OPEN ACCESS
Global Journal of Research in Engineering & Computer Sciences
ISSN: 2583-2727 (Online)
Volume 06 | Issue 03 | May-June | 2026
Journal homepage: https://gjrpublication.com/gjrecs/

Research Article

Prediction of Compaction Parameters and Permeability of Black Cotton Soil Stabilized with Fine Sand Using Artificial Neural Network

*Abdussamad Maaruf Fagge[1,2], Ibrahim Umaru[1], Ibrahim Abdulkarim Ikara[1], Halilu Aliyu[1], Ibrahim Umar Ibrahim[2]

[1]Department of Civil Engineering, Abubakar Tafawa Balewa University, Bauchi, Nigeria.
[2]National Space Research and Development Agency

DOI: 10.5281/zenodo.20492886 **Submission Date: 23 April 2026 | Published Date: 01 June 2026**

***Corresponding author: Abdussamad Maaruf Fagge**
Department of Civil Engineering, Abubakar Tafawa Balewa University, Bauchi, Nigeria / National Space Research and Development Agency.

Abstract

This study investigates the influence of particle size distribution on the compaction parameters and permeability of black cotton soil stabilized with fine sand and evaluates the predictive capability of Artificial Neural Networks (ANN). Seventy (70) soil samples were prepared by stabilizing black cotton soil with varying proportions of fine sand, with mix ratios ranging from 0% to 90% sand content to determine the optimal range for stabilization. Laboratory tests were conducted to determine the index properties, particle size distribution, compaction characteristics, and permeability of the stabilized soil. The experimental results showed that the addition of fine sand significantly modified the particle size distribution of the soil and improved its engineering behavior. The Optimum Moisture Content (OMC) ranged from 6.7% to 12.7%, while the Maximum Dry Density (MDD) varied between 1.76 g/cm³ and 2.02 g/cm³. The coefficient of permeability ranged from 1.24×10^{-9} *to* 1.57×10^{-7} *m/s. The plasticity index of the stabilized soils ranged from 8.2% to 30.3%. The results further indicated that as the sand content increased from 0% to 90%, OMC decreased, MDD increased and permeability increased. The most important improvements were observed at higher sand contents, specifically in the range of 60% to 90% fine sand, where the reduction in the clay fraction improved particle packing, decreased compaction moisture requirements and increased the interconnected pore spaces responsible for improved drainage. An Artificial Neural Network model based on a multilayer perceptron architecture (8-10-10-3) was developed to predict the compaction parameters and permeability using Liquid Limit (LL), Plastic Limit (PL), Linear Shrinkage (LS), Plasticity Index (PI), Specific Gravity (Gs), Sand Content (S), Percentage Passing 0.45mm Sieve* ($P_{0.45}$) *and Percentage Passing 0.075mm Sieve* ($P_{0.075}$) *as input parameters. The model was trained and validated using normalized experimental data divided into training and testing datasets. The predictive performance of the ANN model was evaluated using statistical indicators including the coefficient of determination (R²), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results demonstrated high predictive accuracy with Coefficient of Determination (R²) values of 0.977 for Optimum Moisture Content (OMC), 0.823 for Maximum Dry Density (MDD) and 0.983 for permeability. The Mean Absolute Error (MAE) values for the output parameters were 0.472% for OMC, 0.043 g/cm³ for MDD, and 0.183 for permeability, while the Mean Absolute Percentage Error (MAPE) values were 3.10%, 2.40%, and 4.67% for all output parameters.*

Keywords: *Artificial Neural Network, Black Cotton Soil, Maximum Dry Density, Optimum Moisture Content, Permeability.*

1.0 Introduction

The process of densifying soil by removing air from its pores is known as soil compaction, and it needs mechanical energy to be accomplished. The dry density of the soil is used for determining the degree of compaction. When water is added to the soil during the compaction process, it acts as a medium to soften the soil particles. As a result, the soil particles slide past one another rather than moving to a location where they are closer together. Following compaction, the dry density first rises as the water content rises. If the compaction effort is kept constant, the weight of the soil solids per unit volume will likewise gradually increase as the water content is raised. Water is occupying pore spaces that should have been occupied by solid particles, which is the cause of this occurrence. As the maximum dry density is reached at a given water content, this is commonly known as the optimal moisture content (Salahudeen *et al.,* 2018).

Compaction increases soil density by applying stress, which significantly improves the performance of earthwork structures. It enhances slope stability, boosts the bearing capacity of subgrades, minimizes swelling and shrinkage caused by volume changes, and reduces settlement problems. Moreover, compaction directly affects two critical engineering properties: shear strength and permeability. As soil density increases, the angle of internal friction—a key measure of shear strength improves. Simultaneously, permeability decreases as soil grains are packed closer together, reducing the void ratio. For geotechnical designs, achieving the required shear strength and permeability often depends on obtaining the soil's MDD and OMC simultaneously.

Geotechnical challenges are inherently complex and involve numerous uncertainties, making it difficult for engineers to rely solely on conventional methods. This has led to the growing adoption of machine learning (ML) techniques. ML algorithms excel at identifying patterns and correlations within data without requiring prior assumptions, offering an efficient way to address these challenges (Zhang *et al*., 2021).

Soil compaction is a critical factor in various engineering and construction applications, influencing the mechanical properties and stability of structures. Accurate prediction of compaction parameters is essential for optimizing construction processes and ensuring the long-term performance of engineered systems. Additionally traditional methods, such as laboratory testing is not economical and time consuming require a huge quantity of soils if the numbers of tests are many (Mujtaba *et al.,* 2015), (Shafaei *et al.,* 2018), (Gurtug *et al.*, 2018), (Hasnat et al., 2019),(Kurnaz and Kaya, 2020), (Teklehaymanot and Alene, 2021) and (H.Liu *et al.,* 2024). Empirical correlations, have limitations in capturing the complex relationships between soil properties and compaction parameters (Soltani *et al*., 2021) and (F.E Jalal *et a*l., 2021).The arrival of data-driven techniques, particularly Artificial Neural Networks (ANN) offers promising avenues for improved predictive modeling in geotechnical engineering.

2.0 Materials and Methods

2.1 Materials

Black cotton soil was obtained from Biu Local Government Area of Borno State, northeastern Nigeria (coordinates: approximately 10.6167°N latitude and 12.20°E longitude). Samples were collected from 500 mm below ground level to avoid contamination from organic matter and surface disturbances. Fine sand was obtained and passed through seven different sieve sizes: 5.00 mm, 4.75 mm, 2.38 mm, 2.00 mm, 1.18 mm, 1.00 mm, and 800 µm.

2.2 Sample Preparation

The natural black cotton soil was stabilized using fine sand in varying proportions: 0%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90% by dry weight. For each sieve size, ten different mix ratios were produced, resulting in 70 experimental samples. All mixtures were thoroughly homogenized prior to testing to ensure uniform distribution of soil particles.

2.3 Laboratory Testing

All laboratory tests were conducted in accordance with British Standards (BS 1377). The following tests were performed:

Standard Proctor Compaction Test (BS 1377-4:1990): Compacted in three layers using a 2.5 kg rammer with 27 blows per layer. OMC and MDD were determined from compaction curves.

Falling-head Permeability Test (BS 1377-5:1990): Conducted using a cylindrical permeameter (75 mm internal diameter, 300 mm height) to determine the coefficient of permeability for fine-grained soils.

Atterberg Limits Test (BS 1377-2:1990): Liquid limit was determined using the Casagrande apparatus, plastic limit by rolling soil threads to 3 mm diameter.

Particle Size Distribution (BS 1377-2:1990): Combined mechanical sieve analysis and hydrometer analysis.

Specific Gravity Test (BS 1377-2:1990): Performed using a pycnometer.

2.4 Artificial Neural Network Development

An ANN model was developed using MATLAB version 2019b. The multilayer perceptron (MLP) architecture consisted of:

- Input layer**:** 8 neurons (specific gravity, liquid limit, plastic limit, plasticity index, linear shrinkage, percentage passing 0.425 mm sieve, percentage passing 0.075 mm sieve, sand content)
- Hidden layer 1: 10 neurons
- Hidden layer 2: 10 neurons
- Output layer: 3 neurons (OMC, MDD, permeability)

The data were randomly divided into training (80%) and validation (20%) subsets. The calibration data were further divided into 70% for training and 30% for testing. Data normalization was performed to scale all variables to a uniform range [0,1] to prevent variables with larger magnitudes from dominating weight updates.

The Levenberg-Marquardt backpropagation algorithm was employed for training. Model performance was evaluated using coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE).

3.0 Results and Discussions

3.1 Index Properties of Stabilized Black Cotton Soil (BCS)

The physical and consistency properties of the Black Cotton Soil (BCS) modified with varying percentages of fine sand are summarized in Table 1. These index properties serve as the primary input variables for the Artificial Neural Network (ANN) model to predict compaction parameters and permeability.

Table 1: Statistical properties of the index properties of stabilized BCS

Property	Minimum	Maximum	Mean	Standard Deviation
Specific Gravity Gs	2.05	2.69	2.32	0.17
Linear Shrinkage LS %	4	14	10.02	2.14
Liquid Limit LL %	28.8	53.4	42.66	6.01
Plastic Limit PL %	15.8	25.6	21.4	2.02
Plasticity Index PI %	14	30.3	20.98	5.27

3.1.1 Effect of fine sand on plasticity characteristics

The addition of fine sand significantly reduced the liquid limit from 53.4% to as low as 28.8% and the plasticity index from 30.3% to 8.2%. This reduction is attributed to the replacement of expansive clay minerals with sand particles, which reduces the specific surface area and the thickness of the diffused double layer, resulting in a less water-sensitive soil matrix. Linear shrinkage showed a consistent decline from 14% to a minimum of 4%, indicating improved volumetric stability. The inclusion of fine sand creates a granular "internal skeleton" that resists volume changes during moisture fluctuations. Specific gravity increased from 2.05 to 2.69 across the dataset, reflecting the increasing dominance of the denser sand fraction. This upward trend is directly proportional to maximum dry density.

3.2 Particle size distribution of stabilized black cotton soil

The particle size distribution of the stabilized black cotton soil was determined using sieve analysis to evaluate the percentage passing the 0.075 mm sieve, percentage passing the 0.425 mm sieve, and the sand content (S) of the mixtures. These parameters are essential for understanding the gradation characteristics of the soil and how the addition of different grades of sand modifies the particle size distribution of black cotton soil. The statistical summary of the particle size distribution parameters obtained from the experimental results is presented in Table 2.

Table 2: Statistical Properties of Particle Size Distribution Parameters

Parameters	Minimum	Maximum	Mean	Standard Deviation
Sand content S	38.44	90.5	68.3	11.42
P0.425	5.12	91	46.6	22.54
P0.0.75	1.56	46.2	27.05	12.15

3.2.1 Effect of sand grades on soil gradation

The results demonstrate that the introduction of different sand grades significantly modified the gradation characteristics of the black cotton soil. Fine sand particles tend to occupy the void spaces between clay particles, thereby improving the packing arrangement and potentially increasing maximum dry density during compaction. Medium sand particles, on the other hand, contribute to the formation of a more coarse-grained soil structure by reducing the proportion of fines.

Overall, the particle size distribution results indicate that the addition of sand gradually transformed the natural black cotton soil from a predominantly fine-grained material into a more well-graded soil mixture. This improvement in gradation is expected to positively influence important engineering properties such as compaction characteristics and permeability, which are key parameters investigated in this study.

3.3 Compaction Characteristics of Black Cotton Soil Stabilized with Fine Sand

Compaction characteristics are important parameters used to evaluate the suitability of soils for engineering applications such as road subgrades and foundation materials. The compaction behaviour of the stabilized black cotton soil was assessed in terms of Optimum Moisture Content

(OMC) and Maximum Dry Density (MDD) obtained from laboratory compaction tests conducted on seventy (70) samples. The results are summarized in Table 3 below.

Table 3: Statistical Summary of Compaction Characteristics

Parameters	Minimum	Maximum	Mean	Standard Deviation
OMC %	6.7	12.7	9.72	1.54
MDD g/m^3	1.76	2.02	1.88	0.08

The Optimum Moisture Content (OMC) represents the amount of water required for a soil to achieve its maximum dry density under a given compactive effort. The OMC values obtained from the compaction tests for the stabilized soil samples ranged from 6.7% to 12.7%. Lower OMC values were observed in samples containing higher proportions of sand-sized particles, while higher OMC values were recorded in samples dominated by fine clay fractions. This behaviour is expected because clay particles possess a large specific surface area and highwater adsorption capacity, which increases the moisture required to lubricate the particles during compaction.The introduction of fine sand reduces the plasticity and water affinity of the soil mixture. As the sand content increases, the soil becomes more granular, thereby reducing the amount of water required for effective particle rearrangement during compaction. Consequently, the stabilized soil mixtures with higher sand fractions exhibited relatively lower optimum moisture contents compared to mixtures with higher clay content.

Maximum Dry Density (MDD) represents the highest dry unit weight that a soil can attain through compaction at its optimum moisture content. The MDD values obtained from the experimental results ranged from 1.76 g/cm^3 to 2.02 g/cm^3.The lowest dry density values were observed in samples with a higher proportion of clay particles. Clay soils tend to form flocculated structures with relatively large void spaces, which limit the achievable density during compaction. However, as the proportion of sand-sized particles increases, these particles fill the void spaces within the clay matrix, resulting in improved packing and a denser soil structure. The increase in dry density observed in the stabilized mixtures therefore indicates that the addition of fine sand enhances the compaction characteristics of the black cotton soil by improving particle arrangement and reducing the overall void ratio.

3.4 Permeability Characteristics of Black Cotton Soil Stabilized with Fine Sand

Permeability describes the ability of soil to transfer water through its pore spaces. The permeability coefficient (K) obtained from the laboratory tests for the black cotton soil stabilized with fine sand is presented in Table 4 and discussed in relation to the influence of sand particle size on the drainage behavior of the soil.

Table 4: Statistical Summary of Permeability Results

Parameter	Minimum	Maximum	Mean	Standard Deviation
Permeability m/s	$1.24x\text{-}10^{-9}$	$1.57x10^{-7}$	$2.6x10^{=8}$	$3.83x10^{-9}$

The permeability values obtained from the tests range from 1.24×10^{-9} m/s to 1.57×10^{-7} m/s, indicating a significant change in the hydraulic conductivity of the stabilized soil samples. The average permeability value of 2.56×10^{-8} m/s suggests that the stabilized black cotton soil falls within the low to moderate permeability range, which is typical for fine-grained soils modified with granular materials. When fine sand is introduced into the soil, the particle size distribution becomes broader, altering the soil structure and increasing the size and connectivity of pore spaces, as the sand particle size and sand content increase, the permeability generally increases due to the following reasons increase in sore Size, reduction in clay dominance, reduction in water retention capacity, improved soil structure.

3.5 Correlation Analysis

Table 5: Results of correlation analysis

	Gs	LS	LL	PL	PI	S	P0.425	P0.075	OMC %	MDD g/m^3	K m/s
Gs	1.00										
LS	-0.62	1.00									
LL	-0.60	0.96	1.00								
PL	-0.33	0.63	0.78	1.00							
PI	-0.52	0.89	0.85	0.52	1.00						
S	0.82	-0.66	-0.67	-0.48	-0.46	1.00					
P0.425	-0.40	0.35	0.31	0.01	0.43	-0.29	1.00				
P0.075	-0.51	0.72	0.72	0.44	0.79	-0.55	0.72	1.00			
OMC %	-0.57	0.49	0.45	0.17	0.45	-0.43	0.39	0.53	1.00		
MDD g/m^3	0.38	-0.53	-0.52	-0.27	-0.59	0.28	-0.54	-0.74	-0.54	1.00	
K m/s	0.30	-0.46	-0.44	-0.20	-0.64	0.10	-0.58	-0.68	-0.61	0.53	1.00

The results presented in Table 5 indicate strong relationships among the soil plasticity parameters. A very strong positive correlation exists between Linear Shrinkage (LS) and Liquid Limit (LL) (r = 0.96), indicating that soils with higher liquid limits tend to exhibit greater shrinkage characteristics. Similarly, Plasticity Index (PI) shows strong positive correlations with LS (r = 0.89) and LL (r = 0.85), suggesting that these parameters collectively represent the plasticity characteristics of the black cotton soil.

Plastic Limit (PL) shows a moderate positive relationship with LL (r = 0.78) and LS (r = 0.63), indicating that soils with higher plastic limits generally exhibit higher liquid limits and shrinkage potential. In contrast, Specific Gravity (Gs) shows negative correlations with most plasticity parameters, including LS (r = −0.62) and LL (r = −0.60), suggesting that soils with higher clay content and plasticity tend to have relatively lower specific gravity values.

The particle size distribution parameters also show notable relationships with soil properties. Sand content (S) exhibits strong negative correlations with LS (r = −0.66) and LL (r = −0.67), indicating that increasing sand content reduces soil plasticity and shrinkage potential. Similarly, sand content is negatively correlated with P0.075 (r = −0.55), confirming that higher sand fractions correspond to lower fines content.

The percentage passing 0.075 mm sieve (P0.075) shows strong positive correlations with PI (r = 0.79), LL (r = 0.72), and LS (r = 0.72). This indicates that an increase in fines content significantly increases the plasticity and shrinkage characteristics of the soil. The percentage passing 0.425 mm sieve (P0.425) shows moderate correlations with several variables, including PI (r = 0.43) and P0.075 (r = 0.72), indicating the influence of finer particles on soil plasticity.

Regarding compaction characteristics, Optimum Moisture Content (OMC) shows moderate positive correlations with P0.075 (r = 0.53), LS (r = 0.49), and LL (r = 0.45). This suggests that soils with higher fines content and greater plasticity require higher moisture content to reach optimum compaction. Conversely, OMC shows negative correlations with Gs (r = −0.57) and sand content (r = −0.43), indicating that soils with higher sand fractions require less moisture during compaction.

The Maximum Dry Density (MDD) shows strong negative correlations with P0.075 (r = −0.74), PI (r = −0.59), and LL (r = −0.52), indicating that soils with higher fines content and plasticity achieve lower dry densities due to reduced particle packing efficiency. However, MDD shows positive correlations with Gs (r = 0.38) and sand content (r = 0.28), indicating that soils with heavier minerals and higher sand fractions tend to achieve higher dry densities during compaction.

Permeability (K) shows strong negative correlations with P0.075 (r = −0.68) and PI (r = −0.64), indicating that higher fines content and plasticity reduce the ability of water to flow through the

soil due to smaller pore spaces. Permeability also shows negative correlations with LS (r = −0.46) and LL (r = −0.44). However, permeability exhibits a moderate positive correlation with MDD (r = 0.53), suggesting that better particle packing and the presence of coarser particles may slightly enhance drainage characteristics.

Overall, the correlation analysis indicates that percentage passing 0.075 mm sieve, plasticity index, liquid limit, and linear shrinkage are the most influential parameters affecting compaction and permeability behavior. These parameters therefore serve as important predictors in the development of the Artificial Neural Network (ANN) model used to estimate OMC, MDD, and permeability of black cotton soil stabilized with fine sand.

3.6 Artificial Neural Network Model Performance

The performance metrics for the predicted geotechnical parameters Optimum Moisture Content (OMC), Maximum Dry Density (MDD), and Permeability (k) are summarized in Table 6.

Table 6: Statistical Performance Metrics for Predictive Models

Parameter	R^2	MAE	RMSE	MAPE (%)
OMC (%)	0.977	0.472	0.504	3.10%
MDD (g/cm³)	0.823	0.043	0.044	2.40%
Permeability (k)	0.983	0.183	0.188	4.67%

3.6.1 Optimum moisture content (OMC)

The model demonstrated excellent predictive performance for OMC, achieving an R^2 of 0.977. This indicates that the model captures 97.7% of the variability within the moisture content data. The MAE of 0.472% and RMSE of 0.504% are notably low, suggesting that predictions are both accurate and consistent across the trial range. Furthermore, a MAPE of 3.10% confirms that the average deviation is negligible for standard geotechnical engineering applications. Figure 1 shows that the observed and predicted OMC values are very close to each other, with points that are very close to the 45-degree line of perfect prediction. This shows that the model captures the relationship between the input variables and OMC and have generalization ability.

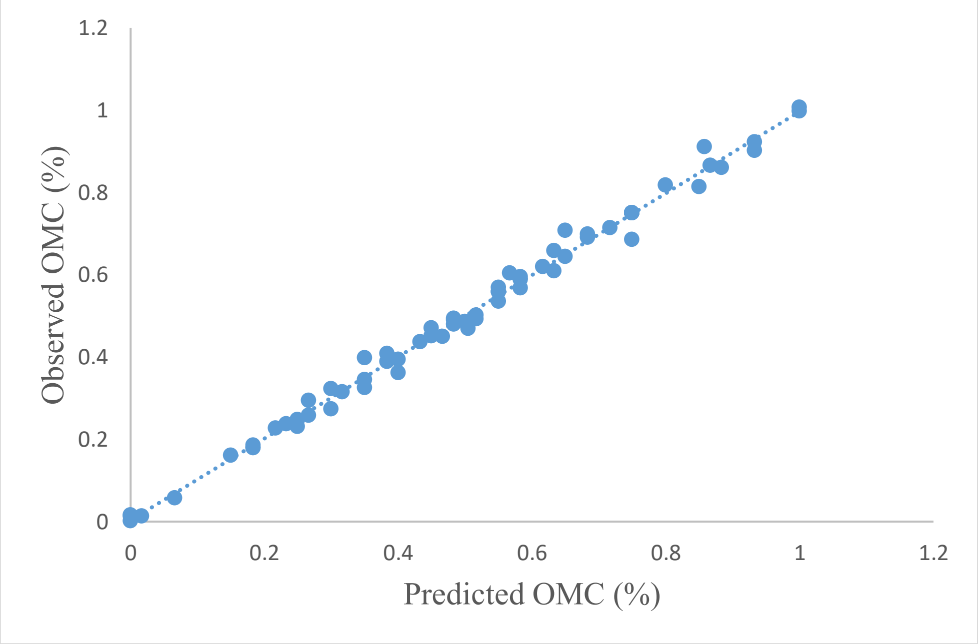

Figure 1: relationship between observed and predicted omc

3.6.2 Maximum dry density (MDD)

For MDD, the model yielded an R^2 of 0.823. While the correlation is slightly lower than that of the other parameters, the absolute error metrics are remarkably low (MAE = 0.043 g/cm³; RMSE = 0.044 g/cm³). Given that typical MDD values range from 1.61 to 1.94 g/cm³, these errors represent a very small fraction of the total magnitude. This high precision is further evidenced by a MAPE of only 2.40%, indicating the model's high efficacy in predicting soil compaction density. Figure 2 shows relationship between observed and predicted MDD values, with the points lying very close to the line of equality, which showing excellent accuracy of the model but a general pattern shows that MDD is strongly correlated and can be predicted reliably across the range studied.

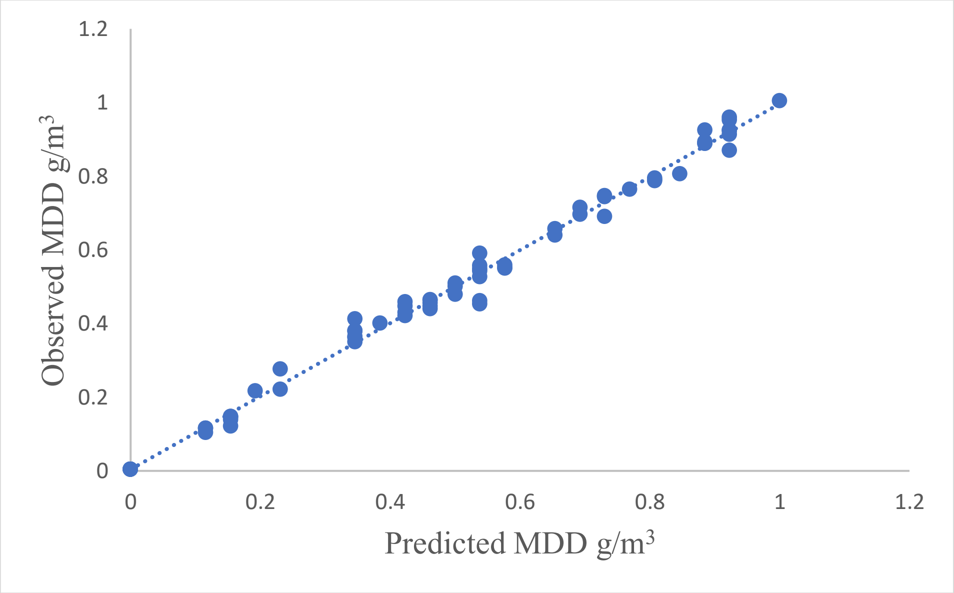

Figure 2: relationship between observed and predicted mdd

3.6.3 Permeability (k)

Predicting hydraulic conductivity showed the strongest statistical correlation, with an R^2 of 0.983. In geotechnical modeling, k is notoriously difficult to predict due to its high sensitivity to soil micro-structure; however, the model maintained a low RMSE of 0.188×10^{-7} m/s. The MAPE of 4.67% demonstrates that even at the 10−7 scale, the model's error remains well within an acceptable threshold for permeability analysis. The convergence of R^2 values toward unity and the consistently low MAPE across all three parameters (all remaining below 5%) validate the robustness of the proposed models. Furthermore, the close proximity between MAE and RMSE values across all parameters suggests a lack of significant outliers in the dataset. This implies that the models are well-generalized and provide a reliable framework for predicting the compaction and drainage characteristics of the investigated soil samples. Figure 3 shows that the observed and predicted permeability values are almost similar, with most points very close to the line of equality. This means that the model is very good at predicting permeability.

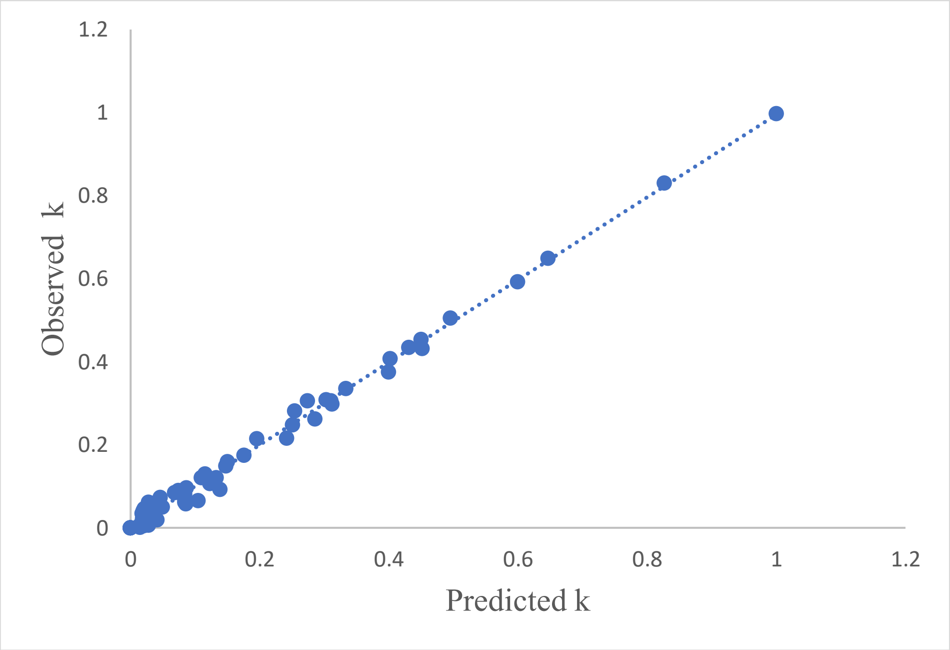

Figure 3: Relationship between observed and predicted permeability

3.7Model Validation and Comparative Analysis

Model validation was carried out by comparing the experimental data with the Artificial Neural Network (ANN) model predicted results. This process was important to evaluate the model's reliability, generalization capability, and predictive accuracy for Maximum Dry Density (MDD), Optimum Moisture Content (OMC), and permeability using statistical indicators such as R^2, RMSE, and MAPE.

3.7.1 Sample observation of Predicted and experimental values

A comparison between selected experimental values and the corresponding Artificial Neural Network (ANN) predictions was carried out to evaluate model performance. The comparison shows a very close agreement between observed and predicted values for Optimum Moisture Content (OMC), Maximum Dry Density (MDD), and permeability (K). Residual values are generally very small and remain within acceptable tolerance limits, confirming the reliability of the developed model.

The predictive capability of the Artificial Neural Network (ANN) model was validated through a point-by-point comparison with experimental datasets. The model demonstrated high fidelity across various soil stabilization scenarios, particularly at the established control parameters.

For instance, in Observation 1, the experimental Optimum Moisture Content (OMC) value of 0.7500 was predicted as 0.7505, yielding a negligible residual of +0.0005. Similarly, for Maximum Dry Density (MDD) in Observation 10, the measured value of 1.0000 was predicted at 1.0050, resulting in a residual of +0.0050.

In the evaluation of Permeability (K) for Observation 20, the experimental value of 0.8267 was predicted as 0.8298, producing a marginal error of +0.0031. Comparable levels of precision were maintained in Observations 57 and 70, where residuals consistently remained below +0.0060.

4.0 Conclusions

The research successfully integrated laboratory investigations with computational modeling. Based on the findings in relation to the research objectives, the following conclusions are drawn:

1. The findings of the study revealed that particle size distribution has a significant impact on the compaction characteristics and permeability of the stabilized black cotton soil and its prediction using Artificial Neural Networks (ANN). As the fine sand content was increased from 0 % to 90 %, the clay fraction reduced and the sand fraction increase, causing the Optimum Moisture Content (OMC) to decrease from 12.7 % to 6.7 % and the Maximum Dry Density (MDD) to increase from 1.76 g/cm³ to 2.02 g/cm³. Concurrently, the permeability increased from 1.24×10^{-9} m/s to 1.57×10^{-7} m/s. The most distinct improvements happened when the fine sand content was in the range of 60 % to 90 %, where the plasticity index of the soil decreased to as low as 8.2 % (from an unsterilized value of 30.3 %). These particle-size-distribution parameters enabled the ANN model to predict Optimum Moisture Content (OMC), Maximum Dry Density MDD, and permeability with high accuracy.
2. The Artificial Neural Network (ANN) model based on a multilayer perceptron approach (8-10-10-3) has been proven to be efficient in predictive analysis for the estimation of OMC, MDD, and permeability. The artificial neural network model has resulted in high coefficients of determination (R^2) of 0.977, 0.823, and 0.983 for the estimation of OMC, MDD, and permeability, respectively. The error indicators of the model are as follows Mean Absolute Error (MAE) values of 0.472 % for OMC, 0.043 g/cm³ for MDD, and 0.183 for permeability, Root Mean Square Error (RMSE) values of 0.504 %, 0.044 g/cm³, and 0.188, respectively; and Mean Absolute Percentage Error (MAPE) values of 3.10 % for OMC, 2.40 % for MDD, and 4.67 % for permeability – all below 5 %. These metrics confirm that the ANN model is both accurate and reliable for routine geotechnical prediction of the three engineering properties.
3. Laboratory testing of the seventy (70) stabilized soil samples demonstrated that stabilizing black cotton soil with fine sand consistently enhanced its engineering behavior. Across the 0 %–90 % fine sand blends, OMC ranged from 6.7 % to 12.7 %, MDD from 1.76 g/cm³ to 2.02 g/cm³, and permeability from 1.24×10^{-9} m/s to 1.57×10^{-7} m/s. The plasticity index decreased markedly from 30.3 % (high-plasticity clay) to 8.2 % with the addition of sand, confirming the transformation of the soil into a less moisture-sensitive material. The experiments showed that higher sand contents consistently reduced the moisture required for compaction, increased the achievable dry density, and enhanced drainage characteristics. The most significant stabilisation effect was observed at sand contents of 60 %–90 %, validating that fine-sand stabilisation is an effective technique for improving the engineering properties of black cotton soil for construction purposes.

References

1. A.B. Salahudeen, T.S. Ijimdiya, A.O. eberemu, K. J. O. (2018). Artificial Neural Networks Prediction of Compaction Characteristics of Black Cotton Soil Stabilized with Cement Kiln Dust. *Journal of Soft Computing in Civil Engineering Journal*, *2*(3), 50–71. https://doi.org/https://doi.org/10.22115/SCCE.2018.128634.1059 ARTICLE
2. Alene, T. F. G. and E. (2021). CBR Predictive Model Development from Soil Index and Compaction CBR Predictive Model Development from Soil Index and Compaction Properties in case of Fine-Grained Soils of Debre – Tabor City , Ethiopia. *International Journal of Science and Engineering* ·, *8*(2), 2224–2234. https://doi.org/10.29294/IJASE.8.2.2021.2224-2234
3. Hasnat, A., Hasan, M., Islam, R., & Alim, A. (2019). *Prediction of Compaction Parameters of Soil using Support Vector Regression*. *0183*(6), 1–7. https://doi.org/10.33552/CTCSE.2019.04.000580
4. Jalal, F. E., Xu, Y., Iqbal, M., Jamhiri, B., & Faisal, M. (2021). Transportation Geotechnics Predicting the compaction characteristics of expansive soils using two genetic programming-based algorithms. *Transportation Geotechnics*, *30*(May), 17. https://doi.org/10.1016/j.trgeo.2021.100608
5. Kurnaz, T. F., & Kaya, Y. (2020). *The performance comparison of the soft computing methods on the prediction of soil compaction parameters*. 1–13.
6. Liu, H., Su, H., Sun, L., & Dias, D. (2024). State - of - the - art review on the use of AI - enhanced computational mechanics in geotechnical engineering. In *Artificial Intelligence Review* (Issue july). Springer Netherlands. https://doi.org/10.1007/s10462-024-10836-w
7. Mujtaba, K. F. U. K. H. (2015). Prediction of Compaction Characteristics of Fine-Grained Soils. *Arab Journal of Science and Engineering*. https://doi.org/10.1007/s13369-015-1918-0
8. Shafaei, S. M., Loghavi, M., & Kamgar, S. (2018). A comparative study between mathematical models and the ANN data mining technique in draft force prediction of disk plow implement in clay loam soil. *AgricEngInt: CIGR Journal*, *20*(2), 71–79.
9. Soltani, A., Azimi, M., & Kelly, B. C. O. (2021). *Modeling the Compaction Characteristics of Fine-Grained Soils Blended with Tire-Derived Aggregates*. 1–21.
10. Yesim Gurtug, A. Sridharan, S. B. I. (2018). Simplified Method to Predict Compaction Curves and Characteristics of Soils. *Iran Journal of Science Transportation and Civil Engineering*, *0123456789*.
11. Zhang, W., Li, H., Li, Y., Liu, H., & Chen, Y. (2021). Application of deep learning algorithms in geotechnical engineering : a short critical review. In *Artificial Intelligence Review* (Vol. 54, Issue 8). Springer Netherlands. https://doi.org/10.1007/s10462-021-09967-1

CITATION

Fagge, A. M., Umaru, I., Abdulkarim, I. I., Aliyu, H., & Umar, I. I. (2026). Prediction of Compaction Parameters and Permeability of Black Cotton Soil Stabilized with Fine Sand Using Artificial Neural Network. Global Journal of Research in Engineering & Computer Sciences, 6(3), 17–25. https://doi.org/10.5281/zenodo.20492886