

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

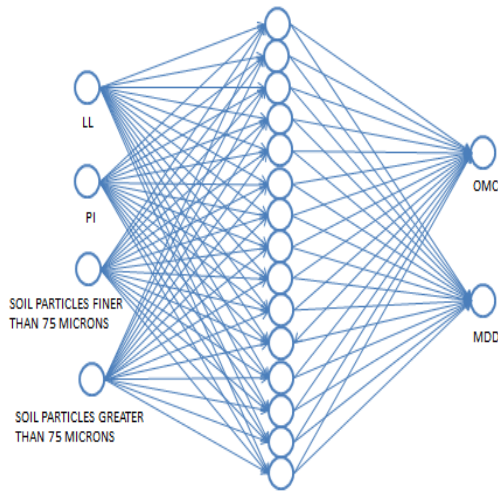
Database used in the present study is based on the data collected from various state authorities, consultants and test conducted in the Soil Mechanics laboratory. A total of 210 datasets were collected of which 80% were employed to develop the model called training sets. 10% of the data is used for validation 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:

$$X_n = \frac{(X_i - X_{min})}{(X_{max} - X_{min})}$$

Where,

X_n= normalized value

X_i = original value of the parameter

X_{min}= Minimum value of the parameter

X_{max}= 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.

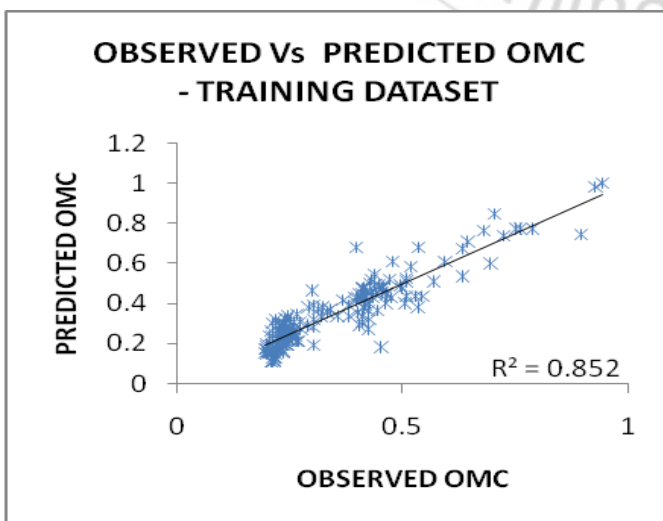


Figure 5.1: Observed OMC Vs Predicted OMC values during Training

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

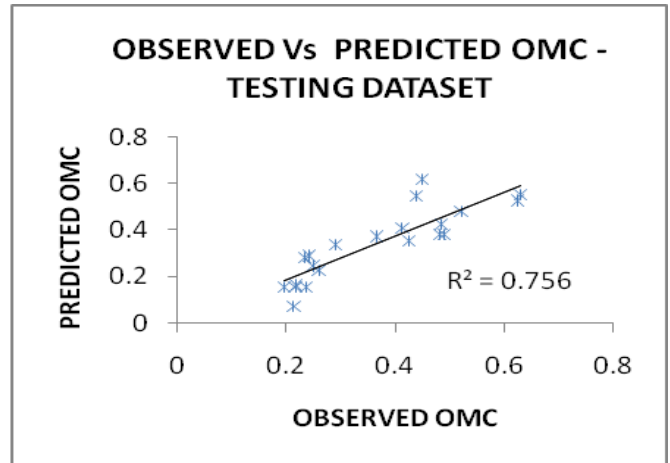


Figure 5.2: Observed OMC Vs Predicted OMC values during Testing

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

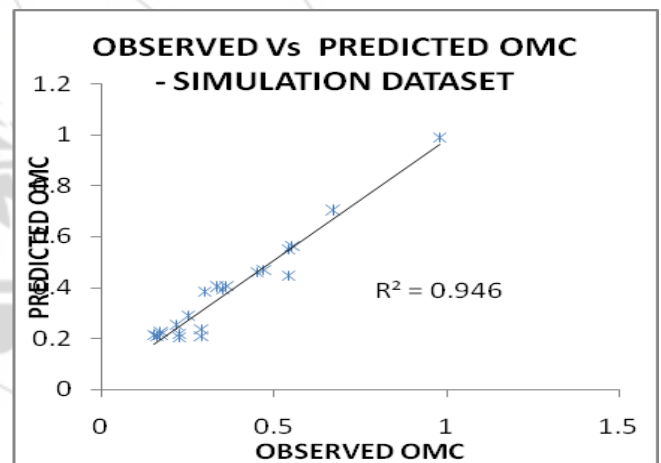


Figure 5.3: Observed OMC Vs Predicted OMC values during Simulation

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

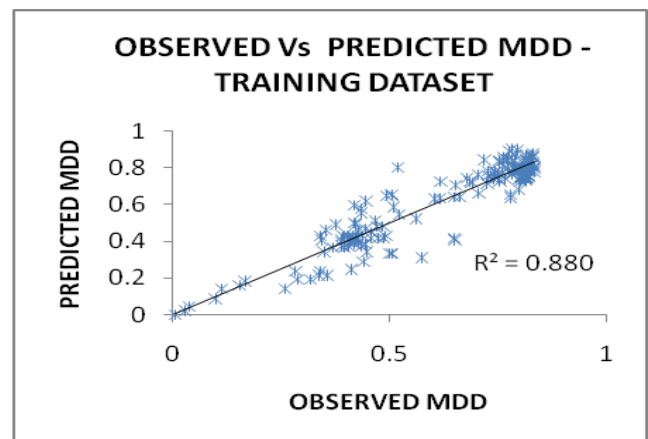


Figure 5.4: Observed MDDVs Predicted MDD values during Training

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

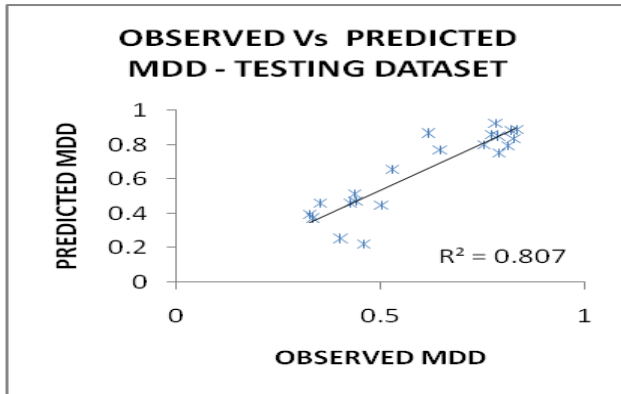


Figure 5.5: Observed MDD Vs Predicted MDD values during Testing

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

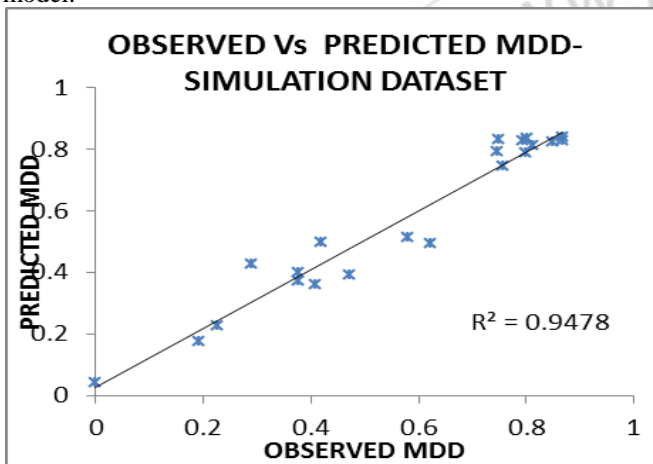


Figure 5.6: Observed MDD Vs Predicted MDD values during Simulation

5.1 Performance of Neural Network indicated by coefficient 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.

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