

Predicting Soil Electrical Resistivity Using Geotechnical Properties and Artificial Neural Networks

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Abstract

This study investigates the influence of key geotechnical parameters—water content, dry density, and plasticity index—on soil electrical resistivity, with the goal of improving prediction accuracy for substation grounding system design. A dataset comprising 150 laboratory test results was compiled from soil samples collected at three substations in Thailand, representing diverse moisture conditions to reflect field variability. Two modeling approaches were applied: multiple regression (MR) and artificial neural networks (ANN), evaluated using the coefficient of determination (R^2) and root mean square error (RMSE). The MR models achieved relatively strong correlations, with R^2 values up to 0.8281; however, their higher RMSE values indicated limited precision under variable conditions. In contrast, the ANN models, particularly those incorporating the plasticity index, demonstrated superior performance, achieving lower RMSE values—down to 0.057—highlighting their ability to capture complex nonlinear relationships. In comparison to prior studies that often relied on single-variable models or uniform soil datasets, this research adopts a more integrative and generalizable framework. By incorporating multiple soil parameters into the ANN model and validating against a diverse dataset, the study offers practical insights for engineering applications. The findings are particularly valuable in tropical regions where soil moisture variation significantly impacts resistivity and grounding system performance.

Keywords: Artificial Neural Networks (ANN); Geotechnical Properties; Moisture Content and Resistivity; Regression Analysis in Geotechnical Engineering; Soil Electrical Resistivity; Substation Grounding Systems.

1. Introduction

Soil resistivity is one of the most critical parameters in the design of grounding systems, especially for power substations. In these facilities, the safe dissipation of fault currents is essential to protect both personnel and electrical equipment. Numerous studies have investigated this topic, examining not only theoretical principles but also practical engineering challenges. Grounding systems are designed to limit voltage surges during fault conditions, ensuring safety and maintaining operational reliability. Among the factors that influence ground grid performance, soil resistivity stands out due to its direct impact on ground resistance and the associated step and touch voltages.

The IEEE Std. 80 outlines comprehensive guidelines for the design of AC substation grounding systems, even in regions with high-resistivity soils. Importantly, the standard emphasizes safety over merely achieving low ground resistance. Instead, it promotes careful management of ground potential rise (GPR) and fault current dissipation without necessarily altering existing soil properties [1]. Precise measurement of soil resistivity is therefore essential to ensure

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both effective design and regulatory compliance. Several studies have emphasized the importance of selecting sites with favorable resistivity values. For instance, the Electricity Generating Authority of Thailand (EGAT) recommends that resistivity values should not exceed 80 ohm-m [2, 3].

However, designing grounding systems in areas with naturally high resistivity presents significant technical and economic challenges. Traditional mitigation strategies include increasing the length or number of electrodes, applying soil conditioning agents, and increasing grid density. Although effective in some cases, these solutions can be costly and are not always practical. As a result, selecting appropriate backfill materials has gained attention as a viable alternative. Backfilling offers a targeted way to reduce soil resistivity around grounding systems without large-scale soil modification. Tao et al. [4] explored the effect of low resistivity backfill materials on grounding performance using simulations and field experiments. Their findings revealed that while localized use of such materials helps reduce step voltages, extensive coverage may lead to undesirable voltage peaks along the periphery of the grid. This introduces new safety risks. Consequently, engineers must consider not only the resistivity of the backfill itself but also its spatial configuration and boundary interaction.

Soil resistivity can vary significantly across a site and over time due to factors such as moisture content, soil type, porosity, ionic composition, and temperature. Seasonal fluctuations in particular play a major role. These variations affect the consistency and effectiveness of grounding systems, making accurate and site-specific measurement critical. Techniques like the Wenner four-pin method remain standard practice for field assessments [2, 5, 6]. Real case studies reinforce this point. For example, fieldwork in Lagos, Nigeria, found much higher soil resistivity during dry seasons compared to wet ones, directly affecting grounding reliability [2]. Similar trends have been documented in other regions, including parts of China and South Africa, underscoring the importance of incorporating seasonal and geographic variables into grounding system models [6, 7]. In recent decades, researchers have increasingly focused on the connection between soil electrical resistivity and geotechnical parameters. This interest stems from the key role that resistivity plays in subsurface exploration and site characterization. Electrical resistivity testing, which is both cost-effective and non-invasive, offers a valuable means of indirectly assessing soil behavior [8-11].

Several studies have pointed to the strong influence of geotechnical factors on soil resistivity. Among these, moisture content has been used as a key variable. As water content increases, resistivity typically decreases, likely due to greater ionic mobility and the formation of more conductive pathways within the soil matrix [12, 13]. This trend appears especially consistent in sandy soils, which tend to have uniform pore spaces and low water-holding capacity [14]. For instance, Siddiqui & Osman [15, 16] found strong power-law correlations in clean sands, whereas soils with mixed or silty textures displayed weaker relationships, possibly due to variability in pore structure. Likewise, Oborie & Akana [17] observed that silty sands showed diminished sensitivity to moisture at higher saturation levels. In clay-silt mixtures, Kibria & Hossain [18] reported that resistivity declined markedly up to about 20% moisture content, beyond which it plateaued. At the drier end, particularly below 15% moisture, resistivity tended to rise sharply, likely due to restricted charge movement in bound water films. Supporting this, Abu-Hassanein et al. [19] documented a strong negative correlation in marine clay samples. Overall, the relationship between moisture and resistivity is not linear, often aligning with power-law or exponential functions. In addition, Kizlo & Kanbergs [5] highlighted the role of dissolved ion concentration, noting its significant impact on both water and soil resistivity values.

The relationship between electrical resistivity and the plasticity index (PI) varies depending on soil type, though an overall inverse relationship is frequently observed across studies. In silty sand soils, this correlation tends to be moderate. For example, Osman et al. [20] reported a strong inverse correlation under laboratory conditions and a moderate one in the field. Likewise, Siddiqui & Osman [16] identified an exponential relationship, with an R^2 of 0.15, which notably improved to 0.56 when modeled using artificial neural networks (ANN). In clayey-silt soils, the correlation was slightly stronger, likely due to the enhanced ionic conduction associated with finer grain sizes. The trend becomes even more pronounced, albeit more complex, in marine clays. Abu-Hassanein et al. [19] documented a strong inverse correlation in such soils, suggesting that plasticity index could serve as a meaningful indicator of resistivity in these environments. Similarly, Zhang et al. [21] found that when the plasticity index exceeded 10% in marine clays, resistivity values tended to plateau at around 8 ohm-m, pointing to a potential threshold beyond which further increases in plasticity index have limited impact. It is also important to consider other influential factors such as salt content and mineralogical composition, both of which can significantly alter resistivity behavior. In sandy soil, for instance, correlations with plasticity index are generally weak. This is likely attributable to their coarse texture and low plasticity, which reduces the soil's capacity for ionic exchange. Siddiqui & Osman [15, 16] noted that in such conditions, plasticity index alone offered limited predictive value. Moreover, the presence of salinity further complicates resistivity interpretation. In summary, the effect of plasticity index on resistivity is more distinct in fine-grained soils, whereas in coarser materials like sand, the trend is less evident and less reliable for predictive modeling.

Several studies have shown that an increase in clay content typically results in lower electrical resistivity. This effect is largely attributed to the high surface area and elevated cation exchange capacity (CEC) of clay minerals, both of which promote ionic conduction within the soil. For instance, Zhang et al. [21] identified a strong inverse exponential relationship in marine clays, where resistivity declined steeply up to approximately 60% clay content before reaching a plateau. Similarly, Abu-Hassanein et al. [19] observed a consistent inverse trend, although the statistical fit was only

moderate, indicating that clay content alone may not sufficiently account for resistivity variability in all cases. Other particle-size characteristics also appear to play a role. Siddiqui & Osman [15] reported a moderate positive correlation between the D_{10} grain size and resistivity in sandy soils, whereas in silty sands, the relationship was notably weaker. These findings suggest that while finer particles and greater clay content tend to reduce resistivity, coarser-grained soils typically exhibit higher values due to reduced surface reactivity and water retention. Overall, soil resistivity is governed by a combination of physical, mineralogical, and chemical factors. As such, relying on a single parameter may not yield accurate predictions across diverse soil types. This underscores the importance of using multivariable or nonlinear models that integrate multiple geotechnical properties to better capture the complex behavior of soil resistivity under varying conditions.

A wide range of studies have investigated how electrical resistivity relates to soil density parameters such as dry unit weight, bulk density, and total unit weight with findings often varying depending on soil type, moisture levels, and the specific conditions under which tests are conducted. Under controlled laboratory settings, an inverse relationship is commonly observed, particularly in connection with dry unit weight. For example, Islam et al. [22, 23] documented strong negative correlations between dry density and resistivity in compacted soils, suggesting that increased compaction improves conductivity through reduced air voids. In contrast, results reported by Memon et al. [24] indicated weaker correlations, where pore water properties played a more dominant role than soil density itself. When it comes to unit weight, the trends appear less consistent. Kibria & Hossain [18] found inverse correlations in clay-rich soils, whereas Siddiqui & Osman [16] noted that in sandy soil, the relationship was minimal or negligible. Interestingly, Abu-Hassanein et al. [19] observed positive site-specific correlations in marine clays, indicating that local mineralogy and environmental conditions may also shape resistivity behavior. These findings suggest that dry unit weight offers the most reliable predictive value for resistivity in laboratory scenarios. However, under field conditions where factors such as moisture variability, salinity, and soil composition come into play a multivariate approach becomes essential for accurate interpretation.

The approaches to correlate geotechnical properties with electrical resistivity have limitations in capturing the nonlinear and heterogeneous behavior of soils. Alternative methodologies, such as regression analysis and artificial neural networks (ANN), offer promising solutions for developing reliable and adaptable predictive models. Regression analysis provides a statistical framework for identifying significant relationships, while ANN enable modeling complex, nonlinear dependencies through self-learning mechanisms. Studies have demonstrated the potential of ANN in predicting soil properties by leveraging electrical resistivity data as an input, emphasizing their flexibility and accuracy in handling complex datasets. For example, artificial neural networks have been successfully applied to predict some geotechnical properties based on electrical resistivity. These models outperform traditional methods in scenarios with high variability and limited data points, which obscures the interpretability of model parameters. Nevertheless, integrating ANN-based approaches with neural interpretation diagrams and sensitivity analyses has enhanced our understanding of the relationships between input variables and outputs [25–27].

In the context of grounding system design for substations, the interplay between soil resistivity and geotechnical properties becomes even more crucial when dealing with layered soil profiles. Variations in resistivity across layers can significantly affect the performance of grounding grids, necessitating accurate modeling to account for such stratifications. For instance, the amount of ground rod may be required to reach lower-resistivity layers beneath high-resistivity strata, optimizing grid performance. The selection of backfilling materials with favorable resistivity and geotechnical characteristics further underscores the importance of comprehensive soil analysis.

This study aims to integrate regression analysis and ANN techniques to explore the intricate relationships between soil resistivity and key geotechnical properties. By leveraging these advanced modeling tools, the research seeks to develop predictive frameworks that facilitate accurate resistivity assessments and inform the design of efficient grounding systems. Ultimately, this approach enhances the safety and reliability of electrical infrastructure and contributes to the broader understanding of soil behavior in engineering applications.

2. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN), often called neural networks, are computational systems inspired by the human brain's structure and functioning. Unlike conventional digital computers, which follow a deterministic and step-by-step process, ANN compute differently by mimicking the brain's ability to process and adapt to nonlinear data. These networks are designed to perform specific tasks by modeling patterns observed in biological neural systems. ANN can be implemented using electronic components or simulated in software, making them highly versatile [25–27].

This study's architecture of artificial neural networks (ANN) comprises multilayer feedforward networks consisting of three primary layers: an input layer, one or more hidden layers, and an output layer. Communication between these layers occurs through interconnected neurons, each transmitting signals weighted by bias values. This weighting reduces the discrepancy between predicted outputs and actual targets during training, iterated through multiple cycles called epochs. Each neuron in one layer connects to every neuron in the next, creating an entirely interconnected structure for complex data processing. The typical structure of multilayer feedforward is shown in Figure 1 that shows typical

structure of the ANN used in this study. The diagram illustrates the multilayer feedforward architecture comprising an input layer, one or more hidden layers, and an output layer. The Levenberg-Marquardt algorithm was utilized to optimize the learning process, enhancing the model's ability to generalize from training data and improve prediction accuracy. Because the Levenberg-Marquardt algorithm combines gradient descent and the Gauss-Newton method [27], enabling it to converge rapidly, especially for small to medium-sized networks that accord with this study. The soil resistivity data exhibited complex, nonlinear relationships with geotechnical properties such as moisture content, plasticity index, and dry density. The Levenberg-Marquardt algorithm is well-suited for such problems. Moreover, the dataset in this study was relatively small (30 soil samples). The Levenberg-Marquardt algorithm is known to perform well with smaller datasets, as it can extract meaningful patterns without overfitting.

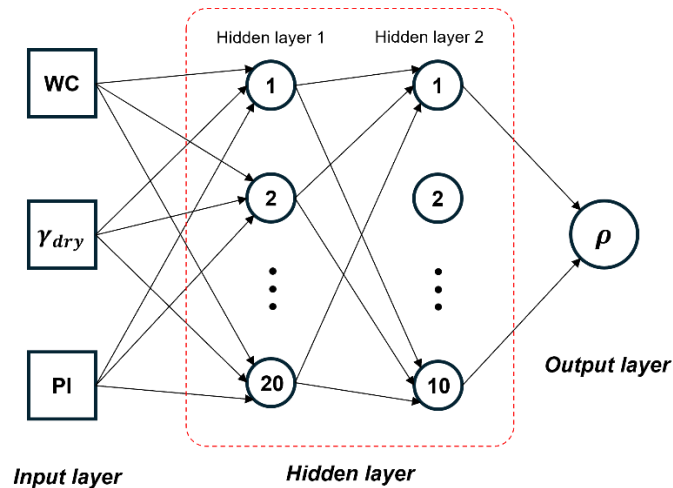


Figure 1. The typical structure of the artificial neural network used for predictive analysis [22]

For Model validation, it is a critical phase following the successful training of an Artificial Neural Network (ANN) model. This phase ensures that the model can generalize within the constraints of the training data in a robust manner rather than merely memorizing the input-output relationships present in the training set. The validation process typically involves assessing the performance of the trained ANN on an independent validation dataset, which is not used during the model development phase. This approach is widely recognized in the literature for evaluating the model's generalization capability [25–27].

Several performance metrics are employed to quantify ANN models' robustness and predictive accuracy. Among these, the coefficient of correlation (r) and the root mean squared error (RMSE) are particularly significant. The coefficient of correlation measures the strength and direction of the linear relationship between predicted and observed data, serving as an indicator of goodness-of-fit. A high correlation coefficient suggests a strong agreement between predictions and actual outcomes.

Smith (1986) [28] provides guidelines for interpreting the coefficient of correlation, which ranges from 0.0 to 1.0. When the absolute value of the coefficient of correlation ($|r|$) is greater than 0.8, it indicates a strong correlation between two sets of variables. Values between 0.2 and 0.8 suggest a moderate correlation, while values less than 0.2 indicate a weak correlation.

Hecht-Nielsen (1990) [29] highlights using the Root Mean Squared Error (RMSE) as a critical metric for evaluating predictive performance. RMSE is calculated using the following Equation 1:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (1)$$

where N represents the number of data point, ρ denotes the actual value (target out) and, ρ denotes the predicted value (The dataset in this study has been divided into training, validation, and testing subsets for developing an Artificial Neural Network (ANN). Seventy percent of the dataset was allocated to training, during which the network identifies patterns and relationships within the data by iteratively adjusting its weights and biases to minimize prediction error. Fifteen percent of the dataset was assigned for validation and utilized during the training phase to monitor the model's performance and mitigate overfitting by assessing its ability to generalize to unseen data. After the training phase, the remaining 15% was reserved for testing to evaluate the model's final performance. The test set provides an objective and unbiased measure of the model's capacity to handle new, unseen data. Moreover, this study chose the RMSE as a performance metric for evaluating predictive models because it can quantify the size of prediction errors and penalizes large errors more significantly than metrics like Mean Absolute Error (MAE) due to the squaring of residuals [30].

3. Data Acquisition

This study collected disturbed soil samples from 30 points located at three representative power grid substations. The soil was taken from the backfill layers near the ground surface (within 2 meters depth). In substation construction, backfill soil plays a crucial role in both geotechnical stability and electrical grounding performance. In Thailand, its use is governed by strict regulations to ensure compliance with required specifications [31].

Soil sampling was conducted following standardized procedures to capture representative variability in soil conditions across diverse geographic areas. The collected samples were then transported to the laboratory, where a series of geotechnical and electrical tests were carried out to characterize their properties. Although the samples were disturbed, they were suitable for laboratory-based resistivity testing. To investigate the influence of moisture content on soil electrical resistivity, each sample was prepared and tested under five distinct moisture levels. This approach was designed to simulate real-world variations in field moisture conditions and improve the model's generalizability. As a result, the experimental design yielded a total of 150 data points, providing a robust and diverse dataset for statistical analysis and model development using multiple regression and artificial neural networks.

3.1. Geotechnical Laboratory Test

The geotechnical laboratory analyses in this study were conducted to comprehensively assess the physical and mechanical properties of soil samples collected from representative substations. The tests included evaluations of water content, plasticity index, liquid limit, specific gravity, clay content, and maximum dry density.

Specific gravity testing, performed using a pycnometer, quantified the ratio of soil particle density to water density, providing critical insights into the soil's mineralogical composition and serving as a basis for calculations in hydrometer testing. The plasticity index and liquid limit tests were used to characterize the soil's water content behavior. The plasticity index, defined as the difference between the plastic and liquid limits, provided information on soil consistency and the proportion of fines passing through a No. 200 sieve. Clay content was determined using a combination of sieve analysis and hydrometer testing, with classification conducted by the Unified Soil Classification System (USCS). To replicate the properties of substation, backfill soils, standard Proctor compaction tests were carried out to achieve the soil's maximum dry density and optimum water content. These tests informed the preparation and reconstitution of soil samples for electrical resistivity laboratory testing. All procedures were performed in strict accordance with the relevant ASTM standards [32–37] to ensure methodological rigor and accuracy. Table 1 summarizes the results of these analyses.

Table 1. Summary of geotechnical properties of clayey silt and silty clay soils [31]

Geotechnical properties	ASTM	Soil type	
		Clayey silt	Silty clay
Specific gravity, G_s	ASTM D854	2.68 to 2.80	2.70 to 2.77
Plasticity index, PI (%)	ASTM D4318	9.8 to 16.5	27.1 to 37.2
Maximum dry unit weight, γ_{dry} (g/cm ³)	ASTM D298	1.77 to 1.83	1.78 to 1.86
Optimum moisture content (%)		13.2 to 15.6	13.2 to 16.4

In the classification framework detailed by Sangprasat et al. [31], the soil samples were systematically categorized into two distinct types based on their position relative to the A-line: (1) silty clay, which is situated above the A-line, and (2) clayey silt, which falls below the A-line. The characteristics and properties of these two soil types are outlined in Table 1.

For the silty clay group, the plasticity index, which reflects the soil's plasticity and ability to retain water, was found to range between 27.1% and 37.2%. This relatively high plasticity index indicates a significant clay content and a higher tendency for the soil to undergo deformation under varying moisture conditions. The specific gravity values, which provide insight into the density of soil particles compared to water, were observed to range from 2.70 to 2.77. Furthermore, the maximum dry density of the silty clay soils was determined to be between 1.78 g/cm³ to 1.86 g/cm³, while the optimum water content, representing the moisture level required to achieve maximum compaction, ranged from 13.2% and 16.4%. These properties collectively suggest that silty clay exhibits a substantial capacity for compaction and water retention.

On the other hand, the clayey silt group demonstrated a lower plasticity index compared to silty clay, with values ranging from 9.8% to 16.5%. This lower range indicates a reduced clay content and, consequently, less pronounced plasticity and water retention behavior. Despite this difference in plasticity, the specific gravity of clayey silt was found to be similar to that of silty clay, with values ranging from 2.68 to 2.80. Similarly, the maximum dry density values for clayey silt, which ranged between 1.77 g/cm³ and 1.83 g/cm³, showed only a slight variation compared to the silty clay group. The optimum water content for clayey silt was observed to range from 13.2% to 15.6%, which closely aligns with the values reported for silty clay.

3.2. Electrical Resistivity Laboratory Test

Smith [28] and Wenner [39] highlighted the importance of electrical resistivity as a key soil property influenced by material composition and pore water ionic concentration. Using a four-electrode configuration, they measured resistivity

on core samples encased in PVC cylinders (7.5 cm in diameter and 11 cm in length) with copper disks as current electrodes and copper needles as potential electrodes. The method showed consistent resistivity values across varying electrode depths, indicating minimal disturbance is sufficient for accurate measurements, particularly in clay soils. Additionally, the approach is adaptable to various sample geometries, making it versatile for geotechnical applications.

Specific gravity testing, conducted using a pycnometer, quantified the ratio of soil particle density to water density. This provided critical insight into the soil's mineralogical composition and served as a basis for calculations in hydrometer testing. The plasticity index and liquid limit tests were used to characterize the soil's water content behavior. The plasticity index, defined as the difference between the plastic and liquid limits, provided information on soil consistency and the proportion of fines passing through a No. 200 sieve. Clay content was determined through a combination of sieve analysis and hydrometer testing, with classification conducted by the Unified Soil Classification System (USCS). To replicate the properties of substation's backfilled soils, standard Proctor compaction tests were carried out to determine the soil's maximum dry density and optimum water content. These tests informed the preparation and reconstitution of soil samples for electrical resistivity measurements.

According to Zhou et al. [40], in line with IEEE guidelines, soil resistivity exhibits a three-stage response to temperature variations: (1) a gradual decrease in resistivity above 0°C, (2) a sudden change at 0°C, and (3) a significant increase below 0°C. For sandy loam soil with 15.2% moisture content, resistivity decreases approximately exponentially as temperature rises above 0°C [3]. Similar findings were reported by Abu-Hassanein et al. [19], reinforcing the inverse relationship between electrical resistivity and temperature. In addition, Kizlo & Kanbergs [5] observed that the resistivity of rocks increases markedly during the freezing of pore moisture, underscoring the influence of phase changes on electrical properties.

In this study, cylindrical soil samples measuring 6.4 cm in diameter and 12 cm in length were used, with electrical resistivity measured using the Wenner array configuration [36]. The IRIS SYSCAL R2 instrument, powered by a 1.5V battery [38], was used to evaluate resistivity. To ensure accuracy in current measurements, brass disc electrodes were placed at both ends of each soil sample to function as current electrodes. Additionally, two brass electrodes were inserted at fixed positions within the sample, spaced 4 cm apart, to serve as potential electrodes. The electrical resistivity of the soil was then calculated using Equation 2.

$$\rho = \frac{V\pi r^2}{Ia} \quad (2)$$

where ρ is the resistivity in ohm-meters, V represents the potential difference, I is the applied current, r is the sample radius, and a is the distance between the potential electrodes.

Sample preparation was carefully controlled to ensure consistency. The soil was first dried and then mixed with distilled water before being sealed in a bag for 24 hours to allow uniform water distribution. The moistened soil was subsequently compacted into cylindrical molds using a 5.5-pound hammer to achieve 95% of the maximum dry density and 85% of the optimum water content, as determined by the standard Proctor test.

The experimental procedure followed a structured timeline, with resistivity measurements taken on Days 0, 7, 14, and 28, as outlined in the flowchart in Figure 2. Throughout the 28-day testing period, temperature and humidity were strictly regulated to maintain conditions of 25±2 °C and 50%–55% relative humidity. Prior to each measurement, the samples were weighed, and their water content was monitored by reweighing the samples at the end of the experiment. This controlled preparation and measurement process ensured reliable results and accurate monitoring of moisture changes, providing robust data for analyzing the electrical resistivity of the soil samples.

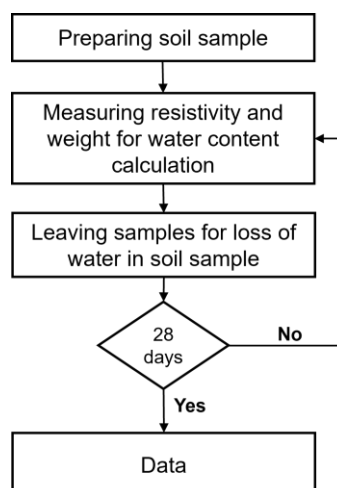


Figure 2. The flowchart of electrical resistivity laboratory measurement

4. Results and Discussion

4.1. Correlation Between Resistivity and Each Geotechnical Property by Regression Analysis

Sangprasat et al. [31] highlighted the significant impact of water content on soil resistivity, demonstrating an inverse relationship in which resistivity increases as moisture decreases, particularly within specific soil types. While the overall power correlation was weak, strong correlations were observed within individual soils. This trend aligns with prior research showing that higher water content reduces resistivity due to increased ion mobility and the formation of conductive paths [21, 41–43]. Conversely, at low moisture levels, resistivity rises sharply, especially below 15% moisture content, due to limited charge mobility [44]. Studies also reveal that resistivity becomes relatively stable above 22% moisture content, indicating saturation. Factors such as grain size, soil compactness, and heterogeneity influence this relationship, leading to variability across soil types. Nonlinear models further confirm the strong moisture–resistivity correlation within distinct soil types. Additionally, the type of water in the soil, as noted by Kizlo & Kanbergs [5], affects resistivity, with bound water contributing less to conduction than free water.

The relationship between resistivity and dry density based on a power correlation yielded weak overall correlations when all soil samples were considered, indicating a limited connection [31]. However, trends differed among individual soil types. These results suggest that power correlation is insufficient to conclusively establish a relationship between resistivity and dry density, primarily due to the overriding influence of moisture content. The variability in observed trends highlights moisture's dominant role in affecting soil resistivity.

Furthermore, Sangprasat et al. [31] investigated the relationship between soil resistivity and plasticity index, primarily using power correlation. The results showed that resistivity generally increases as the plasticity index decreases, though exceptions were observed, such as in clayey silt compacted at 95%, where the correlation was weaker. This trend aligns with findings from Siddiqui et al. [16] and Abu-Hassanein et al. [19], who reported a significant inverse relationship between electrical resistivity and plasticity index. Higher clay content, characterized by a greater proportion of fine particles, typically leads to lower resistivity due to improved ion conduction pathways. Other studies have also confirmed the significant influence of soil composition, particularly clay content, on resistivity.

The correlation between soil resistivity and specific gravity is relatively weak, as specific gravity primarily reflects the mineralogical composition of the soil rather than directly predicting resistivity. In this study, the soil samples contained mineral components such as Kaolinite (2.60–2.68), Illite (2.642–2.688), Quartz (2.65), and Goethite (3.3–4.3) [45]. Sarip & Madun [46] investigated the influence of clay minerals (Kaolinite, Illite, and Montmorillonite) on electrical resistivity and chargeability for groundwater interpretation. Their findings indicate that although Montmorillonite exhibited the highest specific gravity, soil samples dominated by Kaolinite demonstrated the highest resistivity values.

This suggests that clay minerals, particularly Kaolinite and Illite, contribute to lower soil resistivity due to their higher porosity and chargeability compared to non-clay minerals. While specific gravity does not establish a direct relationship with soil resistivity, it serves as a valuable indicator of mineralogical composition, which indirectly influences resistivity behavior. Consequently, the mineralogical characteristics of the soil play a more significant role in determining resistivity than specific gravity alone.

4.2. Multiple Regression Model

Sangprasat et al. [31] employed a nonlinear regression approach and found that moisture content plays a dominant role in influencing soil resistivity. This strong influence poses challenges in precisely quantifying the relationship between these variables. To overcome this limitation, several multiple regression models were constructed using different combinations of geotechnical parameters, as outlined in Table 2:

Table 1. Multiple regression equations for predicting soil resistivity from geotechnical parameters

Model	Parameters		Equations	The coefficient of determination
	Input	Output		
MR-1	WC	ρ	$\rho = 482.2808(WC^{-1.0347})(\gamma_{dry}^{-0.37478})$	0.8281
	γ_{dry}			
MR-2	WC	ρ	$\rho = 4856.2384(WC^{-1.0756})(PI^{-0.76963})$	0.7742
	PI			
MR-3	WC	ρ	$\rho = 15360.31(WC^{-1.0658})(\gamma_{dry}^{-1.1034})(PI^{-1.0171})$	0.8102
	γ_{dry}			
	PI			

where ρ is the resistivity in ohm-meters, γ_{dry} represents dry density g/cm^3 , WC is water content in % and PI is plasticity index in %.

Model MR-1, which included water content and dry density as inputs, produced a coefficient of determination (R^2) of 0.8281 and an RMSE of $445.0 \Omega \cdot \text{m}$. The regression analysis showed that water content had a statistically significant effect ($P < 0.001$), whereas dry density did not ($P = 0.676$). Model MR-2, comprising water content and plasticity index, achieved better predictive performance, with $R^2 = 0.7742$ and $\text{RMSE} = 426.0 \Omega \cdot \text{m}$. Both parameters were found to be statistically significant ($P < 0.001$), suggesting a strong relationship with resistivity. Model MR-3 combined all three variables, water content, dry density, and plasticity index, and resulted in $R^2 = 0.8102$ and $\text{RMSE} = 430.0 \Omega \cdot \text{m}$. While water content and plasticity index continued to show significant influence ($P < 0.001$), dry density again did not contribute meaningfully to the model ($P = 0.741$). Figures 3-a, 4-a, and 5-a present the comparison between measured and predicted resistivity values for each model. These results underscore the importance of incorporating multiple geotechnical properties, particularly moisture-related factors, when developing predictive models for soil electrical resistivity.

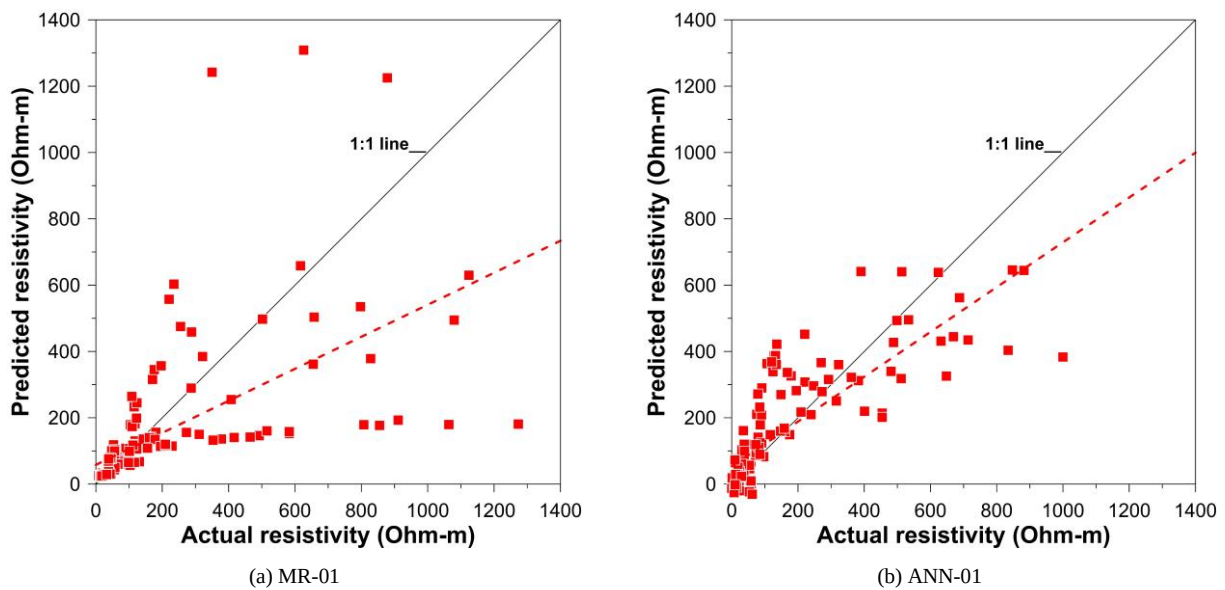


Figure 3. Comparison of predicted vs. actual resistivity values for (a) MR-01 (multiple regression) and (b) ANN-01 (artificial neural network) models using water content and dry density

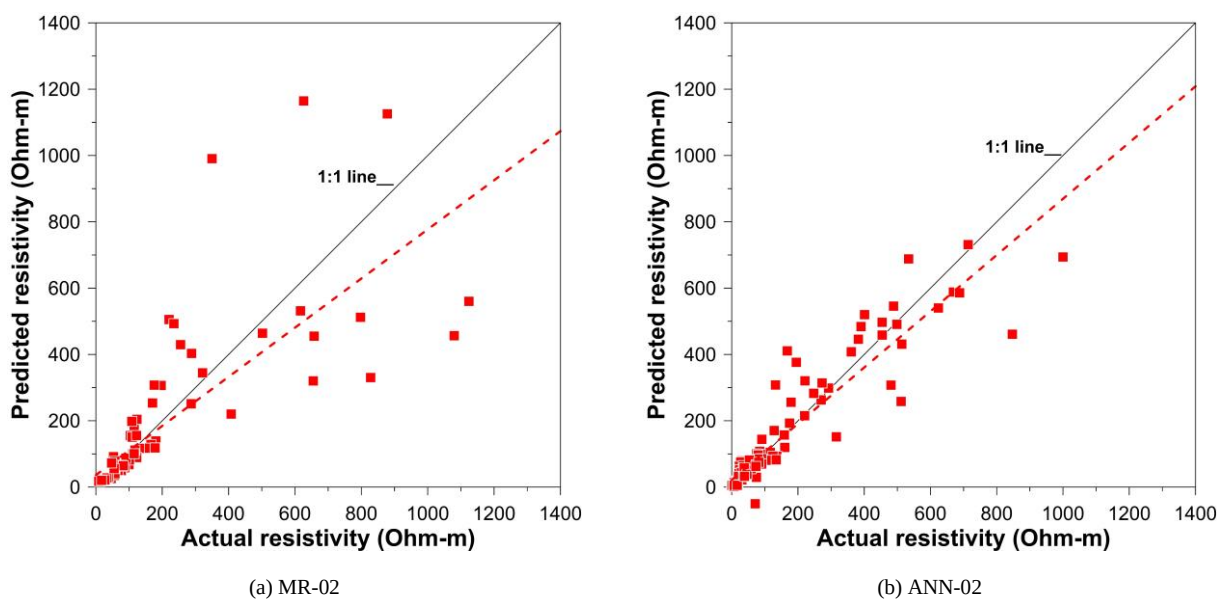


Figure 4. Comparison of predicted vs. actual resistivity values for (a) MR-02 (multiple regression) and (b) ANN-02 (artificial neural network) models using water content and plasticity index

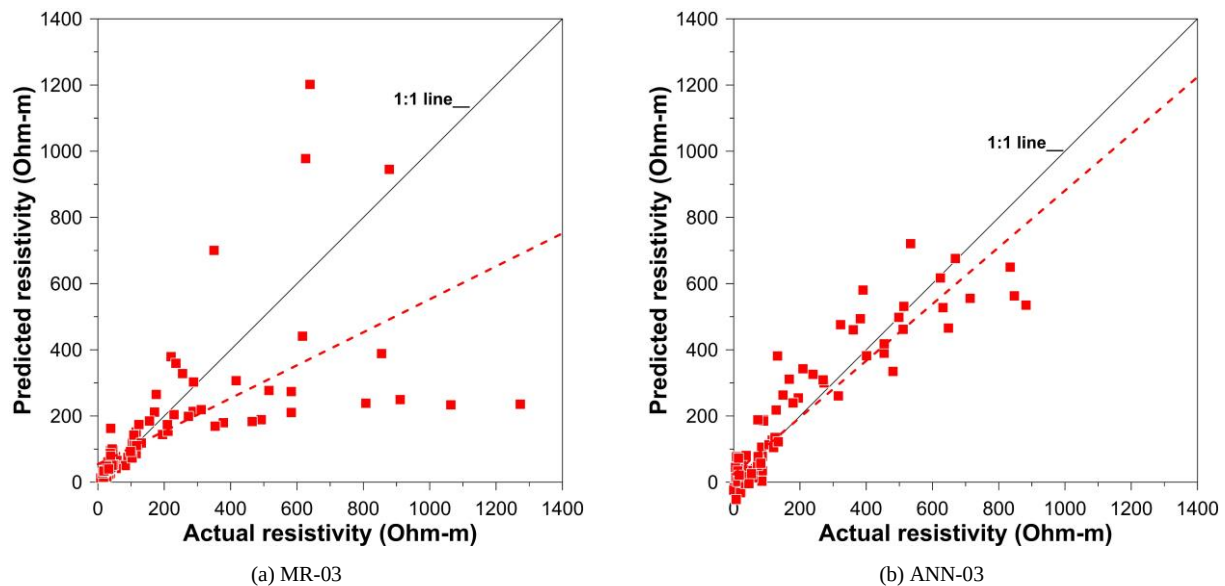


Figure 5. Comparison of predicted vs. actual resistivity values for (a) MR-03 (multiple regression) and (b) ANN-03 (artificial neural network) models using water content, dry density, and plasticity index

From an engineering perspective, these findings offer practical insights for geotechnical site evaluation and the design of electrical grounding systems. The pronounced influence of water content and plasticity index on soil resistivity underscores the need to account for seasonal moisture fluctuations and soil classification when estimating resistivity in the field. Soils with higher plasticity, for instance, tend to retain moisture for extended periods, which can lead to lower resistivity and, consequently, impact the long-term performance of grounding systems.

In contrast, dry density consistently demonstrated a limited contribution across all models, suggesting that its role in resistivity prediction is less significant compared to parameters linked to pore water and clay content. This observation indicates that electrical conduction in soils is more closely tied to physicochemical characteristics than to compaction alone. Therefore, relying on dry density or any single-parameter approach may not be sufficient, particularly in moisture-sensitive or fine-grained soils. These results highlight the importance of selecting input variables that capture both the hydrological and mineralogical behavior of soils to improve the accuracy of resistivity modeling.

4.3. Artificial Neural Networks

An Artificial Neural Network (ANN) model was developed to predict soil electrical resistivity using three geotechnical input parameters: water content, dry density, and plasticity index. The feedforward neural network was constructed with one hidden layer and trained using the Bayesian Regularization backpropagation algorithm (`trainbr` in MATLAB). Prior to training, all input and output data were normalized to the [0,1] range to enhance numerical stability and learning efficiency. To identify the optimal network architecture, a parametric study was conducted by varying the number of neurons in the hidden layer from 1 to 10. For each configuration, the network was trained, and its performance was evaluated based on the root mean squared error (RMSE) and coefficient of determination (R^2) on the test dataset. The data were split into training (70%), validation (15%), and testing (15%) subsets.

To explore the effectiveness of artificial neural networks (ANNs) in predicting soil electrical resistivity, we tested three model configurations using different combinations of geotechnical inputs. Their performances, summarized in Table 3, were evaluated based on the coefficient of determination (R^2) and the root mean square error (RMSE). In the first setup (ANN-1), we used water content and dry density as inputs. The model produced an R^2 of 0.6809 and an RMSE of 0.093. While this suggests a moderate level of prediction accuracy, it also indicates that these two parameters alone do not sufficiently capture the complexity of resistivity behavior, especially in fine-grained or clay-rich soils where moisture retention and mineral composition have stronger influence. The ANN-2 model, tested with water content and plasticity index, showed a notable improvement, achieving an R^2 of 0.8588 and an RMSE of 0.064. The results highlight the critical role of the plasticity index, which reflects the presence and characteristics of clay minerals and their contribution to electrical conduction under moist conditions. The third model, ANN-3, combined all three parameters—water content, dry density, and plasticity index. This configuration slightly outperformed ANN-2, reaching an R^2 of 0.8608 and an RMSE of 0.057. Although the gain in R^2 was marginal, the reduced RMSE indicates a more reliable prediction. Interestingly, dry density still had a minor yet measurable contribution when added to the model, even though its standalone influence appeared limited.

Table 2. Predictive Performance of Artificial Neural Network Models Using Geotechnical Parameters

Model	Parameters		The coefficient of determination	RMSE
	Input	Output		
ANN-1	WC	ρ	0.6809	0.093
	γ_{dry}			
ANN-2	WC	ρ	0.8588	0.064
	PI			
ANN-3	WC	ρ	0.8608	0.057
	γ_{dry}			
	PI			

where ρ is the resistivity in ohm-meters, γ_{dry} represents dry density g/cm³, WC is water content in % and PI is plasticity index in %.

To interpret the influence of each input variable on the model output, the Garson algorithm was employed to estimate the relative importance of each input parameter based on the absolute contribution of the connection weights from input to hidden and hidden to output layers. The analysis revealed that water content had the highest relative importance, contributing 80.25%, followed by plasticity index with 15.59%, and dry density with only 4.16%. These results are consistent with the known physical behavior of soil resistivity, which is predominantly influenced by moisture content.

4.4. Comparative Analysis

To evaluate the predictive performance of multiple regression (MR) and artificial neural network (ANN) models, three configurations for each approach were tested using different combinations of geotechnical parameters. The results, summarized in Tables 2 and 3 and illustrated in Figures 3 to 5, reveal both strengths and limitations of each modeling technique.

Among the MR models, MR-1 achieved the highest coefficient of determination ($R^2 = 0.8281$), indicating a strong fit to the data. However, its root mean square error (RMSE = 445.0 $\Omega \cdot m$) was relatively high, suggesting that despite the good fit, the model may still produce large absolute errors, particularly for soils with high resistivity values. In contrast, ANN-1, which used the same input parameters, produced a lower R^2 of 0.6809 but achieved a much lower normalized RMSE of 0.093. This implies that while ANN-1 explained less of the overall variance, it provided more consistent predictions with smaller average errors. In practical terms, this could make ANN-1 more reliable when precision is prioritized over statistical fit. A more notable advantage of ANN models emerged when plasticity index was included. ANN-2 and ANN-3 achieved R^2 values of 0.8588 and 0.8608, respectively, with the lowest RMSEs of 0.064 and 0.057. These results indicate that ANN models not only captured complex, nonlinear patterns more effectively but also reduced prediction errors. Meanwhile, the corresponding MR models (MR-2 and MR-3) yielded lower R^2 values (0.7742 and 0.8102) and higher RMSEs (426.0 and 430.0 $\Omega \cdot m$), reflecting weaker performance.

RMSE plays a critical role in assessing model accuracy, as it directly quantifies the average magnitude of prediction errors. While R^2 measures how well a model explains data variability, RMSE is more relevant in applications where minimizing absolute error is essential. For instance, in grounding system design or soil monitoring, lower RMSE translates to more dependable estimates and better engineering outcomes. To further interpret the contribution of each variable in the ANN models, the Garson algorithm was applied. The analysis showed that water content had the greatest relative importance (80.25%), followed by plasticity index (15.59%), and dry density (4.16%). These findings are consistent with both regression results and prior studies [31, 47, 48], reinforcing the conclusion that moisture-related factors—especially water content—dominate the behavior of soil resistivity.

In summary, while MR-1 provided the highest R^2 in a two-variable setting, the ANN models—particularly ANN-2 and ANN-3—demonstrated better overall performance when both R^2 and RMSE were considered. The inclusion of plasticity index significantly enhanced predictive accuracy, and the ANN framework proved more effective at capturing nonlinear relationships. These results support the use of ANN-based models for reliable and accurate prediction of soil electrical resistivity. While the ANN models performed well in estimating soil resistivity, it's important to acknowledge a key limitation: the dataset used in this study contained only 150 samples. In the context of machine learning, especially for nonlinear problems like soil behavior, small datasets can sometimes hinder the model's ability to generalize and increase the risk of overfitting.

Interestingly, prior research suggests that small datasets aren't necessarily a barrier to effective ANN modeling. Pasini [49], for instance, noted that with proper design, such as careful selection of network architecture, robust preprocessing, and the use of regularization, ANNs can still deliver solid performance even with limited data. A simple feedforward network with one hidden layer, when well-tuned, can achieve strong nonlinear regression results.

This observation is echoed by Bagińska & Srokosz [50], who found that ANN models in engineering contexts—where collecting large numbers of field measurements can be difficult, still performed accurately with fewer than 150

samples. However, they emphasized the need for strong validation strategies, such as cross-validation, to ensure the model's reliability.

Similarly, Izonin et al. [51] pointed out that researchers working with small datasets should be especially cautious about model complexity. They recommended minimizing the number of hidden neurons or using techniques like dropout to prevent overfitting and help the model generalize better.

Overall, while a dataset of 150 samples is within the acceptable range for ANN modeling, it does call for careful interpretation of results, particularly when extending conclusions to other soil types or regions. Future work could explore expanding the dataset or adopting transfer learning methods to further improve model robustness and applicability.

5. Conclusion

This study examined the predictive performance of multiple regression (MR) and artificial neural network (ANN) models in estimating soil electrical resistivity using water content, dry density, and plasticity index as input variables. A total of 150 laboratory data points, gathered from three substations under varying moisture conditions, served as the dataset for model development. While MR models produced relatively high coefficients of determination (up to $R^2 = 0.8281$), their higher root mean square error (RMSE) values indicated less precise predictions. In contrast, ANN models—especially those incorporating the plasticity index—achieved both higher R^2 values (up to 0.8608) and lower RMSEs (down to 0.057), suggesting superior performance in capturing nonlinear patterns in soil resistivity.

The study also addressed a major limitation found in prior literature, where models were often built using either oversimplified input parameters or data from homogeneous soil types. By incorporating a more diverse set of inputs and validating across multiple soil types, the models presented here offer improved generalizability. The Garson algorithm highlighted the dominant influence of water content (80.25%) over plasticity index and dry density, in line with prior findings but providing clearer quantitative insight.

The results highlight the practical advantages of ANN-based models for applications in tropical and subtropical environments where soil moisture varies significantly. Although the sample size was modest, careful parameter selection and moisture variation contributed to strong generalization. Future research could benefit from incorporating additional soil characteristics—such as mineralogy, salinity, or cation exchange capacity—and validating the models on larger, more heterogeneous datasets to further improve predictive capability for geotechnical and electrical infrastructure design.

6. Declarations

6.1. Author Contributions

Conceptualization, S.I.; methodology, K.S. and S.I.; software, K.S.; validation, K.S., A.P., and S.I.; formal analysis, K.S.; investigation, K.S. and A.P.; resources, K.S. and A.P.; data curation, K.S.; writing—original draft preparation, K.S.; writing—review and editing, S.I.; visualization, K.S.; supervision, S.I.; project administration, S.I.; funding acquisition, S.I. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Conflicts of Interest

The authors declare no conflict of interest.

7. References

- [1] Ackerman, A., Sen, P. K., & Oertli, C. (2013). Designing safe and reliable grounding in AC substations with poor soil resistivity: An interpretation of IEEE Std. 80. IEEE Transactions on Industry Applications, 49(4), 1883–1889. doi:10.1109/TIA.2013.2256092.
- [2] Amadi, H. (2017). Soil Resistivity Investigations for Substation Grounding Systems in Wetland Regions: a Case Study of Lagos State, Nigeria. Asian Journal of Natural and Applied Sciences, 6(3), 90–99.
- [3] IEEE. (2015). 80-2013 - IEEE Guide for Safety in AC Substation Grounding. doi:10.1109/ieeestd.2015.7109078.
- [4] Tao, Y., Wei, J., Li, Q., Shi, Y., Zhang, T., Zhang, J., & Liu, X. (2018). The effect of a large backfill area on grounding grid performance. Energies, 11(4), 698. doi:10.3390/en11040698.

- [5] Kizhlo, M., & Kanbergs, A. (2009). Research of the parameter changes of the grounding system. 2009 World Non-Grid-Connected Wind Power and Energy Conference, 5335821. doi:10.1109/wnwec.2009.5335821.
- [6] Malanda, S. C., Davidson, I. E., Singh, E., & Buraimoh, E. (2018). Analysis of Soil Resistivity and its Impact on Grounding Systems Design. 2018 IEEE PES/IAS PowerAfrica, 324–329. doi:10.1109/powerafrica.2018.8520960.
- [7] Adegboyega, G. A., & Odeyemi, K. O. (2011). Assessment of soil resistivity on grounding of electrical systems: A case study of North-East Zone, Nigeria. *Journal of Academic and Applied Studies*, 1(3), 28-38.
- [8] Bienibuor, A. K., Preko, K., Aning, A. A., Menyeh, A., Wemegah, D. D., Appiah, M. K., & Gyilbag, A. (2025). Application of the electrical resistivity tomography (ERT) method in identifying high groundwater potential sites in the Atebubu municipality of Ghana. *Discover Geoscience*, 3(1), 14. doi:10.1007/s44288-025-00120-x.
- [9] Musty, S. B., & Bery, A. A. (2024). Application of Electrical Resistivity Tomography and Induced Polarization for Pre-Construction Site Assessment in Ipoh, Perak, Malaysia. *BIO Web of Conferences*, 131, 04014. doi:10.1051/bioconf/202413104014.
- [10] Putra, M. S. G. P., Salleh, S. N., & Anggraini, N. (2024). Correlation of CPT, SPT, and ERT data for a better understanding of soils condition: A case study in SPG Merbau, South Sumatra. *IOP Conference Series: Earth and Environmental Science*, 1416(1), 12008. doi:10.1088/1755-1315/1416/1/012008.
- [11] Thapa, S., Asha Rani, N. R., & Sharma, R. P. (2025). Prediction of compressive strength, static modulus and wenner resistivity for normal concrete using different percentages of recycled concrete as a coarse aggregate. *Asian Journal of Civil Engineering*, 26(5), 2135–2152. doi:10.1007/s42107-025-01303-0.
- [12] Pozdnyakov, A. I., Pozdnyakova, L. A., & Karpachevskii, L. O. (2006). Relationship between water tension and electrical resistivity in soils. *Eurasian Soil Science*, 39(S1), S78–S83. doi:10.1134/s1064229306130138.
- [13] Prasad, D., & Sharma, H. C. (2012). Soil resistivity and earthing system. *International Journal of Management, IT and Engineering*, 2(9), 369-380.
- [14] Bhatt, S., & Jain, P. K. (2014). Correlation between electrical resistivity and water content of sand—a statistical approach. *American International Journal of Research in Science, Technology, Engineering and Mathematics*, 6(2), 115-121.
- [15] Siddiqui, F. I., & Osman, S. B. A. B. S. (2012). Electrical Resistivity Based Non-Destructive Testing Method for Determination of Soil's Strength Properties. *Advanced Materials Research*, 488-489, 1553-1557. doi:10.4028/www.scientific.net/amr.488-489.1553.
- [16] Siddiqui, F. I., & Osman, S. B. A. B. S. (2012). Simple and multiple regression models for relationship between electrical resistivity and various soil properties for soil characterization. *Environmental Earth Sciences*, 70(1), 259–267. doi:10.1007/s12665-012-2122-0.
- [17] Akana, T. S., & Oborie. (2020). Relationship between Soil Plasticity Index and Resistivity of Geomaterials. *IOSR Journal of Applied Geology and Geophysics (IOSR-JAGG)*, 8(6), 1–9.
- [18] Kibria, G., & Hossain, M. S. (2012). Investigation of Geotechnical Parameters Affecting Electrical Resistivity of Compacted Clays. *Journal of Geotechnical and Geoenvironmental Engineering*, 138(12), 1520-1529. doi:10.1061/(asce)gt.1943-5606.0000722.
- [19] Abu-Hassanein, Z. S., Benson, C. H., & Blotz, L. R. (1996). Electrical Resistivity of Compacted Clays. *Journal of Geotechnical Engineering*, 122(5), 397–406. doi:10.1061/(asce)0733-9410(1996)122:5(397).
- [20] Osman, S. B. S., Siddiqui, F. I., & Behan, M. Y. (2013). Relationship of plasticity index of soil with laboratory and field electrical resistivity values. *Applied Mechanics and Materials*, 353–354, 719–724. doi:10.4028/www.scientific.net/AMM.353-356.719.
- [21] Zhang, T., Liu, S., & Cai, G. (2018). Correlations between electrical resistivity and basic engineering property parameters for marine clays in Jiangsu, China. *Journal of Applied Geophysics*, 159, 640–648. doi:10.1016/j.jappgeo.2018.10.012.
- [22] Islam, T., Chik, Z., Mustafa, M. M., & Sanusi, H. (2012). Modeling of electrical resistivity and maximum dry density in soil compaction measurement. *Environmental Earth Sciences*, 67(5), 1299–1305. doi:10.1007/s12665-012-1573-7.
- [23] Islam, S. M. T., Chik, Z., Mustafa, M. M., & Sanusi, H. (2013). Model with artificial neural network to predict the relationship between the soil resistivity and dry density of compacted soil. *Journal of Intelligent and Fuzzy Systems*, 25(2), 351–357. doi:10.3233/IFS-2012-0641.
- [24] Memon, M. B., Yang, Z., Qazi, W. H., Pathan, S. M., & Chalgri, S. R. (2024). Assessing Soil Bulk Density, Plasticity Index, Porosity, and Degree of Saturation through Electrical Resistivity using Correlation Analysis. *Malaysian Journal of Soil Science*, 28.
- [25] Shahin, M. A., Jaksa, M. B., & Maier, H. R. (2001). Artificial neural network applications in geotechnical engineering. *Australian Geomechanics*, 36(1), 49-62.
- [26] Shahin, M. A., Jaksa, M. B., & Maier, H. R. (2008). State of the art of artificial neural networks in geotechnical engineering. *Electronic Journal of Geotechnical Engineering*, 8(1), 1-26.

- [27] Haykin, S. (2008). *Neural Networks and Learning Machines* Third Edition, Pearson Education, London, United Kingdom.
- [28] Smith, G. N. (1986). *Probability and statistics in civil engineering*. Collins professional and technical books, London, United Kingdom.
- [29] Hecht-Nielsen, R. (1990) *Neurocomputing*. Addison-Wesley, Boston, United States.
- [30] Hyndman, R.J. and Athanasopoulos, G. (2018) *Forecasting: Principles and Practice*. OTexts, Washington, United States.
- [31] Sangprasat, K., Puttiwongrak, A., & Inazumi, S. (2024). Comprehensive analysis of correlations between soil electrical resistivity and index geotechnical properties. *Results in Engineering*, 23, 102696. doi:10.1016/j.rineng.2024.102696.
- [32] ASTM D4318-17e1. (2018). *Standard Test Methods for Liquid Limit, Plastic Limit, and Plasticity Index of Soils*. ASTM International, Pennsylvania, United States. doi:10.1520/D4318-17E01.
- [33] ASTM C92-95(2015). (2022). *Standard Test Methods for Sieve Analysis and Water Content of Refractory Materials*. ASTM International, Pennsylvania, United States. doi:10.1520/C0092-95R15.
- [34] ASTM D7928-17. (2021). *Standard Test Method for Particle-Size Distribution (Gradation) of Fine-Grained Soils Using the Sedimentation (Hydrometer) Analysis*. ASTM International, Pennsylvania, United States. doi:10.1520/D7928-17.
- [35] ASTM D698-12(2021). (2021). *Standard Test Methods for Laboratory Compaction Characteristics of Soil Using Standard Effort (12,400 ft-lbf/ft³ (600 kN-m/m³))*. ASTM International, Pennsylvania, United States. doi:10.1520/D0698-12R21.
- [36] ASTM D854-14. (2023). *Standard Test Methods for Specific Gravity of Soil Solids by Water Pycnometer (Withdrawn 2023)*. ASTM International, Pennsylvania, United States. doi:10.1520/D0854-14.
- [37] ASTM D2216-19. (2019). *Standard Test Methods for Laboratory Determination of Water (Moisture) Content of Soil and Rock by Mass*. ASTM International, Pennsylvania, United States. doi:10.1520/D2216-19.
- [38] Giao, P. H., Chung, S. G., Kim, D. Y., & Tanaka, H. (2003). Electric imaging and laboratory resistivity testing for geotechnical investigation of Pusan clay deposits. *Journal of Applied Geophysics*, 52(4), 157–175. doi:10.1016/S0926-9851(03)00002-8.
- [39] Wenner, F. (1915). A method for measuring earth resistivity. *Journal of the Franklin Institute*, 180(3), 373–375. doi:10.1016/s0016-0032(15)90298-3.
- [40] Zhou, M., Wang, J., Cai, L., & Fan, Y. (2015). Laboratory investigations on factors affecting soil electrical resistivity and the measurement. *IEEE Transactions on Industry Applications*, 2015(6), 5358–5365. doi:10.1109/TIA.2015.2465931.
- [41] Hidayawanti, R., Latief, Y., & Gaspersz, V. (2024). Risk-Based Method-Technology Integration on Spun Pile Production for Product and Service Quality. *Civil Engineering Journal*, 10(11), 3683–3698. doi:10.28991/CEJ-2024-010-11-015.
- [42] Salam, M. A., Rahman, Q. M., Ang, S. P., & Wen, F. (2017). Soil resistivity and ground resistance for dry and wet soil. *Journal of Modern Power Systems and Clean Energy*, 5(2), 290–297. doi:10.1007/s40565-015-0153-8.
- [43] Hazreek, Z. A. M., Aziman, M., Azhar, A. T. S., Chitral, W. D., Fauziah, A., & Rosli, S. (2015). The behaviour of laboratory soil electrical resistivity value under basic soil properties influences. *IOP Conference Series: Earth and Environmental Science*, 23, 12002. doi:10.1088/1755-1315/23/1/012002.
- [44] Mostafa, M., Anwar, M. B., & Radwan, A. (2018). Application of electrical resistivity measurement as quality control test for calcareous soil. *HBRC Journal*, 14(3), 379–384. doi:10.1016/j.hbrj.2017.07.001.
- [45] Mursky, G. A., & Thompson, R. M. (1958). A specific gravity index for minerals. *The Canadian Mineralogist*, 6(2), 273-287.
- [46] Sarip, M. K., & Madun, A. (2021). The Influence of Clay Minerals Towards Resistivity and Chargeability Value for Groundwater Interpretation. *Recent Trends in Civil Engineering and Built Environment*, 2(1), 629-637.
- [47] Ozcep, F., Yildirim, E., Tezel, O., Asci, M., & Karabulut, S. (2010). Correlation between electrical resistivity and soil-water content based artificial intelligent techniques. *International Journal of Physical Sciences*, 5(1), 47–56.
- [48] Kundu, S. K., Dey, A. K., Sapkota, S. C., Debnath, P., Saha, P., Ray, A., & Khandelwal, M. (2024). Advanced predictive modelling of electrical resistivity for geotechnical and geo-environmental applications using machine learning techniques. *Journal of Applied Geophysics*, 231, 105557. doi:10.1016/j.jappgeo.2024.105557.
- [49] Pasini, A. (2015). Artificial neural networks for small dataset analysis. *Journal of Thoracic Disease*, 7(5), 953–960. doi:10.3978/j.issn.2072-1439.2015.04.61.
- [50] Bagińska, M., & Srokosz, P. E. (2019). The Optimal ANN Model for Predicting Bearing Capacity of Shallow Foundations trained on Scarce Data. *KSCE Journal of Civil Engineering*, 23(1), 130–137. doi:10.1007/s12205-018-2636-4.
- [51] Izonin, I., Tkachenko, R., Berezhsky, O., Krak, I., Kováč, M., & Fedorchuk, M. (2024). Improvement of the ANN-Based Prediction Technology for Extremely Small Biomedical Data Analysis. *Technologies*, 12(7), 112. doi:10.3390/technologies12070112.