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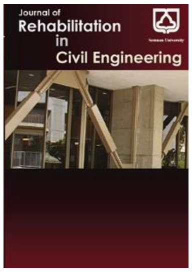

Predicting Resilient Modulus of Clayey Subgrade Soils by Means of Cone Penetration Test Results and Back-Propagation Artificial Neural Network

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ABSTRACT

Resilient modulus (M_r) of subgrade soils is considered as one of the most important factors for designing flexible pavements using empirical methods as well as mechanistic-empirical methods. The resilient modulus is commonly measured by a dynamic triaxial loading test, which is complex and expensive. In this research, back-propagation artificial neural network method has been employed to model the resilient modulus of clayey subgrade soils based on the results of the cone penetration test. The prediction of the resilient modulus of clayey subgrade soil can be possible through the developed neural network based on the parameters of the cone tip resistance (q_c), sleeve friction (f_s), moisture content (w), and dry density (γ_d). The results of the present study show that the coefficients of determination (R^2) for training and testing sets are 0.9837 and 0.9757, respectively. According to the sensitivity analysis results, the moisture content is the least important parameter to predict the resilient modulus of clayey subgrade soils, while the importance of other parameters is almost the same. In this study, the effect of different parameters on the resilient modulus of clayey subgrade soil was evaluated using parametric analysis and it was found that with increasing the cone tip resistance (q_c), the sleeve friction (f_s) and the dry density (γ_d) and also with decreasing the moisture content (w) of soils, the resilient modulus of clayey subgrade soils increases.

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1. Introduction

The most important geo-materials are fine and coarse grained soils and granular materials that make up the subgrade and pavement layers. An economic method of pavement design requires a reliable characterization of the stiffness properties of the subgrade soils. At the moment, the resilient modulus is known as a reliable parameter of the elastic stiffness of subgrade soils. The resilient modulus represents the soil elastic modulus at different stress levels, which is described as the ratio of the applied deviator stress to the reversible axial strain under the effect of the dynamic load. The repeated triaxial load test under different confining and deviator stresses is a time-consuming and costly laboratory test to determine the resilient modulus [1]. This parameter is one of the most important and basic characteristics of the road materials in mechanistic analysis and the structural design of the flexible pavement in both empirical methods (e.g. AASHTO 1993) and mechanistic- empirical methods (e.g. MEPDG) [2,3].

Subgrade characteristics can significantly affect the resilient modulus of geo-materials. These characteristics including dry density, moisture content, gradation, and the shape of soil particles, fine-grained percentage, and the state of stress have a relatively high influence on the resilient modulus of subgrade soils [2,4–7]. The resilient modulus (M_r) of the soil is usually measured through a repeated load triaxial test [2,8]. This modulus can also be calculated by carrying out various in-situ and ring triaxial, torsional shear and resonance column tests [9–15]. These tests are complex and expensive [16]. On the other hand, providing an undisturbed soil specimen for laboratory tests is time-consuming and unprofitable. Extensive research has been done on the developing of empirical relationships to establish the relationship between the main characteristics of soil that can be determined experimentally and the resilient modulus of subgrade soil [16–19]. On the other hand, several studies have been conducted on the correlation between the resilient modulus and in-situ indices of the subgrade soils [20–25].

The cone penetration test (CPT) is an accurate and repeatable in-situ test which is widely used in geotechnical engineering [26–32]. In the CPT test, two parameters of cone tip resistance (q_c) and the sleeve friction (f_s) are measured. This test also gives some information on the classification of underground soils. So far, several research has been done to predict the resilient modulus of soils using the results of dynamic cone penetration (DCP) and CPT tests. The results of dynamic cone penetration (DCP) and CPT tests have been used by several researchers for predicting the resilient modulus of soils.

In the present research, a back-propagation artificial neural network (BPNN) model has been developed to calculate the resilient modulus of clayey subgrade soils based on the results of CPT test (e.g. cone tip resistance and sleeve friction), moisture content and dry density of soils. Moreover, the accuracy of the proposed BPNN model has been compared with the accuracy of previous proposed methods as well. Sensitivity analysis and parametric analysis were also performed to determine the importance degree of each input parameter on predicting the resilient modulus of fine-grained subgrade soils and also to recognize the influence of variations in the input parameters on the variations of the resilient modulus.

2. Background

Hassan (1996) proposed the first correlation between the dynamic cone penetration index and the resilient modulus of fine-grained soils as follows [33]:

$$\mathrm{M_r} = 7013.065 - 2040.783\mathrm{Ln(DCPI)} \quad (1)$$

where, DCPI is the dynamic cone penetration index in millimeters per impact and M_r is the resilient modulus in MPa.

In 1999, a model was proposed by Mohammad et al. to predict the M_r using results of CPT test on fine-grained soils. The equation is defined as follows [22].

$$\mathrm{M_r} = -5.69q_c - 26.51f_s + 69.34w + 11.78\gamma_d - 137.47 \quad (2)$$

Predictor parameters in this equation are as cone tip resistance (q_c), sleeve friction (f_s), dry density (d_γ) and moisture content (w) of soil.

By evaluating manual and automatic types of DCP, George and Uddin (2000) found that these two test types are generally similar. [34]. The following relationship was proposed by them to predict the resilient modulus:

$$\mathrm{M_r} = 532(\mathrm{DCPI})^{-0.492} \quad (3)$$

Gudishala (2004) presented the relationship between fine-grained soil resilient modulus and DCPI parameters, dry density (d_γ) and moisture content (w) in the form of Equation 4 [4]. He also showed that the percentage of moisture content strongly affects the resilient modulus of fine-grained subgrade soils.

$$\mathrm{M_r} = \frac{1100(\mathrm{DCPI})^{-0.44}}{w} + 2.39\gamma_d \quad (4)$$

Herath et al. (2005) proposed two equations for estimating the resilient modulus of fine-grained soils [35]. These equations were highly reliable, but they showed that the Equation (6) is more appropriate and reliable to use for all types of soil compared to Equation (5).

$$\mathrm{M_r} = 16.28 + \frac{928.24}{\mathrm{DCPI}} \quad (5)$$

$$\mathrm{M_r} = 520.62(\mathrm{DCPI})^{-0.738} + 0.4\left(\frac{\gamma_d}{w}\right) + 0.44\mathrm{PI} \quad (6)$$

where, PI is the plastic index.

In order to predict M_r of the fine-grained subgrade soils using the output parameter of DCP test and soil properties, two nonlinear models were proposed by Mohamad et al. (2007) [25]. The proposed models obtained acceptable results based on the experimental results. The proposed models by Mohammad et al. (2007) were defined as follows:

$$M_R = \frac{151.8}{\mathrm{DCPI}^{1.096}} \quad (7)$$

$$M_R = \frac{165.5}{\mathrm{DCPI}^{1.147}} + 0.0966\left(\frac{\gamma_d}{w}\right) \quad (8)$$

where Mr denotes the resilient modulus in MPa, DCPI denotes dynamic cone penetration index in millimeters per impact, γ_d denotes the dry density of the soil in kN/m^3, and w denotes the moisture content.

The multivariate normal distribution method was used in Liu et al. (2016) research for modeling the M_r of fine-grained soils by the piezocone penetration test (CPTU) and essential parameters of soil [36]. The method mentioned above has led to the creation of better models by reducing the uncertainty and increasing numbers of variables compared to traditional methods of the regression [36–39]. The model based on the multivariate normal distribution is as follows:

$$M_R = (1.13{q_c}^{0.53} + 13.06{f_s}^{1.4} - 0.75w^{0.34} + 0.0007{\gamma_d}^{2.33} + 4.75)^{2.44} \quad (9)$$

In order to predict the resilient modulus of fine-grained soils, a model was presented by Sadrosadat et al (2020) using the results of CPT test based on gene expression programming (GEP) [40]. This model predicts the resilient modulus in terms of cone tip resistance (q_c), sleeve friction (f_s), dry density (γ_d) and moisture content (w) of soils. According to the results, the proposed model accurately predicts the resilient modulus of fine-grained soils. The following relationship expresses the developed model:

$$M_R = 34.17\sqrt{\frac{\gamma_d q_c}{w}\sqrt{\left(\frac{\gamma_d}{q_c} + w\right) f_s}} \quad (10)$$

Ghorbani et al. (2020) employed a hybrid firefly algorithm (FA) and the multilayer perceptron (MLP) neural network to predict the resilient modulus of fine-grained soils [41]. They predicted the resilient modulus as a function of cone tip resistance (q_c), sleeve friction (f_s), dry density (γ_d), and moisture content (w) of soils. The results ensured that the developed model accurately predicts the resilient modulus of the fine-grained soils.

Ghanizadeh and Delaram (2021) predicted the resilient modulus of fine-grained subgrade soils using an evolutionary polynomial regression (EPR) method [42]. According to the results, the presented equation obtained a higher accuracy than the multivariate normal distribution and GEP methods.

3. Artificial neural network

Artificial neural network (ANN) is a new mathematical method for machine learning, representing science, and the application of acquired science to predict the output responses of complex systems. The way biological neural networks function to process data and information and create knowledge is the inspiration by which the basic concept of such neural networks is established. The main factor of this concept is the creation of new structures for the information processing systems. ANN consists of a great number of interconnected and parallel processing elements named neurons working together to solve a problem. Learning in artificial neural networks is done by adjusting the connection weights between neurons by introducing the training dataset, and after ANN training, if new inputs are introduced, it will produce the correct output value [43–46]. The neural network performance is formed by a neuron which is the smallest unit of information processing. Various layers are assigned to these neurons which lead to forming a special architecture using the connections between neurons in different layers [47,48]. Neurons can be a nonlinear mathematical function. As a result, the combination of these neurons forms a neural network that can be considered as a complex and nonlinear system. The neurons have independent operations in the neural network and the behavior of several neurons forms the total behavior of the network. On the other hand, neurons correct each other in a cooperation process. Figure 1 shows the structure of an artificial neuron. The input values of x_i are multiplied by the connection weights of w_i and then add together. After adding the bias value, the corresponding result (net) enters into the transfer function of *f (.)*, and thus the neuron output is produced [49,50]. There are several types of transfer functions, the most important of which are the linear, sigmoid and tangent sigmoid functions.

A set of parallel neurons forms a layer. Each artificial neural network can be composed of several layers to produce its outputs, which will include hidden layers and output layers, and these layers are connected to each other in series. Each input in the neural network has its own weight, then it will enter into the transfer function under influence of its weight with the aim of processing and generating the inputs of the subsequent layers. So far, different types of artificial neural networks have been introduced based on the type of transfer functions of network layers and the way of the influence of weights on the inputs. In this research, to model the resilient modulus of the clayey subgrade soil, a back-propagation neural network (BPNN) has been used, whose architecture is shown in Figure 2.

Back-propagation neural network is trained in two steps [51]:

1. In the first step, which is called the forward phase, the input vector is applied to the network and is propagated to the output layer using the hidden layers, and the output vector presented in the output layer forms the real response of the network. In the path above, the network parameters are considered fixed and constant.

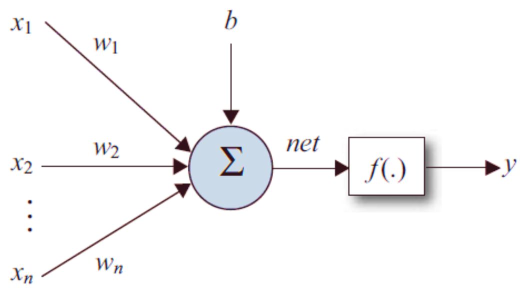


Fig. 1. Structure of an artificial neuron [52].

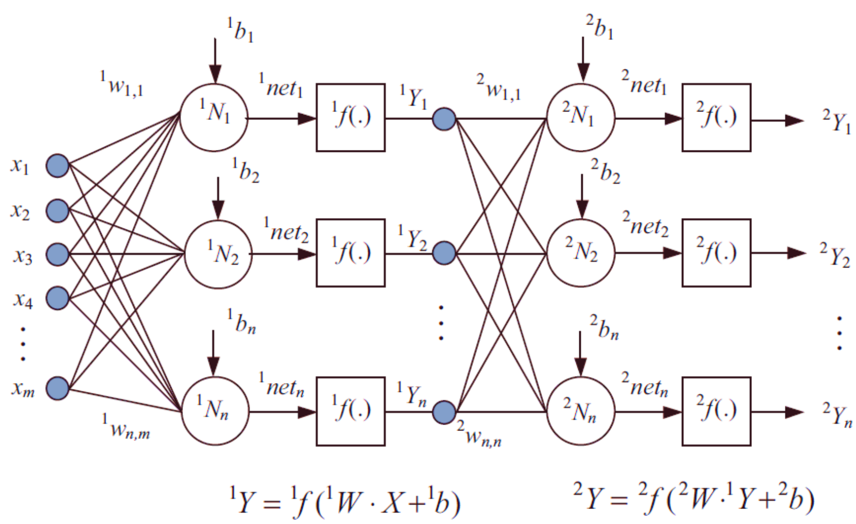


Fig. 2. Architecture of back-propagation neural network (BPNN) with one hidden layer [52].

2. In the second phase, which is called the backward phase, the change and adjustment of parameters will be accomplished. This adjustment is based on an error-correcting rule and the error signals generated in the output layer of the network.

Networks will be defined to have training mode by converging their responses to the real corresponding values. In addition, it is expected that if the data with the desired variety and number are entered, the predicted responses by the network will have the least possible difference with their corresponding measured values.

4. Evaluating the model accuracy

In order to assess the accuracy of BPNN models and compare different proposed models with each other, five statistical parameters including coefficient of determination (R^2), root-mean-square error (RMSE), mean squared error (MSE), and mean absolute percentage error (MAPE) were employed [53,54]. These parameters can be calculated using Equations (11) to (14).

$$R^2 = \left[\frac{1}{N}\frac{\sum_{i=1}^{N}(T_i-\bar{T})(O_i-\bar{O})}{\sigma_T \cdot \sigma_O}\right]^2 \quad (11)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(T_i - O_i)^2 \quad (12)$$

$$RMSE = \sqrt{\frac{1}{N}\cdot\sum_{i=1}^{N}(T_i - O_i)^2} \quad (13)$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{(T_i - O_i)}{T_i}\right| \quad (14)$$

where, N denotes number of observed data, T_i denotes the vector of measured values, O_i denotes the vector of predicted values, $\bar{T}$ denotes the mean of measured values, $\bar{O}$ denotes the mean of predicted values, σ_O denotes the standard deviation of predicted values, and σ_T denotes the standard deviation of the measured values.

5. Dataset

5.1. Dataset description

The used dataset in this study is taken from the article by Liu et al. (2016) [36]. Their aim was to obtain a correlation between the indices of cone penetration test and the resilient modulus of clayey subgrade soils. For this purpose, 124 CPT test results at 16 different sites in Jiangsu Province of China were used. CPT tests were carried out according to the international standards [55,56]. The substrate in this area mainly consisted of soft and hard clayey soils and silty clay soils with high variability in terms of strength and stiffness [36]. According to soil specimens from test sites, laboratory tests were performed to obtain soil characteristics including moisture content (w), dry density (γ_d) and resilient modulus (M_r). Resilient modulus tests have been performed based on the AASHTO T 307 standard [57]. In CPT tests, a cylindrical cone penetrometer with an area of 10 cm^2 and a tip angle of 60° was used. The depth of the groundwater table (GWT), which varied from 0.4 to 4.5 m in test sites, was recorded straight away after the CPT test. To predict the resilient modulus (M_r) under in-situ stress, CPT tests were performed at locations adjacent to boreholes where soil specimens were taken from. The horizontal distance between boreholes to determine soil specifications at the CPT test site for each data point of {M_r, q_c, f_s and γ_d} was less than 2 m. In this study, the units for measuring M_r, q and f_s are in MPa, w is in percentage (%) and γ_d is in kN /m^3 [36]. Further details on the specifications of the materials and the tests performed can be found in [36].

5.2. Statistical parameters

For modeling, the data were first randomly divided into training and testing sets. For this purpose, 65%, 10%, and 25% of the data were selected as the training, validating, and testing sets, respectively. Table 1 presents the statistical characteristics of the input and output parameters.

As can be seen, the moisture content varies between 6.9 and 78.1, the dry density varies between 10.5 and 19.9 kN/m^3, the cone tip resistance varies between 0.22 and 3.93 MPa, and the sleeve friction varies between 0.006 and 0.14 MPa. The measured resilient modulus also varies between 12.5 and 95.8 MPa. The wide range of variability of each input and output variable indicates the diversity of the specimens in the dataset and the generalizability of the developed models based on the data in this dataset.

6. Modeling using ANN

6.1. Optimal architecture of ANN

To obtain the optimum architecture of BPNN a program was developed in MATLAB in the present study. The toolbox of the neural network of MATLAB was also used to train the BPNN. The toolbox of the neural network of MATLAB randomly assigns initial values of neural network weights in each time of running the program. This issue causes the performance of the BPNN changes in each run, despite the fixed neural network architecture and the fixed number of neurons in hidden layers. For this purpose, a program was developed in MATLAB that assesses networks with a hidden layer and different numbers of neurons in this layer to select the optimal architecture of the neural network. The number of neurons in the hidden layer was considered to be between 2 and 10 neurons. Based on the random selection of weights of each network architecture, each architecture was executed ten times and the network with the least error was considered as a representative of the assumed architecture. In the study, 65% (81 records), 10% (12 records), and 25% (31 records) of the data were considered as the training, validation and testing sets respectively. In addition, the activation function was considered as a sigmoid function in the hidden layer and linear in the output layer. The study showed that the network with 7 neurons in the hidden layer provides the best predictive accuracy based on the training and testing sets. Therefore, the neural network with a hidden layer and 4-7-1 architecture has the highest accuracy to predict the resilient modulus of subgrade soils. BPNN inputs include cone tip resistance (q_c), sleeve friction (f_s), moisture content (w) and dry density (γ_d), and BPNN output is the resilient modulus of subgrade soils.

Table 1. Statistical characteristics of the dataset.

Statistical characteristics	w (%)	γ_d (kN/m^3)	q_c (MPa)	f_s (MPa)	M_r (MPa)
Minimum	6.90	10.50	0.22	0.01	12.50
Maximum	78.10	19.90	3.93	0.14	95.80
Mean	31.92	15.85	1.76	0.08	46.09
Median	28.30	16.20	1.63	0.087	44.65
Standard deviation	14.24	2.08	0.85	0.03	17.30

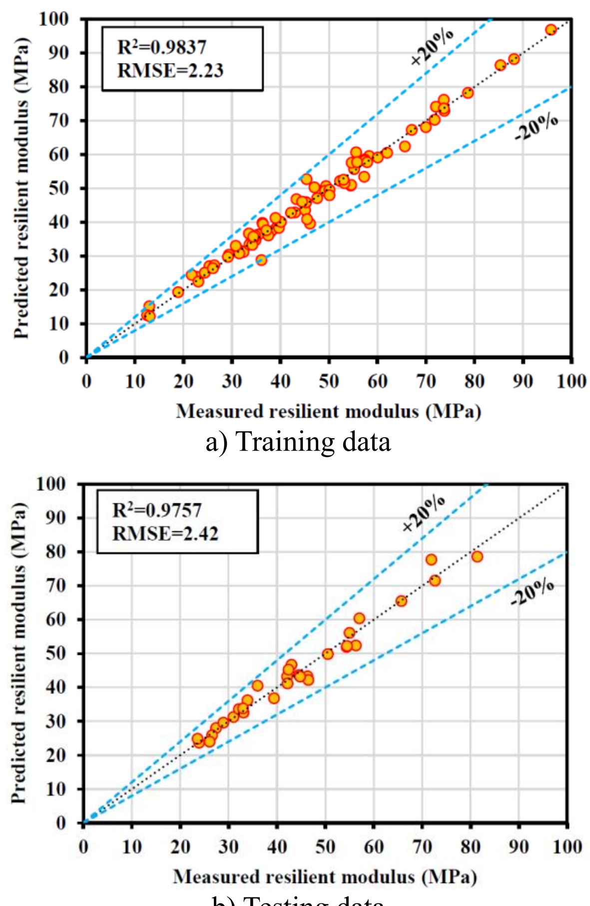
6.2. Model performance evaluation

The performance of the artificial neural network for predicting the resilient modulus of clayey subgrade soils is shown in Table 2 based on the training, validating, testing, and total sets. As it is shown, the coefficient of determination for the testing set is about 0.9757, which shows the high accuracy of the developed neural network. In addition, the proximity of R^2 and RMSE values for the training, validating, and testing sets indicates the generalizability of the developed neural network.

In Figure 3, the capability of the developed BPNN has been demonstrated by the comparison of the measured resilient modulus and the predicted resilient modulus based on the training and testing sets.

Table 2. Accuracy and performance of the neural network for predicting the resilient modulus of subgrade soils.

Data set	MSE	RMSE	MAPE	R^2
Training set	4.9769	2.2309	3.8804	0.9837
Validation set	7.2255	2.688	4.7147	0.9920
Testing set	5.8520	2.4191	4.4470	0.9757
Total	5.4133	2.3266	4.1166	0.9818



a) Training data

b) Testing data

Fig. 3. Comparing the results of the predicted and measured resilient modulus.

An error range of 20% is also shown. As can be seen, the maximum predicted error of the developed model is about 20%. Furthermore, the value of R^2 in training set is equal to 0.9837 and in testing set is equal to 0.9757 and the value of RMSE for training and testing set is equal to 2.23 and 2.42, respectively. These values show the suitable accuracy of the model. Figure 4 shows the capability and accuracy of an artificial neural network by comparing the measured resilient modulus with the predicted resilient modulus for a set of training, validating, and testing sets. As can be observed, in most cases the predicted resilient modulus is matched well with the measured resilient modulus, which confirms the high accuracy of the developed neural network.

7. Comparison of the developed model with other models

To evaluate the capability of BPNN method, the results of this method were compared with the results of previously developed models in this field. For this purpose, the multivariate normal distribution model developed by Liu et al. (2016) [36], gene expression programming (GEP) model developed by Sadrosadat et al. (2020) [40] and the hybrid FA-MLP model developed by Ghorbani et al. (2020) [41], and the evolutionary polynomial regression (EPR) model developed by Ghanizadeh and Delaram [42] were considered. These models were introduced in the introduction section. Considering that in the research of Liu et al. (2016) [36], Sadrosadat et al. (2020) [40], and Ghanizadeh and Delaram (2021) [42] the form of the equation for predicting resilient modulus was explicitly introduced, these equations were employed for predicting the resilient modulus for the training and testing sets.

Table 3 presents the values of coefficient of determination (R^2) and root mean square error (RMSE) which are obtained from multivariate normal distribution model, GEP model, FA-MLP model, EPR model and the method used in this research (BPNN).

As shown in this table, the model developed based on the BPNN method has the highest coefficient of determination for the training set and also has the lowest RMSE error for the training and testing sets. It is also observed that the coefficient of determination (R^2) reported based on the FA-MLP method has the same value for the training and testing set, while the RMSE values for these two sets are significantly different. This issue may be due to incorrect selection of training and testing sets in this study. Another reason for this claim is the high value of R^2 as well as the high value of RMSE in this method. In general, considering that the BPNN method has the lowest RMSE, it can be stated that this method has a higher accuracy compared to other methods.

Table 3. A comparison of different developed models.

Researchers	**Method**	**RMSE**		**R^2**	
		Training	Testing	Training	Testing
Liu et al. (2016) [36]	Normal Distribution	2.80	2.75	0.9800	0.9699
Sadrosadat et al. (2020) [40]	GEP	3.55	3.32	0.9616	0.9513
Ghorbani et al. (2020) [41]	FA-MLP	2.29	2.68	0.9801	0.9801
Ghanizadeh and Delaram (2021) [42]	EPR	2.50	2.58	0.9808	0.9714
This study	BPNN	2.23	2.42	0.9837	0.9757

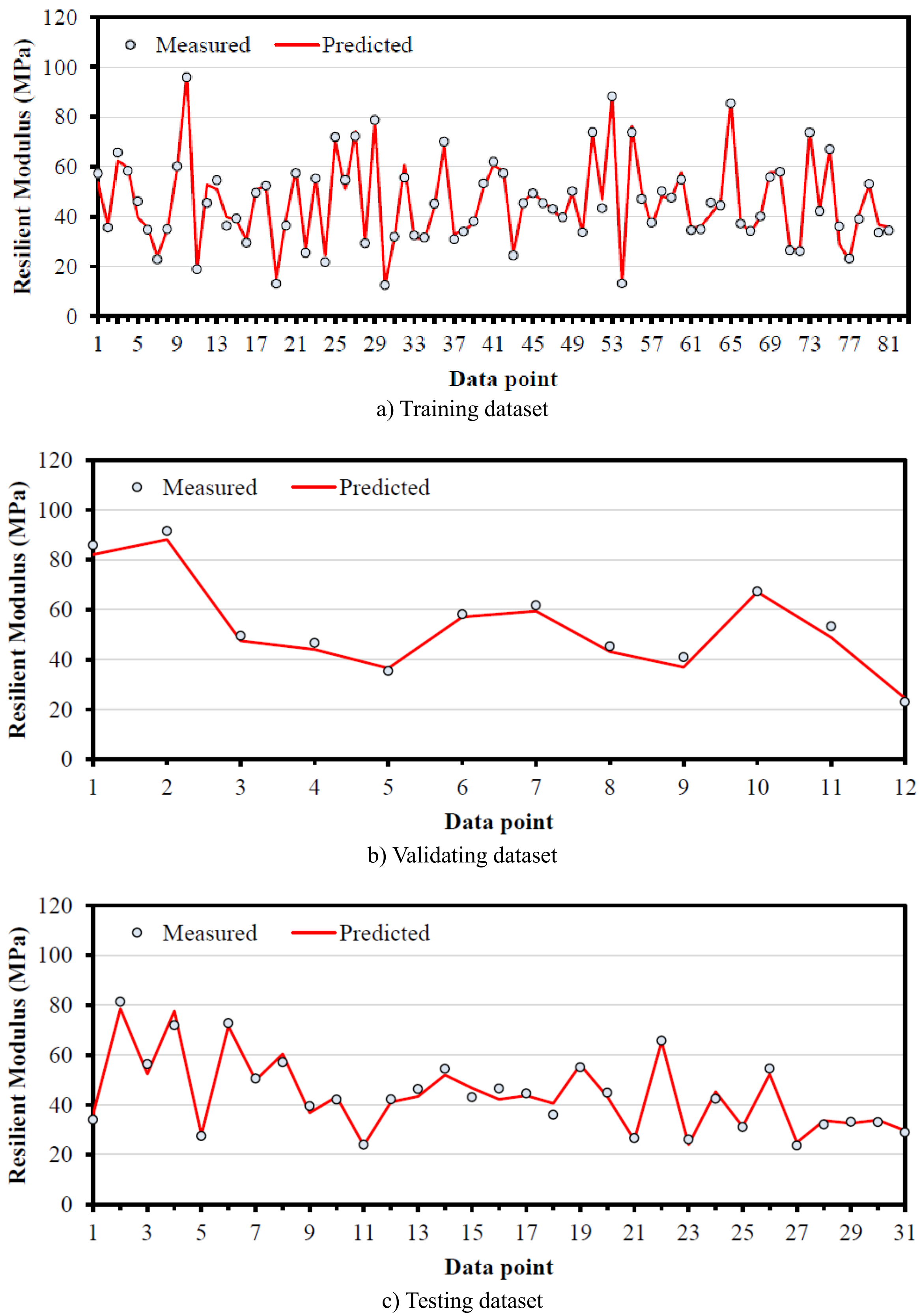


Fig. 4. Comparing measured resilient modulus and predicted resilient modulus.

8. Sensitivity analysis

In the present research, the cosine amplitude method (CAM) has been employed to obtain the importance level of each of the input parameters for predicting the resilient modulus of clayey subgrade soils based on the degree of the sensitivity index. The degree of sensitivity index can be calculated by Equation 15:

$$R_i = \frac{\sum_{j=1}^{n} x_{ij} \cdot y_j}{\sqrt{\sum_{j=1}^{n} x_{ij}^2 \cdot \sum_{j=1}^{n} y_j^2}} \tag{15}$$

In this equation, x_{ij} represents the independent variable of i for data point j and y_j represents the dependent variable for data point j (for x_{ij}). When the value of R_i is close to 1, it indicates that the input parameter is more important in estimating the output parameter, and when R_i is equal to zero, no correlation can be inferred. Figure 5 shows the significance of the input variables according to the results of the measured and predicted values of the resilient modulus.

As can be seen, the significance degree of the parameters of q_c, γ_d, and f_s is approximately equal, and w is the least important parameter for predicting resilient modulus of clayey subgrade soils according to the results of the cone penetration test. In addition, the difference of R_i between the predicted and measured values of the resilient modulus for the parameters q_c, γ_d, f_s, and w is very little, which shows the high accuracy of the ANN method for predicting the resilient modulus of the clayey subgrade soils.

9. Parametric analysis

Time and cost constraints and limited access to appropriate equipment are generally major barriers to experimental studies. In most cases, assessing the effect of each input variable on the output parameter requires several specimens whose molding and testing is time-consuming and expensive. One of the advantages of the modeling is the use of developed models for parametric studies and the evaluation of the influence of each input parameter on the outputs of the model. As mentioned earlier, in this study the input parameters are q_c, γ_d, f_s, and w. In this study, the effect of each input parameter on the resilient modulus of clayey subgrade soils has been evaluated using the developed BPNN model.

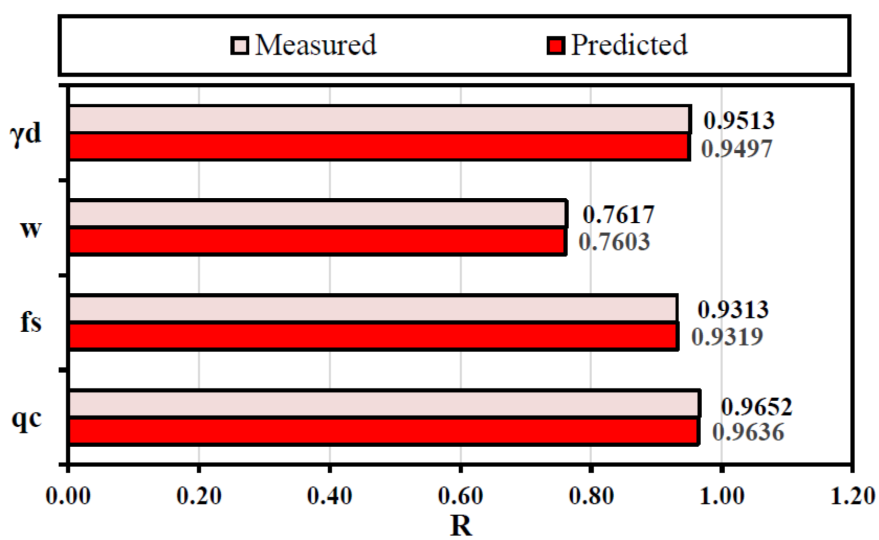


Fig. 5. The importance of each variable based on the CAM method.

To achieve this, all input parameters except the desired input parameter were considered at a specific level and equal to constant values, and then the value of desired input parameter was changed and the resilient modulus value was predicted using the developed BPNN model. The constant input parameters in each case were considered equal to the upper bound (maximum), lower bound (minimum) and average values given in Table 1. In addition, the influence of various input parameter on the resilient modulus at three different levels was determined by changing the desired input parameter. The diagrams of parametric analysis for the parameters of q_c, f_s, w and γ_d are shown in Figures 6 to 9, respectively.

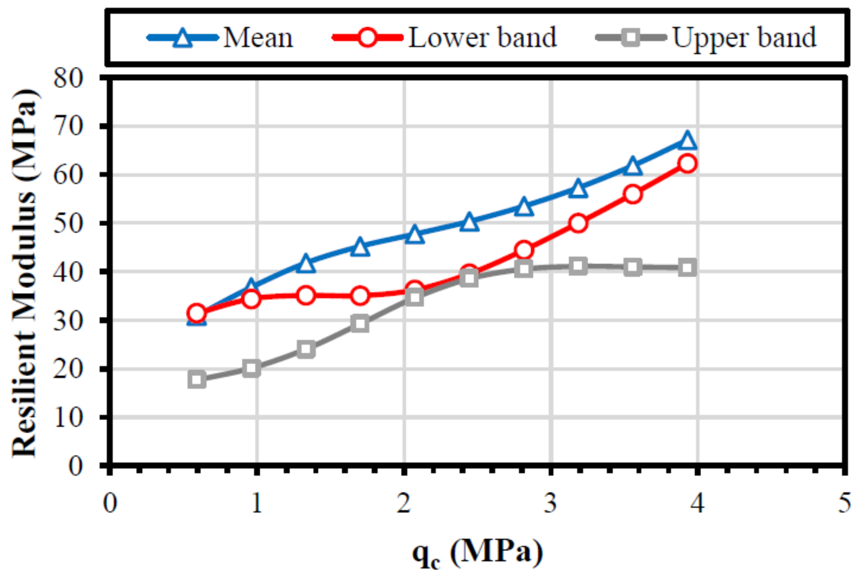


Fig. 6. The effect of the cone tip resistance on the resilient modulus.

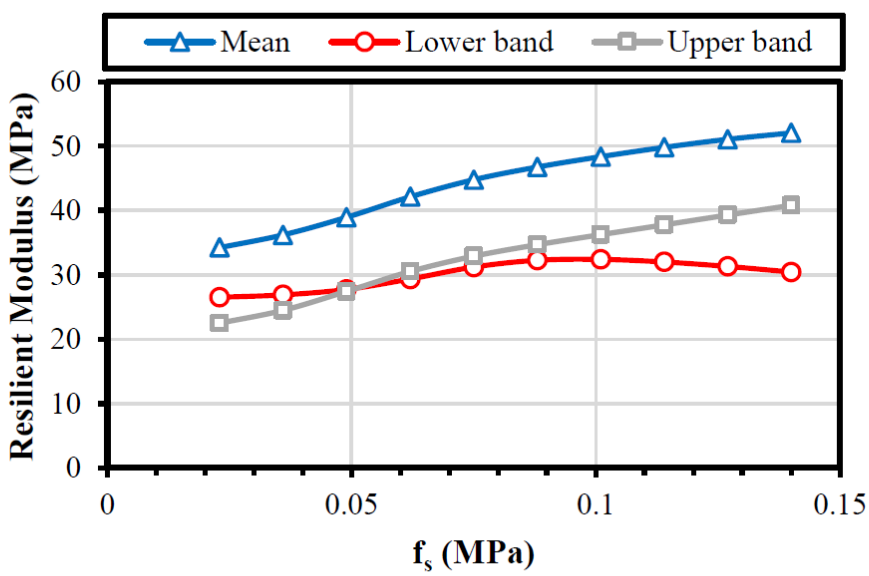


Fig. 7. The effect of sleeve friction on the resilient modulus.

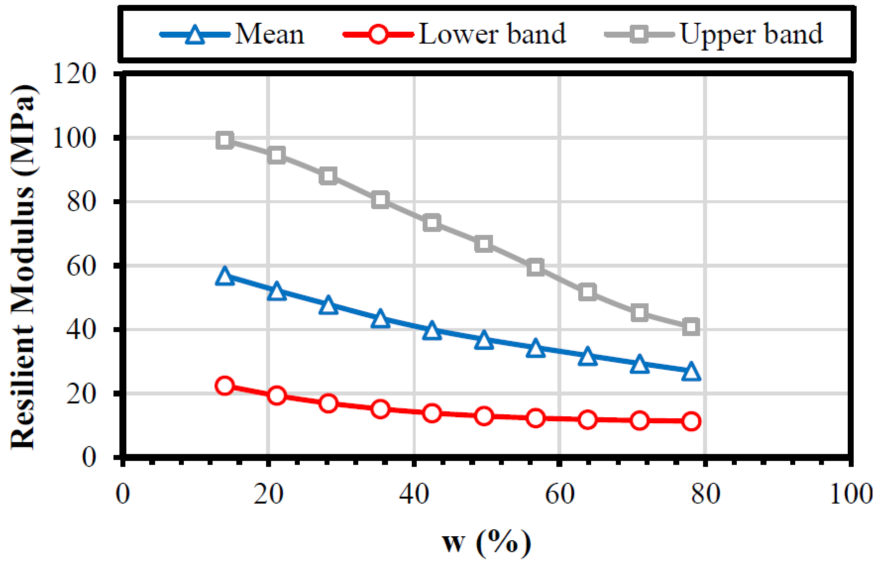


Fig. 8. The effect of moisture content of soils on the resilient modulus.

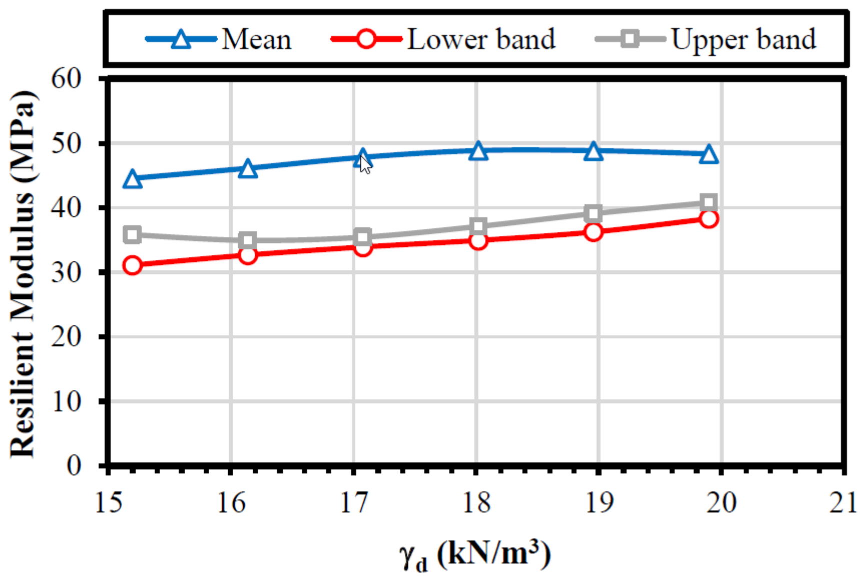


Fig. 9. The effect of the dry density of soils on the resilient modulus.

As can be observed, with increasing the cone tip resistance (q_c), sleeve friction (f_s), and the dry density of soils (γ_d), the resilient modulus shows an upward trend, while with increasing moisture content (w) of soils, the resilient modulus decreases. In fact, increasing the soil resistance parameters in the CPT test and also improving the density, leads to an increase in the resilient modulus of subgrade soils. In addition, by reducing the moisture of clayey soils and also using larger values of the shear strength of these soils, the resilient modulus can be increased. This behavior is in accordance with the expected behavior of fine-grained soils and is consistent with experimental results in this regard [36].

10. Conclusion

In this paper, using the BPNN method, a model has been established for predicting the resilient modulus of subgrade clayey soils based on the results of the CPT test. For this purpose, a dataset containing 124 experimental specimens of CPT was used. The results of this research can be expressed as follows:

1. The developed model is able to predict the resilient modulus of clayey subgrade soils according to the coefficients of determination (R^2) which are equal to 0.9837 for training, 0.9757 for testing, and 0.9818 for total datasets.
2. The maximum error of the developed BPNN model for predicting the resilient modulus of clayey subgrade soils was estimated to be 20%. The high accuracy of the developed model was concluded by comparing the efficiency of the developed model with other soft computing models.
3. The sensitivity analysis that was executed on this model showed that the importance degrees of the parameters of q_c, γ_d, and f_s were almost equal and w was the least important parameter for predicting the resilient modulus of clayey subgrade soils based on the results of the CPT test.
4. The parametric analysis also showed that with increasing the cone tip resistance (q_c), skin frictional resistance (f_s), and dry density (γ_d) of soils and also decreasing the moisture content (w) of soils, the resilient modulus of clayey soils increased.

REFERENCES

[1] Zaman M, Solanki P, Ebrahimi A, White L. Neural network modeling of resilient modulus using routine subgrade soil properties. Int J Geomech 2010;10:1–12. https://doi.org/10.1061/(ASCE)1532-3641(2010)10:1(1).

[2] AASHTO AA of SH and TO (AASHTO). Guide for Design of Pavement Structures. vol. 1. Washington, D.C: American Association of State Highway and Transportation Officials,Washington, D.C; 1993.

[3] ARA. Guide for Mechanistic–Empirical Design of New and Rehabilitated Pavement Structures, Final Report for Project 1-37A. Washington, DC: National Cooperative Research Program; 2004.

[4] Gudishala R. Development of resilient modulus prediction models for base and subgrade pavement layers from in situ devices test results. M.SLouisiana State University and Agricultural and Mechanical College, 2004.

[5] Hicks RG, Monismith CL. Factors influencing the resilient response of granular materials. Highw Res Rec 1971;345:15–31.

[6] Kim W, Labuz JF. Resilient Modulus And Strength Of Base Course With Recycled Bituminous Material. vol. 05. 2007.

[7] Kim SH, Yang J, Jeong JH. Prediction of subgrade resilient modulus using artificial neural network. KSCE J Civ Eng 2014;18:1372–9. https://doi.org/10.1007/s12205-014-0316-6.

[8] NCHRP. (NCHRP), National Cooperative Highway Research Program. Guid. Mech. Des. New Rehabil. Pavement Struct. Part 2, Des. Inputs, 2004.

[9] Drumm E, Boateng P, Johnson P. Estimation of subgrade resilient modulus from standard tests. J Geotech Eng 1990;116:774--789. https://doi.org/https://doi.org/10.1061/(ASCE)0733-9410(1990)116:5(774).

[10] Kim D-G. Engineering properties affecting the resilient modulus of fine-grained soils as subgrade. M.S Thesis, The Ohio State University, 1999.

[11] George K. Prediction of resilient modulus from soil index properties. Washington, D.C: No. FHWA/MS-DOT-RD-04-172,University of Mississippi,; 2004.

[12] Andrei D, Witczak MW, Schwartz CW, Uzan J. Harmonized resilient modulus test method for unbound pavement materials. Transp Res Rec 2004;1874:29–37. https://doi.org/10.3141/1874-04.

[13] Kim, Kim JR. Resilient behavior of compacted subgrade soils under the repeated triaxial test. Constr Build Mater 2007;21:1470–9.

[14] Mazari M, Navarro E, Abdallah I, Nazarian S. Comparison of numerical and experimental responses of pavement systems using various resilient modulus models. Soils Found 2014;54:36–44.

[15] AASHTO. Guide for Design of Pavement Structures. vol. 1. Washington: American Association of State Highway and Transportation Officials,Washington, D.C; 1993.

[16] Park, Kweon G, Lee SR. Prediction of resilient modulus of granular subgrade soils and subbase materials using artificial neural network. Road Mater Pavement Des 2009;10:647–65. https://doi.org/https://doi.org/10.1080/14680629.2009.9690218.

[17] Heidarabadizadeh N, Ghanizadeh AR, Behnood A. Prediction of the resilient modulus of non-cohesive subgrade soils and unbound subbase materials using a hybrid support vector machine method and colliding bodies optimization algorithm. Constr Build Mater 2021;275:122140. https://doi.org/10.1016/j.conbuildmat.2020.122140.

[18] Ghanizadeh, Rahrovan M. Application of artifitial neural network to predict the resilient modulus of stabilized base subjected to wet dry cycles. Comput Mater Civ Eng 2016;1:37–47.

[19] Ghanizadeh AR, Heidarabadizadeh N, Heravi F. Gaussian Process Regression (GPR) for Auto-Estimation of Resilient Modulus of Stabilized Base Materials. J Soft Comput Civ Eng 2021;5:80–94.

[20] Heukelom W, Klomp A. DYNAMIC TESTING AS A MEANS OF CONTROLLING PAVEMENTS DURING AND AFTER CONSTRUCTION 1962;203:495–510.

[21] Duncan JM, Buchignani AL. An Engineering Manual for Settlement Studies. University of California, Berkeley CA.; 1976.

[22] Mohammad LN, Titi HH, Herath A. Evaluation of resilient modulus of subgrade soil by cone penetration test. Transp Res Rec 1999;1:236–45. https://doi.org/10.3141/1652-30.

[23] Mohammad LN, Titi HH, Herath A; Effect of moisture content and dry unit weight on the resilient modulus of subgrade soils predicted by cone penetration test. Washington, DC: Publication FHWA-LA-00-355. U.S. Department of Transportation, FHWA.; 2002.

[24] Dehler W, Labuz J. Cone Penetration Testing in Pavement Design. 2007.

[25] Mohammad LN, Herath A, Abu-Farsakh MY, Gaspard K, Gudishala R. Prediction of Resilient Modulus of Cohesive Subgrade Soils from Dynamic Cone Penetrometer Test Parameters. J Mater Civ Eng 2007;19:986–92. https://doi.org/10.1061/(asce)0899-1561(2007)19:11(986).

[26] Puppala AJ, Acar YB, Tumay MT. Cone Penetration in Very Weakly Cemented Sand. J Geotech Eng 1995;121:589–600. https://doi.org/https://doi.org/10.1061/(ASCE)0733-9410(1995)121:8(589).

[27] Lunne T, Robertson PK, Powell JJM. Cone Penetration Testing in Geotechnical Practice. London: Blackie Academic and Professional,CRC Press; 1997.

[28] Mayne PW. Cone penetration testing: a synthesis of highway practice. Transportation Research Board; 2007.

[29] Liu S, Cai G, Puppala AJ, Tu Q. Prediction of embankment settlements over marine clay using piezocone penetration tests. Bull Eng Geol Environ 2011;70:401–9. https://doi.org/10.1007/s10064-010-0329-4.

[30] Cai G, Liu S, Puppala AJ, Tong L. Assessment of the coefficient of lateral earth pressure at rest (K o) from in situ

seismic tests. Geotech Test J 2011;34. https://doi.org/10.1520/GTJ102520.

[31] Cai G, Liu S, Puppala AJ. Reliability assessment of CPTU-based pile capacity predictions in soft clay deposits. Eng Geol 2012;141–142:84–91. https://doi.org/10.1016/j.enggeo.2012.05.006.

[32] Cai G, Puppala AJ, Liu S. Characterization on the correlation between shear wave velocity and piezocone tip resistance of Jiangsu clays. Eng Geol 2014;171:96–103. https://doi.org/10.1016/j.enggeo.2013.12.012.

[33] Hassan A Bin. The effects of material parameters on Dynamic Cone Penetrometer results for fine-grained soils and granular materials. Oklahoma: Oklahoma State University Stillwater; 1996.

[34] George KP, Uddin W. Subgrade characterization for highway pavement design. Final Report. Jackson: Mississippi Department of Transportation.: 2000.

[35] Herath A, Mohammad L, Gaspard K, Gudishala R, Abu-Farsakh M. The use of dynamic cone penetrometer to predict resilient modulus of subgrade soils. Adv. pavement Eng., Austin, Texas, United States: Geotechnical Special Publication ASCE, Reston; 2005, p. 1–16. https://doi.org/https://doi.org/10.1061/40776(155)2.

[36] Liu S, Zou H, Cai G, Bheemasetti TV, Puppala AJ, Lin J. Multivariate correlation among resilient modulus and cone penetration test parameters of cohesive subgrade soils. Eng Geol 2016;209:128–42. https://doi.org/10.1016/j.enggeo.2016.05.018.

[37] Zou H, Liu S, Cai G, Puppala AJ, Bheemasetti TV. Multivariate correlation analysis of seismic piezocone penetration (SCPTU) parameters and design properties of Jiangsu quaternary cohesive soils. Eng Geol 2017;228:11–38. https://doi.org/https://doi.org/10.1016/j.enggeo.2017.07.005.

[38] Zhang Y, Li T, Wang Y. Theoretical elastic solutions for foundations improved by geosynthetic-encased columns. Geosynth Int 2011;18:12–20. https://doi.org/https://doi.org/10.1680/gein.2011.18.1.12.

[39] Zhang W. MARS Use in Prediction of Collapse Potential for Compacted Soils. MARS Appl. Geotech. Eng. Syst., Singapore: Springer Singapore; 2020, p. 27–46. https://doi.org/10.1007/978-981-13-7422-7_4.

[40] Sadrossadat E, Ghorbani B, Zohourian B, Kaboutari M, Rahimzadeh Oskooei P. Predictive modelling of the MR of subgrade cohesive soils incorporating CPT-related parameters through a soft-computing approach. Road Mater Pavement Des 2020;21:701–19. https://doi.org/https://doi.org/10.1080/14680629.2018.1527241.

[41] Ghorbani, Behnam Arulrajah A, Narsilio G, Horpibulsuk S, Bo MW. Hybrid Formulation of Resilient Modulus for Cohesive Subgrade Soils Utilizing CPT Test Parameters. J Mater Civ Eng 2020;32:06020011. https://doi.org/https://doi.org/10.1061/(ASCE)MT.1943-5533.0003329.

[42] Ghanizadeh AR, Delaram A. Development of Predictting Model for Clay Subgrade Soil Resilient Modulus based on the Results of Cone Penetration Test using Evolutionary Polynomial Regression Method. Civ Infrastruct Res 2021;7:1–22.

[43] Rezazadeh Eidgahee D, Haddad A, Naderpour H. Evaluation of shear strength parameters of granulated waste rubber using artificial neural networks and group method of data handling. Sci Iran 2019;26:3233–44. https://doi.org/10.24200/sci.2018.5663.1408.

[44] Rezazadeh Eidgahee D, Rafiean AH, Haddad A. A Novel Formulation for the Compressive Strength of IBP-Based Geopolymer Stabilized Clayey Soils Using ANN and GMDH-NN Approaches. Iran J Sci Technol - Trans Civ Eng 2020;44:219–

29. https://doi.org/10.1007/s40996-019-00263-1.

[45] Naderpour H, Nagai K, Fakharian P, Haji M. Innovative models for prediction of compressive strength of FRP-confined circular reinforced concrete columns using soft computing methods. Compos Struct 2019;215:69–84. https://doi.org/10.1016/j.compstruct.2019.02.048.

[46] Naderpour H, Rafiean AH, Fakharian P. Compressive strength prediction of environmentally friendly concrete using artificial neural networks. J Build Eng 2018;16. https://doi.org/10.1016/j.jobe.2018.01.007.

[47] Naderpour H, Sharei M, Fakharian P, Heravi MA. Shear Strength Prediction of Reinforced Concrete Shear Wall Using ANN, GMDH-NN and GEP. J Soft Comput Civ Eng 2022;6:66–87. https://doi.org/10.22115/scce.2022.283486.1308.

[48] Khademi A, Behfarnia K, Kalman Šipoš T, Miličević I. The Use of Machine Learning Models in Estimating the Compressive Strength of Recycled Brick Aggregate Concrete. Comput Eng Phys Model 2021;4:1–25. https://doi.org/10.22115/cepm.2021.297016.1181.

[49] Farhangi V, Jahangir H, Eidgahee DR, Karimipour A, Javan SAN, Hasani H, et al. Behaviour Investigation of SMA-Equipped Bar Hysteretic Dampers Using Machine Learning Techniques. Appl Sci 2021;11:10057. https://doi.org/10.3390/app112110057.

[50] Rezazadeh Eidgahee D, Fasihi F, Naderpour H. Optimized Artificial Neural Network for Analyzing Soil-Waste Rubber Shred Mixtures. Sharif J Civ Eng 2015;31.2:105–11.

[51] Rumelhart DE, Hinton GE, Williams RJ. Learning representations by back-propagating errors. Nature 1986;323:533–6. https://doi.org/10.1038/323533a0.

[52] Siddique N, Adeli H. Computational intelligence: synergies of fuzzy logic, neural networks and evolutionary computing. John Wiley \& Sons; 2013.

[53] Naderpour H, Rezazadeh Eidgahee D, Fakharian P, Rafiean AH, Kalantari SM. A new proposed approach for moment capacity estimation of ferrocement members using Group Method of Data Handling. Eng Sci Technol an Int J 2020;23:382–91. https://doi.org/10.1016/j.jestch.2019.05.013.

[54] Jahangir H, Rezazadeh Eidgahee D. A new and robust hybrid artificial bee colony algorithm – ANN model for FRP-concrete bond strength evaluation. Compos Struct 2021;257:113160. https://doi.org/10.1016/J.COMPSTRUCT.2020.113160.

[55] ASTM D5778. International Standard Test Method for Electronic Friction Cone and Piezocone Penetration Testing of Soils. Annual Book of ASTM Standards. ASTM International, West Conshohocken, PA.; 2012.

[56] ISSMFE I. Report of the ISSMFE Technical Committee on Penetration Testing of Soils -TC 16 with Reference Test Procedures. 1989.

[57] AASHTO T 307. Determining the Resilient Modulus of Soils and Aggregate Materials. 2003.