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Model for Prediction and Optimization of Compressive Strengths of Cement Composites using Nanostructured Cassava Peel Ash as Partial Replacement of the Binder

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ABSTRACT

The predictive ability of statistical methods such as Scheffe's and Osadebe's models is apodictic as they are often adopted for optimization of concrete properties. But attention is drawn to their limitations. In this paper, Ibearugbulem's optimization model was applied to predict the compressive strength of nanostructured cassava peel ash (NCPA)-cement composites. Three hundred and six concrete cubes were prepared in the laboratory with varying water-cement ratios and mix ratios with 1.5 % NCPA replacement interval. The 28 days' compressive strength was varied with that of 56 days' strength. The experimental results were modelled using Ibearugbulem's approach. The optimum experimental and modelled outcome of the concrete strength was 24.20 N/mm^2 and 30.10 N/mm^2, 22.61 N/mm^2 and 28.54 N/mm^2 at 28 days and 56 days curing age respectively. These values were obtained at 16.5% and 19.5% NCPA replacement intervals at water-cement ratios of 0.72 and 0.75 for the model and experiment respectively with their mix ratios being 0.835:0.165:1.5:3 and 0.805:0.195:1.5:3. The percentage difference of 7.03 % and 5.47 % being less than 10 % at 28 days and 56 days for the optimum values reveals the adequacy of the model. Fisher's statistical tool was used in the analysis and the calculated value of fisher of 1.11 and 1.08 were lower than the fisher value of 1.94 derived from the statistical f-distribution table. This implies that there was no significant difference between the laboratory-strength values and the modelled-strength values at 95 % confidence level. The formulated model is therefore reliable, safe and recommended for production of cement-composites.

1. INTRODUCTION

Concrete is a composite material consisting of cement, water, fine aggregates and coarse aggregates in a calculated mix measure. It is globally the most used construction material with its increasing-demand on infrastructural development in both the developing and developed countries (Awodiji et al., 2018). The availability of its constituents determines its overall production cost. As demand for concrete rises, the need for cement production increases but the environmental effect such as the depletion of the ozonosphere due to the emission of greenhouse gas and cost implication of cement production has led researchers to developing alternative and suitable replacement materials for the binder.

Cassava peel ash is one of the many alternative materials for cement in concrete production. Cassava peel ash has been used in concrete production (Olonade et al., 2014; Raheem et al., 2015; Ofuyatan et al., 2018; Ettu et al., 2013) but the effect of its nanostructured form on compressive strength of concrete which was not considered in previous studies distinguishes this study. Nanostructured materials incorporated in cement-composites improves its compressive and flexural strength at early age due to its high surface-to-volume ratio (Prasad 2017; Rao et al., 2015; Sanchez and Sobolev 2010). Eco-friendly concrete is produced with the use of nanosized cassava peel ash (NCPA).

The cost of concrete production is also influenced by the vast time and energy spent in performing trial mixes for desired fresh or hardened concrete behaviors. Over time, concrete mix materials within the mixture-matrix have been modelled with previous regression models (Anyaogu and Ezeh 2013; Onwuka and Sule 2017).

Scheffe's and Osadebe's Models were adopted by Mama and Osadebe (2011). They predicted the compressive strength of sandcrete blocks using alluvial deposit. The application of Osadebe's model was confirmed to be easier than Scheffe's model because actual mix-ratio is usually used instead of the pseudo-components ratio that needs to be transformed into real component ratio in Scheffe's. Oba et al. (2019) used Scheffe's simplex theory to investigate the compressive strength of concrete. 5% of fine aggregate was partially replaced with saw-dust ash (SDA). The mix comprised of five components: water-cement ratio, cement, sand, SDA, and granite. 28 days' compressive strengths were determined experimentally using thirty (30) concrete mix ratios. The outcome of the first fifteen strength values were applied for the calibration of the model constant coefficients, while those from the second fifteen were used for the model verification using Scheffe's design. The authors ascertained the adequacy of the model using a two-tailed t-test with 5% significance.

The need for a predetermined set of mixes before the formulation of the model poses a great challenge to the application these models. A new approach was introduced and developed by Ibearugbulem to surmount this challenge (Ibearugbulem et al., 2013). In this approach, a set of mixes that had already been carried out can be modelled without employing predetermined amount of mixes. Ibearugbulem et al. (2013) formulated a new model that predicts 28th day flexural strengths of periwinkle shell-river gravel concrete. The mix ratios used in their study were selected arbitrarily from Scheffe's simplex latex structure for a four-component mixture. Different constituent materials were batched by mass except for the sand stone and periwinkle shells which were volumetrically combined at a mix ratio of 1:1. The adequacy of the model was confirmed with Fisher's test. However, compressive strength was not captured in their study, neither was partial or complete replacement of cement considered.

The concept of nanosization in concrete production is scarce in literatures. Previous studies did not consider the partial replacement of the binder neither was NCPA applied in any of the studies. Antecedent authors did not consider writing a visual basic computer program for their study. The gap in literature is addressed in this study. In this research work, the regression model developed by Ibearugbulem for a four-component-mixture is employed to formulate a new model for the prediction of the 28 days and 56 days' compressive strengths of NCPA-concrete. This study will enhance construction activities as time wasted in using trial mixes is eliminated. The pollution of the environment with cassava peels is also curtailed as it is utilized in production of lightweight-concrete.

2. MATERIALS AND METHODS

2.1. Materials

The materials used for this study include, Ordinary Portland Cement, nanostructured cassava peel ash, water, sharp-river sand, and granite chippings. Each of these materials is discussed below.

i. The BUA brand of Ordinary Portland Cement that conformed to the requirements of BS 12 (1996) was used. It was purchased at the local market in Owerri Municipal area of Imo State.

ii. Cassava peels were collected from cassava peels dump site at a garri processing centre in Owerri district of Imo State. The cassava peels were gathered and dried under the sun. The cassava peel will be burnt in a kiln at a temperature of 700 ^{o}C in 60 minutes in a control incineration set-up to prevent pollution. The burnt material was collected and sieved thoroughly with a nano-sieve of size 200 nm, to produce fine nanostructured ash. The chemical composition and physical characteristics of the nanostructured ash was determined.

iii. Water that is suitable for drinking was obtained from a borehole at the laboratory. The water was clean, fresh, free from dirt, unwanted chemicals or rubbish that may affect the desired quality of concrete, and it conformed to the requirements of BS 3140 (1980).

iv. The sand was obtained from Imo River, Imo State of Nigeria. It was sieved through 10 mm British Standard test sieve to remove cobbles to satisfy the requirements of BS 882 (1992).

v. The crushed granite was sourced from the quarry site at Ishiagu, Ebonyi State, Nigeria. The maximum size of aggregate used for this work is 20 mm diameter. It conformed to the requirements of BS 882 (1992).

2.2. Methods

The concrete used for this study was prepared applying different mix ratios of 1:1.5:3 for varying water-cement ratios while batching of materials was done by mass using intervals of 1.5% replacement of cement with NCPA. 150 mm × 150 mm × 150 mm concrete cubes were cast and replicated into three for the water-cement ratios and for 28 days and 56 days curing period at 51 intervals of 1.5% replacement making a total of 306 cubes. Dry-mix method was used for concrete constituent before the inclusion of water. The mixing was done manually. After mixing properly to a consistent state, the concrete constituents were cast into the 150 mm ×150 mm × 150 mm metal moulds and de-moulded after 24 hrs.

Table 1: Mix ratios for odd serial numbers and their corresponding compressive strength values

S/No	W/C	N/C	S/C	G/C	X_1	X_2	X_3	X_4
A1	0.600	0.000	1.510	2.993	0.118	0.000	0.296	0.587
A3	0.618	0.031	1.556	3.086	0.117	0.006	0.294	0.583
A5	0.638	0.064	1.607	3.185	0.116	0.012	0.292	0.580
A7	0.659	0.099	1.659	3.290	0.116	0.017	0.291	0.576
A9	0.682	0.136	1.716	3.401	0.115	0.023	0.289	0.573
A11	0.706	0.176	1.776	3.521	0.114	0.029	0.287	0.570
A13	0.732	0.220	1.842	3.651	0.114	0.034	0.286	0.567
A15	0.759	0.266	1.911	3.789	0.113	0.040	0.284	0.563
A17	0.789	0.316	1.987	3.938	0.112	0.045	0.283	0.560
A19	0.822	0.370	2.068	4.100	0.112	0.050	0.281	0.557
A21	0.857	0.429	2.157	4.277	0.111	0.056	0.279	0.554
A23	0.895	0.493	2.254	4.468	0.110	0.061	0.278	0.551
A25	0.937	0.562	2.359	4.677	0.110	0.066	0.276	0.548
A27	0.983	0.639	2.475	4.906	0.109	0.071	0.275	0.545
A29	1.035	0.725	2.604	5.162	0.109	0.076	0.273	0.542
A31	1.091	0.818	2.745	5.443	0.108	0.081	0.272	0.539
A33	1.154	0.923	2.903	5.756	0.107	0.086	0.270	0.536
A35	1.224	1.040	3.080	6.107	0.107	0.091	0.269	0.533
A37	1.305	1.175	3.283	6.509	0.106	0.096	0.268	0.530
A39	1.395	1.326	3.511	6.962	0.106	0.100	0.266	0.528
A41	1.500	1.500	3.774	7.482	0.105	0.105	0.265	0.525
A43	1.621	1.701	4.079	8.086	0.105	0.110	0.263	0.522
A45	1.765	1.942	4.442	8.807	0.104	0.115	0.262	0.519
A47	1.935	2.226	4.871	9.656	0.104	0.119	0.261	0.517
A49	2.142	2.570	5.390	10.687	0.103	0.124	0.259	0.514
A51	2.398	2.998	6.035	11.964	0.102	0.128	0.258	0.511

The cubes were cured for 28 days and 56 days after which they were crushed in their saturated surface dry (SSD) state using the universal compression machine and the compressive strength was determined in accordance to BS 1881 (1983).

Ibearugbulem's regression function was introduced and developed to predict and optimize the compressive strength of NCPA-concrete. For each mix portion in the mixture, a domain was provided. This defines the entire mixture space domain. With respect to spatial-domain for each concrete mixture variable, the response-function is expressed as a multivariable-function for the proportions of the constituent materials. Applying the variational approach, the response function was developed within the specified spatial domain and was optimized. Fifty-one mixes were used, which gave a total of 306 cubes. Twenty-six observation points are used to formulate the model and the remaining twenty-five points are used to test the adequacy of the formulated model. The observations points on the odd serial number are the ones selected for the formulation of the model. The ones on the even serial numbers are the ones used for testing the adequacy of the model. They were presented on Table 1 and Table 2 respectively.

Table 2: Mix ratios for even serial numbers and their corresponding compressive strength values

S/No	W/C	N/C	S/C	G/C	X_1	X_2	X_3	X_4
A2	0.609	0.015	1.533	3.039	0.117	0.003	0.295	0.585
A4	0.628	0.047	1.581	3.134	0.117	0.009	0.293	0.581
A6	0.649	0.081	1.632	3.236	0.116	0.015	0.292	0.578
A8	0.670	0.117	1.687	3.345	0.115	0.020	0.290	0.575
A10	0.693	0.156	1.745	3.460	0.115	0.026	0.288	0.571
A12	0.718	0.197	1.808	3.584	0.114	0.031	0.287	0.568
A14	0.745	0.242	1.876	3.719	0.113	0.037	0.285	0.565
A16	0.774	0.290	1.948	3.862	0.113	0.042	0.283	0.562
A18	0.805	0.342	2.026	4.017	0.112	0.048	0.282	0.559
A20	0.839	0.398	2.111	4.185	0.111	0.053	0.280	0.556
A22	0.876	0.460	2.204	4.370	0.111	0.058	0.279	0.552
A24	0.916	0.527	2.305	4.570	0.110	0.063	0.277	0.549
A26	0.960	0.600	2.415	4.789	0.110	0.068	0.276	0.546
A28	1.009	0.681	2.538	5.032	0.109	0.074	0.274	0.543
A30	1.062	0.770	2.673	5.299	0.108	0.079	0.273	0.540
A32	1.121	0.869	2.822	5.595	0.108	0.084	0.271	0.538
A34	1.188	0.980	2.989	5.926	0.107	0.088	0.270	0.535
A36	1.263	1.106	3.180	6.304	0.107	0.093	0.268	0.532
A38	1.348	1.248	3.393	6.728	0.106	0.098	0.267	0.529
A40	1.445	1.409	3.638	7.212	0.105	0.103	0.265	0.526
A42	1.558	1.597	3.920	7.772	0.105	0.108	0.264	0.523
A44	1.691	1.818	4.255	8.436	0.104	0.112	0.263	0.521
A46	1.846	2.077	4.646	9.212	0.104	0.117	0.261	0.518
A48	2.033	2.389	5.117	10.145	0.103	0.121	0.260	0.515
A50	2.263	2.772	5.694	11.289	0.103	0.126	0.259	0.513

2.3. Derivation of Fundamental Equation of the Mathematical Model

The mix quantity (x_i) of each component on a particular observation point is determined by dividing the individual component (s_i) by the sum of the components (S). That is:

$$x_i = \frac{s_i}{S} \quad (1)$$

$$S = s_1 + s_2 + s_3 + s_4 \quad (2)$$

In this work, the spatial domain in which the model is restricted to are mix ratio domains given as:

$$s_{1min} \leq s_1 \leq s_{1max} \quad (3)$$

$$s_{2min} \leq s_2 \leq s_{2max} \quad (4)$$

$$s_{3min} \leq s_3 \leq s_{3max} \quad (5)$$

$$s_{4min} \leq s_4 \leq s_{4max} \quad (6)$$

From Equation 1:

$$s_i = x_i \, . \, S \quad [where\ 1 \leq i \leq 4] \quad (7)$$

Substituting Equation 7 into Equation 2 gives the sum of all the mix quantities to be unity as:

$$x_1 + x_2 + x_3 + x_4 = 1 \quad (8)$$

These equations are obtained from Ibearugbulem's new optimization-model.

The relationship between S and x_1 is:

$$S = -9{,}618{,}754.09x_1^3 + 3{,}272{,}467.70x_1^2 - 371{,}430.83x_1 + 14{,}071.24 \quad (9)$$

The response function to be adopted herein is a quadratic function of the component proportions given as:

$$y = a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5{x_1}^2 + a_6{x_2}^2 + a_7{x_3}^2 + a_8{x_4}^2 + a_9x_1x_2 + a_{10}x_1x_3 + a_{11}x_1x_4 + a_{12}x_2x_3 + a_{13}x_2x_4 + a_{14}x_3x_4 \quad (9a)$$

$$y = [x_i]\,[a_i] \quad (9b)$$

Equation 9b was used to obtain the array response equation for the set of mix ratios used in the formulation as:

$$[y^k] = [{x_i}^k]\,[a_i] \quad (9c)$$

Where k denotes the mix number (or observation point number); $[a_i]$ is the coefficient vector, and $[x_i]$ is the shape function vector. They are:

$$[a_i] = [a_1\ a_2\ a_3\ a_4\ a_5\ a_6\ a_7\ a_8\ a_9\ a_{10}\ a_{11}\ a_{12}\ a_{13}\ a_{14}]^T \quad (10)$$

$$[x_i] = [x_1\ x_2\ x_3\ x_4\ {x_1}^2\ {x_2}^2\ {x_3}^2\ {x_4}^2\ x_1x_2\ x_1x_3\ x_1x_4\ x_2x_3\ x_2x_4\ x_3x_4] \quad (11)$$

Pre-multiplying both sides of Equation 9c with a weighting function (transpose of the shape function) for the set of mixes for the formulation gives the weighted response equation (WRE) as:

$$[{x_i}^k]^T[y^k] = [{x_i}^k]^T.[{x_i}^k]\,[a_i] \quad (12a)$$

This multiplication did not change the generality of the regression function as the weighting function can easily cancel out from both the left and right hand sides of equation 12a. It is clear from here that the approach used in the original work of Ibearugbulem's model (Ibearugbulem et al., 2013) is weighted response approach (WRA).

The weighted response equation (Equation 12a) can be rewritten as:

$$[F] = [CC]\,[a_i] \quad (12b)$$

Where the weighted response vector, F and CC matrix are defined as:

$$[F] = [{x_i}^k]^T[y^k] \quad (13)$$

$$[CC] = [{x_i}^k]^T.[{x_i}^k] \quad (14)$$

In simpler words, [CC] is the matrix whose arbitrary element CC_{ij} is obtained by array multiplication of transpose of Column "i" with Column "j" of the shape function vector.

2.4. Fitting the Model with the Mixes used Herein

Table 1 contains the values of quantities of mix components, x_i. Ensure to normalize and approximate x_i at four decimal places such that condition of Equation 8 will not be violated. The summation of x_i in each mix ratio on Table 1, was ensured to be equal to unity (in accordance with Equation 8). The values of x_i on Table 1 were used to determine the shape function and weighted response. The transpose of the response of the odd number mix ratios is taken directly from Table 1 and is given as:

$[y^k]$ = [20.5 21.2 21.8 22.5 23 23.4 24 23.6 23.1 22.6 22.3
21.7 21.1 20.5 19.3 18.7 18.1 17.1 16.3 16 15.6 14.9 14.3
13.7 13.2 12.3]

The shape function for the 26 mixes (mix A1, A3, A5 to A51) is taken from Table 1 and substituted into Equations 1 and 2. The transpose of the shape function is:

$[x^k]^T =$

5.103	0.118	0.000	0.296	0.587	0.014	0.000	0.088	0.344	0.000	0.035	0.069	0.000	0.000	0.174
5.291	0.117	0.006	0.294	0.583	0.014	0.000	0.087	0.340	0.001	0.034	0.068	0.002	0.003	0.172
5.494	0.116	0.012	0.292	0.580	0.014	0.000	0.086	0.336	0.001	0.034	0.067	0.003	0.007	0.170
5.707	0.116	0.017	0.291	0.576	0.013	0.000	0.085	0.332	0.002	0.034	0.067	0.005	0.010	0.168
5.935	0.115	0.023	0.289	0.573	0.013	0.001	0.084	0.328	0.003	0.033	0.066	0.007	0.013	0.166
6.179	0.114	0.029	0.287	0.570	0.013	0.001	0.083	0.325	0.003	0.033	0.065	0.008	0.016	0.164
6.444	0.114	0.034	0.286	0.567	0.013	0.001	0.082	0.321	0.004	0.032	0.064	0.010	0.019	0.162
6.726	0.113	0.040	0.284	0.563	0.013	0.002	0.081	0.317	0.004	0.032	0.064	0.011	0.022	0.160
7.030	0.112	0.045	0.283	0.560	0.013	0.002	0.080	0.314	0.005	0.032	0.063	0.013	0.025	0.158
7.359	0.112	0.050	0.281	0.557	0.012	0.003	0.079	0.310	0.006	0.031	0.062	0.014	0.028	0.157
7.721	0.111	0.056	0.279	0.554	0.012	0.003	0.078	0.307	0.006	0.031	0.062	0.016	0.031	0.155
8.110	0.110	0.061	0.278	0.551	0.012	0.004	0.077	0.304	0.007	0.031	0.061	0.017	0.033	0.153
8.535	0.110	0.066	0.276	0.548	0.012	0.004	0.076	0.300	0.007	0.030	0.060	0.018	0.036	0.151
9.003	0.109	0.071	0.275	0.545	0.012	0.005	0.076	0.297	0.008	0.030	0.060	0.020	0.039	0.150
9.525	0.109	0.076	0.273	0.542	0.012	0.006	0.075	0.294	0.008	0.030	0.059	0.021	0.041	0.148
10.097	0.108	0.081	0.272	0.539	0.012	0.007	0.074	0.291	0.009	0.029	0.058	0.022	0.044	0.147
10.735	0.107	0.086	0.270	0.536	0.012	0.007	0.073	0.287	0.009	0.029	0.058	0.023	0.046	0.145
11.451	0.107	0.091	0.269	0.533	0.011	0.008	0.072	0.284	0.010	0.029	0.057	0.024	0.048	0.143
12.271	0.106	0.096	0.268	0.530	0.011	0.009	0.072	0.281	0.010	0.028	0.056	0.026	0.051	0.142
13.194	0.106	0.100	0.266	0.528	0.011	0.010	0.071	0.278	0.011	0.028	0.056	0.027	0.053	0.140
14.255	0.105	0.105	0.265	0.525	0.011	0.011	0.070	0.275	0.011	0.028	0.055	0.028	0.055	0.139
15.487	0.105	0.110	0.263	0.522	0.011	0.012	0.069	0.273	0.011	0.028	0.055	0.029	0.057	0.138
16.956	0.104	0.115	0.262	0.519	0.011	0.013	0.069	0.270	0.012	0.027	0.054	0.030	0.059	0.136
18.688	0.104	0.119	0.261	0.517	0.011	0.014	0.068	0.267	0.012	0.027	0.054	0.031	0.062	0.135
20.789	0.103	0.124	0.259	0.514	0.011	0.015	0.067	0.264	0.013	0.027	0.053	0.032	0.064	0.133
23.395	0.102	0.128	0.258	0.511	0.011	0.016	0.067	0.262	0.013	0.026	0.052	0.033	0.066	0.132

The shape function and its transpose were substituted into Equation 14 to obtain CC matrix. This CC matrix as obtained was copied from Microsoft Excel worksheet and pasted on Microsoft word page to discharge inherent formulas and approximate the values to enable it have acceptable inverse. In the same manner, the transpose of the shape function and the response vector from the first ten mixes were Substituted into Equation 13 to obtain the weighted response vector. The CC matrix and the weighted response vector are respectively presented as:

CC matrix =

0.313	0.186	0.789	1.564	0.034	0.016	0.218	0.859	0.02	0.087	0.172	0.050	0.100	0.433
0.186	0.155	0.469	0.929	0.02	0.015	0.126	0.497	0.016	0.050	0.100	0.041	0.082	0.251
0.789	0.469	1.985	3.936	0.087	0.041	0.55	2.161	0.05	0.218	0.433	0.126	0.251	1.090
1.564	0.929	3.936	7.802	0.172	0.082	1.09	4.285	0.100	0.433	0.859	0.251	0.497	2.161
0.034	0.020	0.087	0.172	0.004	0.002	0.024	0.095	0.002	0.010	0.019	0.005	0.011	0.048
0.016	0.015	0.041	0.082	0.002	0.002	0.011	0.043	0.002	0.004	0.009	0.004	0.008	0.022
0.218	0.126	0.550	1.09	0.024	0.011	0.153	0.600	0.014	0.061	0.120	0.034	0.068	0.303
0.859	0.497	2.161	4.285	0.095	0.043	0.600	2.357	0.053	0.238	0.472	0.134	0.266	1.189
0.020	0.016	0.050	0.100	0.002	0.002	0.014	0.053	0.002	0.005	0.011	0.004	0.009	0.027
0.087	0.05	0.218	0.433	0.01	0.004	0.061	0.238	0.005	0.024	0.048	0.014	0.027	0.120
0.172	0.100	0.433	0.859	0.019	0.009	0.12	0.472	0.011	0.048	0.095	0.027	0.053	0.238
0.050	0.041	0.126	0.251	0.005	0.004	0.034	0.134	0.004	0.014	0.027	0.011	0.022	0.068
0.100	0.082	0.251	0.497	0.011	0.008	0.068	0.266	0.009	0.027	0.053	0.022	0.043	0.134
0.433	0.251	1.090	2.161	0.048	0.022	0.303	1.189	0.027	0.120	0.238	0.068	0.134	0.600

$[F]_{28days}$ =

55.31158
30.30701
139.2038
275.9776
6.118340
2.512252
38.75287
152.3172
3.267576
15.39816
30.52751
8.223579
16.30360

$[F]_{56days}$=

70.35465
38.84722
177.0630
351.0351
7.778716
3.230756
49.26950
193.6526
4.187104
19.57686
38.81197
10.53777
20.89159

Substituting the CC matrix and the weighted response vector obtained hitherto into equation (12b) and solving the equation gave the coefficient vector of the model as:

$$[a_i]_{28days} = [346.22 \quad 238.41 \quad -959.49 \quad -54.01 \quad -29.42 \quad -83.29 \quad -41.26 \quad 951.8 \quad 409.29 \quad 107.42 \quad 146.28 \quad -278.29 \quad 29.14 \quad -216.73]^T \tag{15}$$

$$[a_i]_{56days} = [406.17 \quad 280.97 \quad -1117.92 \quad --62.34 \quad -42.56 \quad -95.24 \quad -37.60 \quad 1114.06 \quad 472.30 \quad 130.86 \quad 171.55 \quad -326.21 \quad 33.11 \quad -260.16]^T \tag{16}$$

Substituting the model coefficients into Equation (9a) gives the response function for the mix ratios used herein as:

$$\begin{aligned} y_{28days} = {} & 346.22\, x_1 + 238.41\, x_2 - 959.49\, x_3 - 54.01\, x_4 - 29.42\, x_1{}^2 - 83.29\, x_2{}^2 \\ & - 41.26\, x_3{}^2 + 951.80\, x_4{}^2 + 409.29\, x_1x_2 + 107.42\, x_1x_3 \\ & + 146.28\, x_1x_4 - 278.29\, x_2x_3 + 29.14\, x_2x_4 - 216.73\, x_3x_4 \end{aligned} \tag{17}$$

$$\begin{aligned} y_{56days} = {} & 406.17\, x_1 + 280.97\, x_2 - 1117.92\, x_3 - 62.34\, x_4 - 42.56\, x_1{}^2 \\ & - 95.24\, x_2{}^2 - 37.60\, x_3{}^2 + 1114.06\, x_4{}^2 + 472.30\, x_1x_2 \\ & + 130.86\, x_1x_3 + 171.55\, x_1x_4 - 326.21\, x_2x_3 + 33.11\, x_2x_4 \\ & - 260.16\, x_3x_4 \end{aligned} \tag{18}$$

2.5. Visual Basic Program for Prediction and Optimization of the Developed Model

The visual basic program in accordance to the algorithm below and Equations (17) and (18) was invoked to select the best mix ratios corresponding to a particular desired compressive strength value and vice versa. To optimize the response function (Equation (9)), iteration principle was employed. Since there are four variables, three iterating factors ($e_1 = 0.001$, $e_2 = 0.001$ and $e_3 = 0.001$) were used. The constraints are as set in Equation (2) to Equation (7). The iteration starts with the first quantities, x_{1min}, x_{2min}, x_{3min} and x_{4min}. These quantities were substituted into Equation (1) to get the first set of mix ratios,1[s_1, s_2, s_3 and s_4]. Where: n [ ] denotes nth set. The first quantities, x1min, x_{2min}, x_{3min} and x_{4min} (That is: 1[x_1, x_2, x_3 and x_4]) were substituted into the response function. The first response was taken as y_m (optimum response). The iterating factors (e_1, e_2, and e_3) were added to the first set of quantities, that is, $x_{1min} + e_1$, $x_{2min} + e_2$ and $x_{3min} + e_3$ respectively, to obtain the second set of quantities, 2[x_1, x_2 and x_3]. Their sum was subtracted from unity (that is 1) to obtain 2[x_4]. 2[x_1, x_2, x_3 and x_4] was divided by 2[x_2] to get 2[s_1, s_2, s_3 and s_4]. These mix ratios, 2[s_1, s_2, s_3 and s_4] was subjected to the constraints of Equation (3) to Equation (6). Passing the tests, they were substituted into the response function. The second response was compared with the first one. When it was more than the first one, it replaced it, when it was not, the first one was retained as y_m. This procedure continued within loop until all the possible combinations of the quantities were used.

3. RESULTS AND DISCUSSION

The predicted compressive strength values for the control mixes as obtained from the program were presented on Table 3 and 4. They were compared with the results from the laboratory as shown on Table 3 and 4 using F-statistics test at 95% level of confidence.

Where y_l, y_m are laboratory and predicted values of compressive strength respectively.

For 28 days Compressive Strength;

$$\overline{y_l} = \frac{\Sigma y_l}{n} = 19.368$$

$$\overline{y_m} = \frac{\Sigma y_m}{n} = 19.380$$

$$S_l^2 = \frac{12.84298}{24} = 0.535124$$

$$S_m^2 = \frac{11.51953}{24} = 0.47998$$

The F-statistic is given by:

$$F = \frac{0.535124}{0.47998} = 1.114888$$

From standard statistical table, $F_{0.95} = (24, 24) = 1.94$

The calculated value of F (1.11) is less than the F-value (1.94) obtained from standard statistical table. The model is therefore adequate for the prediction and optimization of compressive strength of NCPA-cement composites.

For 56 days Compressive Strength;

$$\overline{y_l} = \frac{\Sigma y_l}{n} = 25.625$$

$$\overline{y_m} = \frac{\Sigma y_m}{n} = 25.698$$

$$S_l^2 = \frac{20.2209}{24} = 0.8425$$

$$S_m^2 = \frac{18.6816}{24} = 0.7784$$

The F-statistic is given by:

$$F = \frac{0.8425}{0.7784} = 1.08239859$$

From standard statistical table, $F_{0.95} = (24, 24) = 1.94$

The calculated F-values for 28 days and 56 days compressive strength were 1.11 and 1.08 respectively. Both values were less than the F-value (1.94) obtained from standard statistical table. The model is therefore adequate for the prediction and optimization of compressive strength of NCPA-cement composites.

From Table 3, it was observed that compressive strength of the cement composites increased as the curing age increased. The strength increased from points A2 to A14, while from points A16 to A40, the compressive strength dropped. From the laboratory work, the minimum strengths were 12.6 N/mm^2 and 15.5 N/mm^2 at 28 days and 56 days respectively. In Table 4 it was deduced that at 56 days curing age, the concrete had more strength. From the model, the minimum strengths were 11.79 N/mm^2 and 15.3 N/mm^2 for 28 days and 56 days respectively.

Both the experimental and modelled results showed great similarity as represented in Table 3 and 4. The optimum experimental and predicted outcome of the compressive strengths were 24.20 N/mm^2 and 30 N/mm^2, 22.61 N/mm^2 and 28.54 N/mm^2 at 28 days and 56 days respectively. These optimum values were obtained at 16.5 % and 19.5 % NCPA replacement for the predicted and experimental study at water-cement ratios of 0.72 and 0.75 respectively, mix ratios being 0.835:0.165:1.5:3 and 0.805:0.195:1.5:3. The percentage difference between the optimum experimental and modelled results at 28 days and 56 days curing age were 7.03 % and

5.47 % respectively. This variation being less than 10%, revealed the adequacy of the model for prediction of compressive strengths of NCPA-concrete.

Table 3: Comparative analysis of experimental and modelled 28 days compressive strength

Control point	y_l (N/mm^2)	y_m (N/mm^2)	$y_l-\overline{y_l}$	$y_m-\overline{y_m}$	$(y_l-\overline{y_l})^2$	$(y_m-\overline{y_m})^2$
A2	20.80	21.84	1.43	2.46	2.0449	6.0296
A4	21.50	22.15	2.13	2.77	4.5369	7.6475
A6	22.20	22.38	2.83	3.00	8.0089	8.9889
A8	22.70	22.53	3.33	3.15	11.0889	9.9250
A10	23.10	22.61	3.73	3.23	13.9129	10.4219
A12	23.70	22.61	4.33	3.23	18.7489	10.4608
A14	24.20	22.55	4.83	3.17	23.3289	10.0463
A16	23.30	22.42	3.93	3.04	15.4449	9.2304
A18	22.90	22.22	3.53	2.84	12.4609	8.0763
A20	22.50	21.96	3.13	2.58	9.7969	6.6716
A22	22.00	21.64	2.63	2.26	6.9169	5.1023
A24	21.60	21.26	2.23	1.88	4.9729	3.5346
A26	20.70	20.82	1.33	1.44	1.7689	2.0872
A28	20.20	20.33	0.83	0.95	0.6889	0.8987
A30	19.00	19.78	-0.37	0.40	0.1369	0.1637
A32	18.30	19.19	-1.07	-0.19	1.1449	0.0360
A34	17.30	18.55	-2.07	-0.83	4.2849	0.6947
A36	16.50	17.85	-2.87	-1.53	8.2369	2.3537
A38	16.10	17.11	-3.27	-2.27	10.6929	5.1620
A40	15.80	16.33	-3.57	-3.05	12.7449	9.3283
A42	15.10	15.50	-4.27	-3.88	18.2329	15.0494
A44	14.60	14.62	-4.77	-4.76	22.7529	22.6346
A46	14.00	13.72	-5.37	-5.66	28.8369	32.0884
A48	13.50	12.77	-5.87	-6.61	34.4569	43.6970
A50	12.60	11.79	-6.77	-7.59	45.8329	57.6594
	19.37	19.38			12.8430	11.5195

Table 4: Comparative analysis of experimental and modelled 56 days compressive strength

Control point	y_l (N/mm^2)	y_m (N/mm^2)	$y_l-\overline{y_l}$	$y_m-\overline{y_m}$	$(y_l-\overline{y_l})^2$	$(y_m-\overline{y_m})^2$
A2	26.30	27.18	0.67	1.48	0.4489	2.1904
A4	27.40	27.66	1.77	1.96	3.1329	3.8416
A6	27.90	28.03	2.27	2.33	5.1529	5.4289
A8	28.30	28.30	2.67	2.60	7.1289	6.7600
A10	29.00	28.47	3.37	2.77	11.3569	7.6729
A12	29.40	28.54	3.77	2.84	14.2129	8.0656
A14	30.10	28.52	4.47	2.82	19.9809	7.9524
A16	29.50	28.40	3.87	2.70	14.9769	7.2900
A18	28.60	28.21	2.97	2.51	8.8209	6.3001
A20	28.40	27.92	2.77	2.22	7.6729	4.9284
A22	27.90	27.56	2.27	1.86	5.1529	3.4596
A24	27.50	27.11	1.87	1.41	3.4969	1.9881
A26	26.50	26.60	0.87	0.90	0.7569	0.8100
A28	24.90	26.00	-0.73	0.30	0.5329	0.0900
A30	23.90	25.34	-1.73	-0.36	2.9929	0.1296
A32	23.40	24.61	-2.23	-1.09	4.9729	1.1881
A34	22.70	23.81	-2.93	-1.89	8.5849	3.5721
A36	21.80	22.94	-3.83	-2.76	14.6689	7.6176
A38	20.90	22.02	-4.73	-3.68	22.3729	13.5424
A40	20.50	21.04	-5.13	-4.66	26.3169	21.7156
A42	19.90	20.00	-5.73	-5.70	32.8329	32.4900
A44	19.30	18.90	-6.33	-6.80	40.0689	46.2400
A46	18.50	17.75	-7.13	-7.95	50.8369	63.2025
A48	16.90	16.55	-8.73	-9.15	76.2129	83.7225
A50	15.50	15.30	-10.13	-10.40	102.6169	108.1600
	25.63	25.70			20.2209	18.6816

4. CONCLUSION

An excellent, suitable and reliable model for predicting and optimizing of compressive strength of NCPA-Cement composites, have been developed based on Ibearugbulem's new regression function. At 95%

confidence level, the developed model was confirmed to be reliable and adequate. With an iterative approach, the optimum values of compressive strength value and mix ratios can be estimated using the written short Visual Basic program, which predicts the desired mix ratios when the strength is known. For easy forecast of compressive strengths of lightweight-concretes whose mix ratios are within the boundaries provided in this research work, this model is recommended for use in concrete and construction industry.

5. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

REFERENCES

Anyaogu, L. and Ezeh, J.C (2013). Optimization of compressive strength of fly ash blended cement concrete using Scheffe's Simplex Theory. *Natural and Applied Sciences*, 4(2), pp. 177-186.

Awodiji, C.T.G., Onwuka, D.O., Okere, C. E. and Ibearugbulem, O. M. (2018). Anticipating the Compressive Strength of Hydrated Lime Cement Concrete Using Artificial Neural Network Model. *Civil Engineering Journal*, 4(12), pp. 3005-3018.

British Standard (BS) BS 12 (1996). *Specification for Portland cement*. British Standards Institution, London.

British Standard (BS) BS 1881 (1983). *Testing concrete: Method for determination of compressive strength of concrete*. British Standards Institution, London.

British Standard (BS) BS 3140 (1980). *Methods of Test for Water for Making Concrete, Including Notes on the Suitability of the Water),* British Standards Institution, London.

British Standard (BS) BS 882 (1992). *Specification for aggregates from natural sources for concrete*. British Standards Institution, London.

Ettu, L.O., Ezeh, J.C., Ibearugbulem, O. M., Anya, U.C. and Njoku, K. O. (2013). Strength of Binary Blended Cement Composites Containing Cassava Waste Ash, *International Journal of Emerging Technology and Advanced Engineering* 3(4), pp. 15-20.

Ibearugbulem, O.M., Ettu, L.O., Ezeh, J.C. and Anya, U.C. (2013). A new regression model for optimizing concrete mixes. *International Journal of Engineering Sciences and Research Technology*, 2(7), pp. 1735-1742.

Mama, B.O. and Osadebe, N.N (2011). Comparative Analysis of two Mathematical Models for Prediction of Compressive Strength of Sandcrete Blocks using Alluvial Deposit. *Nigerian Journal of Technology,* 30(3), pp. 82-89.

Oba, K. M., Ugwu, O. O. and Okafor, F. O. (2019). Development of Scheffe's Model to Predict the Compressive Strength of Concrete using SDA as Partial Replacement for Fine Aggregate. *International Journal of Innovative Technology and Exploring Engineering (IJITEE),* 8(8), pp. 2512-2521.

Ofuyatan, O., Ede, A., Olofinnade, R., Oyebisi, S., Alayande, T. and Ogundipe, J. (2018). Assessment of Strength Properties of Cassava Peel Ash-Concrete. *International Journal of Civil Engineering and Technology (IJCIET)*, 9(1), pp. 965–974.

Olonade, K.A., Olajumoke, A.M., Omotosho, A.O. and Oyekunle, F.A. (2014). Effects of Sulphuric acid on the compressive strength of blended cement cassava peel ash concrete. *Construction Materials and Structures*, IOS Press, 2014, pp. 764-771.

Onwuka, D.O. and Sule, S. (2017). Prediction of compressive strength of chikoko-cement concrete using Scheffe's polynomial function. *USEP: Journal of Research Information in Civil Engineering*, 14(1), pp. 1338-1358.

Prasad, M. (2017). A Review on Nano Materials in Concrete. *Civil Engineering Research Journal,* 2(2), pp 0021-0022

Raheem, S. B., Arubike, E. D. and Awogboro, O. S. (2015). Effects of Cassava Peel Ash (CPA) as Alternative Binder in Concrete. *International Journal of Constructive Research in Civil Engineering (IJCRCE)* 1(2), pp. 27-32.

Rao, N. V., Rajasekharb, M., Vijayalakshmic, K. and Vamshykrishnad, M. (2015). The Future of Civil Engineering with the Influence and Impact of Nanotechnology on Properties of Materials, 2nd International Conference on Nanomaterials and Technologies. *Procedia Materials Science*, 10, pp. 111 – 115,

Sanchez, F. and Sobolev, K. (2010). Nanotechnology in concrete – A review. *Construction and Building Materials,* 24, pp. 2060–2071.