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Artificial neural network application to the compressive strength of palm kernel shell concrete

Abstract

This work is on the application of Artificial Neural Network (ANN) to study the effects of using palm kernel shells (PKS) as aggregates on the compressive strength of concrete. ANN with an input neuron of 6 factors, 2 hidden layers, 18 and 12 each and 1 output neuron for the compressive strength were used for this work. A mix ratio of 1: 1.5: 3 with cement content of 382kN/m^3, water-cement ratio of 0.55 were used for the work, and cured for 90 days. A total of fifty concrete mixes containing PKS in various proportions of 0 % to 40 % by wt. of the coarse aggregate were used for the training. For the validation and testing ten mixes were used.. Therefore, sixty (60) data sets were generated for which approximately eighty (80) percent was used for the training, and twenty (20) percent for the validation and test. The results showed that the distribution characteristic of PKS-concrete using ANN is adequate for the prediction of compressive strength. The predicted and experimental results are strongly correlation, with a model equation with an intercept, 1.5 and a slope of 0.93. The characteristic distribution results of the predicted with the experimental showed that the parameter estimates (ANN and Statistics), are within the 95 % confidence limits (CI), and very significant (P<0.05).

Keywords: ANN, palm kernel shells aggregate, compressive strength, statistical characteristics, PKs-concrete age

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Abbreviations: ANN, artificial neural network; NWA, normal weight aggregate; MLRA, multiple linear regression analysis; LWAC, lightweight aggregate concrete; NND, neural network design

Introduction

The development and construction pressures on our conventional materials and the growing needs for sustainability have opened up new areas for research, thus motivating researchers to focus their investigations on the use of waste or recycled materials for potential use as construction materials. The use of palm kernel shells as replacement materials for normal weight aggregate (NWA) have attracted the interest of researchers in the palm oil producing nations for use in the concrete industry. Research works on the use of palm kernel shells as aggregate materials to replace conventional aggregates in concrete have been extensively carried out and some of these works were cited as references.[1–12] on the "characteristics of palm kernel shell-concrete." The testing for strength of concrete specimen is complicated. It is equally a time consuming task. The performance of concrete is affected by many non-linear factors, more importantly, is the cost of running these experiments, when the expected strengths are not achieved using the conventional materials and methods of mix design. The reasons are there are no fixed formulations for mixing concrete constituents to obtain the compressive strength because concrete mixing is predominantly a qualitative knowledge-based approach subjected to variations.

Faraqui et al.,[13] and Khashman and Akpinar,[14] have argued the fact that reliance on such an approach compromised the precision and accuracy of concrete properties and hence, necessitates the development of a reliable mixing formulation. They also stated that statistical modeling techniques like multiple linear regression analysis (MLRA) which have been used in the past have failed to accurately predict the compressive strength, because of the highly nonlinear relationship between the concrete proportions and its properties. Researchers therefore, have come with a new trend in modern concretes involving the applications of new methods like the artificial neural network (ANN) which will enhance creditability and acceptability of our concrete works containing additives and non conventional materials. ANNs are software constructs that can be trained by example to recognize (clarify), or estimate (predict) results from a variety of inputs. The ANN ability to learn so quickly is what makes them so powerful and useful for a variety of tasks, and contains three main sections, classified as, input layer, hidden layer, and output layer.

Faruqi et al.,[13] developed a neural network model for predicting the compressive strength of concrete for different mix-design parameters. This was based on five (5) hidden layers and trained using the results of a series of previously conducted experiments. Each experiment consisted of five (5) parameters and a corresponding compressive strength obtained from 28-days cylinders tests. They observed that the neural network model performed with satisfactory results in predicting the 28-day compressive strength of concrete.

Yoon et al.,[14] worked on the mechanical properties of lightweight aggregate concrete using ANN. The study presented the ANN-based prediction for compressive strength and elastic modulus of lightweight aggregate concrete (LWAC), and concluded that the ANN model showed acceptable prediction accuracy with respect to the compressive strength and elastic with respect to compressive strength and elastic modulus of LWAC, and that the highest prediction accuracy was obtained by the ANN model compared to the use of statistical linear and nonlinear regression model.

The reviewed works on this topic were largely to some extent on the strength at 28days, and are equally based on empirical and statistical methods. These methods have limited applications, and are characterized with the issues of accuracies and precisions. Therefore, the present study on the compressive strength of PKS-concrete addressed these issues, firstly, curing beyond the conventional 28 days to 90 days, and secondly, by employing the ANN to address the issues of accuracies and precisions Khashman and Akpinar,[14] Golizadeh and Namini.,[15] Faruqi et al.,[13] Suryadi et al.,[16]. The ANN architecture used had six (6) inputs with six (6) neurons, two (2) hidden layers with eighteen (18) and twelve (12) neurons respectively, and one (1) output layer with one neuron.

Materials

The physical and chemical properties of the cement are shown in Tables 1 & 2 and conformed to BS EN 196-3.[17] The fine aggregate was river sand which is free from deleterious matters with a specific gravity of 2.64, bulk density of 1528 kg/m^3, and moisture content of 0.42. The fine aggregate was uniformly graded and falls into zone 2 of the grading curve. Table 3 is the sieve analysis of the fine aggregate. The coarse aggregate was sourced from a quarry site in Bauchi town and has a maximum size of 20mm. The physical characteristics of the coarse aggregate and PKS are shown in Table 4, while Table 5 is the particle size distribution. Both the fine and coarse aggregates conform to BS EN 1097.[18] The palm kernel shell used was sourced from Ekpoma, Edo State, Nigeria. Ekpoma is a town in the savannah region, in the southern part of the country.

Table 1 Physical properties of ashaka pc

Parameter	Value
Specific gravity	2.98
Bulk density(kg/m^3)	1475
Specific surface area(Blaine)m^2/kg	355
Loss on ignition(%)	1.51
Moisture content	0.39
pH	12.4

Table 2 Chemical properties of ashaka pc

Oxide composition	Percentage by weight (%)
CaO	62.12
SiO_2	20.69
Al_2O_3	6.14
Fe_2O_3	2.32
SO_3	1.63
MgO	1.22
Na_2O	0.9
K_2O	1.01

Table 3 Sieve analysis of fine aggregate

Sieve size	Cumulative % passing
5.00mm	–
2.00mm	93.00
1.18mm	78.00
600µm	43.80
300µm	20.40
150µm	8.20
63µm	8.16
Pan	0.00

Table 4 Characteristics of the coarse aggregate and palm kernel shells

Physical properties	Gravel	PKS
Specific gravity	2.75	1.33
Bulk density (kg/m3)	1,714	694
Water absorption (%)	0.04	17.48
Void ratio	0.38	0.48
Porosity	0.27	0.32
ACV (%)	3.69	0.36
AIV (%)	7.28	1.91

Table 5 Particle size distribution of the coarse aggregate and palm kernel shell

Sieve size(mm)	Cumulative Passing (%)	
	Coarse aggregate	Palm kernel shell
75	-	-
63	-	-
50	-	-
37	-	-
28	-	-
20	94.4	-
14	65.9	98.5
10	24.9	64.8
6.3	3.7	10.7
5	1.5	3.1
3.35	0.6	1
Pan	0	0

Laboratory experiment on PKS-concrete

The experiment to study the characteristics of PKS-concrete was mounted using a concrete mix ratio of 1:1.5:3, with a cement content of 382 kg/m^3 and water-cement ratio of 0.55 (Table 6). Four mix parameters were used and labeled M-00, M-10, M-20, and M-30, respectively. The mix labeled M-00 was the control, while the rest were having the various replacement levels of PKS by wt % of the crushed aggregate. The experiment for the compressive strength test was carried out using mould cube sizes of 100 mm, and tested in accordance with ASTM C192/C192M.[19] They were cured for 3 days to 90 days before testing to failure using a motorized ELE-machine. At the end of each curing regime, three samples were tested to failure and the average recorded. The experimental results are shown in Table 7.

Table 6 Concrete mix proportions for the experiments

Mix type	Cement (kg/m^3)	PKS (kg/m^3)	Sand(kg/m^3)	Cement (kg/m^3)	Water(kg/m^3)	W/C
M-0	1265	----	543	382	210	0.55
M-10	1138.5	126.5	543	382	210	0.55
M-20	1012	253	543	382	210	0.55
M-30	885.5	379.5	543	382	210	0.55

Table 7 Compressive strength experimental result

Mix No	3d	7d	28d	60d	90d
M-00	17.9	21.3	24	28.3	33.8
M-10	22.2	23.3	24	24.8	26.5
M-20	12.9	14.5	16.9	19	21.2
M-30	8.5	10.4	11.8	13.3	15.6

Discussion on the PKS material/compressive strength of PKS-concrete

The compressive strength of PKS-concrete Table 7 showed that as the replacement levels increased, the compressive strength decreased. The maximum strength was at 10%. At this replacement the strengths at 60days and 90 days above the strengths at 28days are 3% and 10% respectively The reductions in strength have been attributed to many factors such as the low strength of PKS compared to the crushed aggregate, the irregular shape of PKS which could prevent adequate compaction, and the bonding between PKS and cement paste because of the smooth surfaces of the PKS.[20]

Characteristics of distribution of PKS-concrete

Table 8 shows the distribution characteristics of the PKS-concrete. Measurements were made on the mean, standard error of the mean (SE.Mean), standard deviation (Std.Dev) and coefficient of variation (Coef.Var) for the curing period curing (90 days). The values achieved on the measurements showed good uniform characteristics of PKS-concrete.

The Reliability/Survival studies of the distribution analysis (Arbitrary Censoring), using the Parametric Distribution Analysis (PDA) method in Minitab 17 Software showed the degree to which these tests were consistent and stable in measuring what were intended to measure, and that the tests actually measured what they claimed to measure. These validate the extent to which inferences, conclusions, and decisions made on the basis of these test measurements are appropriate and meaningful. The results are shown in Table 9. The ninety-five percent confidence interval characteristics of the distributions for three parameters Mean, Std. Dev and Median are given in table

Table 8 Distribution characteristics

Age(Days)	Mean	SE mean	Std. Dev	Variance	CoefVar
3	15.4	3	6	35.5	38.7
7	17.4	3	6	35.8	34.4
28	19.2	3	6	35.4	31
60	21.4	3.3	6.6	43.5	30.9
90	24.3	3.9	7.8	60.1	31.9

Citation: Uchechukwu EA, Austin O. Artificial neural network application to the compressive strength of palm kernel shell concrete. *MOJ Civil Eng.* 2020;6(1):1‒10. DOI: 10.15406/mojce.2020.06.00164

Table 9 Confidence interval (95%) characteristics of distribution of PKS-concrete

Age (days)	Parameter	Estimate	Standard error	95 % Confidence	Interval
	Mean (MITF)	15.44	2.52	11.21	21.26
	Std. Dev	5.02	1.66	2.63	9.6
3	Median	15.43	2.69	10.96	21.71
	Mean (MITF)	17.47	2.49	13.21	23.1
	Std. Dev	4.96	1.67	2.56	9.61
7	Median	17.58	2.64	13.1	23.59
	Mean (MITF)	19.29	2.42	15.08	24.67
	Std. Dev	4.83	1.67	2.45	9.51
28	Median	19.49	2.54	15.09	25.17
	Mean (MITF)	21.45	2.75	16.67	27.58
	Std. Dev	5.49	1.84	2.85	10.58
60	Median	21.65	2.89	16.67	28.13
	Mean (MITF)	24.34	3.39	18.52	31.98
	Std. Dev	6.74	2.15	3.61	12.58
90	Median	24.51	3.58	18.41	32.62

Mix proportions

a. **For Training**: The mix proportions used for both the training and validation for the ANN are shown in Tables 10 & 11 respectively. A total of 60 data sets were used and they formed both the input and output data sets. Eighty (80) percent of the data sets were used for the training, and twenty (20) percent for testing and validation. The experiments were divided into two sets, one for the network learning, called learning set, and the other for validating the network, called testing set. Each set consisted of six components, cement (kg/m^3), FA and CA (kg/m^3), PKS (kg/m^3), Age and water (kg/m^3). The output vector had only one strength component, which is the compressive strength. There were fifty (50) pairs of vectors in the learning set, and ten (10) in the testing set.

Table 10 Mix proportions for network training

		Mix for the training input				
Runs	**Mix no**	**Cement(kg/m^3)**	**Fine agg.(kg/m^3}**	**Coarse agg.(kg/m^3)**	**PKS(kg/m^3)**	**Water(kg/m^3)**
1	M-00	382	543	1265	0	210
2	M-00	382	543	1265	0	210
3	M-10	382	543	1138.5	126.5	210
4	M-10	382	543	1138.5	126.5	210
5	M-10	382	543	1138.5	126.5	210
6	M-20	382	543	1012	253	210
7	M-20	382	543	1012	253	210
8	M-20	382	543	1012	253	210
9	M-30	382	543	885.5	379.5	210
10	M-30	382	543	885.5	379.5	210
11	M-00	382	543	1265	0	210
12	M-00	382	543	1265	0	210

Table continue

		Mix for the training input				
Runs	**Mix no**	**Cement(kg/m^3)**	**Fine agg.(kg/m^3}**	**Coarse agg.(kg/m^3)**	**PKS(kg/m^3)**	**Water(kg/m^3)**
13	M-00	382	543	1265	0	210
14	M-10	382	543	1138.5	126.5	210
15	M-10	382	543	1138.5	126.5	210
16	M-20	382	543	1012	253	210
17	M-20	382	543	1012	253	210
18	M-30	382	543	885.5	379.5	210
19	M-30	382	543	885.5	379.5	210
20	M-30	382	543	885.5	379.5	210
21	M-00	382	543	1265	0	210
22	M-00	382	543	1265	0	210
23	M-10	382	543	1138.5	126.5	210
24	M-10	382	543	1138.5	126.5	210
25	M-10	382	543	1138.5	126.5	210
26	M-20	382	543	1012	253	210
27	M-20	382	543	1012	253	210
28	M-20	382	543	1012	253	210
29	M-30	382	543	885.5	379.5	210
30	M-30	382	543	885.5	379.5	210
31	M-00	382	543	1265	0	210
32	M-00	382	543	1265	0	210
33	M-00	382	543	1265	0	210
34	M-10	382	543	1138.5	126.5	210
35	M-10	382	543	1138.5	126.5	210
36	M-20	382	543	1012	253	210
37	M-20	382	543	1012	253	210
38	M-30	382	543	885.5	379.5	210
39	M-30	382	543	885.5	379.5	210
40	M-30	382	543	885.5	379.5	210
41	M-00	382	543	1265	0	210
42	M-00	382	543	1265	0	210
43	M-10	382	543	1138.5	126.5	210
44	M-10	382	543	1138.5	126.5	210
45	M-10	382	543	1138.5	126.5	210
46	M-20	382	543	1012	253	210
47	M-20	382	543	1012	253	210
48	M-20	382	543	1012	253	210
49	M-30	382	543	885.5	379.5	210
50	M-30	382	543	885.5	379.5	210

Table 11 Mix proportions for the validation

Runs	Mix No	Mix Proportion for the Validation				
		Cement(kg/m^3)	Fine agg (kg/m^3)	Coarse agg(kg/m^3)	PKS(kg/m^3)	Water(kg/m^3)
1	M-00	382	543	1265	0	210
2	M-30	382	543	88.5	379.5	210
3	M-10	382	543	1138.5	126.5	210
4	M-20	382	543	1012	253	210
5	M-00	382	543	1265	0	210
6	M-30	382	543	885.5	379.5	210
7	M-10	382	543	1138.5	126.5	210
8	M-20	382	543	1012	253	210
9	M-00	382	543	1265	0	210
10	M-30	382	543	885.5	379.5	210

b. **For Testing and Validation:** The Artificial Neural Network (ANN, The neural network architecture used for this investigation is the ANN. Advantages of ANN is its adaptability to new data inputs, and it is simpler and more accurate in prediction.[14] A computer program was developed using the neural network design (NND) toolbox in MATLAB. The model had a 6-2-1 configuration as shown in Figure 1. There were 6 nodes in the input layer with 6 neurons, corresponding to the 6 parameters, 2 in the hidden layers with 18 neurons in the first hidden layer, 12 neurons in the second layer, and 1 in the output layer with 1 neuron corresponding to the compressive strength. It was observed from literature that feed forward neural networks have the ability to do complex mapping of non-linear relations. Hence, the multilayer feed forward network was used in this model. To minimize the error the back propagation was used to perform the training. The feed forward neural network model which has the ability to do complex mapping of nonlinear relations was chosen, based on the accuracy of strength validation, and mean square error (MSE), given as:

$$MSE = \frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m}\left(t_{ij} - y_{ij}\right)^2 \quad (1)$$

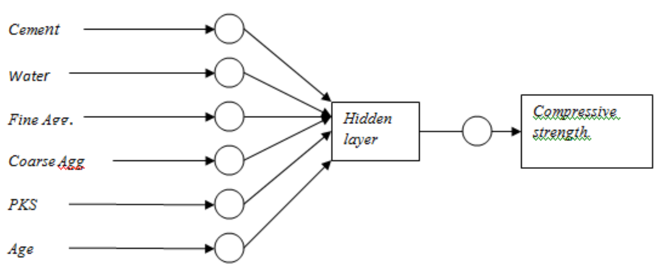

Figure 1 Neural network architecture.

Where t is the largest target value and y is the output value.

The activation function was the sigmodal function with the epoch number set to 10000 to avoid over fitting and training. The process is defined as a nonlinear input-output relation between the influencing factors (Cement content, FA content, CA content, PKS content, Water content and Age of concrete [3-90days] and the compressive strength cured [3-90days].

The Levenberg Marquardt algorithm was chosen as the most efficient one for the training of the ANN. Approximately; eighty(80) percent of the data in Table 12 was used for the training, and was stopped when the network prediction closely matched the experimental results to avoid over fitting of the network. Figure 2 is the MSE/Epoch results for the training output with a minimum final mean square error of 0.0176 (1.76%). This stabilized at an epoch value of 412. Twenty(20) percent of the total data as shown in Table 13 were used for validation and testing. Figure 3 showed the test and validation of the MSE/Epoch results. The minimum final mean square error for the validation and test was 0.0267 or 2 67%, and stabilizes at 229. After the testing and validation the predicted results were compared with the experimental data. Table 14 shows the predicted output with respect to the experimental results and the error is approximately ±5. This shows a very strong correlation between the two results. The output against target model generated for the predicted and experimental results of the compressive strength is shown in Figure 4, and the model equation is given as:

$$f_{predicted} = 1.5 + 0.93 f_{experimental} \quad (2)$$

with a correlation coefficient (r^2) of 97.0 %. This shows a very high correlation between the experiment and the predicted. Sensitivity analysis on the experimental and predicted results using the Minitab 17 Statistical Software is given as:

$$f_{predicted} = 3.99 + 0.806 f_{experimental} \quad (3)$$

The regression model is significant with a p-value of 0.000, a standard deviation (s) of 2.532, and a correlation coefficient (r^2) of 87.24%, The constant and experiment are significant with p-values of 0.116 and 0.000, respectively. Figures 5,6 are the normality and residual plots.

Figures 7, 8 are the 3D surface plots of the experimental, predicted and age of PKS-concrete on one hand and the experimental, predicted and the error. The errors are within ±5.

The distribution characteristics of the experiment and the predicted results Table 15 are within the 95% CI, and very significant ($p<0.05$). The narrower the CI the better it is Mannan MA et al.[21] If the CI is narrow, we can be quite confident that any effects far from this range had been ruled out by the study.[22,23]

Table 12 Output results (training)

		Training				Training	
Runs	Mix No	Age (Days)	Comp. str(kN/m^3)	Runs	Mix No	Age(Days)	Comp. str. (kN/m^3)
1	M-00	3	18	26	M-20	28	17.2
2	M-00	3	17.7	27	M-20	28	17.2
3	M-10	3	22.7	28	M-20	28	16.5
4	M-10	3	24	29	M-30	28	11.8
5	M-10	3	20.1	30	M-30	28	12
6	M-20	3	14.4	31	M-00	60	28
7	M-20	3	10.8	32	M-00	60	28
8	M-20	3	13.5	33	M-00	60	29
9	M-30	3	8.4	34	M-10	60	25
10	M-30	3	8.6	35	M-10	60	24.8
11	M-00	7	23.2	36	M-20	60	24.6
12	M-00	7	19.2	37	M-20	60	18.8
13	M-00	7	21.6	38	M-30	60	13.5
14	M-10	7	24	39	M-30	60	13.5
15	M-10	7	22	40	M-30	60	13
16	M-20	7	14	41	M-00	90	34.8
17	M-20	7	15.2	42	M-00	90	31
18	M-30	7	10.2	43	M-10	90	17
19	M-30	7	10.4	44	M-10	90	26.4
20	M-30	7	10.6	45	M-10	90	26
21	M-00	28	25,6	46	M-20	90	21
22	M-00	28	23.5	47	M-20	90	21.2
23	M-10	28	24.5	48	M-20	90	21.4
24	M-10	28	23.5	49	M-30	90	16
25	M-10	28	24	50	M-30	90	15.8

Table 13 Validation results

		Validation output results	
Runs	Mix No	Age (days)	Comp. Str
1	M-00	3	17.9
2	M-30	3	8.6
3	M-10	7	23.8
4	M-20	7	15.2
5	M-00	28	23
6	M-30	28	11.5
7	M-10	60	24.6
8	M-20	60	19.2
9	M-00	90	35.6
10	M-30	90	15

Table 14 Experimental versus predicted results

Property		Experimental versus predicted			
	Mix no	**Age(days)**	**Experiment**	**Predicted**	**Error**
Compressive Strength	M-00	3	17.9	22.9	-5
	M-30	3	8.6	10.1	-5.2
	M-10	7	23.8	19.1	4.7
	M-20	7	15.2	14.7	0.5
	M-00	28	23	25.6	-2.6
	M-30	28	11.5	12.1	-0.6
	M-10	60	24.6	24.2	0.4
	M-20	60	19.2	19.4	-0.2
	M-00	90	35.6	32	3.6
	M-30	90	15	16.5	-1.5

Table 15 Characteristics of distribution for the experimental and predicted results

	Goodness of fit. [Anderson-Darling Adj]	Basic statistics	Estimates	Std. error	95 % Normal CI	
					Lower	**Upper**
Parameter		Mean (MTTF)	19.47	2.37	15.33	24.71
Experiment Result	1.443	Standard Deviation	7.46	1.48	5.05	11.02
		Median	19.2	2.53	14.83	24.85
			14.06	2.56	9.84	20.09
		Mean (MTTF)	19.69	2.03	16.09	24.1
Predicted Result		Standard Deviation	6.4	1.27	4.34	9.44
	1.365	Median	19.68	2.16	15.87	24.4
			15.1	2.32	11.25	20.5

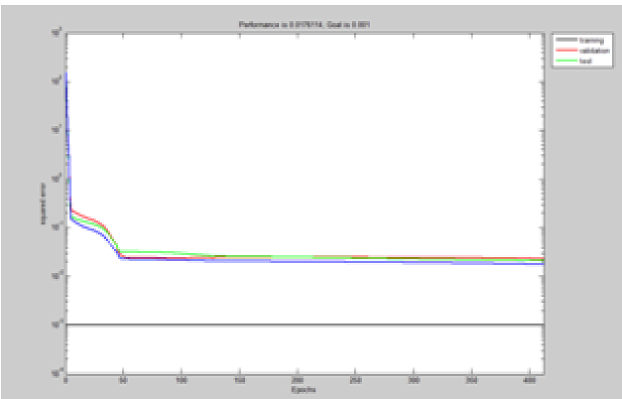

Figure 2 Training epoch for compressive strength.

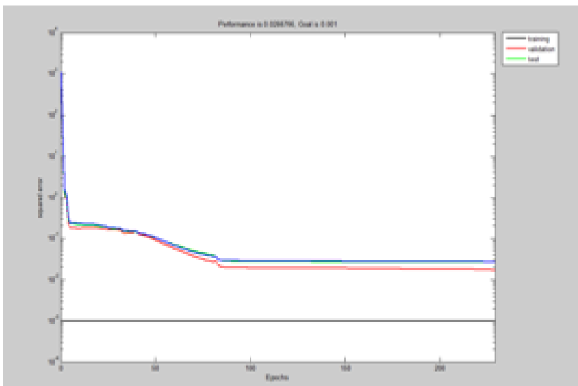

Figure 3 Training epoch for test and validation.

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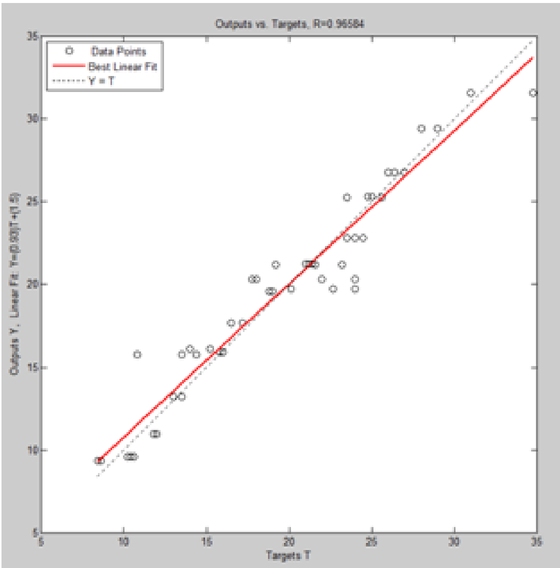

Figure 4 Neural network output against target.

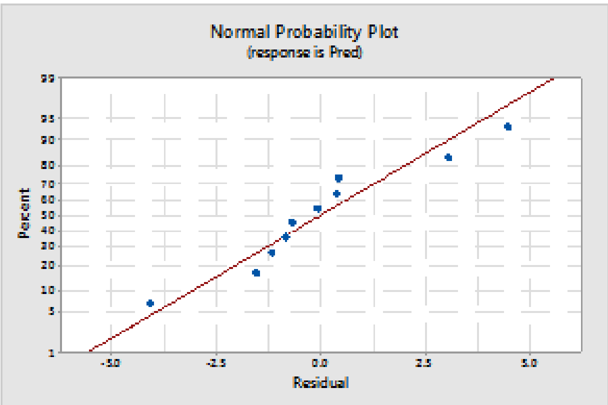

Figure 5 Normal probability plots.

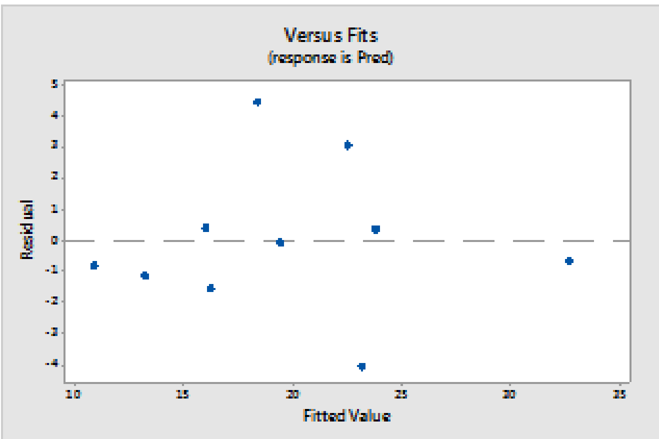

Figure 6 Residual Plot.

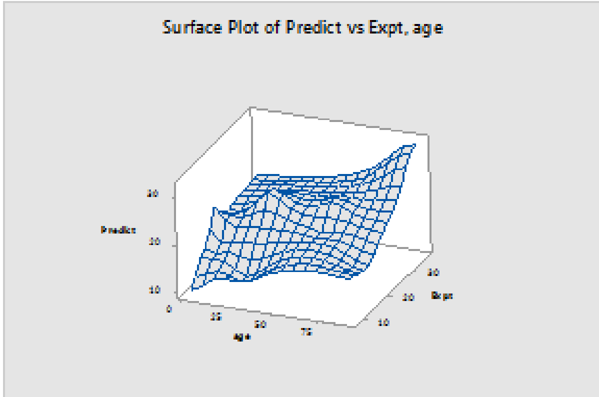

Figure 7 Surface plots of the experiment, prediction and age.

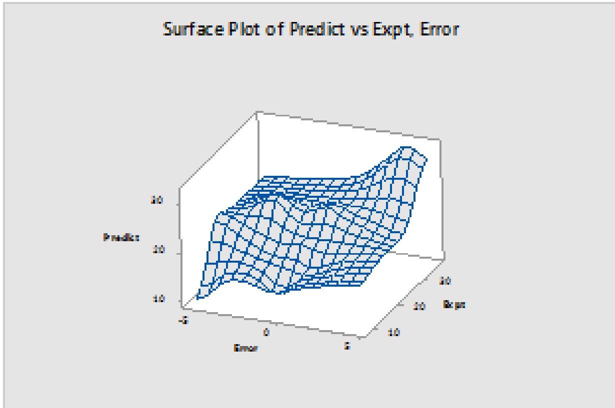

Figure 8 Experiment, predicted and error.

Conclusion

The application of ANN to study the compressive strength of palm kernel shell (PKS) concrete has been evaluated, and the following are the conclusions.

a) The compressive strength of PKS-concrete decreased as the percentage replacement increased, and the optimum replacement level was at 10%.

b) The reduction in strength have been attributed to factors like PK.S lower strength, irregular shapes and poor bonding of the cement paste.

c) The distribution characteristics of PKS-concrete showed that PKS can be used for producing good concrete.

d) The use of ANN for compressive strength evaluation gives reliable results.

e) The comparison of the predicted and experimental results shows very strong correlation, and model equation has an intercept of 1.5, and a sloe of 0.93. The correlation coefficient is 97.0%.

f) The Minitab 17 Statistical Software values for the predicted and experimental has an intercept of 3.99 and a slope of 0.806, with a correlation coefficient of 87.24%. This shows that the ANN gives more refined model output.

g) The characteristic distribution results showed that the estimates are within the 95% confidence limits (CI), and very significant (P<0.05). The estimated values are within the specified lower and upper limits of CI.

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Conflicts of interest

The author declares that there are no conflicts of interest.

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