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Prediction of Compaction Parameters of Soils using Artificial Neural Network

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ABSTRACT— ***This research was conducted for prediction of compaction parameters of soils from its index properties using artificial neural network. The study consists of database of 177 obtained from laboratory measurements. Seven Parameters are mainly considered as input variables to get most accurate results. Plastic limit, Liquid Limit, Plasticity Index, Percentage fines, Percentage sands, Percentage gravels, specific gravity are the input variables and maximum dry density and optimum moisture content were the outputs.***

The training operation is performed mainly by multilayer perceptron-back propagation algorithm. The network topology was selected after fixing number of hidden neurons. Statistical parameters are used to evaluate the performance of ANN model and also to compare the model with other compaction prediction methods.

Keywords— *Artificial Neural Network, Index Properties, Maximum Dry Density, Optimum Moisture Content*

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1. INTRODUCTION

Soil compaction involves a reduction in volume of the soil mass instead of settlement, to increase strength of geomaterials in geotechnical engineering. Proctor Compaction Test (Proctor, 1933) is generally used to obtain the maximum dry unit weight and the optimum moisture content. The objective of compaction is to increase the bearing capacity of foundations, decrease the undesirable settlement of structures, control undesirable volume changes, reduction in hydraulic conductivity, increasing the stability of slopes.

Compaction is the most oldest and common method for soil stabilisation. It is one of the important aspects of earth construction. Soil compaction decreases porosity. It improves the engineering properties of soil. It is the most important part which is to be done in building process. If done improperly, settlement would occur which causes unnecessary maintenance cost and failure. But the compaction test doing in the lab is laborious and time consuming. And also since large quantity of sample is needed to conduct a test, that much quantity of sample may not be available in some cases. Therefore, it seems more reasonable to use the indirect methods for estimating the compaction parameters. In recent years, the artificial neural network (ANN) modelling has gained an increasing interest and is also acquiring more popularity in geotechnical engineering applications.

Over the last few years, artificial neural networks (ANNs) have been used successfully for modelling almost all aspects of geotechnical engineering problems. It has been observed that ANN can be used to find solutions for most complex geotechnical problems. So ANN can be used to find compaction parameter from easily measured index properties of soils.ANN is a data driven approach in which output parameters are determined based on input-output data pairs.

2. SIGNIFICANCE

The proctor compaction test to determine the compaction parameters requires greater efforts. But all experiments for determining index properties of soils are inexpensive and simple. It does not require much time and expensive testing equipments. The compaction parameters of soils are greatly influenced by its texture and plasticity characteristics

(Whitlow1990).So it is very adequate and realistic to develop an ANN model for compaction parameter prediction from index properties of soils.

This paper utilised MATLAB based on back propagation training algorithm for the prediction of neural network. The data base containing 177 laboratory experiments conducted by geotechnical engineering laboratory of NIT, Calicut at various places in Kerala was obtained. The neural network structure and its selection, the effect of neural network structure on performance of ANN model were studied. Parametric study was also conducted to compare the performance of ANN model based on geotechnical theories.

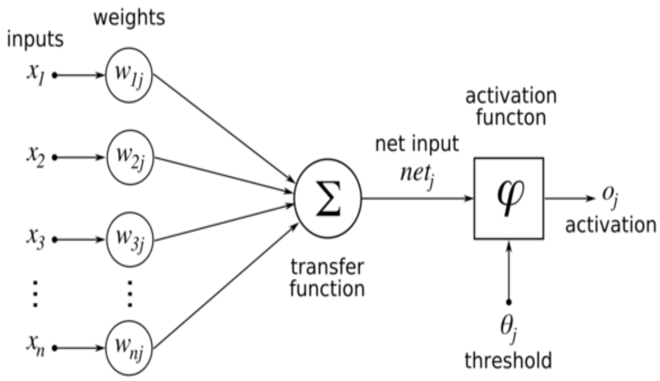
3. ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANN) are computational models which are inspired by structure and function of biological neural network. In ANN, usually output vector is produced from input vector. The relationship between input and output is determined from network architecture. Computationally and algorithmically and its self- organizing feature to allow it to hold for a wide range of problems are the unique feature of ANN.

Basic building block of every artificial neural network is artificial. Such a model has three simple sets of rules: multiplication, summation and activation. The nodes in each layer are joined to nodes in next layer by weighted connections.

These inputs are multiplied by individual weights, and then summed up all weighted inputs and bias. Then it undergoes through the activation function, i.e., also called transfer function (fig 1).

The training of a network by back propagation involves three stages: the feed forward of the input training pattern, the calculation and back propagation of the associated error, and the adjustments of weights.



. **Figure 1:** Artificial Neural Network

4. METHODOLOGY

The various steps involved in development of artificial neural network are selection of model inputs, data acquisition and preparation, Pre–processing of data, Architecture and activation function, Training operation, Model validation.

4.1 Selection of Model inputs

The selection of input variables for the model is most important step. The seven input variables which have most significant impact on the output variables were selected. The selected input variables were Plastic limit (PL), Liquid Limit (LL), Plasticity Index (PI), Percentage fines, Percentage sands, Percentage gravels, specific gravity.

4.2 Data acquisition and Division

It is made use of compaction test data from the various soil investigation projects carried out by geotechnical engineering laboratory of NIT Calicut. The data obtained consists of c-ϕ soils only. The Laboratory data collected from NITC lab is divided into training and testing data based on their statistical parameters. For compaction parameter prediction, about 20 data (20%) were classified as testing data from out of 177 data set. Remaining 157 data (80%) were used as training data.

4.3 Pre–processing of data

It is important to pre–process the data in a suitable form before it's applied to the ANN's. Data pre–processing includes normalization, scaling, and transformation. It is necessary to ensure all variables receive equal attention during the training process. Moreover, pre–processing usually speeds up the learning process, and obtains better convergence.

For ANN modelling, they were scaled between -1 and 1 to eliminate their dimension.

Table 1: Statistical Parameters of Variables

Variable	Mean		Standard Deviation	
	Training data	Testing data	Training data	Testing data
LL (%)	37.43	34.88	24.16	27.90
PL (%)	21.11	20.33	13.69	16.56
PI (%)	16.32	14.55	12.35	13.26
%fines	34.41	36.05	19.39	26.91
%sands	45.67	45.86	20.99	25.57
%gravels	20.60	18.08	18.78	22.31
specific gravity	2.75	1.63	2.63	0.09
MDD	1.69	1.75	.21	0.21
OMC	19.35	17.35	6.04	6.54

4.4 Neural network Architecture and activation

Determining the network architecture is one of the most important and difficult tasks in ANN's model development. After selecting number of inputs and outputs, number of hidden nodes has to be decided.

Hidden Neurons Optimization

The trial and error procedure was used for optimising the number of neurons in the hidden layer. The process was started with one hidden neuron initially and was increased up to (two times the number of inputs nodes) neurons with step size of 1 in each trial. For each set of hidden neuron the network was trained in batch mode to minimise the error in the output layer. Number of neurons corresponding to the minimum mean square error (MSE) was taken as the optimum number of neurons in the hidden layer. In this study, network was trained between 1 to 14 hidden neurons minimum MSE at the output layer was obtained for network trained with 7 hidden neurons for model. Hidden neuron optimisation of OMC and MDD prediction model is shown in the graph below (Fig 2).

Binary sigmoid which has a range of 0 to 1 is used as activation function in this paper.

4.5 Training operation

The training operation is performed mainly by Levenberg–Marquardt back propagation algorithm.

4.6 Model validation

After the training phases, the performance of ANN Model was assessed using root mean squared error (RMSE), and mean absolute error (MAE).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(fi-yi)^2}{n}} \qquad \text{Equation (1)}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|fi-yi| \qquad \text{Equation (2)}$$

Where f_i is the prediction and y_i the true value. Lower the MAE and RMSE value, more accurate the prediction result is.

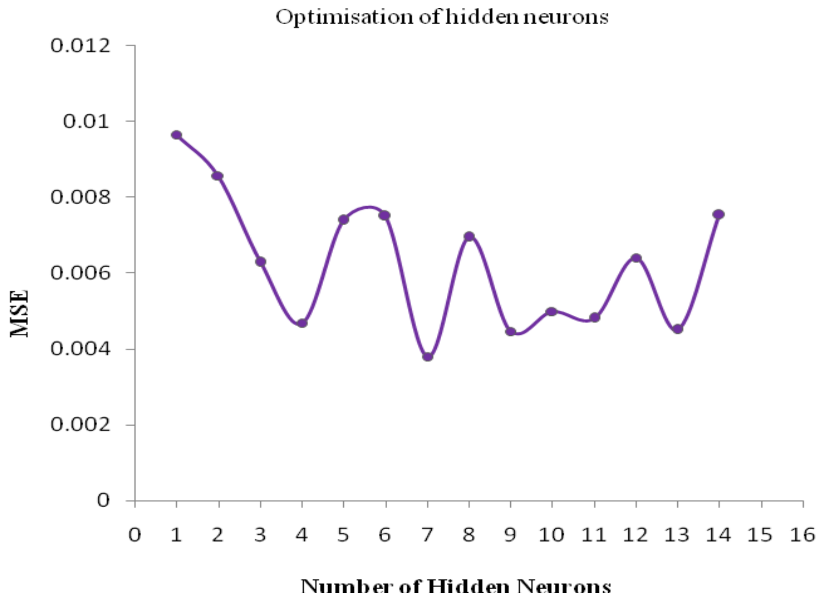


Figure 2: Optimisation of Hidden Neurons

5. RESULTS AND DISCUSSIONS

After the training process, the optimized weights were obtained. The performance of ANN model is validated using RMSE and MAE. The coefficient of regression and performance of the model obtained are as listed below (Table 2).

The correlation graph between predicted MDD and measured MDD as well as predicted OMC and measured OMC were plotted as shown in Figure 3 and Figure 4.

Table 2. Model Validation

	Model validation	
Index	MDD	OMC
R_{train}	0.91	0.9
R_{test}	0.92	0.91
MSE	0.0075	.0051
MAE (%)	0.8	0.39

5.1 Model Validation

The performance of ANN model was validated by using two criteria which are RMSE and MAE (Equation (1) and Equation (2)). And also the obtained RMSE and MAE values for ANN model is compared with those obtained for traditional methods/equations for computation of both MDD and OMC.The traditional method s referred here are the equations derived by Torrey (1970) and U.S.Navy Design Manual (1960).

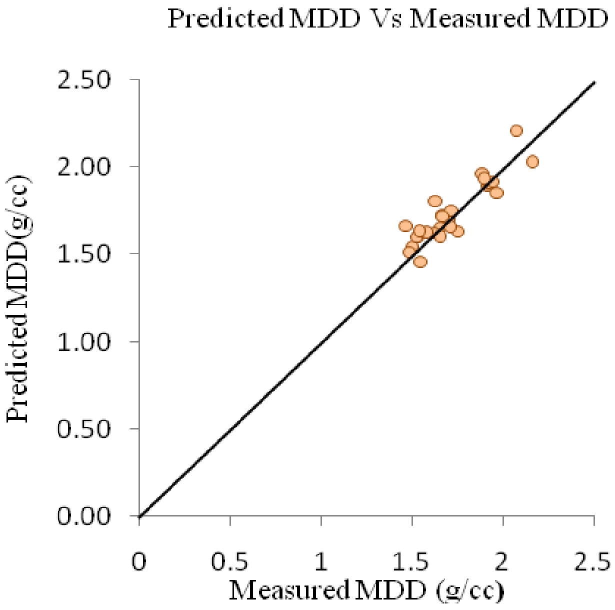


Figure 3 : Predicted MDD Vs Measured MDD

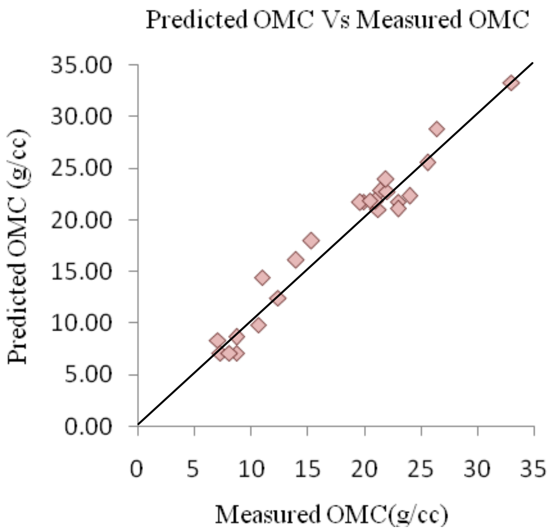


Figure 4: Predicted OMC Vs Measured OMC

The obtained RMSE AND MAE values are as shown in TABLE 3.It can be observed that RMSE and MAE value obtained for ANN is very low compared to traditional methods.

Table 3: Comparison Of Ann Model With Other Mdd Prediction Methods

Statistical parameter	ANN		Torrey Equation		U.S Design Manual	
	OMC	*MDD*	*OMC*	*MDD*	*OMC*	*MDD*
RMSE	1.96	2.1	18.37	62.6	12.44	59
MAE	0.39	0.8	15.91	58.8	9.5	55.3

A comparison between predicted OMC and Computed OMC as well as predicted MDD and computed MDD were also carried out. The results obtained are depicted in the graph below.

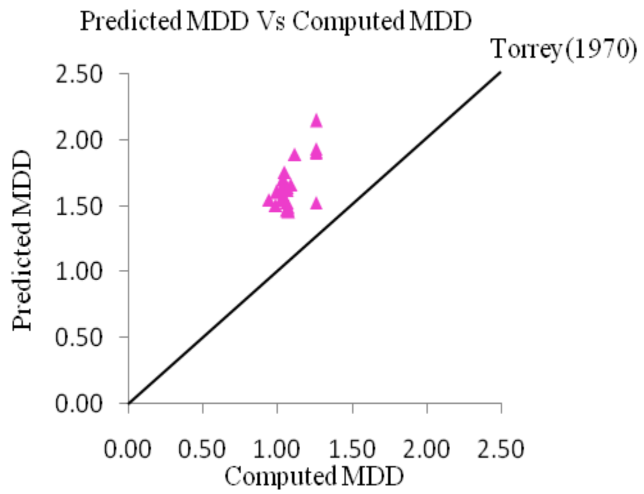


Figure 5: Predicted MDD Vs Computed MDD

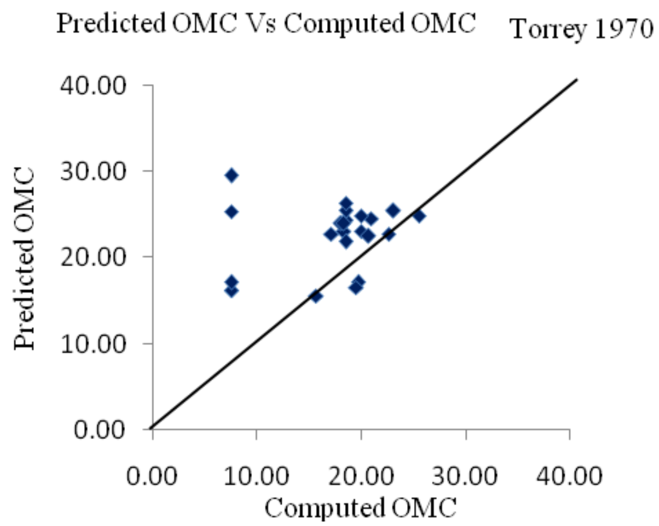


Figure 6: Predicted OMC Vs Computed OMC

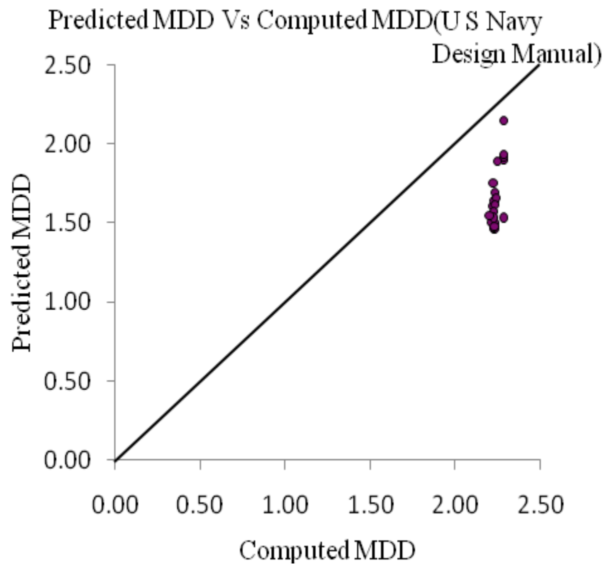


Figure 7: Predicted MDD Vs Computed MDD

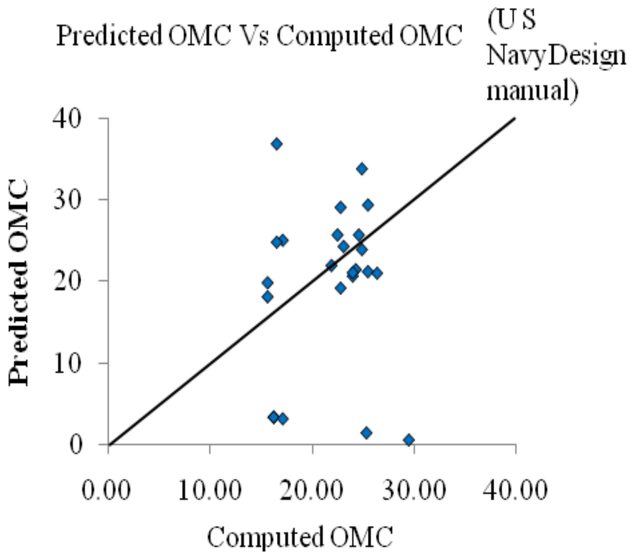


Figure 8: Predicted OMC Vs Computed OMC

6. CONCLUSION AND FUTURE ENHANCEMENT

The present paper targeted the development of ANN models for predicting compaction parameters using CPP. A total number of 180 plus laboratory test data were used for model development and verification. The OMC and MDD prediction could be done with high accuracy using basic index parameters of soil such as Liquid Limit, Plastic Limit, Plasticity Index, %fines, % sands and %gravels and specific gravity. The data normalisation and division methods have quite importance on the performance of ANN Model. The statistical parameters of data are used to divide the data into training, testing and validation data.

Even though ANN have the good ability to predict the compaction parameter with high accuracy, it should be kept in mind that using ANN's does not always guarantee good results. Even though the obtained model can be used for the preliminary assessment of preliminary design phases and site investigation projects.

7. ACKNOWLEDGMENT

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8. REFERENCES

[1]. A Mukherjee and Deshpande, M., Modeling Initial Design Process Using Artificial Neural Networks, Journal of Computing in Civil Engineering, Vol. 9, No. 3, July, 194-200(1995).

[2]. A.T.C Goh. "A back propagation approach for predicting seismic liquefaction potential in soils". In: Neural Net- works, IEEE World Congress on Computational Intelligence,5:33223325, Orlando, USA 1994.

[3]. A. T. C. Goh, "Experiments with Neural Networks as a Design-Support Tool for Complex Engineering Systems", Civil Engineering Systems, Vol. 12, pp. 327-342 (1995).

[4]. Ben-yu Liu *et. Al (2006)* ", Artificial neural network methodology for soil liquefaction evaluation using CPT values", ICIC, LNCS 4113, PP.3229-336

[5]. Brig Gen Md Gazi Ferooz Rahman, Major M. D. H. Talukder and Major A. H. M. M. Rahman, "Assessment Of Soil Compaction–A Project Study", Department of Civil Engineering, Military Institute of Science and Technology, Corp of Engineers, Bangladesh Army.

[6]. Fatih Isik , Gurkan Ozden, "Estimating compaction parameters of fine- and coarse-grained soils by means of artificial neural networks", Environ Earth Sci (2013) 69:2287–2297.

[7]. Maria J. Sulewska, "Applying Artificial Neural Networks for analysis of geotechnical problems, Computer Assisted Mechanics and Engineering Sciences", 18: 231–241, 2011.

[8]. Mohamed A. Shahin , Mark B. Jaksa, Holger R. Maier , "State of the Art of Artificial Neural Networks in Geotechnical Engineering",electronic journal of geotechnical engineering 2008.

[9]. P.U Kurup., N.K. Dudani. "Neural Networks for profiling stress history of clays from PCPT data". Journal of Geotechnical and Geoenvironmental Engineering, 128: 569–579, 2002.

[10] . Raghdan Zuhair Al-saffar, Dr. Suhail I.Khattab, Dr. Salim T. Yousif, "Prediction of Soil's Compaction Parameter Using Artificial Neural Network", University of Mosul

[11]. R. Whitlow, "Basic soil Mechanics", Prentice Hall; 4th edition July 2000.

[12]. T. C Lambed, and Whitman, R. V. 1969. "Soil Mechanics". John Wiley & Sons, New York.

[13]. Y.M. Najjar, I.A. Basheer, W.A. Naouss. " identification of compaction characteristics by Neuronets". Computers and Geotechnics,18:167–187,1996.