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Research paper

# Prediction of the residual strength of clay using functional networks

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ABSTRACT

Landslides are common natural hazards occurring in most parts of the world and have considerable adverse economic effects. Residual shear strength of clay is one of the most important factors in the determination of stability of slopes or landslides. This effect is more pronounced in sensitive clays which show large changes in shear strength from peak to residual states. This study analyses the prediction of the residual strength of clay based on a new prediction model, functional networks (FN) using data available in the literature. The performance of FN was compared with support vector machine (SVM) and artificial neural network (ANN) based on statistical parameters like correlation coefficient ($R$), Nash–Sutcliff coefficient of efficiency ($E$), absolute average error (AAE), maximum average error (MAE) and root mean square error (RMSE). Based on $R$ and $E$ parameters, FN is found to be a better prediction tool than ANN for the given data. However, the $R$ and $E$ values for FN are less than SVM. A prediction equation is presented that can be used by practicing geotechnical engineers. A sensitivity analysis is carried out to ascertain the importance of various inputs in the prediction of the output.



## 1. Introduction

Stability of natural slopes or landslides depends upon the shear strength parameters of clay, which varies significantly between the peak and residual states. At residual strength, due to remoulding, clay exhibits negligible cohesion and a decreased value of friction angle as compared to the peak state. Right from the early studies, residual strength has been associated with both reactivated landslides and first-time slope failures in terms of residual friction angle ($\phi_r$).

Skempton (1964) was the first to study the effect of drained residual shear strength of soil for stability analysis of reactivated landslides and suggested that the decrease of shear strength is partly due to changes in orientation of clay particles upon unidirectional shearing. Kenney (1967) reported the effect of mineralogical composition of soils on their residual strength. Based on an analysis of 99 cases of landslide failure in 36 types of soft clays, stiff clays and clay shales, Mesri and Shahien (2003) observed that residual strength also develops in first-time slope failures.

Several attempts have been made in the past to correlate the residual friction angle of soils and their index properties such as Atterberg limits and clay fraction (CF). Skempton (1964) related the residual friction angle ($\phi_r$) value with the clay fraction. Many researchers (Voight, 1973; Kanji and Wolle, 1977; Bucher, 1975; Vaughan and Walbancke, 1975; Seycek, 1978; Vaughan et al., 1978; Fleischer and Scheffler, 1979; Lupini et al., 1981) postulated relationships between $\phi_r$ and plasticity index (PI). Relationships between $\phi_r$ and liquid limit (LL) were also proposed by Jamiolkowski and Pasqualini (1976), Cancelli (1977), Mesri and Cepeda-Diaz (1986), Stark and Eid (1994) and Stark et al. (2005). For sedimentary soil, Stark and Eid (1994) observed that the type of minerals and percent of clay governs the value of $\phi_r$. Using LL as an indicator of clay mineral, they proposed correlations of $\phi_r$ with LL for various ranges of CF. Wesley (2003) observed that, most of the soil above the A-line have the $\phi_r < 10°$, while those below the A-line have higher values of $\phi_r$. A good relationship was found between $\phi_r$ and deviation from the A-line (ΔPI) for soils with LL > 50. The ΔPI is denoted as

$$\Delta PI = PI - 0.73 \times (LL - 20) \quad (1)$$

Based on direct shear test results on simulated soil–rock mixtures that were developed by mixing kaolinite clay with sand,

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Vallejo and Zhou (1994) indicated that the shear strength of the whole mixture was governed by the concentration of sand in the mixture. For sand content <50%, the shear strength was influenced by clay. For sand concentration between 50 and 80%, the shear strength was provided partly by the shear strength of kaolin and partly by the frictional resistance between sand grains.

Based on an experiment on 80 specimens, Tiwari and Marui (2005) presented a triangular correlation chart to calculate $\phi_r$ based on mineralogical composition of soils. The chart provided correlation of $\phi_r$ with the liquid limit, the plasticity index, the clay fraction, the specific surface area and the proportion of the clay mineral smectite. This model gave good results for the specimen tested by them, but failed to correctly predict the values for 53 other samples tested by other researchers.

Wen et al. (2007) examined the residual strength of soils from the slip zones of about 170 landslides in the Three Gorges Project (TGP) area, China, and concluded that clay content and Atterberg limits could be used to estimate the residual strength of soils finer than 2 mm, but they are not appropriate for the evaluation of residual strength of soils containing a considerable amount of gravel-sized particles.

Studies done by Kaya and Kwong (2007) on soil properties of some active landslides in Hawaii showed a poor correlation between soil index properties and $\phi_r$ for colluvial soils, which are rich in an amorphous phase. Another study by Yanrong (2009) on slip zones of large landslides in the Three Gorges Project, China observed Atterberg limits, particle size distribution, normal stress, particle shape and shearing rate as the most influential factors affecting residual shear strength of composite soil. Thus the previous studies suggested that $\phi_r$ is affected by a number of index properties. But most of the relationships cited earlier are in the form of graphs and are not easy to use by geotechnical engineers in practice.

Nowadays Artificial Intelligence (AI) techniques like artificial neural network (ANN), support vector machine (SVM), and genetic programming (GP) are being used as alternate techniques to statistical methods in different fields of science and technology. Yaghouby and Ayatollahi (2009) used SVM for multi-classification of cardiac arrhythmias into five classes with an accuracy of 99.78%. Yaghouby et al. (2009) used heart rate variability (HRV) signal to classify the cardiac arrhythmias into four classes using ANN analysis and found that it was very efficient with 100% accuracy. The use of ANN has been also found to be efficient as a PID controller (Dong et al., 2014). However, GP was found to be more efficient compared to radial basis function (RBF) neural network in the automatic detection of atrial fibrillation based on HRV signals (Yaghouby et al., 2010). AI techniques have been found to be better prediction tools for geoscience problems than conventional techniques (Goh, 2002; Kerh and Chu, 2002). Kerh and Chu (2002) observed that for prediction of peak ground acceleration, ANN based model with strong motion has better prediction performance compared to conventional nonlinear regression models. Similarly, Goh (2002) reported that for liquefaction susceptibility analysis of ground using in-situ data, ANN based model is more efficient compared to available empirical models. Das (2013) presented a comprehensive review of the successful application of ANN in different geotechnical engineering problems.

Das and Basudhar (2008) used artificial neural network (ANN) modelling to predict the $\phi_r$ of clay, but their study was limited to tropical soil of a specific region only. Das et al. (2011) provided an equation for the calculation of $\phi_r$ of soil based on their analysis of data using ANN and SVM.

However, ANN has poor generalization, attributed to attainment of local minima during training and needs iterative learning steps to obtain better learning performances. SVM has better generalization compared to ANN, but the parameters ($C$) and insensitive loss function ($\varepsilon$) need to be fine-tuned by the user. Moreover, these techniques will not produce a comprehensive model equation and are also called as 'black box' system (Giustolisi et al., 2007).

Recently, a new prediction method, functional network (FN), which is based upon the structure of the physical world has been used in many fields of science and engineering including petroleum engineering (El-Sebakhy et al., 2007), signal processing, pattern recognition, function approximations (Castillo et al., 1999), real-time flood forecasting, science, bioinformatics, medicine (El-Sebakhy et al., 2006), mining, and structural engineering (Rajasekaran, 2004). FN was introduced by Castillo (Castillo, 1998; Castillo et al., 2000a), Gomez (Castillo and Ruiz-Cobo, 1992), and Castillo et al. (Castillo et al., 1998, 2000b) as a powerful alternative to ANN.

FN as a new modelling scheme has been used in solving both prediction and classification problems. Hence, in the present study an attempt has been made to predict the residual friction of soil using FN based on a set of index properties including LL, PI, CF and ΔPI. The data set used for the study is the same as used by Das et al. (2011). Functional Networks have not been applied to geotechnical engineering issues to the best of the knowledge of the authors. The following section briefly describes the concepts of FN. The results from FN have been compared with the results from ANN and SVM as obtained by Das et al. (2011).

## 2. Functional networks

FN is a recently introduced extension of neural networks. In FN, the network's initial topology is derived based on modelling of the properties of the real world, i.e. the domain knowledge of the problem, whereas in ANN, the number of hidden layers and neurons in the hidden layer is selected by trial and error until a good fit to the data is obtained. Once the initial topology is available, functional equations can be used to arrive at a much simpler topology. FN, thus, eliminates the problem of neural networks being 'black boxes' by using both the domain knowledge, i.e., associative, commutative, distributive etc. and the data knowledge to derive the topology of the problem. Although FN can deal only with data, the class of problems where FN are most convenient is the class where knowledge about both the domain and the data are available.

FN uses domain knowledge to determine the structure of the network and data to estimate the unknown neuron functions. In FN, arbitrary neural functions are allowed and they are initially assumed to be multiargument and vector valued functions.

### 2.1. Differences between FN and ANN

The characteristic features of the FN and their respective differences from the neural networks can be enumerated as follows:

(1) In FN, the information for selection of topology can be derived either from the data or from domain knowledge or from combinations of the two, whereas, in neural networks, only the data is used.
(2) In FN the functions are learned during the structural learning and estimated during the parametric learning whereas in neural networks, the neuron functions are assumed to be fixed and known and only the weights are learned.
(3) FN can use arbitrary multiargument and vector valued functions, whereas in neural networks they are fixed sigmoidal functions.
(4) Intermediate layers of units are introduced in functional network architectures to allow several neuron outputs to be