

## A COMPUTER PROGRAM FOR ANALYZING CONCRETE MIXTURE EXPERIMENTS BASED ON OSADEBE'S REGRESSION MODEL

IFEANYI AGWUOCHA<sup>1</sup>, UCHECHUKWU COLLINS ANYA<sup>1</sup>, CHIOMA TEMITOPE GLORIA AWODIJI<sup>\*2</sup>, LAWRENCE ETTU<sup>1</sup>

<sup>1</sup>*Department of Civil Engineering, Federal University of Technology, Owerri, Imo State, Nigeria*

<sup>2</sup>*Department of Civil and Environmental Engineering, University of Port-Harcourt, Rivers State, Nigeria*

**Abstract:** The Osadebe's regression model is associated with lots of strenuous mathematical computations. In this research work, a MATLAB based computer program, named MIX-PRE, was formulated for analyzing concrete mixture experiments using the Osadebe's regression model. It was tested by comparing results obtained from it to previous studies by Anya and Okere. The highest percentage difference between strength results from MIX-PRE and from these studies was about 3%. The % differences for all other parameters studied were close to zero showing little contrast in the predicting ability of MIX-PRE when compared to the direct use of the Osadebe's regression model.

**Keywords:** MIX-PRE, Osadebe's regression model, concrete, mixture experiment

### 1. INTRODUCTION

The combination of two or more components results in the making of products. Paints, concrete and gasoline are some examples of these articles. Concrete, a mixture usually made from water, aggregates and cement, is a very important building material in Nigeria. Most of the places of residences and infrastructural amenities in Nigeria are built using concrete [1]. Before preparing a concrete mix, the right material elements and their particular amount must be known. This first stage is very important since it determines whether the concrete produced will acquire the needed qualities. Making this decision can be very challenging since the designer will have to use the most acceptable ingredients among the obtainable materials and find out the most profitable blend that will generate concrete with the needed performance features.

Most of the times, former information, codes and guidelines are used in the implementation for the design of new concrete mixtures. Some examples of mix combination methods and guidelines can be seen from the [2, 3], British Department of Environment (BDOE), United States Bureau of Reclamation (USBR), and Indian standard (IS). Most of the guidelines issue techniques for proportioning a given mixture. But, do not show how best blends, with respect to economy and desired qualities, can be obtained [4]. This customary method usually involves a trial-and-error perspective to modify the mix proportion. It is typically performed by running a first trial batch, evaluating the results, adjusting the proportions of various components and running further trial batches until all specified criteria are met [5]. Such a method does not objectively provide the best setting of components to meet desired performance criteria as it is unable to both detect the interaction among variables

---

\* Corresponding author, email: [chimbaegbu@yahoo.com](mailto:chimbaegbu@yahoo.com)  
© 2022 Alma Mater Publishing House

and develop prediction equations for subsequent optimization [6]. As such, the need for statistical methods of concrete mixture proportioning.

Statistical fact-finding design methods are tough procedures for realizing desired properties and determining an advanced mixture for a given set of limitations [5]. Data obtained from investigations are prone to error. According to [7], *when the problem involves data that is subject to experimental errors, statistical methods are the only objective approach to analysis*. The use of statistical methods in designing a mix changes the trial batching process and not the overall guidelines for mix design. Hence, there is need for a means that could either partly or completely, reduce this rigorous procedure as well as being highly flexible and reliable. It is already a known fact that the irregularities in the behaviour of concrete makes it very stressful to mathematically imitate its behaviour [8]. Computer programs are lists of instructions that tell a computer how to perform a task. Writing of computer programs are unique to the software that interprets them. MATLAB is a software whose activity can be likened to a large calculator. Therefore, it allows the user solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar non-interactive language such as C or Fortran [9]. One of the reasons for the approval of MATLAB is that it has been used in past times and seen to be adequate [10]. It makes use of the user interface that comes up with an easy and interactive environment for users. There is no need for so much numerical computations. It is versatile, programmable and very flexible. So, it can be applied across several disciplines [10].

Several researchers have carried out works on developing mixture models to solve many real-life problems in different areas such as pharmacy, food industry, engineering etc. The simplex design models for studying the response of a mixture system was first introduced by [11]. In 1958, [12] introduced the simplex-lattice design model and later extended to the simplex-centroid design model. Advancement of these models were done by [13]. While, [14] developed the extreme vertices design model which appeared to have utility for experimentation in constrained mixture spaces. A regression model based on expressing the response ( $y$ ) as a function of the proportions of the constituents of the mixture  $Z_i$  as shown in equation (1) was developed by Osadebe in 2003 [15]:

$$Y = F(z) \quad (1)$$

The Osadebe regression equation is another form of mixture experimental models. In comparison to the other models such as simplex lattice, simplex centroid and simplex axial, Osadebe's regression model does not limit the design points for any mixture experiment to within or on the vertices of the simplex [16]. Rather, it allows for prediction of responses at any point (inside, outside, or on the vertices of the simplex). Basically, the objective of a regression model is to identify correlations between predictor ( $X$ 's) and response ( $Y$ 's). Many researchers have applied the Osadebe's regression model to solving mixture experimental problems in concrete.

The static modulus of elasticity of laterite-quarry dust blocks was predicted by [17] using the Osadebe's regression model. The fitness of the model was tested by comparing its forecast to that of the experimental design. It was seen to be adequate. A mathematical model using the Osadebe's regression model was developed by [1] and used to optimize the compressive strength of concrete with different percentages of termite soil as partial replacement of fine aggregate. The predictions from the model was tested at 95% accuracy level using statistical student's T-test and it proved the model adequate. As such, the developed model was found to be accurate in its ability to predict the compressive strength of termite soil when mix ratios were fed into it. Another mathematical model for the optimization of modulus of rupture of concrete using the Osadebe's regression theory was formulated by [18]. The developed mathematical model was used as an optimization tool for the prediction of the modulus of rupture of the concrete. Tests for adequacy were carried out on the model using the F and T statistical techniques at 95% confidence level and the model was confirmed adequate.

The mixture experimental models was used by [16] to predict the strength and durability characteristics of sandcrete blocks with sand partially replaced with quarry dust. In the research, three mathematical models were considered i.e. Scheffe's simplex lattice, Scheffe's component proportion model and Osadebe's regression model. Upon studying the component interaction through the use of the models, he observed that the Scheffe's models were bounded. While, the Osadebe's model was not. The impact of this observation is that the Osadebe model has a wider range of application.

A model developed from the Osadebe's regression theory for the design of palm bunch ash (PBA) – cement concrete mixtures was presented by [19]. The research work which focused on the partial replacement of cement

with palm bunch ash (PBA) at different percentages, had a mathematical model formulated based on the Osadebe's model. The result from the research affirms that the model is adequate for predicting concrete mixture experiments. Table 1 and Table 2 present the model formulation and validation mix ratios, the mixture components and their corresponding responses used by [16] and [18] respectively. The values on these tables were used in validating the program formulated in this study.

From the works of [1, 16, 18, 19], it has been observed that the procedure involved in formulating the Osadebe's regression model for concrete mixture experiments is associated with a lot of mathematical computations that can be very tiring. Hence, this study seeks to find a solution to this problem by developing a MATLAB based computer program (called MIX-PRE) that can be used to optimize the concrete mix design process using the Osadebe's regression model. The formulated model was used to make predictions using data (mix ratios) from past studies on the use of the Osadebe's regression model. The results obtained were compared to those already gotten from literature. The use of this program will eliminate the process of strenuous mathematical computations and the laboratory investigation to generate trial concrete mixes. Therefore, the objectives of this study are as follows:

- To develop a Matlab program called MIX-PRE, using the Osadebe regression model, for the purpose of concrete mix design.
- To use the developed program to make predictions for various parameters that are already determined in past literatures.
- To compare the values obtained from the developed program to those obtained from the existing studies.
- To determine and check the adequacy of the program predictions w.r.t to the results of the test of adequacy already obtained for the existing literatures.

Table 1. Components, mix-ratio and responses of sand-quarry blocks [16].

Model formulation mixes						Model validation (control mixes)					
Run Order	Water	Cement	Sand	Quarry dust	Compressive Strength (N/mm <sup>2</sup> )	Run Order	Water	Cement	Sand	Quarry dust	Compressive Strength (N/mm <sup>2</sup> )
1.12	0.52	1	5.4	0.6	4.57	3	0.62	1	5.7	1.3	3.73
19	0.565	1	4.5	1.5	4.91	4,5	0.72	1	6	2	3.41
17	0.635	1	7.2	0.8	3.09	5	0.72	1	6	2	3.41
15	0.76	1	5.7	2.3	3.2	6	0.86	1	6	3	3.13
14.18	0.61	1	3.6	2.4	5.23	10	0.735	1	7.5	1.5	3.04
11	0.68	1	6.3	1.7	3.39	20	0.665	1	4.8	2.2	4.05
2	0.805	1	4.8	3.2	3.5						
7.9	0.75	1	9	1	2.76						
8	0.875	1	7.5	2.5	3.07						
13.16	1	1	6	4	2.91						

Table 2. Components, mix-ratio and responses of sand-laterite blocks [18].

Model formulation mixes						Model validation mixes (controls)					
S/N	Water	Cement	River Sand	Laterite	Compressive Strength (N/mm <sup>2</sup> )	S/N	Water	Cement	River Sand	Laterite	Compressive Strength (N/mm <sup>2</sup> )
1	0.8	1	3.2	4.8	3.012	11	1.09	1	3.4045	10.056	2.024
2	1	1	3.75	8.75	2.025	12	1.02	1	3.5085	8.909	1.975
3	1.28	1	3.334	13.336	1.63	13	0.866	1	3.3815	6.1035	2.666
4	2.2	1	2.5	22.5	1.259	14	1.092	1	3.6127	10.263	1.926
5	0.9	1	3.475	6.775	2.321	15	1.052	1	3.4186	9.3994	1.975
6	1.04	1	3.267	9.068	2.074	16	1.1	1	3.432	10.253	1.876
7	1.5	1	2.85	13.65	1.704	17	0.97	1	3.371	7.9215	2.173
8	1.14	1	3.542	11.043	1.926	18	1.32	1	3.196	12.347	1.571
9	1.6	1	3.125	15.625	1.185	19	1.67	1	3.021	16.772	1.21
10	1.74	1	2.917	17.918	1.235	20	1.9	1	2.8125	19.063	1.136

## 2. EXPERIMENTAL SETUP

### 2.1. Materials

The major materials used for developing the program is a computer and the Matlab R2015a software. This software was acquired from MathWorks

### 2.2. Methods

The methods applied for this study can be placed under three headings which are:

- Osadebe's regression modelling method;
- Formulation of the computer program;
- Validation of the formulated computer program.

#### 2.2.1. Osadebe's regression modelling method

[16] expressed the response,  $y$  (of a mixture experiment) as a function of the proportions of the constituents of the mixture,  $Z_i$ . He assumed that the response function  $F(z)$  is continuous and differentiable with respect to its predictors as shown:

$$F(Z^{(0)}) = \frac{1}{m!} \sum f^m(Z^{(0)}) * (Z_i - Z^{(0)})^m \quad (2)$$

where  $m$  is the degree of the polynomial.

The degree of polynomial can be said to be the greatest exponential of a polynomial function. Simply put, it is the number of equal spaces assigned to any vertices. Expanding equation (2) in the neighbourhood of a chosen point,  $Z^{(0)}$  and using Taylor's series, the response function would be:

$$Z(0) = (Z_1^{(0)}, Z_2^{(0)}, \dots, Z_q^{(0)})^T \quad (3)$$

Expanding equation (3) up to the  $n^{\text{th}}$  degree gives:

$$F(Z^{(0)}) = \sum_{i=1}^q \frac{\partial f}{\partial Z_i}(Z^{(0)})(Z_i - Z^{(0)}) + \frac{1}{2!} \sum_{i=1}^{q-1} \sum_{j=1}^q \frac{\partial^2 f(Z^{(0)})}{\partial Z_i \partial Z_j}(Z_i - Z_i^{(0)})(Z_j - Z_j^{(0)}) + \frac{1}{2!} \sum_{i=1}^q \frac{\partial^2 f(Z^{(0)})}{\partial Z_i^2}(Z_i - Z^{(0)}) \dots \dots n \quad (4)$$

The predictor,  $Z_i$  is not the actual quantity of the mixture components rather, it is their respective mixture ratios which have being converted into fractional proportions. Let  $Z_i$  be the "fractional proportion" and  $S_i$  be the 'quantity of each component of the mixture', then for a mixture of five components,  $1 \leq i \leq 5$ , the quantities of each component is expressed as:

$$S_1 + S_2 + S_3 + S_4 + S_5 = S \quad (5)$$

Their fractional proportion is obtained by dividing each component by the sum.

$$\frac{S_1}{S} + \frac{S_2}{S} + \frac{S_3}{S} + \frac{S_4}{S} + \frac{S_5}{S} = \frac{S}{S} \quad (6)$$

Representing the fractions of equation (6) in terms of  $Z$  gives:

$$Z_1 + Z_2 + Z_3 + Z_4 + Z_5 = 1 \quad (7)$$

There have been proven situations where the computed coefficients of the regression results is a singular matrix, which makes the model too sensitive. In such situations, one should consider multiplying equation (7) by 10 to gives equation (8). However, it should be noted that in the course of the research work, equation (8) was not applied as MATLAB could carry out the computation with the singular matrix. Therefore:

$$10Z_1 + 10Z_2 + 10Z_3 + 10Z_4 + 10Z_5 = 10 \quad (8)$$

From equation (3), let:

$$b_o = F(O); b_i = \frac{\partial F(O)}{\partial Z_i}; b_{ij} = \frac{\partial^2 F(O)}{\partial Z_i \partial Z_j}; b_{ii} = \frac{\partial^2 F(O)}{\partial Z_i^2} \tag{9}$$

Substituting equation (9) into equation (4), will give:

$$y(Z) = b_o + \sum_{i=1}^q b_i Z_i + \sum_{i \leq j \leq q} b_{ij} Z_i Z_j + \sum_{i=1}^q b_{ii} Z_i^2 \tag{10}$$

Multiplying equation (7) by  $b_0$  gives the expression:

$$b_o = b_o Z_1 + b_o Z_2 + \dots + b_o Z_q \tag{11}$$

Multiplying equation (7) successively by  $Z_1, Z_2 \dots Z_q$  and rearranging respectively gives:

$$\begin{aligned} Z_1^2 &= Z_1 - Z_1 Z_2 \dots - Z_1 Z_q \\ Z_2^2 &= Z_2 - Z_1 Z_2 \dots - Z_2 Z_q \\ &\dots \dots \dots \\ Z_q^2 &= Z_q - Z_1 Z_q \dots - Z_{(q-1)} Z_q \end{aligned} \tag{12}$$

If we choose to apply equation (12) to a 5 component mixture, we will have:

$$\begin{aligned} Z_1^2 &= Z_1 - Z_1 Z_2 - Z_1 Z_3 - Z_1 Z_4 - Z_1 Z_5 \\ Z_2^2 &= Z_2 - Z_1 Z_2 - Z_2 Z_3 - Z_2 Z_4 - Z_2 Z_5 \\ Z_3^2 &= Z_3 - Z_1 Z_3 - Z_2 Z_3 - Z_3 Z_4 - Z_3 Z_5 \\ Z_4^2 &= Z_4 - Z_1 Z_4 - Z_2 Z_4 - Z_3 Z_4 - Z_4 Z_5 \\ Z_5^2 &= Z_5 - Z_1 Z_5 - Z_2 Z_5 - Z_3 Z_5 - Z_4 Z_5 \end{aligned} \tag{13}$$

Substituting equation (11) and equation (13) into equation (10) for a 5 component mixture ( $q=5$ ) and expanding gives:

$$\begin{aligned} y(Z) &= b_o Z_1 + b_o Z_2 + b_o Z_3 + b_o Z_4 + b_o Z_5 + b_1 Z_1 + b_1 Z_1 + b_2 Z_2 + b_3 Z_3 + b_4 Z_4 + b_5 Z_5 + \\ &b_{12} Z_1 Z_2 + b_{13} Z_1 Z_3 + b_{14} Z_1 Z_4 + b_{15} Z_1 Z_5 + b_{23} Z_2 Z_3 + b_{24} Z_2 Z_4 + b_{25} Z_2 Z_5 + b_{34} Z_3 Z_4 + b_{35} Z_3 Z_5 + \\ &b_{45} Z_4 Z_5 + b_{11} (Z_1 - Z_1 Z_2 - Z_1 Z_3 - Z_1 Z_4 - Z_1 Z_5) + b_{22} (Z_2 - Z_1 Z_2 - Z_2 Z_3 - Z_2 Z_4 - Z_2 Z_5) + \\ &b_{33} (Z_3 - Z_1 Z_3 - Z_2 Z_3 - Z_3 Z_4 - Z_3 Z_5) + b_{44} (Z_4 - Z_1 Z_4 - Z_2 Z_4 - Z_3 Z_4 - Z_4 Z_5) + \\ &b_{55} (Z_5 - Z_1 Z_5 - Z_2 Z_5 - Z_3 Z_5 - Z_4 Z_5) \end{aligned} \tag{14}$$

Factorizing equation (14) will give:

$$\begin{aligned} y(Z) &= (b_o + b_1 + b_{11})Z_1 + (b_o + b_2 + b_{22})Z_2 + (b_o + b_3 + b_{33})Z_3 + (b_o + b_4 + b_{44})Z_4 + (b_o + b_5 + b_{55})Z_5 + \\ &(b_{12} - b_{11} - b_{22})Z_1 Z_2 + (b_{13} - b_{11} - b_{33})Z_1 Z_3 + (b_{14} - b_{11} - b_{44})Z_1 Z_4 + (b_{15} - b_{11} - b_{55})Z_1 Z_5 + \\ &(b_{23} - b_{22} - b_{33})Z_2 Z_3 + (b_{24} - b_{22} - b_{44})Z_2 Z_4 + (b_{25} - b_{22} - b_{55})Z_2 Z_5 + (b_{34} - b_{33} - b_{44})Z_3 Z_4 + (b_{35} - b_{33} - b_{55})Z_3 Z_5 \end{aligned} \tag{15}$$

$$y = \beta_1 = b_o + b_i + b_{ii}; \beta_{ij} = b_{ij} - b_{ii} - b_{jj} \tag{16}$$

Substituting equation (16) into equation (13) will give:

$$\begin{aligned} y &= \beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_3 + \beta_4 Z_4 + \beta_5 Z_5 + \beta_{ij} Z_1 Z_2 + \beta_{ij} Z_1 Z_3 + \beta_{ij} Z_1 Z_4 + \beta_{ij} Z_1 Z_5 + \\ &\beta_{ij} Z_2 Z_3 + \beta_{12} Z_1 Z_2 + \beta_{13} Z_1 Z_3 + \beta_{14} Z_1 Z_4 + \beta_{23} Z_2 Z_3 + \beta_{24} Z_2 Z_4 + \beta_{25} Z_2 Z_5 + \beta_{34} Z_3 Z_4 \\ &\beta_{35} Z_3 Z_5 + \beta_{45} Z_4 Z_5 \end{aligned} \tag{17}$$

Putting equation (17) in a compact form gives:

$$y(Z) = \sum_{i=1}^q \beta_i Z_i + \sum_{i \leq j \leq q} \beta_{ij} Z_i Z_j \tag{18}$$

where,  $y(Z)$  is the response function at any point of observation,  $Z_i, Z_j$  are the predictors, and  $\beta_i, \beta_{ij}$  are the coefficients of the regression equation.

It should be noted that the number of design points is the same as the number of regression coefficients. While the Osadebe’s regression model works with regression coefficients, the simplex lattice uses design points. Equation (18) is the Osadebe’s regression model equation. It is defined if the unknown constant coefficients  $\beta_i$  and  $\beta_{ij}$  are uniquely determined.

2.2.1.1. The coefficients of the Osadebe’s regression model

The least number of experimental runs or independent responses necessary to determine the coefficients of the Osadebe regression model is  $N$ . Let  $y^{(k)}$  be the response at point  $k$  and the vector corresponding to the set of component proportions (predictors) at point  $k$  be  $Z^{(k)}$ . That is:

$$Z^{(k)} = \{Z_1^{(k)}, Z_2^{(k)}, \dots, Z_q^{(k)}\} \tag{19}$$

Substituting the vector of equation (19) into equation (18) gives:

$$y^{(k)} = \sum_{i=1}^q \beta_i Z_i^{(k)} + \sum_{i \leq j \leq q} \beta_{ij} Z_i^{(k)} Z_j^{(k)} \tag{20}$$

where  $k$  is 1, 2, ...,  $N$ .

Substituting the predictor vectors at each of the  $N$  observation points successively into equation (18) gives a set of  $N$  linear algebraic equations which can be written in matrix form as:

$$Z\beta = y \tag{21}$$

where,  $\beta$  is a vector whose elements are the estimates of the regression coefficients,  $Z$  is an  $N \times N$  matrix whose elements are the mixture component proportions as well as the functions of the component proportions,  $y$  is a vector of the observations or responses at the various  $N$  observation points. That is:

$$Z = \begin{pmatrix} Z_1^{(1)} & Z_2^{(1)} \dots & Z_1^{(1)} Z_2^{(1)} & Z_1^{(1)} Z_q^{(1)} & Z_{q-1}^{(1)} Z_q^{(1)} \\ Z_1^{(2)} & Z_2^{(2)} \dots & Z_1^{(2)} Z_2^{(2)} & Z_1^{(2)} Z_q^{(2)} & Z_{q-1}^{(2)} Z_q^{(2)} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ Z_1^{(N-1)} & Z_2^{(N-1)} & \dots Z_1^{(N-1)} Z_2^{(N-1)} & Z_1^{(N-1)} Z_q^{(N-1)} & Z_{q-1}^{(N-1)} Z_q^{(N-1)} \\ Z_1^{(N)} & Z_2^{(N)} & \dots Z_1^{(N)} Z_2^{(N)} & Z_1^{(N)} Z_q^{(N)} & Z_{q-1}^{(N)} Z_q^{(N)} \end{pmatrix} \tag{21a}$$

$$\beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_q \\ \beta_{12} \\ \beta_{13} \\ \vdots \\ \beta_{1q} \\ \vdots \\ \beta_{q-1q} \end{pmatrix} \quad (21b)$$

$$y = \begin{pmatrix} y^1 \\ y^2 \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ y^q \\ \vdots \\ \vdots \\ y^N \end{pmatrix} \quad (21c)$$

The solution to equation (21b) is given as:

$$\beta = Z^{-1}y \quad (22)$$

### 2.2.2. Formulation of the computer program

A computer program named “MIX-PRE” was formulated on MATLAB (R2015a) software to generate model equations and predict responses for any given mix ratios using the Osadebe’s regression model. ‘MIX-PRE’ which is a matlab function file was coded to have five (5) graphical user interfaces namely; About user interface, model prediction user interface, model validation user interface, result user interface and graph user interface.

The about user interface introduces the program. The model formulation user interface oversees model formulation as well as response predictions. The validation user interface takes care of numerical validation (using Anova, F-tests and T-tests techniques) of the formulated model. The results user interface is an output interface which shows all results obtained as well as having a save button which saves all outputs directly to Microsoft excel file format. The graphs user interface handles graphical validation of the formulated model using plots such as residual plot, normal probability plot, scatter plot and observed vs. predicted plot. Figure 1 shows the flowchart used in developing MIX-PRE.

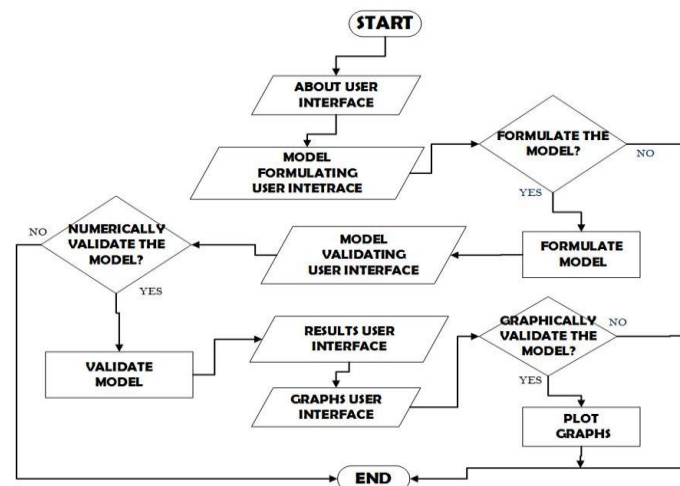


Fig. 1. Flow chart for the formulation of MIX-PRE.

#### 2.2.2.1. Encoding of the different graphical user interfaces

Programming of the graphical user interfaces for Mix-pre was started by using the syntax `figure()`. This command launched an empty graphical user interface. This interface was then customized using the syntax `uitabgroup`. This syntax created a group to be filled with subsequently created tabs.

##### A) The about user interface

Encoding of this user interface was started using the command `uitab`. Afterwards, the command `uicontrol` was called up and used to introduce the purpose of the program as well as initiate a pushbutton which takes the user directly to the model prediction user interface.

##### B) The model predicting user interface.

Similar to the about user interface, creation of the model interface began by using the syntax `uitab` and assigning it to a tab. Afterwards, the command `uipanel` was used to segment the interface in panels. A parent panel called `problem setup` was created. Two subpanels named `model prediction` and `coefficient` were created under the problem setup parent panel. While the coefficient panel was programmed solely as an output panel, the model prediction panel was created as an input-output panel. It comprises of strings, input/output bars and pushbuttons. The model prediction panel oversees the application of the Osadebe's regression model in solving mixture experimental problems. Encoding of the strings in the model prediction panel was done using the syntax `uicontrol` and its properties were set up as is required for a string character. Likewise, the input/output bars and pushbuttons were encrypted into the model prediction panel using the command `uicontrol`. These properties were accurately configured as required. The algorithm for these processes is as shown in Appendix A.

##### C) The model validating user interface

The model validation user interface was encoded to numerically check the accuracy of data as well as render hypothesis statements based on a 95% confidence. Encrypting of this interface started using the syntax `uipanel` to create panels which would segment and harbor the constituents of the interface. Three panels were produced with the syntax `uipanel`. The model validation panel was assigned to be a parent panel. While, the other two called coefficients and error, variance and anova panel were encoded as being sub-panels associated to the model validation panel. After the creation of the panels, the contents of the panels were coded in. This was done using the command `uicontrol` and assigning of the respective controls. Flowchart for this process is depicted in Appendix B.

##### D) The results user interface

The result user interface comprises two panels created using the `uipanel` command. They are; results panel and tables panel. Using the same command, additional four panels were created as sub-panels to the results panel and they are; T-test panel, F-test panel, Anova panel and File panel. The F-test, T-test and Anova panels was programmed using the command `uicontrol` to output the result of their respective numerical validation of data. The File panel was encoded to save all output results in Microsoft excel format in addition to hyperlinking the user to the graphs interface.



### E) The graphs user interface

The graphs user interface comprises two graph areas i.e. plot areas and a pop-up menu. While the pop-up menu comprises four different plot types, the graph areas display any selected plot type. Encoding of this interface began by using the syntax 'axes'. Then, syntax was applied to create the plot areas. Next, the syntax 'uicontrol' was used to arrange the various plot types as displayed in the interface. Appendix D shows the step by step procedure for actualizing this process.

#### 2.2.2.2. Encryption of the Osadebe's model into MIX-PRE

This process was carried out in two stages. The first stage is encoded with the model formulation. MIX-PRE was made to receive inputs. These inputs were the number of components, degree of polynomial, the model formulating Microsoft excel file and the column number of responses. MIX-PRE was scripted to use input data from the number of components and degree of polynomial to compute the number of regression coefficient required for the model equation. Afterwards, the program was encoded to obtain the formulating data uploaded into it; read through this file and fetched out the desired mix-ratios and their corresponding responses required for formulate the model equation. MIX-PRE was again coded to take out these desired mix-ratios; convert them in their respective proportions (z-values) using the procedure described in C1 2.2.1. Afterwards, several matrices were created to harbor the responses (y), the fractional proportions (z-values) and the mix-ratios (s-values). Empty matrices for the regression coefficients ( $\beta$ -values) and the inverse matrix of the z-values were provided for. Next, MIX-PRE was programmed to arrange the response matrix, the fractional proportions matrix and the  $\beta$ -matrix to be of the form shown in equation (22). With this, the elements of the  $\beta$  - matrix were calculated. MIX-PRE would then substitute all required values in equation (22) and output this equation in addition to the number of regression coefficient.

The second stage involved the encoding of the numerical techniques required for validating the formulated model. This process is initiated by MIX-PRE acquiring the model validating Microsoft excel file. It reads through its content; convert the mixture quantities (in the Microsoft excel validating data file) to their respective fractional proportion; substitute these fractional proportions in the formulated model and computes the respective model predicted responses. It also endorses any formulated models using any of the validation techniques i.e Anova, Fisher's test (F-test) and Students T-test. After validation, MIX-PRE makes comparison to the statistical tables at 95% confidence level and outputs a hypothesis statement based on the outcome.

#### 2.2.2.3. Operating the MIX-PRE program

In order to operate the formulated program, the following procedures were carried out.

##### i. Generating the mathematical model

This was achieved by following the process as shown:

- Launch the program;
- Click on the START tab;
- Enter the number of components;
- Enter the degree of polynomial;
- Click on the BROWSE tab to upload the Model formulating data. This input format for the model formulating data file used is as displayed in Table 3.

Table 3. Format for the upload of data into Mix-pre.

Runs Order	Component 1	...	...	$i^{\text{th}}$ component	Response 1	$i^{\text{th}}$ Response
1	...	...	...	...	...	...
2	...	...	...	...	...	...
.	...	...	...	...	...	...
.	...	...	...	...	...	...
j	...	...	...	...	...	...

- Next, enter the column number of response;
- Click on the CHECK INVERSE tab;

- From the MATLAB workspace, get the correction factor and enter it in the correction factor input bar;
- Click REGRESSION COEFFICIENT tab.

At the end of this process, the regression coefficients were determined.

### *ii. Predicting the responses*

Responses were generated from the program after determining the regression coefficients by following the given steps.

For a single mix:

- 1) Enter the mix ratio in the format [x, y, c, g]. It should be noted that the square brackets and comma must be included. Also, the number of components to be used in predicting the response must be the same as the number of components used in generating the model equation;
- 2) Click on the FOR SINGLE MIX button.

For Multiple Mixes:

- 1) Click on the BROWSE tab;
- 2) Select the relevant file. Ensure it is of a similar format to Table 3;
- 3) Click on the FOR MULTIPLE MIXES button.

This procedure resulted to the program coming up with responses to the mix ratios entered into them.

### *iii. Validation of models*

Numerical and graphical validation of the responses from the program where carried out as shown;

For Numerical validation:

- a) From the model prediction user interface, click on the VALIDATE MODEL tab;
- b) Click on the BROWSE tab to upload the Model validating data. The input format for the model formulating data file used is as displayed in Table 3;
- c) Enter the column number of response;
- d) Click on the COMPUTE ANOVA to have the model validated using Anova;
- e) Click on the COMPUTE T-Test tab to have the model validated using T-test;
- f) Click on the COMPUTE F-Test tab to have the model validated using F-test

For Graphical validation:

- I. Click on the GRAPHS tab to launch the graphs user interface;
- II. Choose from the SELECT PLOT TYPE options bar for the desired graphical validation technique.

## **3. RESULTS AND DISCUSSION**

### *3.1. The graphical user interfaces*

Five graphical user interfaces were generated during the course of this study and they are displayed in Figures 2 to 6.

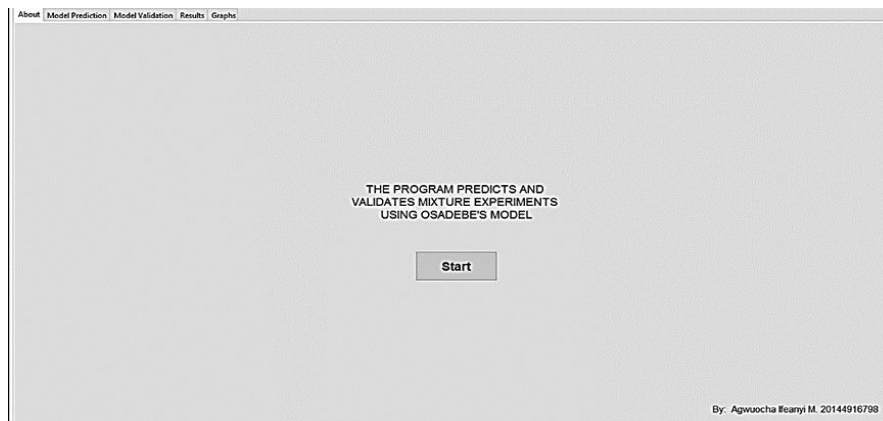


Fig. 2. The about user interface.

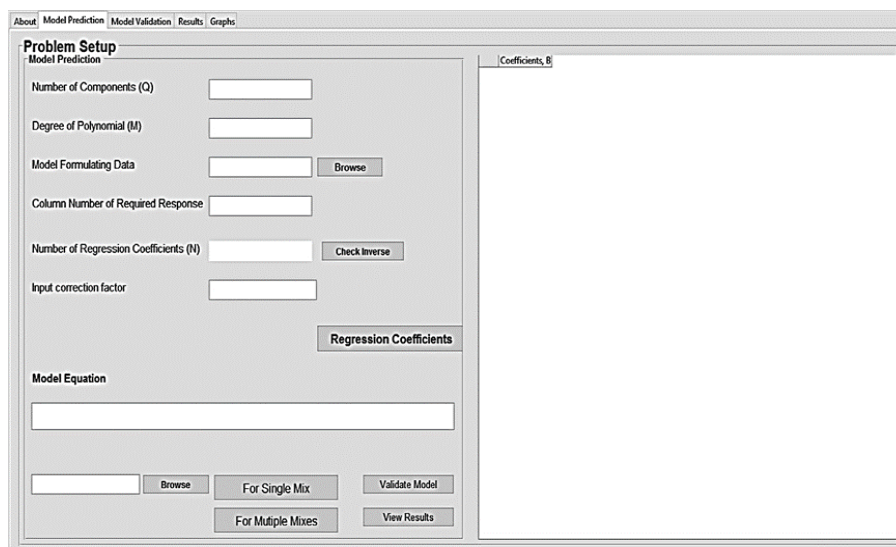


Fig. 3. The model prediction user interface.

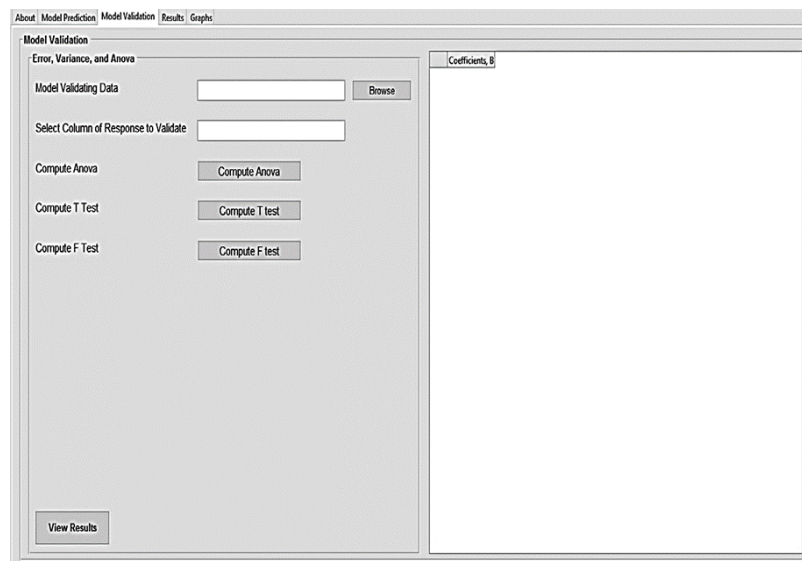


Fig. 4. The model validation user interface.

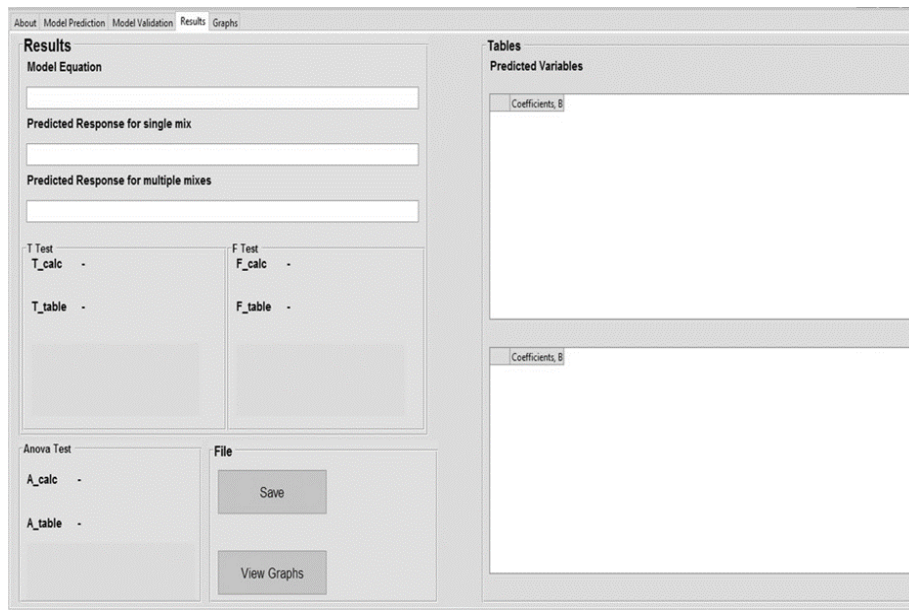


Fig. 5. The result user interface.

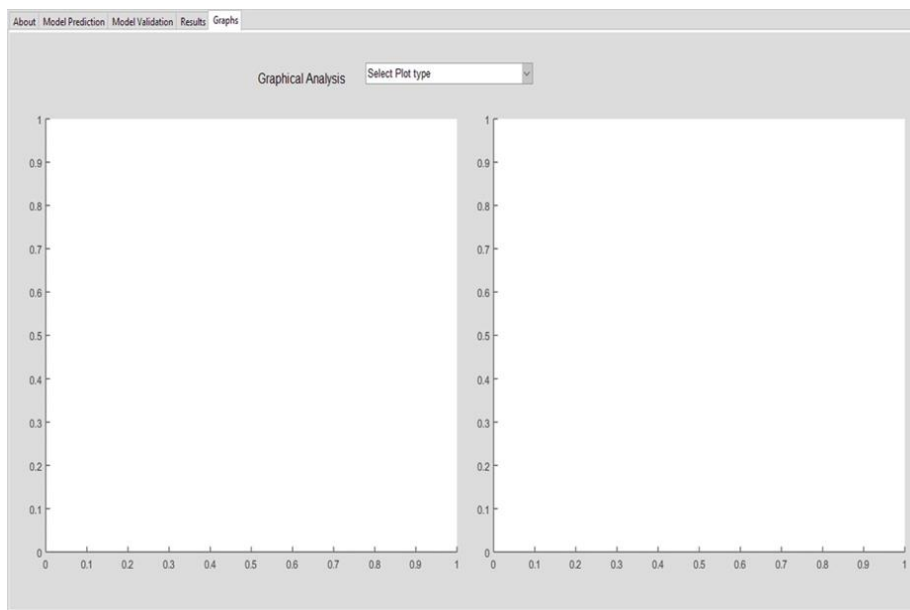


Fig. 6. The graphs user interface.

### 3.2. Validation of MIX-PRE using previous studies

The program formulated was validated using previous research works on mixture experiments by [19] and [17]. The model results obtained from the works of [18] and [16] are compared with those from MIX-PRE as illustrated in equation (23), equation (24), equation (25) and equation (26) respectively.

$$Y_o = 6913.546Z_1 - 14728.4033Z_2 - 414.2423Z_3 - 26.8331Z_4 + 47595.5547Z_1Z_2 + 1358.4342Z_1Z_3 + 7800.5111Z_1Z_4 + 20582.9523Z_2Z_3 + 13098.3289Z_2Z_4 + 835.7422Z_3Z_4 \quad (23)$$

$$\gamma_o = 6966.045Z_1 - 14802.675Z_2 - 418.035Z_3 - 27.196Z_4 + 47847.731Z_1Z_2 + 1380.941Z_1Z_3 + 7862.325Z_1Z_4 + 20697.830Z_2Z_3 + 13162.925Z_2Z_4 + 842.339Z_3Z_4 \quad (24)$$

where  $Y_o$  is the model equation from [18], and  $\gamma_o$  is the model equation from MIX-PRE w.r.t [18].

$$Y_a = -13571.4581Z_1 + 404.6841Z_2 - 39.3372Z_3 - 145.4195Z_4 + 16498.7143Z_1Z_2 + 15221.4221Z_1Z_3 + 16659.3738Z_1Z_4 - 674.1011Z_2Z_3 - 738.1452Z_2Z_4 + 31.8499Z_3Z_4 \tag{25}$$

$$\gamma_a = -13653.5830Z_1 + 403.0600Z_2 - 39.5593Z_3 - 146.7508Z_4 + 16016.3378Z_1Z_2 + 15312.3765Z_1Z_3 + 16763.7698Z_1Z_4 - 673.5780Z_2Z_3 - 738.2746Z_2Z_4 + 32.3042Z_3Z_4 \tag{26}$$

$Y_a$  is the model equation from [16] and  $\gamma_a$  is the model equation from MIX-PRE w.r.t. [16].

Table 4 presents the comparison of the coefficient of the model equations as predicted by MIX-PRE with those from [18] and [16].

From Table 4, the total percentage difference obtained between the coefficients of regression of the model equation generated by MIX-PRE and those from [18] and [16] are 0.23% and 0.02% respectively. Also, the highest and lowest percentage differences obtained from [18] are 1.63% and -0.50% respectively. While, those for [16] were 3.01% and -0.018% respectively. At all of these check points, it was observed that results obtained were all below 4% which is quite insignificant. Hence, substantiating the accuracy of MIX-PRE in generating model equations based on the Osadebe’s regression theory. Similarly, Table 5 shows the comparison of the compressive strength values of the control mixes predicted by MIX-PRE with those obtained from [18] and [16].

Table 4. Comparison of the coefficients of the model equation by MIX-PRE to those from previous studies.

Regression Coefficient	MIX-PRE and [18]			MIX-PRE and [16]		
	MIX-PRE C1 (N/mm <sup>2</sup> )	Okere (2014) C2 (N/mm <sup>2</sup> )	Percentage difference ((C1-C2)/C2)*100	MIX-PRE C1 (N/mm <sup>2</sup> )	Anya (2015) C2 (N/mm <sup>2</sup> )	Percentage difference ((C1-C2)/C2)*100
$\beta_1$	6913.546	6966.045	-0.753641413	13571.4821	13653.583	0.601313955
$\beta_2$	-14728.4033	-14802.675	-0.501745124	404.6841	403.06	0.40294249
$\beta_3$	-414.2423	-418.035	-0.90726853	-39.3372	-39.5593	-0.561435617
$\beta_4$	-26.8331	-27.196	-1.33438741	-145.419	-146.7508	-0.907524865
$\beta_5$	47595.5547	47847.731	-0.527039203	16498.7143	16016.3378	3.011777761
$\beta_6$	1358.4342	1380.941	1.629816191	15221.4221	15312.3765	-0.593992709
$\beta_7$	7800.511	7862.325	0.786205098	16659.3738	16763.7698	0.622747755
$\beta_8$	20582.9523	20697.83	0.555022918	-674.1011	-673.578	0.0776599
$\beta_9$	13098.3289	13162.925	0.490742749	-738.1452	-738.2746	-0.017527354
$\beta_{10}$	835.7422	842.339	0.783152626	31.8499	32.3042	-1.406318683
			$\Sigma = 0.226902126$			$\Sigma = 0.021848079$

Table 5. Comparison of the compressive strength of the control mixes predicted by MIX-PRE with those from [18] and [16].

Predicted Response	MIX-PRE and [18]			MIX-PRE and [16]		
	MIX-PRE C1 (N/mm <sup>2</sup> )	[18] C2 (N/mm <sup>2</sup> )	Percentage difference ((C1-C2)/C2)*100	MIX-PRE C1 (N/mm <sup>2</sup> )	[16] C2 (N/mm <sup>2</sup> )	Percentage difference ((C1-C2)/C2)*100
$\beta_1$	1.9842	1.95	1.753846154	-13571.4821	-13653.583	-0.601313955
$\beta_2$	2.1035	2.063	1.963160446	404.6841	403.06	0.40294249
$\beta_3$	2.492	2.51	-0.717131474	-39.3372	-39.5593	-0.561435617
$\beta_4$	1.9917	1.986	0.287009063	-145.419	-146.7508	-0.907524865
$\beta_{12}$	2.0571	2.02	1.836633663	16498.7143	16016.3378	3.011777761
$\beta_{13}$	1.9705	1.938	1.676986584	15221.4221	15312.3765	-0.593992709
$\beta_{14}$	2.2382	2.22	0.81981982	16659.3738	16763.7698	0.622747755
$\beta_{23}$	1.5702	1.621	-3.133867983	-674.1011	-673.578	0.0776599
$\beta_{24}$	1.2339	1.24	0.491935484	-738.1452	-738.2746	-0.017527354
$\beta_{34}$	1.1858	1.111	2.732673267	31.8499	32.3042	-1.406318683
			$\Sigma = 0.072719406$			$\Sigma = 0.021848079$

From Tables 5, the total percentage difference between the compressive strength values of the control mixes predicted by MIX-PRE and those from [16] and [18] are 0.031328% and 0.07272% respectively. Also, the highest and lowest percentage differences obtained from [16] was 0.27% and -0.10% respectively. While, that for [18] are 0.287% and -3.13% respectively. It is also noted that all values are below 4%. These results further confirm that MIX-PRE can accurately carry out prediction of responses whenever mix ratios are entered into it. Table 6 and Table 7 present the percentage differences between the results of the F and T tests carried out on the compressive strengths obtained by MIX-PRE and [18] as well as from MIX-PRE and [16].

Table 6. Comparison of F-test results from MIX-PRE and previous studies.

	MIX-PRE and [18]		MIX-PRE and [16]	
	MIX-PRE	[18]	MIX-PRE	[16]
F-values	1.13956	1.13406	1.186856	1.1624491
% Difference	0.004826		0.02056	

Table 7. Comparison of T-test from MIX-PRE and previous studies.

	MIX-PRE	[18]	MIX-PRE	[16]
	T- test	1.08227	1.10999	0.7882
%Difference	0.002772		0.040588	

#### 4. CONCLUSIONS

In this work, a computer program called 'MIX-PRE' was formulated on Matlab software. It has the ability to numerically develop models and graphically validate the created models. It applies the models for response-prediction purposes and save all results directly into a Microsoft excel file format. MIX-PRE consist of five graphical user interfaces which are; about user interface, model prediction user interface, model validation user interface, graphs user interface and results user interface. Each interface performed specific tasks such as formulating the model, carrying out numerical and graphical validations of models and displaying/saving its results. The numerical validation techniques used are F-test, T-test and Anova. While, the graphical validation techniques adopted are; residual plot, scatter plot, normal probability plot and observed vs predicted plot.

From the validation exercise carried out, it is recorded that for all parameters used in comparing the outputs from MIX-PRE to those of previous studies by [16] and [18], percentage differences were not up to 4%. This shows that the coding of MIX-PRE was done to a high degree of accuracy as there was no major difference observed. The program can therefore be used to adequately carry out the mix proportioning of the constituent materials for making concrete of desired strengths without going through the conventional trial and error process in the laboratory and the rigorous mathematical calculations of the Osadebe regression method.

#### ACKNOWLEDGEMENT

We want to appreciate the Department of Civil Engineering, Federal University of Technology, Owerri for providing the enabling environment for the start and completion of this study.

#### REFERENCES

- [1] Onwuka, D.O., Anyaogu, L., Anyanwu, T.U., Chijoke, C., Prediction of compressive strength of sawdust ash-cement concrete using Osadebe's regression function, Journal of Mechanical and Civil Engineering, vol. 6, 2013, p. 73 - 82.
- [2] ACI 211.1-91., Standard practice for selecting properties for normal, heavy weight and mass concrete, 2002.
- [3] ACI 363, State of the art report on high strength concrete, 1997.
- [4] Lye, L.M., Hussein, A., Kharazi, M., Designing and optimizing of concrete mix proportion using statistical mixture design methodology, CSCE General Conference, 2013.
- [5] Simon, M.J., Concrete mixture optimization using statistical method: Final report, FHWA- RD-03-060, National Technology Information Service, Spring field, V.A., 2003.
- [6] Lye, L.M., Design of experiments in civil engineering: Are we still in the 1920's?, Annual conference of the Canadian Society for Civil Engineering, 2002.

- [7] Montgomery, D.C., Design and analysis of experiments, 6th ed, John Wiley and Sons Inc. New York, USA, 2005.
- [8] Awodiji, C.T.G., Onwuka, D.O., Okere, C.E., Ibearugbulem, O.M., Anticipating the compressive strength of hydrated lime cement concrete using artificial neural network model, Civil Engineering Journal, vol. 4, no. 12, 2018, p. 3005-3018.
- [9] <http://www.mathworks.com/products/matlab/description1.html> (15.05.2013).
- [10] Palm, W., Matlab for engineering applications, 4<sup>th</sup> Edition. Mc Graw Hill Education, 2018.
- [11] Claringbold, P.J., Use of simplex design in joint action of related hormones, Biometrics, vol. 11, no. 2, 1955, p. 174 -185.
- [12] Scheffe, H., Simplex-centroid designs for experiments with mixtures, Journal of Royal Statistical Society, vol. B, 1958, p. 344-360.
- [13] Gorman, J.W., Hinman., Simplex lattice designs for multicomponent systems, Technometrics, vol. 2, 1962, p. 27-51.
- [14] Mclean, R.A., Anderson, V.L., Extreme vertices design of mixture experiments, Technometrics, vol. 8, 1966, p. 447 - 454.
- [15] Onwuka, D.O., Okere, C.E., Onwuka, S.U., Prediction of concrete mix cost using modified regression theory, Nigerian Journal of Technology, vol. 32, no. 2, 2013, p. 211-216
- [16] Anya, U.C., Models for predicting the structural characteristics of soilcrete blocks, PhD dissertation, University of Nigeria, Nsukka, 2015.
- [17] Okafor, F.O., Egbe, E.A., Predicting the static modulus of elasticity of laterite-quarry dust ash blocks using the Osadebe's regression model', IOSR Journal of Mechanical and Civil Engineering, vol. 14, no. 1, 2017, p. 21-26.
- [18] Okere, C.E., A model for optimization of the compressive strength of sand-laterite blocks using Osadebe's Regression theory, PhD dissertation, Federal University of Technology, Owerri, 2012.
- [19] Onwuka, D.O., Anyanwu, T.U., Awodiji, C.T., Onwuka, S.U., Mix design of Palm Bunch ash-cementitious composite using regression theory, International Journal of Advanced Research in Science, Engineering and Technology, vol. 3, no. 2, 2016, p. 1379 - 1391.