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Artificial Neural Network (ANN) Application for Spatial Interpolation of Standard Penetration Test (SPT) and Soil Profile Data

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ABSTRACT

The physical and mechanical properties of soils typically contain natural and spatial variation and uncertainties. The lack or not having any knowledge of the subsoil conditions at a particular location and depth at any given site due to the limited number of geotechnical investigations in the field have led foundation engineers to apply spatial averaging methods from nearby boreholes to approximate geotechnical and soil parameters for design, with various degrees of uncertainty and reliability. In this study, Artificial Neural Network (ANN) is applied for spatial interpolation of Standard Penetration Test (SPT) and soil profile data. Using the available geospatial information from nearby boreholes as training (global coordinates, SPT-N profile, groundwater table, soil classification with depth, physical and mechanical properties of soils), the similar information may be predicted and estimated at any location and depth at the site that has no available borehole test data using artificial intelligence techniques such as ANN. An example SPT database at a given site is being modeled and studied, and verification and test results have shown that the spatial interpolation method by ANN can be a valuable tool to provide various information that is needed for geotechnical and foundation design.

1. INTRODUCTION

The Standard Penetration Test (SPT) is a popular field test for subsurface geotechnical investigation with the ability to extract soil samples for further laboratory testing. Oftentimes the standard penetration test number of blows per foot or SPT-N (blows/30cm) is directly used with widely established correlations to derive various parameters for foundation design, such as bearing capacity and settlement of shallow footings, load capacity of pile foundations (Kim and Mission, 2011), and analysis of liquefaction potential. Due to the limited number of SPT borehole investigations at any given particular site, geotechnical engineers may often interpolate, extrapolate, or

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average from nearby existing available borehole locations to estimate the unknown subsurface parameters at any other point or location. In this study, the use of Artificial Neural Network (ANN) as applied in geotechnical engineering (Shahin et al. 2001) for spatial interpolation of SPT-N and soil profile data is explored, its various advantages and benefits compared with the other classification and estimation methods are also compared.

2. SPATIAL INTERPOLATION METHODS OF STANDARD PENETRATION TEST (SPT) DATA

2.1. Nearest borehole method

The nearest borehole method is a similar adaptation of the nearest neighbor algorithm (Cover and Hart 1967), which is one of the simplest and most classical non-linear classification algorithms. The method classifies objects based on closest training examples in the feature space. Any point within an area on a site has a known distance to existing SPT borehole locations. When a point is closest to a nearby SPT borehole location, then the area bounded by all these points is assumed to have the same SPT-N data and soil profile with the nearest single borehole as shown in Fig. 1.

2.2. Linear interpolation and spatial averaging method

Instead of copying the SPT-N and soil profile data from the nearest single borehole, another method of estimating the soil SPT-N characteristics of any particular point at a site is to linearly interpolate in two (2D) or three (3D) dimensions from nearby boreholes surrounding the point or location in question. When more than two or more nearby borehole locations are available, then a common approximation is to perform spatial averaging of all the SPT-N data at any specific depth as shown in Fig. 2.

2.3. Spatial interpolation by Artificial Neural Network (ANN)

A major drawback of the spatial method using linear interpolation by averaging is its inability to properly characterize or classify the soil profile at any unknown site in question, especially when dealing with non-numeric data (ex. soil type). The spatial interpolation method by using Artificial Neural Network (ANN) has all these capabilities to perform soil parameter estimation, pattern recognition, classification, and nonlinear fitting.

ANN is a set of connected input-output units, where each connection has weights and biases associated with it. Training and learning is being performed by a feed forward-back propagation algorithm: (a) the inputs are fed simultaneously into the input layer, (b) weights and biases are initially assigned and the weighted input are fed simultaneously into the hidden layer, (c) the hidden layer's weighted outputs can be input to another hidden layer, (d) the weighted outputs of the last hidden layer are inputs to units making up the output layer, (e) predicted output is compared with the target and the error is propagated backwards by updating the weights and biases to reflect the error of the network classification until a specific performance and termination criteria is achieved.

The structure of the ANN network for spatial interpolation of SPT and soil profile data is shown in Fig. 3. Input layer consists of the spatial coordinates (X, Y, Z) data and depth of groundwater table (W) of the respective existing boreholes. Output layer consists of the SPT-N (blows/30cm) profile and a general soil classification (cohesive or cohesionless) at the respective depths Z.

Where the ANN input and output data are generally on widely different scales, it is necessary to normalize them to speed up training and obtain better results, such that they are compatible with the range of hidden layer activation functions (ex. -1.0 to 1.0, or 0 to 1.0). The min-max normalization method is then used to rescale the input and output data for training by linear interpolation within the range from minimum of 0 to maximum of 1.0. Let p be the raw input or output data, and given the maximum (p_{max}) and minimum (p_{min}) value of p, then a normalized data p_n can be derived as follows,

$$p_n = (p - p_{max}) / (p_{min} - p_{max}) \qquad \text{Eq. (1)}$$

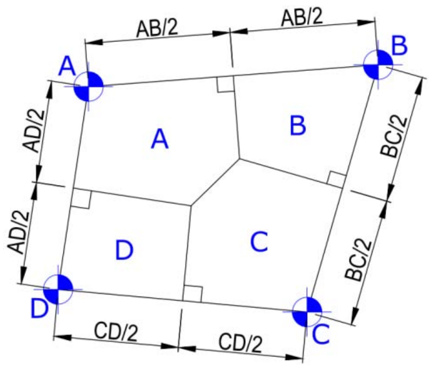


Fig. 1. Nearest borehole method

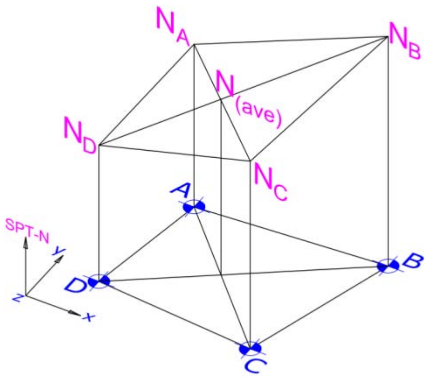


Fig. 2. Linear interpolation and spatial averaging method

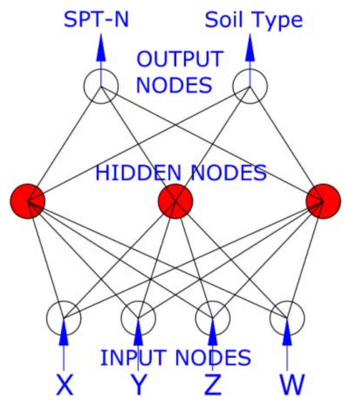


Fig. 3. Artificial Neural Network (ANN) method

3. APPLICATION EXAMPLE

Shown in Fig. 4 is an area that is being modeled and studied, which is part of the IRPC-UHV project site in Rayong, Thailand (MAA Geotechnics 2013). The studied site consists of 17 SPT boring holes, in which 13 were used for ANN training and the remaining 4 for validation and testing. Shown in Fig. 5 is the site classification based on nearest borehole method. Linear interpolation and spatial averaging method using nearby boreholes have to be performed at every depth interval in order to completely define the whole SPT-N profile at every location. Shown in Fig. 6 is an example result of SPT-N contours using linear interpolation method of SPT data from nearby boreholes at depth z=20.0m. As mentioned, the linear interpolation and spatial averaging method, while dealing only with numeric data, lacks the ability to estimate the probable classification of the soil at every depth (since we cannot interpolate or average between say sand and clay). The ANN architecture shown in Fig. 3 is then modeled in Matlab (2012) program, in which input and output data were normalized for training and simulation.

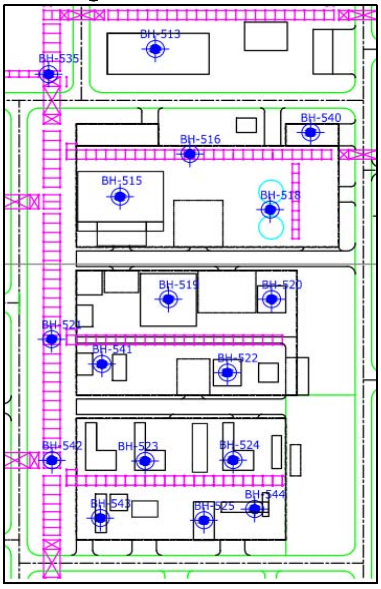


Fig. 4. Project study area and borehole location

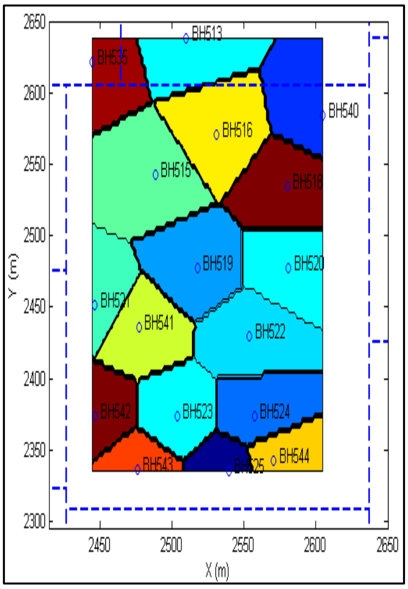


Fig. 5. Nearest Borehole Classification

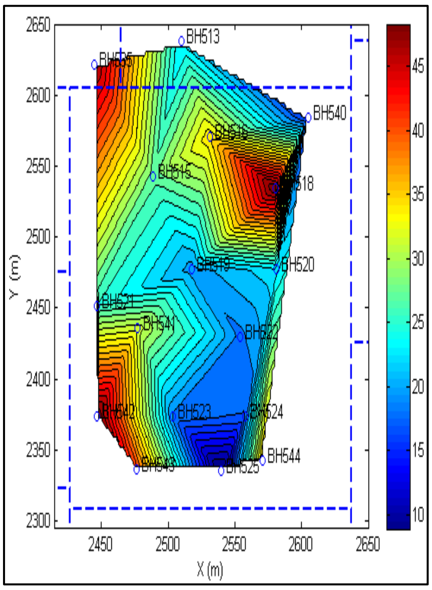
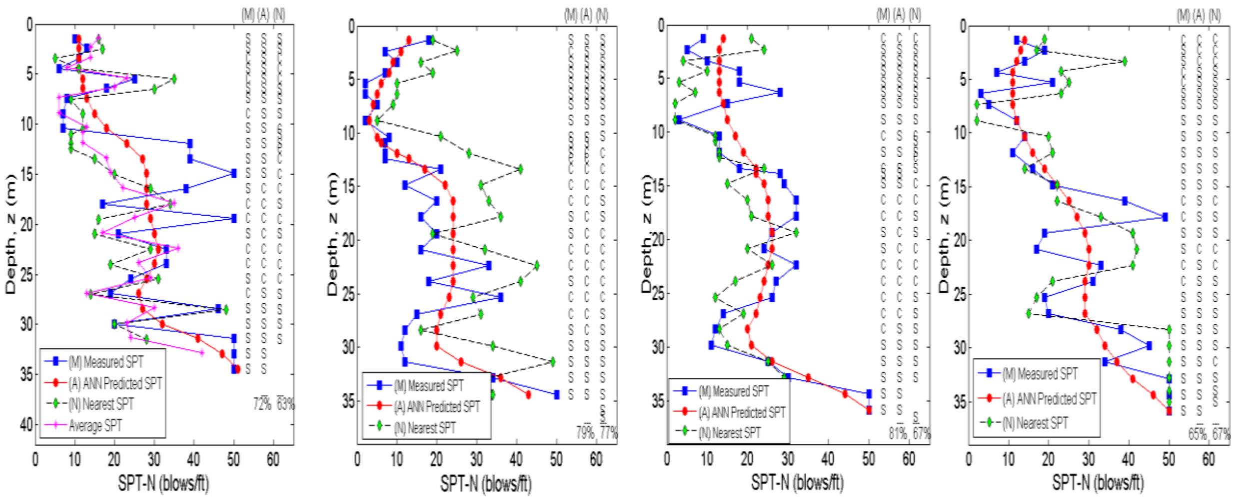


Fig. 6. SPT-N Contour using linear interpolation (at depth=20m)



(a) (b) (c) (d)

Fig. 7. Comparison of measured and predicted SPT-N and soil profiles: (a) BH-18, (b) BH-19, (c) BH-21, and (d) BH-23

Shown in Fig. 7 is the comparison of measured and predicted SPT-N and soil profiles using the different spatial interpolation methods. Fig. 7 shows that ANN has the ability to classify and estimate the SPT and soil profile at any location and depth within the area boundary of the trained network, in which good agreement is seen in comparison with measured data and referred results from nearby boreholes. A distinct feature of the predicted results by ANN is the ability to generalize or smoothen the SPT-N profile throughout the depth and thereby removing spatial variations. Results are also compared in terms of the soil classification at the respective depths, in which general predictions by ANN, either cohesive soil (clay=C) or cohesionless soil (sand=S), showed fair agreement with those from field SPT results. When compared with the reliability of soil classification, ANN achieves up to about 70-80% of the prediction, and in which in most cases exceeding those results from nearest borehole method.

4. CONCLUSIONS

The use of Artificial Neural Network (ANN) as applied in geotechnical engineering for spatial interpolation of Standard Penetration Test (SPT) data and soil profile classification has been demonstrated to be a promising alternative to conventional and classical methods such as nearest borehole, linear interpolation and spatial averaging. Predicted results of SPT-N profile by ANN have been shown to be in good agreement with measured data, with the ability to generalize the soil profile and remove spatial variations. In addition, predicted performance of soil profile classification method by ANN is shown to generally exceed the results from the approximate nearest borehole classification method.

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