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Shear Strength Prediction of Soil based on Probabilistic Neural Network

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Abstract

Background: Shear strength parameter is an essential engineering property of soil which affects different aspects of soil such as bearing capacity of the soil, stability of slope, inclination of dam and retaining structures. **Methods:** In the following study, Probabilistic Neural Network (PNN) is applied as a promising tool for the estimation of shear strength. The input variables used for developing the model are index properties such as (water content (w), Plasticity Index (PI), Dry Density (DD), Gravel %(GP), Sand %(SP), Silt%(STP), and Clay%(CP) of soil and an attempt has been made to develop a neural model to predict the shear strength parameter of soil, viz, cohesion "c" and internal friction angle "φ". **Findings:** The values of c and φ predicted by the model are comparable with the laboratory results. Trained data are validated to confirm the efficiency of PNN for determination of shear strength parameter. **Application:** Unlike other neural network approaches it uses the Bayesian estimation theory and gives time efficient results. These results can be utilized efficiently to determine the shear strength parameter using index properties of soil.

Keywords: Cohesion, Internal Friction Angle, Probability Neural Network (PNN), Shear Strength

1. Introduction

Shear strength is the inherent property of soil that can offer resistance against failure and sliding along a plane in the soil medium. It is generally considered to be a dependent on the cohesion between the soil particles and inter-granular friction. Jain et al.[1] explained that the angle of internal friction is affected by factors such as dry density, water content, particle size distribution, shape of particles, and surface texture. Cohesion also depends upon types of clay minerals, proportion of the clay, size of clayey particles, and valence bond between the particles.

Shear strength of soil can be defined as "the internal resistance per unit area that the soil mass resist". This shearing resistance induced in a soil mass is composed of following types of friction**.** **S**liding friction (called angle of shearing resistance) and glue friction (Provided by the property of soil called cohesion). The shear strength of soil is thus given by the coulomb's Equation. So prior to designing of foundation for structure or road embankment, retaining wall etc, estimation of shear strength of soil is of utmost importance. Further**,** shear strength of soil is one of its most complex properties, as obtaining undisturbed soil sample from the field and conducting no. of triaxial shear test in laboratory is both time consuming and needs careful supervision. Hence there is now a tendency in countries all over the world towards building up correlation equation between the soil properties and index properties of soil[2].

In general practice shear strength parameters can be estimated, both in the field as well as in the laboratory. Tri-axial shear test, unconfined compression test and direct shear box test are among the common laboratory tests. The in-situ tests include standard penetration test, cone penetration test, piezo-cone, field vane shear test and pressure meter reading test. Each test constitutes some advantages and drawbacks. According to[3] "Of all these, while triaxial tests are known to simulate the in situ soil conditions more accurately, direct shear test are known to be capable of simulating the interlocking behaviour in sands".[4-13] are among the researchers who tried to study the correlation between various test indices and undrained shear strength. Many empirical and polynomial models have already been employed for

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estimating shear strength parameters using statistical and neural approach[14-17]. In all the previous studies, some type of clustering technique has been incorporated so that it implements a cluster center technique which represents a group of training patterns. A new model, which is flexible enough to predict the futuristic shear strength as realistic as possible is highly preferable, so that the cumbersome and tedious laboratory work can be avoided. This necessitates the use of modern technological advents like neural networks, an offshoot of Artificial Intelligence, where the principle is to emulate a human brain to study the pattern and predict the outcome.

Neural Networks are developed in other fields also such as Earthquake magnitude[18], prediction of concrete strength[19], Structural deterioration of urban drainage pipe, for large databases[20].

2. Database and Statistical Analysis

In this study, the database were obtained from laboratory testing conducted on soil taken from site of Ranchi, capital city of Jharkhand. A total of 20 bore hole were explored from different places using SPT tests. It is to be noted that 300 soil samples were collected from various site, which include both disturbed and undisturbed samples. Undisturbed samples were subjected to triaxial testing in unconsolidated undrained condition for quick determination of shear strength parameters, c and φ. These undisturbed samples were also subjected to a number of laboratory tests to determine the index properties. These tests included Atterberg Limit test, Grain size distribution, Hydrometer test and Bulk density test. Tests were performed as per (IS:2720) for determination of plasticity Index(PI),

Sand%(STP), Silt%(SP), Clay%(CP), Bulk density(BD), Dry density(DD) and water content(w). The soil database demonstrates that the soils are predominantly Sandy Silt according to IS classification system.

The most dominating factors influencing the shear strength behaviour were observed and based on the literature review[8,21-24].

To study the variation of all the inputs and output parameters considered, histogram were chosen to represent the frequency. Figure 2 depicts the wide distribution of all the parameters. The substantial influence of the above parameters in determining *c* is implicit. According to[25] the basic soil properties (fabric characteristics), the loading history of the soil and the present state of the soil, all affect the cohesion. In the current paper PI, STP, SP and CP parameters indicate the intrinsic soil properties while BD, DD and w indicates the information regarding the present state of the soil and its loading history. Moreover, they also represents void ratio. Over - Consolidation Ratio (OCR) can also be included in this type if analysis, however, the same was omitted due to the constraint of its determination based on time-consuming laboratory tests. At the same time, BD and DD can easily be obtained.

3. Probabilistic Neural Network

Along with (MLPN) multilayer perceptron different kinds of neural network architecture in pattern recognition and prediction analysis have been utilized. These includes neural network, radial basis function neural network, and probabilistic neural network. All of these uses the basic architecture as shown in figure 1. A Probabilistic Neural Network (PNN) is predominately a classifier. Unlike the other ANNs based on the back-propagation neural network, PNN is based on statistical algorithm called Kernel Discriminant analysis in which the operation are organized into a multi-layered feed forward network. The only difference occur in the implementation of rule amongst the pattern layers. There has been increasing interest in pattern recognition using PNN due to unique quality to interpret the network using Probability density function. Researcher[26] introduced Probabilistic Neural Network, which provides a general solution to pattern classification by Bayes decision strategy combined with the Parzen nonparametric estimator of different classes. PNN has many advantages over generally used back-propagation. The most important advantage of PNN is that training can be done easily and instantly. Unlike BP network, existing weights are assigned and not trained. So the existing weights never change but only new vectors are placed in weight matrices while training. So the process takes place in real time. The network classifies input vector into a specific class.

Four layers that makes the PNN are namely, Input layer, Pattern layer, Summation layer and Output layer. Figure 1 shows the basic architecture of the PNN. The first layer is the Input layer which represents the *m* input variables *(x1, x2,...,xm)*. The input layer neurons distribute the variables of *x* to all neurons in the second layer.

$$d_{aj} = \frac{1}{(2\pi)^{p/2} * \sigma^{p}} \exp\left[-\frac{(X - X_{aj})^{T}(X - X_{aj})}{2\sigma^{2}}\right] \tag{1}$$

$$F(x) = \frac{1}{n_a}\sum_{j=}^{n_a} d_{aj}(X) \tag{2}$$

The input layer is wholly connected to the pattern layer, with one neuron for every pattern in the training set[27]. The weight values of the neurons in this layer are set equal to the different training patterns. The summation of probability density function is carried out by the Summation layer neurons. There is one Summation layer neuron for each category. Weights of each neurons on the connections to the Summation layer are set to unity so that the Summation layer simply adds the outputs from the Pattern layer neurons. Each neuron in the Summation layer sums the output from the Pattern layer neurons, which correspond to the category from which the training pattern is selected.

k=arg max $\{f_a(X)\}$
where a=1,2,……………………..,15 (3)

Using equation (3) the output layer neuron produces a binary output value corresponding to the highest probability density function. This indicates the best classification for that pattern.

As such, there is no rule to obtain the smoothing parameter, however, the best value of σ is determined using trial method. In this study six different values of σ were used to evaluate the test pattern and are tested. It suggested that '0.5' is the best smoothing parameter which provided the least estimation error. It is the one at which prediction error is at minimum value. For this a numerical example analysis was performed on soil specimen with sixteen categories, to evaluate the performance of PNN with different values of smoothing parameters. Data was divided randomly. The randomized data was divided into training (85%) and testing (15%) dataset. In general, no definite relationship has been observed between the proportion of data for training, testing, and validation and the performance of the model[28]. Training data set was used for creating and learning the neural network while testing data was used for cross validating and testing the network. The validation set was used to check the efficiency of the trained network in the deployed environment.

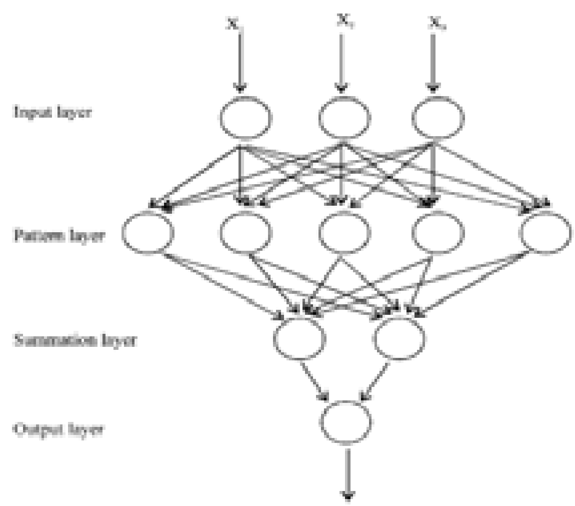

Figure 1. Basic Structure of PNN.

4. The Proposed Model

The input layer has one neuron which takes one set of new input data (test data). The pattern layer consists of 300 neurons. Each neuron contains one set of input data which consists of seven parameters. The summation layer consists of 16 neurons representing one class each. The output layer is of one neuron which represents the best class.

$$p = \begin{bmatrix} 0.528 & 0.546 & - & - & - & - & - & - & - & - & - & - & - & - & 0.845 \\ 0 & 0.67 & - & - & - & - & - & - & - & - & - & - & - & - & 0.063 \\ 0.338 & 0.384 & - & - & - & - & - & - & - & - & - & - & - & - & 0.673 \\ 0.599 & 0.459 & - & - & - & - & - & - & - & - & - & - & - & - & 0.25 \\ 0.303 & 0.379 & - & - & - & - & - & - & - & - & - & - & - & - & 0.227 \\ .405 & 0.367 & - & - & - & - & - & - & - & - & - & - & - & - & 0.456 \\ 0.548 & 0.541 & - & - & - & - & - & - & - & - & - & - & - & - & 0.569 \end{bmatrix}_{7\times 330}$$

$$t = \begin{bmatrix} 0.258 & 0.285 & - & - & 0.199 & - & - & 0.066 & - & - & 0.219 & - & - & - & 0.146 & 0.106 \end{bmatrix}_{1\times 330}$$

$$T_c = \begin{bmatrix} 1 & 2 & - & - & 6 & - & - & 8 & - & - & 10 & - & - & - & 12 & 16 \end{bmatrix}_{1\times 330}$$

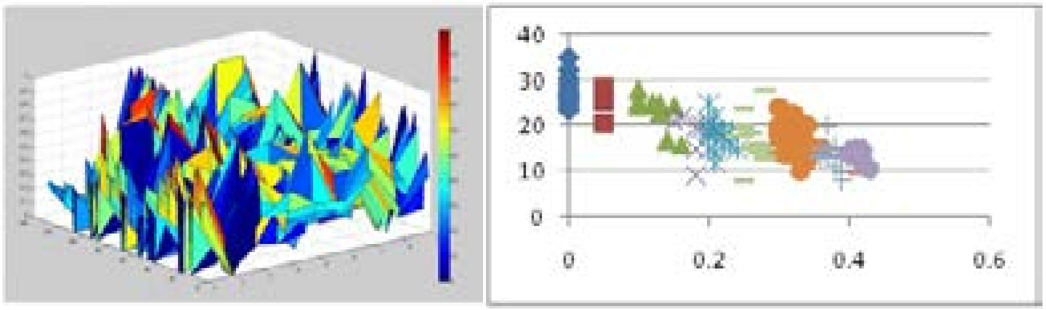

Figure 2. Variation of input parameters.

The target class contains 16 classes whose target outputs are in the range of 0.00 to 1.00.

5. Results and Conclusions

It was found that the trained PNN is able to predict the shear strength of other 6 cases satisfactorily. The results show that probabilistic neural network models generate higher predicting precision for practical application. Table 1. Summarizes the validated dataset for shear strength parameters.

A graph comparing the calculated cohesion and observed cohesion is shown in Figure 3. It is observed that the concentration calculated by PNN and the observed do not vary much. The Graphs are also plotted for observed friction angle vs. predicted friction angle for soil. Variation between both the values is 7% - 14% in most of the cases. It is also seen that neural models are yielding better results than the mathematical model.

Table 1. Validated dataset

Sl. No.	PI	GP%	SP%	STP%	CP%	BD	w	$C_{observed}$	$C_{predicted}$	$\Phi_{observed}$	$\Phi_{predicted}$
1	11.2	0	18	69	13	2.02	24.2	0.41	0.45	15.0	14.54
2	9.6	0	35	57	8	1.98	22.8	0.22	0.28	19.5	19.25
3	12.7	0	10	76	14	1.9	19.5	0.4	0.45	13.5	13.91
4	6.2	0	42	55	3	2.02	20.2	0.05	0.00	27.5	27.5
5	14.79	3.5	63.64	26.86	6	2.03	16.52	0.13	0.10	23.0	25.6
6	11.41	8.78	66.46	20.76	4	2.05	16.24	0.1	0.10	28.0	25.6

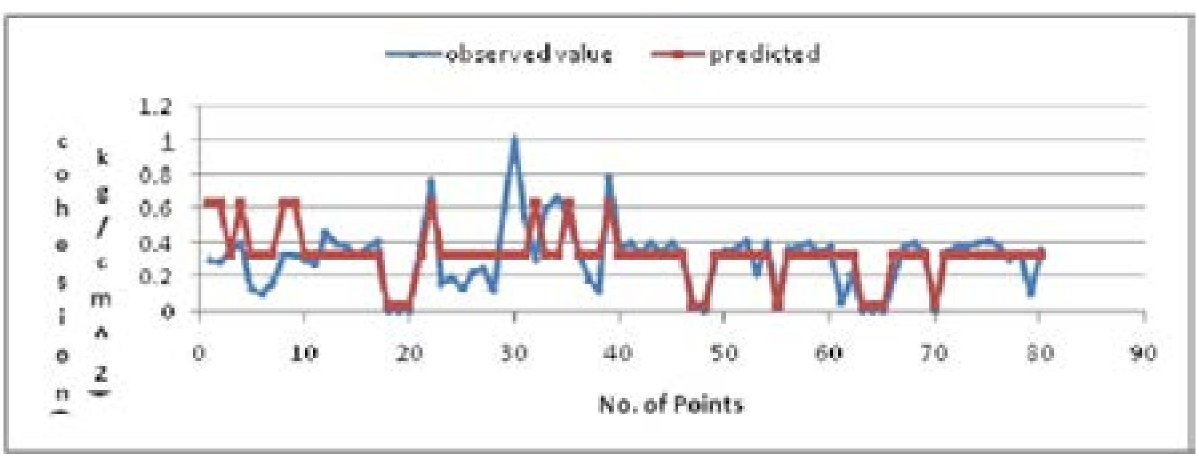

Figure 3. Comparison between the observed and predicted values of cohesion.

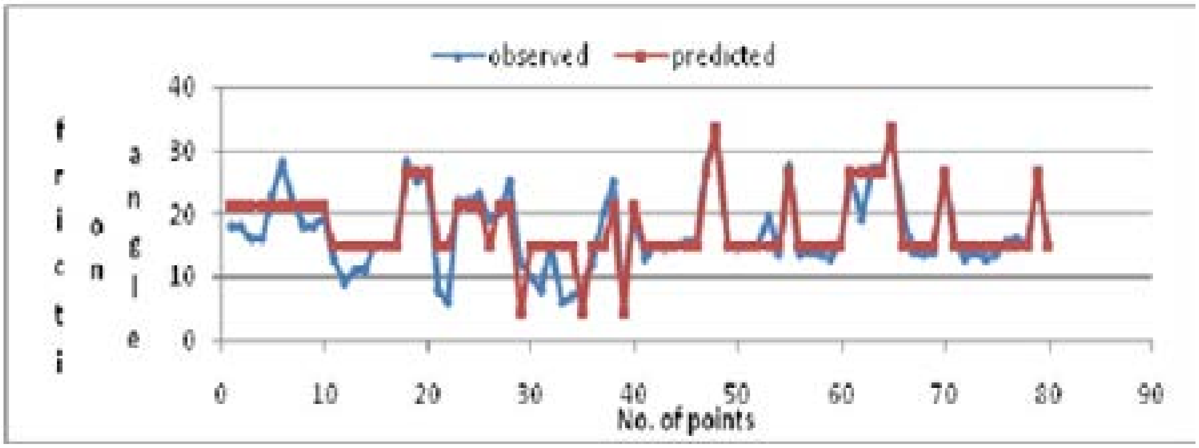

Figure 4. Comparison between the observed and predicted values of internal friction angle.

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