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Strength relationship in compacted lateritic soil liners and covers for waste containment

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Abstract
The suitability of some selected lateritic soils as materials for land liners and covers were sought in the research together with a relationship between Brazilian Tensile Strength (BTS) and Unconfined Compressive Strength (UCS) of the soils. Three different lateritic soil samples that fall into the same Unified Soil Classification System (USCS), British Soil Classification System (BSCS) and American Association of State Highway and Transportation Officials (AASHTO) classes were used in the research. The moisture-density relationship of the samples was investigated at four compactive effort: Reduced British Standard Light (RBSL), British Standard Light (BSL), West African Standard (WAS) and British Standard Heavy (BSH) and seven-point moulding water content. The Unconfined Compressive Strength (UCS) and Brazilian Tensile Strength (BTS) of the samples were determined at each of these compactive effort and moulding water content. The UCS and BTS results obtained from laboratory tests show values > 200 kPa in most cases. This shows that the soils can be used as landfill liners and covers based on strength criterion. The results of UCS and BTS were fitted to correlation analysis and regression analysis with BTS as dependent variable and UCS as independent variable. Significant correlation coefficient (R > 0.75) and coefficient of determination (R-squared = 0.629) were obtained respectively. A linear model was developed from these relationships to predict BTS from UCS.

Keywords: ANN, BTS, Compaction, Laterites, Moisture content, UCS

1. Introduction

According to Fang and Chen (1970) research on the compressive strength of soils have been extensive. This is not usually the case with tensile strength. The determination of the tensile strength of soil is usually based on direct method or indirect method. Direct method usually gives the uniaxial tensile strength while the indirect methods such as Brazilian tensile strength (BTS) test, torsion test, ring tests also exist to determine tensile strength of rocks or soils (Akin & Lukos, 2017). Particular difference between direct methods and indirect methods lies in the application of load. In direct methods, tensile loads are applied at both ends of the specimen while in indirect methods, compressive loads are applied at both ends of the specimen. However, in both direct and indirect methods, the failure mode is tensile with special constraints considered for the geometry and some mechanical properties of test specimen in indirect methods (Akin & Lukos, 2017).

The increased adoption of BTS for tensile strength test lies on its many advantages over direct tensile test. In the list of the advantages are simplicity in preparation, handling and testing of specimen, which helps to facilitate testing of numerous specimens within a short time. Another advantage is its acceptance of small specimen, which permits pre-conditioning such that more consistency and less sensitivity to some differing conditions are attained (Krishnayya & Eisenstein, 1974; Akin & Lukos, 2017). One other factor that justifies the use of BTS is the failure of biaxial stress fields in tension at a material's uniaxial tensile strength when one principal stress is tensile and the other compressive. The material possesses linear elasticity and its strength and elastic properties are homogenous and isotropic (ISRM, 1978; Stirling, Hughes, Davie & Glendinning, 1981; Akin & Lukos, 2017). For these reasons, BTS is mostly used for brittle elastic materials such as rocks, concrete etc as these properties are more prevalent in them. However, their applications are not limited to these as they are also applicable in the analysis of strength in soils.

The conduction of UCS tests on soils aside the above-numerated shortcomings are also time-consuming and expensive. However, according to Nazir, Momeni, Jahed and Mohd (2013) these shortcomings are more applicable to rock samples where it is difficult to obtain sufficient number of high-quality rock samples, which is a pre-requisite for direct method of UCS determination. Most research articles found online on this topic are about the correlation of UCS and BTS applicable to rock samples. Even though no research work found shows the correlation between UCS and BTS for soil samples, the positive results from rock samples is an indication that positive results could be found for soil samples. The correlations found was summarized as follows (Table 1).

Table 1: Correlation between UCS and BTS for some rocks (Nazir et al, 2013)

References	Correlation	R of R^2	Rock Type
Altindag and Guney (2010)	UCS (MPa) = 12.38 x $BTS^{1.0725}$	R = 0.89	Different rock type including limestone
Farah (2011)	UCS (psi) = 5.11 BTS – 133.86	$R^2 = 0.68$	Weathered limestone
Kahraman, Fener, and Kozman, (2012)	UCS (MPa) = 10.61 x BTS	$R^2 = 0.5$	Different rock type including limestone
Nazir et al (2013)	UCS = 9.25 $BTS^{0.947}$	$R^2 = 0.9$	Limestone

Thus, the objective of this paper is to show the suitability of the soil for structural integrity of landfill liners and covers (UCS ≥ 200 kPa) and to establish empirical relationships to predict UCS/BTS from some index parameters and BTS from UCS. The justification of this study is derived from the opinion of Krishnayya and Eisentein (1974) that BTS is advantageous over other methods for the investigation of behavoiur of soils under tension. Besides, it is easier to perform UCS than BTS. Thus, with a significant relationship between UCS and BTS, it would be easier to estimate the BTS of soil from the UCS.

1.1 Artificial Neural network

According to Oludare, Aman, Abiodun, Kemi, Abubakar, Okafor, Humaira, Abdullahi, Usman, and Mahammad, (2017) Artificial Neural Network (ANN) is nonlinear statistical data models that replicate the role of biological Neural Networks (NNs). ANN is a means of forecasting an event that began in the 1990's (Ramos & Martinez, 2013). This method was drawn from Artificial Intelligence (AI) that is characterized by its flexibility and ability to integrate different methodologies to emulate human systems behaviour. The method has many advantages which include but not limited to input-output mapping, non-linearity, adaptability and uniformity in analysis etc (Haykin, 1994; Ramos & Martinez, 2013). The analysis in this paper was carried out with regression tool in Excel Spreadsheet (2013) and ANN tool available in IBM SPSS 20 using the Multilayer Perceptron option.

2.0 Material and methods

2.1 Sample Collection

This research work was carried out using three lateritic soils designated as LS 1, LS2 and LS3. The materials were obtained from Zaria, Northern Nigeria (Latitude 11° 15′ N and longitude 7° 45′ E). The soils belong to the group of ferruginuos tropical soils derived from acid igneous and metamorphic rocks (Osinubi 1998, Osinubi & Nwaiwu, 2008).

2.2 Index Properties tests

Index parameters tests were conducted on the soils to properly classify the soils. The index parameters tests were done in accordance to BS 1377 (1990). Table 2 shows the results of index parameters tested, together with the derived parameters.

2.3 Compaction tests

Compaction tests were carried out for the air-dried soils to examine their moisture-density relationships. Prior to compaction, the soils were first mechanically crushed to sizes small enough to pass through 4.76 mm (BS No.4). The test samples were mixed with potable water to the desired moulding water content which range from 10% to 25% and seven (7) moulding water points were used. The percentage moulding water points were derived based on the dry weight of the sample used for the sample preparation. Four compactive efforts were utilized in the test preparation; viz Reduced British Standard Light (RBSL), British Standard Light (BSL), West African Standard (WAS) and British Standard Heavy (BSH) all according to BS 1377 (1990) and Head (1992). According to Osinubi and Nwaiwu (2008), the BSH and BSL compactions are the British Standards (BS) equivalents of Modified Proctor and Standard Proctor compactions (ASTM D 1557 and ASTM D 698), respectively. The WAS which falls in between the two is commonly used in West African region and consists of the energy derived from a 4.5kg rammer falling through 0.457m height unto five layers of soil, each layer receiving 10 blows (Ola, 1980; Osinubi & Nwaiwu, 2008). The RBSL according to Daniel and Benson (1990) involves compaction of soil at 3 layers but instead using 15 blows against the 27 blows normal in BSL. Figures 1 - 3 show the compaction curves for the three soil samples and four compaction energies.

2.4 Strength tests

Two strength tests were also carried out for the soils. These are the unconfined compressive strength (UCS) test and the Brazilian tensile strength (BTS) test also known as indirect tensile strength (ITS) tests. The UCS test was conducted in accordance to BS 1377 (1990). The BTS test was conducted in accordance to ASTM D3967.

3.0 Results and Discussions

Sections 3.1 to 3.3 show the discussion of the results of the tests carried out using comparison charts.

3.1 Index parameters of soil

Table 2 shows the index properties of the three soil samples used in the research work. The specific gravity of the soils is within the typical range for lateritic soils (Owolabi & Aderinola, 2014). All the properties of the three soils are within close range and they fall within the same class according to AASHTO, USCS and BSCS classification systems. This shows that the three soils must have similar mineralogical content. Owing to this property, the three soils could be used simultaneously in the determination of the relationship that exists between the UCS and BTS.

Table 2: Index properties of the lateritic soils

Index properties of soils			
Property	**LS-1**	**LS-2**	**LS-3**
Natural Moisture Content (%)	5.24	9.68	7.22
Specific Gravity	2.671±0.003	2.682±0.005	2.686±0.0168
Liquid Limit (%)	40.5±2.39	40.267±1.102	43.183±2.941
Plastic Limit (%)	23.066±0.387	23.315±1.187	25.904±3.586
Plasticity Index (%)	17.434±2.757	16.952±2.145	17.279±0.652
Linear Shrinkage (%)	7.857±1.269	8.37±0.712	8.535±0.935
Percentage Passing BS No. 40 Sieve	82.33	85.423	77.282
Percentage Passing BS No. 200 Sieve	66.201	71.524	64.057
Percentage <2μm	34.135	34.045	28.662
Activity	0.5107	0.4979	0.6029
Group index	10	11	10
AASHTO classification	A-7-6	A-7-6	A-7-6
BSCS classification	CI	CI	CI
USCS classification	CL	CL	CL
Liquidity index	-1.0225	-0.8043	-1.0813
Consistency index	1.5287	1.3119	1.3883
Derived parameters			
Grading modulus	0.5301	0.4484	0.6326
Plasticity product	1154.148	1212.475	1106.841
Plasticity modulus	1435.341	1448.091	1335.356
Shrinkage modulus	646.867	714.991	659.602

3.2 Nature of compaction curve

Tests were conducted at 7-point moisture content for the three (3) soils labelled LS1, LS2 and LS3. Figure 1 – 3 shows the relationship between dry unit weight and moisture content for LS1, LS2 and LS3 respectively. As observed in each of the soils, maximum dry unit weight (MDUW) increased with increase in compaction energy while the optimum moisture content (OMC) reduced with increase in compaction energy. The same trend was also expected in the strength of the soil because as unit weight of soil increases, its strength also increases (Mohd Yusoff, Bakar Wijeyeskera, Zainorabidin, & Madun, 2015).

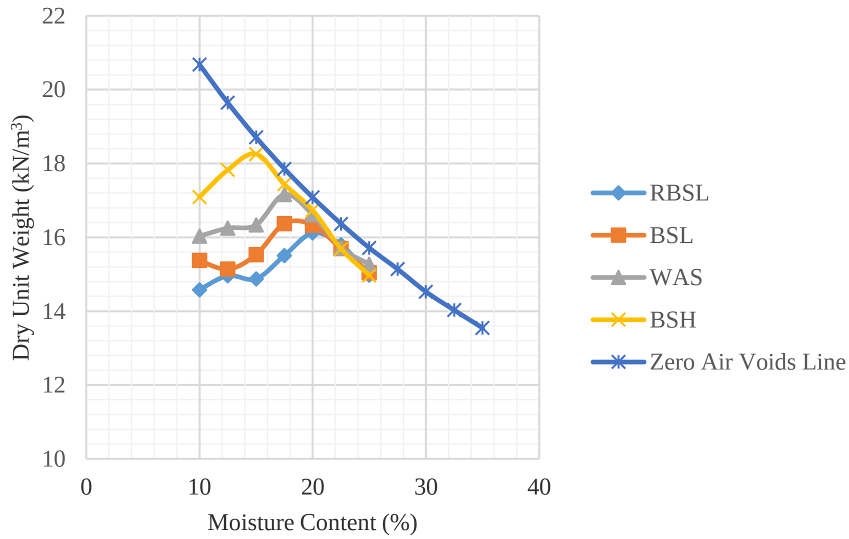

Figure 1: Dry unit weight versus moisture content for LS1

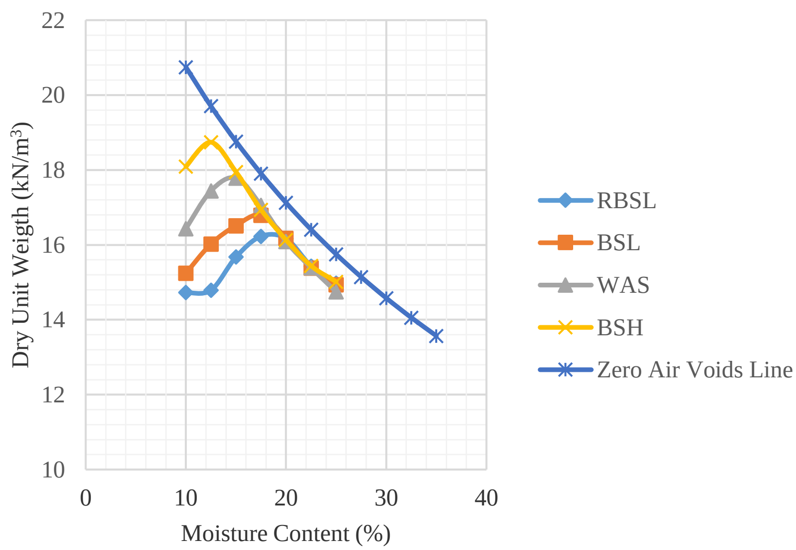

Figure 2: Dry unit weight versus moisture content for LS2

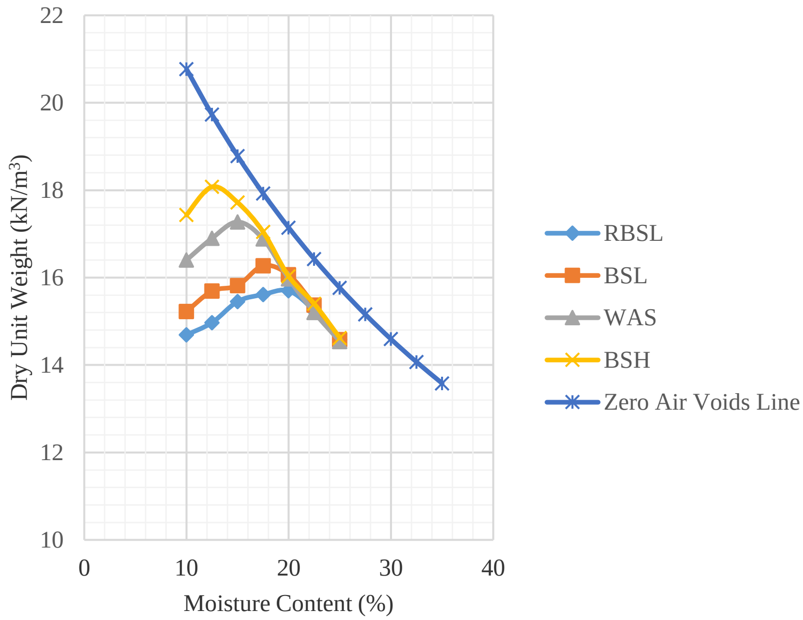

Figure 3: Dry unit weight versus moisture content for LS3

3.3 Variation of UCS/BTS with moulding water content

Figures 4 – 6 show the variation of UCS/BTS with moulding water content. It was shown that maximum value of strength was obtained on moulding water content in each case, at 12.5% moulding water content except for sample LS-3 where the maximum value was obtained at 15% moulding water content. Generally, the strength of the soil increased with increase in the compaction energy in each case which is in agreement with Mohd Yusoff et al (2015). The strength values obtained under UCS testing are generally higher than those obtained under BTS testing. The variation could be attributed to the direction and nature of the applied load. In each case, the values varied non-linearly with the moulding water content which makes it suitable for investigation of the relationship using ANN (Ramos and Martinez, 2013). The influence of increase in compaction energy on the variation of UCS/BTS with moulding water content was not very clear.

The UCS/BTS values of the soils are in most cases greater than 200 kN/m^2 which shows that the soil can effectively be used as liner material in waste containment bin when treated properly. It was also observed that the UCS/BTS values at 10%, 12.5%, 15%, 17.5%, 20%, 22.5% and 25% moulding water contents tend to converge at a particular value of moulding water content (25%). This value is the plastic limit of the soil. It shows that in the neighbourhood of plastic limit of soils, UCS is approximately equal to BTS.

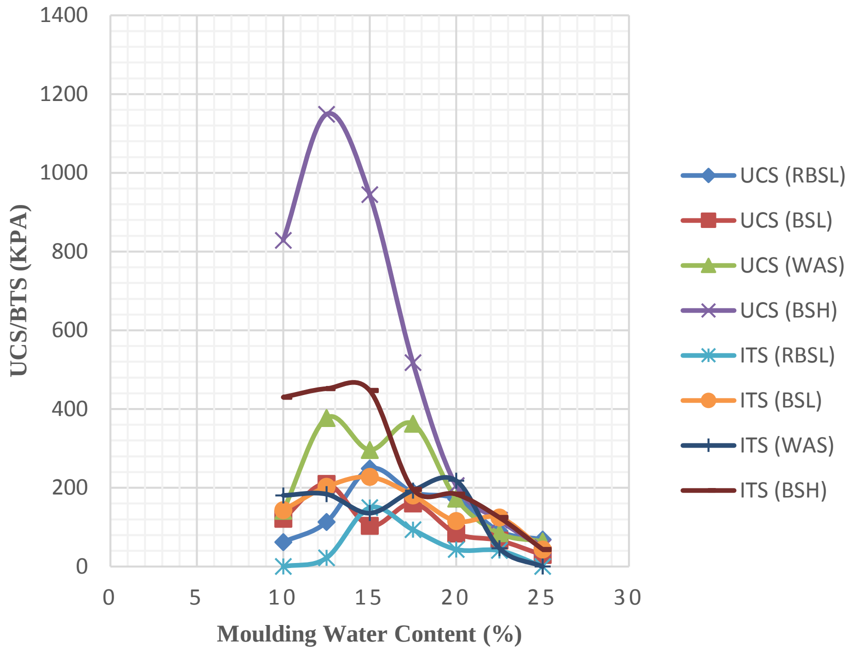

Figure 4: Variation of UCS/BTS with moulding water content for LS1

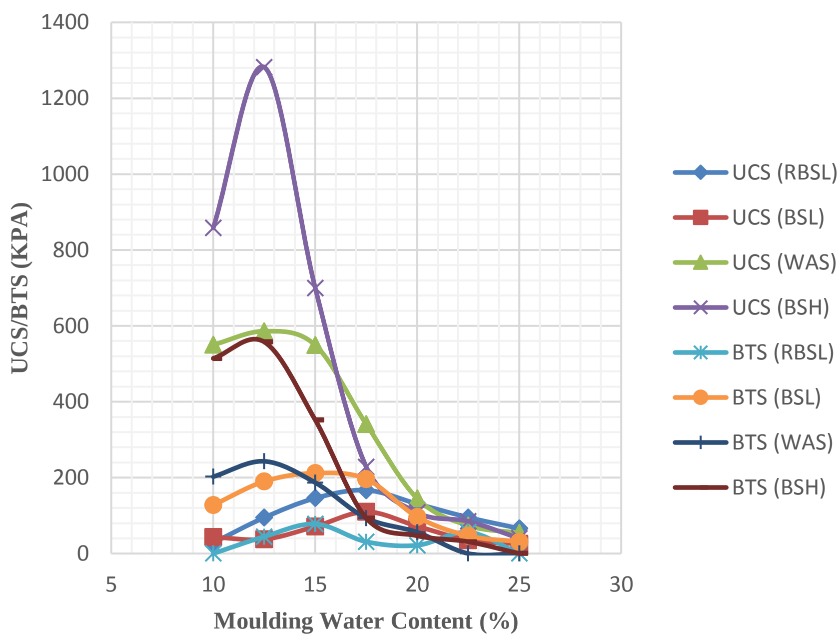

Figure 5: Variation of UCS/BTS with moulding water content for LS2

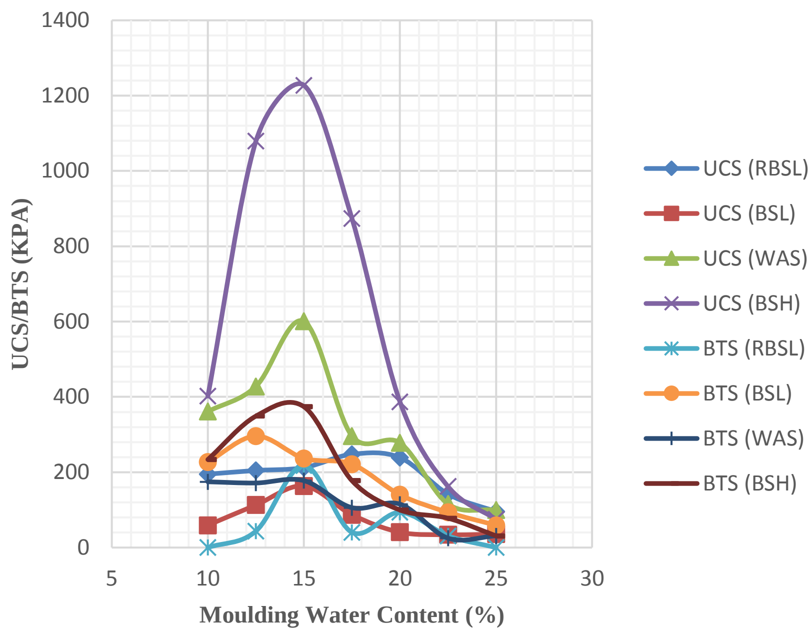

Figure 6: Variation of UCS/BTS with moulding water content for LS3

3.4 Statistical Analysis

3.4.1 Correlation Analysis

Only one variable, BTS was used in the correlation analysis. The results of the correlation analysis using EXCEL Spreadsheet (2013) was shown in Table 3. The correlation coefficient between UCS and BTS is quite high (R ≥ 0.75). This is an indication that there exists a good relationship between the two parameters, UCS and BTS.

Table 3: Correlation matrix for UCS and BTS

	UCS	BTS
UCS	1	
BTS	0.792969	1

3.4.2 Regression Analysis

1. Expression of UCS and BTS as functions of MDUW, OMC, PI and clay content (CC)

UCS and BTS were expressed as a function of MDUW, OMC, PI and CC. Tables 4 and 5 show the coefficients and other parameters respectively.

Table 4: Results of linear regression between UCS, MDUW, OMC, PI and CC

Variables	Coefficients	t -Statistics	P-value	Regression parameters	
Intercept	-9106.083	-1.628	0.148	R-Squared	0.894
MDUW	260.099	1.329	0.226	Adjusted R Squared	0.833
OMC	-50.683	-0.880	0.408	Overall F-Statistics	14.748
PI	383.745	1.371	0.213	Observations	12
CC	-18.082	-0.68	0.518		

Table 5: Results of linear regression between BTS, MDUW, OMC, PI and CC

Variables	Coefficients	t -Statistics	P-value	Regression parameters	
Intercept	-2682.31	-0.881	0.408	R-Squared	0.656
MDUW	98.207	0.921	0.388	Adjusted R Squared	0.460
OMC	-3.919	-0.125	0.904	Overall F-Statistics	3.338
PI	87.088	0.571	0.586	Observations	12
CC	-5.117	-0.354	0.734		

From the regression coefficients, the following equations can be established to predict UCS and BTS of soils.

UCS = -9106 + 260MDUW – 51OMC + 384PI – 18CC (R^2 = 0.894) (1)
BTS = -2682 + 98MDUW – 4OMC + 87PI – 5CC (R^2 = 0.656) (2)

2. Expression of BTS as a function of UCS

The BTS was expressed as a function of UCS because it is easier to determine UCS. The resulting equation based on linear regression analysis, is

BTS = 49.784 + 0.336 UCS (R^2 = 0.629) (3)

The results of linear regression analysis are presented in Table 6 shown below. The coefficient of determination, R-squared for the equation (3) was 0.629 while the adjusted R-squared value was 0.624. The overall F-statistics (138.905) obtained was statistically significant at 95% confidence limit (that is at $\alpha = 0.05$). The p-value for UCS was less than 0.05.

Table 6: Results of Linear Regression Analysis

Variables	Coefficients	t -Statistics	P-value	Regression parameters	
Intercept	49.784	4.432	2.87E-05	R-Squared	0.629
UCS	0.336	11.786	2.49E-19	Adjusted R Squared	0.624
				Overall F-Statistics	138.905
				Observations	84

ANN, which is also a powerful statistical analysis tool, was used in the succeeding section to examine the reliability of our regression output. The ANN analysis gave a slightly higher value of R-squared (0.635) which shows that it could be a more reliable tool in developing the models. The graphical comparison of predicted versus measured values of UCS, together with residual plots is presented in section 3.4.3.

3.4.3 Artificial Neural Network

The following section shows the processes employed in ANN. 84 BTS and UCS test results were used in the analysis. The 84 test results were obtained not from 84 soil samples but from three similar soil samples that were subjected to four compactive effort at seven (7) moulding water content. Thus, there are some levels of repetition in the work. 75% (63) of the samples were used for training while 25% (21) were used for testing. Sum of squares error observed in the training was 11.656 while the relative error was 0.402. In the testing, the sum of squares error observed was 3.035 while the relative error was 0.270. Figure 7 shows the relationship between observed BTS and predicted BTS based on the relationship that exists between the two. The R-squared value was 0.635. This means that the model explains 63.5% of the variation in the response variable. This is not quite significant. However, the repetition in the results used in the analysis may have had influence in the output. It was recommended that similar analysis could be done with as many unique samples with unique properties as possible. Figure 8 shows the plot of residual BTS versus predicted BTS. According to the opinion of Frost (2018), residual plots can expose a biased model more effectively than numeric output by displaying problematic patterns in the residual. He suggested that a good residual plot should be foremost in assessing the goodness of a model. According to him, an unbiased model has residuals randomly scattered around zero in spite of the largeness or smallness of the R-squared value. This seems quite true of our model since majority of the residuals are around zero (Figure 8). Based on this we can conclude that our model is unbiased to an acceptable range.

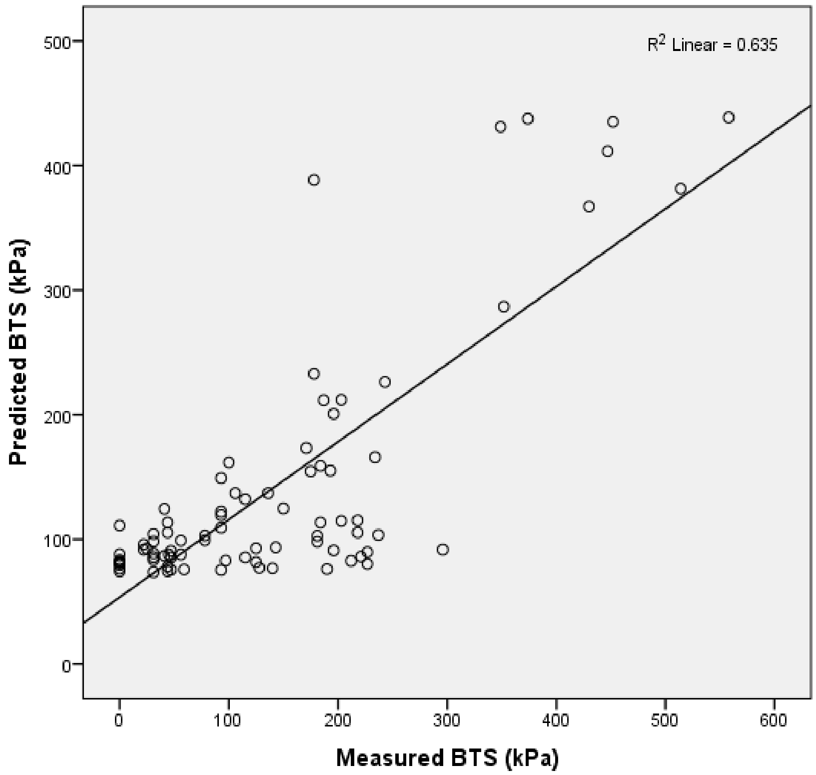

Figure 7: Relationship between Predicted BTS and Measured BTS

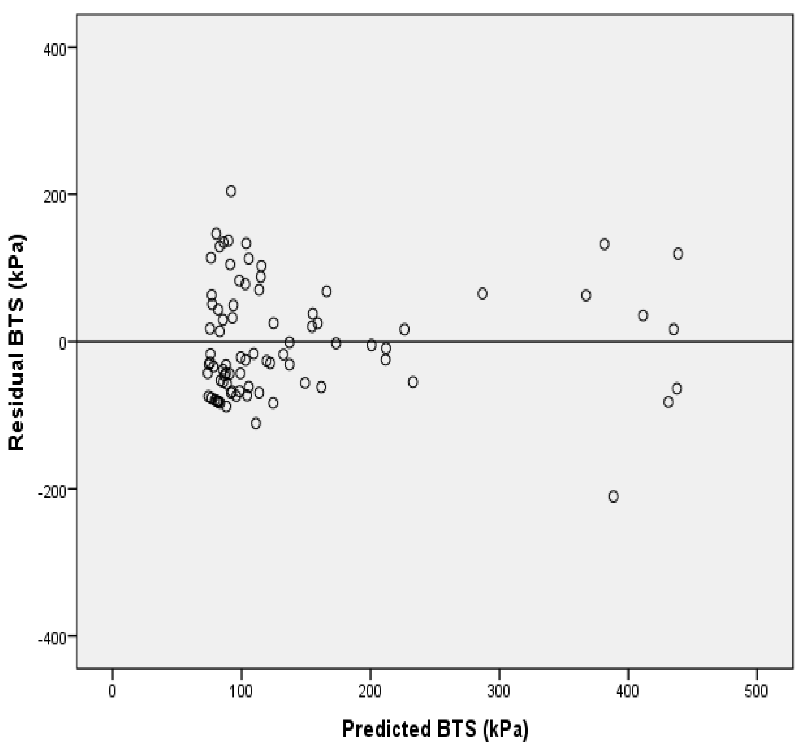

Figure 8: Relationship between Residual BTS and Predicted BTS

4.0. Conclusion

Three lateritic soils LS1, LS2 and LS3 were found as excellent materials for liners in waste containment bins because their UCS/BTS values were greater than 200 kPa. A statistical relationship was sought to enable prediction of BTS from UCS. Correlation analysis carried out gave a significant correlation coefficient between the two parameters ($R \geq 0.75$). Regression analysis gave a significant coefficient of determination ($R^2 = 0.629$) and a p-value much less than 0.05. Through the regression analysis, a model was established to estimate BTS from UCS. ANN was also used to analyse the data and a good fit was observed in the relationship between Predicted BTS and Measured BTS and the relationship between Residual BTS and Predicted BTS. Thus, the model developed can be used with confidence to predict BTS values when the UCS values are known.

5.0 Recommendation

In this research, three samples and repeating results were used and it is recommended that many samples and unique test results should be used in further research in the area. (Note: The aim of the research was not to investigate how suitable the soils are for liner materials but to examine whether it was possible to establish relationship between BTS and UCS and I think this was captured in the conclusion).

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