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Predicting Soaked and Unsoaked California Bearing Ratios Using Simple and Multiple Linear Regression Models Based on Soil Index Properties

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ABSTRACT

Subgrade soil is essential for the design of road structures, whether they are flexible or rigid pavements. As the foundational layer, it supports the weight of the road and the axial loads from vehicles that are considered in the design process. Additionally, a crucial aspect of road design is the investigation of subgrade soil properties. This includes sieve size analysis (% passing through the No. 200 sieve), liquid limit (LL), plastic limit (PL), plasticity index (PI), optimum moisture content (OMC), maximum dry density (MDD), and California Bearing Ratio (CBR). As we know, conducting laboratory experiments to determine subgrade soil properties is time-consuming and costly, particularly when assessing the California Bearing Ratio (CBR) value. This study aims to develop correlation formulas between soil index properties and both soaked (CBR_S) and unsoaked (CBR_{US}), as well as the correlation between CBR_S and CBR_{US} at 95% of MDD, using simple and multiple linear regression analysis models (SLRA and MLRA). The results indicate that, after soaking for four days at 95% of maximum dry density (MDD), the subgrade soil exhibits good to excellent properties, with CBR values ranging from 7% to 20%. In contrast, the other case shows CBR values ranging from 17% to 32%. Furthermore, the results of the simple and multiple linear regression models show strong correlations between index properties and both soaked (CBR_S) and unsoaked (CBR_{US}) values at 95% of MDD. The correlation coefficients (R^2) range from 0.71 to 0.919 for SLRA and from 0.820 to 0.936 for MLRA, indicating good to excellent correlation.

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Introduction

An essential aspect of constructing roads, highways, railways, and airports is understanding the fundamental properties of the subgrade, sub-base, and base course soil layers. These properties must meet specific technical specifications, including index properties such as grain size distribution (% passing of No. 200), liquid limit (LL), plastic limit (PL), maximum dry density (MDD), optimum moisture content (OMC), and soaked California Bearing Ratio (CBR_S). To determine these index properties along construction sites, soil samples must be collected from the project area and analyzed in a laboratory. Due to varying local conditions, the index properties of soil can change. However, laboratory testing of these properties is often time-consuming, labor-intensive, and costly, with soaked CBR measurements taking up to four days per sample. In contrast, tests for index properties like grain size analysis, liquid limit, plastic limit, maximum dry density, and optimum moisture content are relatively straightforward and quicker to perform. To address these challenges, previous studies have sought to establish statistical correlations between CBR values and soil index properties (Katte et al. 2019; Bassey et al. 2017; Teklehaymanot and Alene 2021).

In earlier studies, Desai (2010), Talukdar (2014), Rakaraddi and Gomarsi (2015), Korde and Yadav (2015), Chandrakar and Yadav (2016), and Dandin (2017) explored the relationships between California Bearing Ratio (CBR) values and various soil physical properties, including grain size distribution (% gravel, % sand, % fine), liquid limit (LL), plastic limit (PL), maximum dry density (MDD), optimum moisture content (OMC), and uniformity coefficient (Cu). They utilized both simple and multiple linear regression analysis models for their investigations. Dhinakaran and Assistant (2011), Hn and Naagesh (2014), and Janjua and Chand (2016) applied artificial neural network analysis (ANN) and multiple linear regression (MLR) techniques to estimate CBR values for fine-grained soils, correlating CBR with fundamental soil properties such as OMC, MDD, LL, PL, plasticity index, and percentage of fines. Singh et al. (2011) developed regression-based models to estimate both soaked and unsoaked CBR values for fine-grained subgrade soils (CL, CI, and CH) by examining five different moisture content levels around the optimum moisture content. Talukdar (2014) proposed correlations between index properties and soaked CBR values for MI and ML soil types, especially in flood-prone areas where rural roads may be submerged for extended periods. They employed simple and multiple linear regression models, utilizing Microsoft Excel's LINEST statistics for empirical equation development. Lanckriet et al. (2002) used SLRA, MLRA, and ANN techniques to create predictive models for CBR values across three soil types: CL, CI, and SC. Kumar et al. (2013) developed General Regression Neural Network (GRNN) and Multilayer Perceptron Network (MLPN) models to predict the soaked CBR of remolded CI, GM, and SM soils. Shirur and Hiremath (2014) established relationships between soaked CBR values and the physical properties of various soil samples (SC, CH, MI, CI, SM, and SW) using SLRA and MLRA. Korde and Yadav (2015) correlated index soil properties of SC, CI, CH, and ML with CBR values, focusing on % fines, LL, PL, and plasticity index using MLRA and SLRA techniques. Rakaraddi and Gomarsi (2015) also applied regression techniques to relate CBR to different soil properties. Rehman et al. (2015) developed a model to estimate CBR based on the index properties and compaction characteristics of coarse-grained soils (SP and SW) using SLRA and MLRA. Janjua and Chand (2016) created a predictive model for CBR values based on the index properties of the SW-SM soil type using ANN and MLR methods. Taha et al. (2015) demonstrated the application of MLR and ANN techniques to develop CBR models based on soil index properties, including MDD, grading modulus (GM), and the percentage retained on sieve No. 10. Lakshmi et al. (2016) evaluated the correlation between soaked and unsoaked CBR values in CL soil using various regression models, including linear, power, and polynomial regression. Ahmed et al. (2016) predicted soaked CBR values from index properties, dry density, and unsoaked CBR of lean clay (CL) using MLRA and power-based regression models. Bassey et al. (2017) examined the correlation between soaked CBR values and soil index properties using Microsoft Excel's statistical software, applying both simple non-linear and multiple linear regression analyses across different soil types (A-2-4, A-2-6, A-2-7, A-7-5, and A-7-6). Rehman et al. (2017) established a correlation model for predicting soaked CBR values based on various soil index properties, including CL, ML, CL-ML, SP, SC, SM, and SP-SM. Arshad et al. (2018) conducted a comparative evaluation of soil subgrade strength through laboratory tests, in-situ CBR tests, dynamic cone penetrometer tests, and portable FWD tests using simple linear regression. Katte et al. (2019) applied SLRA and MLRA to determine the correlation between soaked CBR values at 95% compaction and soil index properties of A-2-7, A-7-5, and A-7-6, which included MDD, OMC, plasticity index, PL, LL, % clay/silt, % sand, and % gravel. Sujatha et al. (2019) proposed ANN models to predict soaked CBR values at 97% MDD and OMC based on silty soil index properties such as LL, PL, PI, and grain size distribution. Teklehaymanot and Alene (2021) developed predictive models for fine-grained soils using NCSS-12 data analysis methods, focusing on MH or A-7-5 soils and their index properties, which included grain size distribution, Atterberg limits, compaction characteristics, specific gravity, water content, and liquidity index. Wimalasena and Gallage (2022) created a statistical model to predict CBR values for selected clay materials, validating it against laboratory test results for high plastic silt soil (A-7-6). They used moisture content and the Degree of Compaction (DOC) as independent variables in their prediction model. Ambrose and Rimoy (2021) investigated the prediction of four-day soaked CBR values based on soil index properties for both fine-grained and coarse-grained soils using the MLRA model. More recently, Chansavang et al. (2023) proposed a correlation equation for predicting soaked CBR based on the index properties of GC soil, while Gowda et al. (2024) introduced machine learning techniques, including multivariate linear regression, ANN, and adaptive neuro-fuzzy inference systems (ANFIS), to indirectly predict CBR values across various soil types, including CL, GM, GP, SC, SM, SP, and SW.

This paper presents the correlation between experimental and predicted values of both soaked (CBR_S) and unsoaked (CBR_{US}) California Bearing Ratios, utilizing index properties of SC, CL, and MH soils. The analysis was conducted using single linear regression analysis (SLRA) and multiple linear regression analysis (MLRA) models, with data processed through the Microsoft Excel data analysis tool pack. The correlations established in this study aim to predict soaked CBR values in real-work applications. Additionally, the soaked CBR value is crucial for estimating initial budgets for civil projects such as railways, roads, airport construction, and embankment fill. The equations derived from this research can enhance the accuracy of soaked CBR predictions, ultimately reducing both testing time and costs.

Methodology

The materials and methods outlined in this paper include soil sample collection, identification, modified Proctor compaction test, soaked CBR (CBR_S) and unsoaked CBR (CBR_{US}) tests, and the application of simple linear regression analysis (SLRA) and multiple linear regression analysis (MLRA) models.

1.1 Soil Sample Collection

Nine soil samples were collected from Road No. 7 in Phoukoot District, Xieng Khouang Province. The samples were then transported to the Department of Public Works and Transport laboratory in Vientiane Capital City for property testing, following the standards set by the American Association of State Highways and Transportation Officials (AASHTO). An item of the soil sample tests and location of soil sample collection along Road No. 7 in Phoukoot District, Xieng Khouang Province are provided in Table 1 and Fig. 1.

Table 1: List and standard soil test

No.	Items of soil test	Standard	Number
1	Grain size distribution	AASHTO T27	9
2	Atterberg limit test	AASHTO T89, T90	9
3	Modified proctor compaction test	AASHTO T180	9
4	Soaked CBR test	AASHTO T193	9
5	Unsoaked CBR test	AASHTO T193	9

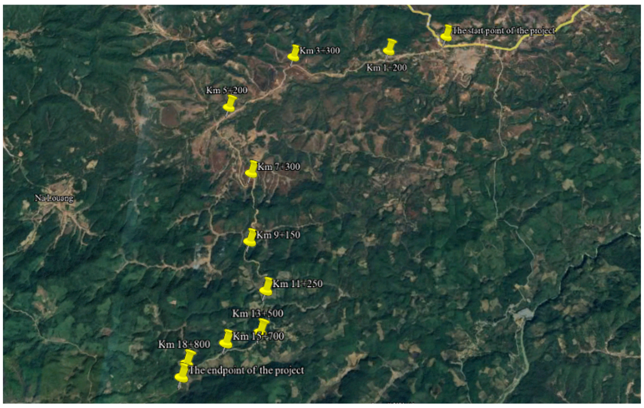


Fig. 1: Location of soil sample collection along Road No. 7 in Phoukoot District, Xieng Khouang Province

1.2 Identification of Soil Sample

The soil samples were classified according to the Unified Soil Classification System (USCS) guidelines (Stevens 1982) as Clayey Sands, Silty Clays, Silty soils, designated with the group symbol SC, CL, and MH respectively. The results are summarized in Table 2 below.

Table 2: Index properties of the collected soil sample

No.	Station	%LL	%PL	%PI	%Fine	Soil Classification
1	Km 1+200	31	17	14	27	SC
2	Km 3+300	36	20	16	36	SC
3	Km 5+200	43	24	19	55	CL
4	Km 7+300	50	29	21	49	CL
5	Km 9+150	39	22	17	37	SC
6	Km 11+250	41	24	17	39	SC
7	Km 13+500	48	29	19	57	MH
8	Km 15+700	47	29	18	56	CL
9	Km 18+800	34	19	15	30	SC

1.3 Proctor Compaction Test

In the laboratory compaction test, soil at a known water content is compacted in a mold of specific dimensions using a controlled compactive effort. The resulting unit weight of the soil is then measured. The modified Proctor compaction test was conducted in accordance with the AASHTO T180 standard to determine the optimum moisture content (OMC) and maximum dry density (MDD) values. The results for OMC and MDD are summarized in Table 3 below.

Table 3: Optimum moisture content and maximum dry density index properties

Sample No.	Maximum dry density (MDD) (g/cm^3)	Optimum moisture content (OMC) (%)
1	2.006	11.0
2	1.900	12.8
3	1.726	17.4
4	1.708	19.0
5	1.758	17.6
6	1.782	16.0
7	1.736	18.0
8	1.714	18.6
9	1.924	12.0

1.4 CBR Test

The soaked CBR (CBR_S) and unsoaked CBR (CBR_{US}) tests for this research were conducted according to the standards of the American Association of State Highway and Transportation Officials (AASHTO T193) to validate both conditions of soaked and unsoaked CBR value of SC, CL, and MH soils in the laboratory. The percentage of the CBR value for subgrade soil was assessed to ensure that the compacted soil in field construction achieved 95% of maximum dry density (MDD). The soaked CBR (CBR_S) and unsoaked CBR (CBR_{US}) values are presented in Table 4 below:

Table 4: Soaked and unsoaked CBR Results

No.	Station	Unsoaked CBR value	Soaked CBR value
1	Km 1+200	32	20
2	Km 3+300	24	13
3	Km 5+200	17	10
4	Km 7+300	17	7
5	Km 9+150	22	14
6	Km 11+250	25	15
7	Km 13+500	20	12
8	Km 15+700	17	8
9	Km 18+800	30	17

Results and discussion

This chapter presents the results of simple linear regression analysis (SLRA) and multiple linear regression analysis (MLRA). The SLRA model is utilized to establish correlations between soaked and unsoaked CBR values and the index properties of %Fine, liquid limit (LL), plastic limit (PL), plasticity index (PI), optimum moisture content (OMC), and maximum dry density (MDD). The MLRA will involve two relationship models for soaked and unsoaked CBR values in relation to the index properties of SC, CL, and MH soils. The first model incorporates %Fine, LL, and PI as index properties. The second model includes %Fine, LL, PI, OMC, and MDD. The third model focuses on PI, OMC, and MDD as its index properties.

2.1 Simple Linear Regression Model

Model 1 illustrates the correlation between the soaked CBR (CBRs) and unsoaked CBR (CBR_{US}) values with the index property of percent fine (%Fine) derived from the grain size distribution test (AASHTO T27). The resulting correlation model yields a coefficient of determination (R^2) of 0.718 and 0.826, represented by Equations (1) and (2) as follows:

$$CBR_S = -0.3073 \times (\%fine) + 26.07 \quad (1)$$

$$CBR_{US} = -0.4411 \times (\%fine) + 41.584 \quad (2)$$

Model 2 establishes the correlation between the soaked CBR (CBRs) and unsoaked CBR (CBRUS) values with the liquid limit index (LL) obtained from the Atterberg limit test (AASHTO T89). The modeling results indicate correlation coefficients of R^2 equal to 0.791 and 0.8008, which can be expressed as Equations (3) and (4) as follows:

$$CBR_S = -0.5661 \times (LL) + 36.099 \quad (3)$$

$$CBR_{US} = -0.7615 \times (LL) + 53.888 \quad (4)$$

Model 3 illustrates the relationship between the soaked CBR (CBRs) and unsoaked CBR (CBRUS) values and the plastic limit (PL) derived from the Atterberg limit test (AASHTO T90). The findings yield correlation coefficients of R^2 equal to 0.728 and 0.731, which can be represented as Equations (5) and (6) as follows:

$$CBR_S = -0.7817 \times (PL) + 31.39 \quad (5)$$

$$CBR_{US} = -1.0476 \times (PL) + 47.46 \quad (6)$$

Model 4 formulates the correlation equation between the soaked CBR (CBRs) and unsoaked CBR (CBRUS) values and the plasticity index (PI), which is calculated from the results of the liquid limit (LL) minus plastic limit (PL). The model development yields correlation coefficients of R^2 equal to 0.805 and 0.827, which can be expressed as Equations (7) and (8) as follows:

$$CBR_S = -0.7818 \times (PI) + 31.39 \quad (7)$$

$$CBR_{US} = -1.0476 \times (PI) + 47.46 \quad (8)$$

Model 5 establishes the correlation equation between soaked CBR (CBRs) and unsoaked CBR (CBRUS) values and the index property of optimum moisture content (OMC), derived from the modified Proctor compaction test in accordance with AASHTO T180. The results of the model development yield correlation coefficients of R^2 equal to 0.710 and 0.841, which can be expressed as Equations (9) and (10) as follows:

$$CBR_S = -1.1534 \times (OMC) + 31.138 \quad (9)$$

$$CBR_{US} = -1.679 \times (OMC) + 49.235 \quad (10)$$

Model 6 formulates a correlation equation between soaked CBR (CBRs) and unsoaked CBR (CBRUS) values and the maximum dry density (MDD) index property obtained from the modified Proctor compaction test (AASHTO T180). The results of this model yield correlation coefficients of R^2 equal to 0.7338 and 0.8647, and the equations can be presented as follows:

$$CBR_S = 32.987 \times (MDD) - 46.685 \quad (11)$$

$$CBR_{US} = 47.891 \times (MDD) - 63.824 \quad (12)$$

Model 7 establishes a correlation equation between soaked CBR (CBRs) and unsoaked CBR (CBRUS) values obtained from the California Bearing Ratio test (AASHTO T193). The results of this model yield a correlation coefficient of R^2 equal to 0.919, and the equations can be presented as follows:

$$CBR_S = 0.7169 \times (CBR_{US}) - 3.3616 \quad (13)$$

2.2 Multiple Linear Regression Model

Model 8 formulates the correlation equation between soaked CBR (CBRs) and unsoaked CBR (CBRUS) values, incorporating soil index properties such as %Fine, liquid limit (LL), and plasticity index (PI). These properties are derived from the sieve analysis test (AASHTO T27) and the Atterberg limit tests (AASHTO T89 and T90). The development of this model yields R^2 values of 0.834 and 0.902, which can be expressed as Equations (14) and (15) as follows:

$$CBR_S = 38.804 - 0.099 \times (\%Fine) - 0.066 \times (LL) - 1.093 \times (PI) \quad (14)$$

$$CBR_{US} = 55.327 - 0.289 \times (\%Fine) - 0.244 \times (LL) - 1.746 \times (PI) \quad (15)$$

Model 9 establishes the correlation equation between soaked CBR (CBRs) and unsoaked CBR (CBRUS) values by incorporating soil index properties such as %Fine, liquid limit (LL), plasticity index (PI), maximum dry density (MDD), and optimum moisture content (OMC). These properties are derived from the sieve analysis test (AASHTO T27), the Atterberg limit tests (AASHTO T89 and T90), and the modified Proctor compaction test (AASHTO T180). The model development results in R^2 values of 0.838 and 0.936, which can be expressed as Equations (16) and (17) as follows:

$$CBR_S = 1.821 - 0.077 \times (\%Fine) + 0.1105 \times (LL) - 0.977 \times (PI) + 0.487 \times (OMC) + 15.592 \times (MDD) \quad (16)$$

$$CBR_{US} = 32.267 - 0.259 \times (\%Fine) + 0.498 \times (LL) - 1.416 \times (PI) - 0.632 \times (OMC) + 8.667 \times (MDD) \quad (17)$$

Model 10 establishes the correlation equation between soaked CBR (CBRs) and unsoaked CBR (CBRUS) values, incorporating soil index properties such as plasticity index (PI), maximum dry density (MDD), and optimum moisture content (OMC). These properties are derived from the Atterberg limit tests (AASHTO T89 and T90) and the modified Proctor compaction test (AASHTO T180). The development of this model results in R^2 values of 0.820 and 0.892, which can be represented as Equations (18) and (19) as follows:

$$CBR_s = -8.831 - 1.326 \times (PI) - 0.429 \times (OMC) + 20.987 \times (MDD) \quad (18)$$

$$CBR_{US} = -27.75 - 0.99 \times (PI) + 0.206 \times (OMC) + 35.66 \times (MDD) \quad (19)$$

In this study, simple linear regression analysis (SLRA) and multiple linear regression analysis (MLRA) models were utilized to establish a correlation between the CBR values and index properties of SC, CL, and MH soils. These models aimed to achieve strong correlation coefficients (R^2), reflecting a good or excellent fit for estimating both soaked and unsoaked CBR values, as noted by Pellinen (2001).

For the 4-day soaked CBR analysis, several observations can be made: the index properties of %Fine and optimum moisture content (OMC) show a weaker relationship with CBR_S (Models 1 and 5). In contrast, the liquid limit (LL) demonstrates a good association with CBR_S, yielding a correlation coefficient of R^2 of 0.791 (Model 2). The plastic limit (PL) also correlates well with CBR_S, with an R^2 value of 0.728 (Model 3), falling within the range of 0.70–0.89. Similarly, the plasticity index (PI) aligns with this range, producing an R^2 of 0.805 (Model 4).

The maximum dry density (MDD) exhibits a favorable relationship with CBR_S, with an R^2 value of 0.733 (Model 6), also within the 0.70–0.89 range. Model 7 shows an excellent relationship between CBR_S and CBR_{US}, achieving an R^2 value of 0.919, exceeding 0.9. Finally, Models 8, 9, and 10 all indicate good correlations with CBR_S, with R^2 values of 0.834, 0.836, and 0.820, respectively, again falling within the 0.70–0.89 range.

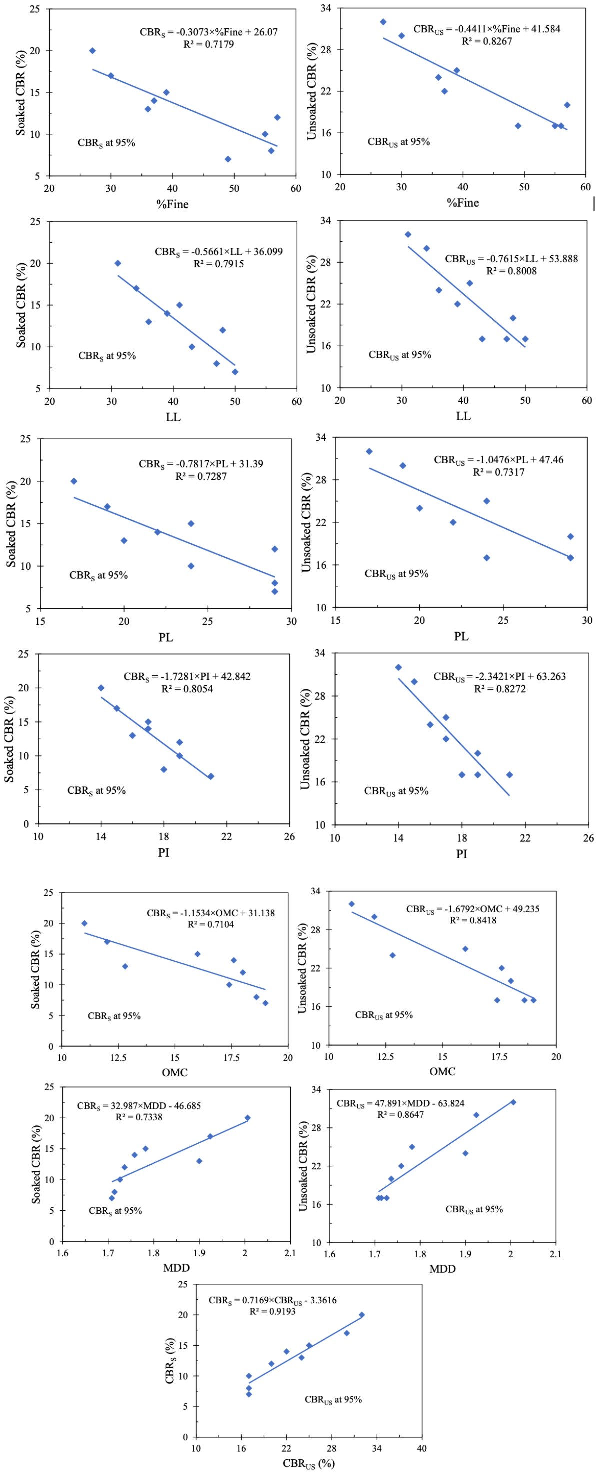
In the analysis of unsoaked CBR (CBR_{US}), several observations can be made: the plastic limit (PL) shows a weaker relationship with CBR_{US} (Model 3). Conversely, the index properties of %Fine, liquid limit (LL), plasticity index (PI), maximum dry density (MDD), and optimum moisture content (OMC) exhibit a strong association with CBR_{US}, with R^2 values of 0.826 (Model 1), 0.801 (Model 2), 0.827 (Model 4), 0.841 (Model 5), 0.864 (Model 6), and 0.892 (Model 10), all falling within the 0.70–0.89 range. Additionally, Models 8 and 9 demonstrate excellent correlations with CBR_{US}, achieving R^2 values of 0.902 and 0.936, respectively, both exceeding the 0.9 threshold.

Conclusions

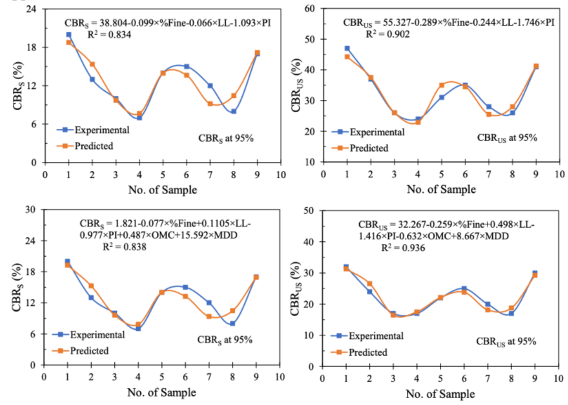
The soaked CBR (CBR_S) value is a crucial factor in the design of flexible or rigid pavements. Thus, obtaining a quick and accurate measurement of CBRs is essential. This study aims to establish a correlation between soaked CBR (CBR_S), unsoaked CBR (CBR_{US}) values, and various soil index properties (i.e., SC, CL, and MH). Based on the results and discussions presented earlier, the findings can be summarized as follows:

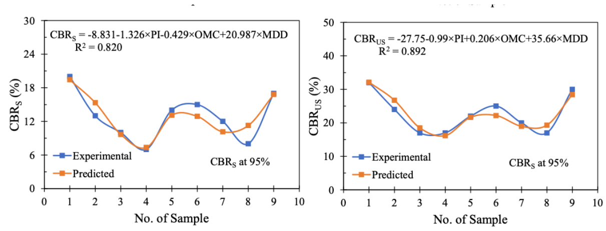
1) The soaked CBR values of subgrade soils exhibit good to excellent properties, making them suitable as the foundation for flexible or rigid road pavements in the Road No. 7 project in Phoukoot District, Xieng Khouang Province.
2) The comparison of unsoaked (CBR_{US}) and soaked (CBR_S) values from the study indicates a difference ranging from 36% to 59%.
3) The correlation formulas derived from simple and multiple linear regression analysis models demonstrate a strong relationship between both soaked CBR (CBR_S) and unsoaked CBR (CBR_{US}) values and the index properties of subgrade soils.
4) The formulas obtained from the SLRA and MLRA models can accurately predict both soaked CBR (CBR_S) and unsoaked CBR (CBR_{US}) values.

Appendix A



Appendix B





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