



Artificial Neural Network Application to the Flexural Strength of Palm Kernel Shell Concrete

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Abstract

Application of Artificial Neural Network (ANN) to study the effects palm kernel shells (PKS) as partial replacement for normal weight aggregates on the flexural strength of concrete has been carried out. A mix ratio of 1: 1.5: 3 with cement content of 382 kN/m³, water-cement ratio of 0.55 were used for the work, and cured for 90 days. The results showed that the distribution characteristic of PKS-concrete using ANN is adequate for the prediction of flexural strength. The predicted and experimental results are strongly correlated with a model equation of intercept 0.32 and a slope of 0.91. The Minitab 17 software output has an intercept and slope of 0.37 and 0.91. This showed an agreement of 86 % and 100 % respectively. 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 (PKS) aggregate, flexural strength, statistical characteristics, PKS-concrete, age

Introduction

Extensive research works on the use of palm kernel shells as aggregate materials to replace conventional aggregates in concrete have been an interest of research recently. The reasons for such interest are the availability of this material as waste in the palm kernel oil industry. Other important reasons are the development and construction pressures on our conventional materials (normal aggregates), and the growing needs for sustainability. The suitability of palm kernel shell (PKS) as aggregate material has been confirmed by many researchers. Details of such work can be found in Elinwa [1]. A further deficiency was echoed on the qualitative knowledge approach of concrete mixes [2], for which Faraqui et al [3] postulated that it compromised the precision and accuracy of concrete properties. It is also stated that the statistical modeling techniques like the multiple linear regression analysis (MLRA) have failed to accurately predict the mechanical strengths of concrete because of highly nonlinear relationship between concrete proportions and its properties.

As a result of all these deficiencies development works using optimization tools like Artificial Neural Network (ANN) have found important use in enhancing credibility and acceptability for concrete works with additives and non-conventional materials like palm kernel shells. It has been reported in the literature that there are three approaches that are commonly used to predict compressive strength [4]. Dao et al (2019) outlined these as computational modelling, parametric multi-variable regression, or the artificial intelligence approach, and that artificial neural network (ANN) approaches have been broadly used by researchers [4]. 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.

The PKS is a waste from the palm oil industry, and majority of the reviewed works in the literature are on PKS cured for the period of 28 days which is the conventional curing period of concrete. This has been reported as a research gap [2], and hence the need to evaluate the performance of PKS beyond the 28 days curing period was stressed by them. They addressed this gap by curing for 3 days to 90 days in water before testing to failure. The second issue raised in their work was the deficiencies in accuracies and precisions inherent in the prescriptive approaches. This they addressed by using artificial neural network (ANN) to predict the compressive strength of PKS-concrete cured for 90 days [2] thus concluding that the predicted and experimental results were strongly correlated. The model equation has an intercept and slope of 1.5 and 0.93, respectively. The results of the characteristics distribution of the predicted compared with the experimental showed that the parameter estimates (ANN and statistics) were within the 95 % confidence limits (CI), and very significant ($P < 0.05$). They therefore, concluded that the distribution characteristics of PKS-concrete using ANN are adequate for the prediction of compressive strength [2].

In this investigation, five (5) flexural grades of PKS-concrete (M-00, M-10, M-20, M-30, and M-40) were designed in accordance to ACI 211-91 [5] and used to investigate the effects of PKS on the flexural strength of concrete. Five (5) constituent materials were used and named as simulation inputs X_1 , X_2 , X_3 , X_4 , and X_5 . These inputs are PKS, cement, fine aggregate, coarse aggregate, water content, and age, respectively, and are presumed to highly influence the final flexural strength of PKS-concrete which is taken as the output Y for the prediction study. The ANN architecture used has Six (6) Inputs with six (6) neurons, One (1) Hidden layer with twelve (12) neurons, and One (1) Output layer with one neuron [2], for predicting the flexural strength of PKS concrete samples, and to evaluate the prediction performance using statistical methods. The sensitivity analysis to evaluate the impact of input variable fluctuations on the output results are quantified using linear regression.

Material

The materials used for this work are 'Ashaka' Portland cement conforming to BS EN 196 Part 3 [6]. The fine, coarse and palm kernel shell aggregates also conforming to BS EN 1097-6 [7], and potable drinking water. The characteristics of these materials and their possible effects on the concrete have been dealt in details in the previous publications and would not be repeated in this work [1, 2].

Experimental Programme

Flexural testing is used to determine the bending properties of a material and sometimes referred as a transverse beam test involving the placement of a sample between two points or supports and initiating load using a third point or two points which are respectively called 3-point bend and 4-point bending testing. For this work, a 4-point bending testing was chosen because of the advantage of producing peak stresses along an extended region of the specimen, hence exposing a larger length of the specimen with more potential for defects and flaws to be highlighted.

Table 1 shows the mix proportions used for the investigation. A mix ratio of 1: 1.5: 3 with a cement content of 382 kg/m^3 and a water-cement ratio of 0.55 was used. In carrying out the experiment using this mix proportions, palm kernel shells were used as coarse aggregate to replace the normal weight aggregate (20 mm) in proportions of 0 %, 10 %, 20 %, and 30 % by weight, respectively, to produce palm kernel shell concrete. The beam specimen dimension used is 150 mm x 150 mm x 460 mm. The actual span of the beam chosen 310 mm. A total of sixty

specimens were cast using four mixes designated as M-00, M-10, M-20, and M-30 according to the specified replacement levels and cured for a period of 90 days in a water curing tank at laboratory temperature. At the end of each curing regime three specimens are tested to failure. The results are shown in Table 2.

Discussion on the PKS Material/Flexural Strength of PKS-Concrete

The flexural strength of PKS-concrete as shown in Table 2 decreased as the replacement with PKS increased, and the maximum strength was at 10 % replacement. 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 [1]. The physical characteristics of the PKS and coarse aggregate led credence to the attributable factors for low strength. At this replacement the strengths at 60 days and 90 days are above the strengths at 28 days by 3 % and 10 % respectively. Traore et al [8] in their work on PKS concrete recorded a flexural strength range of 2.8 to 3.6 MPa at 28 days of curing. Shafigh et al [9] registered in their work a flexural range of 4.42 to 6.99 MPa at 28 days of curing. Other studies on PKS as reported in [9] ranged from 2.13-4.93 MPa. Sulyman [10] gave the flexural strength of three different mixes 2:3:6, 1:2:4, 1:3:6, cured to 28 days as 3.78-1.96, 2.20-1.48, and 2.02-0.37, respectively. The results of the present work showed agreement in the range of flexural strengths with works of past researchers.

Table 1: 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 2: Flexural Strength Experimental Result

Mix No	3 d	7 d	28 d	60 d	90 d
M-00	3.7	4.3	4.9	5.1	5.5
M-10	3.0	3.1	3.9	4.0	4.3
M-20	2.6	2.9	3.6	3.7	3.8
M-30	1.9	2.5	2.6	2.7	3.0

.Characteristics of Distribution of PKS-Concrete

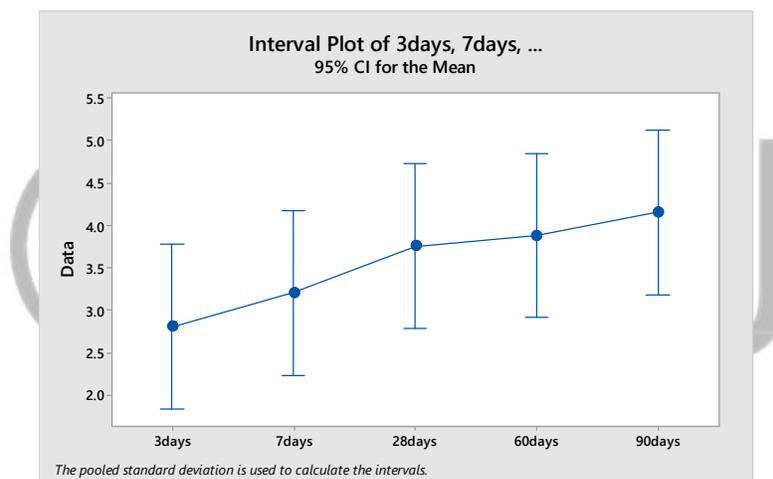
Tables 3 and 4 show the distribution characteristics of the PKS-concrete used for the flexural strengths determination. The measurements that were made were on the mean, standard error of the mean (SE.Mean), standard deviation (St.Dev) and coefficient of variation (Coef.Var) and the confidence limits at $\alpha = 0.05$ for the within and in-between (Batch to Batch) tests for PKS-concrete. The values achieved on the measurements showed good and uniform characteristics of PKS-concrete. Figure 1 (a & b) is the confidence intervals for both the in-between and batch-to-batch test samples at 95 % CI, respectively. The figure shows that the in-between test results increased as the age of the PKS-concrete increased, and decreased as the replacement levels increased.

Table 3: Distribution Characteristics (Within Test)

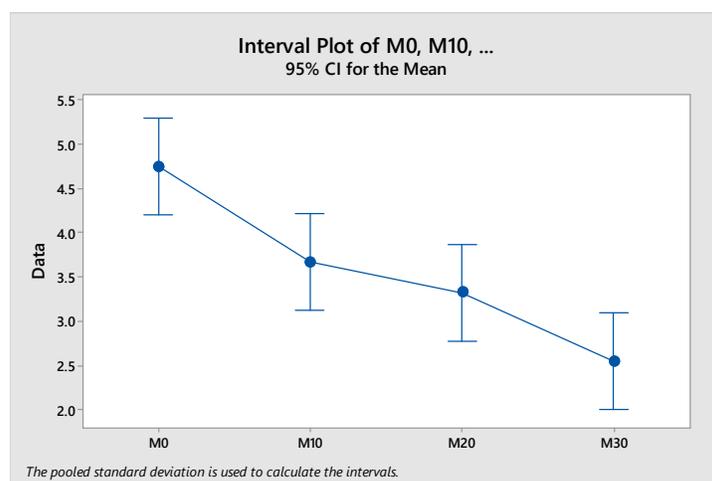
Age (Days)	Mean	SE mean	StDev	Variance	CoefVar	CI ($\alpha = 0.05$)	
						Lower	Upper
3	2.80	0.38	0.75	0.57	26.88	1.831	3.769
7	3.20	0.39	0.78	0.60	24.21	2.231	4.169
28	3.75	0.47	0.95	0.90	25.25	2.781	4.719
60	3.88	0.49	0.99	0.98	25.49	2.906	4.844
90	4.15	0.52	1.05	1.10	25.23	3.181	5.119

Table 4: Distribution Characteristics (In-Between)

Mix	Mean	SE mean	StDev	Variance	CoefVar	CI ($\alpha = 0.05$)	
						Lower	Upper
M0	4.740	0.331	0.740	0.548	15.62	4.193	5.287
M10	3.660	0.258	0.577	0.333	15.77	3.113	4.207
M20	3.320	0.240	0.536	0.287	16.14	2.773	3.867
M30	2.540	0.181	0.404	0.163	15.89	1.993	3.087



[a]



[b]

Figure 1: Confidence Intervals for In-Between and Batch-to-Batch Test Samples

ANOVA is a procedure that uses hypothesis testing to determine whether the factor effects of two or more factors are the same and a common technique for analysing the statistical significance of a number of factors in a model. This method was used for the sensitivity analysis of the test results of this work. The two level factors of treatments considered for this work are the Mix and Age of the PKS-concrete. The generatic data for this is shown in Table 5.

Table 5: Generatic Data Table for 2-Level Factor Experiment

Mix	Age (Days)					Total	Average
	3	7	28	60	90		
M-00	y ₁₁	y ₁₂	y ₁₃	y ₁₄	y ₁₅		
M-10	y ₂₁	y ₂₂	y ₂₃	y ₂₄	y ₂₅		
M-20	y ₃₁	y ₃₂	y ₃₃	y ₃₄	y ₃₅		
M-30	y ₄₁	y ₄₂	y ₄₃	y ₄₄	y ₄₅		
						Σy	ȳ _{..}

The Factor Level for the within test variance (SSE) is considered as the Age of the PKS-concrete for 3 days, 7 days, 28 days, 60 days and 90 days, respectively, and the ‘within’ factor variance is given as:

$$SSE = \sum_{i=t}^v \sum_{t=1}^{r_i} (y_{it} - \bar{y}_i)^2 \dots (1)$$

$$\bar{y}_i = \frac{\sum_{t=1}^{r_i} y_{it}}{r_i} \dots (2)$$

Where:

y_i = the tth observation at the ith level of the factor,

r_i = the number of observations in factor level i,

v = the number of factor levels being tested.

The results of the analysis are shown in Table 6

Table 6: Analysis of Variance (Within Test)

Source	DF	Adj. SS	Adj.MS	F-Value	P-Value
Factor (Within)	4	4.762	1.1905	1.44	0.269
Error	15	12.407	0.8272		
Total	19	17.169			

The Factor Level for the in-between test variance (SSR) is the Mix of the PKS-concrete at M-00, M-10, M-20, M-30, respectively, and the ‘in-between’ factor is given as:

$$SSR = \sum_{i=1}^v r_i (\bar{y}_i - \bar{y}_{..})^2 \dots (3)$$

Where

$$\bar{y}_{..} = \frac{\sum_{i=1}^v \sum_{t=1}^{r_i} y_{it}}{n} = \frac{y}{n} \dots (4)$$

The results are shown in Table 7. The residual plots for these considerations are shown in Figures 3 and 4 respectively.

Table 7: Analysis of Variance (In-Between Test)

Source	DF	Adj. SS	Adj. MS	F-Value	P-Value
Factor (Within)	3	12.501	4.1672	12.52	0.000
Error	16	5.32	0.3327		
Total	19	17.8254			

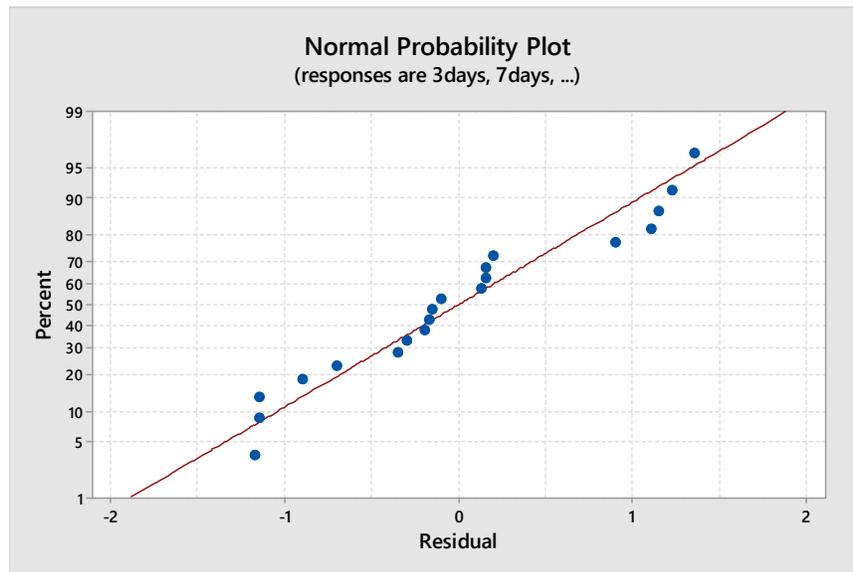


Figure 3:

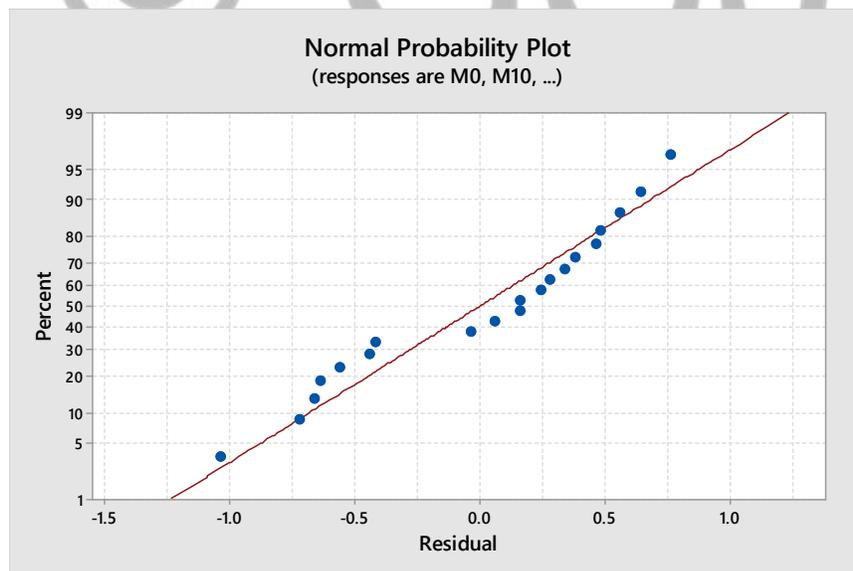


Figure 4:

Artificial Neural Network PKS-Concrete

The second phase of the analysis is the application of artificial neural network to optimize the mix parameters for PKS-concrete. The same ANN architecture is used [2] and the characteristics is shown in Table 8. It is a 6-2-1 configuration defined as six (6) in-put parameters, two (2)

hidden layers comprising of eighteen (18) neurons in the first hidden layer, twelve (12) neurons in the second layer and one (1) output layer with one (1) neuron, corresponding to the flexural strength of the beam. The feed forward neural network was chosen based on the accuracy of strength validation, and mean square error (MSE). The activation function was the sigmodal function with the epoch number set to 10000 to avoid overfitting and training. The process is defined as a non-linear input-output relation between the influencing factors (Cement content, FA content, CA content, PKS content, Water content, and Age of concrete), and the flexural strength cured for 3 to 90 days.

Table 8: Characteristics of ANN Architecture for the Flexural Strength Test

Input Parameter	Hidden Layer		Output Parameter
	1 st Hidden	2 nd Hidden	
Cement			
Fine aggregate			
Coarse aggregate	18 neurons	12 neurons	1 (Flexural strength)
Potable water			
Palm kernel shell			
Age			

Mix Proportions used for ANN Training and Test/Validation

The mix proportions used for both the training and validation for the ANN are shown in Tables 9 and 10, 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 Flexural strength. There were fifty (50) pairs of vectors in the learning set, and ten (10) in the testing set.

Table 9: Mix Proportions for Network Training

Runs	Mix no	Mix for the Training Input				
		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
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 10: 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

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 11 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 5 is the MSE/Epoch results for the training output with a minimum final mean square error of 0.0239 (2.39 %). This stabilized at an epoch value of 253. Twenty (20) percent of the total data as shown in Table 12 were used for validation and testing. Figure 6 showed the test and validation of the MSE/Epoch results. The minimum final mean square error for the validation and test was 0.0230 or 2.30 %, and stabilizes at 85. After the testing and validation the predicted results were compared with the experimental data. Table 13 shows the predicted output with respect to the experimental results and the error is approximately -0.40 to + 0.43. This shows a very strong correlation between the two results. The output against

target model generated for the predicted and experimental results of the flexural strength is shown Figure 7, and the model equation is given as: $f_{predicted} = 0.32 + 0.91f_{experimental}$ (5), with a correlation coefficient (r^2) of 95.1 %. This shows a very high correlation between the experiment and the predicted.

Table 11: Output Result (Training)

Runs	Mix No	Training		Runs	Mix No	Training	
		Age (Days)	Comp. Str. (kN/m ³)			Age (Days)	Comp. Str. (kN/m ³)
1	M-00	3	3.77	26	M-20	28	3.64
2	M-00	3	3.73	27	M-20	28	3.58
3	M-10	3	2.94	28	M-20	28	3.57
4	M-10	3	3.01	29	M-30	28	2.61
5	M-10	3	2.96	30	M-30	28	2.57
6	M-20	3	2.66	31	M-00	60	5.05
7	M-20	3	2.59	32	M-00	60	5.05
8	M-20	3	2.63	33	M-00	60	5.14
9	M-30	3	2.00	34	M-10	60	4.13
10	M-30	3	1.83	35	M-10	60	3.95
11	M-00	7	4.23	36	M-20	60	3.67
12	M-00	7	4.32	37	M-20	60	3.64
13	M-00	7	4.23	38	M-30	60	2.66
14	M-10	7	3.12	39	M-30	60	2.65
15	M-10	7	3.09	40	M-30	60	2.70
16	M-20	7	2.85	41	M-00	90	5.57
17	M-20	7	2.99	42	M-00	90	5.51
18	M-30	7	2.48	43	M-10	90	4.41
19	M-30	7	2.42	44	M-10	90	4.50
20	M-30	7	2.44	45	M-10	90	3.86
21	M-00	28	4.96	46	M-20	90	3.82
22	M-00	28	4.96	47	M-20	90	3.77
23	M-10	28	3.80	48	M-20	90	3.86
24	M-10	28	3.95	49	M-30	90	2.96
25	M-10	28	3.91	50	M-30	90	2.99

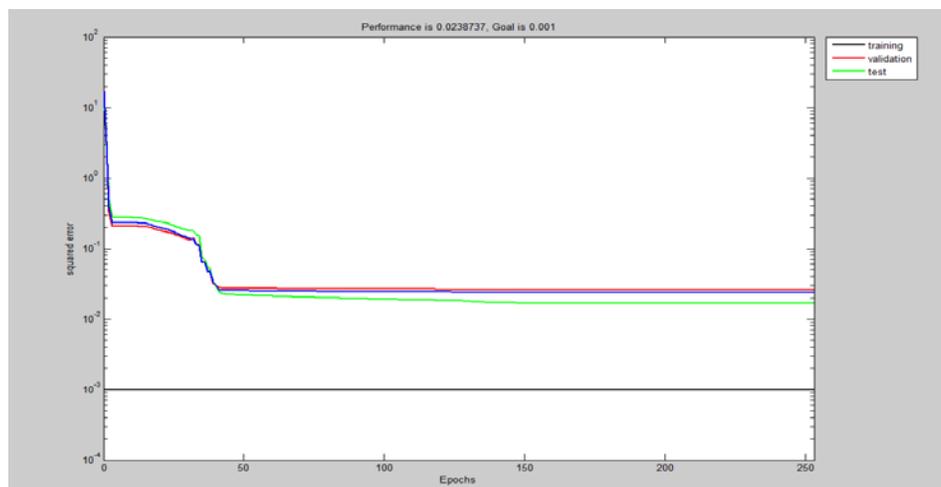


Figure 5: Training Epoch (Square Error versus Epochc) for Flexural Strength

Table 12: Output Result (Testing and Validation)

Runs	Mix No	Validation Output Results	
		Age (days)	Flexural Strength
1	M-00	3	3.67
2	M-30	3	1.95
3	M-10	7	3.14
4	M-20	7	2.99
5	M-00	28	4.86
6	M-30	28	2.57
7	M-10	60	4.00
8	M-20	60	3.73
9	M-00	90	5.27
10	M-30	90	2.92

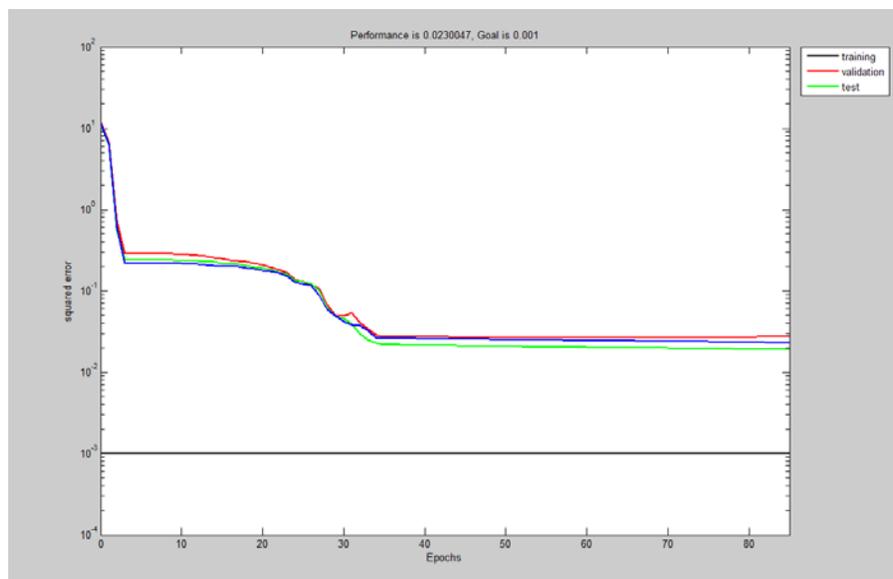


Figure 6: Training Epoch (Square Error versus Epochs) for Test and Validation

Table 13: Experimental Versus Predicted Results

Property	Mix No	Experimental versus Predicted			
		Age (days)	Experiment	Predicted	Error
Compressive Strength	M-00	3	3.67	4.07	-0.40
	M-30	3	1.95	2.28	-0.33
	M-10	7	3.14	3.42	-0.28
	M-20	7	2.99	2.82	+0.17
	M-00	28	4.86	4.43	+0.43
	M-30	28	2.57	2.50	+0.07
	M-10	60	4.00	4.10	-0.10
	M-20	60	3.73	3.39	+0.34
	M-00	90	5.27	5.42	-0.15
	M-30	90	2.92	3.11	-0.19

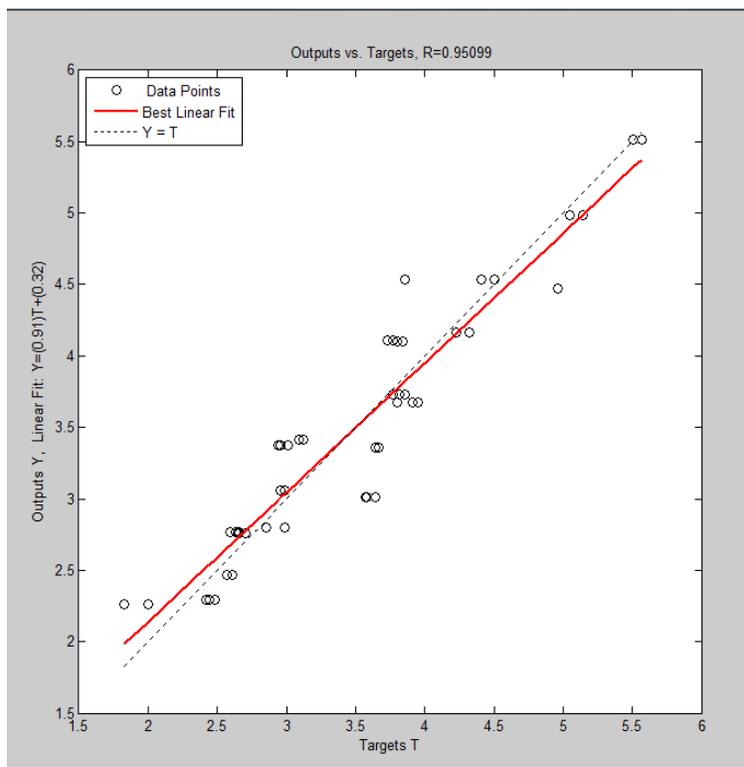


Figure 7: Neural Network Output against Target

- i. Sensitivity analysis on the experimental and predicted results using the Minitab 17 Statistical Software is given as: $f_{predicted} = 0.37 + 0.91f_{experimental} \dots (3)$. The regression model is significant with a p-value of 0.001, a standard deviation (s) of 0.2856, and a correlation coefficient (r^2) of 92.2 %, The constant has a p-value of 0.314 (not significant) and the experimental, 0.001 (significant), respectively. The agreement of the ANN application and Minitab 17 software on the intercept and slope for the predicted and experimental are 86 % and 100 % respectively. Figures 8 and 9 are the fitted line plot and residual plots.

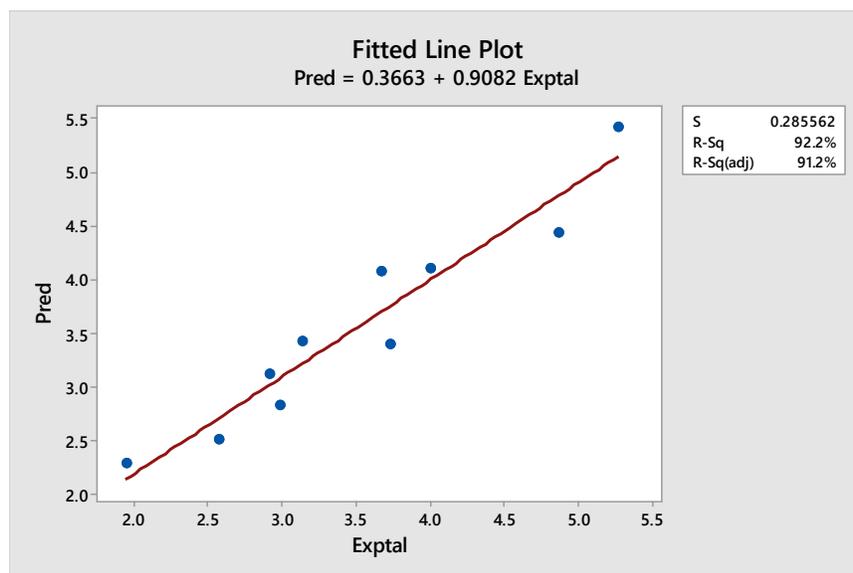


Figure 8: Fitted line plot of the Predicted versus Experimental

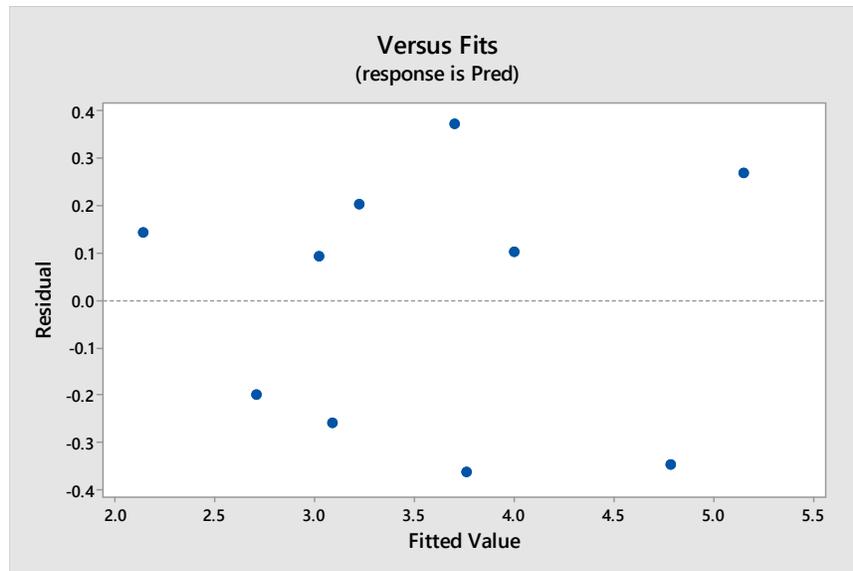


Figure 9: Residual Plot of the Predicted versus Experimental

Figures 10 and 11 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 -0.40 and $+0.43$.

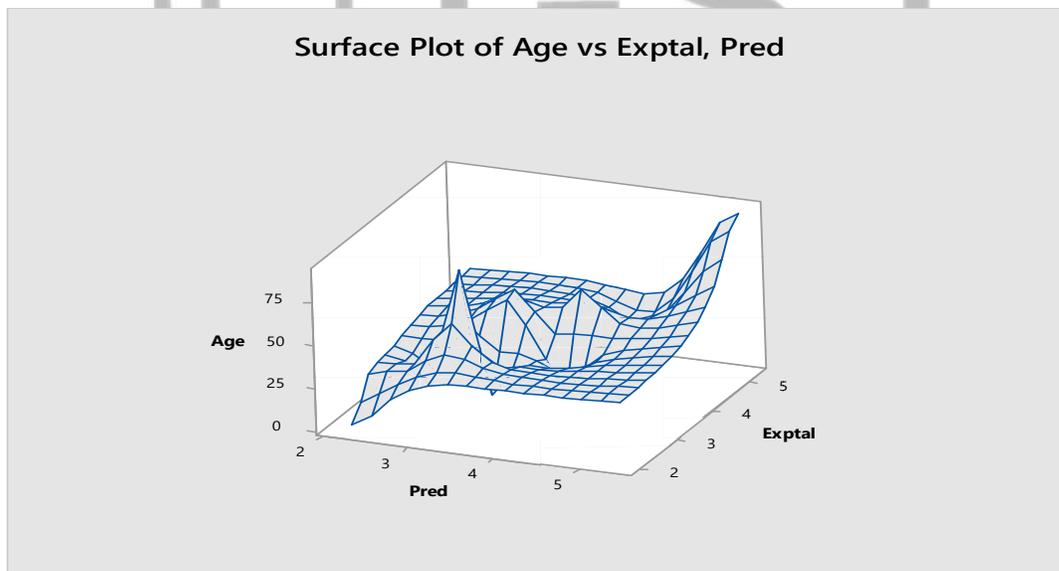


Figure 10: 3D Diagram for the Age, Predicted and Experimental

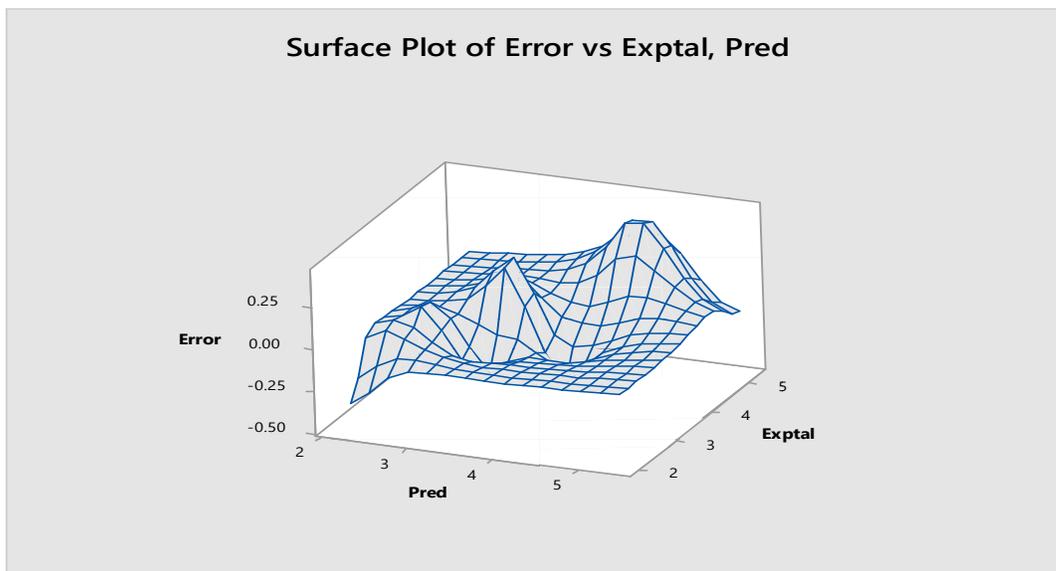


Figure 11: 3D Diagram for the Error, Predicted and Experimental

The distribution characteristics of the experiment and the predicted results (Table 14) are within the 95 % CI, and very significant ($p < 0.05$). The narrower the CI the better it is [11]. If the CI is narrow, we can be quite confident that any effects far from this range had been ruled out by the study [12, 13].

Table 14: Characteristics of Distribution for the Experimental and Predicted Results

Parameter	Goodness of fit. [Anderson-Darling Adj]	Basic Statistics			95 % Normal CI	
		Estimates	Standard Error		Lower	Upper
Experiment Result	1.461	Mean (MTTF)	3.51	0.32	2.94	4.12
		StD Deviation	0.99	0.19	0.68	1.46
		Median	3.53	0.33	2.94	4.25
Predicted Result	1.437	Mean (MTTF)	3.55	0.31	3.00	4.20
		StD Deviation	0.96	0.18	0.66	1.40
		Median	3.58	0.32	3.01	4.27

Conclusion

The results of the flexural strength of PKS-concrete and the characteristics of PKS mixes using ANN method and Minitab 17 Software have been presented and some of the conclusions are as stated below. They are as follows, that:

- ii. The use of ANN for flexural strength evaluation of PKS-concrete gave reliable results.
- iii. The comparison of the predicted and experimental results showed very strong correlation, and the model equation has an intercept (β_0) of 0.32, and a slope of (β_1) 0.91. The correlation coefficient for this is 95.0 %.
- iv. The Minitab 17 Statistical Software values for the predicted and experimental has an intercept of 0.37 and a slope of 0.91, with a correlation coefficient of 92 %.

- v. The agreement of the ANN application and Minitab 17 software on the intercept and slope for the predicted and experimental are 86 % and 100 % respectively.
- vi. The characteristic distribution results of the PKS-concrete showed that the estimates are within the 95 % confidence limits (CI), and very significant ($P < 0.05$).
- vii. The estimated values are within the specified lower and upper limits of CI.

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