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Estimation of Heavy Compaction Parameters using Light Compaction Parameters of Granular Soil

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Abstract. The maximum dry density and optimum moisture content are the compaction parameters of soil, determined by modified and standard proctor tests. The modified and standard proctor tests are heavy and light compaction tests. In this research, the factor affecting the compaction parameters and the estimation of heavy compaction parameters from light compaction parameters has been studied. The input parameters G, S, FC, D_{60}, D_{50}, D_{30}, D_{10}, C_u and C_c, are used to develop the regression models. Furthermore, Pearson's product-moment correlation coefficient depicts multicollinearity between gravel content and D_{10} for maximum dry density in both compaction conditions. Also, the coefficient of curvature has no relationship with compaction parameters. The results show that the index parameters (D_{60}, D_{50}, D_{30}, D_{10}, C_u and C_c) estimate the maximum dry density of soil better than other parameters (G, S, FC). However, the estimation of optimum moisture content is less accurate than maximum dry density for heavy and light compaction tests. The regression analysis between heavy and light compaction parameters shows that the regression models estimate the heavy compaction parameters with a correlation coefficient of more than 0.95 using light compaction parameters. Finally, this study concludes that the light compaction parameters of granular soil can estimate the heavy compaction parameters with acceptable results.

Keywords: Granular soil, Modified proctor test, Standard proctor test, Regression analysis

1 Introduction

The geotechnical parameters such as gradational, consistency limits, strength, and compaction parameters help to understand the behaviour of soils used in any civil engineering project [20]. The compaction parameters are optimum moisture content and maximum dry density, determined using standard and modified proctor tests. The standard and modified proctor tests are light and heavy compaction methods. The modified proctor test requires more blows than the standard proctor test. The compaction test is performed to determine the optimum moisture content and maximum dry density of soil. However, both the procedures are time-consuming and tedious. Therefore, several investigators have used different methodologies to compute the optimum moisture content and maximum dry density for time-saving. These methodologies are associated with statistics and artificial intelligence.

Salim et al. (2022) have employed the artificial neural network approach to predict the compaction parameters using the different field parameters [15]. The authors have used backpropagation algorithms, namely Levenberg-Marquardt (LM), Bayesian Regulation (BR), Ratios Graded with Adaptive Learning Rate (GDA), Resilient (RP), and Graded Origin with Momentum (GDM). The authors have observed that the LM backpropagation algorithm-based ANN model has outperformed the other models with the MSE of 0.002263 for bulk density and 0.005112 for cone index. Also, the LM backpropagation algorithm-based ANN models have achieved a performance (R^2) of 0.986 and 0.967 in predicting the bulk density and cone index. Finally, the authors have concluded that the artificial neural network (ANN) predicts the compaction parameters better than the mathematical/ statistical model. Yousif et al. (2022) have mapped a relationship between the Atterberg's limits and compaction parameters of soil [20]. The authors have reported that the liquid limit has an excellent relationship with OMC and MDD of soil. Taffese and Abegaz (2022) have predicted the compaction parameters using the optimizable ensemble method (bagging regression tree, boosting regression tree) and artificial neural network approaches based on machine learning [17]. The authors have observed that the optimizable ensemble method (OEM) has outperformed the artificial neural network with a performance (R^2) of 0.56 in predicting the OMC of soil. On the other hand, the artificial neural network has outperformed the OEM model with a performance (R^2) of 0.25 in predicting the MDD of soil. V Hohn et al. (2022) have developed empirical models to compute the compaction parameters of soil [19]. The authors have reported that the models have predicted OMC and MDD with a COD of 0.761 and 0.763, respectively. The authors have developed the empirical models using gravel content, sand content, fine content, liquid limit, plastic limit, and specific unit weight of soils. Finally, the authors have validated the OMC and MDD models by comparing the models available in the literature survey and concluded that the proposed models predict the compaction parameters better than the available models in the literature survey. Maqsoud (2022) has derived a simple relationship to estimate the OMC and MDD of soil [12]. The authors have developed the relationship using the consistency parameters of 56 compacted clay liners. Furthermore, the authors have validated the relationship using consistency parameters of 44 compacted clay liners. Haupt and Netterberg (2021) have mapped a relationship between experimentally determined soaked CBR, unsoaked CBR, OMC, and MDD for standard and modified proctor test efforts [9]. Jalal et al. (2021) have employed OMC, and MDD models based on GEP and MEP approaches using 195 datasets [10]. However, the authors have developed these models using clay fraction, specific gravity, plastic limit, and plasticity index. In addition, the authors have developed MLR models, compared them with GEP & MEP models, and concluded that the GEP models had outperformed the MLR and MEP in predicting MDD and OMC of soil, respectively. The authors have concluded that the gravel content is the most influencing parameter in predicting the compaction parameters of soil. Othman (2021) has constructed the deep neural network (ANN) to predict the compaction parameters of soil [13]. The authors have studied the impact of activation functions, the number of neurons, and the number of hidden layers in predicting OMC and MDD of soil. The authors concluded that the optimum prediction of compaction parameters is affected by the selected hyperparameters of the neural network. Also, the authors have concluded that the hyperbolic tangent activation is better than the linear and logistic activation functions. The authors have used grain size distribution, plastic limit, and liquid limit.

Özbeyaz and Söylemez (2020) have predicted compaction parameters using a support vector machine and decision tree [14]. The authors have carried out the study with 126 datasets. The authors have found that the polynomial SVM models have predicted OMC and MDD better than other SVM models (R=0.93). On the other hand, the decision tree regression models have predicted OMC and MDD with a performance of 0.73 and 0.44, respectively. The study reported that the multiple input parameters enhance the model's performance. In the published work, the polynomial SVM models developed by input parameters (G, S, FC, LL) have outperformed the decision tree models. Ardakani and Kordnaeij (2019) have used GMDH type neural network and genetic algorithm to predict the compaction parameters [1]. The authors have predicted OMC and MDD of soil with the performance of 0.92 and 0.9 using the GMDH neural network. Gurtug et al. (2018) have predicted compaction curves and characteristics of the soil [6]. Taha et al. (2018) have predicted maximum dry density and optimum moisture content of stabilized soil using artificial neural networks [18].

Farooq et al. (2016) have successfully derived regression equations to compute the compaction parameters using LL, PI, and compaction energy parameters [4]. Bera and Ghosh (2011) have employed the regression models in predicting OMC and MDD of fine-grained soils [2]. The authors have concluded that the compaction energy, specific gravity, LL, and grain size play a vital role in predicting the OMC and MDD of soil. Günaydın (2009) has mapped a comparative study between statistical analysis and ANN while predicting the compaction parameters of soil [5]. The author has reported that the ANN models of OMC and MDD developed using input parameters FG, S, G, LL, and PL have achieved better performance predicting OMC (R^2=0.893) and MDD (R^2=0.836) of soil. Günaydın also found that ANN predicts the compaction parameters better than regression approaches. Di Matteo et al. (2009) have estimated the modified compaction parameters of fine-grained soil [3]. The authors have suggested regression equations to predict the compaction parameters, which is useful in designing trench fills, landfill liners, earth dams, and road embankments. Sinha and Wang (2008) have computed soil compaction parameters using an artificial neural network [16]. The authors have used 55 soil samples to carry out the published study. The developed models have predicted the OMC and MDD with a performance of more than 0.92. Gurtug and Sridharan (2004) have studied the effect of compaction energy on the compaction characteristics of fine-grained soil [7]. The authors have successfully derived the equations to predict the compaction parameters using compaction energy for the modified proctor test.

The literature study illustrates that several investigators have employed regression and artificial intelligence techniques to compute the compaction parameters to save time. Many researchers have derived linear, polynomial, and logistic regression equations to predict the compaction parameters of soil. On the other hand, many researchers have constructed artificial neural network models to estimate the OMC and MDD of soil. Still, the investigators have not studied the *relationship between gradational parameters and compaction parameters of the modified proctor test*. In addition, the researchers have not mapped *a relationship between compaction parameters of standard proctor test and modified proctor test*. As per the outcomes of the literature study, the present research has the following aims:

- To draw a relationship between input parameters (G, S, FC, D_{60}, D_{50}, D_{30}, D_{10}, C_U & C_C) and compaction parameters (OMC & MDD) of standard and modified proctor tests. Also, predict the OMC and MDD for standard and modified proctor test parameters using the same input parameters.

- To draw a heat diagram using Pearson's product-moment correlation coefficient for standard and modified proctor tests.
- To map a relationship between standard and modified proctor test compaction parameters to predict the OMC and MDD of soil for the modified proctor test.
- To construct a nomograph for the direct prediction of compaction parameters of the modified proctor test.
- To determine the impact of input parameters in predicting the compaction parameters for the modified proctor test by performing the Cosine Amplitude Sensitivity Analysis (CASA).

2 Data Compilation

The present research has been carried out using the published datasets of Khuntia et al. (2015). The authors have reported 110 datasets of coarse-grained soil [11]. The datasets contain gravel (G), sand (S), fine content (FC), particle size at 60% passing (D_{60}), particle size at 50% passing (D_{50}), particle size at 30% passing (D_{30}), particle size at 10% passing (D_{10}), coefficient of uniformity (C_U), coefficient of curvature (C_C), compaction parameters (OMC & MDD) of standard and modified proctor test of coarse-grained soils. However, a dataset consists of several columns and rows, which makes studying datasets difficult. Therefore, a descriptive statistic for the dataset is drawn, as shown in Table 1.

Table 1. Descriptive Statistics for the compaction datasets

Particulars	Min	Max	Mean	Kurtosis	Skewness	StDev	CL
G (%)	0.00	5.00	1.06	1.78	1.21	1.17	0.22
S (%)	50.00	100.00	88.50	1.96	-1.67	11.66	2.20
FC (%)	0.00	46.00	10.44	1.77	1.63	11.50	2.17
D_{60} (mm)	0.11	1.00	0.36	1.68	1.52	0.22	0.04
D_{50} (mm)	0.09	0.80	0.27	2.45	1.69	0.17	0.03
D_{30} (mm)	0.04	0.43	0.16	1.82	1.28	0.08	0.02
D_{10} (mm)	0.01	0.21	0.09	0.03	0.48	0.04	0.01
C_U	1.38	11.76	4.55	1.38	1.49	2.52	0.48
C_C	0.43	2.14	0.95	4.52	1.97	0.32	0.06
MDD_M (g/cc)	1.63	2.11	1.85	-0.39	0.38	0.11	0.02
OMC_M (%)	8.00	15.50	10.79	0.64	0.87	1.54	0.29
MDD_S (g/cc)	1.55	2.00	1.75	-0.42	0.42	0.11	0.02
OMC_S (%)	10.50	18.50	13.59	0.10	0.76	1.80	0.34

* MDD_M & OMC_M are modified, and MDD_S & OMC_S are standard proctor parameters

The Pearson's product-moment correlation coefficient has been calculated to determine the relationship between input and output of standard and modified proctor test parameters. The correlation coefficient value ±0.81 to ±1.0, ±0.61 to ±0.80, ±0.41 to ±0.60, ±0.21 to ±0.40, and ±0.0 to ±0.20 demonstrates the very strong, strong, moderate, weak and no relationship between input and output parameters [8]. The heat diagrams for standard and modified proctor test parameters have been drawn, as shown in Fig. 1 and 2.

Fig. 1. Heat diagram presenting correlation coefficient for SPT parameters

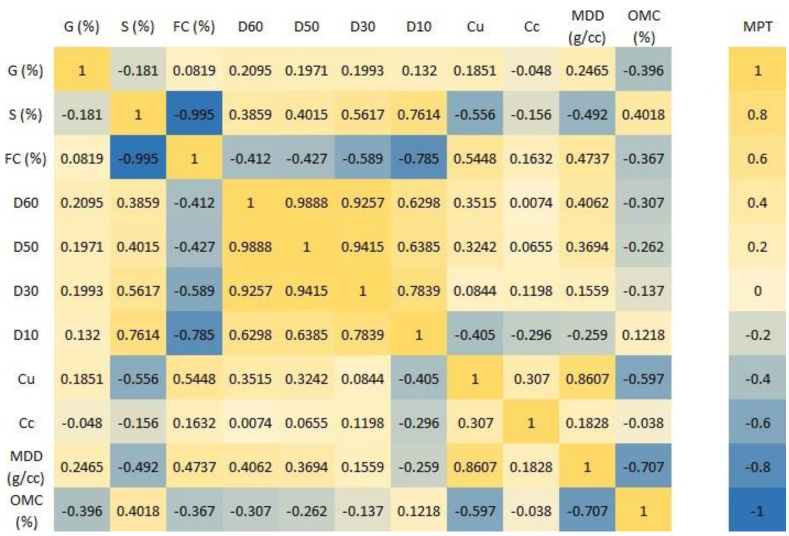

Fig. 2. Heat diagram presenting correlation coefficient for MPT parameters

Fig. 1 illustrates that MDD very strongly correlates with the coefficient of uniformity. Also, sand and fine content moderately correlate with maximum dry density. Furthermore, the gravel content, D_{60}, D_{50}, and D_{10}, weakly correlate with the maximum dry density of the standard proctor test. In addition, optimum moisture content moderately correlates with the coefficient of uniformity. Moreover, the gravel, sand, and fine content, D_{60}, and D_{50}, weakly correlate with the optimum moisture content of the standard proctor test. On the other hand, Fig. 2 demonstrates that the maximum dry density of the modified proctor test very strongly correlates with the coefficient of uniformity. The sand and fine content have a moderate relationship with the maximum dry density of the modified proctor test. Also, the uniformity coefficient has a moderate relationship with optimum moisture content. The rest of the parameters have weak to no relationship with the OMC of the modified proctor test. However, the comparison shows that the modified proctor test compaction parameters have a better relationship with input parameters than the standard proctor test parameters.

In the present study, the total datasets have been divided into 90 training and 20 testing datasets. The selected twenty testing datasets are given in Table 2.

Table 2. Testing datasets collected from Khuntia et al. (2015) [11]

G (%)	**S (%)**	**FC (%)**	**D_{60} (mm)**	**D_{50} (mm)**	**D_{30} (mm)**	**D_{10} (mm)**	**C_U**	**C_C**	**MDD_M** (g/cc)	**OMC_M** (%)	**MDD_S** (g/cc)	**OMC_S** (%)
0	57	43	0.16	0.1	0.055	0.021	7.62	0.90	2.04	9.5	1.93	12
0	71	29	0.2	0.16	0.08	0.021	9.52	1.52	1.96	9	1.86	12
2	96	2	0.4	0.3	0.21	0.11	3.64	1.00	1.91	10.5	1.82	13
0	95	5	0.24	0.2	0.13	0.082	2.93	0.86	1.87	10	1.76	13
2	96	2	0.43	0.31	0.21	0.15	2.83	0.69	1.83	11	1.73	14
0	98	2	0.20	0.18	0.11	0.09	2.23	0.67	1.70	13	1.62	16
0	83	17	0.18	0.17	0.1	0.07	2.57	0.79	1.72	11.5	1.59	14.5
0	94	6	0.2	0.15	0.1	0.08	2.50	0.63	1.78	10.5	1.70	13
2	96	2	0.48	0.36	0.21	0.15	3.20	0.61	1.83	10	1.73	12.5
5	93	2	0.3	0.26	0.2	0.15	2.00	0.89	1.74	9.5	1.65	12.5
2	82	16	0.2	0.17	0.1	0.06	3.33	0.83	1.83	12	1.73	16
3	52	45	0.16	0.09	0.04	0.017	9.41	0.59	2.08	9.5	1.99	10.5
0	83	17	0.21	0.19	0.11	0.05	4.20	1.15	1.77	11.5	1.69	15
0	94	6	0.19	0.15	0.11	0.08	2.38	0.80	1.76	12.5	1.67	15.5
2	96	2	0.5	0.37	0.21	0.15	3.33	0.59	1.82	9.5	1.71	12
0	100	0	0.2	0.19	0.12	0.09	2.22	0.80	1.65	15.5	1.55	18.5
0	64	36	0.3	0.19	0.062	0.03	10.00	0.43	2.04	9	1.94	11.5
2	96	2	0.4	0.3	0.2	0.13	3.08	0.77	1.86	10.5	1.76	13.5
0	95	5	0.24	0.2	0.12	0.08	3.00	0.75	1.83	10	1.73	12.5
2	96	2	0.43	0.31	0.21	0.16	2.66	0.65	1.78	10.5	1.70	13

3 Methodology

In the present research, six cases are developed to predict the compaction parameters for standard and modified proctor tests. However, each parameter, gravel, sand, fine content, D_{60}, D_{50}, D_{30}, D_{10}, C_U, and C_C, plays a vital role in predicting the compaction parameters of coarse-grained soil. Therefore, it has been decided to predict the compaction parameters for standard and modified proctor tests. Moreover, a case is also included to predict the OMC and MDD for the modified proctor test using compaction parameters of the standard proctor test. Thus, seven cases are developed in the present study, as shown in Table 3.

Table 3. Possible case for predicting OMC and MDD of soil

Case No	Input Parameters	Output		Model ID	
		MDD	OMC	MDD	OMC
Case 1	G, S, FC	SPT	SPT	MD 1	MC 1
Case 2	G, S, FC	MPT	MPT	MD 2	MC 2
Case 3	D_{60}, D_{50}, D_{30}, D_{10}, C_U, C_C	SPT	SPT	MD 3	MC 3
Case 4	D_{60}, D_{50}, D_{30}, D_{10}, C_U, C_C	MPT	MPT	MD 4	MC 4
Case 5	G, S, FC, D_{60}, D_{50}, D_{30}, D_{10}, C_U, C_C	SPT	SPT	MD 5	MC 5
Case 6	G, S, FC, D_{60}, D_{50}, D_{30}, D_{10}, C_U, C_C	MPT	MPT	MD 6	MC 6
Case 7	OMC_S, MDD_S	MPT	MPT	MD 7	MC 7

Table 3 shows that the seven models have been developed to compute each maximum dry density and optimum moisture content for the proctor tests. The maximum dry density and optimum moisture content models are MD 1 to MD 7 and MC 1 to MC 7, respectively. Furthermore, the following equations for OMC and MDD models are derived from the regression analysis while training the models.

$$MD\ 1 = G*0 - S*0.0219 - FC*0.0183 + 3.8763 \qquad R = 0.4547 \tag{1}$$

$$MD\ 2 = G*0 - S*0.0242 - FC*0.0206 + 4.2029 \qquad R = 0.4536 \tag{2}$$

$$MD\ 3 = D_{60}*0.2139 + D_{50}*0.1518 - D_{30}*0.8353 + D_{10}*0.3521 + C_U*0.0293 + C_C*0.0308 + 1.5675 \qquad R = 0.8578 \tag{3}$$

$$MD\ 4 = D_{60}*0.3428 - D_{50}*0.0598 - D_{30}*0.6644 + D_{10}*0.1663 + C_U*0.0302 + C_C*0.0246 + 1.6723 \qquad R = 0.8717 \tag{4}$$

$$MD\ 5 = G*0 - S*0.0051 - FC*0.0023 + D_{60}*0.4103 + D_{50}*0.0658 - D_{30}*1.1038 + D_{10}*0.1663 + C_U*0.0208 + C_C*0.0612 + 2.0108 \qquad R = 0.8739 \tag{5}$$

$$MD\ 6 = G*0 - S*0.0063 - FC*0.0039 + D_{60}*0.5230 - D_{50}*0.1276 - D_{30}*0.9477 + D_{10}*0.5591 + C_U*0.0223 + C_C*0.0546 + 2.241 \qquad R = 0.8842 \tag{6}$$

$$MD\ 7 = MDD_S*0.9844 - OMC_S*0.0012 + 0.1465 \qquad R = 0.9720 \tag{7}$$

$$MC\ 1 = G*0 + S*0.4901 + FC*0.4396 - 34.385 \qquad R = 0.4664 \tag{8}$$

$$MC\ 2 = G*0 + S*0.5177 + FC*0.4757 - 40.004 \qquad R = 0.5154 \tag{9}$$

$$MC\ 3 = -D_{60}*4.4287 + D_{50}*13.25 - D_{30}*20.137 + D_{10}*10.412 - C_U*0.5306 + C_C*1.6395 + 14.807 \qquad R = 0.6554 \tag{10}$$

$$MC\ 4 = -D_{60}*2.5163 + D_{50}*10.7 - D_{30}*19.907 + D_{10}*11.962 - C_U*0.4738 + C_C*1.6685 + 11.561 \qquad R = 0.6679 \tag{11}$$

$$MC\ 5 = G*0 + S*0.1786 + FC*0.1042 - D_{60}*10.033 + D_{50}*15.469 - D_{30}*11.691 - D_{10}*1.8003 - C_U*0.2865 + C_C*0.7267 - 1.2734 \qquad R = 0.7147 \tag{12}$$

$$MC\ 6 = G*0 + S*0.2725 + FC*0.2245 - D_{60}*7.1036 + D_{50}*11.646 - D_{30}*10.092 + D_{10}*1.9114 - C_U*0.2694 + C_C*0.7526 - 14.322 \qquad R = 0.7247 \tag{13}$$

$$MC\ 7 = -MDD_S*1.0947 + OMC_S*0.7676 + 2.272 \qquad R = 0.9490 \tag{14}$$

4 Results and Discussion

In the present work, the maximum dry density and optimum moisture content of SPT and MPT have been computed for coarse-grained soil using regression analysis. Also, a comparative study has been mapped between the performance of OMC and MDD models. The performance of developed models for SPT and MPT is computed in terms of root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). The results of OMC and MDD for standard and modified proctor tests are discussed below.

4.1 Prediction of Maximum Dry Density

A total of seven models, MD 1, MD 2, MD 3, MD 4, MD 5, MD 6, and MD 7, have been employed in the present study to predict the maximum dry density of coarse-grained soil for the standard and modified proctor tests. The description of the models is given in Table 3. The common input parameters have been used to predict the maximum dry density of coarse-grained soils, and the test performance of the models has been compared in the present study. Twenty coarse-grained datasets have tested the developed models. However, models MD 1, MD 3 & MD 5 have predicted MDD for SPT, and models MD 2, MD 4 & MD 6 have predicted MDD for MPT. The performance comparison has been drawn between models MD 1, MD 3, MD 5, and MD 2, MD 4, and MD 6, respectively. The performance of the models has been shown in Fig. 3 to Fig. 6.

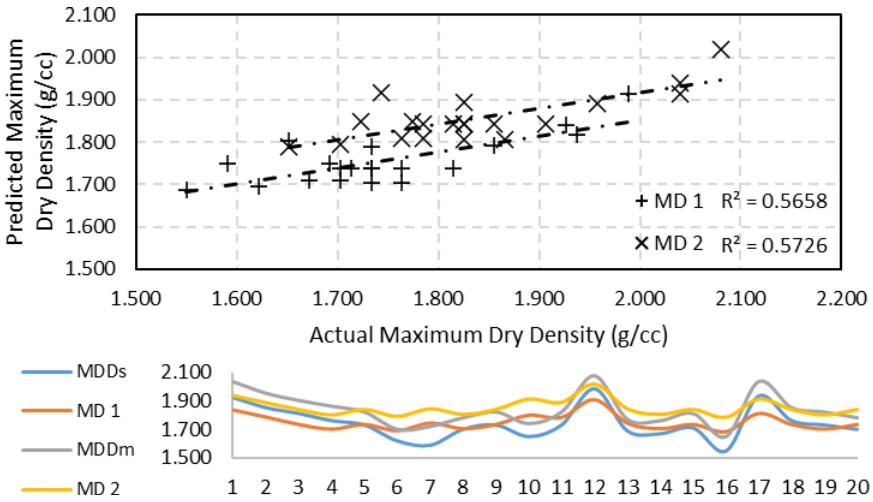

Fig. 3. Comparison of MDD for SPT and MPT using models MD 1 and MD 2

Fig. 3 demonstrates that model MD 1 has predicted MDD for SPT with the RMSE of 0.2297 g/cc, MAE of 0.0514 g/cc, and R of 0.8497 (R^2 of 0.5658). Similarly, model MD 2 has predicted MDD for MPT with the RMSE of 0.1986 g/cc, MAE of 0.0444 g/cc, and R of 0.8793 (R^2 of 0.5726).

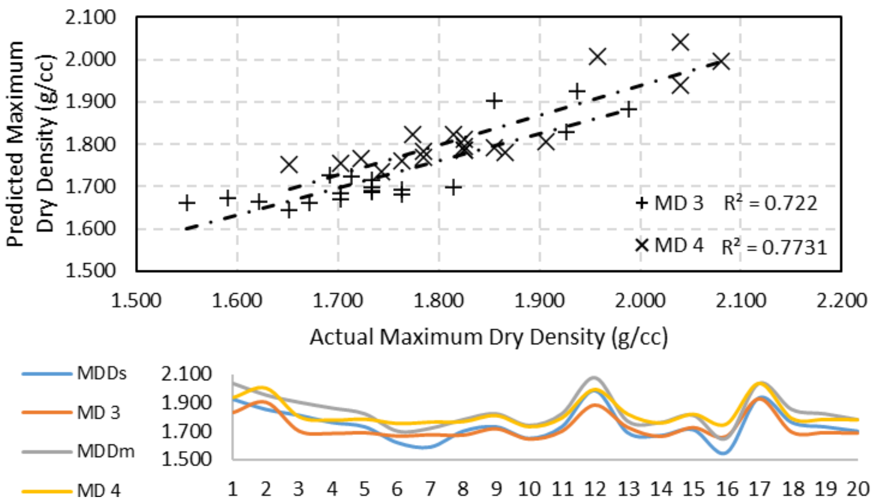

Fig. 4. Comparison of MDD for SPT and MPT using models MD 3 and MD 4

Fig. 4 illustrates that model MD 3 has predicted MDD for SPT with the RMSE of 0.2297 g/cc, MAE of 0.0514 g/cc, and R of 0.8497 (R^2 of 0.722). In addition, model MD 4 has predicted MDD for MPT with the RMSE of 0.1986 g/cc, MAE of 0.0437 g/cc, and R of 0.8793 (R^2 of 0.7731). Furthermore, models MD 5 and MD 6 have been developed using G, S, FC, D_{60}, D_{50}, D_{30}, D_{10}, C_U & C_C and have predicted MDD for SPT and MPT. The results of models MD 5 and MD 6 are shown in Fig. 5.

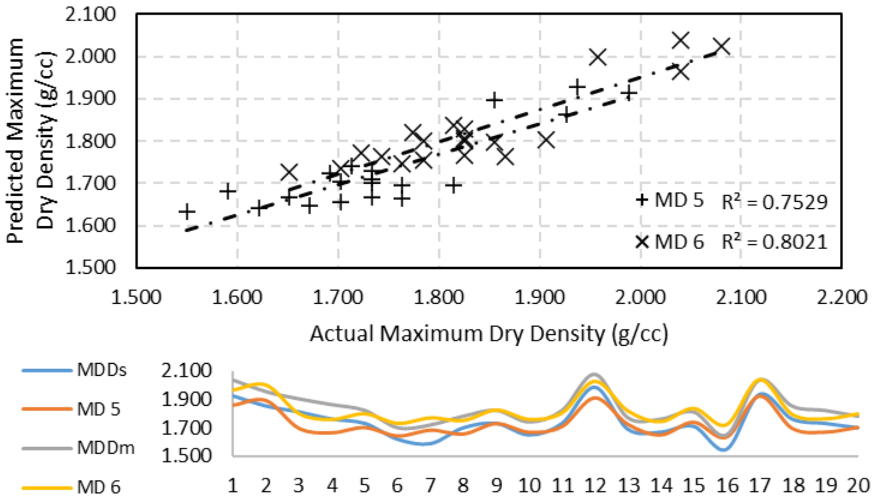

Fig. 5. Comparison of MDD for SPT and MPT using models MD 5 and MD 6

Fig. 5 depicts that model MD 5 has predicted MDD for SPT with the RMSE of 0.2109 g/cc, MAE of 0.0472 g/cc, and R of 0.8677. Similarly, model MD 6 has predicted MDD for MPT with the RMSE of 0.1902 g/cc, MAE of 0.0425 g/cc, and R of 0.8956.

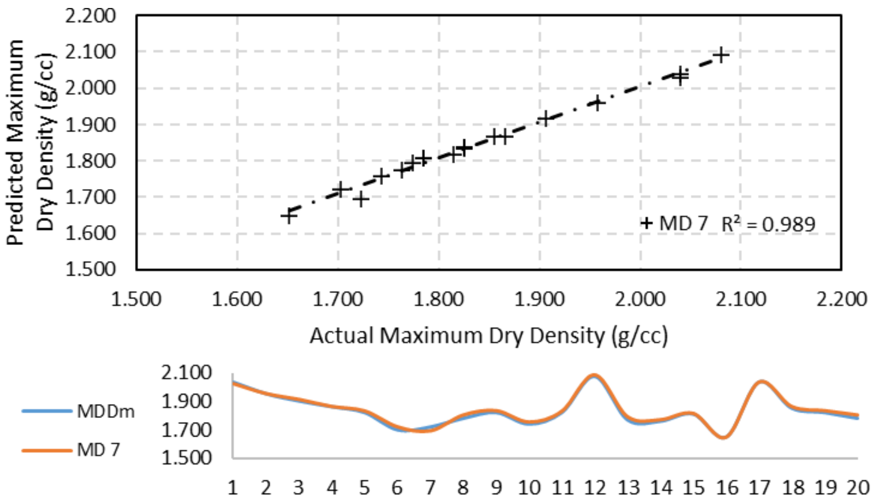

Fig. 6. Comparison of MDD for MPT using model MD 7

Fig. 6 shows that model MD 7 has predicted the maximum dry density for the modified proctor test with the RMSE of 0.01559 g/cc, MAE of 0.0115 g/cc, and R of 0.9945 (R^2 = 0.989). The following points are mapped while predicting the maximum dry density for the standard and modified proctor tests.

- Models MD 1 and MD 2 are developed and trained by the common input parameters (G, S, FC). However, model MD 2 has predicted the MDD for MPT better than model MD 1 (MDD prediction model for SPT). Model MD 2 has predicted maximum dry density with a COD of 0.5726.
- In addition, models MD 3 and MD 4 have been developed and trained by the common input parameters (D_{60}, D_{50}, D_{30}, D_{10}, C_U, C_C). The performance comparison presents that model MD 4 has computed the MDD for MPT with a COD of 0.7731, which is better than model MD 3.
- Furthermore, models MD 5 and MD 6 have been constructed and trained by both input parameters (G, S, FC, D_{60}, D_{50}, D_{30}, D_{10}, C_U, C_C) and found that model MD 6 has outperformed the models MD 5, MD 2, and MD 4 with a COD of 0.8021.
- The performance comparison of models MD 2, MD 4, and MD 6 demonstrate that the number of gradational parameters increases the performance of the regression model. Also, the gradational parameters predict maximum dry density for MPT better than SPT.
- In addition, the standard proctor test compaction parameters (model MD 7) have predicted the MDD for MPT with a COD of 0.989, which is comparatively higher than models MD 2, MD 4, and MD 6.

4.2 Prediction of Optimum Moisture Content

Similarly, seven models (MC 1 to MC 7) have been developed to predict the optimum moisture content for standard and modified proctor tests, and the performance of the models has been compared.

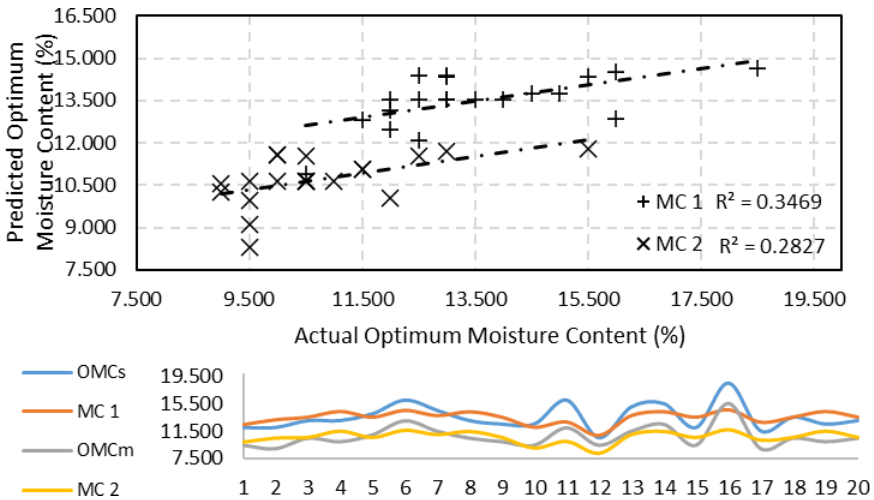

Fig. 7. Comparison of OMC for SPT and MPT using models MC 1 and MC 2

Fig. 7 demonstrates that model MC 1 has predicted OMC for SPT with the RMSE of 5.3959%, MAE of 1.2066%, and R of 0.589 (R^2 of 0.3469). Similarly, model MC 2 has predicted OMC for MPT with the RMSE of 4.5707%, MAE of 1.022%, and R of 0.5317 (R^2 of 0.2827).

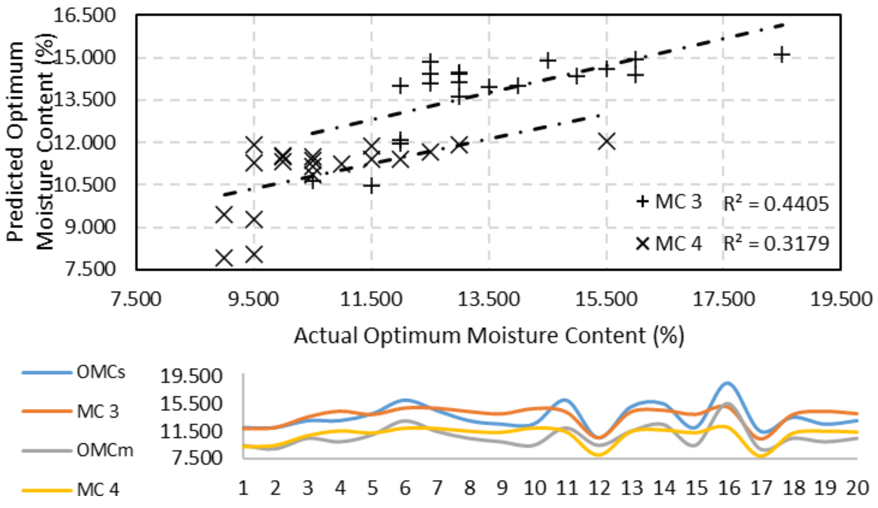

Fig. 8. Comparison of OMC for SPT and MPT using models MC 3 and MC 4

Fig. 8 illustrates that model MC 3 has predicted OMC for SPT with the RMSE of 5.007%, MAE of 1.1196%, and R of 0.6637 (R^2 of 0.4405). Similarly, model MC 4 has predicted OMC for MPT with the RMSE of 4.7575%, MAE of 1.0638%, and R of 0.5639 (R^2 of 0.3179).

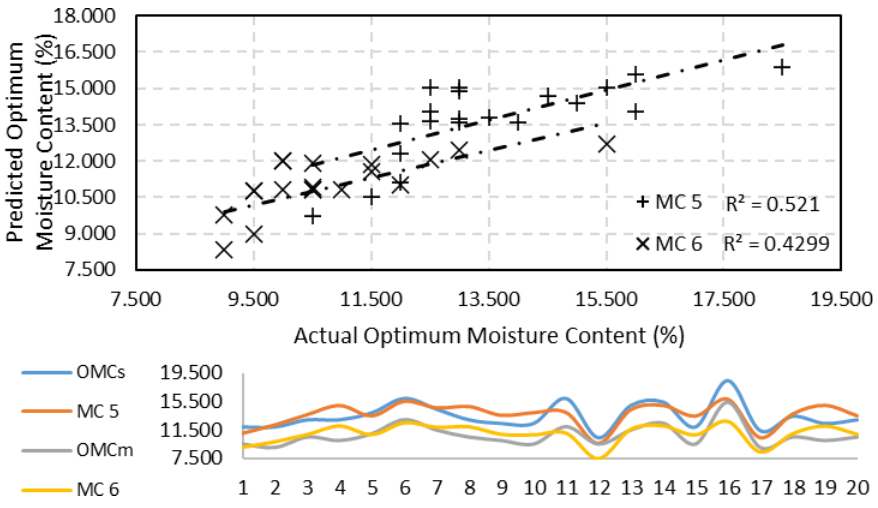

Fig. 9. Comparison of OMC for SPT and MPT using models MC 5 and MC 6

Fig. 9 shows that model MC 5 has predicted OMC for SPT with the RMSE of 4.8874%, MAE of 1.0928%, and R of 0.7218 (R^2 of 0.5210). Similarly, model MC 6 has predicted OMC for MPT with the RMSE of 4.3153%, MAE of 0.9649%, and R of 0.6557 (R^2 of 0.4299).

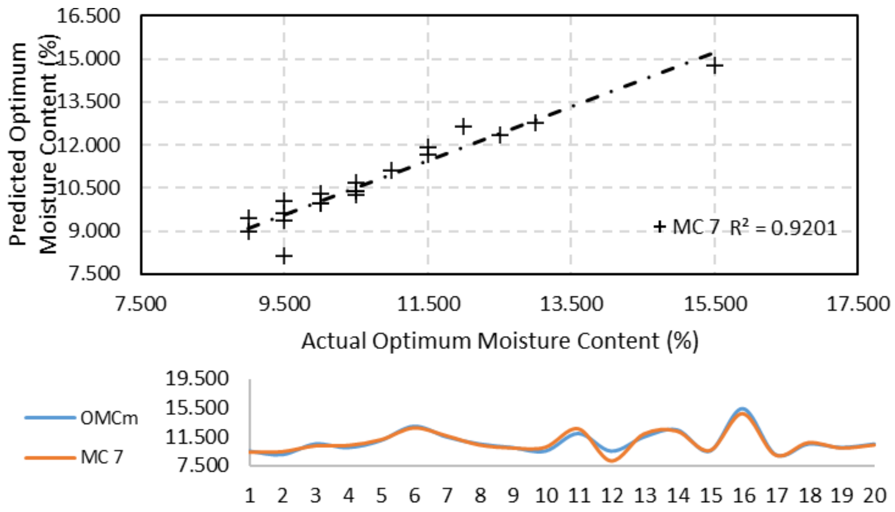

Fig. 10. Comparison of OMC for MPT using models MC 7

Fig. 10 illustrates that model MC 7 has predicted OMC for MPT with the RMSE of 1.3717%, MAE of 0.3067%, and R of 0.9592 (R^2 of 0.9201). Furthermore, the following observations have been made in comparing the performance of models MC 1 to MC 7.

- The performance comparison shows that model MC 1 has predicted OMC for SPT with a COD of 0.3469, which is comparatively higher than model MC 2.
- In addition, model MC 3 has outperformed model MC 4 in predicting OMC for SPT with a COD of 0.4405.
- Moreover, model MC 5 predicts OMC for SPT with a COD of 0.521, comparatively better than MC 6.
- The performance comparison shows that the number of gradational parameters increases the performance and prediction of models. Model MC 1 has been developed using G, S, FC, and model MC 3 has been constructed using D_{60}, D_{50}, D_{30}, D_{10}, C_U, and C_C. In addition, model MC 5 has been designed using G, S, FC, D_{60}, D_{50}, D_{30}, D_{10}, C_U & C_C and achieved higher performance (COD) than models MC 1 and MC 3.
- On the other hand, model MC 7 has been employed using the standard proctor test compaction parameters. Model MC 7 has predicted OMC for MPT with a COD of 0.9201, which is comparatively higher than models MC 1, MC 3, and MC 5.
- The standard proctor test compaction parameters are strongly related to modified proctor test compaction parameters.

5 Sensitivity Analysis

In the present work, the nonlinear sensitivity analysis has been performed using the Cosine Amplitude Sensitivity Analysis (CASA). The following equation is used to determine the sensitivity analysis for input parameters and compaction parameters of SPT and MPT (Ardakani et al., 2017).

$$SS = \frac{\sum_{c=1}^{n}(X_{ic} * X_{jk})}{\sqrt{\sum_{c=1}^{n} X_{ic}^2 \sum_{c=1}^{n} X_{jk}^2}} \tag{15}$$

Where X_{ic} is input parameters G, S, FC, D_{60}, D_{50}, D_{30}, D_{10}, C_U & C_C, and X_{jk} is output parameter MDD_M, MDD_S, OMC_M, and OMC_S of coarse-grained soil. The value near 1 shows the strong relationship between the pair of datasets. The sensitivity for compaction parameters of SPT and MPT Using equation 15 is shown in Fig. 11.

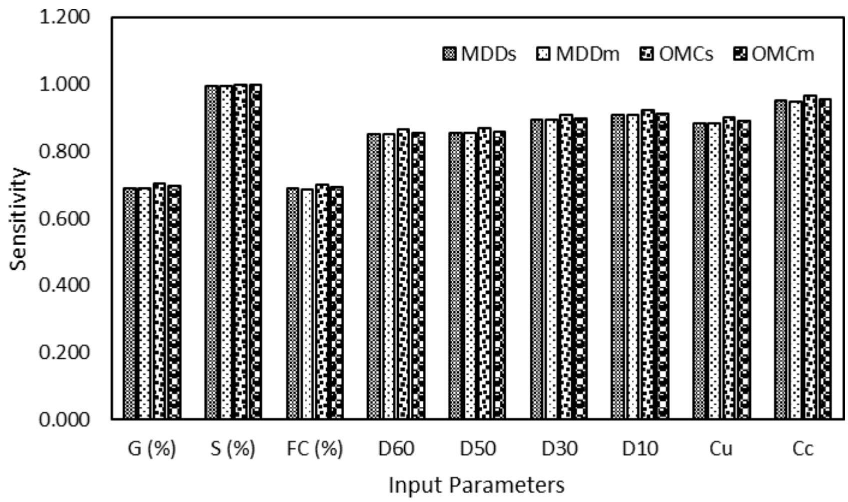

Fig. 11. Cosine amplitude sensitivity analysis for SPT and MPT parameters

Fig. 11 illustrates that the coefficient of curvature and sand content are the most influencing input parameters in predicting the compaction parameters of coarse-grained soil using SPT and MPT. Also, Fig. 11 demonstrates that input parameters D_{60}, D_{50}, D_{30}, D_{10}, C_U, and C_C are less influencing factors than sand content.

6 Model Implication

The sensitivity analysis reveals that the coefficient of curvature and sand content influence the prediction of the compaction parameters for SPT and MPT. Therefore, nomographs have been drawn to directly predict SPT and MPT compaction parameters for coarse-grained soil with more than 50% sand content. Fig. 12, 13, 14, and 15 are the nomographs for predicting MDD_S, OMC_S, MDD_M, and OMC_M directly, respectively.

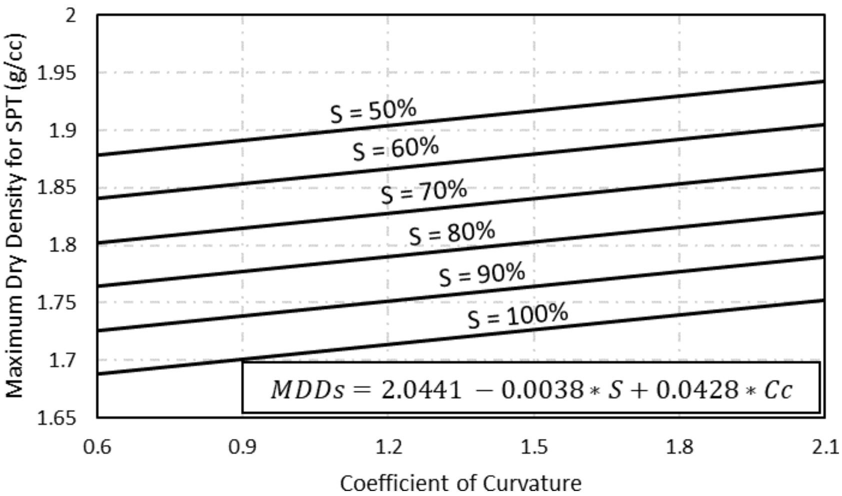

Fig. 12. Nomograph for predicting MDD of SPT

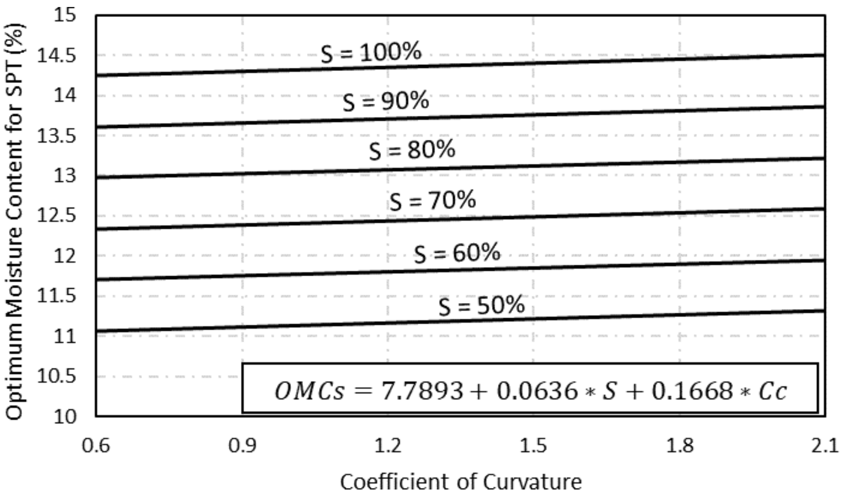

Fig. 13. Nomograph for predicting OMC of SPT

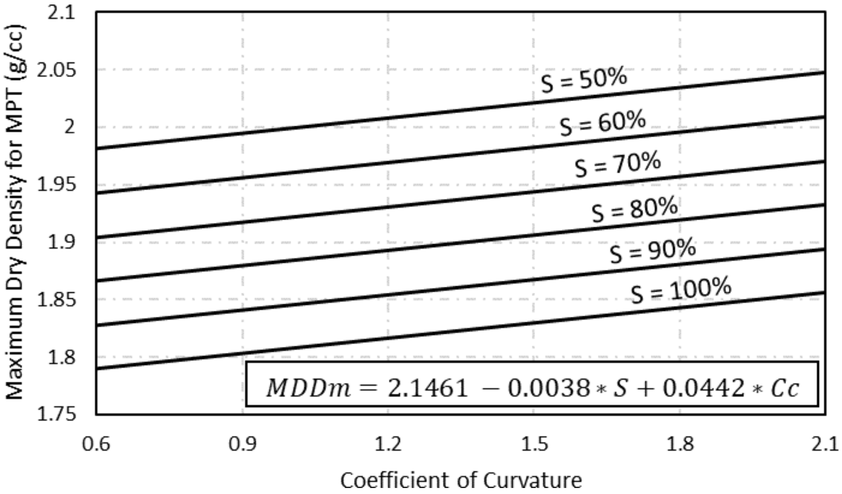

Fig. 14. Nomograph for predicting MDD of MPT

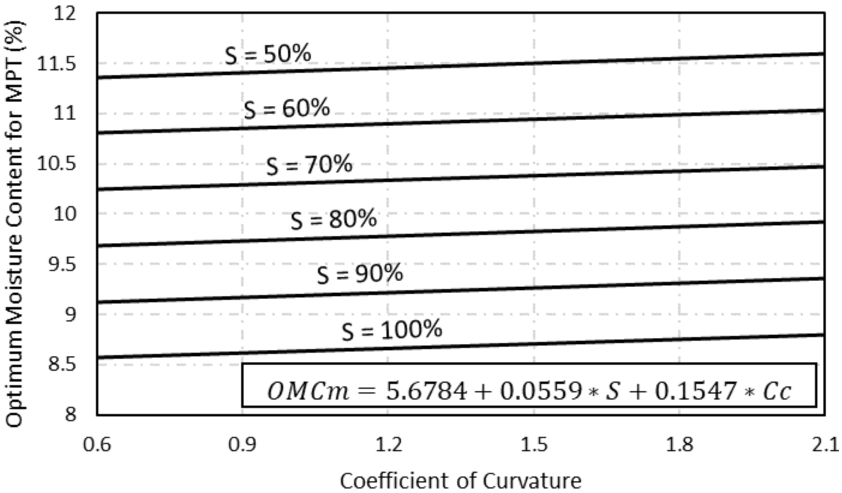

Fig. 15. Nomograph for predicting OMC of MPT

7 Conclusions

The present research demonstrates the relationship between gradational parameters and compaction parameters. The compaction parameters of SPT and MPT have been predicted using the gradational parameters. The following conclusions are mapped as per the outcomes of the present research –

- Pearson's product-moment correlation coefficient demonstrates that the MDD and OMC of both proctor tests are very strongly (1.0>R<0.81)) and moderately (0.6>R<0.41) related to the uniformity coefficient.
- The gradational parameters predict the maximum dry density for the modified proctor test better than MDD for the standard proctor test. Furthermore, the regression models' performance has increased with increasing input parameters. The performance of models MD 5 and MD 6 is more than models MD 1, MD 2, MD 3, and MD 4. However, the models MD 5 and MD 6 have been developed using G, S, FC, D_{60}, D_{50}, D_{30}, D_{10}, C_U, and C_C.
- On the other hand, the gradational parameters predict the optimum moisture content for the standard proctor test better than OMC for the modified proctor test. The optimum moisture content models MC 5 and MC 6 have outperformed the other models.
- The compaction parameters of the standard proctor test are highly related to the compaction parameters of the modified proctor test. Therefore, models MD 7 and MC 7 have predicted the OMC and MDD for the modified proctor test with a correlation coefficient of more than 0.95.
- The sensitivity analysis reports that the sand content, D_{60}, D_{50}, D_{30}, D_{10}, C_U, and C_C parameters influence the compaction parameters of SPT and MPT. The comparative study of sensitivity analysis for input parameters demonstrates that the sand content and coefficient of curvature are the most impacting parameters than the other input parameters.
- The proposed nomograph for MPT and SPT can be used directly to predict the maximum dry density and optimum moisture content of coarse-grained soil.

Finally, the present research concludes that a better prediction of OMC and MDD of the modified proctor test can be achieved using compaction parameters of the standard proctor test instead of gradational parameters.

Abbreviations & Notations

G – Gravel Content
S – Sand Content
FC – Fine Content
D_{60} – Particle Size at 60% Passing
D_{50} – Particle Size at 50% Passing
D_{30} – Particle Size at 30% Passing
D_{10} – Particle Size at 10% Passing
CU – Coefficient of Uniformity
CC – Coefficient of Curvature
LM – Levenberg-Marquardt Algorithm
BR – Bayesian Regulation Algorithm
GDA – Gradient Descent with Adaptive Learning Algorithm
RP – Resilient
GMD – Gradient Descent with Momentum
CBR – California Bearing Ratio
GEP – Gene Expression Programming
SVM – Support Vector Machine
R – Coefficient of Correlation
LL – Liquid limit
PI – Plasticity Index
PL – Plastic Limit
CL – Confidence Level at 95%
MD – Model
SPT – Standard Proctor Test
MPT – Modified Proctor Test
MEP – Multivariate Expression Programming
RMSE – Root Mean Square Error
GMDH – Group Method of Data Handling

ANN – Artificial Neural Networks	MDD_M – MDD for MPT
R^2/ COD – Coefficient of Determination	OMC_M – OMC for MPT
OMC – Optimum Moisture Content	MDD_S – MDD for SPT
MDD – Maximum Dry Density	OMC_S – OMC for SPT
OEM – Optimizable Ensemble Method	MAE – Mean Absolute Error
MD - Model	

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