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Introducing a New Artificial Neural Network Model for prediction of the Pressuremeter Modulus in soils of Tehran

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ABSTRACT

Pressuremeter is one of the most reliable in-situ tests in geotechnical engineering. Soil deformation modulus has been related empirically to the pressuremeter modulus (E_{PM}) obtained from the pressure-volume change curve from this test. In general, the pressuremeter test is time-consuming and costly that requires experienced operators. Various parameters might also affect the test results. With these limitations, it is necessary to introduce equations and models for indirect determination of the E_{PM}. Artificial neural network (ANN) is a very useful technique for modeling complex relationships between input and output data sets. The ANN models often produce more accurate results compared with the linear regression methods. The main purpose of this research is to introduce a new ANN model for prediction of the EPM. The data used in this research is taken from 41 pressuremeter tests in soils of Tehran. In order to estimate EPM, parameters such as grain size distribution, depth of test, and moisture content are considered as input (independent) variables. The coefficient of determination (R^2) for the training, validation, and test data sets were 0.736, 0.906, and 0.801, respectively. Acceptable correlations and errors of network predictions in comparison with the actual values of EPM show the accuracy and efficiency of the designed model. Sensitivity analysis revealed that the grain size distribution is the most effective parameter among the variables on the E_{PM}.

1. Introduction

The soil deformation modulus is usually evaluated from the in-situ and laboratory tests. In-situ tests are more reliable since the initial natural conditions of the medium are preserved and less disturbed to soil samples tested in the laboratory. The pressuremeter is one of the most important in-situ tests for determining the soil deformation modulus. The test has been developed in both technical aspects and theoretical modifications. Menard type pressuremeter equipment consists of two main parts: the read-out unit, which rests on the ground surface, and the probe that is inserted into the borehole. The pressuremeter is lowered into the pre-bored hole and a uniform pressure is applied to the borehole walls by means of an inflatable flexible membrane. The pressure applied to the borehole walls is increased every 60 sec in order to deform the borehole walls (Ozvan et al., 2017). The pressure is held constant for 30 and 60 sec and the increase in volume required maintaining constant pressure is recorded (ASTM 2000; Baguelin et al., 1978; Clarke, 1995; Maier and Wood, 1987; Azarafza et al., 2014).

The pressure - volume curve obtained from this test is used to determine the pressuremeter modulus (E_{PM}). This modulus is calculated using the quasi - linear part of this curve within an interval defined by two specific pressure values: P0 which is roughly equivalent to the horizontal earth pressure at rest and the pressuremeter creep pressure Pf (Fawaz et al., 2014). The EPM has been related empirically to the elastic modulus of the soil as

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$E_{PM}/E = \alpha$, (Menard, 1965), where α is termed by Menard as the rheological coefficient and has a value between 0 and 1.

Using Pressuremeter is expensive and time-consuming, and it requires proficient technical personnel. With these limitations, it is necessary to introduce models for indirect determination of the EPM. In this regard, researchers have proposed various models and relationships for estimating EPM considering the soil properties and results of other tests (Ohya et al., 1982; Yagiz et al., 2008; Bozbey and Toghrol, 2010; Keyabbasi, 2012; Azarafza and Asghari-Kaljahi, 2016).

Recently, intelligent methods such as the artificial neural network (ANN) have been widely applied for predicting such complex problems. For example, Adalag et al. (2013) introduced several ANN models for estimating E_{PM} in clayey soils. Rashed et al. 2012 presented two models to predict of E_{PM} based on linear genetic programming (LGP) and ANN methods. These authors used parameters such as grain size distribution and soil characteristics (liquid index, moisture content, and density) as the independent variables of their models. Although one of the advantages of the pressuremeter test is that it can be carried out in every soil and even in weak rocks, most of these models are for fine-grained clayey soils. Therefore, it is necessary to develop new relations to predict E_{PM} of fine-grained and coarse-grained soils. The present study was conducted to introduce a new ANN model for estimating E_{PM} in soils.

2. Materials and Methods

2.1. Data Collection

The data used in this research were taken from41 Menard pressuremeter tests for fine-grained and coarse-grained soils in 13 geotechnical projects performed in Tehran, Iran (Figure 1). Geologically, Tehran is a city in which sandy and gravelly coarse-grained soils exist in the north part of the city while they are transitionally changed to fine-grained clayey soils in its south part. Table 1 presents the soil type and projects from which the data were supplied. As can be noticed, all soil classes exist in these projects. The range of data variation is given in Table 2. It is noteworthy that all tests were performed with the same apparatus (Menard, GC model, APAGEO, 2016) and Standard (ASTM 2000).

The grain size distribution and mechanical properties of the soils were determined in the laboratory by performing a series of tests on disturbed and undisturbed samples. As mentioned earlier, depth of test, the moisture content and the percentage of various types of soils were used as independent variables. The graph of a pressure versus volume change of the pressuremeter test is shown in Figure 2 for one of these tests.

2.2. Methodology

ANN is a computational approach inspired by the basic functionsof neural architecture of the biological systems and mainly the human brain. Nowadays, ANN can be applied to problems that cannot be easily solved with an algorithm or very complex to describe. ANN formulates a mathematical model for a system in which no clear relationship is available between the inputs and outputs (Kiran and Lal, 2016). Over the last decade, Artificial Intelligence has been applied successfully implemented in many problems in geotechnical engineering (Tarwaneh, 2017; Azarafza et al., 2018). Bendana et al. (2008) described ANN as “massively parallel distributed processor” that can store information taken from a data set that is supplied out of the network. The ANN system consists of at least three layers. The first layer has the input parameters, while the last layer contains the output. Between these two layers, there are one or more hidden layers, which are for delineating and learning the patterns governing the network’s data. The development of an ANN model requires the determination of model inputs and outputs, division, and pre-processing of the available data, the determination of appropriate network architecture, stopping, and model validations.

There are two main types of neural networks; supervised and unsupervised networks. In supervised learning, neural networks are trained to reach from a particular input to a specific target until the network output matches the target (Hannan et al., 2010). In the present study, we used generalized regression neural networks (GRNN) as one of the supervised neural networks algorithms. One of the main advantages of GRNN networks is their high-speed learning (Specht, 2010).

2.3. Assessing the accuracy of the model

To assess the performance of the intelligent methods, four suggested criteria were used in this research (Behnia et al., 2013; Ahangari et al., 2015). Eqs. 1 to 4 expresses absolute error (AE), mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2), respectively.

$$AE = \left| a_t - p_i \right| \tag{1}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| a_i - p_i \right| \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (a_i - p_i)^2} \tag{3}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n} \left(p_i - \bar{p} \right) \left(a_i - \bar{a} \right)}{\sqrt{\sum_{i=1}^{n} \left(p_i - \bar{p} \right)^2 \sum_{i=1}^{n} \left(a_i - \bar{a} \right)^2}} \right)^2 \tag{4}$$

where α and p are the predicted and actual values of E_{PM}, respectively; AE is the mean predicted and actual values, respectively; and n is the number of data sets. When the values of RMSE and MAE are minimum and the value of R^2 was close to 1, it can be stated that the model designed shows a strong correlation between the output and target parameters.

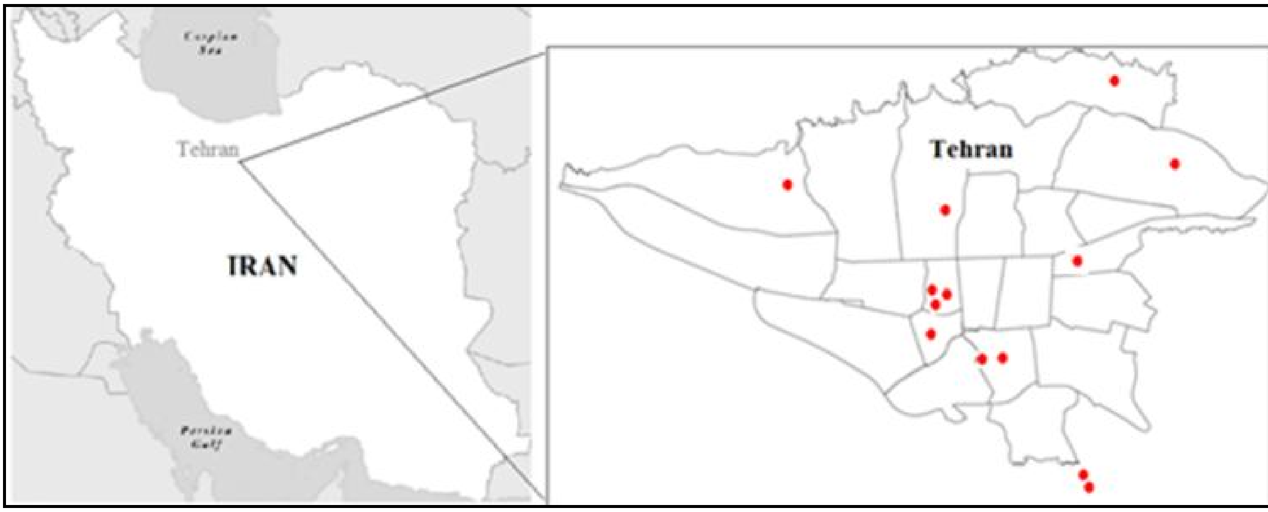

Figure. 1. Location of the studied projects

Table 1 Specifications of the projects analyzed in this study

Region number	1	2	4	10	13	16	17	20	22
Number of projects	1	1	1	3	1	2	1	2	1
Soil type*	GW	GC	SC-GC	CL-ML	GW-GC	CL	SC & CL	CL	GP-GC

GW: Well-graded Gravel, GP: Poorly-graded Gravel, GC: Clayey Gravel, SC: Clayey Sand, GM: Silty Gravel, CL: Low plasticity Clay

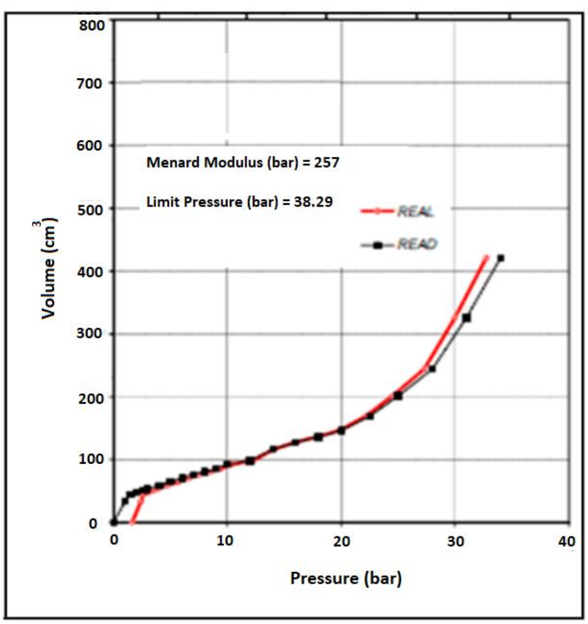

Figure. 2. The pressuremeter curve: pressure versus probe volume change

Table 2 Ranges of soil parameters

Parameter	Value	Min	Max	Mean
Depth (m)	Independent	4	29.5	15.9
Moisture (%)		4.6	22.8	15.3
Fine (%)		6.5	99	63.18
Gravel (%)		12.07	51.6	31.83
E_{PM}(kg/cm^2)	Dependent	195	835	425.82

3. Results and discussion

Based on the available data, 85% and 15%of data sets were assigned randomly for training and validation (train step) and test step, respectively. To design the optimal model, 310architectures were tried and, finally, the network with three hidden layers was selected as the best network (Figure3). The specifications of the five best networks and their corresponding error graphs with the number of iterations are presented in Table 3 and Figure4, respectively. Limited memory quasi-Newton algorithm was used for training the model. After 3500 iterations, the network training was terminated. In this step, the importance of each input variable with the output variable is evaluated and, as shown in Figure5, it was found that the percentage of gravel is the significance. The results of the training step are presented in Table 4. The regression and comparative graphs of actual and predicted values of E_{PM} for training data sets are displayed in Figures 6 and 7, respectively. The coefficients of determination (R^2) for the training and validation data were 0.736 and 0.906, respectively.

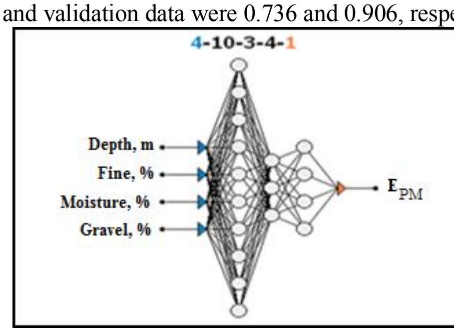

Figure. 3. Optimal ANN model Architecture with three hidden layers

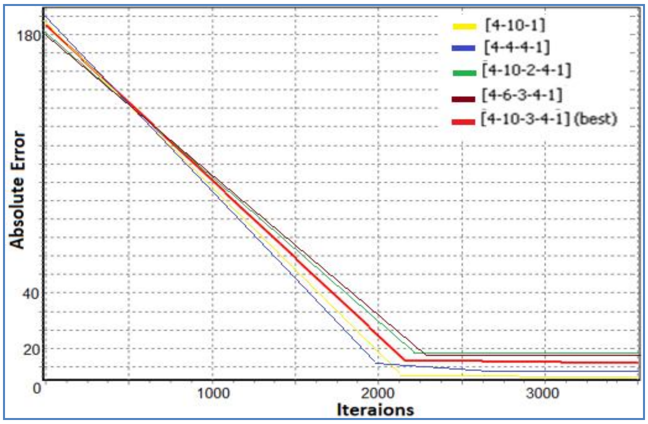

Figure. 4. Error graph of top five designed networks

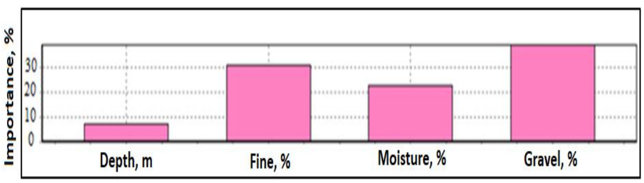

Figure. 5. Results of input importance analysis

Table 3 Characteristics of the five best architectures in the neural network method

Architecture	Input/ Output activation FX	Error FX	Train Error (kg/cm^2)	R^2
[4-10-1]	Logistic/ Logistic	Sum of Squares	6.984	0.985
[4-4-4-1]			11.262	0.906
[4-10-2-4-1]			18.799	0.907
[4-6-3-4-1]			17.113	0.911
[4-10-3-4-1]			14.731	0.993

Table 4 Results and error values of ANN model for training and validation datasets

Data	R^2	MAE	RMSE
Train	0.736	62.672	79.699
Validation	0.906	38.352	59.413

Table 5 Results and error values of ANN model for training, testing, and all data sets

Data	R^2	MAE	RMSE
Test	0.801	65.668	74.858
All	0.783	59.551	76.351

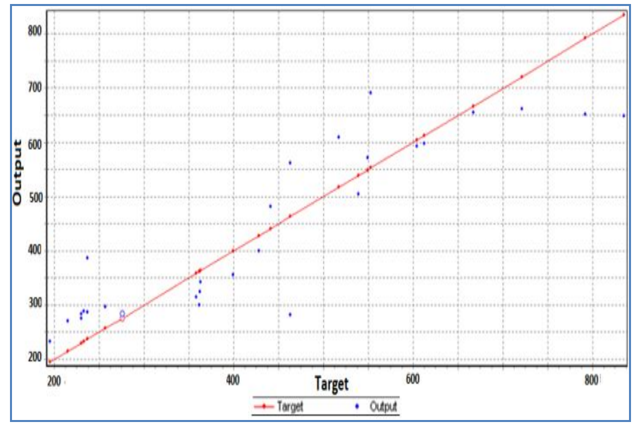

Figure. 6. Relationship between the actual (target) versus predicted modulus for the training data (R^2=0.736)

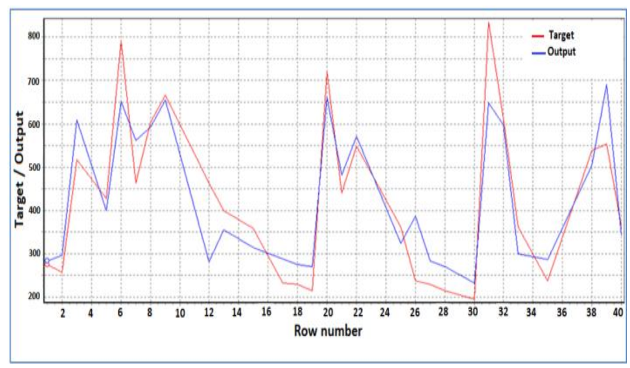

Figure. 7. The comparison of the actual E_{PM} with predicted values

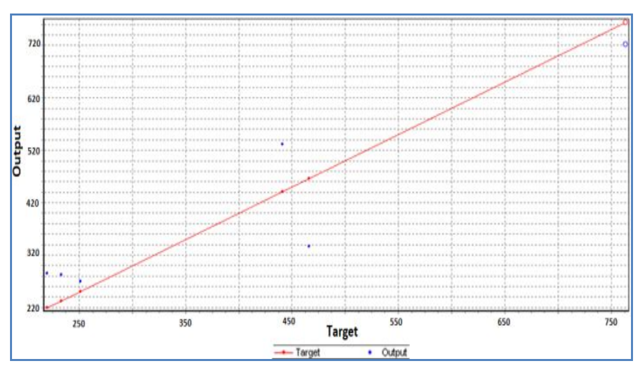

Figure. 8. Relationship between the actual (target) versus predicted modulus for testing data (R^2=0.801)

Table 6 Comparison of predictions from ANN model and the actual EM for test data sets

Depth (m)	Fine (%)	Moisture (%)	Gravel (%)	E_M (kg/cm^2)		AE
				Target	Output	
27.5	37.5	14.8	26.4	763.6	722.1834	41.41659
8	79	18	0.2	219.8	284.766	64.96599
22.5	64.3	19.5	1.2	466	336.4795	129.5205
7.5	81.5	22.8	4.2	251	269.2486	18.24858
23.5	87	14.9	2.6	441	530.9009	89.90093
5	85.6	17.8	0.8	233	282.9588	49.9588

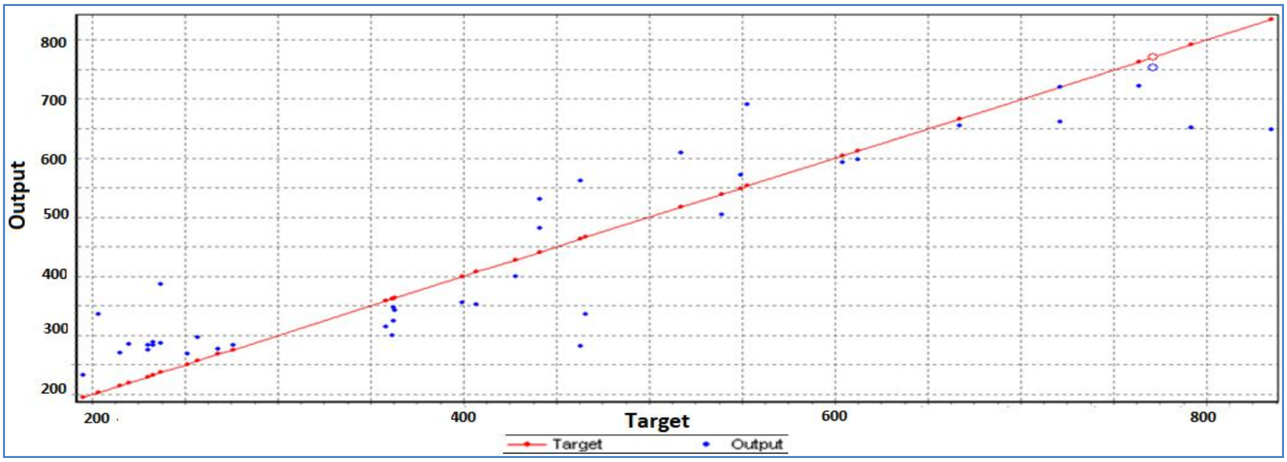

Figure. 9. Relationship between the actual (target) versus predicted modulus for all data sets (R^2=0.783)

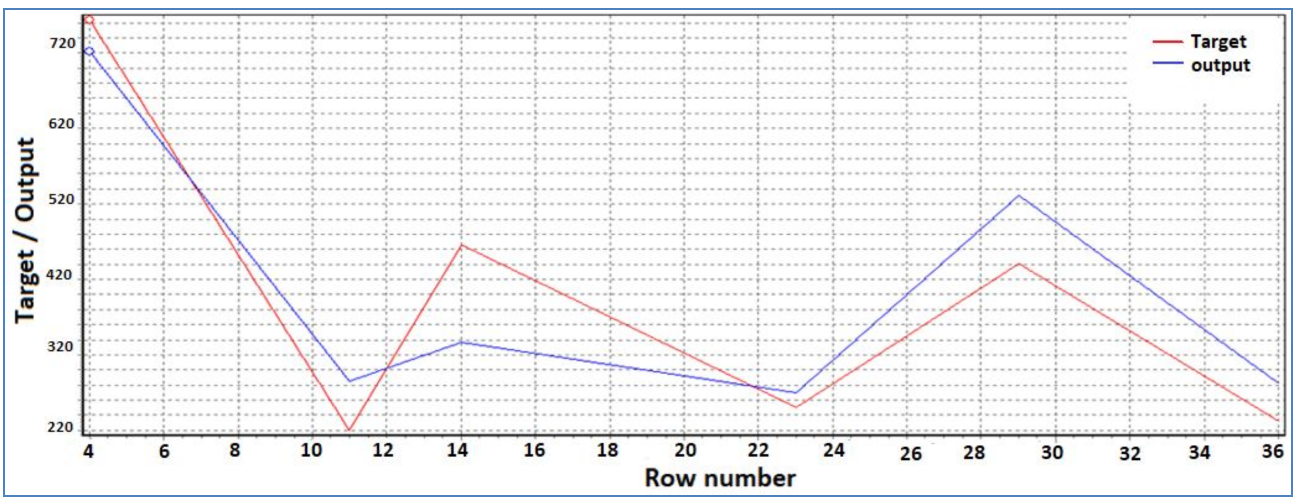

Figure. 10. The comparison of the actual EM with predicted values (for testing data)

After the training step, the final test data were used to test the designed model. The results of the test step are presented in Table 5.According to the obtained results; the ANN model designed in this study gives acceptable predictions. The details of network predictions for test step are shown in Table 6. The regression graphs of test and all data are displayed in Figures 8 and 9. Moreover, a comparative graph of the actual values of EM and the predicted values is illustrated in Figure10.

4. Conclusion

The complexity of evaluating the factors effective on pressuremeter results, the difficulties of performing this test, and the high testing costs, this study was conducted to present a new model to predict the pressuremeter modulus (EPM) of soils indirectly using artificial neural network (ANN) method. Soils samples had a variation range from coarse-grained to low-plasticity clay and thus the proposed model can cover a large range of changes in the EPM.

The designed model was trained by the limited memory quasi-Newton method and then was validated using a number of test data. In general, the results of this study can be outlined as follows:

- The results for all stages of training and the test confirm a statistically significant and acceptable relationship between input variables and EPM. Comparing the predicted pressuremeter modulus with their actual values indicates that the errors are erratic and they are affected by the data. Therefore, it is not possible to present a specific pattern to detect data with larger error values.
- In the design phase, 310 network architectures are investigated and it was figured out that a network with three hidden layers has better performance in comparison to one and two layers networks.
- The sensitivity analysis of the ANN model revealed that the gravel and fine percentage of soils are the most effective parameter on the pressuremeter modulus among the input variables. Although the results are reliable only for data of the present research, the ANN

method can be generalized and evaluated for new data sets considering its high accuracy and efficiency.

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