Predicting the Limit Void Ratios of Coarse-Grained Soils Using Artificial Neural Networks

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PREDICTING THE LIMIT VOID RATIOS OF COARSE-GRAINED SOILS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

In this study, the prediction performance of the artificial neural network (ANN) and multiple regression (MR) models in predicting the limit void ratios of coarse-grained soils was investigated and compared. The data available in the literature were collected and used to construct both two distinct ANN-1 and ANN-2 models and two distinct MR-1 and MR-2 models: ANN-1 and MR-1 for the prediction of minimum void ratio \((e_{\text{min}})\) and ANN-2 and MR-2 for the prediction of maximum void ratio \((e_{\text{max}})\) of coarse-grained soils. Two basic soil graining properties such as coefficient of uniformity \((C_u)\) and mean grain size \((D_{50})\) are utilized in the simulation of the feed forward ANN models with back propagation algorithm and the MR models. The \(e_{\text{max}}\) and \(e_{\text{min}}\) values predicted from both ANN and MR models were compared with the experimental values taken from the literature. Moreover, five performance indices i.e. the determination coefficient, variance account for, mean absolute error, root mean square error, and the scaled percent error were calculated to examine the prediction capacity of the ANN and MR models developed in this study. The performance indices calculated indicated that both ANN models showed better performance than both MR models. It has been demonstrated that both ANN models can be used satisfactorily to predict limit void ratio values of coarse-grained soils as a rapid inexpensive substitute for laboratory techniques.

Keywords: artificial neural networks, coefficient of uniformity, limit void ratios, mean grain size.
1. Introduction

The characteristics and properties of granular materials is mostly connected with the relative density (Dr) (Lade et al., 1988). Dr is commonly used in geotechnical engineering to indicate the in-situ denseness or looseness of granular soils (Das, 2010; Sulewska, 2010). The liquefaction resistance of soil is also controlled by the Dr value of soil (Polito and Martin, 2001). The lower the Dr value of the soil, the higher the liquefaction potential of the soil (Seed 1979; Seed 1983; Lade et al. 1998). The Dr value showing the relative position of the field void ratio, e, between the maximum and minimum void ratios, $e_{\text{max}}$ and $e_{\text{min}}$, for a given coarse-grained soil is defined by the following equation:

$$
Dr = \frac{e_{\text{max}} - e}{e_{\text{max}} - e_{\text{min}}} \times 100 \quad (1)
$$

The $e_{\text{max}}$ and $e_{\text{min}}$ values can be usually obtained by following the procedures given by ASTM test designations D-4253 (2006) and D-4254 (2006), respectively. These designations are applicable to soils that may contain up to 15%, by dry mass, of soil particles passing 0.075-mm sieve (fines) (Das et al. 2012). However, there are other methods such as Japanese Geotechnical Society (2000) method to be used for determining $e_{\text{max}}$ and $e_{\text{min}}$ values. Japanese Geotechnical Society (2000) are applied to determine $e_{\text{max}}$ and $e_{\text{min}}$ of soils having fines less than 5% fines. These methods may provide slightly different values both for the limit void ratio ($e_{\text{max}}$ and $e_{\text{min}}$) values. The limit void ratios are functions of soil properties, namely, grain size distribution, uniformity coefficient, angularity, and percentage of fine contents (Das et al. 2012). Based on the results in the literature, it appears that the difference between the maximum and minimum void ratios, not maximum void ratio or minimum void ratio alone, is the controlling parameter for compressibility, relative density, and strength of granular soils (Das et al. 2012).

In this study, the data available in the literature were collected and used to develop both two distinct artificial neural network models (ANN-1 and ANN-2) and two distinct multiple regression models (MR-1 and MR-2): ANN-1 and MR-1 for the prediction of the $e_{\text{min}}$ values of coarse-grained soils and ANN-2 and MR-2 for the prediction of the $e_{\text{max}}$ values of coarse-grained soils. The results predicted from the ANN and MR models were compared with the experimental results taken from the literature (Polito, 1999; Santamarina and Cho, 2001; Sukumaran and Ashmawy, 2003; Tika et al., 2003; Erzin, 2004; Park and Byerne, 2004; Cho et al., 2006;
Bareither, 2008; Wichtmann and Triantafyllidis, 2013; Belkhatir, 2014; Oh, 2014; Bensoula et al., 2015; Salvatore et al., 2015; Erzin et al. 2016). Moreover, different performance indices, namely, the determination coefficient ($R^2$), the relative root mean square error (RMSE), the mean absolute error (MAE), variance account for (VAF) and, scaled percent error (SPE) were computed for evaluating the prediction performance of the ANN and MR models developed. Both ANN models have shown higher prediction performance then MR models according to the performance indices computed.

2. Database compilation

The compiled data obtained from the literature (Polito, 1999; Santamarina and Cho, 2001; Sukumaran and Ashmawy, 2003; Tika et al., 2003; Erzin, 2004; Park and Byerne, 2004; Cho et al., 2006; Bareither, 2008; Wichtmann and Triantafyllidis, 2013; Belkhatir, 2014; Oh, 2014; Bensoula et al., 2015; Salvatore et al., 2015; Erzin et al. 2016) to form a wider database were used to establish a predictive relationship between the limit void ratios ($e_{\text{max}}$ and $e_{\text{min}}$) of coarse-grained soils and their two graining parameters, namely, mean particle size ($D_{50}$) and uniformity coefficient ($C_u$). The descriptive statistics of the data containing the graining parameters and limit void ratios of different 181 soils are given in Table 1. To visualize the distribution of the samples, the data are presented by frequency histograms (Fig. 1). As it can be observed from the figure, the distributions of the predictor variables are not uniform.

The relationship between the soil graining parameters ($C_u$ and $D_{50}$) and limit void ratios ($e_{\text{min}}$ and $e_{\text{max}}$) are shown in Fig. 2. Correlation analysis were carried out the strength of the relationship between these two soil graining parameters and limit void ratios and the Pearson correlation coefficient ($r$) values are given in Table 2. It can be noted from Table 2 that there is no significant relation between the soil gaining parameters and limit void ratios, as the determined $r$ values are very low.

In order to examine the relationship between $e_{\text{min}}$ and $e_{\text{max}}$ for the data utilized in this study, the $e_{\text{min}}$ values were plotted against the $e_{\text{max}}$ values, as shown in Fig. 3. It can be seen from the figure that a strong linear relationship exists between the $e_{\text{min}}$ and $e_{\text{max}}$ values, as $r$ value of 0.94. This observation is consistent with the past researchers (Cubrinovski and Ishihara, 2002; Gomaa and Abdelrahman, 2007). The equation obtained from the relationship between the $e_{\text{min}}$ and $e_{\text{max}}$ values can be expressed as follows:

$$e_{\text{min}} = 0.67e_{\text{max}} - 0.051$$ (2)
3. Brief overview of artificial neural networks

An Artificial Neural Network (ANN), a form of artificial intelligence, based on the biological structure of the human brain and nervous system (Banimahd et al., 2005). ANNs are very refined modeling techniques to be able to model extremely complex functions (Choobbasti et al. 2009). The architectures of ANNs are constructed by three or more layers; one input layer, one or more hidden layers, and one output layer. Each layer consists basically of a large number of highly interconnected processing elements named neurons. Each neuron is linked with all the neurons in the next layer by means of weighted connections. (Erzin et al., 2009). In the input layer, data are presented to the network (Erzin et al., 2009). The hidden layers are intermediate layers between input and output layers, where all the computation is done (Erzin et al., 2009). The output layer produces the results of the network for the entered data (Erzin et al., 2009). Both the number of hidden layers and the neurons in the hidden layer relies on the nature of the problem and so the degree of the complexity of the problem (Erzin et al., 2010). If the number of neurons in the hidden layers is chosen as too large, the network will produce an overfit, in which the network will have a problem in generalization. ANNs with one or two hidden layers and sufficient number of hidden neurons in the hidden layer(s) are found to be quite convenient for large majority of problems (Orbanic´ and Fajdiga, 2003).

The neural network “learns” by adjusting the weights of the neurons in response to the errors between the actual and target output values. Various learning algorithms have been developed for training neural networks. In these algorithms, the back-propagation learning algorithm is most widely used neural network algorithm (Rumelhart et al. 1986; Goh 1994; Najjar et al. 1996; Kim et al. 2004; Singh et al. 2006). The back-propagation neural network has been applied with great success for modelling complex problems in the field of geotechnical engineering (Goh 1995a, b; Shahin et al. 2001, 2002). In the back-propagation neural network, learning is done using gradient descent, which is the process of updating weights for all training patterns so that the error rate decreases (Rumelhart et al. 1986; Goh 1995a). Training is performed by repeatedly presenting the entire set of training patterns and updating the weights at the end of the each epoch up to the average sum squared error over all the training patterns being minimal and within the tolerance determined for the problem.
4. Artificial neural network models

In this study, a feed-forward artificial neural network with a back-propagation algorithm, most commonly used neural network structure (Khattab and Al-Dabbagh, 1995; Gunaydin, 2009; Aydin et al., 2014), was used to develop two distinct ANN models demonstrated as ANN-1 and ANN-2: ANN-1 for predicting minimum void ratio \( e_{\text{min}} \) and ANN-2 for predicting maximum void ratio \( e_{\text{max}} \) of coarse-grained soils. For this purpose, the data reported by Polito (1999), Santamarina and Cho (2001), Sukumaran and Ashmawy (2003), Tika et al. (2003), Erzin (2004), Park and Byerne (2004), Cho et al. (2006), Bareither et al. (2008), Wichtmann and Triantafyllidis (2013), Belkhatir et al. (2014), Oh (2014), Bensoula (2015), Salvatore et al. (2015) and Erzin et al. (2016) for different types of coarse-grained soils, whose descriptive statistics listed in Table 1, were used to develop both ANN models.

4.1. Development of ANN-1 model for the prediction of minimum void ratio \( e_{\text{min}} \)

A three-layered feed forward ANN model denoted as ANN-1 has been constructed to estimate the minimum void ratio \( e_{\text{min}} \) value of soil. The ANN-1’s architecture is given in Figure 4. As shown in the figure, in this ANN model, soil graining properties, namely, coefficient of uniformity \( C_u \) and mean grain size \( D_{50} \) are used as input parameters and measured \( e_{\text{min}} \) value was the only output parameter. These input and output parameters were scaled between 0 and 1 by using the following equation:

\[
x_{\text{norm}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}
\]

where \( x_{\text{norm}} \) is the normalized value, \( x \) is the actual value, \( x_{\text{max}} \) is the maximum value and \( x_{\text{min}} \) is the minimum value.

A training set to evaluate the ANN model and a testing set to control the performance of the ANN model were generated by dividing remaining data (Shahin et al., 2004). Usually, the use of 80% of the data are suggested for while training the ANN model and the use of remaining for while testing the ANN model (Kanibir et al., 2006 and Erzin et al., 2012). Therefore, in total, 80 % of the data taken from the literature were utilized for training of the ANN-1 model and 20 % for testing of the ANN-1 model.

A neural network with one hidden layer can approximate any continuous function, provided that sufficient connection weights are entered [66]. Thus, ANN model with one hidden layer was used while constructing the ANN model. A trial-and-error approach method was used for the determination of the optimal
geometry of the ANN-1 model. The optimum number of neurons in the hidden layer was determined by changing their number by starting with a minimum of 1 and then increasing the network size in steps by adding 1 hidden neuron each time. Two different transfer functions (log-sigmoid [67] and tan-sigmoid [36]) were used in the hidden and output layers to obtain the best performance in training as well as in testing. Two momentum factors (=0.01 and 0.001) were chosen for the training stage to obtain for the most efficient ANN architecture. The neural network toolbox of MATLAB7.0, a well-known numerical computation and visualization software [68], was used in the training and testing stages of MLPs. The coefficient of determination, $R^2$, and the mean absolute error, MAE, were used to assess the performance of the developed ANN models. In order to decide the optimum network geometry, the performance of the network during both the training and testing stages was examined for each network size until no significant improvement in the error took place.

### 4.2. Development of ANN-2 model for the prediction of maximum void ratio ($e_{\text{max}}$)

A four-layered feed forward ANN model denoted as ANN-2 has been constructed to estimate the maximum void ratio ($e_{\text{max}}$) value of soil. The ANN-2’s architecture is presented in Figure 5. As shown in the figure, in the ANN-2 model, two soil graining properties, namely, coefficient of uniformity ($C_u$) and mean grain size ($D_{50}$) are the input parameters and the measured $e_{\text{max}}$ value was the single output parameter. The input and output parameters used while developing the ANN-2 model were scaled between 0 and 1 by using Equation 2, given in Section 4.1. As in the development of the ANN-1 model, in total, 80 % of the data taken from the literature were utilized for training of the ANN-2 model and 20 % for testing of the ANN-2 model. Firstly, one hidden layer was chosen. Then, two hidden layers were chosen to obtain better performance. During the design of optimal geometry of the ANN-2 model, the trials were formed similar to the trials made in modeling of minimum void ratio.

### 5. Multiple regression model for the prediction of the limit void ratio values ($e_{\text{max}}$ and $e_{\text{min}}$)

Multiple regression (MR) analysis was done for estimating the limit void ratio values ($e_{\text{max}}$ and $e_{\text{min}}$) of coarse-grained soils from the two graining soil parameters ($D_{50}$ and $C_u$). To achieve this, by using SPSS 9.0.0, two MR models (MR-1 and MR-1) were developed: MR-1 for prediction of $e_{\text{max}}$ and MR-2 for the prediction of $e_{\text{min}}$ of coarse-grained soils. The data used while developing both the ANN-1 and ANN-2 models, were used in
the development of two MR models. The MR-1 and MR-2 models revealed the following correlations in Eqs. (4) and (5), respectively:

\[ e_{\text{min}} = 0.469 + 0.088D_{50} \quad R^2 = 0.288 \]  

(4)

\[ e_{\text{max}} = 0.756 + 0.003C_u + 0.136D_{50} \quad R^2 = 0.351 \]  

(5)

6. Results and discussion

The \( e_{\text{min}} \) values predicted by the ANN-1 model were compared with the \( e_{\text{min}} \) values obtained from the literature (Polito, 1999; Santamarina and Cho, 2001; Sukumaran and Ashmawy, 2003; Tika et al., 2003; Erzin, 2004; Park and Byerne, 2004; Cho et al., 2006; Bareither, 2008; Wichtmann and Triantafyllidis, 2013; Belkhatir, 2014; Oh, 2014; Bensoula et al., 2015; Salvatore et al., 2015; Erzin et al. 2016) in Figs. 6 and 7, for training and testing samples, respectively. These figures illustrate that predicted \( e_{\text{min}} \) values are found to be quite close to the obtained \( e_{\text{min}} \) values from the literature. From here, it can be concluded that the \( e_{\text{min}} \) value could be predicted with acceptable accuracy from easily determined two soil grain properties (\( C_u \) and \( D_{50} \)) with the use of trained ANN-1 values.

Similarly, the \( e_{\text{max}} \) values predicted by the ANN-2 model were compared with the \( e_{\text{max}} \) values obtained from literature (Polito, 1999; Santamarina and Cho, 2001; Sukumaran and Ashmawy, 2003; Tika et al., 2003; Erzin, 2004; Park and Byerne, 2004; Cho et al., 2006; Bareither, 2008; Wichtmann and Triantafyllidis, 2013; Belkhatir, 2014; Oh, 2014; Bensoula et al., 2015; Salvatore et al., 2015; Erzin et al. 2016) in Figs. 8 and 9, for training and testing samples, respectively. These figures illustrate that predicted \( e_{\text{max}} \) values are found to be quite close to the obtained \( e_{\text{max}} \) values, which is similar to ANN-1 model.

It is noted from the results of the MR analysis that MR-1 and MR-2 models (Eqs. (8) and (9)) reveal coefficient of determination \( (R^2) \) values of 0.288 and 0.351, respectively, indicating poor correlations between limit void ratios \( (e_{\text{max}} \) and \( e_{\text{min}} \)) and soil properties, namely, coefficient of uniformity \( (C_u) \) and mean grain size \( (D_{50}) \). Also, in order to examine the prediction capacity of the MR models, \( e_{\text{min}} \) values predicted from MR-1 model were compared with \( e_{\text{min}} \) values obtained from the literature, as shown in Fig. 10 for all samples taken from the literature. Similarly, \( e_{\text{max}} \) values predicted from MR-2 model were compared with \( e_{\text{max}} \) values obtained from the literature, as shown in Fig. 11 for all samples taken from the literature. Figures 10 and 11 show that there is not a good agreement between the predicted and experimental \( (e_{\text{max}} \) and \( e_{\text{min}} \)) values.
Additionally, four performance indices, namely, the determination coefficient ($R^2$), given by Eq. (6), variance account for (VAF), given by Eq. (7), mean absolute error (MAE), given by Eq. (8), and root mean square error (RMSE), given by Eq. (9) were calculated for comparing and evaluating the prediction performance of the ANN and MR models developed in this paper. The computed indices are listed in Table 3.

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2}$$  

(6)

$$VAF = \left[1 - \frac{\text{var}(y - \hat{y})}{\text{var}(y)}\right] \times 100$$  

(7)

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |(y_i - \hat{y}_i)|$$  

(8)

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2}$$  

(9)

where $\text{var}$ denotes the variance, $y$ is the measured value, $\hat{y}$ is the predicted value.

In addition to the four performance indices computed, in order to gain an insight into the prediction capabilities of the proposed ANN and MR models, a graph between the scaled percent error (SPE), as given by Eqs. (10) and (11) for $e_{\text{max}}$ and $e_{\text{min}}$, respectively, and cumulative frequency was also plotted as shown in Figs. 12 to 15.

$$SPE = \frac{(e_{\text{max}} - e_{\text{max}})}{(e_{\text{max}})_{\text{max}} - (e_{\text{max}})_{\text{min}}}$$  

(10)

$$SPE = \frac{(e_{\text{min}} - e_{\text{min}})}{(e_{\text{min}})_{\text{max}} - (e_{\text{min}})_{\text{min}}}$$  

(11)

where $e_{\text{max}}$ and $e_{\text{max}}$ are the predicted and the measured maximum void ratio values; and $(e_{\text{max}})_{\text{max}}$ and $(e_{\text{max}})_{\text{min}}$ are the maximum and minimum measured maximum void ratio values, respectively.

$$SPE = \frac{(e_{\text{min}} - e_{\text{min}})}{(e_{\text{min}})_{\text{max}} - (e_{\text{min}})_{\text{min}}}$$  

(11)
It can be observed from Fig. 12 that about 92% of $e_{\text{min}}$ value predicted from the ANN-1 model fall into 
± 10% of the SPE, indicating a perfect estimate for the $e_{\text{min}}$ value of coarse-grained soils. It can be observed from 
Fig. 13 that about 80% of $e_{\text{min}}$ value predicted from the MR-1 model fall into ± 10% of the SPE, indicating a poor estimate for the $e_{\text{min}}$ value of coarse-grained soils. It can be noted from Fig. 14 that and about 96% of $e_{\text{max}}$ 
value predicted from the ANN-2 model fall into ± 20% of the SPE, indicating a perfect estimate for the $e_{\text{max}}$ 
value of coarse-grained soils from the ANN-2 model. It can be noted from Fig. 15 that and about 73% of $e_{\text{max}}$ 
value predicted from the MR-2 model fall into ± 20% of the SPE, indicating a poor estimate for the $e_{\text{max}}$ value of 
coarse-grained soils from the MR-2 model. It can be concluded from Figs. 12 to 15 that both ANN models 
developed in this study can be used more efficiently than both MR models for the estimation of the limit void 
ratios of coarse-grained soils. Similar ANN models could be developed for the prediction of the limit void ratios 
($e_{\text{min}}$ and $e_{\text{max}}$) for other materials by using same input and output variables.

7. Conclusion

In this study, the performance of the ANN and MR models to predict the limit void ratios ($e_{\text{max}}$ and $e_{\text{min}}$) 
of coarse-grained soils has been investigated and compared. For this purpose, both two distinct ANN-1 and 
ANN-2 models and two distinct MR-1 and MR-2 models were developed by using the compiled data taken from 
the literature: ANN-1 and MR-1 models for predicting $e_{\text{min}}$ and ANN-2 and MR-2 models for predicting $e_{\text{max}}$ of 
coarse-grained soils. The $e_{\text{max}}$ and $e_{\text{min}}$ values predicted from both ANN and MR models were compared with 
the experimental values taken from the literature. The results indicated that the limit void ratio values predicted 
from both ANN models matched the measured limit void ratio values much better than those obtained from both 
MR models.

In order to evaluate the prediction performance of the ANN and MR models developed, several 
performance indices, such as $R^2$, MAE, RMSE, VAF, and SPE were also calculated. The computed indices make 
it clear that both constructed ANN models (ANN-1 and ANN-2) were able to estimate the limit void ratios ($e_{\text{max}}$ 
and $e_{\text{min}}$) of coarse-grained soils quite efficiently and outperformed the MR models. Thus, the developed ANN 
models can be used satisfactorily to predict the limit void ratios of coarse-grained soils from their two graining 
parameters, namely, coefficient of uniformity ($C_u$) and mean grain size ($D_{50}$), as a rapid inexpensive substitute 
for laboratory techniques.
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Figures

Fig. 1

Figure 1

Histograms of the variables used while developing the ANN and MLR models
Figure 2

Relationship between the limit void ratios ($e_{\text{min}}$ and $e_{\text{max}}$) and graining parameters ($D_{50}$ and $C_u$) for the data obtained from the literature.
Figure 3

Correlation between $e_{\min}$ and $e_{\max}$ for the data obtained from the literature.
Figure 4

The ANN-1’s architecture for the prediction of minimum void ratio ($e_{\text{min}}$) of coarse grained soils

Fig. 4

Fig. 5
Figure 5

The ANN-2’s architecture for the prediction of maximum void ratio (emax) of coarse grained soils

Fig. 6

The comparison of the measured emin values with the predicted emin values from the ANN-1 model for training samples
The comparison of the measured $e_{\text{min}}$ values with the predicted $e_{\text{min}}$ values from the ANN-1 model for testing samples.
Figure 8

The comparison of the measured $e_{max}$ values with the predicted $e_{max}$ values from the ANN-2 model for training samples.
The comparison of the measured emax values with the predicted emax values from the ANN-2 model for testing samples
The comparison of the measured $e_{\text{min}}$ values with the predicted $e_{\text{min}}$ values from the MR-1 model

Figure 10

The comparison of the measured $e_{\text{min}}$ values with the predicted $e_{\text{min}}$ values from the MR-1 model
The comparison of the measured $e_{\text{max}}$ values with the predicted $e_{\text{max}}$ values from the MR-2 model

Fig. 11

Figure 11

The comparison of the measured $e_{\text{max}}$ values with the predicted $e_{\text{max}}$ values from the MR-2 model
Figure 12

Scaled percent error of the emin predicted from the ANN-1 model
Figure 13

Scaled percent error of the emin predicted from the MR-1 model
Figure 14

Scaled percent error of the emax predicted from the ANN-2 model
Figure 15

Scaled percent error of the emax predicted from the MR-2 model