Artificial Neural Network Modeling for Predicting Compaction Parameters based on Index Properties of Soil

Ashwini Tenpe[1], Dr. Suneet Kaur[2]

[1]Mtech Scholar, Civil Department, MANIT, Madhya Pradesh, India

[2]Associate Professor, Civil Department, MANIT, Madhya Pradesh, India

Abstract*: Compaction is simple ground improvement technique where the soil is densified through external compactive effort. The important parameters of compaction are Optimum Moisture Content (OMC) and Maximum Dry Density (MDD) which depends on the index properties of soil. Compaction increases the density of soil thereby, increasing shear strength and bearing capacity. These above parameters which are determined from laboratory tests are laborious and time consuming. However index soil properties test is relatively inexpensive, simple and can be performed within less time with utmost accuracy. In this research work, an attempt has been made to predict the compaction parameters from index properties of the soil in terms of Liquid Limit, Plasticity Index, soil particles finer than 75microns and greater than 75microns size. A feed forward neural network model is developed to predict the compaction parameters of the soil using index properties of the soil and the analysis is done by using Artificial Neural Network (ANN) methodology. Using this model, compaction parameters can be easily predicted by performing simple index properties tests in the laboratory. The R^2 values of OMC of ANN model for training and testing dataset were found to be 0.8526 and 0.7568 respectively. The R^2 values of MDD of ANN model for training and testing dataset were found to be 0.8801 and 0.8071 respectively. The R^2 values of OMC and MDD for simulation dataset for this parameter are 0.9463 and 0.9478 respectively. Hence, it was proved that the developed neural network model can predict OMC and MDD with reasonable degree of accuracy.

Keywords: Optimum moisture content, maximum dry density, artificial neural network, index properties of soil**.**

1. Introduction

Compaction of soil mass is done to improve its engineering properties for increasing the shear strength, stability and bearing capacity of soil. It is also useful in reducing the permeability and compressibility of the soil. Compaction of soil is required for the construction of earth dams, canal embankment, highways and in many other engineering applications. The compaction method has become one of the most widely used soil improvement techniques around the world, as most of the laboratory and field test programs are concerned with the physical properties of the soil at MDD.

Empirical relationships are often used to estimate correlations which are usually derived with the help of soft computational method. In recent years, a new field of soft computing has emerged for modeling geotechnical problems. Artificial Neural Network (ANN) is one such tool widely used successfully for predicting many geotechnical properties of soil. It is known as “Black Box System”, as it is not possible to explain the weights/parameters of the network and it is still a subject of research (Goh et. al. 2005).

The highly interconnecting processing elements called neurons are referred to as Neurodes, processing elements and nodes. The input layer neurons receive the input signals and the output layer neurons receive the output signals. The synaptic links carrying the weights connect every input neuron to the output neuron. The neural network basically consist inputs which is multiplied by weights and computes the output.

Neural Network learns by examples. Therefore, they can be trained with known examples of a problem to acquire knowledge about it. Once appropriately trained, the network can be put to effective use in predicting various parameters. ANN has been successfully applied to problems in the fields of pattern recognition, image processing, data compression, forecasting and optimization.

The ANN's are becoming more reliable than statistical methods due to their special attributes of identifying and mapping complex systems when the input and output are known from either laboratory or field experimentation. In the present work, a Feed Forward Back Propagation (FFBP) neural network has been developed to predict compaction parameters based on Liquid Limit, Plasticity Index, soil particles finer than 75 microns and greater than 75 microns size.

2. Literature Review

Most of the literature reveals that ANN’s have been used successfully in predicting, pile capacity, modeling soil Behaviour, site characterization, earth retaining structures, settlement of structures, slope stability, design of tunnels and underground openings, liquefaction, soil permeability and hydraulic conductivity, soil swelling and classification of soil.

Mini and Pandian (2005) have reported the feasibility of using ANN for estimating the Optimum moisture content and Maximum dry density values for different types of soil subjected to different compactive efforts.

P. Kakarla et. al. (2013) developed the ANN based model to predict the shear parameters of the soil in terms of different soil parameters such as dry density and plasticity index, %gravel, percentage sand, percentage silt, percentage clay as input parameters obtained through laboratory tests for soil samples from different parts of India and cohesion and angle of internal friction as output parameters.

Ch. Sudha Rani et. al. (2013) developed ANN model to predict the engineering properties of soil such as Permeability, Compressibility and Shear Strength parameters in terms of Fine Fraction, Liquid Limit, Plasticity Index, Maximum Dry Density, and Optimum Moisture Content as input parameters obtained through laboratory tests for soil samples.

Sarat Kumar Das et. al. (2008) made various attempts using neural network model to predict the residual friction angles based on clay fraction, Atterberg's limits i.e. PL, LL, PI, %fines as input parameters obtained from laboratory tests for different soil samples and angle of internal friction as output parameters. Based on the statistical parameters, for training and testing dataset, they have concluded that the ANN model with Clay Finer and Plasticity Index as input parameters is the best model.

Khanlari et. al. (2012) introduced artificial neural network models to predict friction angle and cohesion of soils in terms of different soil parameters such as gravel percentage, sand percentage, silt percentage, clay percentage, dry density and plasticity index as input parameters obtained through laboratory tests for soil samples from different parts of India and shear parameters as output parameters.

Mohamed A. Shahin et al. (2002) developed a model for predicting settlement of shallow foundations on cohesion less soil using neural networks. Their results indicate that ANNs are useful and accurate technique for settlement prediction of shallow foundation on cohesionless soils.

Rani et. al. (2013) developed the multilayer perceptron network with feed forward back propagation to predict soil cohesion and soil angle of internal friction in terms of fine fraction, liquid limit and plasticity index, optimum moisture content and maximum dry density.

Shang et al (2004) developed Artificial Neural Networks model to capture the multivariable relationship between the complex permittivity and the soil properties such as density, water content, and degree of saturation. Sinha et al. (2007) have proposed ANN prediction models to relate permeability, maximum dry density, optimum moisture content with classification properties of the soil. Authors had reported that predictions within 95% confidence interval could be obtained from the ANN models.

3. Basic Concept of ANN

An ANN is a data processing system consisting of a large number of simple highly interconnected processing elements inspired by the structure of the cerebral cortex of the brain. The NN exhibits mapping capabilities, as they can map input patterns to their associated output patterns. The NN also possesses the capability to generalize as they predict new outcomes from past trends.

The feed forward neural network is the simplest type of artificial neural network. Thus, architecture of this network besides processing input and output layer also have one or more intermediary layers called hidden layers. The neurons of the hidden layer are known as hidden neurons. The input layer neurons are linked to the hidden layer neurons and the weights on these links are referred to as input-hidden layer weights. The hidden layer neurons are linked to the output layer neurons again and the corresponding weights are referred to as hidden-output layer weights.

In back propagation neural network, the data is propagated forward to input and output layer to obtain the output of the model. The error between target values and predicted values are propagated back to update weights and biases of the neurons. This process is continued until the error reaches a value less than the error goal.

4. Model Methodology

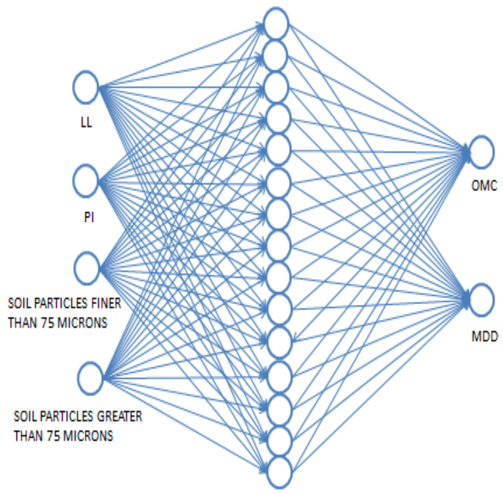
A feed forward neural network model is developed to predict the values of compaction parameters. The architecture of our ANN consists of an input layer, output layer and one intermediary layer called hidden layer. Input layer consists of 4 neurons namely liquid limit, Plasticity limit, soil particles finer than 75 microns and greater than 75 microns size. They are sustained 15 neurons in the hidden layer and 2 neurons namely OMC and MDD output layer. Levenberg-Marquardt is adopted as a learning function and "tan sigmoid" transfer function was used for input layers and output layers.

4.1 Database

Database used in the present study is based on the data collected from various state authorities, consultants and test conducted in the Soil Mechanics laboratory. A total of 210 datasets were collected of which 80% were employed to develop the model called training sets. 10% of the data is used for validation and remaining 10% soil data is used for the testing the model. An independent datasets called as Simulation dataset consisting of 21 samples were used to estimate the performance of developed model. Four variables are selected as input, to develop the NN model. These variables are-
a) Liquid Limit
b) Plasticity Index
c) Soil particles less than 75 microns size
d) Soil particles greater than 75 microns size

The two variables in the output layer are-
a) Optimum Moisture Content (OMC)
b) Maximum Dry Density (MDD)

There are 15 neurons in the hidden layer. The Architecture of the ANN model is shown in figure [4.1]



Input Hidden Output

Figure 4.1: illustrates an architecture of ANN model

4.2 Normalization of Data

Data normalization can speed up training time by starting the training process for each feature within same scale. Due to this, all input values and output values were lie between 0 to1. The soil data sets were arranged in EXCEL software. This datasets were normalized by following:

$$Xn = \frac{(Xi - Xmin)}{(Xmax - Xmin)}$$

Where,
Xn= normalized value
Xi = original value of the parameter
Xmin= Minimum value of the parameter
Xmax= Maximum value of the parameter

5. Result & Analysis

Fig. 5.1 exhibits the observed OMC and Predicted OMC values for training dataset during training stage of NN model.

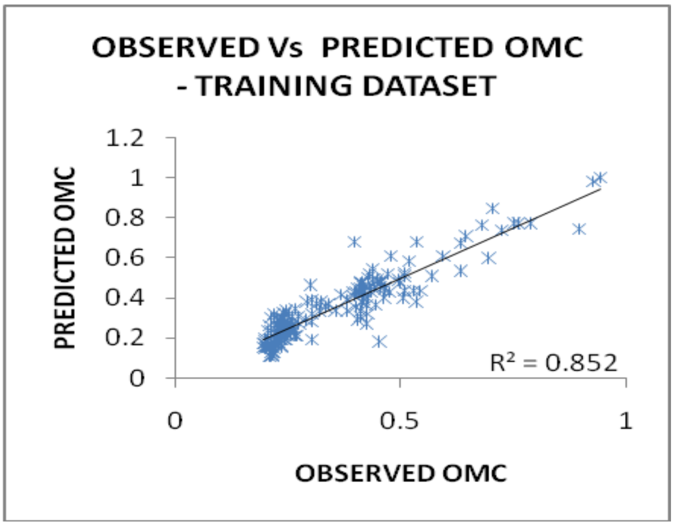


Figure 5.1: Observed OMC Vs Predicted OMC values during Training

Fig. 5.2 exhibits the observed OMC and Predicted OMC values for testing dataset during testing stage of NN model.

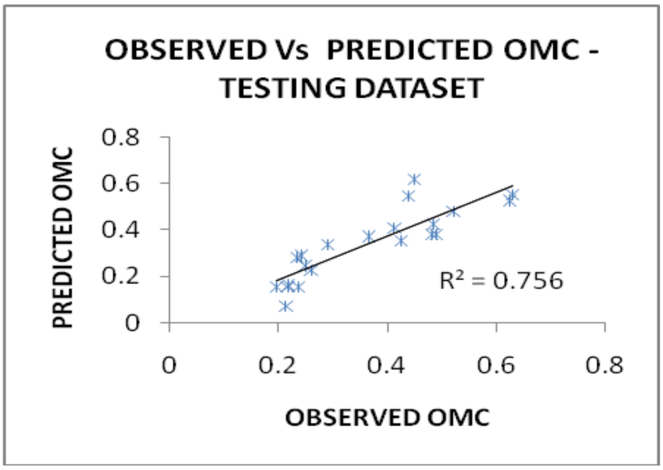


Figure 5.2: Observed OMC Vs Predicted OMC values during Testing

Fig. 5.3 exhibits the observed OMC and Predicted OMC values for simulation dataset during simulation stage of NN model.

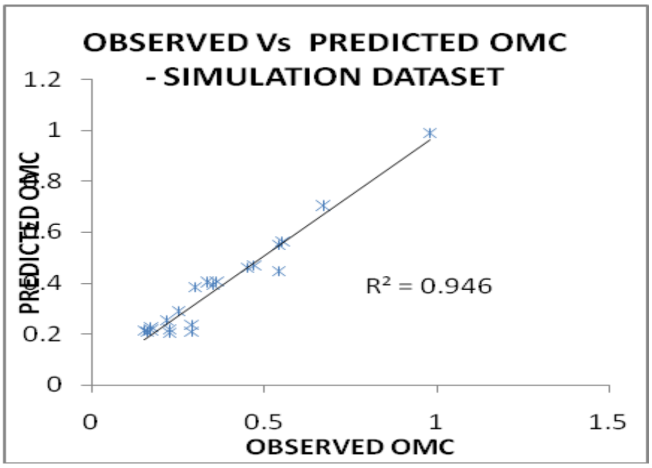


Figure 5.3: Observed OMC Vs Predicted OMC values during Simulation

Fig. 5.4 exhibits the observed MDD and Predicted MDD values for training dataset during training stage of NN model.

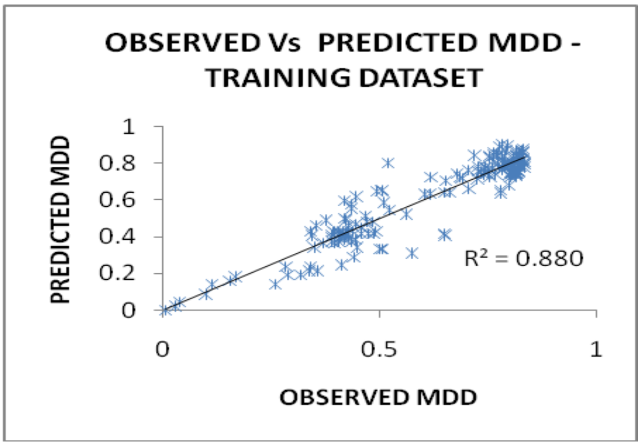


Figure 5.4: Observed MDDVs Predicted MDD values during Training

Fig. 5.5 exhibits the observed MDD and Predicted MDD values for testing dataset during testing stage of NN model.

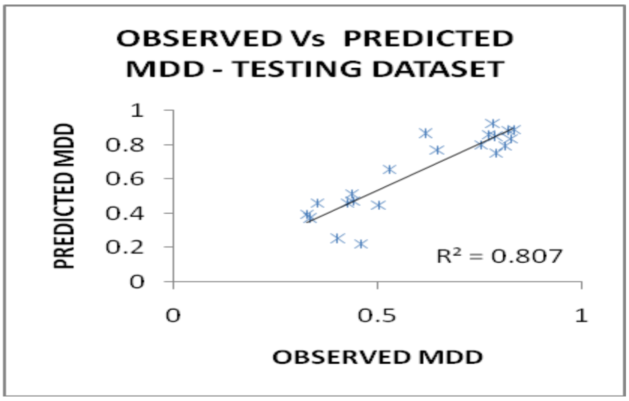


Figure 5.5: Observed MDD Vs Predicted MDD values during Testing

Fig. 5.6 exhibits the observed MDD and Predicted MDD values for simulation dataset during simulation stage of NN model.

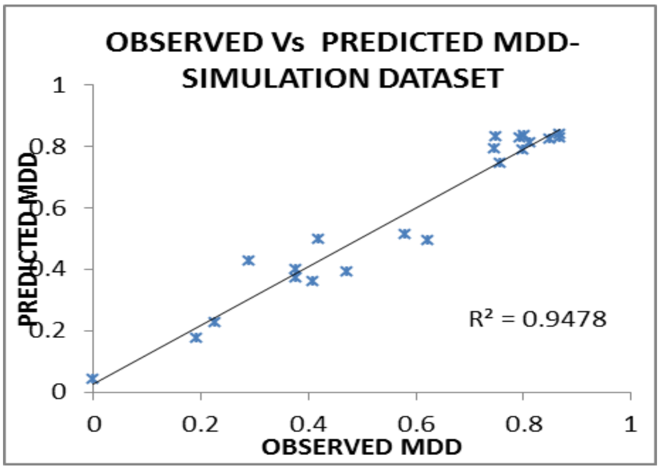


Figure 5.6: Observed MDD Vs Predicted MDD values during Simulation

5.1 Performance of Neural Network indicated by co-efficient of determination (R^2), Mean Square Error (MSE), Root Mean Square Error (RMSE), Absolute Average Relative Error(AARE) for OMC and MDD parameters as given in table 5.1 and table 5.2 respectively.

Table 5.1: ANN Model Statistical Parameter Performance of OMC

Statistical Parameter	*Training*	*Testing*	*Simulation*
R^2	0.8526	0.7568	0.9463
MSE	0.0044	0.0061	0.0023
RMSE	0.0669	0.0785	0.0482
AARE	0.0506	0.0663	0.0396

Table 5.2: ANN Model Statistical Parameter Performance of MDD

Statistical Parameter	*Training*	*Testing*	*Simulation*
R^2	0.8801	0.8071	0.9478
MSE	0.0060	0.0116	0.0034
RMSE	0.0780	0.1079	0.0584
AARE	0.0560	0.0873	0.0448

6. Conclusion

Based on the results of the study, the performance of ANN is better compared to the empirical methods used for prediction of compaction parameters. The Artificial Neural Networks (ANN) can handle large amount of data sets. This model can be further improved by testing and validating with additional datasets of large range. Hence, it is concluded that the proposed neural network model is found to be satisfactory in predicting desired output.

References

[1] Dihoru L., “A neural network for error prediction in a true triaxial apparatus with flexible boundries”, Computer and Geotechnics, vol. 32, pp. 59-71, (2005).

[2] Dr. Ch. Sudha Rani, “Artificial Neural Networks (ANNS) For Prediction of Engineering Properties of Soils”, International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-3, Issue-1, (June 2013)

[3] Ellis G. W., Yao. C. Zhao R., and Penumadu D. “Stress-strain modeling of sand using artificial neural network”, Journal of geotechnical engineering, ASCE, vol. 121, no. 5, pp. 429-435, (1995).

[4] Farzaneh Namdarvand, “Estimation of Soil Compression Coefficient Using Artificial Neural Network and Multiple Regressions”, International Research Journal of Applied and Basic Sciences, ISSN 2251-838X / Vol. 4 (10): 3232-3236.

[5] Ghaboussi J and Sidarta DE, “New nested adaptive neural networks (NANN) for constitutive modeling”, Comput. Geotech; 22:29–52, (1998).

[6] Kakarla P., “Artificial Neural Network approach based indirect estimation of shear strength parameters of soil”, Proceedings of Indian Geotechnical Conference, December 22-24, Roorkee, (2013).

[7] Maria J. Sulewska, “Applying Artificial Neural Networks for analysis of geotechnical problems”, Computer Assisted Mechanics and Engineering Sciences, 18: 231–241, Poland, (2010).

[8] Mini K. M. and Pandian N. S., “Assessment of Compaction Behaviour of soils Using ANN”, Proc. Indian Geotechnical Conference, Dec 17-19, Ahmedabad, India, pp.257-260, (2005).

[9] Rajashekaran, S. and Vijayalaxmi Pai, “Neural Networks, Fuzzy Logic and Genetic Algorithms, Synthetic and Applications”, published by Ashok K. Ghosh, Prentice Hall of India private limited, New Delhi.

[10] Rajeev Jain, “COMPUTATIONAL APPROACH TO PREDICT SOIL SHEAR STRENGTH”, International Journal of Engineering Science and Technology Vol. 2(8), 2010, 3874-3885,(2010).

[11] Saad Abdulrahman Al Hamed, “Artificial neural network for soil cohesion and soil internal friction angle prediction from soil physical properties data”, International Research Journal of Agricultural Science and Soil Science (ISSN: 2251-0044) Vol. 4(5) pp. 85-94, (June 2014).

[12] Sarat Kumar Das and Prabir Kumar Basudhar, “Prediction of residual friction angle of clays using

Artificial Neural Network", Engineering Geology, Volume 100, Issues 3-4, 1 September 2008, Pages 142-145, (2008).
[13] Sinha Sunil K., Mian C. Wang, "Artificial Neural Network prediction models for soil Compaction and Permeability", Journal of Geotech Geology Engg., vol. 26, pp. 47-64, (2008).
[14] Zhu JH, "Modeling of shearing behaviour of residual soil with recurrent neural network", International Journal Numer. Anal. Meth Geomech; 22:671–87, (1998).