Novelty Journals

ISSN 2394-7357

International Journal of Novel Research in Civil Structural and Earth Sciences
Vol. 3, Issue 3, pp: (6-14), Month: September - December 2016, Available at: www.noveltyjournals.com

COMPRESSIVE STRENGTHS PREDICTION MODEL FOR BAGASSE ASH CONCRETE

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***Abstract*: This paper deals with development of regression models for prediction of compressive strength of bagasse ash (BA) concrete. The compressive strength of dry BA concrete was determined using two variables, namely, curing period and pozzolanic Portland cement (PPC) content for BA grain size < 0.075 and water – PPC ratio of 0.55. The polynomial regression models were developed by varying PPC replacements (0, 5, 10, 15, 20, 25 and 30 percent) and curing periods (7, 14 and 28 days). Effort was made to modify the polynomial models using a three step approach. First step was identifying the best curve fitting technique (least square and interpolation methods). The second step of model development was to compute *adjusted* R^2 for the polynomial Regression models. The final step was model validation. Least square quadratic polynomial (LSQP) with degree of the regression n = 4 was established as the most effective and accurate model in compressive strength prediction of BA concrete.**

***Keywords:* Regression Models, Compressive Strength, Baggase Ash Concrete, Pozzolanic Portland cement, Least square quadratic polynomial.**

1. INTRODUCTION

Regression models for prediction of compressive strength of bagasse ash (BA) concrete were developed. Two variables, namely, curing period and pozzolanic Portland cement (PPC) content for BA grain size < 0.075 and water – PPC ratio of 0.55 were used to determine the compressive strengths of dry BA concrete. PPC replacements (0, 5, 10, 15, 20, 25 and 30 percent) and curing periods (7, 14 and 28 days) were varied to develop the polynomial regression models. Some related research has been conducted in the recent past to develop models for prediction of other properties of concrete when it's blended with various other admixtures. Among the research works conducted on concrete was by Rachna *et al*. 2015 [1], in their paper models were developed for variations in fly ash replacements (0 and 15 percent), aggregates and curing ages (28, 56 and 91 days) with the proposed quadratic regression models yielding coefficient of determination $R^2 \geq 0.99$. Charvez *et al*. (2015) [2] focused on the mechanical and physical evaluation of Portland cement mortars with the addition of BA and a high-range water-reducing and super-plasticizing admixture. From the results of the destructive and non-destructive testing, correlations were obtained using multiple linear regressions which indicated the best model according to the correlation factor obtained. An implicit response analysis of the compressive strength of concrete was carried out by Nwoye *et al*. (2015) [3], based on its ageing periods and extent of cement replacement with BA. Regression model was used to generate results of compressive strength of concrete, and its trend of distribution was compared with that from derived model as a mean of verifying its validity relative to experimental results. Ettu *et al*. (2013) [4] investigated the strength characteristics of binary blended cement composites made with Ordinary Portland Cement (OPC) and Saw Dust

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Ash (SDA). Mathematical models were developed for predicting compressive strengths of OPC-SDA binary blended cement composites using polynomial regression analysis. Ettu *et al.* (2013) [5] also investigated the strength characteristics of binary blended cement composites made with OPC and Cassava Waste Ash (CWA). Mathematical models were developed for predicting compressive strengths of OPC-CWA binary blended cement composites using polynomial regression analysis. Hamed and Saeed [6] developed an empirical model to predict the compressive strength of concrete using Palm Oil Fuel Ash (POFA) as a cement replacement material and other properties of the concrete such as the slump and modulus of elasticity using an artificial neural network. In his effort to optimize BA content in cement-stabilized lateritic soil, Okonkwo (2015) [7] developed regression models involving relationships of cost of BA, cement content, optimum moisture content, California bearing ratio and unconfined compressive strength at 7 days curing period. Radhakrishna (2013) [8] developed compressive strength prediction models for fly ash concrete. Cement in concrete mix, proportioned according to American Concrete Institute (ACI) method, was replaced with various percentages of fly ash by weight. Ettu *et al*. (2013) [9] investigated the strength of binary blended cement composites containing pawpaw leaf ash (PPLA). Mathematical models were developed for predicting compressive strengths of OPC-PPLA binary blended cement composites using polynomial regression analysis.

The mode used in developing the compressive strength of BA concrete is distinct from the other previous research. The first step adopted in this research was to identify a best curve fitting techniques. Two methods of curve fitting were generally considered, depending on the amount of error in the data. When the data are known to be precise, the method of *interpolation* is normally used. For significantly “noisy” data, a single curve representing the general trend of the data is derived by the method of *least-squares regression* McKinney (2013) [10]. The second step of model development was to compute *Adjusted* R^2 for polynomial Regression models. One pitfall of applying R^2 without adjustment is that it can only increase as predictors are added to the regression model. This increase is artificial when predictors are not actually improving the model’s fit. To remedy this, Karen (2015) [11] indicated that *adjusted R-squared*, incorporates the model’s degrees of freedom. Further, applying R^2 alone is not a good strategy for picking out a good model, because you can get increasingly better R^2 values by adding spurious variables. One attempt to correct for this is to compute the *adjusted* R^2 statistic Spring (2003) [12]. *Adjusted R-squared* is an *unbiased* estimate of the variance, taking into account the sample size and number of variables Bartlett (2013) [13]. Frost (2013) [14] further showed that for simplified regression output, the adjusted R^2 peaks, and then declines and the R^2continues to increase. The final step in model development was model validation. Cross validation was the mode adapted in this research and specifically the Leave One Out (LOO) technique. Leave-one-out cross-validation. (LOOCV) is often used in model selection, partly as it is known to be approximately unbiased but also because it can be implemented very efficiently in the case of regression equations methods Gavin (2009) [15].

For purpose of this study, average values of concrete compressive strengths for the various curing ages (7, 14 and 28days) and percentages of PPC replacement with BA (0, 5, 10, 15, 20, 25 and 30%) were obtained and presented in tables. From these results, polynomial regression models were then developed after both graphical and tabular evaluation and adopting MATLAB software.

2. MATERIALS

The BA used for this research was fetched from Nzoia Sugar Company (NSC), one of the key players in Kenya’s Sugar Industry. BA samples were sampled from three sites purposely selected. The furnace temperature was around 450°C. Cement used in this study was type 1 Portland Pozzolanic Cement (PPC), and procured locally. This binder complied with requirement of BS 12, 1996 [16]. Ballast was also purposefully purchased locally. This coarse aggregate passing through 20 mm sieve and retained on 12.5 mm sieve as recommended in BS 882 (1983) [17] was used for all the specimens. The water used was of drinking quality in accordance with the recommendations stipulated in BS 3148 (1980) [18]. The test apparatus for compressive strength of BA concrete were a compressive strength machine, moulds, tapping rod, a vibrator, a mallet and various measuring devices.

3. METHOD

3.1 Experiment

The compressive strength was determined using 150 mm cubes at the age of 7, 14, and 28days respectively as curing periods. During compression test, the load on the cube was applied at a constant rate of 3.0 KN/s according to BS 1881: Part 111, 1983 [19]. Three (3) concrete cubes for each percentage replacement of PPC with BA for grain size < 0.075mm including the control were tested to obtain their compressive strengths at 7, 14 and 28 days of curing, hence a total of 63 samples. The constituent materials of concrete remained uniformly distributed within the concrete mass during the various stages of handling and until full compaction was achieved. Immediately after molding and finishing. The specimens were stored for a period up to 48 h in a temperature range from 16 and 27°C and in an environment preventing moisture loss from the specimens. Upon completion of the given curing period the samples were then set to undergo the compression test.

3.2 Model Development

The compressive strength of dry BA concrete was predicted using two variables, namely, curing period and PPC content for BA grain size < 0.075 and water – PPC ratio of 0.55. The polynomial regression models were developed for variations in PPC replacements (0, 5, 10, 15, 20, 25 and 30 percent) and curing periods (7, 14 and 28 days). Effort was made to modify the polynomial models using a three step approach. First step was identifying the best curve fitting technique (least square and interpolation methods). The second step was to compute adjusted R^2 for identified polynomial regressions. The third and the final step were to cross validate the models applying LOO technique.

3.2.1 Curve Fitting Techniques

Data are often given for discrete values along a continuum. However, there was need to get estimates at points between the discrete values. One way to do this was to compute values of the function at a number of discrete values along the range of interest. Then, a simpler function was derived to fit these values. Both of these applications are known as **curve fitting**. According to Chapra (2012) [22], there are two general approaches for curve fitting that are distinguished from each other on the basis of the amount of error associated with the data. One approach of this nature is called **least-squares regression** and the other is **interpolation.** This research will attempt to test both these curve techniques to ultimately come up with the most suitable curve fitting technique. The techniques used were:

I. Least Square regression

i. Least Square Quadratic Polynomial (LSQP)

II. Interpolation.

i. Simultaneous Equation Polynomial (SEP)

ii. Newton Interpolation Polynomial (NIP)

iii. Lagrange Interpolating Polynomial (LIP)

(i) Least Square Quadratic Polynomial

One method to accomplish curve fitting is to fit polynomials to the data using Least Square Quadratic Polynomial (LSQP).

$f(s) = p_1 s^{n-1} + p_2 s^{n-2} + \ldots + p_{n-1} s + p_n$ ……………………………………………………eq. 1

(ii) Simultaneous Equation Polynomial

SEP is a way of computing polynomial coefficients of a parabola that passes through 3 predetermined values. This enable generation of 3 linear algebraic equations that was solved simultaneously after determination the 3 coefficients for equation 2.

$f(s) = p_1 s^2 + p_2 s + p_3$ ……………………………………………………………………eq. 2

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(iii) Newton Interpolating Polynomial (NIP)

There are a variety of alternative forms for expressing an interpolating polynomial beyond the familiar format. Newton's interpolating polynomial is among the most popular and useful forms Chapra (2012) [20].

$f(s) = p_1 + p_2(s - s_1) + p_3(s - s_1)(s - s_2)$……………………….……………….……………….eq. 3

(iii) Lagrange Interpolating Polynomial

Three parabolas were used with each one passing through one of the points and equaling zero at the other two. Their sum would then represent the unique parabola that connects the three points. Such a second-order Lagrange interpolating polynomial can be written as

$$f(s) = \left\{\frac{(s - s_2)(s - s_3)}{(s_1 - s_2)(s_1 - s_3)}\right\} f(s_1) + \left\{\frac{(s - s_1)(s - s_3)}{(s_2 - s_1)(s_2 - s_3)}\right\} f(s_2) + \left\{\frac{(s - s_1)(s - s_2)}{s_3 - s_1)(s_3 - s_2}\right\} f(s_3 \quad \text{……..……………eq. 4}$$

All these procedures can be readily extended to fit the data to a higher-order. p and s are regression coefficients and % age PPC replacement of BA in concrete respectively. In this research a second-order polynomial or quadratic will be fitted for all the curve fitting techniques. MATLAB was applied to represent polynomial coefficients using uses decreasing powers.

3.2.2 Computing Adjusted R^2 for LSQP Regression

Residuals in a model usually be reduced by fitting a higher degree polynomial, hence adding more terms, will lead to increase of the R^2 statistic, getting closer fit to the data, but at the expense of a more complex model, for which R^2 cannot account Bartlett (2013) [13]. However, a refinement of this statistic, *adjusted* R^2, does include a penalty for the number of terms in a model. *Adjusted* R^2, therefore, is more appropriate for comparing how different models fit to the same data Frost (2013) [14].

The *adjusted* R^2 is defined as:

$R^2_{adjusted} = 1 - (SS_{resid} / SS_{total})*((d-1)/(d-n-1))$…………………………………………eq. 5

Where d is the number of observations in your data, and n is the degree of the polynomial. SS_{resid} is the sum of the squared residuals from the regression. SS_{total} is the sum of the squared differences from the mean of the dependent variable (*total sum of squares*). Both are positive scalars. (A linear fit has a degree of 1, a quadratic fit 2, a cubic fit 3, and so on.)

3.2.3 Model Validation

Cross validation was the mode adapted in this research because it emphasis more on evaluation aspects than simply looking at the residuals. Residuals do not indicate how well a model can make new predictions on cases it has not already seen Bharatand Glenn (2013) [22]. This method is generally reserved for small data sets (n not greater than 20). Specifically, this research adopted leave-one-out (LOO) cross-validation, a method which leaves a single data point out, fit the model on the remaining data point, predicts the left-out data point, and repeat this whole process for every single data point. r^2 statistic will then be applied to quantify how close the model prediction match the data.

4. RESULTS AND DISCUSSIONS

Average values of concrete compressive strengths for the various curing ages (7, 14 and 28days) and percentages of PPC replacement with BA (0, 5, 10, 15, 20, 25 and 30%) were obtained and presented in tables and graphs. Various authors among them Sirirat and Supaporn (2010) [20] and Ahmed et al. (2008) [21] have explained that reduced BA size enhance both the filler and the pozzolanic effects, hence the choice of BA grain size of < 0.075mm in this research. This BA grain size of < 75µm was achieved through sieve analysis tests. Table 1 show the compressive strength of BA blended concrete for curing periods 7, 14 and 28 days denoted as L_{7d} , L_{14d} and L_{28d} respectively. Each of the former was determined from the average of 3 compressive strengths; L1, L2 and L3. C was the control mix or 0% BA replacement of cement in concrete.

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Table 1 Compressive strength of blended PPC- $D_{<0.075}$ BA concrete

BA %	Compressive Strength (N/mm^2)											
	L_{7d}				L_{14d}				L_{28d}			
	L1	L2	L3	L_{7d}	L1	L2	L3	L_{14d}	L1	L2	L3	L_{28d}
C	15.2	15.1	15.1	**15.1**	17.2	17.1	17.0	**17.1**	22.9	23.2	23.5	**23.2**
5	15.5	15.5	15.6	**15.5**	18.3	18.0	17.5	**17.9**	23.3	23.4	23.5	**23.4**
10	15.6	15.9	15.5	**15.7**	18.4	18.2	18.0	**18.2**	24.2	24.1	24.0	**24.1**
15	9.2	9.2	9.2	**9.2**	12.5	12.5	12.4	**12.5**	16.7	16.8	16.8	**16.8**
20	7.9	8.3	8.1	**8.1**	9.5	9.0	9.3	**9.3**	13.3	13.4	13.5	**13.4**
25	5.1	4.9	4.7	**4.9**	7.2	7.2	7.1	**7.2**	9.2	8.8	8.7	**8.9**
30	3.6	3.6	3.5	**3.6**	5.4	5.4	5.5	**5.4**	7.3	7.2	7.1	**7.2**

To formally establish which curve fitting technique is the 'best', the approach will be to quantify the fit quality of each technique model using statics standard error of the estimate (s_e) and correlation coefficient (r^2), and then determine one with the highest fit quality. The standard error of the estimate is a measure of the dispersion (or variability) in the predicted scores in a regression. When s_e is small, one would expect to see that most of the observed values cluster fairly closely to the regression line Hugh (2008) [21]. Like the standard error, r^2 gives an indication of how well a regression model serves as an estimator of values for the dependent variable. So the higher the r^2, the better the predictive nature of the regression model Frost (2013) [14]. Table 2 shows summary of the error analysis of the four curve fitting techniques.

Table 2 Error Analysis of the Curve Fitting Techniques

#	CFT	7 days		14 days		28days	
		r^2	s_e	r^2	s_e	r^2	s_e
1.	LSQP	0.9110	1.8483	0.9182	1.8729	0.9340	2.2397
2.	LIP	0.6524	3.7943	0.6448	3.8943	0.7039	4.7949
3.	SEP	0.65994	3.776919	0.6472	3.89719	0.7310	4.5199
4.	LIP	0.6524	3.7943	0.6680	60.6680	0.7939	4.7949

From the above analysis LSQP techniques has the highest correlation coefficient and least standard error, hence the preferred or best fitting technique. The first step of identifying the best curve fitting technique was achieved. The polynomial regression models for 7, 14 and 28 days curing periods were thus developed from the LSQP curve fitting technique with their respective adjusted R^2 summarized in Table 3. From the various fits, computation of adjusted R^2 values were obtained for the curing periods to evaluate whether the extra terms improve predictive power of the modified LSQP model by varying n in equation 5.

Table 3: Regression coefficients of LSQP with adjusted R^2 for 7 days curing period

Regression Coefficients (p)	n = 3	n = 4	n = 5	n = 6
p_1	16.2595	15.0762	14.9418	15.0215
p_2	-0.2593	0.5292	0.7940	0.1521
p_3	-0.0068	-0.0778	-0.1243	0.0600
p_4	0.0000	0.0016	-0.0041	-0.0134
p_5	0.0000	0.0000	0.0000	0.0006
R^2	0.9110	0.9611	0.9629	0.9661
Adjusted R^2	0.8665	0.9221	0.8887	0.7966

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Table 4: Regression coefficients of LSQP with adjusted R^2 for 14 days curing period

Regression Coefficients (p)	n = 3	n = 4	n = 5	n = 6
p_1	18.476	16.947	16.8736	17.0557
p_2	-0.2007	0.6660	0.8115	-0.6541
p_3	-0.0089	-0.0869	-0.1125	-0.0368
p_4	0.0000	0.0017	-0.0031	-0.0368
p_5	0.0000	0.0000	0.0000	0.0015
R^2	0.9139	0.9728	0.9738	0.9895
Adjusted R^2	0.8708	0.9455	0.9199	0.9009

Table 5: Regression coefficients of LSQP with adjusted R^2 for 28 days curing period

Regression Coefficients (p)	n = 3	n = 4	n = 5	n = 6
p_1	24.4619	22.9286	22.9948	23.1317
p_2	-0.2307	0.7915	0.6612	-0.4404
p_3	-0.0132	-0.1052	-0.0823	0.02339
p_4	0.0000	0.0022	0.0008	-0.0292
p_5	0.0000	0.0000	0.0000	0.0012
R^2	0.9340	0.9805	0.9806	0.9858
Adjusted R^2	0.9010	0.9605	0.9419	0.9149

It can be seen from Tables3, 4 and 5 that the adjusted R^2 is highest for all curing periods when n = 4. Hence the best prediction of compressive strength of concrete with BA is when the model gives the value of the adjusted R^2 is 0.9221, 0.9455 and 0.9605 for 7, 14 and 28 day curing periods respectively. Also, it is observed that predictions are better for 28 compressive strength in comparison to 7 and 14 days strength for concrete BA. This computation of adjusted R^2 was also been carried out to identify the quadratic terms that should be added to the regression models in order to improve the prediction of compressive strength of concrete. BA. Bartlett (2013) [13] attempted to reduce bias in models by modifying estimators by applying the adjusted R^2 approach and showed that the later is always smaller than the standard one, similar results were as in this study. Frost (2013) [14] showed that the regression output of models, the adjusted R^2 peaks, and then declines. This phenomenon also applied in this research as is shown in tables 3, 4 and 5 where adjusted R^2 peaks at n = 4 and then declined.

Validation results for the corrected LSQP Model (n = 4) at 7, 14 and 28 days are summarized graphically and also tabulated. Experimental, Corrected (n = 4) and Validated Compressive Strength are shown in figure 1. Regression coefficients and adjusted R^2 for the corrected and the validated model are shown in Table 1.

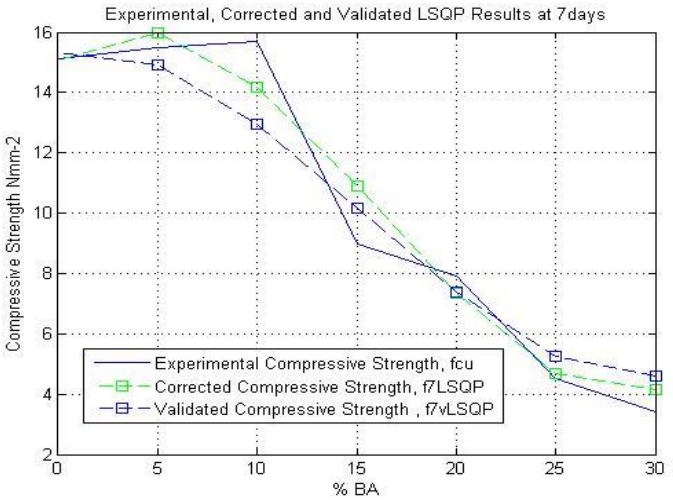

Figure 1.Experimental Compressive Strength at 7, 14 and 28 days curing

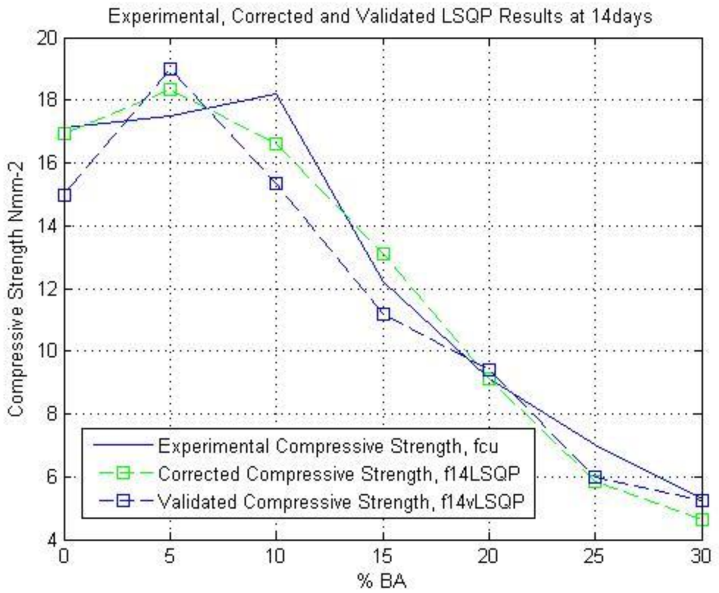

Figure 2.Corrected Compressive Strength at 7, 14 and 28 days curing

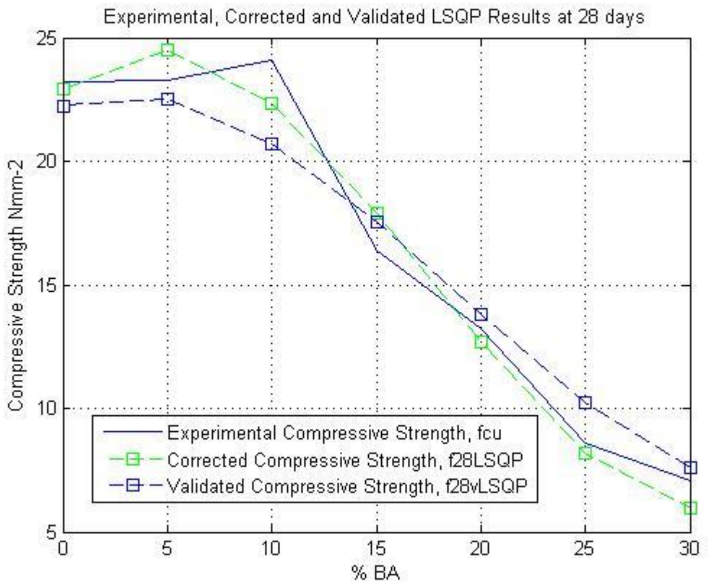

Figure 3.Validated Compressive Strength at 7, 14 and 28 days curing.

Table 6.Regression coefficients and adjusted R^2 of for the Corrected and Validated LSQP model

Regression Coefficients (p)	7 Days		14 Days		28 Days	
	n =4	f^{7}_{vLSQP}	n =4	f^{28}_{vLSQP}	n =4	f^{28}_{vLSQP}
p_1	15.0762	14.5541	16.947	15.3804	22.9286	22.250
p_2	0.5292	0.3101	0.666	1.0456	0.7915	0.3121
p_3	-0.0778	-0.0524	-0.0869	-0.1258	-0.1052	-0.0567
p_4	0.0016	0.0009	0.0017	0.0028	0.0022	0.0010
R^2	0.9611	0.9856	0.9728	0.9822	0.9805	0.9912
Adjusted R^2	0.9221	0.9712	0.9455	0.9624	0.9605	0.9742

It is observed from the above graphs that experimental, corrected and validated compressive strength relationship all exhibited similar trends. The table shows that both the R^2 and the adjusted R^2 of the validated LSQP model increased which indicates that the predictive ability of the corrected model is good.

5. CONCLUSIONS AND RECOMMENDATIONS

Appropriate compressive strength prediction models of BA concrete at curing ages 7, 14 and 28 days were developed. The compressive strength of dry BA concrete was predicted using two variables, namely, curing period and pozzolanic Portland cement (PPC) content for BA grain size < 0.075 and water – PPC ratio of 0.55. LSQP with degree of the regression n = 4 was established in this study as the most effective and accurate models in compressive strength prediction of BA concrete. Compressive strengths of curing periods beyond 28 days and effects of creep for similar prediction models can be areas of further consideration.

REFERENCES

[1] Rachna A, Maneek K, Sharmac R, Sharmac L. (2015). *Predicting Compressive Strength of Concrete* International Journal of Applied Science and Engineering 2015. 13, 2: 171-185 Retrieved 7th July 2016.

[2] Chavez G, Martinez M, Alonso G, Torres A, Perez Q, Bedolla A, Gómez L and Gonzalez V. (2015). *Prediction of Compressive Strength and Modulus of Rupture of Mortar Containing Added Ash Bagasse*.2nd International Conference on Green Materials and Engineering (GMEE 2015). Retrieved 7th July 2016.

[3] Nwoye C, Chinwuko E, Nwosu P, Idenyi N.*An Implicit Response Analysis of Compressive Strength of Concrete Based on Its Ageing Periods and Cement Replacement with Bagasse Ash*. International Journal of Materials LifetimeVol. 2, No. 1, 2015, pp 13-21. doi: 10.12691/ijml-2-1-3 | Research Article 2888. Retrieved 10th July 2016.

[4] Ettu L, Ibearugbulem M, Anya C, Awodiji T, and Njoku F. *Strength of Binary Blended Cement Composites Containing Saw Dust Ash*. The International Journal Of Engineering And Science (IJES) ||Volume||2 ||Issue|| 4 ||Pages|| 51-56||2013|| ISSN(e): 2319 – 1813 ISSN(p): 2319 – 1805. Retrieved 10th July 2016.

[5] Ettu L, Ibearugbulem M, Anya C, Awodiji T, and Njoku F. *Strength of Binary Blended Cement Composites Containing Cassava Waste Ash* International Journal of Emerging Technology and Advanced Engineering Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 3, Issue 4, April 2013). Retrieved 10th July 2016

[6] Hamed Gand Saeed B. (2015).*Predicting the Significant Characteristics of Concrete Containing Palm Oil Fuel Ash.* Journal of Construction in Developing Countries, 20(1), 85–98, 2015. Retrieved 15th July 2016

[7] Okonkwo U. (2015). *Optimization Of Bagasse Ash Content In Cement- Stabilized Lateritic Soil*. A thesis submitted in partial fulfillment of the requirements for the award of doctor of philosophy (PhD) in civil engineering (geotechnical engineering), department of civil engineering, university of Nigeria, Nsukka.Retrieved 15th July 2016.

[8] Radhakrishna Krishna (2013*). Prediction of compressive strength of f fly ash concrete based on replacement level*. ArticleinIndianConcreteJournalMarch2013. Retrieved 11th July 2016.

[9] Ettu L, Ezeh C, and Mbajiorgu S. (2013). *Strength of Binary Blended Cement Composites Containing Pawpaw Leaf Ash.* International Journal of Advancements in Research&Technology,Volume2,Issue5,May-2013236 ISSN 2278-7763.19th July 2016.

[10] McKinney D (2014). *Numerical Methods for Civil Engineers*. CE 311K Daene C. McKinney Introduction to Computer Methods Department of Civil, Architectural and Environmental Engineering The University of Texas at Austin. 17thJuly 2016.

[11] Karen P (2015). Assessing the Fit of Regression Models. Manitab.com. Retrieved 28th Aug 2016.

[12] Spring K (2003) *Polynomial Regression in R.* Manitab. Com . Retrieved 20th July 2016.

[13] Bartlett J (2013). *R squared and adjusted R squared.* The Stats Geek.Retrieved 24th July 2016.

International Journal of Novel Research in Civil Structural and Earth Sciences
Vol. 3, Issue 3, pp: (6-14), Month: September - December 2016, Available at: www.noveltyjournals.com

[14] Frost J (2013). *Multiple Regression Analysis: Use Adjusted R-Squared and Predicted R-Squared to Include the Correct Number of Variables*. Manitab.com. Retrieved 28thAug 2016.

[15] GavinC.NicolaL.Talbot C. (2009). *Efficient Approximate Leave-One-Out Cross-ValidationforKernel Logistic Regression.*School of Computing Sciences University of East Anglia Norwich, United Kingdom. NR4 7TJ e-mail: gcc@cmp.uea.ac.uk Retrieved 12thJuly 2016.

[16] BS 12, 1996. *Specifications for Portland Cement.* British Standards Institute, London. 6th September 2014. Retrieved 7th July 2016.

[17] BS 882 (1983). Specification for aggregates from natural sources for concrete. Retrieved 23rd April 2014.

[18] BS 3148 (1980). Methods of test for water for making concrete. Retrieved 23rd April 2014.

[19] BS 1881: Part 111, 1983. Method for Determination of Compressive Strength of Concrete. British Standards Institute, London. Retrieved 7th September 2014

[20] Sirirat J and Supaporn W. (2010). *Pozzolanic Activity of Industrial Sugar Cane Bagasse ASH*. National Metal and Materials Technology Center (MTEC), National Science and Technology Development. Retrieved 20th April 2014.

[21] Mary L. (2008). Standard error: meaning and interpretation. Biochemia Medica 2008; 18(1):7-13. http://dx.doi.org/10.11613/BM.2008.002School of Nursing, University of Indianapolis, Indianapolis, Indiana, USA.

[22] Bharat and Glenn(2013). On the Dangers of Cross-Validation. An Experimental Evaluation. Romer Rosales IKM CKS Siemens Medical Solutions USA. Retrieved 30thJuly 2016.