NAPOVED KALIFORNIJSKEGA INDEKSA NOSILNOSTI (CBR) IN LASTNOSTI ZGOSTITVE ZRNATIH ZEMLJIN

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Ključne besede

CBR, regresija, model, napoved, karakteristike zgostitve

Izvleček

V pričujoči študiji je podan poskus korelacije indeksnih lastnosti zrnatih zemljin s kalifornijskim indeksom nosilnosti (CBR) in lastnosti zgostitve. Na naravnih in kompozitnih vzorcih peskov so bile skladno z ASTM metodami izvedene klasifikacija zemljin, modificirani Proctorjev preizkus in CBR preizkus. Rezultati laboratorijskih preiskav so pokazali, da vzorci v študiji spadajo med kategorije SW, SP in SP-SM, skladno s sistemom enotne klasifikacije zemljin in v skupini A-1-b in A-3, skladno z AASHTO klasifikacijskim sistemom. Na podatkih eksperimentov je bila izvedena multipla linearna regresijska analiza in razvite korelacije za napoved CBR, maksimalne suhe gostote in optimalne vlažnosti glede na indeksne lastnosti vzorcev. Med različnimi parametri so se za napovedovanje izkazali za najboljše koeficient enakomernosti (C_u), velikost zrn pri 30 % presejku (D_{30}) in pri 50 % presejku (D_{50}). Predlagani modeli za napoved zgornjih lastnosti so bili potrjeni na bazi neodvisnih podatkov CBR preizkusov peščenih zemljin. Primerjalni rezultati kažejo, da je variacija med eksperimentalnimi in napovedanimi rezultati za CBR znotraj ±4 % intervala zaupanja, in za maksimalno suho gostoto ter optimalno vlažnost znotraj ±2 %. Na osnovi korelacij, razvitih za CBR, maksimalno suho gostoto in optimalno vlažnost, so predlagane napovedovalne krivulje za hitro oceno teh lastnosti na osnovi C_u, D_{30} in D_{50}. Predlagani modeli in napovedovalne krivulje za oceno CBR vrednosti in lastnosti zgostitve so lahko zelo uporabni v geotehničnem inženirstvu in dimenzioniranju voziščnih konstrukcij, ne da bi izvedli laboratorijske preiskave zgostitve in CBR preizkuse.

PREDICTION OF CALIFORNIA BEARING RATIO (CBR) AND COMPACTION CHARACTERISTICS OF GRANULAR SOILS

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Keywords

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Abstract

This research is an effort to correlate the index properties of granular soils with the California Bearing Ratio (CBR) and the compaction characteristics. Soil classification, modified proctor and CBR tests conforming to the relevant ASTM methods were performed on natural as well as composite sand samples. The laboratory test results indicated that samples used in this research lie in SW, SP and SP-SM categories based on Unified Soil Classification System and in groups A-1-b and A-3 based on the AASHTO classification system. Multiple linear regression analysis was performed on experimental data and correlations were developed to predict the CBR, maximum dry density (MDD) and optimum moisture content (OMC) in terms of the index properties of the samples. Among the various parameters, the coefficient of uniformity (C_u), the grain size corresponding to 30% passing (D_{30}) and the mean grain size (D_{50}) were found to be the most effective predictors. The proposed prediction models were duly validated using an independent dataset of CBR tests on sandy soils. The comparative results showed that the variation between the experimental and predicted results for CBR falls within ±4% confidence interval and that of the maximum dry density and the optimum moisture content are within ±2%. Based on the correlations developed for CBR, MDD and OMC, predictive curves are proposed for a quick estimation based on C_u, D_{30} and D_{50}. The proposed models and the predictive curves for the estimation of the CBR value and the compaction characteristics would be very useful in geotechnical & pavement engineering without performing the laboratory compaction and CBR tests.

1 INTRODUCTION

An appropriate and sound foundation is always required for the construction of all kinds of engineering projects, especially those involving large quantities of earth works, like pavements, runways, railway formations and pavement embankments, etc. Bearing capacity, swell potential and the settlement of different layers of pavements should be within tolerable limits. Therefore, it is necessary to have reliable methods to access the engineering properties of such projects. The California Bearing Ratio (*CBR*) is one of the most common methods to design and assess the strength of different pavement layers by comparing them with the strength of standard California crushed rock. The *CBR* value is used to determine the thickness of pavement layers and also to evaluate the shear strength and stiffness modulus of sub-grade material. Similarly, an evaluation of the compaction characteristics (*OMC* and *MDD*) for projects involving large quantities of earthworks is also an essential requirement, and these parameters are also used in the evaluation of the *CBR* value. Both the *CBR* value and the compaction characteristics are very much dependent on soil gradation and other index properties in the case of granular soils.

Engineers encounter many difficulties in obtaining a reliable *CBR* value because of insufficient soil investigation data and limited time during the pre-feasibility stages of the project. At least 4 days are required to generate a soaked *CBR* value for a single soil specimen and multiple *CBR* tests are required on subgrade samples along the length of the pavement to obtain a representative design *CBR* value. In order to save time during the pre-feasibility stages, researchers have therefore developed prediction models to correlate the *CBR* value with various index properties of the soils.

As mentioned earlier, the *CBR* value is mainly dependent on various index properties of the soil; therefore, many researchers have conducted research studies to understand the effect of soil type and soil characteristics on the *CBR* value of both coarse-grained and fine-grained soils. Based on their research, various researchers including Agarwal and Ghanekar [1], National Cooperative Highway Research Program(NCHRP)[2], Breytenbach [3], Roy et al. [4], Ferede [5], Patel and Desai [6], Saklecha et al. [7], Yildirim and Gunaydin [8], Singh et al. [9], Taha et al. [10] and Talukdar [11] have proposed correlations to predict the *CBR* value for various types of soils based on their index properties. These correlations are summarized in Table 1, followed by their relevant discussion.

Agarwal and Ghanekar [1] used forty-eightfine-grained soil samples to correlate the *CBR* value with the liquid limit (*LL*) and optimum moisture content (*OMC*). The National Cooperative Highway Research Program (NCHRP) [2] presented a correlation between the grain size corresponding to 60% passing (D_{60}) and the *CBR* value. The applicability of the proposed correlation is limited for D_{60} varying between 0.01 mm to 30 mm. The recommended value of *CBR* is 5 when D_{60} is less than 0.01 mm and the *CBR* value is 95 when D_{60} is greater than 30 mm. Breytenbach [3] correlated the *CBR* value with the plasticity index (*PI*) and grading modulus (GM) based on the research work conducted on a variety of soils present in various parts of South Africa. Roy et al. [4] proposed an equation to estimate the *CBR* value on the basis of the maximum dry unit weight, the unit weight of water and the optimum moisture content for fine-grained soils. Ferede [5] developed correlations to predict the *CBR* value using D_{60} , the optimum moisture content (*OMC*) and the maximum dry density (*MDD*) for granular soils and liquid limit (*LL*), plastic limit (PL), plasticity index (*PI*) and percentage of fines (F_{200}) for fine-grained soils. Pateland Desai[6] proposed correlations to estimate the soaked and unsoaked *CBR* values based on compaction parameters (*MDD* and *OMC*) and the plasticity index of fine-grained soil. Saklecha et al. [7] performed multiple

Table 1. Correlations for predicting *CBR* proposed by various researchers.

Correlations	Reference
$CBR = 2 - \log(OMC) + 0.07\ LL$	Agarwal and Ghanekar (1970)
$CBR = 28.09\ (D_{60})^{0.358}$	NCHRP (2001)
$CBR = 26.382 \times (0.458\ PI) + 5.278\ GM$	Breytenbach (2009)
$\log CBR = \log(\gamma_{dmax} / \gamma_w) - \log OMC$	Roy et al. (2009)
$CBR = 68.789 - 11.925\ D_{60} + 0.897\ D_{60}^2 - 0.025\ D_{60}^3$	Ferede (2010)
$CBR = -27.998 + 0.029\ OMC^2 + 4.796\ MDD^4$	
$CBR = 4.175 - 0.029\ LL - 0.009\ F_{200}$	
$CBR(\text{Soaked}) = 43.907 - 0.093\ I_p - 18.78\ MDD - 0.3081\ OMC$	Patel and Desai (2010)
$CBR(\text{Unsoaked}) = 17.009 - 0.0696\ I_p - 0.296\ MDD + 0.0648\ OMC$	
$CBR = 0.26O\ MC + 42.55\ MDD - 73.62$	Saklecha et al. (2011)
$CBR = 0.22\ G + 0.045\ S + 4.739\ MDD + 0.122\ OMC$	Yildirim and Gunaydin (2011)
$CBR(\text{Soaked}) = -2.213 - 0.055[(MC/OMC)\times 100] + 0.328[(\text{Density}/MDD)\times 100] - 1.147\ PL$	Singh et al. (2011)
$CBR = 0.025\ F_{200}^4 + 30.130(MDD) - 25.813$	Taha et al. (2013)
$CBR(\text{Soaked}) = 0.127\ LL - 0.16\ PI + 1.405\ MDD - 0.259\ OMC + 4.62$	Talukdar (2014)

CBR = California Bearing Ratio, *LL* = Liquid limit, *PL* = Plastic limit, *PI* = I_p = Plasticity index. *OMC* = Optimum moisture content, *MDD* = Maximum dry density, γ_{dmax} = Maximum dry unit weight, γ_w = Unit weight of water, D_{60} = grain size corresponding to 60% passing, *G* = Percentage of gravels, *S* = Percentage of sand, F_{200} = Percentage of fines, *GM* = Grading modulus regression analyses to correlate the *CBR* with the compaction parameters (*MDD* and *OMC*) of sub-grade soil. Yildirim and Gunaydin [8] utilized fine-grained as well as coarse-grained soils comprising a wide range of grain sizes to develop prediction models for the estimation of *CBR* values based on the compaction parameters (*MDD* and *OMC*), the percentage of gravel (G) and the sand content (S). Singh et al. [9] collected five different soils from West Bengal and tested them in the laboratory at four different compaction energy levels and five different moisture contents. A prediction model for soaked *CBR* was proposed by considering the effect of the degree of compaction and moisture content. Taha et al. [10] correlated the *CBR* value with the index properties of Egyptian soil. They found after their study that the percentage of fines (F_{200}) and *MDD* are the most effective parameters to predict the *CBR* value. Talukdar [11] used multiple linear regression analysis (MLRA) to correlate the soaked *CBR* value with the index properties of fine-grained soil from the Assam state of India.

Also, various researchers proposed correlations to predict the compaction characteristics based on soil index properties. Sivrikaya et al. [12] focused on the prediction of compaction parameters for granular soils and used two approaches, named multiple linear regression (MLR) and Genetic Expression Programming (GEP), to develop correlations. Mujtaba et al. [13] used granular soil samples to propose predictive models using gradation parameters and compaction energy (CE) for predicting the maximum dry unit weight (γ_{dmax}) and the optimum moisture content (*OMC*). The prediction models presented by [13] are given in Eq.(1)and Eq. (2), respectively.

Omar et al.[14] developed prediction models to estimate the compaction characteristics of granular soil present in the United Arab Emirates.The prediction models developed in their research are presented in Eqs. (3) and (4). Noor et al. [15] collected 106 samples of fine-grained soils from various Indian Hydropower projects to develop prediction models for the estimation of compaction parameters given in Eq. (5) and Eq. (6). Boltz et al. [16] proposed correlations for fine-grained soil based on the liquid limit (*LL*) and the compaction energy (*E*), as presented in Eqs.(7) and (8). Sridharan and Nagaraj [17] found that only the plastic limit (ω_p) can give good estimates of compaction parameters. Their proposed correlations are presented in Eqs. (9) and (10).

$$\gamma_{dmax} = 4.49 \log(C_u) + 1.51 \log(CE) + 10.2 \tag{1}$$

$$\log OMC\,(\%) = 1.67 - 0.193 \log(C_u) - 0.153 \log(CE) \tag{2}$$

$$\rho_{dmax}(\mathrm{kg/m^3}) = [4804574\, G_s - 195.55(LL^2) + 156971(\mathrm{R\#4})^{0.5} - 9527830]^{0.5} \tag{3}$$

$$\ln(\omega_0) = 1.195\times10^{-4}\,(LL^2) - 1.964\, G_s - 6.617\times10^{-3}\,(\mathrm{R\#4}) + 7.651 \tag{4}$$

$$MDD = \sqrt{\mathrm{PL}} - 0.089\, LL + 33.97/(PL+1.37) + 19.05 \tag{5}$$

$$OMC = PI/\mathrm{G} + 3.424 + 0.462\, PL - G \tag{6}$$

$$MDD = (2.27 \log LL - 0.94) \log E - 0.16\, LL + 17.02 \tag{7}$$

$$OMC = (12.39 - 12.21 \log LL)\log E + 0.67\, LL + 9.21 \tag{8}$$

$$\gamma_{dmax} = 0.23(93.3 - \omega_P) \tag{9}$$

$$OMC = 0.92\, \omega_P \tag{10}$$

The present research is mainly focused on proposing prediction models to estimate the *CBR*, the *MDD* and the *OMC* in the case of granular soils present in various areas of the Punjab province of Pakistan, based on their index properties. The index parameters including D_{50}, D_{30} and C_u obtained from the results of grain size analysis were used for the estimation of the *CBR*, *MDD* and *OMC* of the coarse-grained soils.

2 MATERIALS AND METHODS

The major sources of soil samples were local deposits of granular soils commercially known as Ravi, Chenab and Lawrencepur sands, which have been used in this study. A total of seventy soil samples were tested, including natural sand samples and composite sand samples prepared by mixing the above-mentioned sands in different proportions. The soil samples were classified as poorly graded sand (SP), well-graded sand (SW) and poorly graded sand with silt (SP-SM),as per the Unified Soil Classification System (USCS) [18]. Similarly, according to the AASHTO classification system, soil samples lie in A-1-b and A-3 groups [19]. All the tests were conducted on every sample according to the standard test procedures described in the relevant ASTM standards. The grain size analysis test was performed in accordance with ASTM-D422 [20], where a modified Proctor compaction test was carried out in the laboratory following the test procedure of ASTM-D1557 [21]. For the determination of the California Bearing Ratio (*CBR*), soil samples were compacted at optimum moisture content, corresponding to the maximum dry density, which was obtained by performing a modified Proctor test on every sample.

Compacted soil samples were then soaked in water for 96 hours under excess weight as specified in a standard test procedure. Afterwards, the samples were tested in a *CBR* machine by penetrating a plunger in soil samples at the specified rate stipulated in ASTM-D1883 [22]. All the experimentation was performed in the Geotechnical Engineering Laboratory of Civil Engineering Department, University of Engineering and Technology, Lahore, Pakistan.

A summary of the results based on the above-mentioned tests is shown in Table 2. The outcomes of the laboratory tests were analyzed using multiple linear regression analysis to develop prediction models for the estimation of the California Bearing Ratio (*CBR*) and the compaction characteristics. A statistical package for the social sciences (SPSS) software was utilized to perform multiple linear regression analysis. Before starting the analysis process, data was divided into two categories, i.e., the input and the output parameters. For predicting the *CBR* value, the *CBR* value was considered as an output parameter and parameters like D_{30}, D_{50}, D_{60}, C_u, *MDD* and *OMC* were considered as probable input parameters. For predicting the compaction characteristics, *OMC* and *MDD* were the output parameters, whereas D_{30}, D_{50}, D_{60} and C_u were possible input parameters. The potential input parameters for the prediction of the *CBR* value and the compaction characteristics were identified as D_{30}, D_{50} and C_u, on the basis of passing t-test, while the rest of the parameters were neglected. The formulated correlations were calibrated using simple linear regression analysis by having a plot between the experimental and the predicted results.

The developed prediction models are validated using an independent database, which was not used in the development of the models. A correlation coefficient, a standard error of estimates and a relative error of estimates for every prediction model were examined to check the reliability of the developed models.

3 RESULTS AND DISCUSSIONS

The laboratory test results and the classification group based on the USCS and AASHTO classification system of the tested soil samples are summarized in Table 2.

Table 2. Test data used for the development of the predictive models.

Sr. No.	D_{10} mm	D_{30} mm	D_{50} mm	D_{60} mm	C_u	C_c	G_s	*OMC* %	*MDD* kN/m^3	*CBR* %	USCS Classification	AASHTO Classification
S1	0.10	0.18	0.25	0.36	3.79	0.95	2.67	15.4	18.4	13	SP	A-3
S2	0.13	0.18	0.25	0.30	2.31	0.83	2.70	13.1	17.6	10	SP	A-3
S3	0.11	0.19	0.24	0.32	2.91	1.03	2.66	12.2	18.6	13	SP-SM	A-3
S4	0.30	1.00	2.20	2.40	8.00	1.39	2.72	8.2	21.9	24	SW	A-1-b
S5	0.28	0.90	2.30	2.40	8.57	1.21	2.65	8.2	21.9	34	SW	A-1-b
S6	0.21	0.48	0.74	0.90	6.00	1.22	2.60	12.0	20.0	21	SW	A-1-b
S7	0.19	0.28	0.50	0.58	3.05	0.71	2.63	11.6	20.0	16	SP	A-1-b
S8	0.17	0.27	0.45	0.60	3.53	0.71	2.71	12.4	20.1	14	SP	A-1-b
S9	0.12	0.22	0.36	0.47	3.92	0.86	2.69	11.1	18.1	8	SP	A-3
S10	0.17	0.30	0.73	1.30	7.65	0.41	2.72	11.2	20.3	20	SP	A-1-b
S11	0.16	0.21	0.28	0.33	2.06	0.84	2.64	13.4	19.4	7	SP	A-3
S12	0.15	0.20	0.27	0.45	3.00	0.59	2.70	14.8	19.2	13	SP	A-3
S13	0.15	0.21	0.25	0.32	2.13	0.88	2.65	14.0	19.3	11	SP	A-3
S14	0.16	0.21	0.28	0.32	1.97	0.88	2.60	13.5	19.2	12	SP	A-3
S15	0.16	0.20	0.27	0.31	4.50	0.82	2.63	12.3	19.3	12	SP	A-3
S16	0.14	0.19	0.26	0.29	2.07	0.89	2.71	13.1	19.5	7	SP	A-3
S17	0.12	0.19	0.22	0.27	4.20	1.06	2.72	12.0	19.0	14	SP-SM	A-3
S18	0.19	0.19	0.25	0.56	4.50	0.35	2.64	14.5	19.2	16	SP	A-3
S19	0.13	0.20	0.26	0.48	3.69	0.61	2.70	13.8	19.4	6	SP	A-3
S20	0.13	0.19	0.25	0.51	3.92	0.54	2.67	14.8	19.0	10	SP	A-3
S21	0.10	0.17	0.21	0.25	2.60	1.20	2.65	11.9	18.5	12	SP-SM	A-3
S22	0.12	0.18	0.23	0.27	2.35	1.04	2.60	13.7	18.6	12	SP-SM	A-3
S23	0.12	0.19	0.24	0.28	2.33	1.07	2.63	14.0	18.7	12	SP-SM	A-3
S24	0.13	0.20	0.25	0.30	2.27	0.99	2.71	13.8	18.8	12	SP	A-3
S25	0.13	0.19	0.25	0.30	2.31	0.93	2.65	12.9	18.9	14	SP	A-3
S26	0.16	0.22	0.33	0.43	2.74	0.73	2.61	11.6	19.4	12	SP	A-3
S27	0.16	0.25	0.30	0.52	3.25	0.75	2.68	12.4	18.7	6	SP	A-3

Sr. No.	D_{10} mm	D_{30} mm	D_{50} mm	D_{60} mm	C_u	C_c	G_s	*OMC* %	*MDD* kN/m^3	*CBR* %	USCS Classification	AASHTO Classification
S28	0.16	0.23	0.40	0.45	2.90	0.76	2.72	12.5	19.0	10	SP	A-3
S29	0.17	0.19	0.88	1.00	5.88	0.20	2.65	12.8	19.8	18	SP	A-3
S30	0.17	0.18	0.20	0.53	3.12	0.36	2.60	13.2	19.7	9	SP	A-3
S31	0.13	0.17	0.22	0.25	1.92	0.89	2.63	13.7	17.8	11	SP	A-3
S32	0.17	0.19	0.92	1.20	7.06	0.18	2.70	11.7	20.5	20	SP	A-3
S33	0.14	0.19	0.22	0.27	7.96	1.01	2.63	13.5	18.4	12	SW	A-3
S34	0.23	0.41	0.53	0.73	3.17	1.00	2.71	11.3	20.2	8	SP-SM	A-1-b
S35	0.18	0.44	1.50	1.70	9.71	0.65	2.69	9.7	21.2	24	SP	A-1-b
S36	0.16	0.20	0.75	0.80	5.00	0.30	2.72	13.0	18.9	9	SP	A-3
S37	0.15	0.20	0.26	0.30	2.07	0.92	2.64	11.8	19.1	8	SP	A-3
S38	0.16	0.21	0.90	1.20	7.50	0.22	2.65	11.6	19.4	14	SP	A-3
S39	0.17	0.22	1.20	1.40	8.48	0.21	2.60	11.2	19.6	17	SP	A-3
S40	0.15	0.22	0.70	1.00	6.67	0.32	2.63	11.6	18.9	9	SP	A-3
S41	0.17	0.25	1.00	1.30	7.65	0.28	2.71	10.0	21.2	19	SP	A-3
S42	0.18	0.27	1.40	1.70	9.71	0.25	2.63	10.1	20.4	21	SP	A-3
S43	0.17	0.26	1.00	1.55	9.39	0.26	2.71	11.8	20.1	19	SP	A-3
S44	0.23	0.30	0.56	0.76	3.30	0.51	2.69	10.3	20.8	10	SP	A-1-b
S45	0.16	0.20	0.24	0.27	1.69	0.88	2.70	13.6	18.3	9	SP	A-3
S46	0.17	0.20	0.80	1.10	6.47	0.20	2.63	14.6	18.5	13	SP	A-3
S47	0.18	0.21	0.60	0.67	6.50	0.38	2.71	11.2	20.5	20	SP	A-3
S48	0.16	0.22	0.30	0.37	2.31	0.82	2.69	11.2	19.0	13	SP	A-3
S49	0.18	0.26	1.30	1.50	8.33	0.25	2.72	11.4	20.2	18	SP	A-3
S50	0.18	0.30	0.54	0.71	3.94	0.70	2.64	11.2	20.4	12	SP	A-1-b
S51	0.19	0.47	1.10	1.20	6.32	0.97	2.68	12.0	20.5	21	SP	A-1-b
S52	0.20	0.50	0.90	1.30	6.50	0.96	2.63	11.0	20.8	20	SP	A-1-b
S53	0.22	0.55	1.00	1.50	6.82	0.92	2.71	11.0	21.4	21	SP	A-1-b
S54	0.21	0.57	1.30	1.70	8.10	0.91	2.69	9.2	21.0	29	SP	A-1-b
S55	0.22	0.60	1.30	1.85	8.41	0.88	2.72	9.0	21.2	28	SP	A-1-b
S56	0.28	0.88	1.40	1.80	6.43	1.54	2.64	9.3	21.6	24	SW	A-1-b
S57	0.27	0.83	1.90	2.10	9.00	1.21	2.60	8.9	21.7	29	SW	A-1-b
S58	0.33	1.10	2.20	2.60	7.88	1.41	2.63	8.2	21.0	34	SW	A-1-b
S59	0.32	0.90	2.10	2.70	8.44	0.94	2.71	8.3	21.5	33	SP	A-1-b
S60	0.30	1.00	2.20	2.80	9.33	1.19	2.68	8.1	21.9	35	SW	A-1-b
S61	0.10	0.14	1.10	1.50	5.00	0.13	2.63	11.5	19.0	20	SP	A-3
S62	0.17	0.12	1.60	2.40	4.12	0.04	2.70	11.0	18.5	27	SP	A-1-b
S63	0.90	1.20	1.70	1.90	2.11	0.84	2.63	11.0	19.2	32	SP	A-3
S64	0.07	0.11	1.50	1.80	5.71	0.10	2.71	11.0	19.6	33	SP	A-3
S65	0.60	0.90	1.20	1.30	2.17	1.04	2.69	9.5	20.9	22	SP-SM	A-3
S66	0.60	0.90	1.20	1.50	2.50	0.90	2.72	7.5	21.4	23	SP	A-3
S67	0.40	0.60	2.20	2.50	6.25	0.36	2.64	6.5	21.6	32	SP	A-1-b
S68	0.90	1.60	2.00	2.40	2.67	1.19	2.65	9.5	19.5	26	SP-SM	A-1-b
S69	0.10	0.40	0.70	0.90	9.00	1.78	2.60	9.5	18.7	24	SW	A-3
S70	0.70	1.10	1.40	1.60	7.29	1.08	2.63	7.5	20.7	32	SW	A-1-b

Based on the grain size analysis, it can be inferred that the samples used in the study contain a sand content (percent passing 4.75 mm, and percent retained on 0.075 mm) varying between 80 and 100 %. The gravel content (percent retained on 4.75 mm) in the samples varies from 0 to 20% and the fines (percent finer than 0.075 mm) vary from 0 to 7%. The mean grain size (D_{50}) of all the samples is in the range 0.2 mm to 2.3 mm and the effective grain size (D_{10}) is in the range 0.45 mm to 0.07 mm. The particle sizes at 30% and 60% passing (D_{30} and D_{60}) were also determined from the grain size analysis curve. The coefficient of uniformity ($C_u = D_{60}/D_{30}$) of the tested samples ranges from 1.7 to 9.7 and the coefficient of curvature ($C_c = D_{30}^2 / D_{60} \times D_{10}$) varies in between 0.04 and 1.78. The specific gravity of the samples is in the range 2.60–2.72. The results of the modified Proctor and *CBR* tests presented in Table 2 indicated that the maximum dry density (*MDD*) ranges from 17.64kN/m^3 to 21.92kN/m^3 and the optimum moisture content (*OMC*) ranges from 6.5% to 15.4% and the *CBR* values vary from 6 to 35.

More specifically, the *MDD* for the SP samples varies from 17.64kN/m^3 to 21.6kN/m^3, while for the SP-SM samples it fall between 18.45kN/m^3 and 20.89kN/m^3 and for the SW samples it varies from 18.37kN/m^3 to 21.92kN/m^3. The *OMC* for the SP samples varies from 6.5% to 15.4%, while for the SP-SM samples it falls between 9.50% and 14%,and for SW samples it varies from 7.5% to 13.5%. Similarly, the *CBR* for the SP samples varies from 6% to 33%, while for the SP-SM samples it falls between 8% and 26%, and for the SW samples it varies from 12% to 35%.

The laboratory test results mentioned in Table 2 were analyzed using multiple linear regression analysis to develop prediction models for the estimation of the California Bearing Ratio (*CBR*) and the compaction characteristics. A statistical package for the social sciences (SPSS) software was utilized to perform multiple linear regression analysis. The best-fit prediction models obtained as a result of the regression analysis carried out on the test data presented in Table 2 are as follows:

$$CBR = 6.508D_{50} + 1.48C_u + 3.970 \qquad (R^2 = 0.85) \qquad (11)$$

$$MDD = 0.171C_u + 2.408D_{30} + 18.168 \qquad (R^2 = 0.81) \qquad (12)$$

$$OMC = 0.026C_u - 2.53D_{50} + 13.456 \qquad (R^2 = 0.74) \qquad (13)$$

D_{50} and D_{30} are the grain sizes corresponding to 50% finer and 30% finer, respectively and D_{50} and D_{30} are in mm for the above-mentioned equations.

The coefficient of determination is a quantitative measure to represent how well the predicted results are replicated by the model. The standard error of estimate (SEE) is a quantitative measure to check the variance between the predicted and the experimental results. The relative standard error of the estimate is obtained by dividing SEE by the mean of the output values to provide a standard measure of fit. The formulated correlations in the present research have high values for the coefficient of determination (R^2) and relatively low values for the standard error of the estimate (SEE) and the relative standard error of the estimate. The SEE was computed mathematically;

$$SEE = \sqrt{\frac{\sum\left(y_{experimental} - y_{predicted}\right)^2}{v}} \qquad (14)$$

where

v = Degree of freedom = number observations - number of variables

$y_{experimental}$ = Experimental results

$y_{predicted}$ = Predicted results

The SEEs for Eqs.(11), (12) and (13) are 3.13, 0.49 and 0.93, respectively. The SEE values indicate that the proposed models have a good prediction capability.

Analysis of variance (ANOVA) is carried out to determine the F- statistic for the output parameters and the t-statistics for input parameters for Eqs. (11), (12) and (13). The model F value for Eq.(11) is 147.7,for Eq.(12) is 105.63 and for Eq.(13) is 69.35. These values of the F- statistic are greater than the critical F, indicating that Eq.(11), (12) and (13) are significant. Similarly, absolute t- statistics for the input parameters for these equations are greater than the t- significance of the model.

Figures 1, 2 and 3 represent a comparison between the experimental and predicted results of *CBR*, *MDD* and *OMC* using equations (11), (12) and (13), respectively. These plots show that the variation between the experimental versus the predicted results for *CBR* are within ±4% confidence interval and within ±2% confidence interval for both the *MDD* and *OMC*.

The prediction models developed in this research were validated using an independent database. For this purpose, laboratory test results from 37 samples were utilized, which were not used in the development process of the models. The experimental results from the laboratory data were plotted against the predicted values using the proposed models, as represented in Figures1, 2 and 3, which show that the predicted results almost fall within the confidence interval of ±4% for *CBR* and±2% for both *MDD* and the *OMC*. The correlations proposed by NCHRP (National Co-operative Highway Research Program) [2], Ferede [5] and Saklecha et al. [7] were used for comparison purposes of the *CBR* value.

The predictions using the above-mentioned correlations are plotted in Figure 4. The predictions made by the NCHRP[2] correlation show that 7 out of 37 predictions fall outside ±4% confidence interval. The predictions made by Ferede's [5] correlation show that 10 out of 37 predictions fall outside ±4% confidence interval, and the predictions by Saklecha [7] correlation show that 11 out of 37 predictions fall outside ±4% confidence interval. The probable reason for this variation is the different

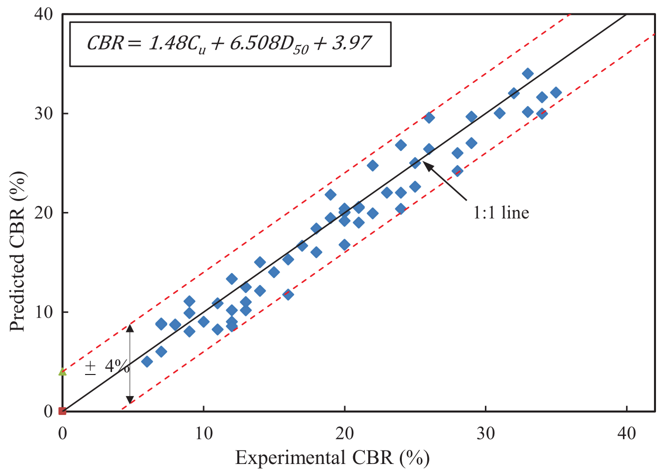

Figure 1. Experimental vs Predicted values of *CBR* by Eq. (11).

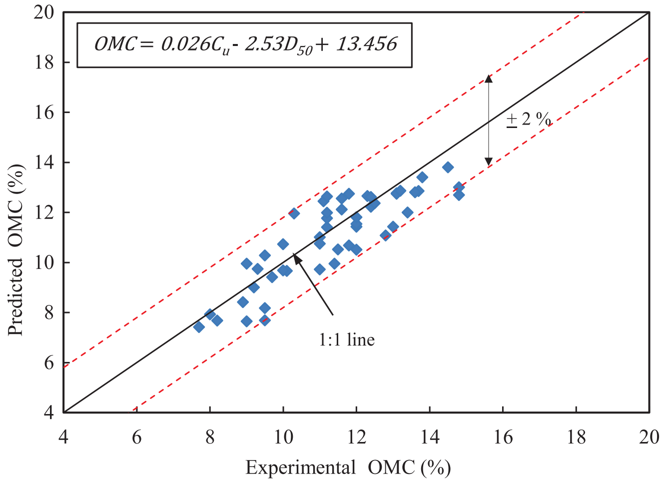

Figure 3. Experimental vs Predicted *OMC* by Eq. (13).

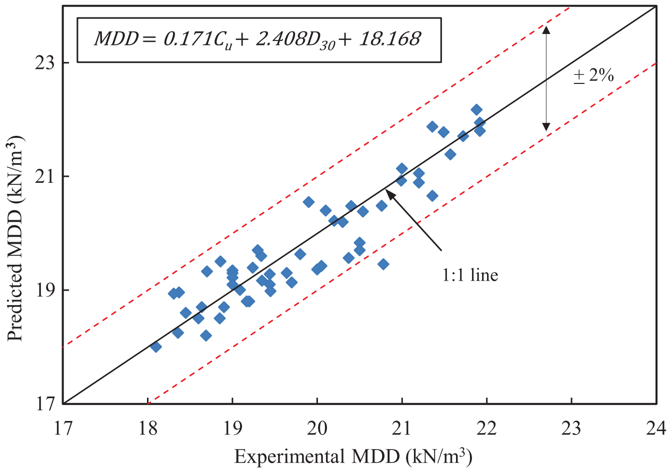

Figure 2. Experimental vs Predicted *MDD* by Eq. (12).

mineralogical composition, soil texture, fabric and deposition mode of the soils present in various regions of the world.

The correlations presented by Mujtaba et al. [13] and Omer et al.[14] were used for predicting the compaction characteristics using validation data. It can be observed from Figures 5 and 6 that the predicted results of the *MDD* and *OMC* fall almost within the ±2% envelopes, except for a few predicted results that exceed the prediction band of ±2%.

Figure 5 illustrates that the predictions by Eq. (3) show that 8 out of 37 predictions fall outside the ±2% confidence interval. Whereas the predictions by Eq. (1) show that 13 out of 37 predictions fall outside the ±2% confidence interval. The soil samples used in this

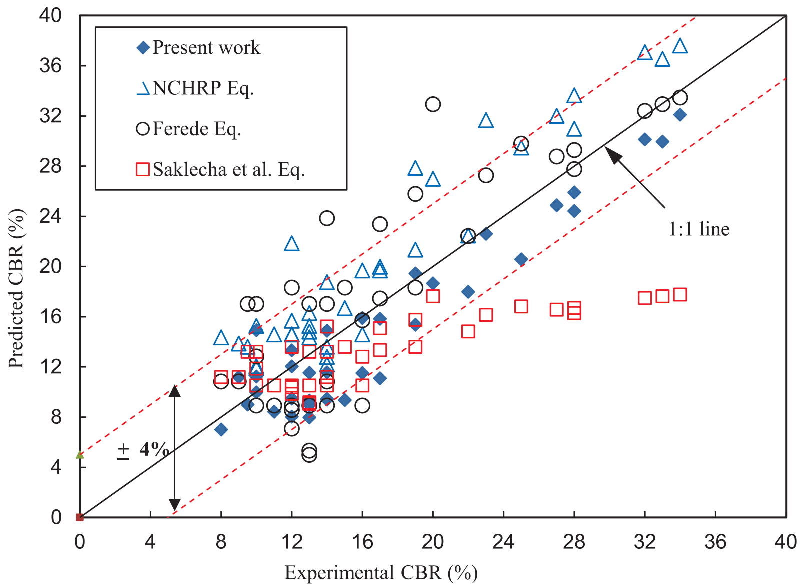

Figure 4. Experimental vs Predicted values of *CBR* by various models using the validation data.

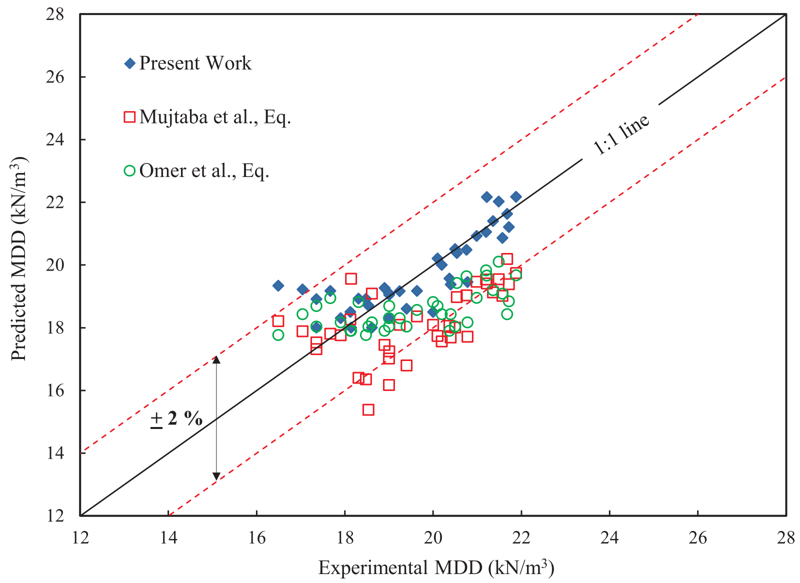

Figure 5. Experimental vs Predicted MDD by various predictive equations using validation data.

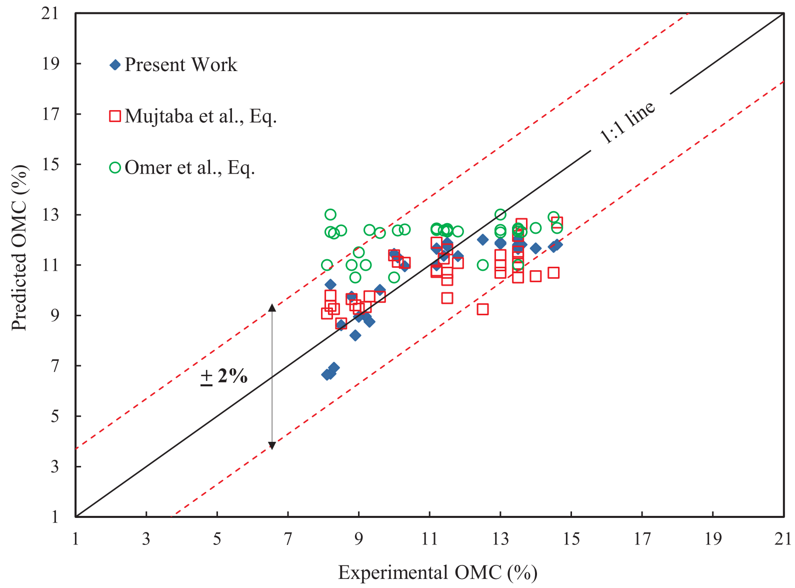

Figure 6. Experimental vs Predicted values of *OMC* by various models using the validation data.

research and those used by Mujtaba et al. [13] in his research were from same region, but the reason for this difference is the variation in the grain size distribution range of the soil samples used to develop these correlations. Mujtaba et al. [13] used 110 granular soil samples with a fine content varying from 0 to 47% and 70 samples of granular soil were used in this research with a fines content varying from 0 to 7%. So the difference in the fines content may be the cause of the variation in the predicted results, as illustrated in Figure 5.The predictions of the *OMC* by equations (2) and (4) show that only 4 and 6, respectively, out of 37 predictions fall outside the ±2% prediction band.

4 MODEL IMPLICATION

The *CBR* and the compaction parameters of granular soils depend on the number of physical soil parameters; however, based on extensive laboratory testing during this research, correlations have been proposed to predict

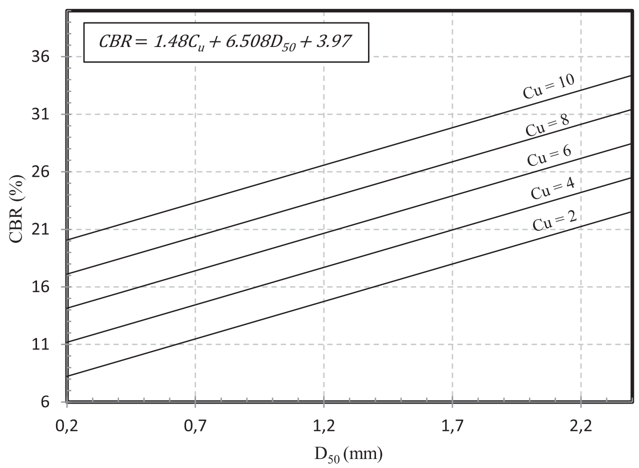

Figure 7. Nomograph for estimation of *CBR* value based on Eq. (11).

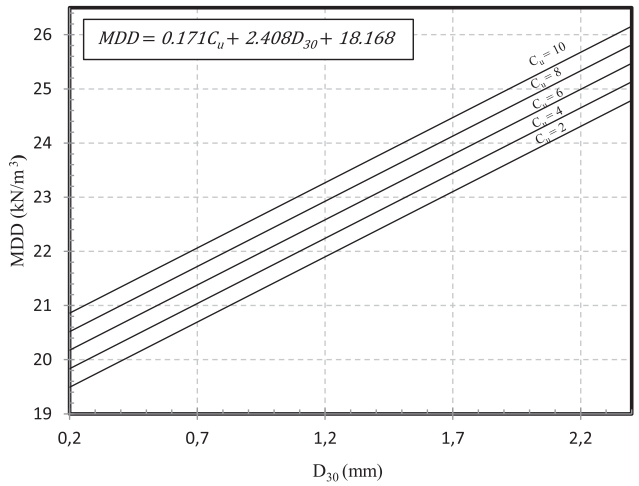

Figure 8. Nomograph for estimation of *MDD* value based on Eq. (12).

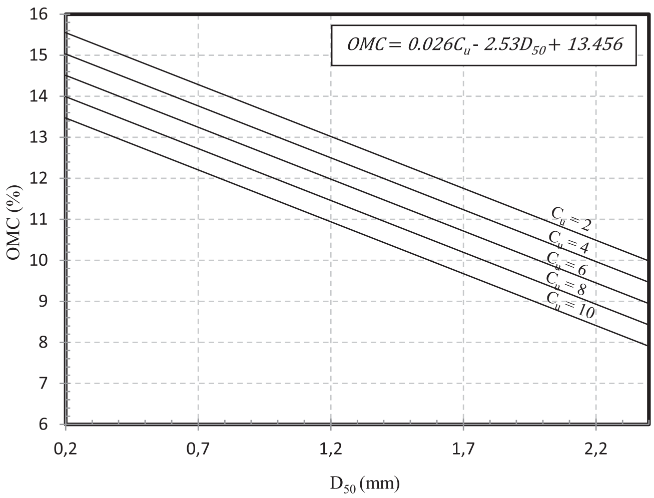

Figure 9. Nomograph for estimation of *OMC* value based on Eq. (13).

the *CBR* and the compaction characteristics of sandy soils with reasonable accuracy. These equations may be quite useful in estimating the engineering properties of granular soils used in the construction of earth structures. In addition, these models can be used during the planning and prefeasibility stages of the projects for a quick estimation of the *CBR* and the compaction parameters without performing any laboratory testing. In order to simplify the use of these correlations, nomographs or predictive curves have been developed based on the models presented in this research paper and the nomographs are presented in Figure 7 through Figure 9. By using these predictive curves, the *CBR*, *MDD* and *OMC* values of the granular soils can be readily estimated using the gradation data like D_{30} , D_{50} and C_u. Although the prediction models proposed in this article are quite valuable and user friendly, their use is applicable only for coarse-grained soils with a gravel content up to 20% and for non-plastic fines up to 10%.

5 CONCLUSIONS

On the basis of the above research study, the following conclusions can be drawn:

– The *CBR* value varies with the grain size parameters of coarse-grained soils; *CBR* varies from 6 to 35 when the mean grain size (D_{50}) varies from 0.2mm to 2.3mm and the coefficient of uniformity (C_u) varies from 1.7 to 9.7.
– Multiple linear regression analysis showed that the *CBR* values can be predicted based on mean grain size (D_{50}) and the coefficient of uniformity (C_u) using the correlation: CBR=6.508D_{50}+1.48C_u+3.970. The experimental versus predicted values fall within ±4%, indicating good prediction accuracy of the model.
– The *MDD* can also be predicted based on the coefficient of uniformity (C_u) and grain size corresponding to 30% passing (D_{30}) using the correlation: MDD=0.171C_u+2.408D_{30}+18.168.The prediction accuracy of this model is within ±2%.
– The optimum moisture content (*OMC*) is related to the coefficient of uniformity (C_u) and the mean grain size (D_{50}) as: OMC=0.026C_u-2.53D_{50}+13.456. The prediction accuracy of this correlation is also within ±2%.
– The predictive correlations and the curves presented in this research are valid for granular soils with a gravel content up to 20% and the fines up to 10% and above for non-plastic fines.

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