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Full Length Research Paper

A new approach for classification of clayey soil: A case study for Adapazari region, Turkey

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Adapazari city is founded on very deep alluvial deposits which mainly consist of gravel, sand, silt, silty and clayey sands and clay. In this study, neural networks (NN) are used in the classification of clay samples existence in north of Adapazari. NN is a powerful data modeling tool capable of capturing and representing complex relationships between input and output. It has been used as alternative method in engineering analyses and estimations. In order to define general soil condition of Adapazari region, the NN model was trained and tested using liquid limit and plasticity index of clay samples obtained from drillings and laboratory works. By this developed of new NN model, the formula for Adapazari clays was found out and presented.

Key words: Adapazari clay's, soil classification, plasticity card, neural networks, explicit formulation.

INTRODUCTION

Turkey is located on one of the most active earthquake and its seismic history is well known (Tan et al., 2008; Taymaz et al., 2008; Durukal and Erdik, 2006; Sahin and Tari, 2000; Sosyal et al., 1981; Ergin et al., 1971). The study area is located on the western part of North Anatolian Fault (NAF) which is the largest and the most active one in Turkey (Barka and Kadinsky-Code, 1988; Barka and Gulen, 1987; Sengor, 1980).

In geotechnical engineering applications, soil classification system is one of the communication languages among engineers. Engineers have discovered transfering their experiences through this way. By only knowing soil class does not eliminate necessary detailed of soil investigations and other laboratory tests which measure engineering properties. However, knowing soil class will provide significant information regarding soil behavior under structural loads during and after any engineering applications.

In recent years, NN has been effectively applied in many engineering applications (Cabalar and Cevik, 2009; Pala et al., 2008; Caglar and Arman, 2007; Bhattacharya and Solomatine, 2006; Shahin et al., 2001; Paolucci et al., 2000; Kumar et al., 2000; Wang and Rahman, 1999; Zhang and Tumay, 1999; Haykin, 1999;Tao and Cui, 1996; Juang et al., 1996; Bishop, 1995; Fausett, 1994; Kulkarni, 1994). Clayey soil samples frequently faced in soil mechanics problems have an inevitable wide range of engineering characteristics. In this study, the classification of clayey samples obtained by standard penetration test (SPT) from Adapazari region which is located on northwest of Turkey is investigated by using Neural Network (Figure 1).

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CLASSIFICATION OF FINE GRAINED SOILS

Number of soil classification systems was proposed in last 50 years. As mentioned by Casagrande (1948), most of classification systems used in engineering comes from soil science in agricultural. In recent, Unified Soil Classification System (USCS) and American Association of State Highways and Transportation officials are widely used in most of engineering applications (Holtz and Kovacs, 1981).

In this study, Turkish Standards (TS 1500) which was adopted from Unified Soil Classification System (USCS)

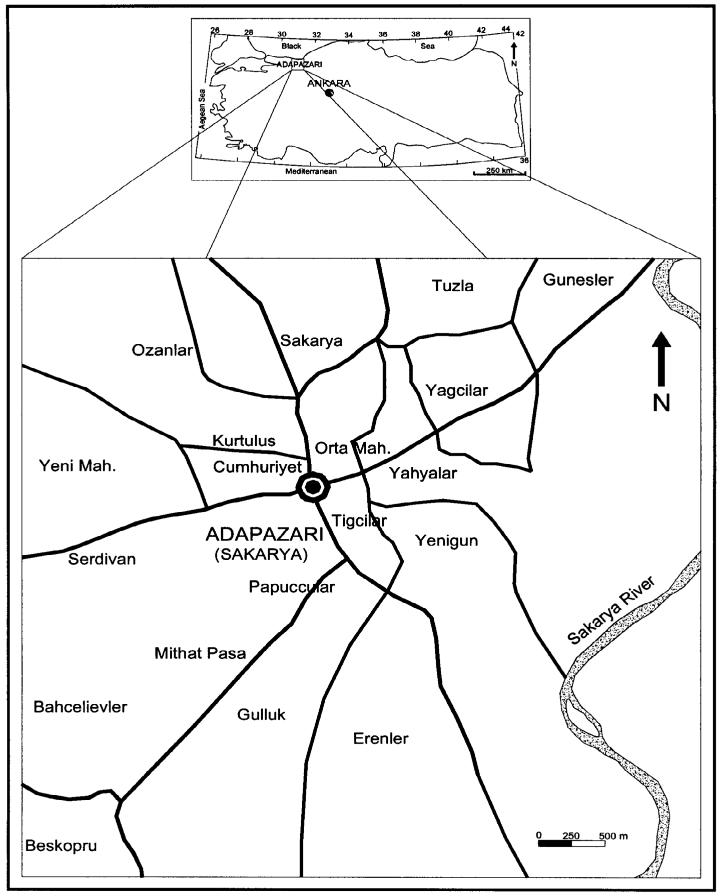

Figure 1. Location map of Adapazari region and its surroundings.

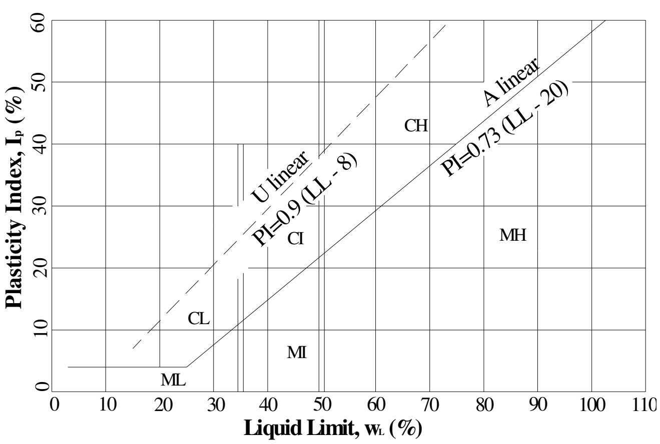

Figure 2. Plasticity card.

(ASTM D 2487-83) was used for soil classification. Fine-grained soils having liquid limit (w_L) and plasticity index (I_P) parameters can be defined with different symbols in TS 1500 soil classification system by the mean of plasticity card (Figure 2) (ASTM D 2487-83, 1985; TS 1500, 2000).

GENERAL SOIL CONDITION OF THE STUDY AREA

The study area is mainly made of Quaternary aged alluvial deposits consisting mostly of gravel, sand, silt, clay, silty and clayey sands. In Adapazari region, various geological formations can be seen at different locations as follows; Orencik formation, Yigilca Members, Caycuma formation, Akveren formation, Akcay Metamorphic, Cakraz and Yilanli formation (Arman et al., 2005). Details of the geological map are presented in Figure 3.

Adapazari region has been mainly influenced by the regime of Sakarya River for many years. Therefore, ground layer exhibit lens kind deposit. Generally, silty and clayey series exist on the ground and gravel-sand-silt series continuously follow the surface series. Dominant ground consist of gravely and silty sand having different densities and contains low plasticity silty and clay bandage at some places (Tezcan, 1975).

To understand the geotechnical characteristics of Adapazari region, a number of boreholes were drilled by either private or state owned companies. The depth of

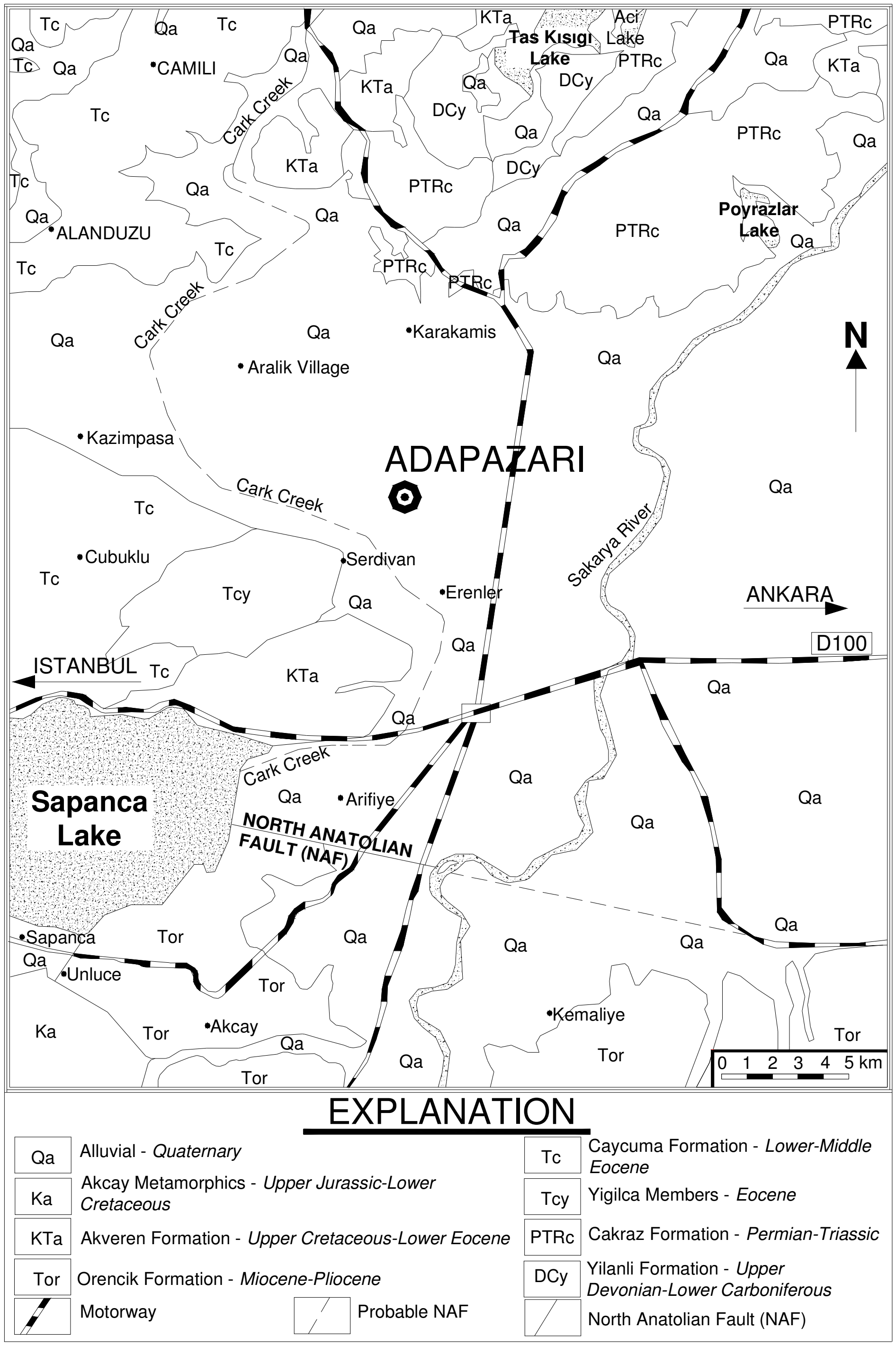

Figure 3. Geological map of the study area.

these boreholes varies from 10 - 300 m. Some deep boreholes drilled in the region were failed to reach bedrock (Arman et al., 2005). Also, some researchers stated that alluvial thickness might reach more than 1000 m (Komazawa et al., 2001). Typical borehole data obtained from different districts such as Yagcilar, Yenigun, Serdivan and Ozanlar are given in Figure 4.

NEURAL NETWORKS (NN)

NN is a computational tool that attempts to simulate the architecture and internal operational features of the human brain and nervous system. NN architectures are formed by three or more layers, which comprise of an input layer, output layer and a number of hidden layers.

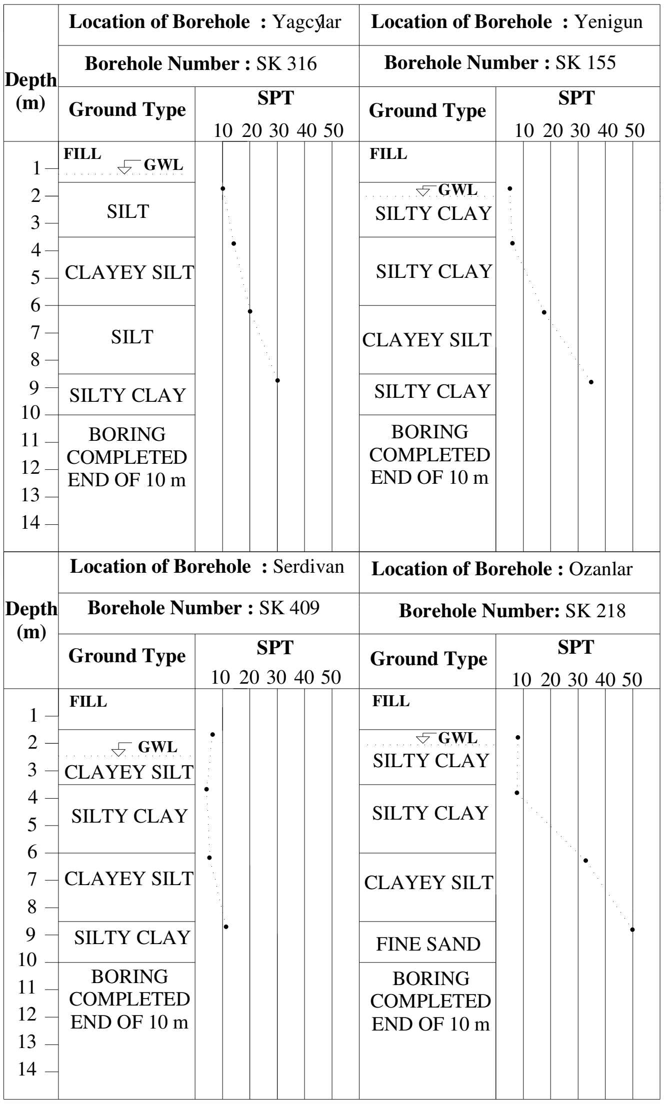

Figure 4. Typical ground cross-section of Adapazari region.

In these layers of neurons connected to each other with modifiable weighted interconnections and this NN architecture is commonly referred to as a fully inter-connected feed forward multilayer perception. In addition, there is also a bias, which is only connected to nodes in the hidden and output layers with modifiable weighted connections. The number of neurons in each layer may vary depending on the problem.

The most widely used training algorithm for multi-layered feed forward networks is perhaps the back-propagation (BP) algorithm. The back-propagation algorithm basically involves two phases: the forward phase where the activations are propagated from the input to the output layer, and the backward phase, where the error between the observed actual and the desired nominal value in the output layer is propagated back-wards in order to modify the weights and bias values. Before training a feed work network, the inputs and outputs of training and testing set must be initialized. In the forward phase, the weighted sums of input components are calculated as:

$$net_j = \sum_{i=1}^{n} w_{ij} x_i + bias_j \quad (1)$$

where net_j is the weighted sum of the j th neuron for the input received from the preceding layer with n neurons, w_{ij} is the weight between the j th neuron and the i th neuron in the preceding layer, x_i is the output of the i th neuron in the preceding layer. The output of the j th neuron out_j is calculated with a sigmoid function as follows:

$$out_j = f(net_j) = \frac{1}{1 + e^{-(net_j)}} \quad (2)$$

The training of the network is accomplished by adjusting the weights and is carried out through a large number of training sets and training cycles. The goal of the training procedure is to find the optimal set of weights, which in the ideal case would produce the right output for any input. During training the weights of the network are iteratively adjusted to capture the relationship between the input patterns and outputs.

The output of the network is compared with a desired response to produce an error. In this study, the performance function for feed forward networks is the mean square error (MSE) and the average squared error between the network outputs and the target outputs. The process of feed forward and back-propagation continues until the required mean squared error has been reached. The mean square error (MSE), is expressed as:

$$MSE = \frac{1}{m} \sum_{i=1}^{m} (T_i - out_i)^2 \quad (3)$$

where T_i and out_i are the target outputs and output of neural network values respectively for i th output neuron, and m is the number of neurons in the output layer. In addition, the error (E) is defined as follows:

$$E = \frac{out_i - T_i}{T_i} x100 \quad (4)$$

As the back-propagation training algorithm with gradient descent and gradient descent with momentum are slow, several adaptive training algorithms for NN have recently been discovered such as Conjugate Gradient Algorithm (CG) and Scaled Conjugate Gradient Algorithm (SCG). In this study, SCG has been used as optimization algorithm,

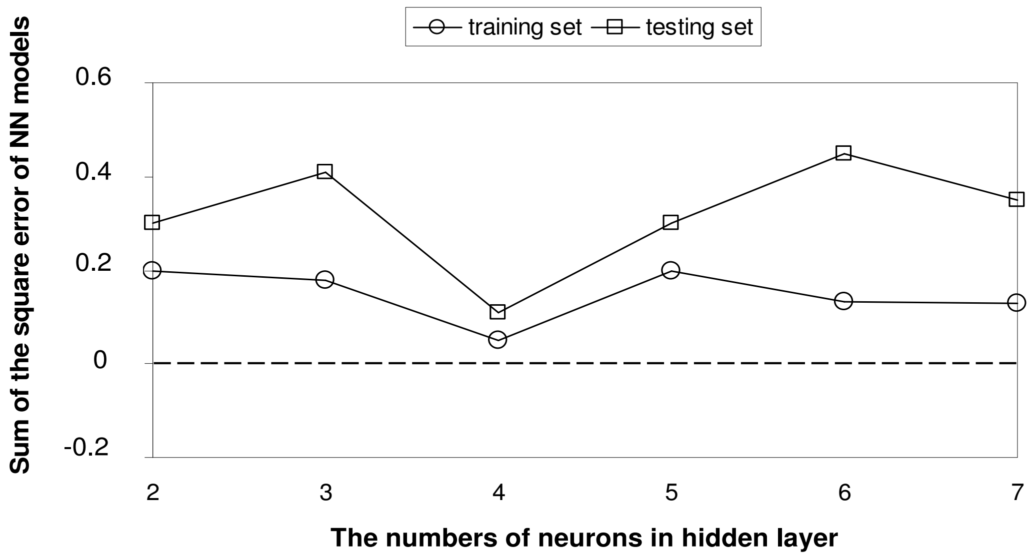

Figure 5. The SSE of NN models with number of neurons in hidden layer.

in which all were set to standard values suggested by Moller (1993).

NUMERICAL STUDY

In the study, the NN based model was applied to classify clayey soil samples existing in north of Adapazari and obtained from SPTs. The total number of 456 liquid limit (w_L) and plasticity index (I_P) values was used for analysis. The results of NN model were disposed to develop a formula, based on the logarithmic sigmoid transfer function, for classification of clayey soil samples in Adapazari region.

After August 17, 1999 Marmara Earthquake, the number of boreholes was drilled by either private or state owned companies in the Adapazari region and laboratory tests are set down in the classification of soils. The database of NN model was established from these experimental results. The number of training and testing sets, which were selected randomly, are 400 and 56, respectively. Testing set, which was not used in the training process, were used to validate the generalization capability of NN model.

A MATLAB based program with a graphical user interface (GUI) was developed to train and test the NN model (Pala and Caglar, 2007). The numbers of neurons in input and output layers were determined by trial and error method in the study.

In order to determine most appropriate NN model, a lot of different NN models with various neurons in hidden layers were trained and tested for just 1000 epochs (iterations). The criteria to establish the most appropriate NN model was selected as the sum of the mean square error (MSE). The most appropriate NN models are chosen corresponding to performance of training and testing sets in terms of MSE. The sum of the squares errors of NN models with number of neurons (from 2 - 7) in hidden layer are determined and drawn in Figure 5.

It is clear that the most appropriate neuron number is 4 for both performance of training and testing sets (Figure 5). Therefore, the chosen network architecture is 2 - 4 - 1 with a binary sigmoidal transfer function (Figure 6). There are two input parameters in the input layer namely; the liquid limit (w_L) and plasticity index (I_P). The output is the classification of clay samples (Table 1). The soil class will be selected based on the outcomes of the proposed NN model which is close to NN values given in Table 1.

Inputs and outputs are normalized in the (0 - 1) range by using simple normalization methods and values are given in Table 2. The maximum and minimum values of inputs and outputs are also given in Table 2.

The learning algorithm used Scaled Conjugate Gradient (SCG). In order to check the performance of NN model, selected criteria was the sum of the mean square error (MSE). The required MSE was selected as 10^{-5}. After 8000 iterations (epochs), the learning stage stopped since the required MSE was reached. The estimation of NN models is generally quite close to the experimental results. Thus the trained NNs showed satisfactorily good results.

The statistical parameters of the trained NN are given in Table 3. As can be seen, the statistical parameters are quite okay, which proves the high accuracy of the trained NN model.

EXPLICIT FORMULATION FOR CLASSIFICATION OF CLAYEY SOIL

The explicit formulation of classification of clay samples

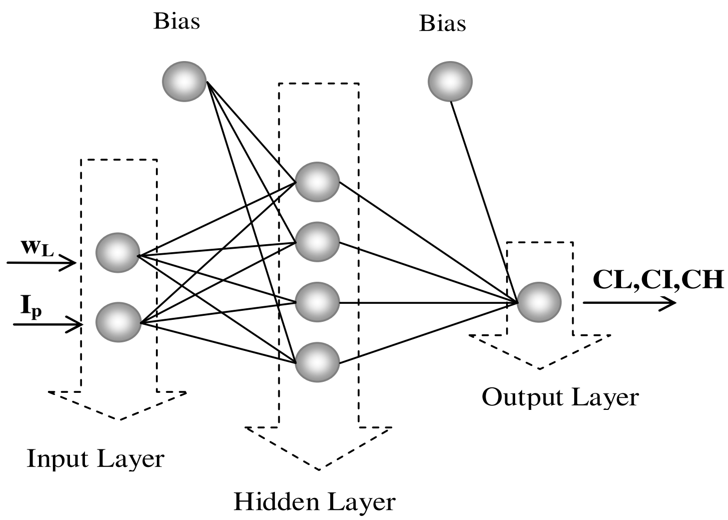

Figure 6. The architecture of NN model.

Table 1. The parameters of output.

Soil class	NN value	Explanation
CL	0.01	Low plasticity clay
CI	0.50	Medium plasticity clay
CH	1.00	High plasticity clay

Table 2. The maximum, minimum and normalization values of input.

Parameters	Range of values		Normalization value (%)
	Min (%)	Max (%)	
w_L	25	89	100
I_p	5	68	100

Table 3. Statistical parameters of NN formulation.

	Training set	Test set
MSE	0.0061	0.0065
RMS	0.0035	0.0040
cov	0.0060	0.0068
R^2	0.99994	0.99992

in Adapazari region is derived by using the parameters (inputs, weights, normalization factors) of the proposed NN model. All necessary parameters are obtained from the trained NN, and the explicit expression was formed from the weights of the trained NN model. Each input was multiplied by a connection weight. In the simplest case, products and biases were simply summed, then transformed through a transfer function (logarithmic sigmoid) to generate a result, and finally outputs are obtained more easily.

During the training and testing progress, the input values, I_P and w_L, were normalized. To get an accurate result from the proposed formula in this study, normalization values have to be considered as well. It means that the values of I_P and w_L must be normalized when the proposed formula is used to classify clayey soil.

It should be noted that the proposed formulation is valid only to define clayey soil type (*CST*). The classification of clayey soil samples in a functional form in terms of w_L and I_P, is given as follows in Equations 5 – 9:

$$F_1 = 606.9254xw_L + 2.168xI_P - 306.6991 \quad (5)$$

$$F_2 = 25.1419xw_L + 18.3315xI_P + 54.7934 \quad (6)$$

$$F_3 = 424.3047xw_L + 0.03135xI_P - 141.6602 \quad (7)$$

$$F_4 = -233.7759xw_L - 0.14151xI_P + 76.0586 \quad (8)$$

$$CST = \frac{1}{1 + e^{\left(-\frac{89.1237}{1+e^{-F1}} + \frac{34.8691}{1+e^{-F2}} - \frac{79.0033}{1+e^{-F3}} - \frac{27.3248}{1+e^{-F4}} + 44.1358\right)}} \quad (9)$$

Functions F_1, F_2, F_3 and F_4 were obtained by employing the independent variables w_L and I_P. The soil type was obtained by using functions F_1, F_2, F_3 and F_4 in Equations (5 - 8). The last terms in the functions, F_1, F_2, F_3, F_4 and 44.1358 in the Equation 9, are bias values which are constant. Parameter ranges should be selected to envelop the majority of the suitable range of applications. High deviation could be attributed to the fact that some of the input data used in the method were outside the input range where the formula is valid. As mentioned before, determining the proposed NN formula using any input parameters outside the input range could cause the deviation to increase.

CONCLUSION

This paper deals with the proposal and validation of the NN based the classification of clayey soil samples and formula for Adapazari region. The explicit formulation of clayey soil classification was extracted by the use of experimental data. Results obtained from the formulation were truly competent and showed good generalization. The generalization capability of the explicit formulation obtained using NNs was confirmed by experimental results. The proposed explicit formulation in the study is an alternative method to classify clayey soil samples. The reliability of previous clayey soil classification done in Adapazari region is also tested by the proposed and presented numerical method. It is concluded that the soil classification for clayey soil in the region was confident. In addition, this method can be easily use for other region which exhibit clayey soil samples. In future, there is a plan to extend this study for other type of soils.

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