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Artificial Neural Networks Prediction of Compaction Characteristics of Black Cotton Soil Stabilized with Cement Kiln Dust

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ABSTRACT

Artificial neural networks (ANNs) that have been successfully applied to structural and most other disciplines of civil engineering is yet to be extended to soil stabilization aspect of geotechnical engineering. As such, this study aimed at applying the ANNs as a soft computing approach that were trained with the feed forward back-propagation algorithm, for the simulation of optimum moisture content (OMC) and maximum dry density (MDD) of cement kiln dust-stabilized black cotton soil. Ten input and two output data set were used for the ANN model development. The mean squared error (MSE) and R-value were used as yardstick and criterions for acceptability of performance. In the neural network development, NN 10-5-1 and NN 10-7-1 respectively for OMC and MDD that gave the lowest MSE value and the highest R-value were used in the hidden layer of the networks architecture and performed satisfactorily. For the normalized data used in training, testing and validating the neural network, the performance of the simulated network was satisfactory having R values of 0.983 and 0.9884 for the OMC and MDD, respectively. These values met the minimum criteria of 0.8 conventionally recommended for strong correlation condition. All the obtained simulation results are satisfactory, and a strong correlation was observed between the experimental OMC and MDD values as obtained by laboratory tests and the predicted values using ANN.

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1. Introduction

The optimum moisture content (OMC) and maximum dry density (MDD) of soils are phenomena whose study is unavoidably vital in field and laboratory soil compaction works. Soil compaction which is the process of densification of soil by pore air removal requires the application of mechanical energy to achieve. The degree of compaction of soil is determined in terms of the dry density of the soil. The application of water to the soil in the process of compaction makes the water acts as a medium for softening the soil particles. This makes the soil particles slip over each other than relocate to a more densely packed position. The dry density first increases after compaction with an increase in water content. As the water content is gradually increased, if the used compaction effort is maintained, the weight of the soil solids per unit volume also increases gradually. Beyond a certain water content, a further increase in the water content causes a decrease in the dry density. This phenomenon is as a result of the water occupying the pore spaces that supposed to have been occupied by the solid particles. The water content at which the maximum dry density (MDD) is attained, is generally referred to as the optimum moisture content (OMC).

Artificial Neural Networks (ANNs), which is a form of artificial intelligence, that in its architecture tries to mimic the biology of the human brain and nervous system was used in this study. The important component of this simulation is the novel structure of the information processing system which consists of a huge amount of well-interconnected processing elements (neurons) focused on solving a particular problem [1,2]. Just as it is the case in human beings, ANNs also learn by training. An ANN is developed for a distinct application. These applications include patterns recognition and data classification through a learning process. There are several types of ANNs with different applications, such as data association, data prediction, data classification, data conceptualization and data filtering. The most common type of ANN has three interconnected layers: input, hidden and output. Multi-layer networks make use several types of learning techniques; the most popular of which is back-propagation [3–5], which is also employed in this study.

In the last two decades, ANNs have been used in many geotechnical engineering applications. Shahin *et al.* [6] have used back-propagation neural networks to predict foundation settlements. The predicted settlements obtained based on the use of ANNs were compared with those obtained by three commonly used conventional methods. The study results revealed that ANNs are a promising method for foundations settlement prediction, as they perform better than the deterministic methods considered. Kolay et al. [1] made use of ANN programming in predicting the compressibility characteristics of soft soil settlement in Sarawak, Malaysia. Benali et al. [7] used ANNs for principal component analysis and predicting capacity of pile based on SPT results. All these literature are a source of hope for the beneficial use of ANNs in geotechnical applications.

Black cotton soils (BCS) are expansive soils which are so named due to their mostly dark color and suitability for growing cotton. BCS is confined to the semi-arid regions of tropical and temperate climatic zones. They are abundant in regions where the annual evaporation is more than the precipitation [8]. BCS is common in flat terrains that has poor drainage system [9]. The mineralogy of BCS is dominated by montmorillonite clay mineral which has the characteristics of high change in volume from dry to wet seasons and vice versa. Deposits of BCS occupy an estimated area of 104 x 10^3 km^2 in the North-Eastern part of Nigeria. These areas are generally known with a pattern of cracks during the dry season. These cracks measure up to 70mm wide and over 1m deep and may extend beyond 3m in areas with high deposit [10,11].

The increasing cost of soil stabilizers coupled with the need to reduce the cost of waste disposal has led to a serious global research focus on the beneficial use of wastes in engineering applications [12–14]. The safe disposal of wastes from industries needs fast and economic solutions due to the destructive effect of these materials on our environment and also the health hazards they constitute [15]. Cement kiln dust (CKD) is a solid highly alkaline waste which is fine-grained removed from the cement kiln exhaust gas by air pollution control devices of cement production plants in cement industries. [16].

In this study, standard laboratory procedures were used to determine the properties of natural and CKD-treated BCS using three compaction energies. The study aimed at using the soil properties to develop an optimized neural network for the OMC and MDD of natural and CKD-stabilised black cotton soil using multi-layer networks variety of learning technique of back-propagation in Artificial Neural Networks (ANNs).

2. Materials and methods

2.1. Materials

2.1.1. Soil

The disturbed BCS samples used herein were obtained from Deba, Gombe State of Nigeria.

2.1.2. Cement kiln dust

The CKD used for this study was sourced from Sokoto Cement, Sokoto, Nigeria. The oxide composition of the BCS and CKD used for this study is shown in Table 1. The only benefit of including the oxide composition of the materials is to distinguish them from any other materials that may be used to reproduce the research and results compared since material properties is the best characteristics to differentiate materials.

Table 1
Oxide composition of black cotton soil (BCS) and cement kiln dust (CKD)

Oxide	BCS (%)	CKD (%)
CaO	4.53	44.28
SiO_2	42.45	7.23
Al_2O_3	13.19	1.90
Fe_2O_3	16.75	4.47
MgO	-	0.82
MnO	0.62	0.11
TiO_2	3.17	0.23
V_2O_5	0.22	0.03
Cr_2O_3	0.031	0.02
ZnO	-	0.01
K_2O	3.03	-
LOI (1000^0C)	15.34	39.28

2.2. Methods

2.2.1. Laboratory tests

Laboratory tests procedures outlined in BS 1377 [17] were used to carry out tests on the natural soil samples while those outlined in BS 1924 [18] were used to carry out tests on all CKD treated BCS. The tests conducted include particle size distribution, specific gravity, linear shrinkage, free swell, Atterberg limits and compaction characteristics test to determine the OMC and MDD. All tests were performed in steps of 0, 2, 4, 6, 8 and 10% CKD content by dry weight of the BCS. Three compaction energies used in this study are the BS Light, WA Standard and the BS Heavy.

The standard Proctor equipment used for laboratory soil compaction is shown in Figure 1 while an average compaction test results for BCS is shown in Figure 2.

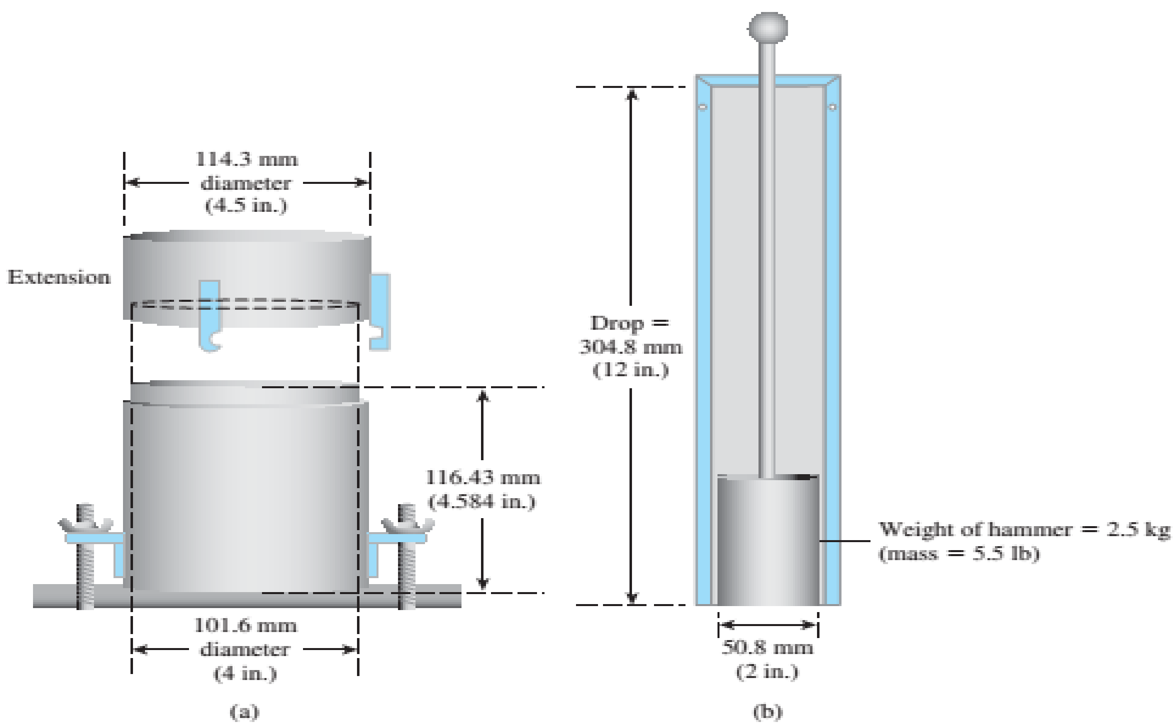

Fig. 1. Standard Proctor test equipment: (a) mould (b) hammer.

For each of the compaction test, the bulk density of compacted soil, γ, was computed from:

$$\gamma = \frac{W}{V_{(m)}} \tag{1}$$

With the known moisture content value, w (%), for each of the compaction tests, the dry unit weight can be calculated from:

$$\gamma_d = \frac{\gamma}{1+\frac{w}{100}} \tag{2}$$

The values of dry density obtained from equation (2) was plotted against the corresponding water contents to get the MDD and the corresponding OMC for the soil. A typical density test results for BCS is shown in Figure 2.

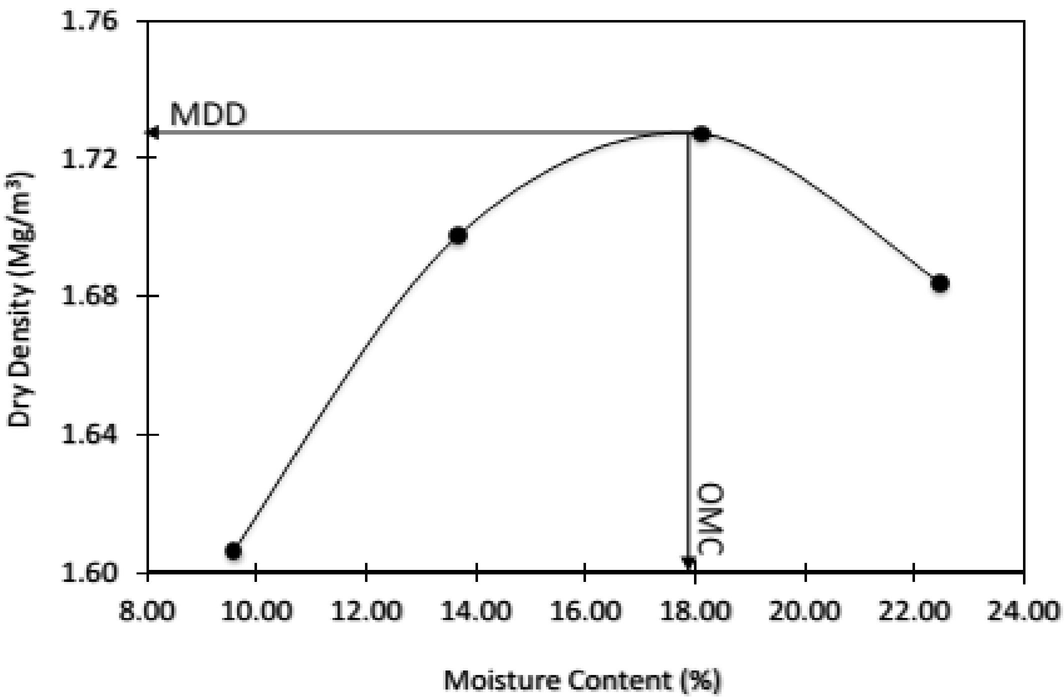

Fig. 2. Typical compaction test results for black cotton soil.

2.2.2. ANNs model development

The types of NNs used herein are MLPs trained with the feed forward back-propagation algorithm. The typical MLP has a number of processing elements generally known as neurons which are arranged in layers consisting of an input layer, an output layer, and two hidden layers. Each neuron in the specific layer is connected to the neuron of other layers through weighted connections. The input from each neuron in the previous layer is multiplied by an adjustable connection weight. This combined input then passes through a nonlinear transfer function (TANSIG function for layer one and PURELIN function for layer two were used in this study) to produce the output of the processing element. The neurons use the following transfer or activation function:

$$X = \sum_{i=1}^{n} x_i w_i \qquad Y = \begin{cases} +1, \text{if } X \geq \theta \\ -1, \text{if } X < \theta \end{cases} \tag{3}$$

The ANN model was developed with MATLAB R2014a. Ten input and two outputs were used separately for the ANN model development herein. The input data are specific gravity (SG), linear shrinkage (LS), free swell (FS), D_{10}, D_{30} and D_{60} (the effective soil particle sizes, which are the largest size of the smallest 10, 30 and 60 %), uniformity coefficient (C_u) coefficient of gradation (C_c), liquid limit (LL) and plastic limit (PL) with the outputs (targets) been the optimum moisture content (OMC) and maximum dry density (MDD). Multilayer perceptron architecture of networks used for the ANN model development for OMC and MDD are shown in Figures 3 and 4, respectively.

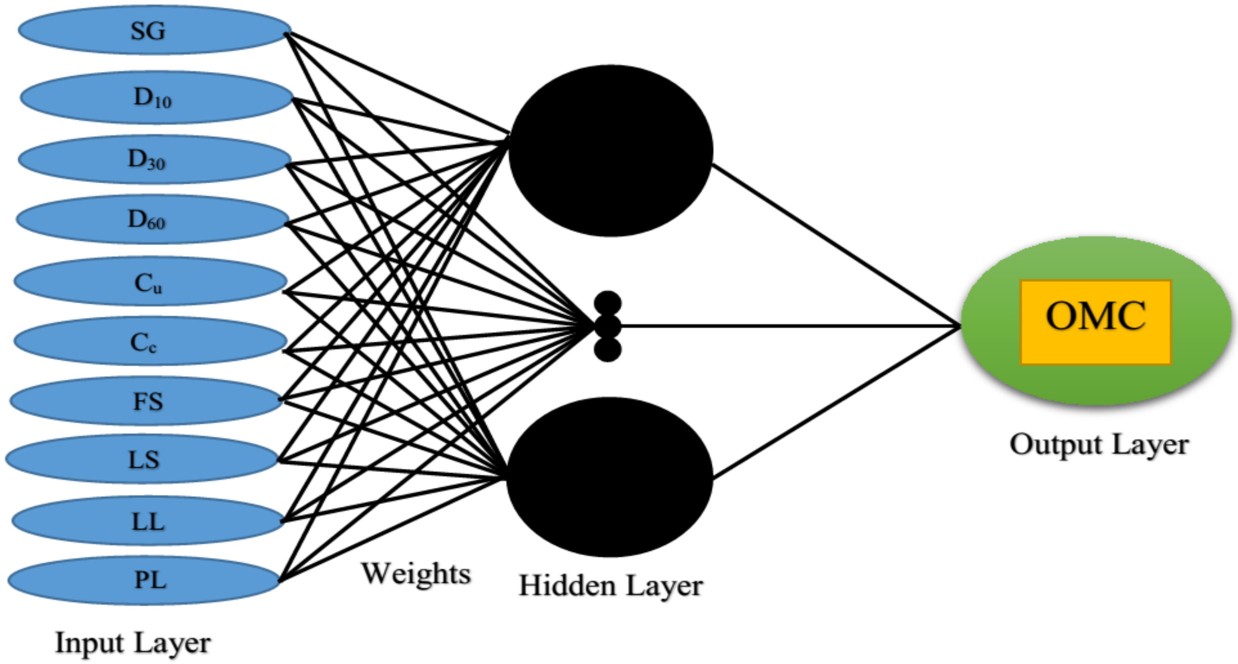

Fig. 3. Multilayer perceptron architecture of network used for ANN model development for OMC.

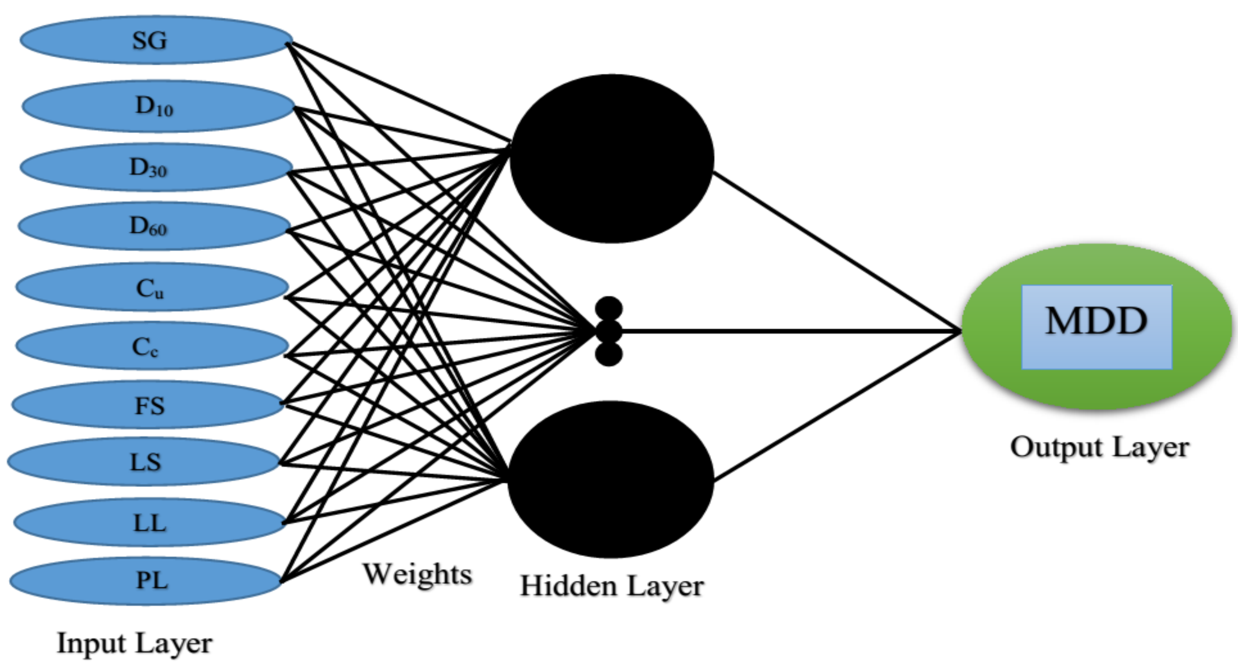

Fig. 4. Multilayer perceptron architecture of network used for ANN model development for MDD.

2.2.3. Data division and processing in ANNs

In developing the ANN model, the available data were divided into their subsets. In this study, the data were randomly divided into three sets: a training set for model calibration, testing set for testing the developed model and an independent validation set for model verification. In total, 70% of the total data set were used for model training, 15% were used for model testing, and the remaining 15% were used for model validation. This division has been used successfully and reported by Shahin *et al.* [6] in the literature. As the available data were divided into their sub-sets, the input and output data were pre-processed and were normalized between -1.0 and 1.0.

2.2.4. Model performance evaluation

The performance of the developed ANNs model was evaluated to ensure that the model can generally perform within the pre-defined limits set by the data used for training instead of been peculiar to the input-output relationships contained in the training data. The conventional approach is to evaluate the model performance on an independent validation set of data that was not used in the training process. In the literature, the common measures often used are statistical measures which include the correlation coefficient (R), the mean absolute error (MAE) and the root mean square error (RMSE). The formulas of these measures are:

$$R = \frac{\sum_{i=1}^{N}(O_i-\bar{O})(P_i-\bar{P})}{\sqrt{\sum_{i=1}^{N}(O_i-\bar{O})^2 \sum_{i=1}^{N}(P_i-\bar{P})^2}} \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(O_i-P_i)^2}{N}} \quad (5)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|O_i - P_i| \quad (6)$$

where N = number of data points used for the model development; O_i and P_i are respectively the measured and predicted outputs, while $\bar{O}$ and $\bar{P}$ are respectively the mean of measured and predicted outputs.

3. Results and discussions

3.1. Data Processing for ANN

In ANN prediction modeling, the efficiency of input data and their ability to accurately predict the output (target) is largely dependent on the relationship between the input and the output [19,20]. In this study, ten input geotechnical soil parameters that have direct effects on the two outputs were considered. The descriptive statistics of the experimental data as obtained from various laboratory tests used for the ANN model development are presented in Table 2. In order to give a detailed insight of the general data used for the study, a frequency bar chart was used to present the research data of a total of 90 set as shown in Figures 5(a) – (l).

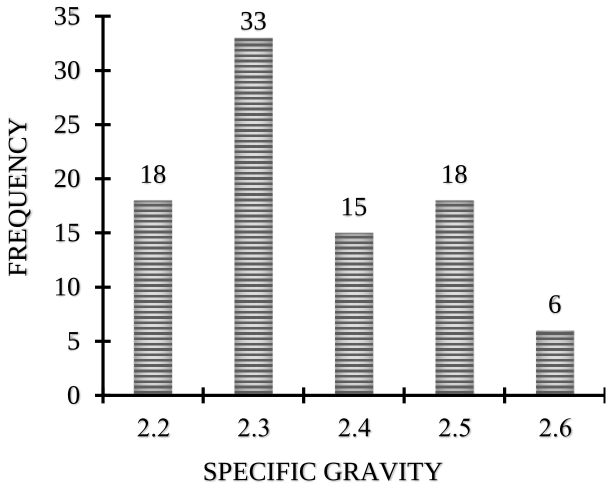

Fig. 5(a): Frequency of SG used for ANN

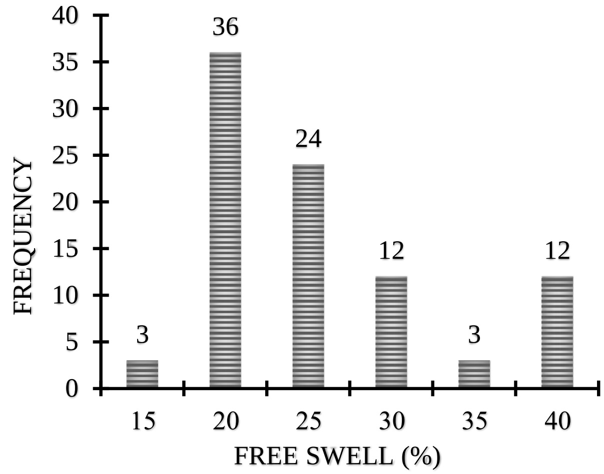

Fig. 5(b): Frequency of FS used for ANN

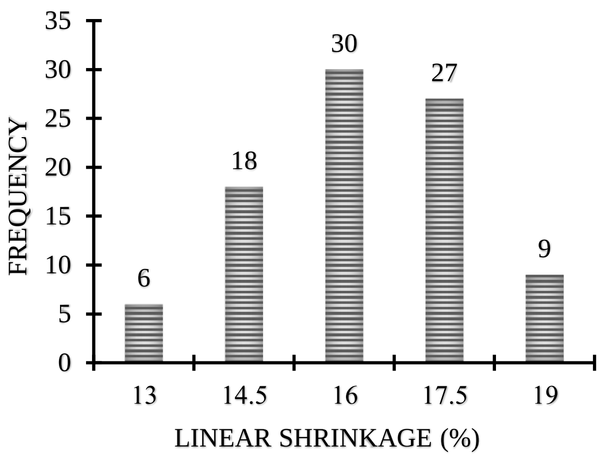

Fig. 5(c): Frequency of LS used for ANN

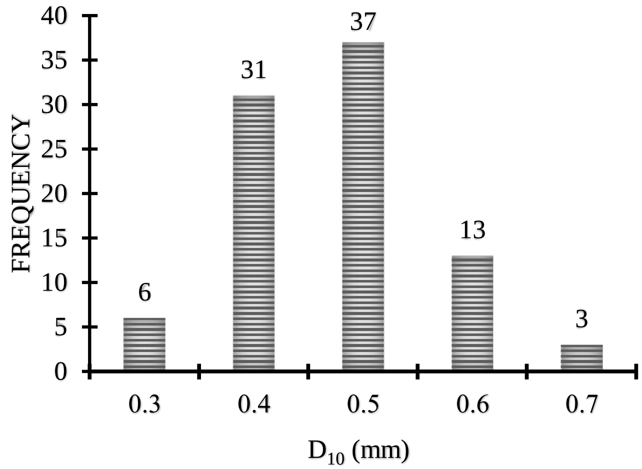

Fig. 5(d): Frequency of D_{10} used for ANN

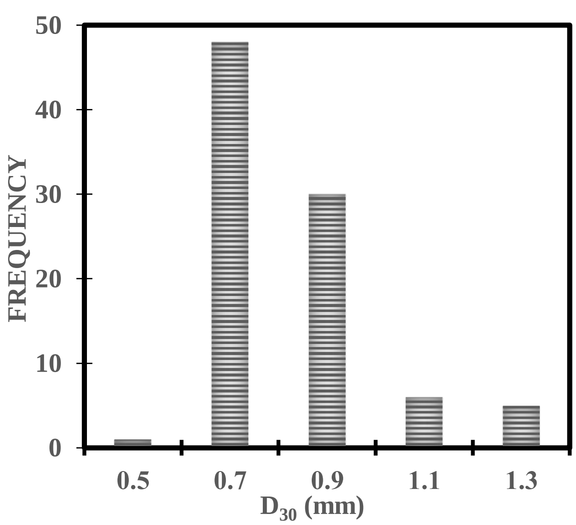

Fig. 5(e): Frequency of D_{30} used for ANN

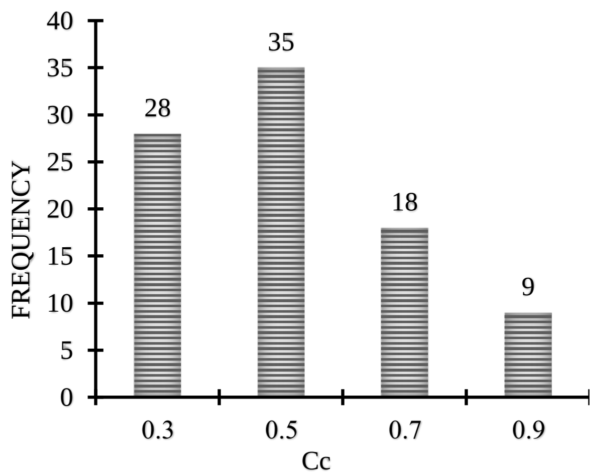

Fig. 5(f): Frequency of C_c used for ANN

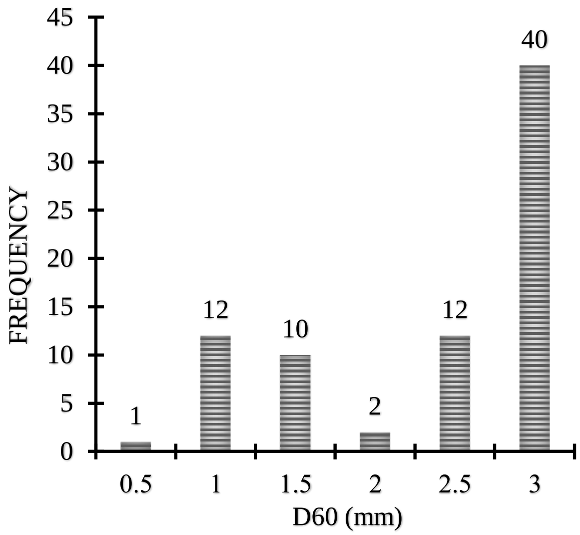

Fig. 5(g): Frequency of D_{60} used for ANN

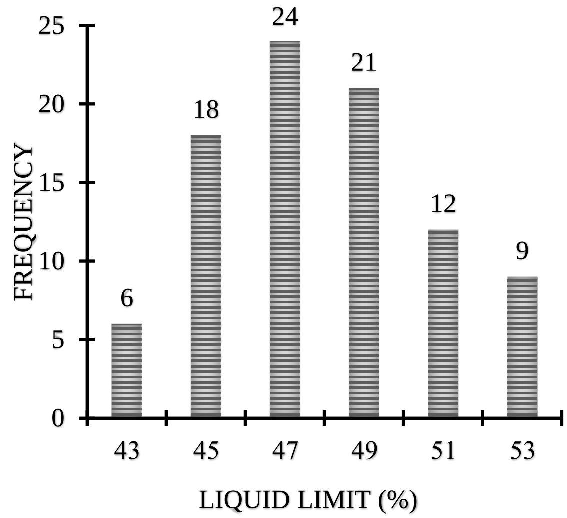

Fig. 5(h): Frequency of LL used for ANN

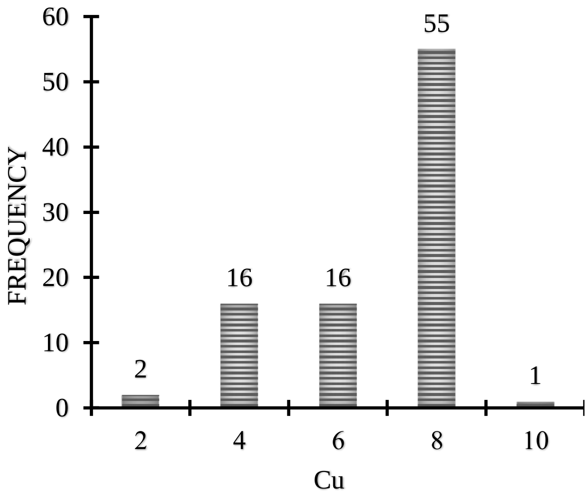

Fig. 5(i): Frequency of C_u used for ANN

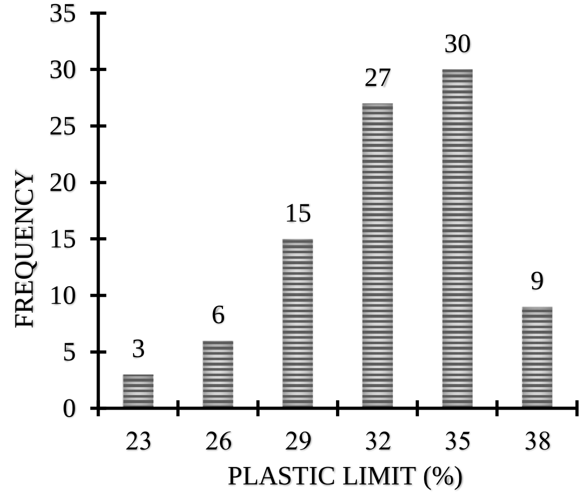

Fig. 5(j): Frequency of PL used for ANN

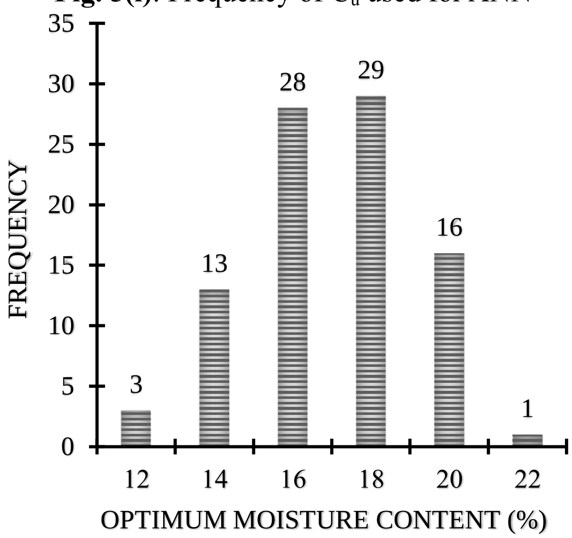

Fig. 5(k): Frequency of OMC for ANN

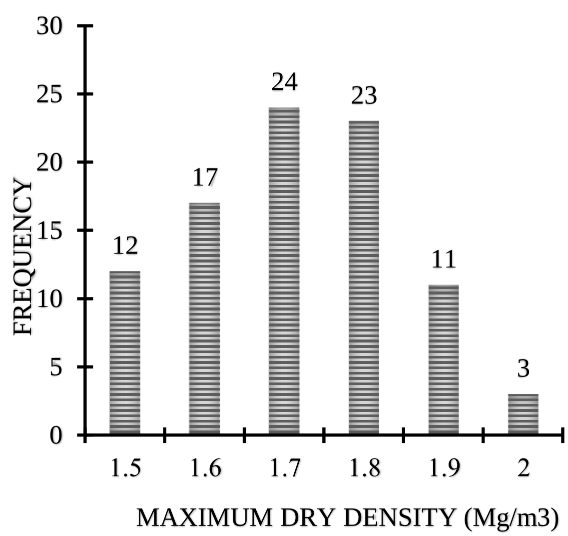

Fig. 5(l): Frequency of MDD for ANN

Table 2
Descriptive statistics of experimental data used for ANN model development.

Soil parameter	Minimum	Maximum	Mean	Standard deviation	Coefficient of variation
SG	2.11	2.53	2.308	0.115	0.05
LS (%)	12.44	18.69	15.546	1.531	0.099
FS (%)	14.59	40	23.556	7.19	0.305
D_{10} (mm)	0.25	0.66	0.429	0.087	0.203
D_{30} (mm)	0.48	1.25	0.721	0.174	0.241
D_{60} (mm)	0.47	3.5	2.336	0.882	0.378
C_u	1.925	8.293	5.716	1.62	0.283
C_c	0.203	0.839	0.417	0.172	0.413
LL (%)	42.4	52.34	47.143	2.668	0.057
PL (%)	22.98	36.8	30.911	3.385	0.11
OMC (%)	11.33	20.07	16.019	2.091	0.131
MDD (Mg/m^3)	1.342	1.958	1.658	0.144	0.087

3.2. The optimized network

The NN 10-n-1 network architecture was used for the network optimization herein. The first digit of the component is the number of input nodes, n is the number of hidden nodes (number of neurons), and the third digit is the number of output nodes. These NN 10-n-1 network architectures are shown in Figures 3 and 4. In this study, ten different number of hidden nodes (NN 10-1-1 to NN 10-10-1) were tried in order to determine the best performing n-number. The MSE and R-value were used as yardstick and criterions in this regard. The choice of 1 – 10 neurons was based on the study of Kolay et al. [1] on soft tropical soil using ANN. Kolay et al. [1] concluded that the use of neuron number above ten could cause saturation of the network which results in lesser quality simulated results due to undesirable feedbacks to the network. This phenomenon may lead to network confusion that could result to lower accuracy in the simulated results. Therefore, five and seven neurons for OMC and MDD respectively that yielded the lowest MSE value and the highest R-value on the average were used in the hidden layers. Shahin [21] and Eidgahee et al. [22] stated that the best measure for the performance of the ANN developed models should be based on the lowest MSE values and the highest R-values. However, other researchers like Naderpour et al. [23] used only MSE values as a criterion. The MSE and the R-values that led to the choice of NN 10-5-1 and NN 10-7-1 networks respectively for the OMC and MDD are shown in Figures 6 - 9. It should be noted that in situations whereby it is difficult to make a reliable choice of the neuron numbers based on the R-values, the MSE values takes preference to yield better results.

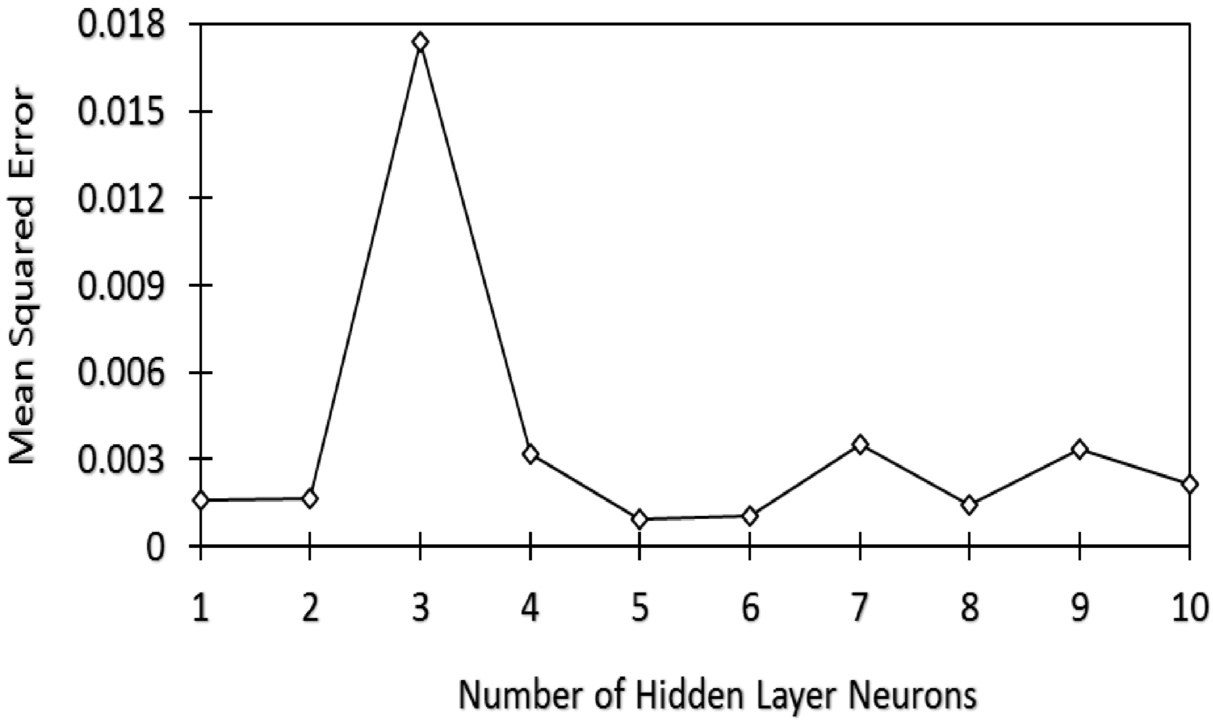

Fig. 6. Variation of MSE with number of hidden layer neurons for OMC.

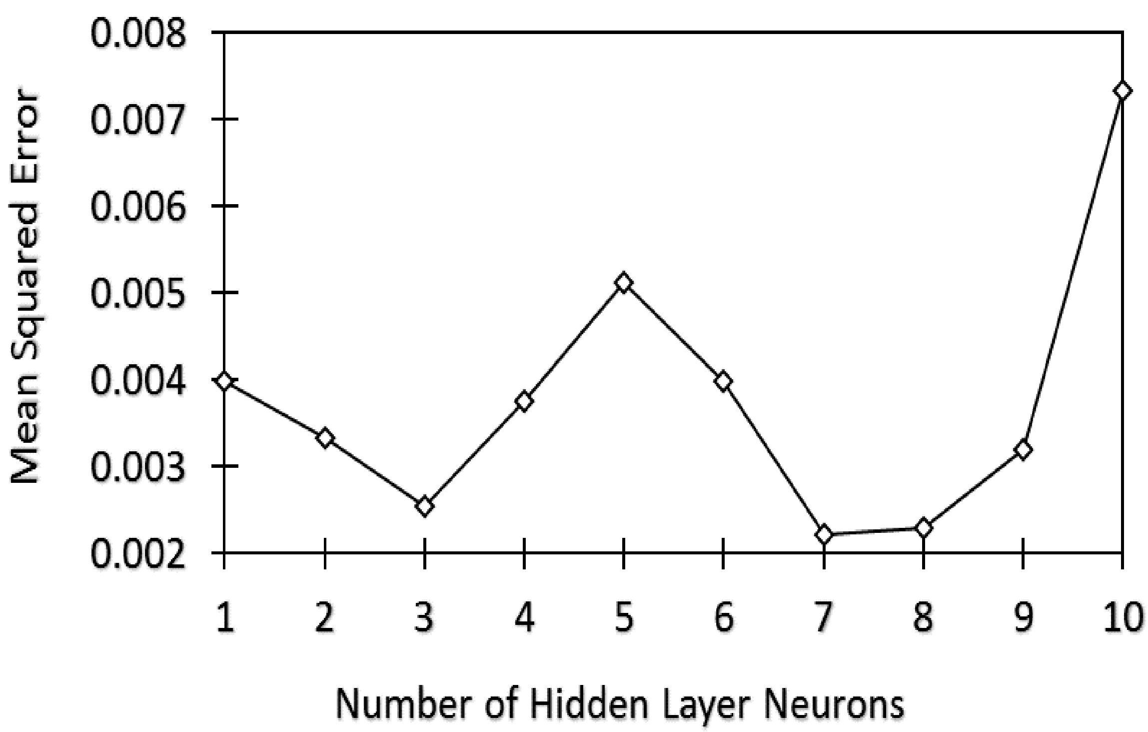

Fig. 7. Variation of MSE with number of hidden layer neurons for MDD.

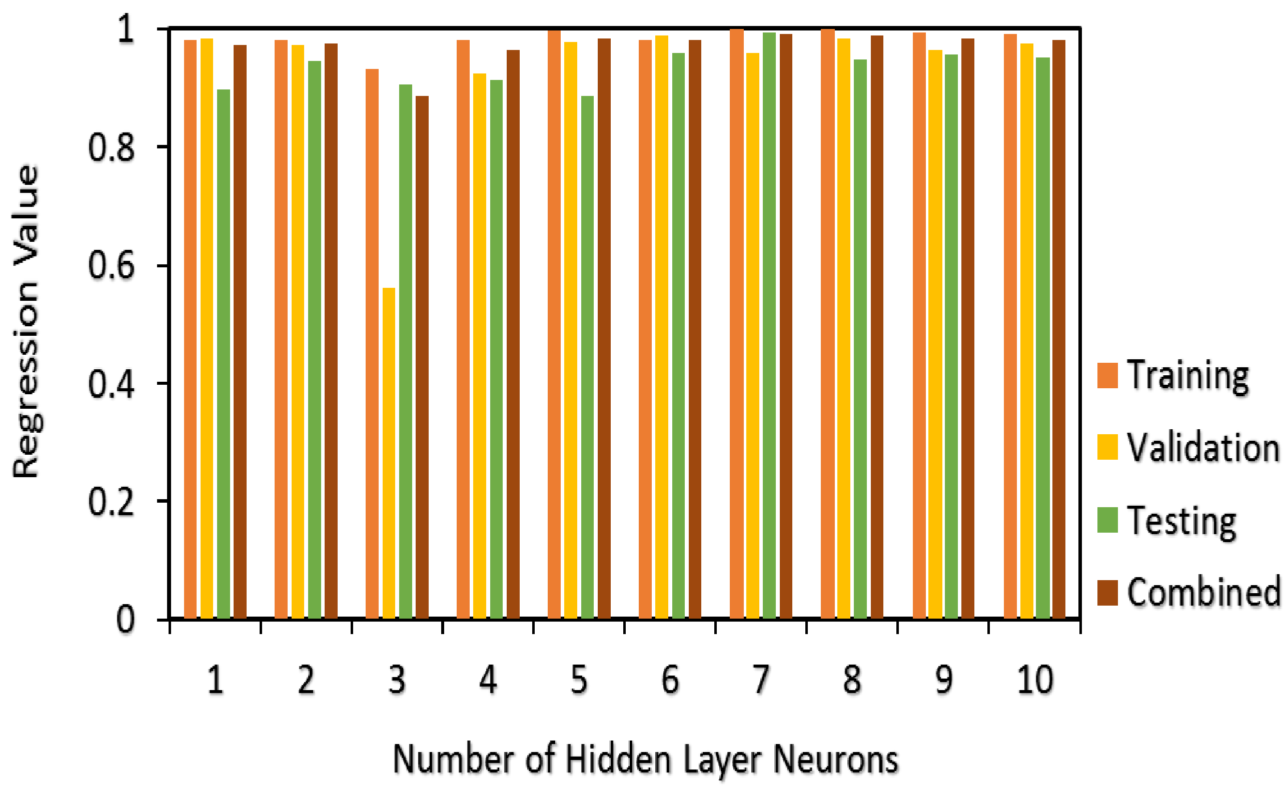

Fig. 8. R-values for ANN performance with number of hidden layer neurons for OMC.

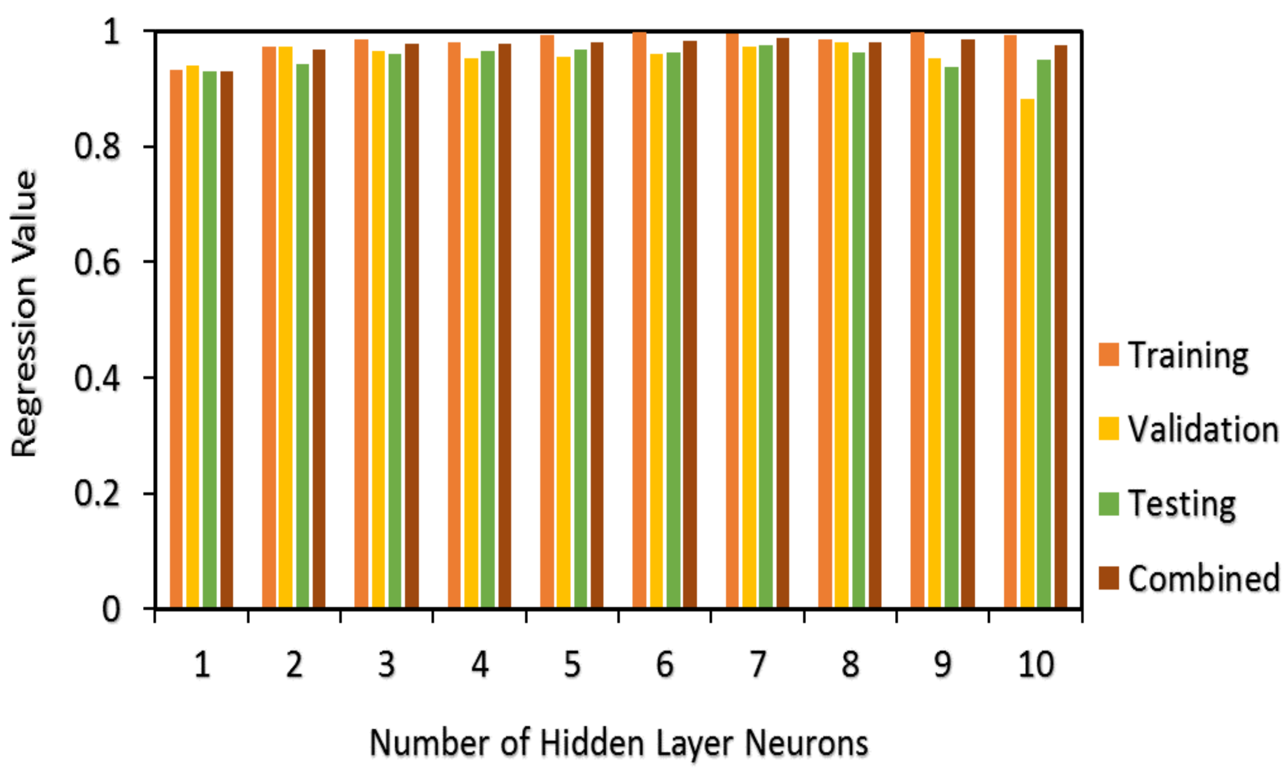

Fig. 9. R-values for ANN performance with number of hidden layer neurons for MDD.

3.3. ANN model development

The regression values for model performance evaluation showing the k (slope), R-values, MAE, MSE and the RMSE are presented in Table 3. It is obvious from these statistical results that the models developed in this study performed satisfactorily having high R-values and low error values. The statistical parameters give acceptable results that make the confirmed the best generalization of the developed model.

The variation of experimental and ANN predicted OMC and MDD values are shown in Figures 10 and 11 respectively. The performance of the simulated network was very good having k values of 0.9654 for the OMC and 0.9364 for the MDD, where k is the slope of the regression line through the origin in the plot of the experimental values to the predicted values. It was reported by Alavi *et al.* [24] and Golbraikh and Tropsha [25] that the value of k should be close to unity as a criterion for excellent performance.

Table 3
Parameters and regression values for model performance evaluations.

Parameters	OMC	MDD
Number of Neurons	5	7
k	0.9654	0.9364
MSE (ANN)	0.0009	0.0022
R-Training	0.9977	0.9946
R-Testing	0.8855	0.9754
R-Validation	0.9779	0.9715
R-All Data	0.983	0.9884
MAE	0.0208	0.0229
MSE (Statistical)	0.0013	0.0010
RMSE	0.0358	0.0321

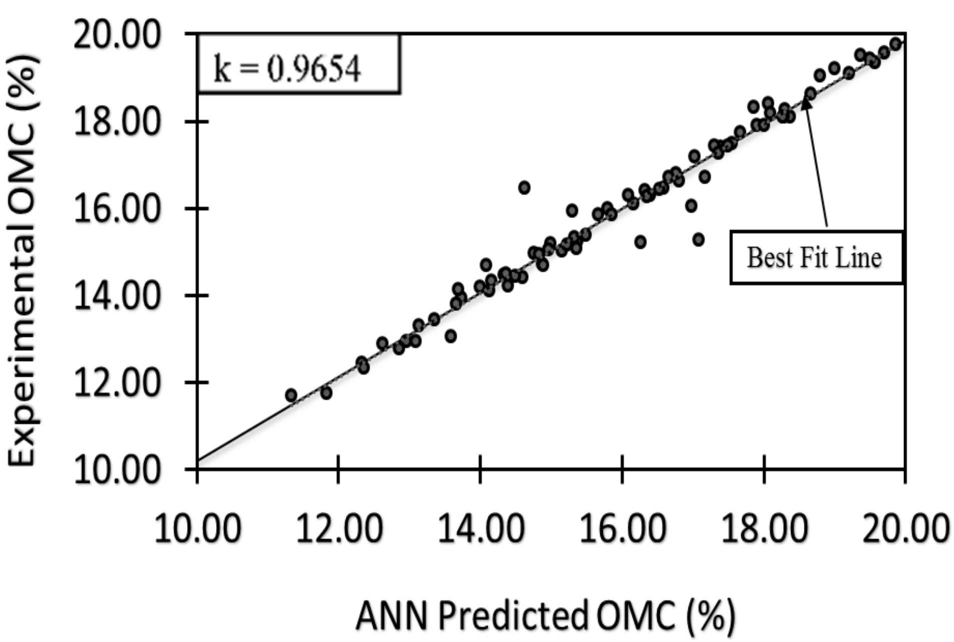

Fig. 10. Variation of experimental and ANN predicted OMC values.

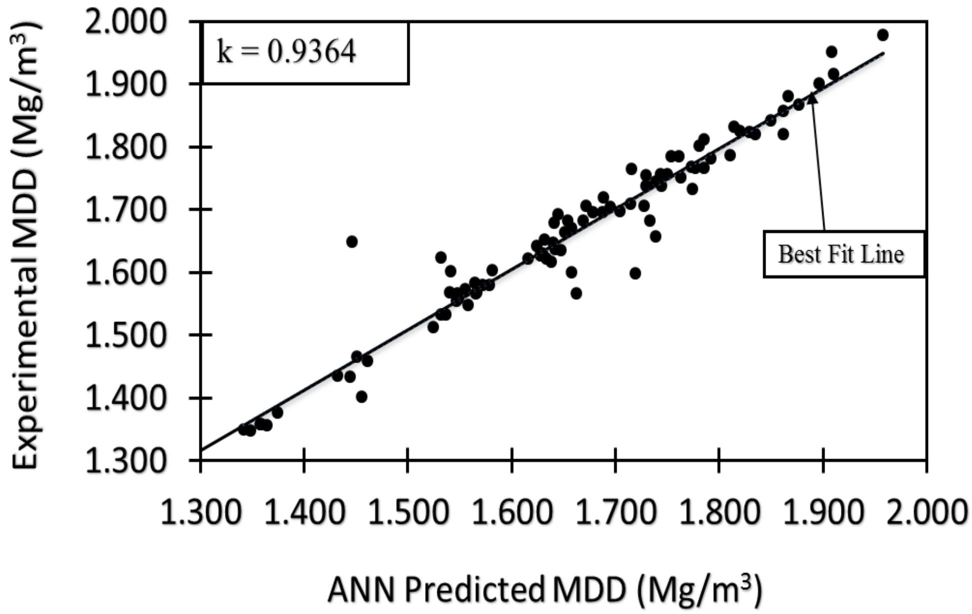

Fig. 11. Variation of experimental and ANN predicted MDD values.

After the most acceptable and desirable network was chosen based on the highest R-value and minimum MSE values and NN 10-5-1 and NN10-7-1 were selected as the best networks for OMC and MDD respectively, the ANN was trained, and the training results are presented in Figures 12 – 17 for the two targets. Figures 12 and 13 show the MSE of the network starting with a higher value and decreasing to a smaller value. This shows that the network is learning until an optimal target is achieved when the MSE is at its minimum. The three curves in these Figures represent the three sets of data (training, testing, and validation) into which the total input and output data were divided. The training of the neurons continues until the error reduced to its minimum at which the network memorizes the training set then the training process is stopped. This technique automatically avoids the problem of over-fitting, which plagues many optimizations and learning algorithms.

The performance of the network based on its R-values for the three data sets are shown in Figures 14 and 15 for the OMC and MDD respectively while the training state values showing the gradient, input matrix of means (Mu) and the validation checking are shown in Figures 16 and 17 for OMC and MDD respectively.

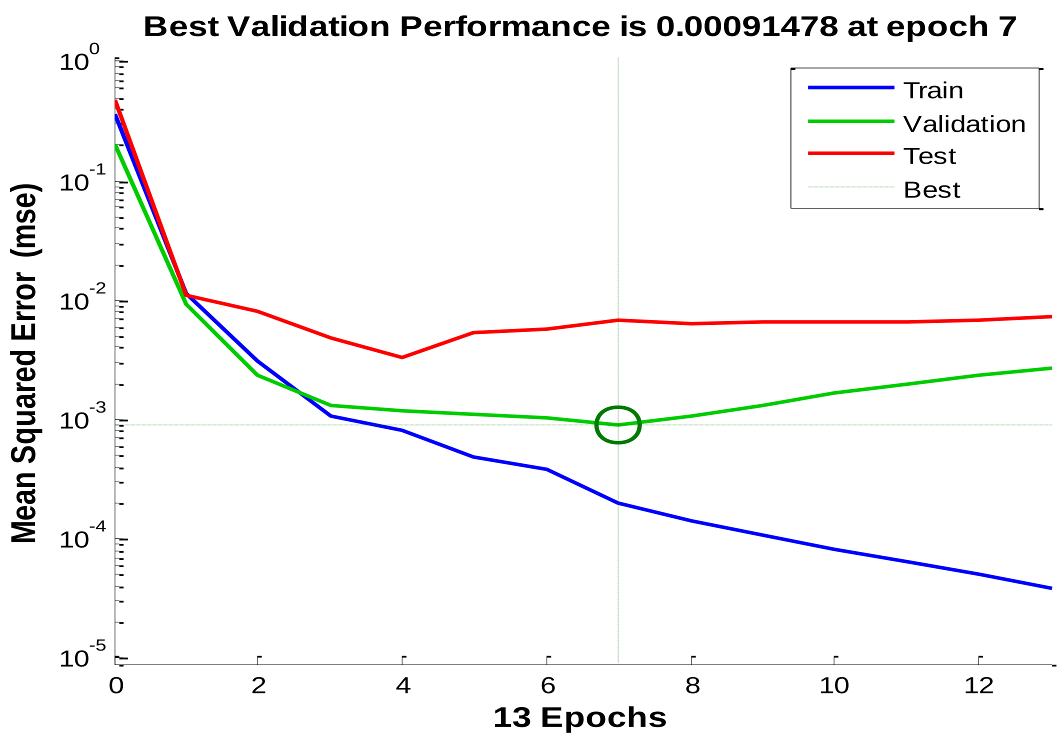

Fig. 12. Performance of NN 10-5-1 by mean squared error for OMC.

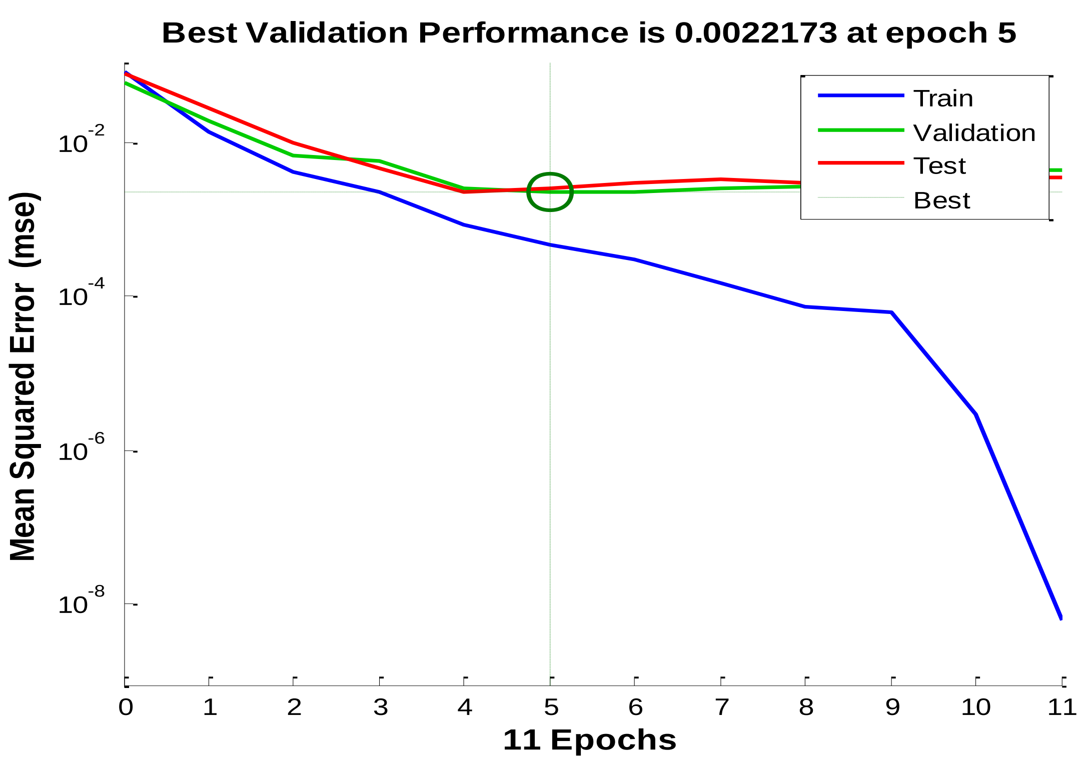

Fig. 13. Performance of NN 10-7-1 by mean squared error for MDD.

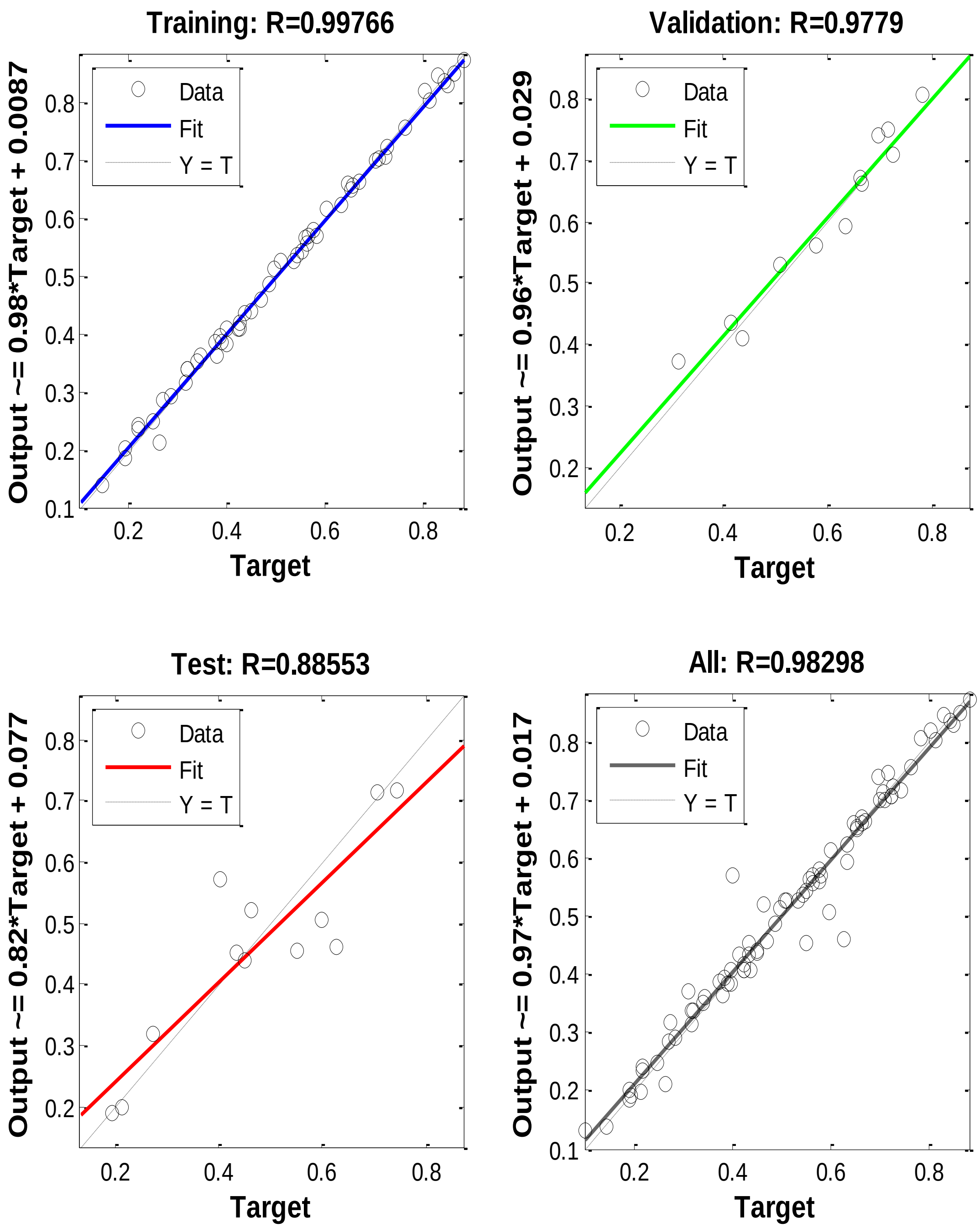

Fig. 14. Regression values of NN 10-5-1 for OMC.

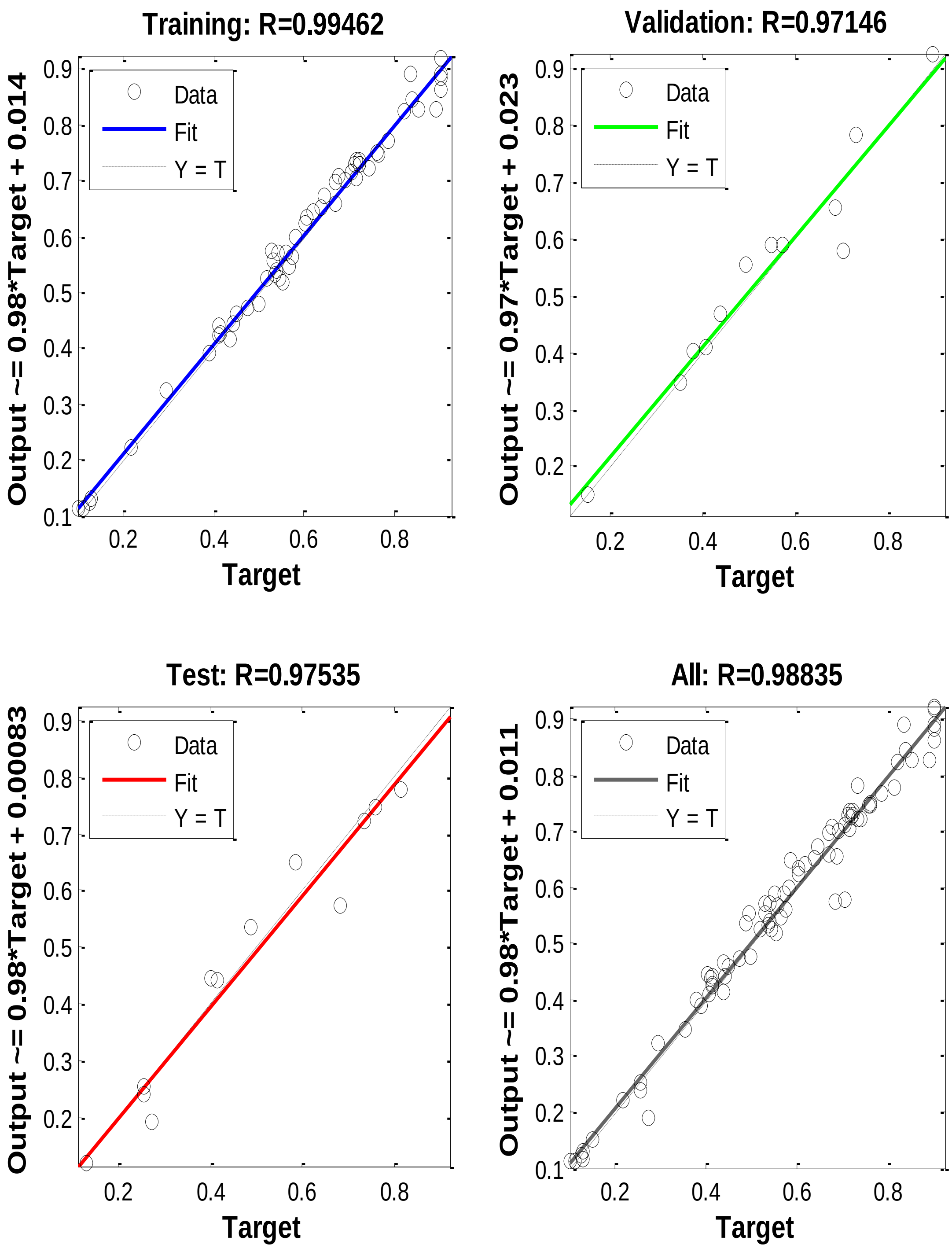

Fig. 15. Regression values of NN 10-7-1 for MDD.

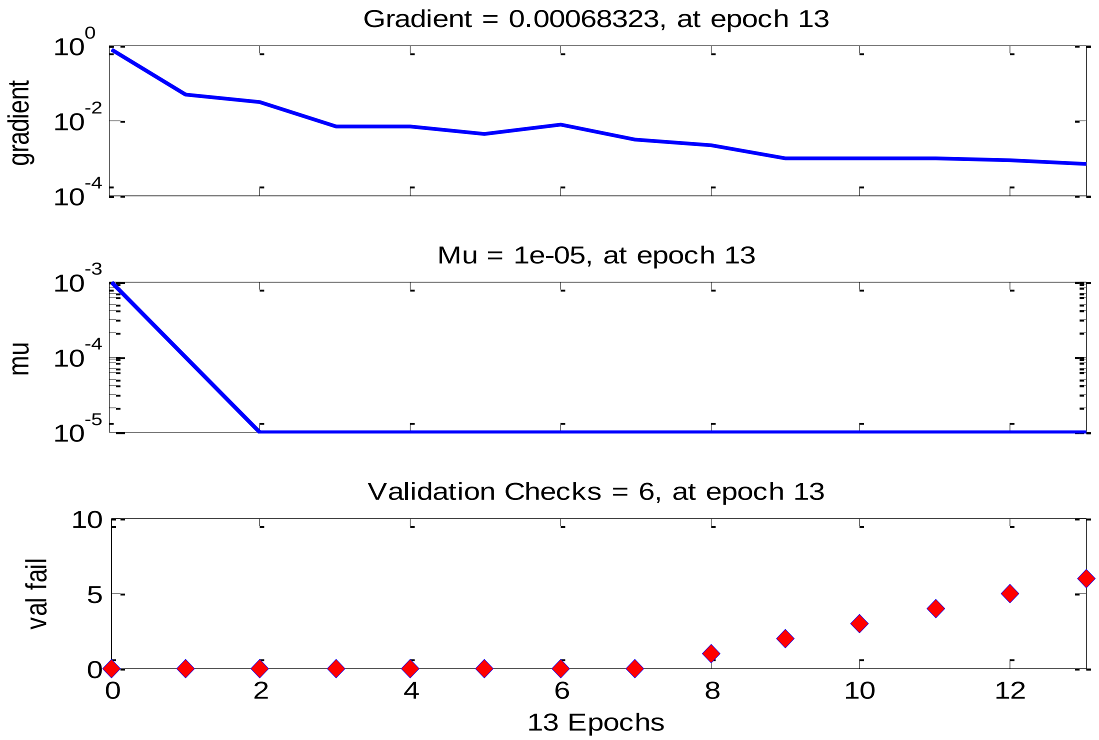

Fig. 16. Training state of NN 10-5-1 for OMC.

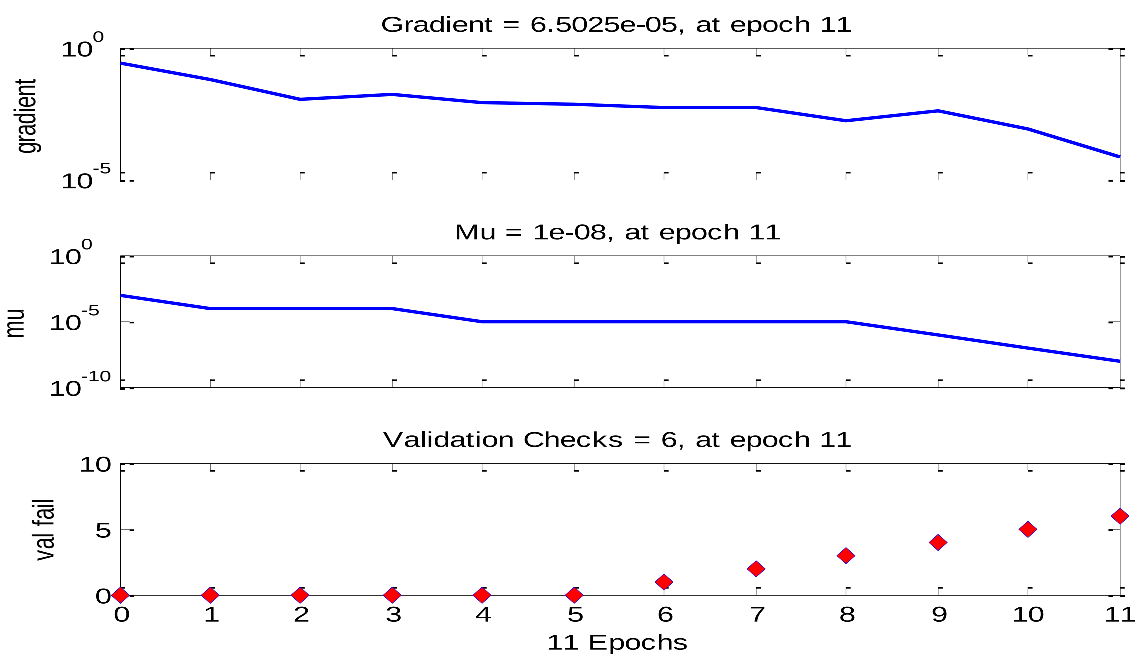

Fig. 17. Training state of NN 10-7-1 for MDD.

3.4. Model validation

The coefficient of correlation (R) is a measure used to evaluate the relative correlation and the goodness-of-fit between the predicted and the observed data. Smith [26] suggested that a strong correlation exists between any two sets of variables if the R-value is greater than 0.8. However, Das and Sivakugan [27] are of the opinion that the use of R-value alone can be misleading arguing that higher values of R may not necessarily indicate better model performance due to the tendency of the model to deviate towards higher or lower values in a wide range data set.

The RMSE, on the other hand, is another measure of error in which large errors are given greater concern than smaller errors. However, Shahin [21] argued that in contrast to the RMSE, MAE eliminates the emphasis given to larger errors and that both RMSE and MAE are desirable when the evaluated output data are continuous. Consequently, the combined use of R, RMSE and MAE was found to yield a sufficient assessment of ANN model performance and allows comparison of the accuracy of generalization of the predicted ANN model performance. This combination is also sufficient to reveal any significant differences among the predicted and experimental data sets.

Table 4
Conditions of model validity.

Target	Statistical parameter	Condition	Obtained value	Remarks
OMC	R	> 0.8	0.983	Satisfactory
	k	Should be close to 1	0.9654	Satisfactory
	MAE	Should be close to 0	0.0208	Good
	MSE	Should be close to 0	0.0013	Satisfactory
	RMSE	Should be close to 0	0.0358	Good
MDD	R	> 0.8	0.9884	Satisfactory
	k	Should be close to 1	0.9364	Satisfactory
	MAE	Should be close to 0	0.0229	Good
	MSE	Should be close to 0	0.001	Satisfactory
	RMSE	Should be close to 0	0.0321	Good

The conditions of model validity in this study are stated in Table 4. Based on the results of different NN 10-n-1 networks used in this study, it was observed that the errors are at their best performance when they are greater than 0.01 but still yield good and acceptable performance when greater than 0.1 in a value range of 0 to 1. Based on the suggestion of Smith [26], the argument of Das and Sivakugan [27], conclusions of Shahin [21] and observations in this study, it is obvious from Table 4 that the developed model in this study performed satisfactorily and had a good generalization potential. The achieved high R values and low values of errors are highly desirable in ANN simulation as they indicate acceptable results. A strong correlation was observed between the experimental OMC and MDD values as obtained by laboratory tests and the predicted values using ANN. Ahmadi et al. [28], Naderpour et al. [29] and Eidgahee et al. [22] reported that strong correlation exists between the experimental and predicted values if the R-value is greater than 0.8, and the MSE values are at their minimum possible value. In a related study by Naderpour et al. [23], R-values of 0.9346, 0.9686, 0.9442 and 0.944 were reported for training, testing validation and their combination which were concluded to be satisfactory and yielded good simulation results.

4. Conclusion

In this study, a soft computing approach, artificial neural networks (ANNs) was used to develop an optimized predictive model for optimum moisture content (OMC) and maximum dry density (MDD) of a cement kiln dust-stabilized black cotton soil. Based on the results of the developed ANN model in this study, the following conclusions were made:

1. The multilayer perceptrons (MLPs) ANN used for the simulation of OMC and MDD of CKD-stabilized black cotton soil that are trained with the feed forward back-propagation algorithm performed satisfactorily.
2. The mean absolute error (MAE), root mean square error (RMSE) and R-value were used as yardstick and criterions. In the neural network development, NN 10-5-1 and NN 10-7-1 respectively for OMC and MDD that gave the lowest MSE value and the highest R-value were used in the hidden layer of the architecture of the network and performed satisfactorily.
3. For the normalized data used in training, testing and validating the neural network, the performance of the simulated network was very good having R values of 0.983 and 0.9884 for the OMC and MDD respectively. These values met the minimum criteria of 0.8 conventionally recommended for strong correlation condition.
4. All the obtained simulation results are satisfactory, and a strong correlation was observed between the experimental OMC and MDD values as obtained by laboratory tests and the predicted values using ANN.

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