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Kasinathan Muthukkumaran
R. Ayothiraman
Sreevalsa Kolathayar *Editors*

Soil Dynamics, Earthquake and Computational Geotechnical Engineering

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Editors

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Preface

The Indian Geotechnical Society, Trichy (IGS-Trichy) Chapter, and National Institute of Technology (NIT), Tiruchirappalli, India, organized the Indian Geotechnical Conference (IGC-2021) at Trichy during 16–18 December 2021. The main theme of the conference was **"GEO–INDIA"**—**GEO**TECHNICS FOR **IN**FRASTRUCTURE **D**EVELOPMENT AND **I**NNOVATIVE **A**PPLICATIONS.

The sub-themes of the conference included:

1. Soil Behaviour and Characterization of Geomaterials
2. Geotechnical, Geological and Geophysical Investigation
3. Foundation Engineering
4. Ground Improvement Techniques
5. Geo-Environmental Engineering
6. Soil Dynamics and Earthquake Geotechnical Engineering
7. Earth Retaining Structures, Dams and Embankments
8. Slope Stability and Landslides
9. Transportation Geotechnics
10. Geosynthetics Application
11. Computational, Analytical and Numerical Modelling
12. Rock Engineering, Tunnelling, Deep Excavations and Underground Constructions
13. Forensic Geotechnical Engineering and Case Studies
14. Others: Behaviour of Unsaturated Soils, Offshore & Marine Geotechnics, Remote Sensing & GIS, Instrumentation & Monitoring, Retrofitting of Geotechnical Structures, Reliability in Geotechnical Engineering, Geotechnical Education, Codes & Standards, & any other relevant topic.

The proceedings of this conference consists of selected papers presented at the conference. The proceedings are divided into six volumes. A special issue on IGC-2021 keynote and theme lecture presentations were published by Indian Geotechnical Journal.

We sincerely thank all the authors who have contributed their papers to the conference proceedings. We also thank all the theme editors and reviewers who have been instrumental in giving their valuable inputs for improving the quality of the final papers. We greatly appreciate and thank all the student volunteers for their unwavering support that was instrumental in preparation of this proceedings. Finally, thanks to the Springer team for their support and full cooperation for publishing six volumes of this IGC-2021 proceedings.

Trichy, India

Kasinathan Muthukkumaran
Chairman

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About the Editors

Dr. Kasinathan Muthukkumaran is currently Professor in Civil Engineering at National Institute of Technology, Tiruchirappalli, India. He obtained Ph.D. in Soil-Structure Interaction and Marine Geotechnical Engineering from Indian Institute Technology Madras. He has published more than 150 papers in international and national journals and conferences. He has completed 5 R&D (including ISRO—**Chandrayaan-2 Mission project**) and 70 major consultancy projects in Geotechnical Engineering and published two patent including **"Moon Soil"** (A Method for Manufacture of Highland Lunar Soil Simulant). He has guided 10 Ph.D. scholars and 6 more are in progress, 5 MS (by research) and more than 40 M.Tech. students in Geotechnical and allied research areas. He is the **Founder Chairman** of Indian Geotechnical Society (IGS-Trichy) Trichy Chapter. He is a member of Technical Committee (TC-301 on **"Preservation of Historic Sites"**) of International Society for Soil Mechanics and Geotechnical Engineering. Prof. Muthukkumaran area of research is in geotechnical engineering, which includes pile foundation, soil-structure interaction, marine geotechnics and foundations, field instrumentation, geotechnical physical modeling, ground improvement and forensic geotechnical engineering. He has received DST Young Scientist Award, IGS-Smt. Indra Joshi Biennial Award and Keynote Paper Award—GEOMATE Conference 2015 at Osaka, Japan. He is an Associate Editor of *Australian Journal of Civil Engineering and Serving* editorial board member of several journals. Prof. Muthukkumaran has significant administrative contribution as Estate Officer, Associate Dean (Planning and Development), Member of Buildings and Works Committee and Member of **Board of Governors (BoG)** of National Institute of Technology, Tiruchirappalli and Member of Buildings and Works Committee, IIM Trichy. He has received **NIT Trichy Achiever Awards** for research publications, research projects, maximum citation and consultancy projects.

Dr. R. Ayothiraman is currently working as Professor in the Department of Civil Engineering, Indian Institute of Technology (IIT) Delhi. He completed his Graduation in Civil Engineering from Madurai Kamaraj University in April 1998 and Post-Graduation from College of Engineering Guindy in 2000 with Gold Medal. He obtained his Ph.D. in the area of Soil Dynamics from IIT Madras in 2005. His areas of research interest include soil dynamics, pile foundations, tunnelling in soils and rocks and ground improvement. He has published about 95 papers in reputed journals and conferences. He supervised nine Ph.D. theses and is currently supervising 13 Ph.D. research scholars, in addition to the supervision of about 85 M.Tech./B.Tech. students. He is a recipient of Young Engineer Award from IEI and DST and DAAD Fellowship. He has actively participated in organizing several short courses, workshops and national/international conferences. He has delivered invited lectures at many short courses, workshops, seminars and conferences. He is a member of several professional societies and reviewer of several reputed international and national journals. He is also serving as member of BIS for revising National Building Code and Codes related to machine foundation. He has been a consultant in providing technical advice for several metro projects including Delhi Metro, Kolkata Metro and Lucknow metro and several other projects of national importance.

Dr. Sreevalsa Kolathayar pursued M.Tech. from Indian Institute of Technology (IIT) Kanpur, Ph.D. from Indian Institute of Science (IISc) and served as International Research Staff at UPC Barcelona Tech Spain. He is presently Assistant Professor in the Department of Civil Engineering, National Institute of Technology (NIT) Karnataka, Surathkal, India. Dr. Sreevalsa has authored five books, edited 12 books and published over 80 research papers. He is associate editor of two international journals and acted as a reviewer for many. His research interests include ground motion attenuation and seismic hazard assessment, local site effects and liquefaction susceptibility, pseudo-dynamic approach for seismic loading, disaster risk reduction, geogrids and geocells and water geotechnics. He is currently the Secretary Indian chapter of International Association for Coastal Reservoir Research (IACRR) and Executive Committee Member of Indian Society of Earthquake Technology. In 2017, The New Indian Express honoured Dr. Sreevalsa with South India's Most Inspiring Young Teachers Award. He is the recipient of ISET D. K. Paul Research Award from Indian Society of Earthquake Technology in 2018. He is in the roster of two technical committees of ASCE Geo-Institute. He received "IEI Young Engineers Award" by The Institution of Engineers (India), in recognition of his contributions in the field of Civil Engineering. Recently, Dr. Sreevalsa was featured by the American Society of Civil Engineers in their Geostrata Magazine.

Chapter 1
Evaluation of Compactive Parameters of Soil Using Machine Learning

Jitendra Khatti and Kamaldeep Singh Grover

Introduction

The surface and subsurface of the earth are formed by soil and rocks. These soils are classified by engineering properties and index properties of soil. The compressibility, permeability, and strength properties are engineering properties of soil. The engineering properties is determined using laboratory and field methods. The maximum dry density and optimum moisture content are the most important engineering properties of soil, and these are determined using standard proctor test and modified proctor test [8]. The optimum moisture content and maximum dry density are the compaction parameters. The experimental procedure for determining the compaction parameters is a tedious and time-consuming task, and it also requires human resources.

Escaping from the tedious and time-consuming process, numerous researchers and scientists evolved different methods and methodologies to determine or predict soil parameters. The authors proposed MEP models to predict the OMC and MDD of soil, and authors predicted OMC and MDD with 0.9607 and 0.9263, respectively [10]. The investigators developed a regression model using SVM [6]. The investigators concluded that the proposed models predicted OMC and MDD with 0.9237 and 0.9487, respectively. The authors suggested that the AI approaches can be used to predict the OMC and MDD for modified and standard proctor tests [20]. The researchers evolved ANN models to predict the OMC and MDD of soil and reported that the performance of NN 10-5-1 OMC and NN 10-7-1 MDD model was 0.8855 and 0.9754, respectively [1]. The authors proposed a model to predict the dry density using the thermal conductivity of the soil [15]. The authors concluded that

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the proposed model is able to predict the dry density with 0.9923 performance. The authors stated that the genetic algorithm approach is able to predict the MDD of soil [15]. The researchers developed ANN models to predict MDD and UCS [18] and reported that the BRNN, DENN, LMNN, SVM, FN, MARS, MLR models predicted MDD with 0.84, 0.88, 0.76, 0.93, 0.92, 0.94, and 0.45 performance. The authors evolved regression and ANN models. The performance of models was compared, and it was concluded that the CFB-10 predicted OMC and MDD with 0.9323 and 0.9263, respectively [2]. The authors evolved ANN models to predict the compaction parameters and reported that the evolved ANN models predicted OMC and MDD with 0.92 and 0.91 performance [12]. The investigators proposed a MARS model to predict the compaction parameters of coarse-grained soil [19]. The authors concluded that the performance of OMC and MDD models was 0.9381 and 0.9000 and that is more acceptable to previous models. The authors proposed MLR models to predict the OMC and MDD of soil [13]. The authors reported that the proposed MLR models have the potential to predict the OMC and MDD of soil. The author evolved the regression model to predict the OMC and MDD of soil using index properties [14]. The authors concluded that the MLR analysis provides reliable results. Many authors and researchers stated that the artificial intelligence approaches required fewer human resources and it is less time-consuming [3, 4, 7, 11, 16, 17]. It was also concluded that the AI approaches give reliable results of OMC and MDD of soil. From the literature study, it has been observed that the authors used different numbers of data for predicting OMC and MDD of soil. The MLR and ANN models have not been compared for same datasets. Hence, the optimum performance AI models is still doubtable.

Problem Statement

The present study has the following aims:

- Develop the artificial neural network models using different hyperparameters and determine the best performance ANN model.
- Draw the comparison between the best architecture ANN model and regression model to determine the optimum performance AI models.
- Map the comparison between the optimum performance AI models with published models in literature study.
- Predict the OMC and MDD of soil using the optimum performance AI models.

Methodology

Regression analysis and artificial neural network approaches have been used to predict the compaction parameters of the soil in this work. The detail of regression analysis and artificial neural network is given below.

Detail of Multilinear Regression Analysis

Regression analysis is a traditional method of prediction or forecasting of data. Regression analysis is two types; one is simple regression analysis, and the second is multiple regression analysis. The relationship is drawn between the one input and output variable in the simple regression analysis. The proposed relationship gives an equation to predict the output variable by input variable. In multiple regression analysis, the input and output variables are more than one, and the input variables with respect to output variables propose an equation. The simple regression analysis and multiple regression analysis are based on the linear or nonlinear approaches.

The multilinear regression (MLR) analysis has been performed in the present research work to evaluate the compaction parameters of soil. The fine content (FC), sand content (SC), specific gravity (SG), liquid limit (LL), and plasticity index (PI) have been used to develop the MLR models to predict the OMC and MDD of soil. The MLR_OMC and MLR_MDD models have been developed using the data analysis tool of Microsoft Excel 2019. An equation has been proposed by MLR_OMC and MLR_MDD model to predict the optimum moisture content and maximum dry density of soil, as written in Eqs. 1.1 and 1.2.

$$\begin{aligned} \mathrm{OMC}' = {} & 15.992 + 0.0243 * \mathrm{FC} - 0.083 * \mathrm{S} - 2.102 * \mathrm{SG} \\ & + 0.2508 * \mathrm{LL} - 0.071 * \mathrm{PI} \end{aligned} \tag{1.1}$$

$$\begin{aligned} \mathrm{MDD}' = {} & 1.725 - 0.002 * \mathrm{FC} + 0.0018 * \mathrm{S} + 0.0596 * \mathrm{SG} \\ & - 0.005 * \mathrm{LL} + 0.0058 * \mathrm{PI} \end{aligned} \tag{1.2}$$

where OMC′ and MDD′ are the predicted optimum moisture content and maximum dry density of 19 soil specimens.

Detail of Artificial Neural Network

An artificial neural network is an approach to machine learning techniques, and the machine learning techniques are a subset of artificial intelligence. The artificial neural network is nothing, but it is a network of different layers. The artificial neural network consists of an input layer, hidden layer(s), and output layer. Neurons connect these layers and transmit the information from one layer to another layer. The hidden layer(s) consists of activation function and bias. Similarly, the output layer consists of an activation function. These activation functions can be linear or nonlinear.

The multilayer perceptron (MLP) class-based artificial neural network models have been developed with different hidden layers and neurons in the present research work using MATLAB R2020a. The number of hidden layers has been selected in

Table 1.1 Hyperparameters of ANN models

Hyperparameters	Value
Hidden layers	One, two, three, four, five
Neurons	Two to eleven
Backpropagation algorithm(s)	Levenbergs–Marquardt
Normalizing function(s)	Min–max for input and log for output parameters
Activation function(s)	Sigmoid at hidden layers, Linear at the output layer
Train: Validation ratio	70: 30
Epochs	1000 (default)
Network type	Feed-forward backpropagation
Network class	Multilayer perceptron class (MLP)
Mu	0.001
Max fail	6
Min gradient	10e−7

Table 1.2 Architecture of ANN models

Model	Architecture	Remarks
Optimum moisture content	ANN_OMC_XHY	Where X, Y is the number of hidden layers and neurons
Maximum dry density	ANN_MDD_XHY	

the range of one to five with two to eleven neurons. The hyperparameters of artificial neural network models are given in Table 1.1.

A total of one hundred artificial neural network models have been developed to predict the OMC and MDD of soil. Fifty NN models of OMC and fifty NN models of MDD have been developed. The architecture of NN models of OMC and MDD is given in Table 1.2.

Data Analysis

In the present research work, 53 datasets have been used to develop the AI models and predict the compactive parameters of soil. The experiments were performed in the geotechnical laboratory to obtain these datasets. The tests of specific gravity, consistency limits, standard proctor test were performed as per IS 2720: 1980 (P-3), IS 2720: 1985 (P-5), and IS 2720: 1980 (P-7), respectively. The consistency limits of soil are liquid limit, plastic limit, and plasticity index, and standard proctor test is performed to determine the OMC and MDD of soil.

Dataset of Soil

A total of 53 datasets of soil have been used to carry out the present research work. The datasets consist of fine-grain content (FC), sand content (SC), specific gravity (SG), liquid limit (LL), plasticity index (PI), maximum dry density (MDD), and optimum moisture content (OMC). The datasets of soil are given in Table 1.3.

Statistics of Dataset of Soil

The statistics of datasets of soil have been mapped using the data analysis tool of Microsoft Excel 2019. The statistical parameters such as minima, maxima, mean, median, standard deviation, and confidence level (95%) of soil datasets have been calculated as shown in Table 1.4.

The sand content, fine content, LL, and PI affect the compaction parameters of soil. The correlation coefficient method has been used to map the relationship between input parameters (sand content, fine content, LL, and PI) with compaction parameters. The relationship between input parameters and compaction parameters of soil has been drawn in the form of Pearson matrix, as given in Table 1.5.

The coefficient of correlation of sand content, fine content, specific gravity, liquid limit, plasticity index with optimum moisture content is 0.96, 0.86, 0.31, 0.96, and 0.68. Similarly, the correlation coefficient of sand content, fine content, specific gravity, liquid limit, plasticity index with maximum dry density is 0.92, 0.92, 0.31, 0.91, and 0.54. The relationship between input and output parameters is shown in Fig. 1.1.

From Fig. 1.1, it has been observed that the fine content, sand content, liquid limit have strong correlation with OMC and MDD. The specific gravity and plasticity index have good correlation with OMC and MDD [9].

Training and Testing Datasets

Regression analysis and artificial neural network models have been developed to predict the compaction parameters of the soil. The linear approach has been used to develop regression models. Thirty-four datasets of soil have been used to train the proposed MLR and ANN models, and the rest of the datasets have been used to test the proposed models. These thirty-four soil datasets have been subdivided into 70 and 30% to train and validate the ANN models.

Table 1.3 Datasets of soil

S. No	FG (%)	S (%)	SG	LL (%)	PI (%)	OMC (%)	MDD (gm/cc)
1	87.00	13.00	2.62	46.80	18.43	22.79	1.58
2	4.00	96.00	2.71	26.40	9.29	8.09	1.97
3	0.00	82.00	2.70	26.86	11.59	8.75	2.01
4	37.00	25.00	2.62	38.57	15.68	19.35	1.74
5	18.00	82.00	2.69	26.07	12.07	10.12	1.93
6	5.00	95.00	2.71	26.26	9.18	8.21	1.96
7	16.00	84.00	2.70	25.74	11.10	9.89	1.94
8	17.20	70.40	2.69	28.45	17.86	10.90	1.95
9	35.17	60.88	2.53	28.61	10.87	11.94	1.85
10	13.04	68.84	2.69	28.62	18.09	11.20	1.94
11	8.39	72.87	2.69	28.26	15.25	10.22	1.96
12	0.80	97.46	2.70	26.46	9.80	7.61	1.98
13	72.00	28.00	2.64	38.29	15.12	16.73	1.72
14	28.00	63.00	2.53	28.84	13.19	11.85	1.89
15	42.00	55.00	2.65	28.23	10.62	12.28	1.81
16	15.00	85.00	2.70	25.63	10.63	9.76	1.94
17	27.00	34.00	2.58	32.41	15.92	15.80	1.81
18	60.00	40.00	2.73	32.98	12.46	15.21	1.76
19	8.00	92.00	2.71	25.88	9.02	8.65	1.96
20	9.00	78.00	2.70	27.23	13.32	9.34	1.99
21	100.00	0.00	2.65	54.18	22.08	24.72	1.53
22	52.00	30.00	2.80	35.51	13.91	17.35	1.73
23	85.00	15.00	2.62	45.81	18.04	21.99	1.60
24	39.00	35.00	2.64	32.05	12.94	16.02	1.80
25	6.00	20.00	2.73	42.04	30.90	15.02	1.94
26	21.00	31.00	2.65	34.39	21.84	15.67	1.79
27	44.00	50.00	2.71	28.59	10.93	12.46	1.80
28	2.00	98.00	2.71	26.71	9.56	7.91	1.97
29	14.00	86.00	2.71	25.57	10.21	9.62	1.94
30	15.00	84.00	2.70	25.77	11.11	9.66	1.95
31	0.00	100.00	2.70	27.06	9.85	7.81	1.97
32	10.00	88.00	2.71	25.66	9.69	8.83	1.97
33	21.00	35.00	2.64	32.38	19.15	15.34	1.81
34	3.00	94.00	2.70	26.09	9.64	7.74	1.99
35	97.00	3.00	2.65	52.42	21.36	24.63	1.54
36	15.00	64.00	2.69	28.95	19.79	12.49	1.91

(continued)

Table 1.3 (continued)

S. No	FG (%)	S (%)	SG	LL (%)	PI (%)	OMC (%)	MDD (gm/cc)
37	19.00	81.00	2.69	26.28	12.51	10.22	1.93
38	65.00	34.00	2.67	34.67	13.53	15.74	1.76
39	3.00	66.00	2.69	29.22	16.50	11.41	1.88
40	5.00	65.00	2.69	29.16	17.49	11.74	1.89
41	29.00	21.00	2.63	41.40	23.00	19.59	1.71
42	26.00	16.00	2.68	45.11	19.00	21.83	1.70
43	31.00	60.00	2.52	28.88	11.69	12.09	1.87
44	14.00	43.00	2.79	30.45	19.90	14.44	1.83
45	24.40	65.20	2.59	28.81	15.82	11.72	1.91
46	9.70	88.70	2.71	25.65	9.41	8.89	1.96
47	99.00	1.00	2.65	53.61	21.87	24.70	1.54
48	84.00	16.00	2.62	45.33	17.86	21.54	1.60
49	75.00	25.00	2.63	40.40	15.92	17.53	1.69
50	11.00	88.00	2.71	25.61	9.62	9.06	1.96
51	9.00	79.00	2.70	27.01	12.89	9.20	1.99
52	5.00	58.00	2.69	29.38	19.77	12.81	1.84
53	60.00	30.00	2.76	35.91	14.20	16.32	1.71

Table 1.4 Statistics of datasets of soil

Statistical parameters	FG (%)	S (%)	SG	LL (%)	PI (%)	OMC (%)	MDD (gm/cc)
Min	0.00	0.00	2.52	25.57	9.02	7.61	1.53
Max	100.00	100.00	2.80	54.18	30.90	24.72	2.01
Mean	30.11	56.46	2.67	32.39	14.74	13.49	1.84
Median	18.00	63.00	2.69	28.84	13.53	11.94	1.89
St. deviation	29.25	30.06	0.06	7.96	4.70	4.95	0.14
Confi. level (95%)	8.06	8.28	0.02	2.19	1.30	1.37	0.04

Table 1.5 Pearson matrix of datasets of soil

(r)	FG (%)	S (%)	SG	LL (%)	PI (%)	OMC (%)	MDD (gm/cc)
FG (%)	1.0000						
S (%)	0.6558	1.0000					
SG	0.3275	0.3024	1.0000				
LL (%)	0.8324	0.9075	0.2639	1.0000			
PI (%)	0.3513	0.7408	0.1222	0.7001	1.0000		
OMC (%)	0.8573	0.9643	0.3098	0.9598	0.6801	1.0000	
MDD (gm/cc)	0.9248	0.9208	0.3136	0.9161	0.5368	0.9666	1.0000

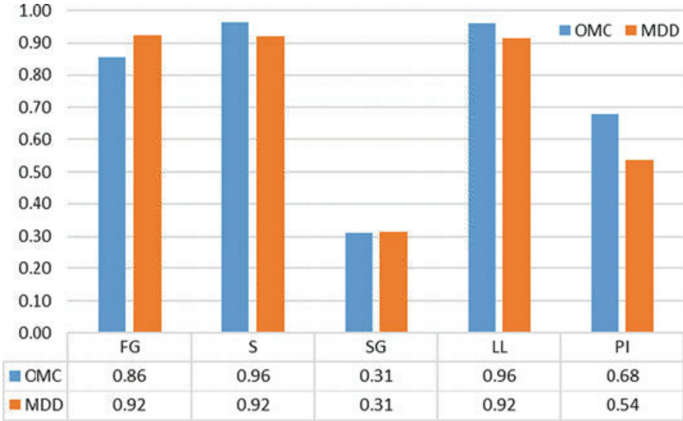


Fig. 1.1 Relationship (r) between input and output parameters

Results and Discussion

The performance and results of multilinear regression analysis and artificial neural network models has been discussed in this section. The RMSE, R, and MAE have determined the performance of the proposed models using the following formulas:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(T_i - P_i)^2} \tag{1.3}$$

$$\mathrm{MAE} = \frac{1}{N}\left(\sum_{i=1}^{N}\mathrm{abs}(T_i - P)_i\right) \tag{1.4}$$

$$R = \frac{\sum_{i=1}^{N}\left(T_i - \overline{T}\right)\left(P_i - \overline{P}\right)}{\sqrt{\sum_{i=1}^{N}\left(T_i - \overline{T}\right)^2 \sum_{i=1}^{N}\left(P_i - \overline{P}\right)^2}} \tag{1.5}$$

Multilinear Regression Analysis

The MLR_OMC and MLR_MDD models have been developed to predict the optimum moisture content and maximum dry density of soil specimens. Equations 1.1 and 1.2 have been proposed by MLR_OMC and MLR_MDD models and used for predicting OMC and MDD of soil. The training and testing performances of MLR_OMC and MLR_MDD models have been recorded and given in Table 1.6.

Table 1.6 Performance of MLR_OMC and MLR_MDD models

Model architecture	Training performance			Testing performance		
	RMSE	*R*	MAE	RMSE	*R*	MAE
MLR_OMC	0.7532	0.9888	0.6023	1.1132	0.9763	0.8384
MLR_MDD	0.0226	0.9866	0.0164	0.0500	0.9456	0.0376

Artificial Neural Network

The ANN_OMC_XHY and ANN_MDD_XHY models have been developed to predict the optimum moisture content and maximum dry density of soil specimens. The artificial neural network models have been developed with the different numbers of hidden layers and neurons. The ANN_OMC_1H8, ANN_OMC_2H6, ANN_OMC_3H8, ANN_OMC_4H9, and ANN_OMC_5H3 models of one, two, three, four, and five hidden layers for optimum moisture content have been identified as the best architecture neural network models. The performance of artificial neural network models for optimum moisture content is given in Table 1.7.

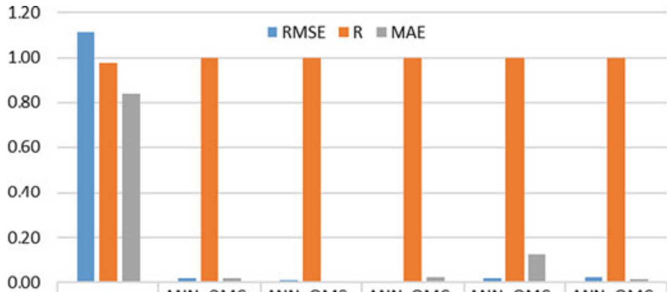
Similarly, the ANN_MDD_1H6, ANN_MDD_2H7, ANN_MDD_3H5, ANN_MDD_4H7, and ANN_MDD_5H1 models of one, two, three, four, and five hidden layers for maximum dry density have been identified as the best architecture neural network models. The performance of artificial neural network models for maximum dry density is given in Table 1.8.

Table 1.7 Performance of ANN_OMC models

Model architecture	Training performance			Testing performance		
	RMSE	*R*	MAE	RMSE	*R*	MAE
ANN_OMC_1H8	0.0144	0.9986	0.0170	0.0184	0.9992	0.0177
ANN_OMC_2H6	0.0049	0.9999	0.0060	0.0101	0.9990	0.0029
ANN_OMC_3H8	0.0064	0.9998	0.0401	0.0049	0.9998	0.0239
ANN_OMC_4H9	0.0188	0.9989	0.1011	0.0199	0.9983	0.1259
ANN_OMC_5H3	0.0259	0.9961	0.0071	0.0236	0.9988	0.0153

Table 1.8 Performance of ANN_MDD models

Model architecture	Training performance			Testing performance		
	RMSE	*R*	MAE	RMSE	*R*	MAE
ANN_MDD_1H6	0.0027	0.9985	0.0006	0.0037	0.9977	0.0006
ANN_MDD_2H7	0.0020	0.9992	0.0024	0.0021	0.9978	0.0020
ANN_MDD_3H5	0.0015	0.9994	0.0018	0.0037	0.9982	0.0026
ANN_MDD_4H7	0.0055	0.9952	0.0002	0.0037	0.9963	0.0005
ANN_MDD_5H1	0.0068	0.9889	0.0005	0.0015	0.9997	0.0008



	MLR_OMC	ANN_OMC_1H8	ANN_OMC_2H6	ANN_OMC_3H8	ANN_OMC_4H9	ANN_OMC_5H3
RMSE	1.1132	0.0184	0.0101	0.0049	0.0199	0.0236
R	0.9763	0.9992	0.9990	0.9998	0.9983	0.9988
MAE	0.8384	0.0177	0.0029	0.0239	0.1259	0.0153

Fig. 1.2 Comparison of performance MLR_OMC and ANN_OMC models

Optimum Performance Model

The performance of the ANN and MLR models of optimum moisture content and maximum dry density has been compared to recognize the optimum performance AI models. The performance of the best architecture ANN_OMC_1H8, ANN_OMC_2H6, ANN_OMC_3H8, ANN_OMC_4H9, and ANN_OMC_5H3 models of optimum moisture content has been compared to MLR_OMC to recognize the optimum performance AI models. The comparison of the performance of MLR and ANN models is shown in Fig. 1.2.

From Fig. 1.2, it has been observed that the ANN_OMC_3H8 model has predicted OMC with 0.0049 RMSE. It has also been observed that the ANN_OMC_3H8 model has outperformed the MLR_OMC and other ANN_OMC with 0.9998 performance.

Similarly, the performance of the best architecture ANN_MDD_1H6, ANN_MDD_2H7, ANN_MDD_3H5, ANN_MDD_4H7, and ANN_MDD_5H1 models of maximum dry density has been compared to MLR_MDD to recognize the optimum performance AI models. The comparison of the performance of MLR and ANN models is shown in Fig. 1.3.

From Fig. 1.3, it has been observed that the ANN_MDD_5H1 model has predicted MDD with 0.0015 RMSE. It has also been observed that the ANN_MDD_5H1 model has outperformed the MLR_OMC and other ANN_OMC with 0.9997 performance.

The ANN_OMC_3H8 and ANN_MDD_5H1 models have been recognized as the optimum performance model to predict the OMC and MDD of soil. The optimum performance ANN_OMC_3H8 model has been used to predict the optimum moisture content of 19 soil specimens. From the results of predicted OMC, it has been observed that the predicted OMC is approximately equal to laboratory test results. The comparison of laboratory and predicted OMC is shown in Fig. 1.4.

Similarly, the optimum performance ANN_MDD_5H1 model has been used to predict the maximum dry density of 19 soil specimens. From the results of predicted

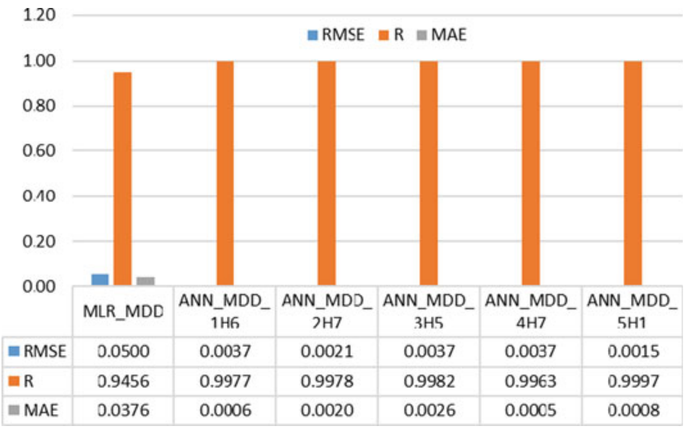


Fig. 1.3 Comparison of performance of MLR_MDD and ANN_MDD models

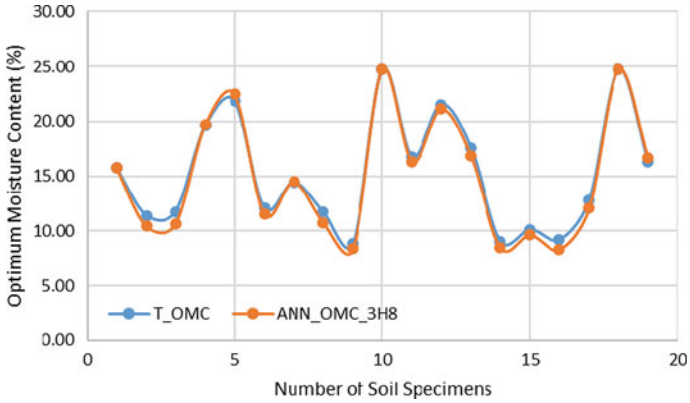


Fig. 1.4 Comparison of laboratory OMC (T_OMC) and predicted OMC

MDD, it has been observed that the predicted MDD is approximately equal to laboratory test results. The comparison of laboratory and predicted MDD is shown in Fig. 1.5.

Comparison with Literature Survey

The performance of the proposed ANN models has been compared with the literature survey, and it has been found that the proposed ANN model outperformed the models available in published research work. The comparison of the presently proposed model with the literature survey is given in Table 1.9.

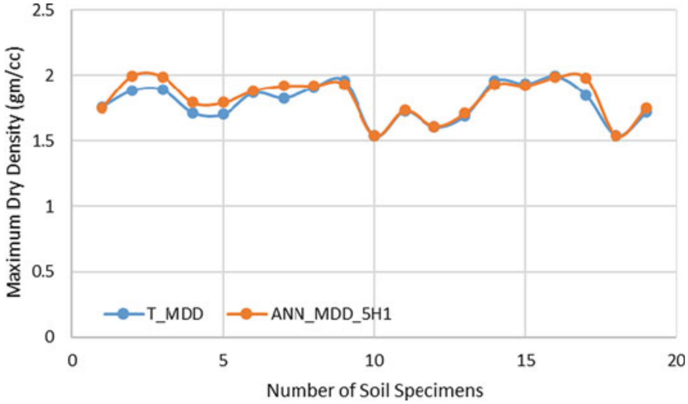


Fig. 1.5 Comparison of laboratory MDD (T_MDD) and predicted MDD

Table 1.9 Comparison of performance of models with the literature survey

Author(s)	Model performance		AI approach
	OMC	MDD	
Wang et al. [10]	0.9607	0.9263	Multi-expression programming
Hasnat et al. [6]	0.9237	0.9487	Regression with SVM
Salahudeen et al. [1]	0.8855	0.9754	Artificial neural networks
Sanuade et al. [15]	–	0.9923	Artificial neural networks
Suman et al. [18]	–	0.8400	BRNN (ANN)
	–	0.8800	DENN (ANN)
	–	0.7600	LMNN (ANN)
	–	0.9300	SVM
	–	0.9200	FN
	–	0.9400	MARS
	–	0.4500	MLR
Shrivastava et al. [2]	0.9323	0.9263	CFB-10 (ANN)
Jayan et al. [12]	0.9200	0.9100	Artificial neural network
Khuntia et al. [19]	0.9381	0.9000	MARS
Khatti et al. (present study)	0.9998	0.9997	Artificial neural network

Conclusion

Regression analysis and artificial neural network models were developed to predict the OMC and MDD of soil. The ANN_OMC_1H8, ANN_OMC_2H6, ANN_OMC_3H8, ANN_OMC_4H9, and ANN_OMC_5H3 models of optimum moisture content and ANN_MDD_1H6, ANN_MDD_2H7, ANN_MDD_3H5, ANN_MDD_4H7, and ANN_MDD_5H1 models of maximum dry density were identified as the best architecture ANN models. The performance of the best architecture ANN models of OMC and MDD was compared to MLR_OMC and MLR_MDD to identify the optimum performance model. The ANN_OMC_3H8 and ANN_MDD_5H1 ANN models were identified as the optimum performance models for predicting the OMC and MDD of soil. The comparison of the performance of the optimum performance model with presently available AI models in the literature survey was mapped. It was found that the optimum performance models have better performance and can be used to predict the OMC and MDD of soil.

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Chapter 2
Numerical Study of Tapered Pile Subjected to Cyclic Loading

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Introduction

With an increase in the depletion of non-renewable sources of energy and the alarming condition of the environment due to increased pollution, the new generation has shifted to renewable sources of energy so that our society can be more oriented towards sustainable development. Offshore wind energy, primarily offshore wind turbines, has become a large clean, renewable energy supplier. Onshore wind has been successfully harnessed in many countries. However, the land requirements and aesthetics of onshore turbines are often considered undesirable. Offshore wind farms have a number of clear advantages, namely (a) their limited aesthetic impact by locating them far from land; (b) high unrestricted wind speeds, which are generally more consistent than onshore; (c) higher power generation through the use of large-capacity turbines [1–3]. In general, the choice for an offshore wind support structure depends on water depth, soil conditions, and environmental conditions at the project location. Based on the structural configuration, the type of offshore wind support structures was divided into monopile structures, gravity structures, jacket structures, tripod structures, and floating structures (Fig. 2.1).

Pile is also being used to construct embankments on the side of bridges which are regularly subjected to the cyclic load as vehicles move over them. A pile support structure is exposed to both horizontal and vertical loads. The horizontal loads are transferred to the soil by mobilizing lateral resistance of the soil through bending, while the vertical loads are carried by the pile wall friction and tip resistance. The pile diameter shall be large enough to provide the required stiffness. Fabrication and installation of very large diameter piles can be difficult due to limitations on available

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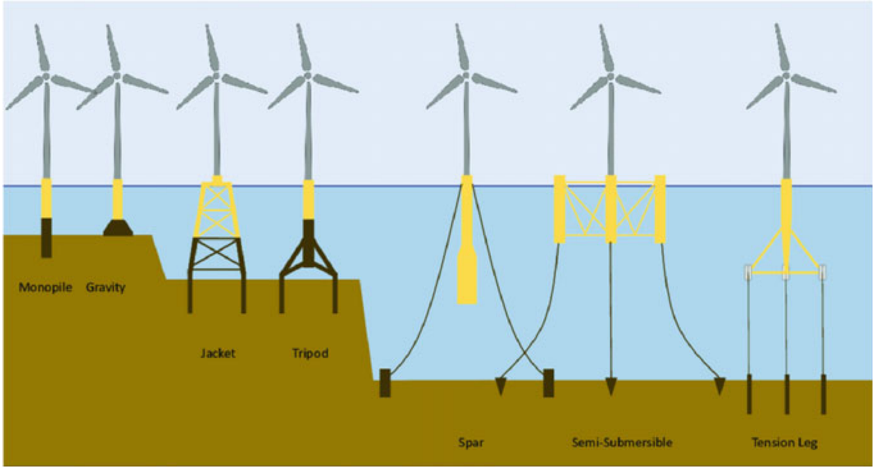

Fig. 2.1 Types of offshore wind support structures. *Source* Google image

steel plate sizes and pile driving capacity, respectively. In addition, conventional pile driving techniques generate noise that concerns surrounding marine life [4–6]. For a pile foundation, the self-weight generates the axial loads while wind and wave generate torsional loads, lateral loads, and bending moments in the structure. The main objective of the support structure design is to determine the dimensions of its components, taking into account operability, load resistance, and economics. This paper explains the numerical study on the tapered piles subjected to cyclic loading. The PLAXIS 3D was used for the analysis, and the results are validated and discussed. For analysis, two different materials, such as steel and aluminium piles, were taken and analysed for different loading conditions.

Validation in PLAXIS 3D

The HS small strain model has been validated, and the results obtained are discussed. Further, the results of the parametric study considering the three parameters have been discussed. A pile was tested in the field for its lateral capacity. The field situation has been simulated in the PLAXIS 3D by the use of HS small strain modelling [1]. HS small incorporates the loading history of soil and a strain-dependent stiffness. Therefore, it can, to some extent, be used to model cyclic loading. It accounts for increased stiffness of soil at small strain. The soil and pile properties for the PLAXIS analysis are given in Tables 2.1 and 2.2. The boundary of 36 m * 36 m * 15 m with a water table at 20 m below the ground surface was considered for the analysis. One-way cyclic load with a maximum amplitude of 960 kN and minimum amplitude of 480 kN for a duration of 40 s applied at a distance of 1 m from the top of the pile.