ =	3.5511		$\sum(D_A - Di)^2$ =	5.852489
					$S^2 = [\sum(D_A - Di)^2]/(N-1) =$		0.254456	
					$S = \sqrt{S^2} =$		0.504436	
					$D_A \times \sqrt{N} =$		0.724865	
					$T = [D_A \times \sqrt{N}]\,/S =$		1.436981	

Calculated 'T' values for the compressive strength artificial neural network is 1.437. This value fell below the allowable 'T' value from Table which is, 2.064. This means that the null hypothesis (H_0) is accepted and alternative hypothesis is rejected as there is no significant difference between the neural network model results and the experimental results. This test of adequacy further affirms that the result from the neural network model obtained herein are reliable and the model could be used to predict the 7, 14, 21 and 28 days compressive strength of hydrated lime cement concrete at 95% confidence level. This means that neural networks have been satisfactorily trained, as all the outputs given by the network are close to the values of the experimental results

4. Conclusion

In this study, the compressive strength of hydrated lime cement concrete were obtained at 7 days, 14 days, 21 days and 28 days. This concrete was made of portland cement, hydrated lime, river sand, granite chippings and water. The highest value of compressive strength recorded from experimental works at 28 days of curing was 30.83 N/mm^2. This occurred at a water-cement (w/c) ratio of 0.562, having a percentage replacement of portland cement with hydrated lime of 18.75%. Generally, for hydrated lime cement concrete to be used as a structural concrete, potland cement replacement with hydrated lime must not be up to 30%.

The outcome of results of the created network was close to that of the experimental efforts. The lowest and highest correlation coefficient recorded for all data samples used for developing the network were 0.901 and 0.984 for the test and training samples respectively. These values were close to 1. The adequacy of the network was further tested using the Student's T test. The T-value calculated for the compressive strength of hydrated lime cement concrete was lower than that from the T table at 95% confidence level, proving that the network predictions are reliable.

With the use of the developed artificial neural network, mix design procedure for lime cement concrete can be carried out with lesser time and energy requirements, when compared to the traditional method. This is because, the need to prepare trial mixes that will be cured, and tested in the laboratory, will no longer be required.

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6. Conflicts of Interest

The authors declare no conflict of interest.

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