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# Multivariate Regression Approach to Predict Volume / Quantity of Variables of Plastic-Sand Bricks

#### Ubak, E.M.

Institute of Geosciences and Environmental Management, Rivers State University, Port Harcourt, Rivers State, Nigeria Email: etty.ubak[at]gmail.com

Abstract: Regression analysis is a quantitative research method commonly used to investigate relationship between variables. The variables are identified as either dependent or independent, an independent variable is a known variable and has an impact on a dependent variable. In order to predict the value of the dependent variable for factors in which some information concerning the defined variable is available, or estimate the effect of some defined variable on the dependent variable, regression analysis was performed on the research data. Regression allows researchers to predict or explain the variation in one variable based on another variable. Plastic – sand bricks manufactured from recycling poly ethylene terephthalate (PET) plastic waste was tested for compressive strength and other mechanical characteristics after different plastic: sand ratios experimentation. A desirable brick with appreciable characteristics was obtained which enhanced sound environmental waste management. A viable prediction model for determining the volume/quantity of plastic: sand ratio used was the multivariate regression model, which gives more information in which variables relates and determine the quantity/volume of the data set to produce a brick of any given compression strength. This reduces amount of time, energy and financial resources required during experimental trials of varied plastic: sand ratios to achieve expected compressive strength of the brick. The XLSTAT version 2022 was used for the analysis and the results are presented as Hierarchical Cluster Analysis (HCA) and Principal Component Analysis (PCA).

Keywords: Environment, Plastic - sand bricks, Poly ethylene terephthalate, Regression analysis

#### 1. Introduction

Conventional bricks composed of sand or laterite with cement as its binding agent. Plastic – sand bricks are manufactured by mixing sand with degraded plastic fluid which serves as its binding agent. Plastic – sand brick was manufactured from recycling plastic wastes composed mainly of Low Density Poly Ethylene(LDPE) and Poly Ethylene Terephthalate (PET) bottles and sand.

The resultant bricks found to be of appreciable mechanical properties as conventional cement – sand brick (Ubak, 2023).

The materials used for the production of the bricks were varied to determine bricks of highest compressive strength. Shiri *et al.*, (2015), worked on different types of plastic wastes processed into composite brick alongside with brick made with one hundred percent (100%) clay, it was observed that the maximum compressive load sustained by the polypropylene/rubber composite brick is 17.05 tons followed by Low Density Poly Ethylene (LDPE) /Rubber composite brick with 16.55 tons which is much higher than the clay brick which sustained only 9.03 tons.

The production of plastic –sand bricks leads to sound management of plastic wastes as the littered, untreated plastic wastes usually dumped at landfills and our environment are recycled to useful product and environment better managed (Ubak,2023). However, the challenge to determine the ratios of the different components (plastic waste and river sand) that will give desired plastic – sand brick presents a major drawback in the production of plastic – sand bricks.

Recent studies focus on the search for environmental waste

management of plastic wastes that minimize the environmental problems associated with plastic waste management at our dumpsites and landfills. Mondal et al., (2017), carried out experimental work on bricks made of: non- recyclable waste thermoplastic granules constituting 0 to ten percent (10%) by weight, fly ash fifteen percent (15%), cement fifteen percent (15%) and sand making up the remainder. The resulting bricks are strengths are found to be lightweight, porous, of low thermal conductivity, and of appreciable mechanical strengths. Different researches have been performed on the production of plastic - sand bricks with great success. However, the amount of time, energy and financial resources required during experimental trials so as to produce brick of appreciable characteristics requires appropriate attention. It is therefore expedient to use statistical models to predict the mechanical and physical characteristics of plastic - sand bricks.

Generally, prediction of missing data is provided with regression model to verify the observed value (Obianyo *et al.*, 2020). Various analysis and modelling methods have been developed and applied to predict the behavious of soil bricks (compressive strength, modulus of elasticity, indirect tensile strength; and Californian load capacity (Jin *et al.*, 2018a, Jin *et al.*, 2018b, Obianyo *et al.*, 2020). Obianyo *et al.*, 2020 also used multiple Independent Variables (IVs) in an appropriate data analysis approach to predict the specific response random variables (SRV) of bone ash stabilized laterite soil bricks.

This research attempted to develop a viable prediction model for determining the volume/quantity of plastic and sand to be used in producing a brick of any given compressive strength via regression model analysis to reduce amount of time, energy and financial resources required during experimental trials of varied plastic/sand ratios to achieve expected compressive strength of the bricks. Scattered plot of compressive strengths of bricks and different plastic waste content gave a low regression coefficient of 27.5%. A linear equation could not be properly specified for a good fit and prediction, thus, multivariate analysis, that captures better relations between the compressive strength and plastic waste content was used (Ubak, 2023). A multivariate analysis of the data set gave more information in which variables relates and determine the quality/quantity of the data set. XLSTAT version 2022 was used with results presented as Hierarchical Cluster Analysis (HCA) and Principal Component Analysis (PCA). The data set from the experiment used is presented in Table 1.

# 2. Materials and Methods

Low Density Poly Ethylene (LDPE) and Poly Ethylene Terephthalate (PET) bottles were collected, sorted, cleaned, shredded and degraded to mix with river sand and allowed to cure to produce the required plastic – sand bricks. The materials used for the process includes: -

- 1) LDPE & PET bottles
- 2) River sand
- 3) Electronic weighing machine
- 4) Hand trowel
- 5) Prepared sample mould
- 6) Reactor
- 7) Stirrer rod
- 8) Thermometer
- 9) Curing tank
- 10) Water for mixing11) Heat source
- 12) Compressive Testing Machine

The procedure of casting plastic – sand bricks is indicated below:



Figure 1: Procedure of Casting Plastic Sand Bricks

From the produced bricks, the compressive strength can be determined using the compressive testing machine. The brick is placed in the CTM basin, load is applied on the brick without any shock, the load is increased continuously till specimen's resistance to load breaks down and cannot withstand any greater load further, then the maximum load applied is recorded (Singh *et al.*, 2017). The compressive strength can be determined using the formula below:

The stress on the specimen is given by:



Stress = P/A

Where, P = Maximum load (kN) and A = Area of the specimen (mm<sup>2</sup>)

# 3. Results and Discussion

The physical and mechanical properties of the experimental brick is shown in Table 1 below: Table1: Physical and Mechanical properties of Plastic-Sand Bricks

S/N	Plastic (%)	Sand (%)	Size of the Brick (mm <sup>3</sup> )	Weight of Brick (kg)	Density of Brick g/cm <sup>3</sup>	Load KN	Compressive Strength N/mm <sup>2</sup>
1	36.0	64.0	19600 (55)	2.10	1.962	120	6.12
2	43.0	57.0	19600 (55)	2.10	1.96	40	2.04
3	48.0	52.0	19600 (55)	1.70	1.58	40	2.04
4	50.0	50.0	19600 (55)	1.60	1.495	40	2.04
5	53.0	47.0	19600 (55)	1.50	1.401	100	5.10
6	57.0	43.0	19600 (55)	1.40	1.308	40	2.04
7	60.0	40.0	19600 (55)	1.60	1.495	20	1.02
8	63.0	37.0	19600 (55)	1.30	1.262	60	3.06
9	66.0	34.0	19600 (55)	1.20	1.121	60	3.06
10	77.0	23.0	19600 (55)	1.40	1.28	50	1.02

The results of Hierarchical Cluster Analysis (HCA) of the data set is presented in Figure 2 and Figure 3 below. The Principal Component Analysis (PCA) result and varimax rotation for the data set is presented as Figure 4 and Figure 5 respectively.

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Figure 2: Hierarchical Cluster Analysis (HCA) Dendrograms of Plastic – Sand Bricks

# Agglomerative hierarchical clustering (AHC) / Number of clusters = 4:



Figure 3: Hierarchical Dendrograms of Interlock Bricks Cluster Plots

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Figure 5: Principal Component Analysis (PCA) Varimax Rotation for Interlock Brick

# Hierarchical Cluster Analysis (HCA) and Principal Component Analysis (PCA)

The Hierarchical Cluster Analysis (HCA) is a combination of techniques to classify large set of data into clusters on the basis of similarities or dissimilarities. The resulting groups are similar to each other but distinct from other groups. HCA have been used by researchers for classification and interpreting experimental data (Granato et al., 2018). The Principal Component Analysis (PCA) on the other hand, reduces the dimensionality of the data set into few data set arranged in principal components and displays diagrammatically some of the hidden patterns of the entire data set. The data set is first analyzed into first principal component (factor) which is called Factor 1, (F1). This has the highest percentage of the proportion of the data. This is followed by second principal component (factor), F2, and the next till Fn. In this present study, hierarchical cluster analysis, HCA, was used to group the compressive strengths as per mix ratios based on their similarities. The complete linkage method along with correlation coefficient distance was applied. The derived dendrogram and biplots are shown in figures 2 and 3.

The result of Hierarchical Cluster Analysis (HCA) of plasticsand brick is presented in Figure 2 and Figure 3 in Hierarchical Dendrograms. In Figure 2, the cleavage line at -0.534718271 divides the parameters into three clusters. The first cluster contains plastic percentage (%). The second cluster contains load (KN) and compressive strength (N/mm<sup>2</sup>). The third cluster consists of three parameters which are sand percentage (%), weight of the brick (kg) and density of brick (kg).

Dendrograms parameters in Figure 3 involved the mixture of sand and plastic of different percentages producing mixture

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A, B, C...J with each producing interlock brick of same volume of 1,078,000 mm<sup>3</sup> (19600(55) mm<sup>3</sup>) or 1,078cm<sup>3</sup>. Each mixture have other physical and mechanical parameters of varying magnitudes and units.

The cleavage line at 0.899818149 in Figure 3 divides the parameters into four clusters. The first cluster contains parameters A and E. The second cluster contains J, H and I. The third cluster consists of three parameters which are B, C and D while the last i.e. fourth cluster contains two parameters F and G. Figure 3 showed the similarity among the mixing ratio parameters (A to J) with the highest correlation/similarity of 0.999 i.e. 100 % recorded between C and D and 0.998 i.e. 100 % recorded between H and I. The mixing ratio parameters A and E with the high correlation/similarity of 0.966 i.e. 97 % has the greatest influence on compressive strength of interlock bricks.

#### Principal Component Analysis of Parameters of Plastic-Sand Bricks

The result of Principal Component Analysis (PCA) presented in Figure 4 show the PCA biplot with F1 and F2 on horizontal and vertical axis respectively depicting the loads on the two principal components. The principal component 1(PC-1) as shown in Factor 1 explained 69.20 % of the total variance and heavily loaded with plastic waste. The principal component 2 as shown in Factor 2 is dominated by load (KN) and compressive strength (N/mm<sup>2</sup>) and accounted for 25.73 % of the total variance. Therefore, these two principal components PC1 and PC2 were extracted in brick that accounted for 94.93 % of the total variance.

With varimax rotation, bricks parameters (i.e. load (KN) and compressive strength  $(N/mm^2)$ , sand (%), weight of the brick (kg) and density of brick (kg)) moved/rotated into the first  $(1^{st})$  quadrant as shown in Figure 5 as more items with positive correlation strengthen the principal components in consideration.

It is observed that the results of both the Principal Component Analysis, PCA and Hierarchical Component Analysis, HCA are consistent as load (KN) and compressive strength (N/mm<sup>2</sup>) of interlock parameters are the closer to each other in Principal Component Analysis, PCA biplots in Figure 4 with the strongest influence (on the principal component) and small included angle between them from origin and they are in the same cluster 2 on Hierarchical Component Analysis, HCA dendrogram Figure 2 with high percentage similarity of 96% on Hierarchical Component Analysis, HCA dendrogram. Similarly, the weight of the brick (kg) and density of brick (kg) are also closer to each other in PCA biplots in Figure 4 with the influence on the principal component comparatively lower to the pair above and small included angle between them from origin and they are in the same cluster 3 on HCA dendrogram Figure 2 with high percentage similarity of approximately 100 % on HCA dendrogram.

**Development of Regression Model for Brick and Prediction of Variables Components** From the three clusters (Figure 2), four parameters /independent variables (Plastic, Load, Density and Weight), were used for the compressive strength regression model.

To model the relation between percentage of plastic and compressive strength

 $CS=\alpha_0 + \alpha_1 w + \varepsilon$ 

CS  $\rightarrow$  Plastic, Weight, Density and Load

 $y = \alpha_0 + \alpha_1 w_1 + \alpha_2 w_2 + \dots \alpha_n w_n + e$ 

 $CS = \alpha 0 + \alpha 1w1 + \alpha 2w2 + \alpha 3w3 + \alpha 4w4 + e$ 

 $CS = \alpha_0 + \alpha_1(\text{plastic}) + \alpha_2(\text{Weight}) + \alpha_3(\text{Density}) + \alpha_4$ (Load)

Equation of the model Compressive Strength N/mm<sup>2</sup>) generated by XLSTAT:

CS = 5.471 - 5.830E-02\*Plastic - 8.312\*Weight + 7.438\*Density + 4.678E-02\*Load

CS = 5.471 - 5.830E-02\*Plastic - 8.312\*Weight + 7.438\*Density + 4.678E-02\*Load

The model equation generated by the XLSTAT can be used to determine volume or quantity of plastic and sand with any given compressive strength.

The percentage of plastic or sand needed to produce brick of a certain given compressive strength can be determined using the generated model equation. If percentage of plastic is excluded and percentage of sand is not, obtained sand percentage can be used to determine the volume of plastic required to produce the required brick of given compressive strength. The derived model equation has a high predictive power to determine the ratio of plastic and sand component for brick of a given compressive strength. Both sand and plastic percentages will sum up to one hundred percent of the admixture.

From the data set in Table 1, we can randomly pick any required compressive strength for the brick we desire, say we pick  $6.12 \text{ N/mm}^2$ . Given a brick of say  $6.12 \text{ N/mm}^2$  strength and we want to determine or predict the mix ratio of the required bricks, we can use the model equation to do this. We can proceed thus.

From Equation 1.5, we have

$$\begin{split} &CS = 5.471 - 5.830E-02*Plastic - 8.312*Weight + \\ &7.438*Density + 4.678E-02*Load From Table 1, CS = 6.12, \\ &w = 2.1kg, Density = 1.962, load = 120KN, Plastic \% = ? CS \\ &= 5.471 - 5.830E-02*Plastic - 8.312*(2.1) + 7.438*(1.962) + \\ &4.678E-02*(120) CS = 5.471 - 5.830 x 10^{-2} *P - 8.312 * \\ &(2.1) + 7.438*(1.962) + 4.678 x 10^{-2} * 120 \\ &6.12 = 5.471 - 0.0583 x P - 17.455 + 14.493 + 0.04678 * 120 \end{split}$$

6.12 = 5.471 - 0.0583P - 17.455 + 14.493 + 5.614 P = 2003/0.0583 = 34.356%

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The percentage of plastic waste contained in the admixture is 34.36%.

To get the percentage of sand to be added, we subtract 34.36% from 100. This gives 65.44%

Therefore, the mix ratio predicted from the model equation for the interlock plastic sand brick is P(34%): S(66%).

# 4. Conclusion

The multivariate regression method used in this work for prediction of the quantity of plastic and sand needed to produce a brick of a given compressive strength shows regression model is a viable tool to predict or determine the volume/quantity of variables needed in producing brick of any given compressive strength and reduce amount of time, energy and financial resources required for experimental trials of varied plastic/sand ratios to achieve expected results. Since multivariate analysis works best for wider range of variables, for more practical application of this approach to predict variable ratios, it is suggested that large data base should be used.

# 5. Recommendations

Since plastic waste is a major source of environmental pollution, recycling of these waste instead of dumping at dumpsites and landfills should be encouraged through the production of plastic – sand bricks.

Incentives should be introduced for all plastic wastes recovered for recycling, this way there would be enough recovered plastic wastes available for industrial scale production of plastic – sand bricks.

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