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# Prediction of the Compressive Strength of Concrete with Palm Kernel Aggregate Using the Artificial Neutral Networks Approach

*P. N. Onuamah*
*Civil Engineering Department,*
*Enugu State University of Science and Technology, Enugu, Nigeria*
*E-mail Address:* ponuamah@yahoo.co.uk

**ABSRACT:** In the construction of engineering structures it sometimes becomes necessary to use light weight aggregate to reduce costs from forced use of heavy concrete mixes. In this paper, the artificial network method is applied to search for a simpler and quicker way of arriving at optimal mix ratio using light kernel shell aggregates. The method serves as an alternative to the time consuming experimental trial and error methods of arriving at the required lightweight aggregate concrete for construction. The work involves building a multi-layer perceptron neural network model whose input data are the same experimental data used to obtain the compressive strength values for the formulation of the concrete compressive strength regression model of palm kernel shell (PKS) aggregate. The result of the study is validated using correlation analysis between the ANN result and regression model result.

***Keywords***: *kernel shell, perceptron, model, multilayer, training*

## 1 INTRODUCTION

PALM kernel shells are not common materials in the construction the industry. This is either because they are not available in very large quantities as sand or gravel, or because their use for such construction has not been encouraged. For some time now, the Nigerian government has been calling for the use of local materials in the construction industry to limit costs of construction. There has therefore been a greater call for the sourcing and development of alternative, non conventional local construction materials.

It is absolutely necessary that constructed structure stay stable throughout the desired life as any collapse results in massive loss of lives and properties. Olajumoke etal [1] supports that weak concrete mixes are the main causes of that failure of most buildings in Nigeria and this has a disastrous effect on the socio-economic life of the country [2].

It cannot be overstressed that building structures with the right raw materials and proper strength characteristics is indispensably against the influences of the collapse of building and other structures. The possibility and ease of determining the proportions of the required components of the concrete mixes needed for the structure is a crucial factor as various methods vary both in practical complexity and time consumptions.

The concrete for building structures is made with four major constituent materials including cement, coarse aggregates, fine aggregates, and water. In this work a computational model based on artificial network technology was investigated for predicting the strength of concrete with palm kernel shell as aggregates. The approach makes for obtaining the ultimate strength of the concrete which must enable the structure to be safe under loads and makes for easy estimation of the developed and achieved strength as construction progress.

## 2 NEURAL NETWORK IN CONSTRUCTION

Researchers have done much on the application of the Artificial Neural network in the prediction of the strength of engineering materials including concrete. The concept of artificial neurons was first introduced in 1943 [3]. As stated by [4], since the introduction of the concept of artificial neurons, realistic models have been developed both for neurons and for larger systems in the systems in the brain leading to the modern field of neuroscience. In the recent years, the

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Artificial Neuron Networks (ANNs) have become very popular in the prediction and forecasting in a number of areas including water resources, environmental science, power generation, medicine, finance, etc.

In their works, [5] applied the ANNs to the prediction of the mechanical behaviour of concrete materials at high temperature, and came out with encouraging results with the conclusion that the ANNs performed better than the existing analytical methods in the prediction in the prediction of confined flexural strength and the corresponding strength circular concrete columns.

Artificial Neural Networks have vast utility hinged on their applicability in inferring functions from observations especially in applications where the complexity of the data of task makes the design of such functions, by hand, not practical [4]. ANNs' application fall within the categories of (a) Function approximation or expression analysis including time series prediction, (b) Classification including pattern and sequence recognition, (c) Data processing including filtering, clustering, blind source separation and compression, and (d) Robotics including directing manipulators and computer numerical control.

Artificial network modeling is purely a computational technique. If one wants to explain the underlying process or mathematical framework that produces the relationships between the dependent and independent variables, it would be better to use a more traditional statistical model like the regression analysis. If however, the model interpretability is not important, one can often obtain good model results more quickly using a neural network.

## 2.1 Artificial Neurons

Artificial neurons are building blocks for artificial neural networks. The network simulate the manner of operation of natural neurons in the human body. Fig 1 shows a typical neuron, the input to the neuron, $x_i$, and the output $a_i$. The input to the neuron $x_i$ is multiplied by a weighting function, $W_i$, to generate the transformed input, $W_i x_i$, and the summed transformed inputs constitute the variables to the activation/transfer function, g, which generates the activation output $a_i$.

Hence, given the input vector $x=x_1, x_2, \ldots, x_n$, the activations of the input unit are set to $(a_1, a_2, \ldots, a_n) = (x_1, x_2, \ldots, x_n)$ and the network computes to

$$Ln_i = \sum_{j=1}^{n} W_{j,i} a_j$$

Applying the sigmoid activation function

$$a_i = g(Ln_i) = \frac{1}{1-e^{-Ln_i}}$$

The output of the function is compared to the threshold value, and if the output is greater than threshold value, the neuron is activated, and signal is transferred to the neuron output. Alternatively, if the value is less, the signal is blocked.

For a four inputs network and single layer perceptron with four-nodes neuron, the network architecture is as below:

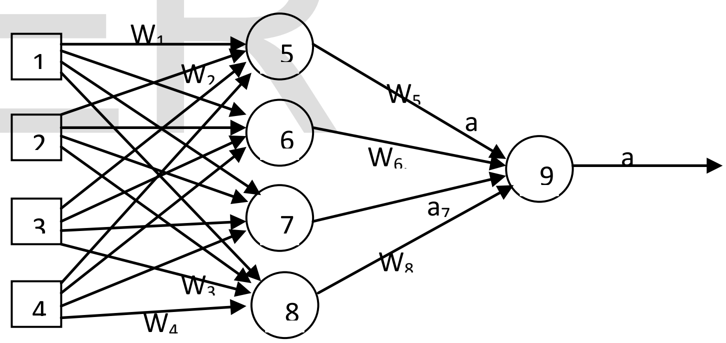


Fig. 2 Four Input Neural Network

Applying Eqn (2) on the network of fig. 2, the activation $a_9$ computes to:

$$a_9 = g(W_{5,9}a_5 + W_{6,9}a_6 + W_{7,9}a_7 + W_{8,9}a_8)$$

$$a_5 = g(W_{1,5}a_1 + W_{2,5}a_2 + W_{3,5}a_3 + W_{4,5}a_4)$$

$$a_6 = g(W_{1,6}a_1 + W_{2,6}a_2 + W_{3,6}a_3 + W_{4,6}a_4)$$

$$a_7 = g(W_{1,7}a_1 + W_{2,7}a_2 + W_{3,7}a_3 + W_{4,7}a_4)$$

$$a_8 = g(W_{1,8}a_1 + W_{2,8}a_2 + W_{3,8}a_3 + W_{4,8}a_4)$$

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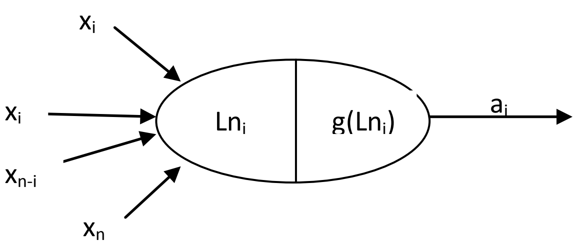


Fig.1 An Artificial Neuron

The learning process uses the sum of squares error criterion, E, to measure the effectiveness of the learning algorithm [n2]:

$$E = {E_{rr}}^2 = \frac{1}{2}\,(y - h_w(x))^2 \qquad (4)$$

where y=experimental value and $h_w(x)$ is the output of the perceptron. The error E is the difference between the network result and the desired result.
The learning process uses the Cauchy Steepest Descent or Gradient algorithm optimization method given by the formula [6]:

$$W_j(t+1) = W_j(t) + \gamma \times \nabla E(W_j) \qquad (5)$$

where t = time, and $\gamma$ = non negative scalar that minimizes the function, $E(W_j)$, in the direction of the gradient, $\nabla$, and it is equal to the network learning rate, while

$$\nabla E(W_j) = \frac{\partial W}{\partial W_j} \qquad (6)$$

But

$$\frac{\partial E}{\partial W_j} = \frac{\partial E}{\partial E_{rr}} \times \frac{\partial E_{rr}}{\partial W_j} \qquad (7)$$

Since

$$E_{rr} = \frac{\partial E}{\partial E_{rr}} \qquad (8)$$

i.e

$$\frac{\partial E}{\partial W_j} = E_{rr} \times \frac{\partial E_{rr}}{\partial W_j} \qquad (9)$$

With

$$\frac{\partial E_{rr}}{\partial W_j} = \frac{\partial}{\partial W_j}\left(yg\left(\sum_{j} = 1^n W_j x_j\right)\right) \qquad (10)$$

$$\frac{\partial E_{rr}}{\partial W_j} = g'(in) \times x_j \qquad (11)$$

Putting (11) in (9) we get that

$$\frac{\partial E_{rr}}{\partial W_j} = -E_{rr} \times g'(in) \times x_j \qquad (12)$$

$$W_j(t+1) = W_j(t) + \gamma \times E_{rr} \times g'(in) \times x_j \qquad (13)$$

### 2.1.1 Training and Learning Processes

The network training could be supervised or unsupervised. In supervised training the network is provided with the inputs and appropriate outputs. That's, the network is trained with a set of examples in a specified manner, while in the unsupervised adaptive learning, the network is provided with inputs but no outputs. The supervised training is used in this work with the appropriate feed-forward network architecture.

As shown in fig. 2, the developed neural model is from a feed forward single perceptron layer network with four nodes and uses the sigmoid activation function. In the process the network learns the error and tries to minimize it. The learning could use any natural optimization algorithms [4, 6] like the Levenberg-Marquardt, gradient descent, genetic algorithm, etc.

## 3 METHODOLOGY

The concrete under study is a four-component mix of cement, sand, palm kernel coarse aggregates and water. Among other properties of the mix such as flexural strength, deformation, durability, permeability, etc, compressive strength is considered most important in determining the quality of concrete.

The samples of the concrete cube specimens were prepared from the mix materials and crushed after curing to determine the compressive strength values. The aggregates were sampled in accordance with the methods prescribed in BS 882, Part 1:1992 [7]. The test sieves were selected according to BS 410, Part 1:1986 [8]. The water adsorption, apparent specific gravity and bulk density of the coarse aggregate were determined following procedures prescribed in the BS 812, Part 2: 1975 [10]. The Los Angeles abrasion test was carried out in accordance with American Society for Testing and materials (ASTM) Standard C131: 1976 [11]. The sieve analysis of the fine aggregates and coarse aggregate samples was done in accordance with BS 812, Part 1: 1975 [n10] and which also satisfied BS 882: 1983 [12]. The sieving was performed by a sieve shaker, and the water used in preparing the experimental samples satisfied BS 3148:1980 [13]. The specimens were cured for 28 days in accordance with BS 1881, Part 111: 1983 [14]. The crushing test was done in accordance with BS 1881, Part 116: 1983 [15], using the compressive testing machine.

### 3.1 Modeling Procedure

In the procedure, it was assumed that each of the components of concrete: cement, sand palm kernel and water could be zero or one, but in reality, none of these components could be zero or one. Hence, an appropriate transformation of the actual components: $z_1$, $z_2$, $z_3$ and $z_4$ was done to get the pseudo components $x_1$, $x_2$, $x_3$ and $x_4$ for use in deriving the regression equation [16].

The experimental cube strength values of mixes of the actual components were used in a normalized and re-arranged second degree polynomial equation to obtain the coefficients [17] of the model equation:

$$\grave{Y} = 3.20x_1 + 14.00x_2 + 12.70x_3 + 13.80x_4 - 0.08x_1x_2 + x_1x_3 - 4.00x_1x_4 + 0.80x_2x_3 + 0.40x_2x_4 - 0.20x_3x_4 \qquad (15)$$

where $\grave{Y}$ is the compressive strength value from the model and $x_i$ are the mix components.

The neural network approach has an intuitive and theoretical appeal, and developed based on the assumption that the experimental results were generated by a stochastic process, and the theoretical model based on Sheffe's [18] (4,2) lattice matrix design.

### 3.2 Network Testing and Validation

The supervised learning was used to train the network and 70% to the data was used for training while 30% was used for validation. The number of iterations (epoch) was set to 1000.

## 4 RESULTS AND DISCUSSION

### 4.1 Physical Properties of Aggregates

The physical characteristics tests of the aggregates carried out as stated in Section 3 are given in Table 1 and figs 3 and 4.

Table 1 Physical Properties of Palm Kernel Shell

| | |
|---|---|
| Specific Gravity | 1.31 |
| Uncompacted Density | 656 Kg/m$^3$ |
| Compacted Density | 545 Kg/m$^3$ |

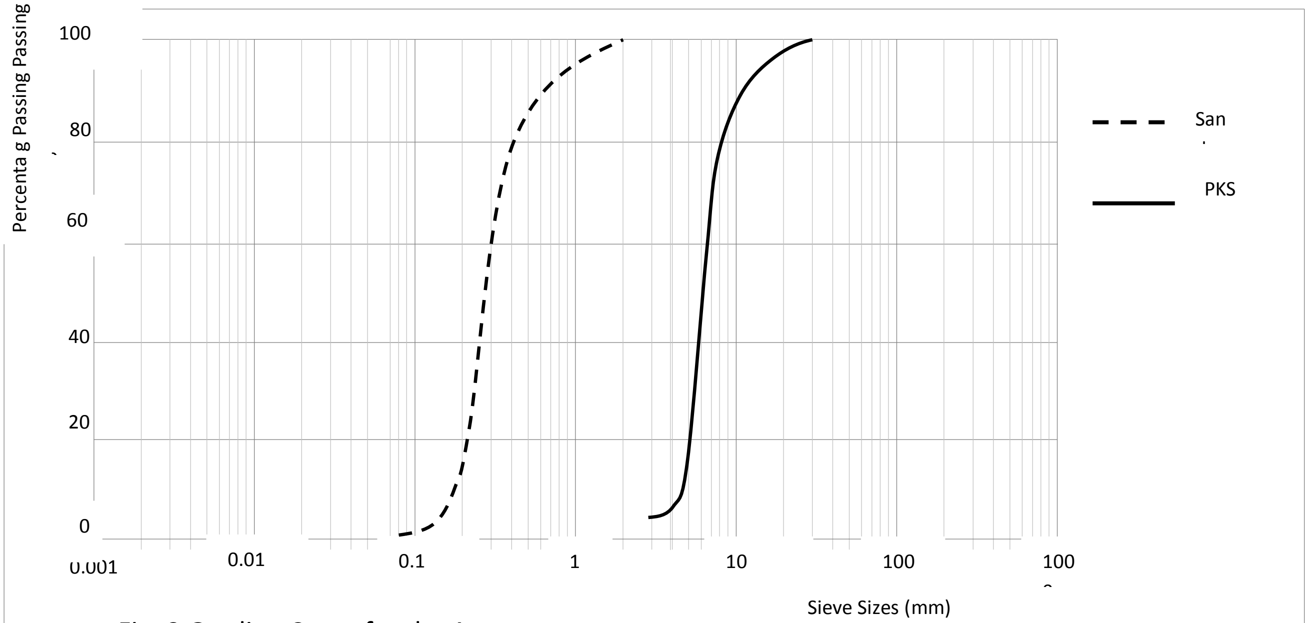


Fig. 3 Grading Curve for the Aggregates

### 4.2 Experimental and ANN Results of Compressive Strength

The results of the mix componet ratios obtained stochastically and the compressive cube strengths of specimens tested and those resulting from the ANN approach, according to the procedures in Section 3, are presented in Tables 2 and 3. The relative errors and the sum of squares errors based on the experimental and ANN results are displayed in Table 4. The correlated results of the predicted and experimental compressive results is displayed in fig. 4.

Table 2 Results of Compressive Strength Obtained Experimentally

| S/No | Cement | Sand | PKS | W/C | $Y_{exp}$ |
|---|---|---|---|---|---|
| 1 | 1.00 | 2.60 | 5.00 | 0.55 | 13.20 |
| 2 | 1.00 | 2.65 | 5.00 | 0.50 | 14.00 |
| 3 | 1.00 | 2.70 | 7.00 | 0.60 | 12.70 |
| 4 | 1.00 | 2.75 | 6.50 | 0.60 | 13.80 |
| 5 | 1.00 | 2.63 | 5.00 | 0.53 | 13.58 |
| 6 | 1.00 | 2.65 | 6.00 | 0.58 | 13.20 |
| 7 | 1.00 | 2.68 | 5.75 | 0.58 | 12.50 |
| 8 | 1.00 | 2.68 | 6.00 | 0.55 | 14.10 |
| 9 | 1.00 | 2.70 | 5.75 | 0.55 | 14.00 |
| 10 | 1.00 | 2.73 | 6.75 | 0.60 | 13.20 |
| 11 | 1.00 | 2.68 | 5.88 | 0.56 | 14.50 |
| 12 | 1.00 | 2.64 | 5.50 | 0.55 | 14.30 |
| 13 | 1.00 | 2.68 | 6.00 | 0.55 | 13.24 |

| | | | | | |
|---|---|---|---|---|---|
| 14 | 1.00 | 2.66 | 6.00 | 0.56 | 12.80 |
| 15 | 1.00 | 2.65 | 5.50 | 0.54 | 13.20 |
| 16 | 1.00 | 2.66 | 5.88 | 0.58 | 13.50 |
| 17 | 1.00 | 2.73 | 6.75 | 0.60 | 13.28 |
| 18 | 1.00 | 2.66 | 5.38 | 0.54 | 14.30 |
| 19 | 1.00 | 2.68 | 5.75 | 0.58 | 13.90 |
| 20 | 1.00 | 2.69 | 5.75 | 0.56 | 14.15 |

Table 2 Results of Compressive Strength Obtained with ANN

| S/No | Cement | Sand | PKS | W/C | $Y_{ANN}$ |
|---|---|---|---|---|---|
| 1 | 1.00 | 2.60 | 5.00 | 0.55 | 13.11 |
| 2 | 1.00 | 2.65 | 5.00 | 0.50 | 13.89 |
| 3 | 1.00 | 2.70 | 7.00 | 0.60 | 12.68 |
| 4 | 1.00 | 2.75 | 6.50 | 0.60 | 13.77 |
| 5 | 1.00 | 2.63 | 5.00 | 0.53 | 13.55 |
| 6 | 1.00 | 2.65 | 6.00 | 0.58 | 13.74 |
| 7 | 1.00 | 2.68 | 5.75 | 0.58 | 12.47 |
| 8 | 1.00 | 2.68 | 6.00 | 0.55 | 14.34 |
| 9 | 1.00 | 2.70 | 5.75 | 0.55 | 13.44 |
| 10 | 1.00 | 2.73 | 6.75 | 0.60 | 13.2 |
| 11 | 1.00 | 2.68 | 5.88 | 0.56 | 14.88 |
| 12 | 1.00 | 2.64 | 5.50 | 0.55 | 13.41 |
| 13 | 1.00 | 2.68 | 6.00 | 0.55 | 13 |
| 14 | 1.00 | 2.66 | 6.00 | 0.56 | 13.03 |
| 15 | 1.00 | 2.65 | 5.50 | 0.54 | 13.11 |
| 16 | 1.00 | 2.66 | 5.88 | 0.58 | 13.14 |
| 17 | 1.00 | 2.73 | 6.75 | 0.60 | 13.3 |
| 18 | 1.00 | 2.66 | 5.38 | 0.54 | 14.2 |
| 19 | 1.00 | 2.68 | 5.75 | 0.58 | 13.66 |
| 20 | 1.00 | 2.69 | 5.75 | 0.56 | 13.55 |

Table 4 Comparison of ANN and Regression Models

| Description | Sum of Squares Error | Correlation Coefficient |
|---|---|---|
| ANN Model | 1.8388 | 0.85 |
| Regression Model | 7.2705 | 0.61 |

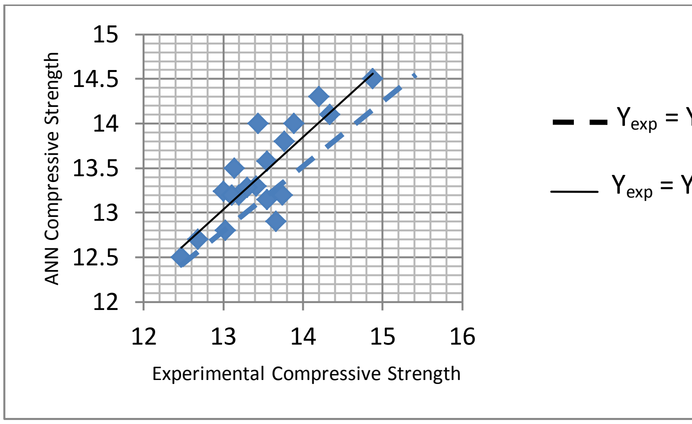


Fig. 4 Comparison of ANN Predictions with Experimental Results



### 4.3 Discussion of Results

It can be seen from the results of the study that the strength of the mixes depends on the proportion of the ingredients: cement, sand, PKS and water. From fig. 4, it could be seen that the ANN compressive strength change has the same pattern as that of the experiment with the ANN predicting slightly higher values.

With the Sum of Squares Error of the ANN model lower than that of the regression model and the reverse being the case in the case of their correlation coefficients (Table 4), it goes, generally, that the ANN models predicted better than the regression models.

The result obtained came after trials of varied ANN architectures and vary with change in the network configuration. This means that the ANN model performance depends on the selection of the network architecture.

## 5 CONCLUSION

As has been noted by [1, 2] concrete is a major construction material in the Nigerian construction industry and any poor application of the material due to improper selection of mix ratios of its components results directly in construction doom. Computational models using the ANNs are handy with solutions to concrete strength prediction as this paper demonstrates.

The ANNs' overriding advantage of not involving complex manual mathematical analysis and yet, providing results very close to experimental results reduces the task of the engineer in selecting the appropriately safe concrete component ratios even under frequent changes in the properties of the component materials. All that is required therefore, is for the engineer to get handy with the computer installed with the neural network software. Using the software, the engineer can quickly check the results from different network architectures to see which would give the best result, as done in this application.

It is recommendable that this novel concrete prediction aid be adopted by all construction engineers and technicians while similar models using other concrete material mix should be developed by engineers and scientists.

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