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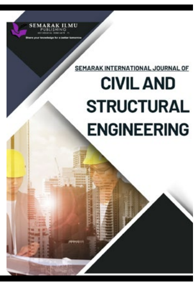

Model Prediction of Soil Parameters via Experimental Analysis for the Geotechnical Design

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ABSTRACT

The geotechnical properties of soils play a crucial role in civil engineering projects. This study uses experimental design techniques to develop predictive models for soil properties such as cohesion, friction angle, and bulk density. The problem addressed is the need for reliable, data-driven models to predict these properties based on easily measurable soil characteristics, thus facilitating better infrastructure planning and construction. This research aims to apply the Taguchi method, a robust design of experiments (DOE) approach, to identify the significant factors affecting soil properties and develop accurate predictive models. Soil samples from various locations in Malaysia were analysed for different percentages of clay, silt, sand, resistivity, and moisture content. These variables were chosen as factors in Taguchi's design, with four factors at two levels. The predictive formulas derived offer a practical means to estimate soil properties based on measurable parameters. Formulas were developed for the cohesion, angle of friction and bulk density, demonstrating the systematic influence of the factors studied. Results show that the sand's percentage and 1D resistivity had the most significant effects, with moisture content contributing to variations in the cohesion.

1. Introduction

The geotechnical properties of soils play a crucial role in civil engineering projects, especially in regions with diverse soil types like Malaysia. This study focuses on developing predictive models for soil properties.

In geotechnical engineering, understanding and predicting soil properties is fundamental for designing and constructing safe and efficient infrastructure [1]. Soil properties such as cohesion, friction angle, and bulk density are critical parameters that influence structures' stability and load-

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bearing capacity. However, due to soil composition's inherent variability and complexity, accurately predicting these properties based on readily available data remains challenging [2].

The motivation for constructing predictive models for soil properties arises from the need for efficient, data-driven tools that can enhance decision-making processes in civil engineering projects. Accurate predictive models can reduce the need for extensive and costly field testing, streamline project planning, and improve the reliability of engineering designs [3]. The data collection involved analysing soil samples from multiple locations across Malaysia. Each sample tested was for clay, silt, sand percentages, resistivity, and moisture content. These variables were selected as they commonly measured and significantly influenced the soil properties.

The Taguchi method was employed to develop the predictive models, which are robust designs of experiments under the Design of Experiment (DOE) approach. The Taguchi method is known for its effectiveness in optimising processes and identifying the most influential factors with a minimal number of experiments [4]. Using the Taguchi design with four factors at two levels, the impact of each variable on the soil properties of interest was systematically evaluated.

This study aims to demonstrate the application of the Taguchi method in geotechnical engineering and to develop accurate predictive models for soil properties, thereby contributing to more efficient and reliable infrastructure development.

2. Methodology

2.1 Concept

DOE is a systematic and efficient method for planning, conducting, analysing, and interpreting controlled tests to evaluate factors influencing a particular outcome or process [5]. The primary goal of DOE is to identify and understand the relationships between inputs (factors) and outputs (responses), optimising the process performance and ensuring robustness against variability. In this study, the DOE approach is utilised to develop predictive models for soil properties, specifically for cohesion, friction angle, and bulk density. Given the complexity and variability of soil characteristics, DOE offers a structured method to identify the significant factors that influence these properties and develop accurate predictive models [6].

The Taguchi method is a robust design of experiment approaches renowned for its efficiency and simplicity in optimising processes and identifying critical factors. It systematically uses orthogonal arrays to study many variables with a minimal number of experiments [7]. This method is particularly suitable for our study due to the following reasons:

a) The four key factors, clay and silt percentage, sand percentage, resistivity, and moisture contents, were selected as hypotheses that influence the soil properties.
b) Each factor was tested at two levels (high and low), which simplifies the experimental design while still providing valuable insights.
c) A specific Taguchi orthogonal array (L8) was chosen to structure the experiments, ensuring a balanced and unbiased evaluation of each factor's effect on the responses.

In this study, the main effects of each factor on the soil properties were focused without studying the interactions between the factors. This approach is justified given the scope and objectives of the research, where the primary aimed to identify the most influential factors rather than explore their interactions.

Soil samples were collected and analysed to determine the percentages of clay, silt, and sand, along with resistivity and moisture content measurements. These measurements served as the input factors for the DOE. Using the Taguchi L8 orthogonal array, a series of experiments were performed to systematically vary the levels of the input factors and measure the corresponding outputs, which were the cohesion, friction angle, and bulk density. The results from the experiments were analysed to determine the main effects of each factor on the soil properties. By applying the Taguchi method in this structured manner, developing reliable predictive models for key geotechnical properties provides valuable tools for civil engineering applications and infrastructure [8].

2.2 Method

The first step in creating an experiment design is choosing the experimental table. The Taguchi L8 orthogonal array was selected based on the following criteria:

a) Experimental Efficiency: The L8 array allows for the study of up to seven factors at two levels, requiring only eight experimental runs. This makes it a highly efficient choice for the study, focusing on four key factors.
b) Simplicity: The L8 array provides a straightforward framework to evaluate the main effects of each factor on the response variable (soil cohesion) without delving into complex interactions.
c) Balanced Design: The L8 array ensures a balanced distribution of factor levels across the experimental runs, minimising bias and enhancing the robustness of the results.

The L8 orthogonal array can be found in standard DOE references and statistical software tools, providing pre-constructed arrays for various experimental scenarios. Given the study's design requirements, the L8 array was selected to systematically vary the levels of the four selected factors: clay and silt percentage, sand percentage, resistivity, and moisture content. The structure of the Taguchi L8 orthogonal array used in this study is as in Table 1:

Table 1
Taguchi L8 orthogonal array

Clay + Silt	Sand	1D Resistivity	Moisture Content
-1	-1	-1	-1
-1	-1	1	1
-1	1	-1	1
-1	1	1	-1
1	-1	-1	1
1	-1	1	-1
1	1	-1	-1
1	1	1	1

In the context of DOE, each factor can be set at different levels to study its effect on the response variable. Typically, in a two-level DOE, these levels are denoted as "high" and "low" and represented by the notations +1 and -1, respectively.

i. Low Level (-1): It represents a lower value or set of a factor. For example, considering the clay percentage as a factor, the low level might correspond to a lower percentage of clay in the soil sample.
ii. High Level (+1): It represents a factor's higher value or setting. Continue with the clay percentage example; the high level would correspond to a higher percentage of clay in the soil sample.

In addition to high and low levels, defining each factor's central value and step size is often helpful. *Central value* is the midpoint between a factor's high and low levels. It represents the average setting and helps understand the baseline effect of the factor [9]. *Step size* is the difference between the central value and either the high or low level [10]. It indicates the magnitude of change for each step from the central value to the high or low level. The formulas to calculate these values as in Eq. (1):

$$Central\ Value\ (CV) = \frac{High\ level\ (1) + Low\ level(-1)}{2}$$
$$Step\ Size\ (CV) = \frac{High\ level\ (1) - Low\ level(-1)}{2} \tag{1}$$

Based on 28 data samples collected, the key factors affecting soil cohesion, such as clay + silt percentage, sand percentage, inverted resistivity, and moisture content, were analysed. From these data, information on the minimum value (-1), maximum value (1), step size (STEP), and central value (CENTRAL) for each factor was extracted. These values are essential for implementing the Taguchi L8 orthogonal array in the experimental design, as in Table 2.

Table 2
Key factors data collected

Factors	-1	1	STEP	CENTRAL
Clay +silt	0	92	46	46
Sand	8	100	46	54
Inverted resistivity	1572	7155	34989	36561
Moisture content	826	158	7487	8313

2.3 Calculation of Factor Effects

To determine the effect of each factor on soil cohesion, the method of averaging the products of the factor levels (coded as -1 and 1) with the corresponding cohesion values was used. This approach allowed us to systematically quantify each factor's impact on the response variable (cohesion, for example). For each run, the levels of the factors (coded as -1 or 1) and the corresponding measured cohesion values were calculated. The average of these products was computed to determine the effect of the factor. The eight experimental runs were extracted from the L8 orthogonal array in Table 3.

Table 3
L8 orthogonal array for 8 samples

Clay + Silt (A)	Sand (B)	Inverted Resistivity (C)	Moisture Content (D)	Cohesion (C)
-1	-1	-1	-1	C1
-1	-1	1	1	C2
-1	1	-1	1	C3
-1	1	1	-1	C4
1	-1	-1	1	C5
1	-1	1	-1	C6
1	1	-1	-1	C7
1	1	1	1	C8

The calculation steps are as follows; Multiply the factor level by the cohesion value for each run. For each experimental run, multiply the level of the factor (either -1 or +1) by the corresponding cohesion value (C). This product captures the contribution of the factor at each specific level. Mathematically, for n experimental runs, where Ai represents the level of the factor (clay + silt), and Ci represents the corresponding cohesion value, the product was calculated as in Eq. (2):

$$P_i = A_i . C_i \tag{2}$$

Here, Pi is the product for the i-th run.

Averaging; After calculating the products for all runs, the average of these products was computed to determine the factor's effect on cohesion. The average provides a measure of the factor's overall influence across all experimental conditions.

The effect (E) of factor A is calculated as in Eq.(3):

$$E_A = \frac{1}{n}\sum_{i=1}^{n} P_i = \frac{1}{n}\sum_{i=1}^{n} A_i . C_i \tag{3}$$

2.3.1 Example calculation

Consider the following data in Table 4 with actual cohesion values (C) and factor levels (A) for eight experimental runs:

Table 4
Cohesion value and factor levels for the samples

Factor A Level	Cohesion (C)	Product P_i
-1	39.17	-39.17
-1	1.94	-1.94
-1	45.54	-45.54
-1	24.29	-24.29
1	39.17	39.17
1	10.13	10.13
1	29.96	29.96
1	36.23	36.23

2.3.2 Calculating the sum of the products

The sum for the samples was calculated as in Eq. (4).

$$\sum_{i=1}^{8} P_i = -39.17 - 1.94 - 45.54 - 24.29 + 39.17 + 10.13 + 29.96 + 36.23 = 4.55 \tag{4}$$

Then, the average effect (E) of factor AAA (clay + silt) on cohesion as in Eq. (5):

$$E_A = \frac{1}{8}\sum_{i=1}^{8} A_i . C_i = \frac{4.55}{8} = 0.57 \tag{5}$$

This means that the average effect of increasing the level of clay + silt from -1 to +1 is to increase the cohesion by 0.57 kPa. By following this procedure, the effects of all factors involved in the experiment (clay + silt, sand, inverted resistivity, and moisture content) on soil cohesion and the angle of friction and bulk density were calculated. These effects help to understand and relate the importance and impact of each factor.

2.4 Predictive Formula

After calculating the effects of each factor on cohesion, we can use these effects to develop a predictive formula. This formula will allow us to estimate the cohesion of soil samples based on the levels of the factors (clay + silt, sand, inverted resistivity, and moisture content). The process involves using the main effects to construct a linear model.

Calculate the overall mean cohesion: The overall mean cohesion $\bar{C}$ is the average of all cohesion values from the experimental runs as in Eq. (6).

$$\bar{C} = \frac{1}{n}\sum_{i=1}^{n} C_i \tag{6}$$

Include the main effects: Incorporate the main effects of each factor into the predictive model. If E_A, E_B, E_C, and E_D are the effects of clay + silt, sand, inverted resistivity, and moisture content, respectively, the predictive model can be written as in Eq. (7):

$$\mathrm{C} = \bar{\mathrm{C}} + \mathrm{E_A}.\mathrm{A} + \mathrm{E_B}.\mathrm{B} + E_C.C + E_D.D \tag{7}$$

Here, A, B, C, and D represent the levels of clay + silt, sand, inverted resistivity, and moisture content, respectively.

2.5 Using the Predictive Formula with Coded Values

To utilise the predictive formula developed from the Taguchi method, it is essential to transform the actual values of the factors into coded values ranging between -1 and 1 [11]. This standardisation allows the application of the formula across different scales and units of measurement. The transformation of actual values into coded values can be achieved using the following formula as in Eq. (8):

$$Coded\ Value = \frac{Real\ value - Central\ Value}{Step} \tag{8}$$

3. Results

3.1 Cohesion

The effects of each factor on soil cohesion were calculated using the Taguchi method, as shown in Table 5 where the average cohesion = 28.30375.

Table 5
Effects of the Taguchi method on the soil cohesion factors

Clay + Silt (%)	Sand (%)	1D Resistivity	Moisture Content (%)
0.56875	5.70125	-10.5625	2.41625

Using the calculated effects, the predictive formula for cohesion (c) can be expressed as:

$$C = 28.30375 + 0.56785 * (Clay + Silt) + 5.70125 * (Sand) - 10.15625 * (1D\ resistivity) + 2.41625 * Moisture\ content)$$

3.2 Graphs of Effects

Figures 1-4 show the effect of soil properties on the cohesion factor. The reason behind this phenomenon is due to soil becomes sandy at the trend resulting in a lesser cohesion [12]. Another factor for cohesion value to be low or high is the pH of the soil. When pH of the soil decreases, as a consequence, the diffuse double layer will be thicker and hence carrying the individual particles to be more dispersed where in dispersion will reduce cohesion [13]. The relationship between cohesion and 1D resistivity value of soil is shown in Figure 3. The relationships between these variables have shown a significant trend based on the previous studies where a polynomial curves have been plotted [14,15]. The soil has more clay particles that eventually will have higher moisture content resulting in lower cohesion value.

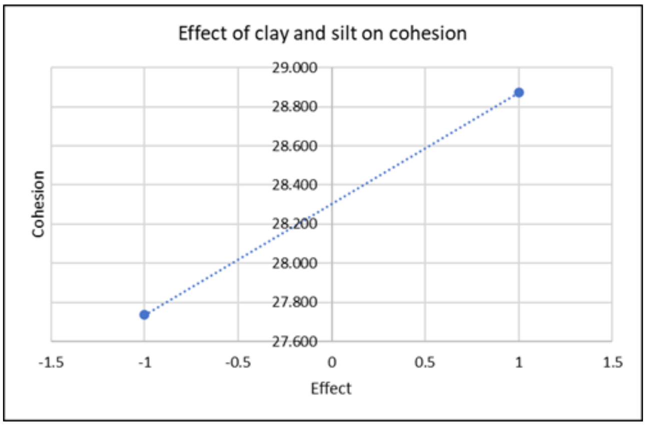

Fig. 1. Effect on clay and silt

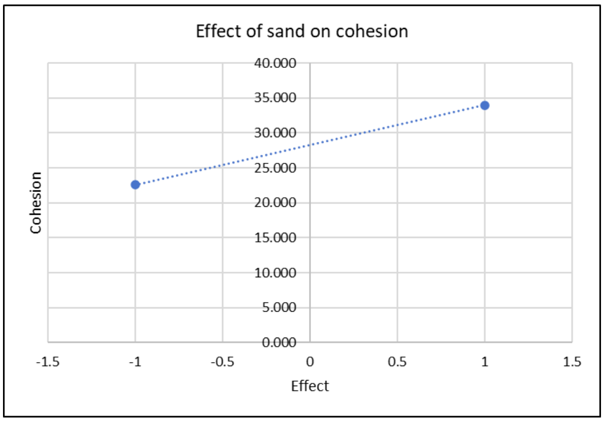

Fig. 2. Effect on sand

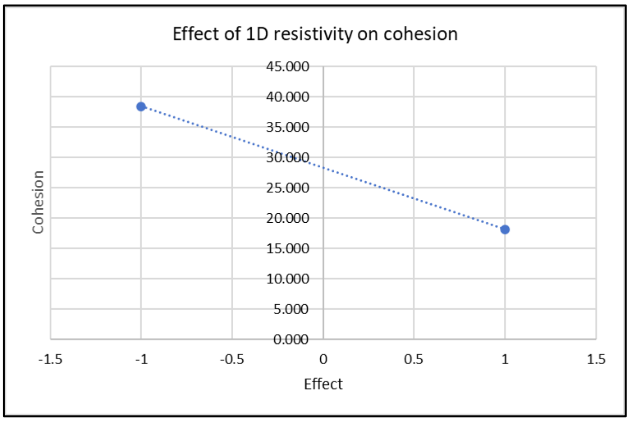

Fig. 3. Effect on 1D resistivity

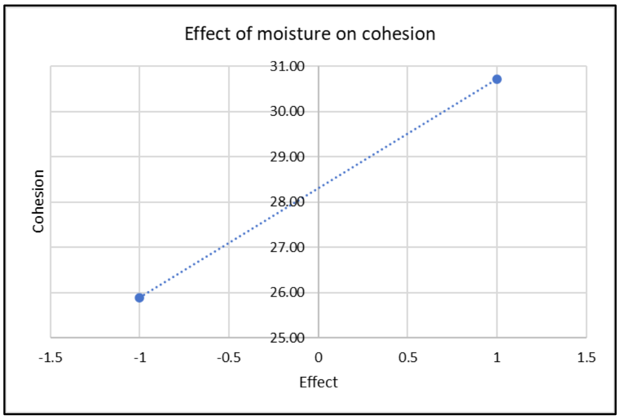

Fig. 4. Effect on moisture content

3.2 Angle of Friction

The effects using the Taguchi method were calculated to evaluate the angle of friction in the soil cohesion, as shown in Table 6 and the average angle of friction = 21.62125.

Table 6
The angle of friction in the soil cohesion

Clay + Silt (%)	Sand (%)	1D Resistivity	Moisture Content (%)
-2.29875	-2.48875	-1.98625	-0.18625

Using the calculated effects, the predictive formula for friction angle (A) can be expressed as:

$$Angle\ of\ friction, = 21.62125 - 2.29875 * (Clay + Silt) - 2.48875 * (Sand) - 1.98625 * (1D\ resistivity) - 0.18625 * (Moisture\ )$$

3.2.1 Graphical representation of effects

To visualise the impact of each factor on the friction angle, the following graphs illustrate the main effects of each factor in Figure 5-8. The possible factor that contributes to the increase of friction angle is due to the decreased of moisture content. In conclusion A similar relationship between friction angle and resistivity was found by researchers in their published report and concluded that soil with higher greater coarse fraction generally have higher friction angle and electrical resistivity [15,16]. Also, it is expected that increase size of particles contribute to a rougher texture which increase the angle of friction [17]. In addition, small plasticity index values have the tendency to make the angle of friction value becomes higher than angle of friction with large plasticity index [18]. In clayey soil which contain clay and silt, the presence of high percentage of moisture content can reduce the angle of friction by losing its soil particles chain and also able to reduce the resistivity of soil [19].

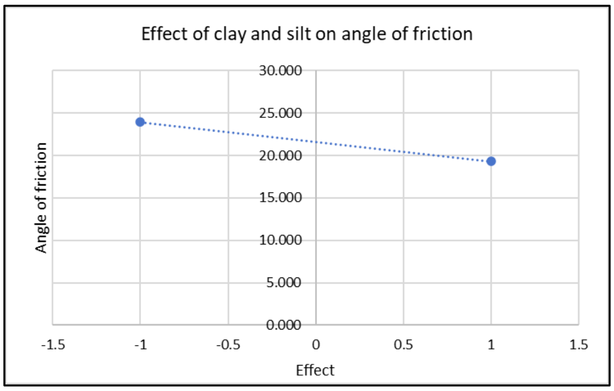

Fig. 5. Effect on clay and silt

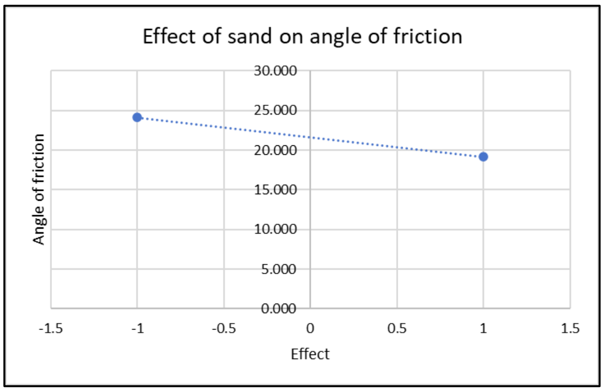

Fig. 6. Effect on sand

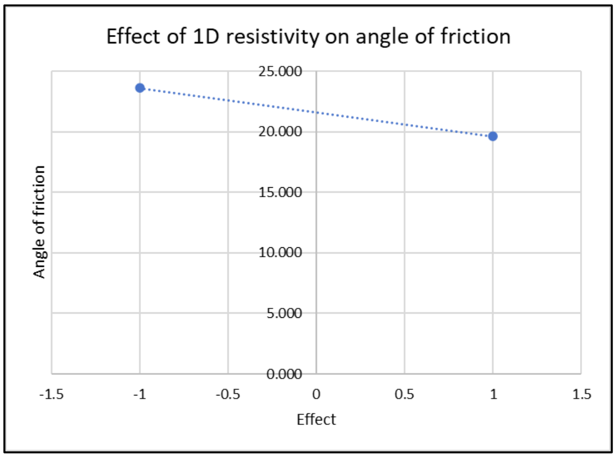

Fig. 7. Effect on 1D resistivity

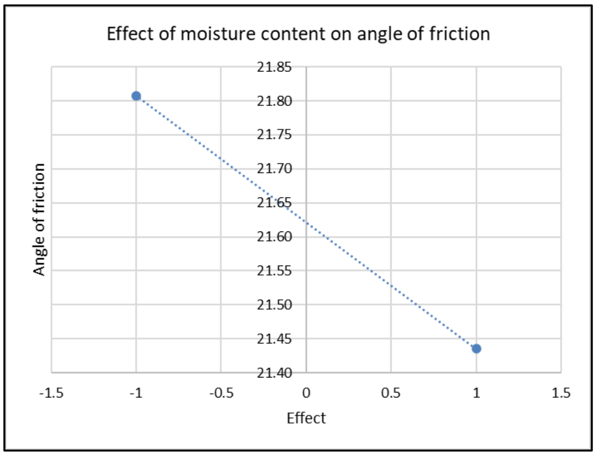

Fig. 8. Effect on moisture content

These graphs highlight the relative importance of each factor in determining the soil's friction angle, with clay + silt and sand having more pronounced effects compared to 1D resistivity and moisture content.

3.3 Bulk Density

The effects using the Taguchi method were calculated to evaluate bulk density as shown in Table 7 and the average bulk density = 15.6575.

Table 7
Bulk density effect on the soil

	Clay + Silt (%)	Sand (%)	1D Resistivity	Moisture Content (%)
Effects	-2.015	-0.1625	0.6825	1.435

Using the calculated effects, the predictive formula for friction angle can be expressed as:

$$Bulk\ density = 15.6575 - 2.015 * (Clay + Silt) - 0.1625 * (Sand) + 0.6825 * (1D\ resistivity) + 1.435 * (Moisture\ )$$

3.3.1 Graphical representation of effects

Figures 9-12 represent the effect of the properties on the bulk density. Based on these figures, it can be summarized that as soils become denser the resistivity value increases whereas the moisture content will become less [20]. The only plausible explanation why bulk density is increasing as 1D resistivity increases (in both sandy and clayey soil) because the volume of voids in the soil decreases and hence results in the reduction of moisture content. Soil with higher coarse grain size causes the smaller particles to fill the voids in between the bigger particles thus producing a more denser pack condition with less voids [21]. Furthermore, increase the coarse grain size resulting in decrease in surface conductance causing an increment in resistivity of the soil.

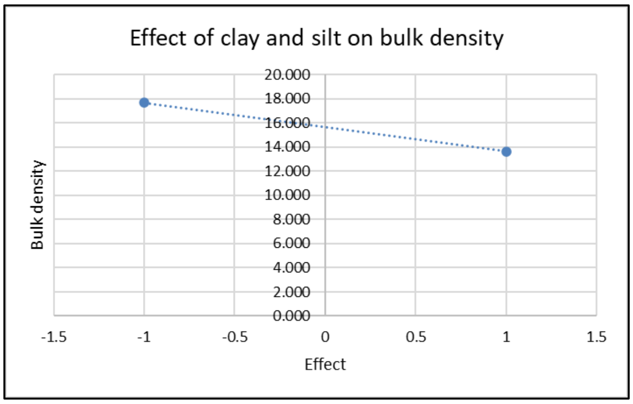

Fig. 9. Effect of clay and silt on bulk density

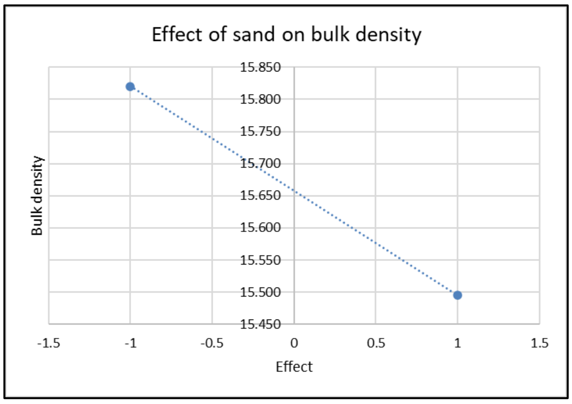

Fig. 10. Effect of sand on bulk density

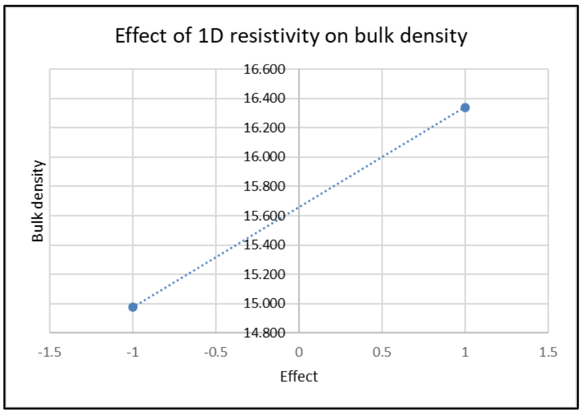

Fig. 11. Effect of 1D resistivity on bulk density

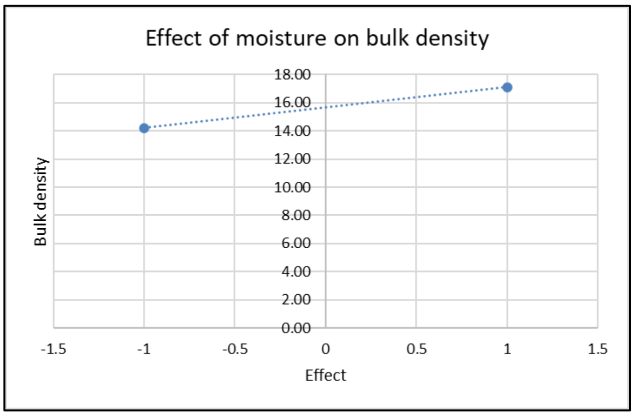

Fig. 12. Effect of moisture content on bulk density

4. Conclusions

This study successfully developed predictive models for crucial soil properties, such as cohesion, friction angle, and bulk density, by applying the Taguchi method to recall, as the objective was to systematically analyse and predict these soil properties based on multiple influencing factors, specifically clay + silt content, sand content, 1D resistivity, and moisture content. The soil samples collected were from various locations in Malaysia, and a series of laboratory tests were conducted to measure the relevant soil properties. The Taguchi L8 orthogonal array was employed as the experimental design framework, allowing the exploration of the effects of four factors at two levels for each efficiently and comprehensively. The effects of each factor on the soil properties were collected by analysing the data generated from the experiments.

The result shows that in terms of the cohesion factor, the sand percentage and 1D resistivity had the most significant effects, with moisture content also contributing to variations in the cohesion. Secondly was the angle of friction. It shows that all the factors influenced the friction angle to varying extents; however, the moisture content has a lower impact. Thirdly, the bulk density shows that clay and silt have the most critical impact on the bulk density.

The predictive formulas derived from the analysis offered a practical means to estimate these soil properties based on measurable parameters. Formulas were developed for the cohesion, friction angle, and bulk density, demonstrating the systematic influence of the factors studied. To ensure the practical application of these models, the real-world values were transformed into coded values. This transformation allows for the direct use of predictive models in various civil engineering applications.

In conclusion, the study underscores the efficacy of the Taguchi method in experimental design and analysis for predicting soil properties. The developed models provide civil engineers with valuable tools for estimating soil behaviour, thereby enhancing the efficiency and accuracy of geotechnical assessment.

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