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Artificial neural network models for predicting electrical resistivity of soils from their thermal resistivity

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A B S T R A C T

The knowledge of soil electrical and thermal resistivities is essential for several engineering projects such as laying of high voltage buried power cables, nuclear waste disposal, design of fluidized thermal beds, ground modification techniques etc. This necessitates precise determination of these resistivities, and relationship between them, which mainly depend on the soil type, its origin, compaction density and saturation. Such a relationship would also be helpful for determining one of these resistivities, if the other one is known. With this in view, efforts were made to develop artificial neural network (ANN) models that can be employed for estimating the soil electrical resistivity based on its soil thermal resistivity and the degree of saturation. To achieve this, measurements of electrical and thermal resistivities were carried out on different types soils compacted at different densities and moisture contents. These models were validated by comparing the predicted results vis-à-vis those obtained from experiments. The efficiency of these ANN models in predicting the soil electrical resistivity has been demonstrated, if its thermal resistivity is known. These ANN models are found to yield better results as compared to the generalized relationships proposed by the earlier researchers.

1. Introduction

The soil electrical resistivity, R_E, is a measure of the resistance offered by the soil against passage of current through it. The knowledge of R_E has been used to predict various soil parameters, phenomenon and mechanisms occurring in soils, such as for obtaining the soil water content [1], degree of compaction [2] and saturation [3], estimating liquefaction potential of the soil [4], detecting and locating geomembrane failures [5], to estimate corrosive effects of soil on buried steel [6], for designing earthing resistance of the grounding systems [7], to study the electro-osmosis phenomenon in soils [8], investigating the effects of soil freezing [9] and for estimating the soil salinity for agricultural activities [10].

These studies highlight that determination of R_E, depends on several parameters such as frequency of the current used, geometry and type of the electrodes used etc., and is a cumbersome process [11]. While, soil thermal resistivity, R_T, can be determined easily and rapidly by employing the transient heat method [12–15]. In addition, both R_E and R_T are strongly influenced by soil type, its origin and the degree of saturation. Based on the transient heat method generalized relationships have been developed, which can be utilized for determining R_T [15,16].

Hence, determination of R_E of the soil by relating it to its R_T would be of great help to professionals. Singh et al. [17] have proposed the following generalized relationship between R_E and R_T as follows:

$$\log(R_E) = C_R \log(R_T) \tag{1}$$

where C_R is a constant and its values can be obtained from Eq. (2):

$$C_R = 1.34 + 0.0085 \times F \tag{2}$$

where F is the percentage sum of the gravel and sand size fractions in the soil.

However, it must be noted that Eq. (2) does not take into account the saturation, S_r, of the soil, which influences both R_E and R_T [18], quite substantially. To overcome this limitation, Sreedeep et al. [18] proposed Eq. (3).

$$C_R = X + Y \cdot e^{(-S_r \times Z)} \tag{3}$$

where X, Y and Z are constant parameters, which mainly depend on the type of the soil, as depicted in Equations (4)–(6), respectively.

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Nomenclature

γ_d	dry-unit weight of the soil (g/cc)
μ	momentum factor
ρ	resistance per unit length (Ω/cm)
C_R	constant
F	percentage sum of the gravel and sand size fractions (%)
G	specific gravity
i	current (Amp)
I	number of input parameters
Learngdm	gradient descent with momentum weight/bias learning function
MAE	mean absolute error
N_{h1}	lnumber of neurons in the hidden layer
Q	heat input per unit length
R_E	electrical resistivity (Ω m)
RMSE	root mean square error
R_T	thermal resistivity (°C.m/W)
S_r	degree of saturation (%)
Trainlm	Levenberg-Marquardt training algorithm
Trainscg	Scaled Conjugate Gradient training algorithm
VAF	variance account for
var	variance
w	moisture content (%)
x	actual value
X, Y, & Z	constant parameters
x_{max}	maximum value
x_{min}	minimum value
x_{norm}	normalized value
y	measured value
$\hat{y}$	predicted value

$$X = [1.1 + 0.01 \times F] \tag{4}$$

$$Y = [0.9 - 0.01 \times F] \tag{5}$$

$$Z = \left[0.02 + 0.0006 \times e^{(F/25)}\right] \tag{6}$$

Though, the utility and efficiency of these relationships was demonstrated by Sreedeep et al. [18], these relationships are derived based on simple interpolation and extrapolation of experimental results obtained by testing different types of locally available soils compacted at different densities and moisture content. Hence, in order to generate much confidence in using these relationships, better computational algorithms (viz., artificial neural networks) that are capable of incorporating the interdependence of several parameters must be employed.

Artificial neural networks (ANNs) offer an interesting approach for modeling soil behavior [19–21]. ANN is an oversimplified simulation of the human brain [21] and is accepted as a reliable data-modeling tool to capture and represent complex relationships between inputs and outputs [22]. Recently, ANNs have been effectively applied to model the behavior of the soil such as liquefaction of soils [23], soil classification [24], compaction of soils [25], determination of pile capacity [26,27], settlement analysis [28], thermal properties of soils [29] and stress-strain modeling [21,30].

With this in view, efforts were made to develop ANN models that can be employed for predicting R_E by employing different soil properties such as R_T, S_r and F. To show the efficiency of these models, results predicted from them were compared vis-à-vis those obtained from Equations (1)–(3). In addition, the performance indices such as coefficient of determination, root mean square error, mean absolute error, and variance were used to assess the performance of the ANN models.

2. Artificial Neural Networks

Artificial neural networks (ANNs) are computational model, which is based on the information processing system of the human brain [21]. The current interest in ANNs is largely due to their ability to mimic natural intelligence in its learning from experience [31–35]. A typical structure of ANNs is composed of a number of interconnected processing elements (PEs), commonly referred to as neurons. The neurons are logically arranged in layers: an input layer, an output layer and one or more hidden layers. The neurons interact with each other via weighted connections. Each neuron is connected to all the neurons in the next layer. The input layer is the means by which data are presented to the network. The output layer holds the response of the network to the input. The hidden layers enable these networks to represent and compute complicated associations between inputs and outputs. This ANN architecture is commonly referred to as a fully interconnected feed-forward multi-layer perceptron (MLP). In addition, there is also a bias, which is only connected to neurons in the hidden and output layers, with modifiable weighted connections.

Currently, there is no analytical way of defining the network structure as a function of the complexity of the problem. The structure must be manually selected using a trial-and-error process. ANNs with one or two hidden layers and adequate number of hidden neurons are found to be quite useful for most problems [36,37]. The number of neurons in the hidden layers depends on the nature of the problem. There are various methods to determine the number of neurons in the hidden layer [38–41]. However, these methods present general guidelines only for selection of an adequate number of neurons.

The back-propagation learning algorithm is the most popular and extensively used neural network algorithm [42,43]. The back-propagation neural network has been applied with great success to model many phenomena in the field of geotechnical and geo-environmental engineering [44–46]. The back-propagation learning algorithm basically involves two phases: the feed-forward pass and backward pass process. In the forward phase, the processing of information is propagated from the input layer to the output layer. In the backward phase, the difference between obtained network output value from feed-forward process and desired output is propagated backwards in order to modify the weightings and bias values. The training of the network is achieved 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 would produce the right output for any input in the ideal case [22]. Training the weights of the network is iteratively adjusted to capture the relationships between the input and output patterns.

The performance of the overall ANN model can be assessed by several criteria [21,47–49]. These criteria include coefficient of determination R^2, mean squared error, mean absolute error, minimal absolute error, and maximum absolute error. A well-trained model should result in an R^2 value close to 1 and small values of error terms.

In this study, prediction of electrical resistivity, R_E, of the soil has been modeled using the ANN and multiple regression