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Prediction of unconfined compressive strength of soft grounds using computational intelligence techniques: A comparative study

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Abstract

Cement stabilization is one of the commonly used techniques to improve the strength of soft ground/clays, generally found along coastal and low land areas. The strength development in cement stabilization technique depends on the soil properties, cement content, curing period and environmental conditions. For optimal and effective utilization of cement, there is a need to develop a mathematical model relating the gain in strength in terms of the variables responsible. The existing empirical model in the literature assumes linear variation of normalized strength with the logarithm of curing period and hence, different empirical models are required for different conditions of the same soil. Also, the accuracy of strength prediction is unsatisfactory. Due to unknown functional relationships and non-linearity in strength development, in this paper the computational intelligence techniques such as multilayer perceptron (MLP), radial basis function (RBF) and genetic programming (GP) are used to develop a mathematical model. To generate the mathematical model, an experimental study is conducted to obtain the strength of three inland soils namely, red earth (CL), brown earth (CH) and black cotton soil (CH) for different water contents, cement contents and curing periods. In order to generate a generic mathematical model using computational intelligence techniques, two saline soils (Ariake clay-3 and Ariake clay-4) and three inland soils are used. A detailed study of the relative performance of the computational intelligence techniques and the empirical model has been carried out.

Keywords: Soft ground; Saline soil; Cement stabilization; Empirical model; Multilayer perceptron; Radial basis function; Genetic programming; Unconfined compressive strength

1. Introduction

Due to increased urbanization and industrialization, foundation soils with suitable geotechnical properties are not easily available. There is a growing demand for reclamation of marine and inland soft soils/grounds, which are characterized by high plasticity, higher fraction of fines and void ratio, with low strength and high compressibility [1]. In many cases, the natural water content of soft ground is high and at times even higher than the liquid limit of the soils. For such soils, deep mixing is a popular method for improving the strength [2]. In deep mixing, the cement grout or dry cement is injected into the natural soil at the depth required and a blade is pushed into the ground to mix the soil and cement [3]. The extent of the strength improvement depends on the mineralogy, environmental conditions of the soft ground, curing period and the type and amount of cement used [1]. Porbaha [1], Tan et al. [3], Uddin et al. [4], Yin and Lai [5], Miura et al. [6], Suksun [7] and Horpibulsuk et al. [8,9] have carried out experimental studies to understand the strength improvement in soft ground using cement stabilization techniques. In the stabilization of soft ground, Miura et al. [6], Tan et al. [3] and Horpibulsuk et al. [9] have observed that the strength development depends on the initial clay water content and the cement content.

For optimal and effective utilization of cement, a predictive model is required to relate the gain in strength of soil with time in terms of important variables involved. Tan

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et al. [3] have established an empirical relationship to predict the strength development based on cement content, water content and curing period. The strength developed at specific cement and water contents and curing period is used as the reference compressive strength for a given soil and the strength developed under other conditions for the same soil is normalized using the reference strength. Their empirical model assumes linear variation of normalized strength and the model is different under different conditions of the same soil. The model also assumes that the ratio of the strength developed and the reference strength is constant for any soil if the reference conditions are the same. These assumptions will affect the accuracy of the strength prediction. However, it is mentioned in [3] that a careful statistical study needs to be undertaken to generalize the relationship to improve the performance of the model.

One way to improve the performance of the empirical model is to consider the effects of other parameters. Miura et al. [6], Suksun [7] and Horpibulsuk et al. [9] proposed a parameter called the clay water cement ratio (w_c/C), which is analogous to the water cement ratio used in concrete technology, which is the ratio of the initial water content of the clay (w_c) to the cement content (C). Miura et al. [6] observed that the water cement ratio is the principal parameter for analysis of strength and deformation behavior of cement stabilized soft ground. Using the clay water cement ratio (w_c/C), as the principal parameter Suksun [7] and Horpibulsuk et al. [9] developed the normalized empirical model to predict the strength of cement stabilized soft ground. The model requires the reference strength and assumes linear variation of the logarithm of the curing period. However, the empirical model is localized and different equations are considered for different soils depending on the liquidity index. The above limitations of the empirical models suggest the necessity to develop a generic mathematical model for strength prediction.

Computational intelligence techniques are capable of approximating the nonlinear input–output relationship for a wide range of applications. Hence in this paper, computational intelligence techniques such as multilayer perceptron (MLP) network, radial basis function (RBF) network and genetic programming (GP) techniques are used to approximate the functional relationship between the various parameters and strength developed.

Neural networks (NNs) have been used in geotechnical engineering for estimation of unsaturated shear strength [10], predicting settlement of shallow foundations [11–13], profiling stress history of clays [14], modeling of compaction curve [15], site characterization [16], triaxial compression behavior of sand and gravel [17], predicting the capacity of driven piles in cohesion less soils [18], predicting settlements during tunneling [19] and stress stain modeling of sands [20]. A collection of neural network applications in geotechnical engineering are presented in [21,22].

NNs gained prominence in the 1980s due to their ability to learn from past data, and their ability to generalize knowledge obtained during learning. A variety of neural network architectures and associated learning algorithms are available in the literature for various types of applications. Of these, two neural network models namely, MLPs [23] and RBFs [24] are considered. MLPs are feed forward networks with a layered structure. In general, MLPs have an input layer, one or more hidden layers, and one output layer. Each of the nodes in a given layer are connected to the other nodes in the next layer. There are no connections within layers. In most of the applications a feed forward network with a single hidden layer is used with sigmoidal activation functions for the units. The back propagation (BP) algorithm is widely used for training the MLP networks. Although MLPs can be used with any number of hidden layers, it has been shown that only one hidden layer suffices to approximate any function with discontinuities to an arbitrary degree of precision, provided the activation function of the hidden units are nonlinear (the universal approximation theorem) [23].

The RBF network model also consist of three layers; input, hidden and output layers. The nodes within each layer are fully connected to the previous layer. The input variables are each assigned to nodes in the input layer, and pass directly to the hidden layer without weights. The hidden nodes or units contain the radial basis functions. The RBF is similar to the Gaussian density function, which is defined by parameters namely, a 'center' and a 'width' [24]. The Gaussian function gives the highest output when the incoming variables are closest to the center position and the output decreases monotonically as the distance from the center increases. The 'width' of RBFs controls the rate of decrease in the output. Even though RBFs are well suited for function approximation, for large sets of data the problem of 'curse of dimensionality' becomes predominant [24], i.e., the increase in number of features reduces the approximating ability of the RBF network.

In NNs, the basic limitation is that the optimal configuration is not known a priori. Also, often it is not possible to express the relationship between the different parameters governing a phenomenon because the knowledge represented in the weights is generally opaque i.e., the weights do not reveal any information about the input–output relationship. One of the recent developments in computational intelligence techniques is genetic programming (GP) which has the ability to approximate the relationship between the inputs and outputs and express the relationship mathematically [25]. The generated mathematical expression may also provide an insight into the understanding of the problem. Hence in this paper, the MLP, RBF and GP techniques are used to develop a generic model for strength prediction. In order to generate such a model, three inland soils for which experimental studies are carried out, and two saline soils available in the literature [7] are considered. For these soils, empirical models are developed using the concept presented by Horpibulsuk et al. [9] and the performance is compared with the generic models developed using the computational intelligence technique discussed above.