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Comparison of two different application of neural network on Sudan soil profile

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Abstract: The objective of this paper is to compare between two studies that had been carried out using ANNs in prediction of Sudan soil profile. This importance in the design and implementation of all engineering projects which reduce cost and time. Artificial Neural Networks (ANNs) program is applied to realize this aim. The data of 1909 boreholes from 417 sites was used firstly for a single model and then divided to five zones to be used for localized models. The input data is the coordinate and depth and the output data is the soil classification and soil parameters. The result showed that ANNs can be used as a good decision support and source of information for soils profiles. It is more efficient tools to be used for small zones than all area.

Keywords: Soil Profile, Artificial Neural Networks, Sudan, Prediction

1. Introduction

The behavior of every foundation depends on the engineering characteristics of underlying deposits of soil and rock. The theme for this paper is to seek for possible ways to predict some parameter which been guide lines for geotechnical or structure engineering to give out good way to design. [2]

The geotechnical engineering properties of soil exhibit varied and uncertain behavior due to the complex and imprecise physical processes associated with the formation of these materials [9]. Many authors have described the structure and operation of ANNs (e.g. Hecht-Nielsen 1990[9]; Maren et al. 1990[10]; Zurada 1992[11]; Fausett 1994[12]; Ripley 1996[13]).

Neural networks are similar to biological neural networks in performing functions collectively and in parallel by the units, rather than there being a clear delineation of subtasks to which various units are assigned. The term "neural network" usually refers to models employed in statistics, cognitive psychology and artificial intelligence. Neural network models which emulate the central nervous system are part of theoretical neuroscience and neuroscience typical structure of ANNs consists of a number of processing elements (PEs)

Recently, Artificial Neural Network (ANN) models have been applied on various geotechnical engineering problems. It can be used to model complex relationships between input and output, [1] [3] [4] [9].

2. Artificial Neural Network Application on Sudan Soil Profile

Two different studies in Sudan had been carried out using the artificial neural networks (ANNs) to predict the soil profile. The total data was produced from 1909 boreholes distributed in 417 different sites. The first study considered the whole data of Sudan while the second one divided these data to five different zones. Five models for each zone was developed using Multi-layer Back propagation neural networks to demonstrate the feasibility of ANNs to predict soil classification and soil parameters based on the available site data provided from borehole logs bored by Building and Road Research Institute (BRRI) of the University of Khartoum, Dreams tower company, Sudan pile company and Itgan company for different purpose Table (1), [5] [6] [8].

Eight classifier sub-models and two parameter sub-models were developed for different five models to predict their soil profile. These models and their input and output are explained in Table (2).

Table 1. *Neural Network models for soil profile of Sudan.*

Model No	All data	Zone Data	No of boreholes in zones	No of sites in zones
Model 1	Sudan(center)	Center of Sudan	798	137
Model 2	Sudan(east)	East of Sudan	505	137
Model 3	Sudan(west)	West of Sudan	108	105
Model 4	Sudan(south)	South of Sudan	339	90
Model 5	Sudan(north)	North of Sudan	159	28

Table 2. *Input and Output Data of ANN*

Input data	Output Data				
Models	Model 1	Model 2	Model 3	Model 4	Model 5
E,N coordinate and depth	Silty/clay Sand	Silty/gravel Silty/sand	Silty/sand Sandy	Silty/clay clayey	Sand Silty/sand
E,N coordinate and depth	Clayeysilt Clayeysand	Silty/clay Sandy/clay	Silty/clay Sandy/clay	Silty/sand clayey/Sand	Silty/clay Sandy/clay
E,N coordinate and depth	GW	GW GP	GS GC	GP	GM GC
E,N coordinate and depth	GC	GS	GM	GC GM	GS GS
E,N coordinate and depth	SP	GC GM	SW SP	SP	SW SP
E,N coordinate and depth	SC SM	SP	SC SM	SM	SM
E,N coordinate and depth	CH CL	SC SM	CH CL	CH CL	CH CL
E,N coordinate and depth	MH ML	ML CL	MH ML	MH ML	MH ML
E,N coordinate and depth	Pass200%		Pass200%	Pass200%	Pass200%
E,N coordinate and depth	L.L P.I	L.L PI	L.L PI	L.L P.I	L.L P.I

Classifier sub-models are used to classify soil layers at different locations and depth in Sudan depend on type of soil in zones. Parameters sub-models used to estimate some value of soil's parameters in different layers. The result was evaluated according to the value of the coefficient of multiple determinations (R^2).

The value of R^2 is range between (0-1). The general formula of neural network used for R^2 as follows: [7]

$$R^2 = 1 - \frac{SSE}{SSyy}$$

Where:

$$SSE = \sum (Y - \widehat{Y})^2$$
$$SSyy = \sum (Y - \overline{Y})^2$$

Y is acual value.
$\widehat{Y}$ is predict value of Y
And $\overline{Y}$ is mean of theY value.

In this paper the models performance is evaluated depending on R^2. A perfect model fit would result in an R^2value of 1, a very good fit near 1, and a very poor fit is it less than 0. But $R^2$is not the ultimate measure of whether or not network is producing good results. It might be decided of that network is accepted without obtaining a high level of R^2 value and the judgment in this case is due to the number of correct classifications

3. Results

Regarding to the available data and their quality, the input data are chosen from two sector areas and the output concentrated on five predicted models for areas. Figures (1), (2), (3), (4) and (5) show the comparison between Sudan model against: Sudan (center) model, Sudan(north) model, Sudan(south) model, Sudan(east) model, and Sudan(west).

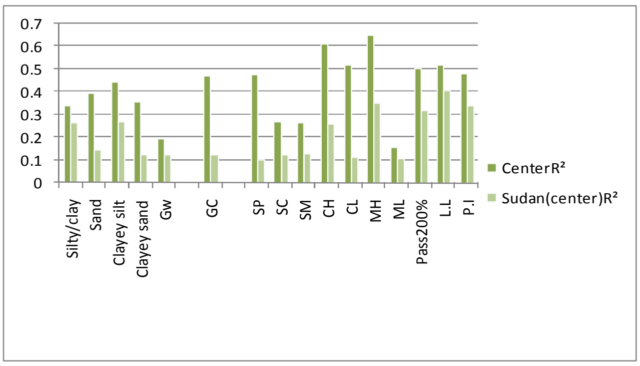

Figure (1). *Comparison between the performance of artificial neural networks in Sudan model & Sudan(center) model*

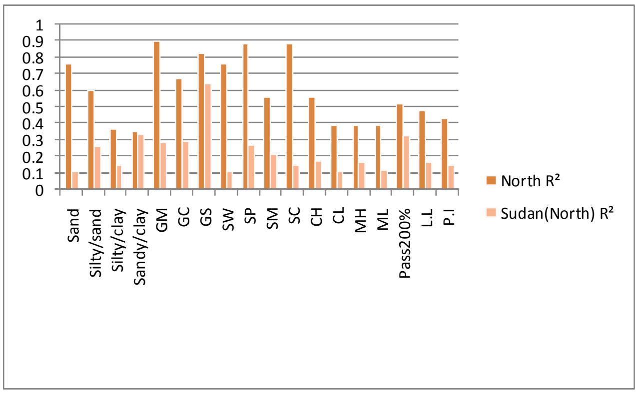

Figure (2). *Comparison between the performance of artificial neural networks in Sudan model & Sudan(north) model*

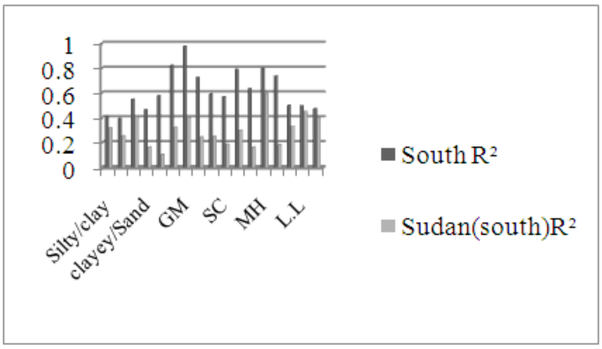

Figure (3). *Comparison between the performance of artificial neural networks in Sudan model & Sudan(south) model*

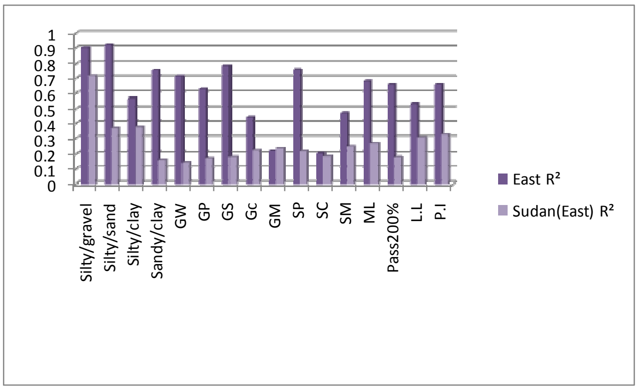

Figure (4). *Comparison between the performance of artificial neural networks in Sudan model & Sudan(east) model*

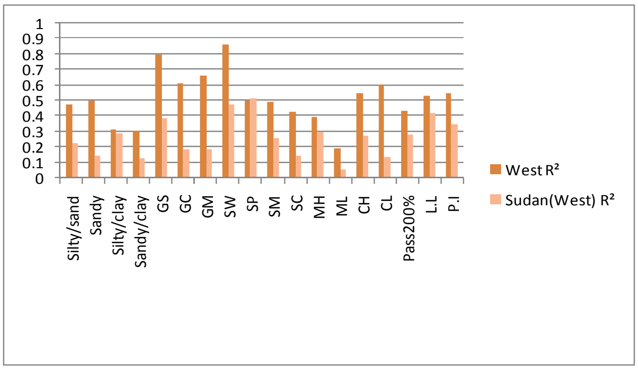

Figure (5). *Comparison between the performance of artificial neural networks in Sudan model & Sudan(east) model*

4. Discussions

The total data collected for this research consist of 1909 boreholes from 417 sites laying on all Sudan area and had been investigated and reported by B.R.R.I of university of Khartoum, Dreams tower Company, Sudan pile Company and Itgan company. The Google earth network program used for reading the actual elevation and coordinate (E, N) for each borehole in each site in universal transverse Mercado system.

Usually, the boreholes depths up to 25 m., and the data include mainly: Site name, borehole number, location (E, N), depth, soil group symbol (USCS), liquid limit (LL), plasticity index (PI), and Sieve analysis.

The information provided from soil reports are used for prediction of soil classification and parameters using neural network technology.

Evaluation for models performance depends on R^2 from previous figures it can be seen in general reasonable result of prediction is obtained. A considerable amount of data was made available for the training process. A better prediction of soil profile was produced from localized zones data than whole data.

This is due to similarity of soil types in the each zone. Using the whole data to predict soil profile in certain location may leads to unacceptable results as it is clear in some Figures. Results obtained from the ANNs Sieve analyses model and Atterberg limits model show that ANNs with proper training is a good tool in prediction using data in localized zones better than using the whole data.

5. Conclusion

From the results obtained from this study, it can be concluded that:

All data is may be not good for the training progress and some of it may leads to week result.

Using zone data to predict soil profile within the zone may give better results than using the whole data for prediction.

These results with good R^2 value indicate that back-propagation neural networks have the ability to predict the global soil classification with an acceptable degree of accuracy.

The predicted results indicate that ANNs have a number of significant benefits that make them a powerful and practical tool to predict the type of soil layers.

Since the soil profile data is more available, ANNs appear to be efficient tool when used as pattern classifier more than used for parameters prediction.

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