Prediction of Compaction Parameters using Regression and ANN Tools

A. K. Shrivastava[1] Dr. P. K. Jain[2]
[1]M.Tech. Student [2]Professor & Head
[1,2]Department of Civil Engineering
[1,2]Maulana Azad National Institute of Technology, Bhopal, Madhya Pradesh, India

Abstract— The compaction parameters are not only important for quality control of earthworks but are required for designing of various works. The engineering properties of soils such as shear strength, CBR, permeability and consolidation parameters are usually determined by testing the samples prepared at optimum moisture content (OMC) and maximum dry density (MDD). On any project, a large number of soil types are generally used. For each soil, besides the basic soil classification parameters, compaction parameters are also determined. Testing of large numbers of soil samples is a cumbersome and time consuming job and requires trained personnel for the purpose. Further, an independent check on the results obtained in the laboratory is also required to make use of test values on site with confidence. Therefore, a need is felt to obtain the required compaction parameters from the basic soil test which are used for the classification of soil viz. Atterberg's limits, gradation, specific gravity etc. In this endeavour, basic soil parameters were collected from literature and Artificial Neural Network (ANN) techniques have been employed on the data collected, as ANN can better model the relation between compaction parameters and basic soil properties than statistical modelling. Present work demonstrates application of five different ANN algorithms viz. LM, GDM, SCG, BR and CFB to predict standard compaction characteristics of varieties of soils with a large range variation in their basic soil properties. Multiple variable non-linear regression analysis was also carried out, in which establishment of an empirical relationship for prediction of compaction characteristics of Modified compaction (i.e., OMC2 and MDD2) by using Standard compaction values (i.e., OMC1 and MDD1) was attempted. Then validation by an independent outside dataset from literature of Horpibulsuk et al. (2009) was also carried out on ANN models and regression analysis done.

Key words: Compaction Parameters, ANN, Regression

I. INTRODUCTION

Compaction can be defined as a process of densification of soil by which the soil particles are rearranged and packed together into a closer state by mechanical means. In this process void ratio of soil decreases and there is a change in its dry density. Compaction process refers to rapid reduction mainly in air voids, with little or no reduction in the water content, using mechanical means under a loading of short duration, and therefore may be accomplished by rolling, tamping, or vibration.

The relationship between the water content and dry density to which a soil can be compacted for a specific amount of compaction energy applied, was first demonstrated by Proctor in 1933. He concluded that there exists a value of water content termed as 'optimum moisture content' (OMC) at which a particular soil attains its closest packing of particles and the corresponding dry density is known as the 'maximum dry density' (MDD). He proposed a procedure of determining the OMC and MDD in laboratory which after his name, is known as Proctor Test or Standard Proctor test.

Since, the compaction which was done on the field using different type of equipment may not reflect to laboratory test. As in laboratory, compaction is done by impact of hammer whereas in field, rollers are used, which may compact the soil using combination of vibration, impact, kneading action etc. As a result, during World War II, Modified Proctor test was developed by U.S. army corps of Engineering to cater with a higher standard of compaction than the Standard Proctor test. It was standardised by American Association of State Highway and Transportation Officials (AASHTO). Both of these tests are used as standard and serve as a guide for field compaction control. The determination of compaction characteristics of soils by these tests is a universally accepted laboratory procedure, and are commonly practiced for earthworks.

In case of structures which do not require much denser packing of soil, lighter compaction is done which corresponds to Standard Proctor Compaction Test. Whereas in case of heavy traffic, airfields, highways etc. Modified Proctor Test compaction parameters are used as a measure to compare soil density in the fields. Generally, 90-95% compaction of laboratory is being specified so that the quality of work can be checked and asserted.

In engineering earthworks, such as earth dams, highway subgrades and embankments, maximum strength is desired to be achieved. The maximum strength is attained when soils are compacted at OMC and MDD. The required compaction is usually attained at certain water content by imparting energy to the soil. Soils are usually compacted in layers by some mechanical means and the degree of compaction is determined with reference to MDD which is obtained in the laboratory by performing compaction test. Both the MDD and OMC are specified for the earthworks and are thus essential input for the design of any compacted soil structure.

There are many advantages of compacting the soil to the MDD because, the other engineering properties of soils like permeability, swelling, pore water pressure, shrinkage, compressibility, shear strength, bearing capacity, CBR etc. depends on the degree of compaction achieved in the field. In general, denser the soil, lesser the problem with soil. Also, the compaction can be done at dry or wet of OMC as per the requirement on the field.

In general, the water content, type of compaction, type of soil, compaction energy are important factors affecting the compaction characteristics of soils.

The type of soil consists of various parameters such as size of particles, grain-size distribution i.e., gradation, shape of the soil grains, specific gravity of soil solids, type and amount of clay minerals present etc.

The compaction energy is also an important parameter, as it greatly affects the MDD and OMC of a given soil. The effect of increasing the compaction energy such as in modified compaction test, results in shifting of compaction curve upward left giving increase in the MDD and decrease in the OMC in comparison to the Standard Proctor test.

Hence researchers in the past have developed empirical/semi-empirical equations for determination of compaction parameters from their basic soil classification parameters. These are based on experimental data, and are developed using numerical and statistical methods. They have limited applicability and hence could not be generalised for large variety of soils.

For the last 25 years or so, the ANN techniques have been in use in geotechnical studies and have demonstrated their superior predictive capability in comparison to traditional methods. ANN don't need prior knowledge regarding the nature of the relationship between the input and output variables. They have been successfully used in developing prediction models for determination of shear strength (Jain et al., 2010), permeability (Erzin et al., 2009), California Bearing Ratio (CBR) (Yildirim and Guanaydin, 2011), bearing capacity (Noorzaei et al., 2008), and load carrying capacity of pile (Kiefa, 1998) from their basic soil properties.

Since compaction parameters are influenced by various factors and it is difficult to establish definite interrelations between them, application of ANN techniques may prove useful in understanding the complex behaviour of soils.

A few attempts have been made to develop prediction models to determine compaction characteristics of soils from basic soil parameters using ANN techniques. However, these models mostly apply multilayer feed forward back propagation algorithms viz. Levenberg Marquardt back propagation (LM) method. This method need not necessarily give the best performance, and there are other training algorithms which may prove to be more accurate, have fast convergence and may result in more efficient models. Hence there is a need to apply different ANN algorithms to predict compaction parameters to arrive at one which performs the best.

In view of this, an attempt has been made and five different ANN algorithms have been used in the present work to develop models for prediction of compaction parameters of Standard Proctor test compaction from basic properties of soil.

Further, researchers have used either Standard Proctor test or Modified Proctor test values only, a need is therefore felt to establish an empirical relationship using regression analysis for prediction of compaction characteristics of Modified Proctor test from Standard Proctor test parameters.

II. LITERATURE REVIEW

Several researchers proposed correlations between compaction parameters and basic soil properties. Semi-empirical, empirical and mathematical fitting relationships to predict MDD and OMC from easily measurable physical properties of soil have been proposed.

The very first attempt to relate compaction characteristics with the index properties of the soil was by Jumikis (1946). A correlation equation was given by him to estimate the OMC with liquid limit and plasticity index. Rowan and Graham (1948) used gradation, specific gravity and shrinkage limit in their correlation equations. Davidson and Gardiner (1949) omitted the specific gravity from the equations of Rowan and Graham (1948), but included plasticity index. Ohio compaction curves were developed by Joslin (1959). Ring et al. (1962) developed two correlations of OMC and MDD, using liquid limit, plastic limit, plasticity index, average particle diameter D_{50}, content of particles finer than 0.001 mm and fineness average. Linveh and Ishai (1978) developed relationships for predicting the line of optimum by using the AASHTO soil classification, specific gravity and liquid limit as input data. Nagaraj (1994) and Blotz et al. (1998) correlated both MDD and OMC with Liquid limit alone. Wang and Huang (1984) used 57 different soils for predicting MDD and OMC of soils by using soil parameters namely specific gravity, fineness modulus, plastic limit, uniformity coefficient, bentonite content, and particle size D_{10} and D_{50} as input. Pandian et al. (1997) proposed a series of predicted compaction curves for Proctor compaction effort. Sridharan and Nagaraj (2005) found that the plastic limit (w_p) bears a better correlation with OMC and MDD than liquid limit or plasticity index. Krystal (2007) brought out relationships for maximum dry density γ_d (psi) and optimum moisture content (%) with liquid limit (w_L) and plasticity index (PI).

From above, it is noted that many researchers have proposed estimation models for predicting OMC and MDD of soils with classification, index properties, specific gravity, compaction energy, average particle diameter, and fineness average. Since most of the available empirical models are based on experimental data of soils used in their work and simplification of assumptions in numerical and statistical methods might have led to very large errors. These models may therefore not be useful for generalisation. It is therefore desirable to develop a prediction model applying more efficient techniques of analysis so that both Standard and Modified compaction characteristics can be evaluated from basic soil properties which are routinely determined for classification of the soils.

ANN, being a powerful and flexible statistical modelling technique for describing complex problems in civil engineering. They have also been employed to model complex relationships between input and output datasets in geotechnical engineering. A few attempts have been made to estimate the compaction characteristics through ANN.

Sinha and Wang (2008) developed an ANN prediction model relating MDD and OMC with classification properties of soil. The data of 55 different types of soils reported by Wang and Huang (1984) was used in the analysis. The five input variables were used. These are density of solid phase (γ_s) in lb/ft^3, fineness modulus (Fm), effective grain size (D_{10}) in mm, plastic limit (PL) and liquid limit (LL). The feed forward with back propagation network having a transfer function log-sigmoid for hidden layer and tan-sigmoid for output function was applied for training of data. They concluded that the developed ANN models were capable of predicting MDD and OMC accurately for a wide range of soil conditions investigated. The ANN model performed better and gave R^2 values of 0.979 and 0.961 for MDD and OMC, as compared to that of in statistical model 0.954 and 0.886, respectively.

Gunaydin (2009) developed a statistical and an ANN model to estimate the compaction characteristics from the data collected from a dam near Nigde-Turkey consisting of gradation and index properties of nine soil types. The input variables were contents of fine grain (FG), sand (S), gravel (G), liquid limit (w_l), plastic limit (w_p) (all in percentage), Specific gravity (G_s) and soil type (ST). The data were analysed using multilayer feed forward back propagation algorithms with transfer functions of tan-sigmoid log sigmoid. It was concluded that use of the basic soil properties such as grain size, consistency limits and specific density (G_s) appears to be reasonable in the estimation of compaction parameters. The liquid limit was the most dominant parameter for the estimation of OMC, whereas grain size is found to affect greatly the MDD. The ANN model performed better and gave R^2 values for OMC and MDD of 0.893 and 0.836, as compared to the values obtained in statistical multi-linear regression (MLR) model 0.82 and 0.74.

Sinivasulu et al. (2012) applied ANN to predict Modified Proctor compaction parameters from index properties of nine different soil types collected from different regions of Hyderabad, (A.P.), India. The study utilized the single hidden layer ANN with Levenberg Marquardt back propagation (LM) algorithm with transfer function of log-sigmoid and poslin for training and testing of the network. A comparison with the experimental results indicated that the accuracy of the developed models was satisfactory and coefficient of correlation (R-value) obtained were 0.911 and 0.882 for MDD and OMC, respectively. It was concluded that use of the basic soil properties such as grain size, Atterberg limits, appear to be reasonable in the estimation of compaction parameters.

III. COLLECTION OF DATA

The data from literature of Puls (2008) was used to prepare database. Thirty-nine soil samples were taken for generating the data. An analysis of the soil classification data shows that in these soils maximum size of particles was limited to 20 mm. The data contains percentage of gravel size particles ranging from 0 to 44%, sand size particles from 1.2 to 94%, and silt and clay size particles from 5-98.4%. The liquid limit data varies from 0-50%, plastic limit from 0-30% and plasticity index from 0-22%. The compaction parameters also had a wide range of variation, 4.8 to 22.4 % for OMC_1 and 15.08-22.5 kN/m^3 for MDD_1 whereas OMC_2 varies from 4-17.9% and MDD_2 varies from 15.74-22.96 kN/m^3. Thus the soils tested in present work represent most of the soils usually used in construction works such as construction of roads, embankments etc.

The soils data used in present work falls in nine types as per IS 1498-1970. For this study, these have nomenclature for coarse grained soils as SM, SC, SW-SM, SP-SM and ML, MI, CL, CI, CH for fine grained soils.

The soils used for determination of compaction parameters have a wide range of its gradation and index properties. The liquid limit of collected soil data covers all the ranges of its compressibility i.e. low, intermediate and high.

The plasticity index also covered all the types of soils below and above A-line in plasticity chart. The percentage content of various ingredients viz. gravel, sand and fine grains also has a wide range of both types of soils (coarse and fine grained soils) were used in the research work. The ranges of OMC_1 and MDD_1 as well as OMC_2 and MDD_2 collected also have wide limits.

Thus the collected data which have 9 varieties of soils and wide range of its parameters give good representation of different types of soils and a model which will be developed on such data will be good for generalisation.

IV. DEVELOPMENT OF ANN MODELS

Neural network technology mimics the brain's own problem solving process. Thus, ANN has the ability to adapt or learn, to generalize, or to cluster or organize data in which the operation is based on parallel processing.

The general neural network model development process comprises of the following steps -

- Collect data
- Create, Configure and Initialize the network
- Train the network
- Validate the network (post training analysis)
- Use the network

Before training the network, the data was normalised first, as normalized data gives better performance and therefore needs to be normalized for several other reasons, as presented here:

- To obtain better convergence,
- To prevent larger values in one parameter from overriding smaller values in other parameters,
- They accelerate the process of training and
- Prior to the training stage, a certain range in which the inputs and target values fall was determined.

The training process requires a set of examples i.e. network inputs and target outputs. The process of training, involves tuning values of weights and biases of the network to optimise its performance.

If the network is not sufficiently accurate, the network is initialised and trained again. Each time the network parameters are different and might produce different solutions. The other approach is to increase the number of hidden neurons or change in different training function. Larger numbers of neurons in the hidden layer give the network more flexibility because the network has more parameters it can optimize.

In the present work, five ANN algorithms were employed namely, Levenberg Marquardt back propagation (LM), Gradient Descent with Momentum back propagation (GDM), Scaled Conjugate Gradient back propagation (SCG), Bayesian Regularization (BR) and Cascade Forward back propagation (CFB).

In back propagation based algorithms many training iterations for a network was performed by assigning different combination of computer generated random weights and biases in input-hidden-output layers.

Model	Training Data					Testing Data			
	R-value				**MSE**	**R^2**		**MSE**	
	Train	**Valid**	**Test**	**All**		**OMC_1**	**MDD_1**	**OMC_1**	**MDD_1**

LM-5	0.869	0.812	0.874	0.8611	4.0526	0.0085	0.3702	12.395	0.8503
LM-10	**0.994**	**0.997**	**0.893**	**0.9360**	**0.1717**	**0.7851**	**0.7230**	**10.550**	**0.2837**
LM-15	0.962	0.973	0.867	0.9484	2.631	0.3484	0.6075	22.698	1.0524
LM-20	0.998	0.822	0.946	0.9558	10.382	0.3530	0.8411	15.593	0.3603
GDM-5	0.798	0.920	0.961	0.8409	6.5433	0.0182	0.8520	32.983	10.398
GDM-10	**0.847**	**0.990**	**0.847**	**0.8673**	**1.5353**	**0.0538**	**0.5717**	**20.448**	**0.6351**
GDM-15	0.809	0.890	0.920	0.8364	7.9567	0.3573	0.5706	47.009	2.8130
GDM-20	0.868	0.845	0.833	0.8583	9.3949	0.1446	0.4038	41.394	4.2397
SCG-5	0.678	0.612	0.746	0.6797	56.280	0.2464	0.6790	98.145	0.6023
SCG-10	**0.707**	**0.753**	**0.902**	**0.7422**	**37.867**	**0.5224**	**0.2270**	**105.98**	**4.3861**
SCG-15	0.712	0.555	0.709	0.6924	136.72	0.0963	0.0506	593.80	3.4437
SCG-20	0.351	0.482	0.701	0.3570	70.804	0.6122	0.7970	70.602	65.999
BR-5	0.995	-	0.829	0.9394	0.1806	0.3883	0.2116	26.849	1.6128
BR-10	0.879	-	0.899	0.8813	4.6731	0.0531	0.2861	17.315	1.8965
BR-15	0.888	-	0.881	0.8843	4.134	0.0243	0.0216	14.155	1.1640
BR-20	**0.954**	**-**	**0.882**	**0.9423**	**1.7495**	**0.2828**	**0.5024**	**15.096**	**0.8285**
CFB-5	0.917	0.990	0.973	0.9441	0.5035	0.0313	0.6053	16.628	0.4250
CFB-10	**0.964**	**0.994**	**0.910**	**0.9544**	**0.3304**	**0.8691**	**0.8531**	**0.8194**	**0.6286**
CFB-15	0.712	0.838	0.790	0.7362	25.612	0.4588	0.7916	93.457	7.9884
CFB-20	0.951	0.900	0.951	0.9454	3.7445	0.1615	0.1802	15.745	1.3326

Table 1: Performance evaluation of all models

The process of iteration is repeated taking feedback from the previous iteration and is continued till the predefined epoch (1000 in present case). The best combination of set of weights for such a network is that which gives highest R-value and minimum MSE. The other networks are configured by changing number of neurons in hidden layers for the same algorithm. Overall, four network architectures (viz., 5x5x2, 5x10x2, 5x15x2 and 5x20x2) were attempted for each algorithm. Thus in all twenty ANN models were developed. The one among all such networks which gives maximum R (i.e. close to 1) and minimum MSE (i.e. close to 0) is then finalized.

All the networks were trained with the same input-output combination. The input parameters were gravel content (G), sand content (S), fine grain content (FG), liquid limit (LL) and plasticity index (PI) whereas the output variables were OMC$_1$ (w_o) and MDD$_1$ (γ_{dmax}) of Standard compaction test.

Also, number of combinations of input parameters can be used to train the networks but, from the earlier studies, it was found that using all input parameters gives best predictive model (Bhatt, 2015).

The four models of each algorithm were compared amongst themselves and then comparison of the best model of each algorithm with that of other algorithms was made. It is noted that out of 5 best, one corresponding to each algorithm (viz., LM-10, GDM-10, SCG-10, BR-20 and CFB-10), CFB-10 was the best among all other optimal models. This model was termed as the key model.

The performance of key model CFB-10 was then validated by using data mentioned in Horpibulsuk et al., (2009). The dataset presented in his paper contains basic soil properties for 15 soils along with their values of OMC$_1$ and MDD$_1$. When input values namely FG, LL, PI, G and S for these soils were presented to CFB-10, it gave predicted values of OMC$_1$ and MDD$_1$ as output. These outputs (predicted) were compared with the target data (measured) given in Horpibulsuk et al., (2009). The maximum relative error for OMC$_1$ was 32.86% while minimum was 0.39836%. In case of MDD$_1$, maximum relative error in prediction was -16.922% and minimum was -1.9646%. Thus the model CFB-10 proved successful in predicting OMC$_1$ and MDD$_1$ on independent dataset and is therefore recommended for practical use with confidence.

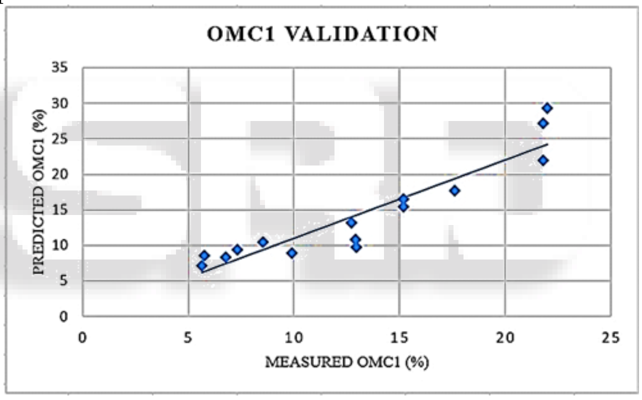

Fig. 1: Measured v/s predicted outputs of OMC1

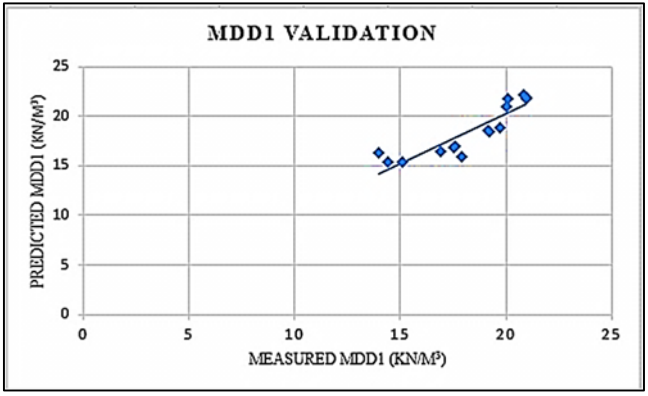

Fig. 2: Measured v/s predicted outputs of MDD1

V. REGRESSION ANALYSIS

Sometimes, after carrying out standard compaction test (as it is relatively easy to perform) one may be interested in knowing the values of modified compaction test. For the same, the data set obtained from literature of Puls (2008) was then also use to develop an empirical relation to predict the modified compaction parameters from the standard compaction parameters values. The logarithmic values of dataset were calculated first so as to carry out Multiple Variable Non-Linear Regression Analysis, as the input-output relationship was not a linear one. Also, it was found out that using multiple variable gives better results as compared to the single variable regression analysis. Therefore, analysis has two inputs namely, OMC_1 and MDD_1 (corresponding to Standard Proctor Test) while OMC_2 and MDD_2 (corresponding to Modified Proctor Test) were the outputs obtained.

For the prediction of Modified Proctor values using this analysis, the Standard Proctor values are prerequisite. To obtain Standard Proctor values from the basic properties of soil, following empirical relationship can also be used, but it is recommended to use ANN key model (CFB-10) for the same.

$$\begin{aligned} \mathrm{OMC1} = {} & (\mathrm{LL})^{-0.0205385} \times (\mathrm{PI})^{0.069080256} \times (\mathrm{G})^{-0.10106486} \\ & \times (\mathrm{S})^{-0.08929950} \\ & \times (\mathrm{FG})^{0.108067234} \times 10^{1.16480891} \end{aligned}$$

$$\begin{aligned} \mathrm{MDD1} = {} & (\mathrm{LL})^{0.013788553} \times (\mathrm{PI})^{-0.032260407} \\ & \times (\mathrm{G})^{0.037417396} \times (\mathrm{S})^{0.030045417} \\ & \times (\mathrm{FG})^{-0.018305615} \times 10^{1.210800293} \end{aligned}$$

Regression Statistics	
R^2	0.95432874
Standard Error	0.03223285
MSE	0.347354089

Table 2: Regression statistics for OMC_2 prediction

Regression Statistics	
R^2	0.916360925
Standard Error	0.012792265
MSE	0.028686145

Table 3: Regression statistics for MDD2 prediction

The regression analysis gives satisfactory results, as the obtained values of R^2, Standard Error and MSE for OMC_2 were 0.95, 0.032 and 0.34 respectively, and corresponding values for MDD_2 were 0.91, 0.012 and 0.028 respectively.

$$\begin{aligned} \mathrm{OMC2} = {} & (\mathrm{OMC1})^{0.66174915} \times (MDD1)^{-0.9013785} \\ & \times 10^{1.40863876} \end{aligned}$$

$$\begin{aligned} \mathrm{MDD2} = {} & (\mathrm{OMC1})^{0.089601282} \times (\mathrm{MDD1})^{1.114620381} \\ & \times 10^{-0.215525513} \end{aligned}$$

From the relationship obtained it is observed that the MDD_1 is dominating factor in prediction of both OMC_2 and MDD_2. Also, the relationship follows the well-known behaviour of decrease in OMC and increase in MDD with greater compactive effort on same soil.

The relationship was then validated by using data mentioned in literature of Horpibulsuk et al., (2009). The dataset presented in his paper contained both standard as well as modified compaction parameters of 15 different soils. When input values namely OMC_1 and MDD_1 were put in the formula, it gave predicted values of OMC_2 and MDD_2 as outputs. These output (predicted) were compared with the target data (measured) given in Horpibulsuk et al., (2009). The statistical analysis yields coefficient of determination (R^2) and MSE as 0.98 and 0.53 for OMC_2, 0.97 and 0.13 for MDD_2. Also, the maximum error for OMC_2 was -15.665% while minimum was 0.35742%. In case of MDD_2 the maximum error in prediction was 4.91288% and minimum was 0.03149%. Thus the formula proved successful in predicting OMC_2 and MDD_2 on independent dataset and is therefore recommended for practical use with confidence.

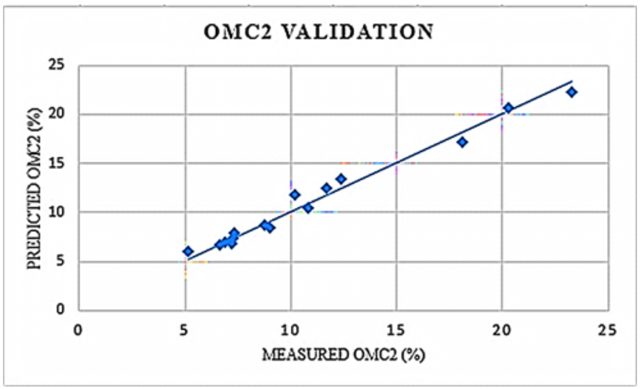

Fig. 3: Measured v/s predicted outputs of OMC_2

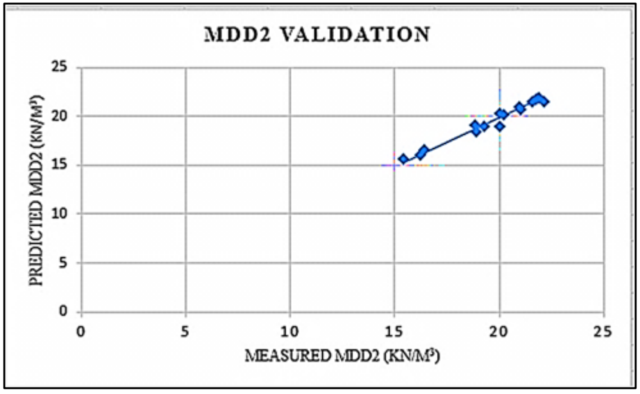

Fig. 4: Measured v/s predicted outputs of MDD_2

VI. CONCLUSIONS

In the present work, an attempt was made to have a generalized relationship so as to easily predict Standard Proctor compaction parameters of soil from its basic properties. For the same, the data was collected from the literature of Puls (2008) and using that data, 20 ANN models were developed, by 5 different algorithms and 4 network architecture for each algorithm. For development of models, input parameters were those basic soil properties which are routinely determined for classification of the soils viz., gravel content (G %), sand content (S %), fine grain content (FG %), liquid limit (LL %) and plasticity index (PI %) whereas the output variables were OMC1 (wo %) and MDD1 (γdmax kN/m3) of Standard compaction test. Among the 20 models, 5 best models corresponding to each algorithm (viz., LM-10, GDM-10, SCG-10, BR-20 and CFB-10) was selected and then 1 key model among the best model was selected, which comes out to be CFB-10. Then performance of key model CFB-10 was validated by using data mentioned in Horpibulsuk et al., (2009). The model CFB-10 proved successful in predicting OMC1 and MDD1 on independent dataset.

Sometimes, Modified Proctor compaction parameters are required instead of Standard Proctor compaction parameters. To bridge this gap, an empirical relationship was established so as to predict the modified compaction parameters from standard compaction parameters. To do so, same data was used to carry out Multi Variable Non-Linear Regression Analysis. The regression analysis has two inputs namely, OMC1 and MDD1 (corresponding to Standard Proctor Test) while OMC2 and MDD2 (corresponding to Modified Proctor Test) were the outputs obtained. The established empirical relationship was then validated by using data mentioned in literature of

Horpibulsuk et al., (2009). It was noted that the formula proved successful in predicting OMC2 and MDD2 on independent dataset.

REFERENCES

[1] Bhatt S. (2015). “Prediction of compaction characteristics of soils using ANN techniques.” PhD Thesis, National Institute of Technology, Bhopal.

[2] Blotz L. R., Benson C. H., and Boutwell G. P., (1998). “Estimating Optimum water content and Maximum dry unit weight for compacted clays.” Journal of Geotechnical and Geo-environmental engineering, September, 124(9):907-912.

[3] Davidson, D.T. and Gardiner W.F. (1949). “Calculation of standard proctor density and optimum moisture content from mechanical analysis, shrinkage factors, and plasticity index.” Proceedings HRB, 29:447–481

[4] Erzin, Y., Gumaste, S.D., Gupta, A.K., and Singh, D.N. (2009). “Artificial neural network model for determining hydraulic conductivity of compacted fine grained soils.” Canadian Geotechnical Journal, Vol. 46, pp. 955-968.

[5] Gunaydin O. (2009). “Estimation of soil compaction parameters by using statistical analyses and artificial neural networks.” Environ Geol, Springer, 57:203-215.

[6] Horpibulsuk S., Katkan W. and Naramitkornburee A. (2009). “Modified Ohio’s Curves: A rapid estimation of compaction curves for coarse and fine-grained soils.” Geotechnical Testing Journal, Vol. 32, No. 1, Paper ID GTJ101659, January, 2009.

[7] Jain, R., Jain, P.K., and Bhadauria, S.S. (2010). “Computational approach to predict soil shear strength.” International Journal of Engineering Science and Technology Vol. 2(8), pp. 3874-3885.

[8] Joslin J.G. (1959). “Ohio’s typical moisture-density curve.” ASTM STP, 239:111– 118

[9] Jumikis, A.R. (1946). “Geology and soils of the Newark (NJ) metropolitan area.” J Soil Mech Found, ASCE 93(SM2), 71–95

[10] Krystal, W. (2007). “Index properties and shear strength of Artificial soil using the Harvard Miniature Method.” Final report of Environment and Civil Engineering University of Houston, TX, pp. 1-17, 2007.

[11] Linveh, M. and Ishai, I. (1978). “Using indicative properties to predict the density moisture relationship of soil.” Trans Res Record, (60P):22–28

[12] Nagaraj, T. S. (1994). “Analysis and prediction of compaction characteristics of soils.” Unpublished work.

[13] Noorzaei J., Hakim S. J. S., and Jafar M.S., (2008). “An approach to predict ultimate bearing capacity of surface footing using neural network”. Indian Geotechnical Journal, Vol. 38, No. 4, pp. 513-526.

[14] Pandian, N. S., Nagaraj, T.S. and Manoj, M. (1997). “Re-examination of compaction characteristics of fine grained soils”. Geotechnique, Vol. 47, No.2 pp. 363-366.

[15] Puls John Michael (2008). “Compaction models for predicting moisture-density-energy relationships for earth materials.” M.S. Thesis, Iowa State University, Iowa.

[16] Ring, G.W., Sallberg, J.R., and Collins, W.H. (1962). “Correlation of compaction and classification test data.” HRB, 325:577–587

[17] Rowan, H.W., Graham, W.W. (1948). “Proper compaction eliminates curing period in construction fills.” Civil Eng, 18:450–451

[18] Sinha Sunil K., Mian C. Wang (2008). “Artificial Neural Network Prediction Models for Soil Compaction and Permeability.” Geotech Geol Eng, Springer 26:47-64.

[19] Sinivasulu S., Padmavathi V., Araki H., Borzooei, and Madhav M.R., (2012). “ANN based prediction and sensitivity analyses of maximum dry unit weight and optimum moisture content values over a large range.” 8th International symposium on lowland technology, September 11-13, 2012 in Bali, Indonesia.

[20] Sridharan A., and Nagaraj H.B., (2005). “Plastic limit and compaction characteristics of fine-grained soils.” Ground Improvement 9(1):17–22.

[21] Wang M.C., Huang C.C. (1984). “Soil compaction and permeability prediction models.” J Environ Eng, ASCE 110(6):1063–1083.

[22] Yildirim B., Gunaydin O. (2011). “Estimation of California bearing ratio by soft computing systems.” Expert Systems with Applications, Elsevier, vol. 38 (2011) 6381-6391.

[23] IS: 1498 -1970 (First Revision - Reaffirmed 2007). “Classification and identification of soils for general engineering purposes.” BIS-New Delhi.