Determination of Coefficient of Lateral Earth Pressure at Rest for Sandy Soils Using Cone Penetration Test and Artificial Neural Network

M. M. Ahmadi*, N. Besharat

Department of Civil Engineering, Sharif University of Technology, Tehran, Iran

ABSTRACT: The estimation of soil parameters in geotechnical practice is always an important step for design of geostructures. In order to control the stability and to perform a stress-deformation analysis of a geotechnical system, it is essential to know the in-situ stress state of the ground. The in-situ vertical stress can be calculated easily if the depth and the soil density are known. However, determination of the in-situ horizontal stress is a complicated task because it depends on several other soil characteristics, such as stress history and over consolidation ratio (OCR). This has always been one of the most challenging geotechnical problems. In the past, attempts have been made to find reliable methods to determine the coefficient of at-rest earth pressure by means of in-situ or laboratory tests. This is especially true for cohesionless soils, using in-situ test results such as pressuremeter test, blade test and cone penetration test (CPT) to name a few. In this study, the calibration chamber data on CPT tests performed at universities worldwide or well known institutes were gathered. Then using these series of reliable CPT calibration chamber test data and a system consisting of three types of neural networks, the coefficient of at rest pressure (K_0) is predicted while it has good agreement with measured data. In this proposed system, a series of neural networks perform some tasks and finally by strategically combining the networks, the system will be able to predict parameter (K_0) with reasonable accuracy. The proposed system uses self organizing map (SOM) for clustering data into training, testing and validating sets and probabilistic neural networks for classifying the sands and back propagation neural networks for conclusive function approximation. Details on the development of such a system are described in the present paper and finally results obtained by this system are compared to the available relations suggested by other researchers.

1- Introduction

During the last three decades, various relations are proposed for predicting effective parameters of sandy soils by using cone penetration test (CPT) data in calibration chamber and by using statistical regression methods. The reason might be due to the difficulty of obtaining undisturbed samples of cohesionless soils in real projects, the growing and more accurate availability of CPT data in calibration chamber. In these chambers, the initial characteristics of tested soil and the boundary conditions of calibration chamber are known and by using the results of CPT data, it would be possible to derive different relations between soil characteristics and CPT test results [1].

Statistical regression is a common way to derive mentioned relations. This method, in some cases, may not be able to produce a relation with enough accuracy. Obviously, having new developments in data analysis techniques, it may be possible to obtain more accurate relations that are yet of interest to geotechnical engineers.

Artificial neural networks (ANN) or briefly called as neural networks, are able to assign a set of inputs and outputs to each other, without knowing the prior mathematical relation implied in them. Researchers such as Ghabusi et al. (1991), Meier & Rix (1994), Agrawal et al. (1995), Najjar et al. (1996), Ni et al. (1996), Juan & Chen (1999), Juang et al. (1999) among others have used artificial neural network to define input-output or cause-effect relations in geotechnical applications.

2- Methodology

The coefficient of lateral earth pressure of sands is one of the most important factors in geotechnical design, and its determination is essential in evaluating soil shear resistance, sleeve friction of piles, designing all types of supporting walls and interpreting in-situ tests.

To propose a model, the calibration chamber test data which were performed at universities or well known institutes worldwide were gathered. The gathered database includes 631 CPT tests which are performed at four different calibration chamber tests [9,16,17,18].

In this database, in addition to CPT test results in calibration chamber (including tip resistance and side friction), there are some information about initial conditions of soil such as dry unit weight of sand (γ_d), relative density (D_r), initial stress conditions in the form of horizontal and vertical stress,

*Corresponding author, E–mail: mmahmadi@sharif.edu

coefficient of lateral earth pressure (K_0), over consolidated ratio (*OCR*) and constrained modulus (*M*). These tests were performed under four different boundary conditions. Also these database includes four types of sands, but it should be mentioned that in this study, it is assumed that the sand type has no effect on the results of tests and consequently the variation of sand type can be ignored.

On the other hand, cone penetration test on sands which is done in small calibration chambers could be under the effect of chamber dimensions, boundary conditions and uncertainties about how the results are assigned to at-field test results. In other words, cone penetration test in a calibration chamber which is limited in dimensions puts tip resistance (q_c) under the effect of boundary conditions and this leads to difference between results of real conditions (field tests) and experiment results, even though all the conditions and specifications are the same [19].

Several studies have been carried out on the effects of boundary conditions such as Parkin (1988), Been et al. (1988), Iwasaki et al. (1988), Jamiolkowski et al. (2003), Ahmadi and Robertson (2008) and Poornaghiazar (2012). By performing numerical study on the effect of chamber and boundary conditions on tip resistance of normally consolidated sands, Ahmadi and Robertson showed that the bigger the ratio of chamber dimensions to cone diameter, the lesser the difference between chamber CPT tests and in-situ tests would be [23]. They concluded that for loose sands, if the ratio of chamber diameter to cone diameter is 33 or more, the boundary conditions will not have any effect on cone tip resistance, but for very dense sands, this ratio should be even more than 100. Besides sand relative density, boundary condition effects is also related to stress level. In addition, for a certain type of sand, with the increase in the ratio of chamber/cone diameter, the amount of cone tip resistance converges to a certain value in various boundary conditions. This is presumably the value of cone tip resistance which could be observed in the field with the same stress conditions [23].

Hence in this study, using this assumption and based on the research performed by Ahmadi and Robertson (2008), a coefficient based on relative density, test boundary condition and chamber/cone diameter ratio (RD) is derived and is multiplied to qc resulted from the experiments in order to remove the effect of boundary conditions on q_c.

Finally, using these series of corrected reliable CPT calibration chamber test data and a system consisting of three types of neural networks, the coefficient of at rest pressure (K_0) is predicted while it has good agreement with measured data. In this proposed system, a series of neural networks perform some tasks and finally by strategically combining the networks, the system will be able to predict parameter (K_0) with reasonable accuracy. The proposed system uses Self Organizing Map (SOM) for clustering data into training, testing and validating sets and probabilistic neural networks for classifying the sands and back propagation neural networks for conclusive function approximation. Details on the development of such a system are described in the present paper and finally results obtained by this system are compared to the available relations suggested by other researchers.

3- Discussion and results

As is discussed in the previous section, by using attainable data in site such as $\{(\gamma_d), (\sigma'_v), (q_c) \text{ and } (f_s)\}$ and based on
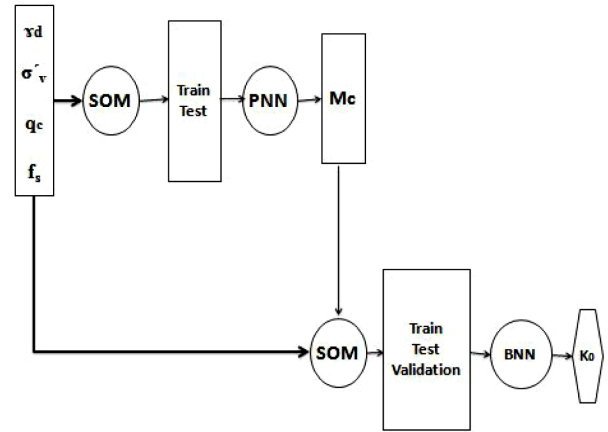

Fig. 1. Schematic structure of proposed system for estimation of K_0

this assumption that sands are categorized by this parameters into different classes, the proposed model was able to predict K_0 which is in good agreement with the measured data. The structure of the model including the combination of neural networks is shown in Fig. 1.

As it can be seen in Fig. 1, the main parameters were given to SOM network to divide them into train and test sets. Now this divided data was given to a PNN network for defining a classifying parameter named M_c. This new defined parameter is an attainable alternative of over consolidation ratio as it is discussed more in the paper. Then the new parameter M_c beside the main parameter were given to a SOM network for dividing them to three sets as train, test and validation. Finally this divided data sets were given a back propagation neural network with Levenberg-Marquardt training algorithm to predicting the goal parameter which is the coefficient of at rest pressure (K_0).

The predictive power of the proposed model for the training set is shown in Fig. 2.

As it can be seen, the proposed model can predict higher than 90% percent of data with an error less than 30 percent. More comparisons and detailed procedure can be found in the main paper.
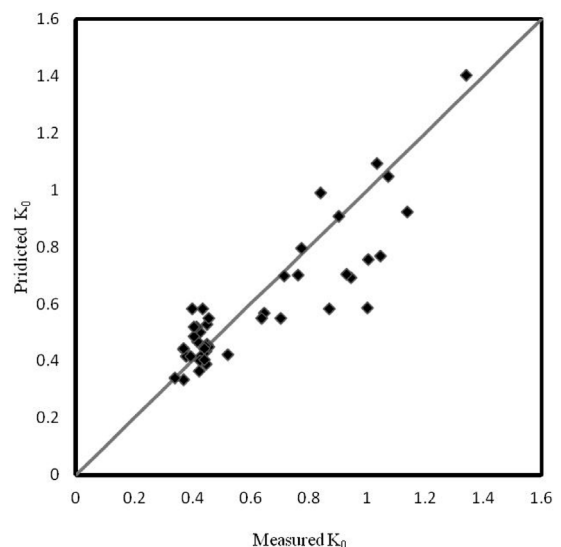

Fig. 2. The prediction results of proposed system

4- Conclusions

In this paper the proposed system, by using the in-situ test parameters such as $\{(\gamma_d), (\sigma'_v), (q_c) \text{ and } (f_s)\}$ a relatively good prediction of K_0 has been achieved.

Through this study, the capability of neural networks to prepare experimental relation was tested and proved. The proposed system derived desirable results of estimating the indicator parameter of sand, by using a structured combination of three self-organizing, probability and back propagation neural network.

Obviously the number of available data and used data in this system was limited, and hence using more data and especially in-situ data to verify the system is necessary, because with all the modifications the effect of boundary condition and calibration chamber dimensions, other issues such as aging and cementation, the types of sands, has effects on derived parameters which in this study are not covered.

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