Use of Artificial Neural Network in Predicting Permeability of Dispersive Clay Treated With Lime and Pozzolan

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Abstract. The treatment of a dispersive core soil can be achieved by mixing with lime and pozzolan, separately or simultaneously. On a dispersive soil treated with lime and pozzolan, experimental measurements of permeability were carried out with varying curing times and percentages of the additives. The results from these measurements were used in establishing an artificial neural network model meant to predict the permeability of more samples while being treated as carrying out laboratory measurements would be time consuming. Six parameters namely percentage passing of the 0.005 mm size (p), plasticity index (PI), maximum dry density (MDD), lime percentage (L), pozzolan percentage (p_p), and curing time (t) were the inputs to the model while the output was permeability value. The prediction performances of various neural network models were evaluated using statistical performance indices such as root of the mean squared error (RMSE), the mean squared error (MSE), and the multiple coefficient of determination (R²). The results show that the multilayer perceptron (MLP) neural network model with nine nodes in the hidden layer was desirable for predicting permeability of dispersive soils while being stabilized by lime and pozzolan, separately or simultaneously. For the model, R²=0.9895 and RMSE=3.5604×10⁻³ cm/sec.

Keywords: Dispersive Soil, Lime, Pozzolan, permeability, Artificial Neural Network.

1. INTRODUCTION

The core of an earth dam is normally made of low permeable material such as clayey soil. An acceptable core material must fulfill various basic criteria in terms of classification, plasticity index, and cohesion. However, the appropriateness of a clayey soil for core material could become doubtful if it is dispersive. Due to the destructive consequence the dispersivity property could bring to an earth dam particularly in the forms of internal erosion and piping, a clayey soil must be screened for such property when considered for use as the core material (Vakili and Selamat, 2014, Indraratna et al., 2012; Vinod et al., 2010; Richards and Reddy, 2007).

Dispersive clay soils are structurally unstable and therefore highly susceptibility to erosion mainly due to the high sodium content (Umeh et al., 2011, Zorluer et al., 2010). A dispersive soil can become rapidly deflocculated even in still water with low dissolved salt concentration (Shoghi et al., 2013). It is generally low in permeability, low in porosity, and high in bulk density (Ouhadi and Goodarzi, 2006, Raine and Loch, 2003, Rengasamy et al., 1984). Such material can be improved or stabilized economically for its dispersivity property by using chemical additives such as lime, cement, pozzolan, and alum.

The addition of a chemical additive could bring significant changes in physical, chemical, and mechanical properties of a clayey soil (Pakbaz and Alipour, 2012; Horpibulsuk et al., 2011; Indraratna et al., 1991; Okagbue, 2007; Al-Rawas et al., 2005; Vinod et al., 2010). The stabilization process however requires a great deal of control (Vakili et al., 2013 a, b, c). The core of an earth dam is expected to be as impermeable as possible but the other aspects of it are also very important in the design namely particle size distribution, fine content, plasticity index, and strength.

Performing the falling head test is the common method for measuring permeability of a fine grained soil (Erzin et al., 2009). Although the falling head test in the laboratory is relatively easy to perform and is not generally expensive, the test is relatively time consuming especially when involving multiple samples, thus the desired response to a problem in the
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The field may not be fulfilled within the given time frame (Erzin et al., 2009). Furthermore, the result of testing a low permeability soil tend to be erroneous thus determining the permeability of such material using a predictive method would probably be justified (Sinha and Wang, 2008).

Generally speaking, the various empirical equations in use today correlate the permeability of fine grained soils to the index properties (Sinha and Wang, 2008; Erzin et al., 2009; Wösten et al., 2001). However, many existing equations are of the single variable type, resulting in a considerable overestimate or underestimate of the permeability due to ignoring other affecting parameters.

In recent decades, the artificial neural network models have been widely used in predicting the nonlinear behaviour of many geotechnical engineering tasks (Habibagahi and Bamdad, 2003; Ozer et al., 2008). An artificial neural network does not require the significant knowledge about the nature of a relationship between variables as required by a traditional modelling, thus could be conveniently used for resolving issues that are structurally, physically, and mathematically more complicated. In addition, an artificial neural network usually performs better than a regression based equation, when there are more than three independent variables (Erzin et al., 2009). One of the most significant advantages of a neural network is that they are continuously updateable in case new characteristic of a database or a new dataset becomes available (Ozer et al., 2008). In contrast to an empirical equation which is created based on limited affecting parameters, the very logical concurrent relationships between a dependent variable and a large array of independent variables would favour use of the artificial neural network.

In the current study, dispersive soil samples were treated with different percentages of pozzolan and lime, separately and simultaneously. Some geotechnical properties of a sample being treated were experimentally determined during curing period. In addition to particle size distribution, plasticity index, and maximum dry density, the permeability was also measured. Hence, in order to predict the permeability of a general sample fast and accurate, a suitable multilayer perceptron network with back propagation algorithms was developed with the affecting parameters as input and permeability as output. Thus, the permeability of a stabilized soil could be predicted based on its other common properties. Some data used for developing the neural network system were sourced from an earlier work (Vakili et al., 2013 a, b, c) and while others were the results of laboratory tests carried out for the current study.

| Table 1: Details of artificial neural network developed in the current study |
|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| Number of nodes in      | Number of datasets used for | Type of transfer function |
| Input layer            | Hidden layer            | Output layer           | training                 | validation               | testing                 |
| 6                      | varied                 | 1                      | 49 (70%)                 | 10 (15%)                 | 10 (15%)               | Log-sigmoid             |

<table>
<thead>
<tr>
<th>Table 2: Properties of the dispersive clay used</th>
</tr>
</thead>
<tbody>
<tr>
<td>MDD (g/cm³)</td>
</tr>
<tr>
<td>1.82</td>
</tr>
</tbody>
</table>

2. MATERIALS AND METHODS

2.1. Sample preparation

Artificial neural networks have been used to create general relationships between variables in a given issue. Artificial neural networks are considered as a form of artificial intelligence and are somewhat capable to simulate the human brain and nervous system (Ozer et al., 2008, Shahin et al., 2008). As shown in Figure 1, artificial neural networks are made of a number of processing elements or nodes or neurons. The most widely used artificial neural networks in engineering purposes are known as feed-forward multilayer perceptron network with back propagation algorithms with an input layer, an output layer, and one or more hidden layers (Ozer et al., 2008, Sinha and Wang, 2008, Erzin et al., 2009).

Although there is no connection between the neurons in the same layer, each neuron is fully connected with the rest of neurons in the next layer (Habibagahi and Bamdad, 2003, Erzin et al., 2009). The output of each node could be defined by Equation 1:

\[ a = f\left( \sum_{i=1}^{n} P_{j,i} W_{j,i} + b_j \right) \]  

(1)

Where \( a \) is the output of node \( j \), \( P_{j,i} \) is the input from \( i \)th node, \( W_{j,i} \) is the connection weight between \( j \)th node of the layer and \( i \)th node of the previous layer, \( b_j \) is the bias at the \( j \)th node, and \( f \) is the transfer function.
Fig. 1: Structure of an artificial neural network in predicting hydraulic conductivity

Table 3: Outcomes of various neural networks developed for the different number of nodes in the hidden layers

<table>
<thead>
<tr>
<th>Number of nodes</th>
<th>RMSE</th>
<th>MSE</th>
<th>R</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>19.393×10⁻⁸</td>
<td>37.609×10⁻¹⁵</td>
<td>0.77038</td>
<td>0.59345</td>
</tr>
<tr>
<td>4</td>
<td>8.4903×10⁻⁸</td>
<td>7.2086×10⁻¹⁵</td>
<td>0.96815</td>
<td>0.93731</td>
</tr>
<tr>
<td>5</td>
<td>6.2649×10⁻⁸</td>
<td>3.9249×10⁻¹⁵</td>
<td>0.98581</td>
<td>0.97182</td>
</tr>
<tr>
<td>6</td>
<td>10.60×10⁻⁸</td>
<td>11.251×10⁻¹⁵</td>
<td>0.93834</td>
<td>0.88048</td>
</tr>
<tr>
<td>7</td>
<td>6.0988×10⁻⁸</td>
<td>3.7195×10⁻¹⁵</td>
<td>0.98382</td>
<td>0.96790</td>
</tr>
<tr>
<td>8</td>
<td>5.0189×10⁻⁸</td>
<td>2.5189×10⁻¹⁵</td>
<td>0.98861</td>
<td>0.97735</td>
</tr>
<tr>
<td>9</td>
<td>3.5604×10⁻⁸</td>
<td>1.2676×10⁻¹⁵</td>
<td>0.99472</td>
<td>0.98947</td>
</tr>
</tbody>
</table>

Although the transfer function of each node is usually expressed by sigmoid functions (Erzin et al., 2009), other functions such as hyperbolic tangent functions and linear functions could also be used, depending on the nature of the variables.

The number of nodes in the input and the output layer respectively represent the number of input and output variables. The neural network models are normally developed by dividing the available datasets into 3 subsets for training, validation, and test. A model is initially trained by using 70% of the data while and 15% of the data is used for validation process in order to minimize over fitting. The performance of the trained model is tested by the
remaining 15% of data. Thus, the training data are used for constructing the model and the validation and testing data are used for controlling the accuracy of the developed model (Erzin et al., 2009). The difference between an experimental value (target) and network prediction value is defined as system error. During training, a minimum error of the network is attempted by changing the weight and the number of nodes in the hidden layer through cycles of trial and error (Sinha and Wang, 2008, Erzin et al., 2009). A number of statistical performance indices are usually used to evaluate the prediction performance of the developed network. For this study, the statistical criteria used were the root of the mean squared error (RMSE), the mean squared error (MSE), and the multiple coefficient of determination ($R^2$).

**Fig. 2:** Hydraulic conductivity versus curing time for soil samples stabilized with various percentages of pozzolan

**Fig. 3:** Hydraulic conductivity versus curing time for soil samples stabilized with various percentages of lime
Soil permeability is affected by various parameters such as compaction degree and water content (Sinha and Wang, 2008, Erzin et al., 2009). In the current study, however the effects of 6 variables on permeability have been considered, thus:

\[ k = f(p, PI, MDD, p_p, L, t) \]  \hspace{1cm} (2)

Where \( k \) = coefficient of permeability (cm/sec), \( p \) = percentage passing the 0.005 mm size (%), \( PI \) = plasticity index (%), \( MDD \) = maximum dry density (gr/cm\(^3\)), \( p_p \) = pozzolan content (%), \( L \) = lime content (%), and \( t \) = curing time (day).

Fig. 4: Hydraulic conductivity versus curing time for soil samples stabilized with 1% lime and various percentages of pozzolan

Fig. 5: Hydraulic conductivity versus curing time for soil samples stabilized with 1.5% lime and various percentages of pozzolan
Thus, the trained neural network system consisted of 6 nodes in the input layer and one in the output layer. A total of 69 datasets were used in the current research, with 49 of those randomly selected for training the network and the rest used for validation and testing. Note that various networks with different nodes in the hidden layer were trained to find the optimum one with the least error. The software used for modelling the discussed neural network was the one by Matlab (2012). Further details of the different neural networks developed in the study are summarized in Table 1.

The properties of the unstabilized dispersive clay provided for the current study is given in Table 2. In the soil stabilization process, samples were cured at optimum moisture content. For stabilization by pozzolan alone, 2, 4, 5, 6, and 8 percents of pozzolan by dry soil mass were added. For stabilization by lime alone, 1, 2, 3, and 4 percents of lime by dry soil mass were added. For simultaneous stabilization, samples stabilized with various pozzolan contents were further treated with 1% and 1.5% lime content. For all of the above mentioned arrangements, the curing times were 1, 7, 14, and 35 days except for the pozzolan-treated samples where an additional 90 days of curing was applied. The ASTM standards were followed in conducting all laboratory tests, i.e. ASTM D 422 for particle size distributing test, ASTM D 4318 for plasticity index test, and ASTM D 698 for standard compaction test. The procedure described by Head (1990) was also used for carrying out the falling head tests.

![Plot of measured permeability, or target, versus predicted permeability from neural network modelling for 3 nodes in the hidden layers](image-url)
3. RESULTS AND DISCUSSIONS

The curves of hydraulic conductivity versus curing time for soil samples stabilized with pozzolan and lime, separately and simultaneously, are given in Figures 2 to 5.

In general, the addition of pozzolan and lime, separately or simultaneously to a dispersive soil sample resulted in increased permeability. Moreover, permeability increased with increasing pozzolan content, lime content, and curing times. For samples stabilized with pozzolan, the permeability kept on changing even up to 90 days of curing, reflecting the role of curing time in the stabilization process. On the other hand, in samples stabilized with lime, the increase in permeability occurred mostly in the first 14 days of curing, reflecting the rapid effects of lime in modifying the properties of soils.

Adding lime or pozzolan caused an increase in permeability, but the highest value of $8.3 \times 10^{-7}$ cm/sec was achieved by adding 1.5% lime and 8% pozzolan, reflecting the merit of using the additives simultaneously. Having a very low permeability is known as one of the unique characteristics of soils with dispersed fabric. A dispersive soil has deflocculated fabrics. The pre-stabilization permeability of the dispersive soils provided for the research was determined as $8.5 \times 10^{-9}$ cm/sec. A similarly unstabilized non-dispersive soil would have a higher permeability due to the flocculated structure.
Soil permeability is governed by physico-chemical properties of both soil and soil pore water (Ouhadi and Goodarzi, 2006). The main reason for change in permeability of a stabilized sample could be attributed to cation exchange, flocculation and agglomeration, and pozzolanic reaction, among others. The lower valence cation like Na\(^+\) is replaced by the higher one like Ca\(^{2+}\) due to cation exchange reaction. Subsequently, particles would flocculate and with thickness of diffused double layer reducing (Mallela et al., 2004). Thus, the flocculation and agglomeration of clay particles may explain the increase in permeability of a treated sample as the soil becomes more granular and in turn creates an open fabric, thus increasing the permeability. In the short term, these actions improve workability and plasticity of the stabilized soil, which is desirable (Bell, 1988, 1989; Mallela et al., 2004, Aldaood et al., 2014). By the end of the curing period however, the pozzolanic reactions have brought a significant improvement to the physical and mechanical properties such as strength and rigidity (Okagbue, 2007; Mallela et al., 2004).

As discussed earlier, one of the aims of this research was to find the optimum network or a network with minimum error. A network error is defined as the difference between measured permeability and predicted permeability. Hence the optimum network is obtained for specific arrangement of the hidden layer after the necessary evaluation. The architecture of the artificial neural network developed for predicting permeability is given in Figure 1. Test results from Vakili et al. (2013 a, b, c) together with those obtained from the current study were used to develop the artificial neural network models.
The measured permeability, or target, was compared to predicted permeability in Figures 6 to 12 for various nodes of the hidden layers. The equality line, y=T, was given in order to observe the network error. A system with zero error would have all plots positioned on the equality line. Thus, the deviation of plots from the equality line explains the system error.

The following statistical methods were used to select the optimum network and to quantify the accuracy of predicted data coming from the neural network modelling where \( n \) is the number of data sets, \( k_{pi} \) is the predicted permeability, and \( k_{mi} \) is the measured permeability:

1. The root of the mean squared error (RMSE)

\[
RMSE = \left( \frac{1}{n} \sum_{i=1}^{n} (k_{pi} - k_{mi})^2 \right)^{0.5}
\]

2. The mean squared error (MSE)

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (k_{pi} - k_{mi})^2
\]

3. Multiple coefficient of determination (\( R^2 \))

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (k_{pi} - k_{mi})^2}{\sum_{i=1}^{n} k_{pi}^2}
\]

Based on the given methods, the optimum network would be the one with least RMSE and MSE; an RMSE=0 and an MSE=0 are the results of a perfect fit. The closeness of fit would be measured by \( R^2 \); an \( R^2 =1 \) is the result of a perfect fit while \( R^2 =0 \) is the result of a poor fit. The abovementioned parameters were calculated for the various neural networks.
developed by various amount of nodes in the hidden layer, and the optimum neural network was selected accordingly. The results are summarized in Table 3. From Table 3, the neural network developed for 9 nodes in the hidden layer was found to be optimum as it has the least value of RMSE and MSE and the most value of $R^2$. The error involved in using the neural network with 9 nodes in the hidden layer is graphically shown in Figure 13.

**Fig. 10:** Plot of measured permeability, or target, versus predicted permeability from neural network modelling for 7 nodes in the hidden layers
4. CONCLUSION

The use of dispersive soil in a construction project requires adequate management, specific measures, and precautions in order to avoid catastrophic failures. Given limited time and budget, and dispersive problems to resolve, various ground improvement techniques will need to be considered in coming up with the most economical solution. One such technique for decreasing the dispersivity potential is by chemical stabilization using lime and pozzolan, separately and simultaneously. In doing that, the dispersivity is not the only parameter improved; various physical and chemical properties changed too, such as the permeability. The permeability of a treated sample increases with flocculation of the dispersed particles. The increase in permeability due to the flocculation could be correlated to the resulting change in dispersivity of the soil from being dispersive to being non dispersive. These results should also be interpreted along with the fact that permeability decreases with higher plasticity index, clay content, and dry density. Measuring the coefficient of permeability of fine grained soils however is time consuming with control measures sometimes need to be delivered fast. By using the artificial neural network modeling, permeability can be determined faster and with reasonable accuracy. In the method of this study, the parameters required for predicting permeability were percentage passing the 0.005 mm size, plasticity index, maximum dry density, lime percentage, pozzolan percentage, and curing time. The proposed neural network with nine nodes in the hidden layer with $R=0.99472$ and $\text{RMSE}=3.5604\times10^{-8}$ cm/sec was found desirable in predicting the permeability of dispersive soils.
stabilized by mixing with lime and pozzolan, separately and simultaneously. Just by using datasets from previous tests and carrying out further tests for the unknown properties, the permeability of samples were determined by the neural network modeling. The alternative would be by carrying out the falling head test for each new sample, which is time consuming.

Fig. 12: Plot of measured permeability, or target, versus predicted permeability from neural network modelling for 9 nodes in the hidden layers

Fig. 13: Plot of measured permeability, or target, versus predicted permeability by neural network model

References


ASTM D 698-91(2000). Standard test method for laboratory compaction characteristics of soils using standard effort (12400 ft-lb/ft3 (600 kN.m/ m3)). ASTM International, West Conshohocken, PA, USA.


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