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Title: Improved interpretations of CPT's in clay using Neural Networks

by

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1 INTRODUCTION

Cone Penetration Testing (CPT) is currently the most widely used in-situ test equipment for the determination of strength properties of soils. The ability to predict soil type and strength properties is in general good, but there is still room for improvement, especially with regards to strength interpretation in cohesive soils.

Through the latest decades, there has been considerable research effort going on in order to improve the ability to predict the undrained shear strength of cohesive soils. The key issue has been to establish an empirical background, relating cone resistance or excess pore pressure to undrained shear strength through a bearing capacity number, N. numerous models have been presented, and a common feature for most of them is that the bearing capacity number is established as a function of only one independent variable. This variable is most often taken as the pore pressure parameter, Bq, being continuously measured during the test, (Lunne et. al. (1985) and Sandven et. al. (1988)). Others have found correlations between the N factor and the friction ratio, or the absolute value of the cone resistance.

Alternatively, parameters from soil classification testing, such as the liquid limit, the soil sensitivity and the plasticity are also being used, (SGI 1995). This will require that soil sampling is carried out in addition to the in-situ testing.

An overview of different interpretation procedures which together defines the "state of the art" within shear strength interpretation of clays is given by Mayne et. al. (1995)

Despite the considerable amount of work that has been put into improving the strength interpretation methods, it is fair to say that there still exists a large uncertainty regardless of prediction method. This uncertainty may however be reduced if local correlations to high quality shear strength measurements on undisturbed soil samples are established. This correlation procedure, involving soil sampling and laboratory testing, supplemented by CPT's to capture local variations, has therefore become common practice for many types of soil investigations, and an enormous amount of data linking undrained shear strength to general classification data as well as to different variables from the CPT does therefore exist.

It may be concluded that the correlation between cone resistance and undrained shear strength of clays is a function of many variables. These variables are both parameters measured during the testing, as well as index data describing the actual soil type. The overall dependency, and the relative importance of the different variables, has yet not been evaluated, simply because no efficient tool has been available for this work. However, by using newly developed Neural Network systems, these correlations can now be efficiently investigated. By using theses systems, it is possible to capture any dependency of a variety of variables simultaneously, and thus most likely significantly improve the current predictability of undrained shear strengths of cohesive soils.

In the following is described the gathering of an extensive database holding sets of data including a variety of variables, and the subsequent investigation of correlations between those using a specifically developed Neural Network program.

2 THE DATABASE

A database has been gathered based on data from a number of recently performed offshore soil investigations. The results from offshore investigations were chosen since these investigations constitute large amount of data, and since thick deposits of homogeneous cohesive layers are more likely to be found here. The appearance of homogeneous layers is a necessity in order to obtain data sets of high quality, since cone tests and high quality strength tests cannot be taken on the same soil sample. The results from the cone tests have therefore been interpolated to the depth of the nearest soil sample where a triaxial shear test has been performed, along with a number of other classification tests. In general, such tests were performed on samples that were taken between the results of two downhole cone tests of maximum 2 – 3 meters vertical distance.

Only strength tests from triaxial tests have been utilized. Mostly, the results are from UU tests but also the results from CAU tests have been used. The UU tests are mostly performed offshore shortly after sample recovery, and the quality of theses tests were therefore generally considered as very good. Strength correlations between UU and CAU tests taken from the same sample were done and no consistent deviation in strength were found. However, a number of data sets were disregarded due to suspiciously low strength, even though evidence of sample disturbance could not be identified. Below is summarized the number of test data recorded and those disregarded from the various soil investigations.

Area	Site	CAU Tests	UU Tests	Disregarded UU tests
Norw. North Sea	Kvitebjørn 2000 soil Investigation	6	13	2
UK North Sea	Buzzard 2003 Soil Investigation	11	50	4
Gulf of Mexico	Lankahusa Soil Investigation	0	32	4
UK North Sea	Britannia 2003 Soil Investigation	6	45	4
Norw. North Sea	Grane 2000 Soil investigation	9	12	1
Norw. North Sea	Utsira High 1999 Soil Investigation	11	11	1
	Total	43	163	16

Table 1 Summary of data records

As seen, a total of 206 data sets were gathered, but 16 sets were disregarded leaving 190 data for further evaluation.

The following sets of measurements from the CPT's and from the laboratory testing have been recorded: Total (or net) cone resistance, q_T (or q_N), cone pore pressure response, B_q, Cone friction ratio, R_f, Effective Soil unit weight, γ' (giving effective and total overburden pressure), water content, w, Liquid Limit, LL, Plastic Limit, PL, Sensitivity, St and undrained shear strength, Su.

As seen, the total cone resistance has been used, indicating that the cone resistance measured already has been corrected for the water pressure acting behind the cone neck. The following definitions for variables interpreted from the cone results have been used:

$$N_{kT} = \frac{q_T - p_o}{Su} = \frac{q_{net}}{Su} \quad (1) \qquad Bq = \frac{\Delta U}{q_{net}} = \frac{U - U_o}{q_T - p_o} \quad (2) \qquad R_f = \frac{f_s}{q_T} \quad (3)$$

The cone number, N_{kT} were then calculated for all datasets, and the following distribution of datasets with varying N_{kT} was found as shown in Figure 1 below:

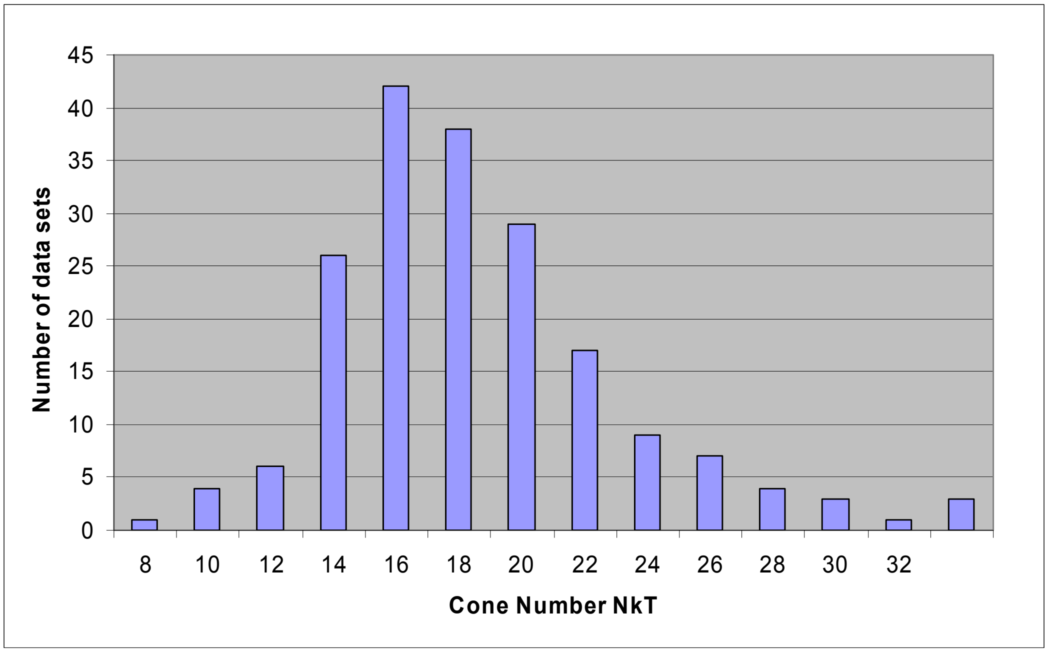


Figure 1 Frequency distribution of N_{kT} number

As seen, the most frequent cone number lies around 16 – 18, thus very similar to the commonly used range of 15 to 20. However, the spread in Nk value is large, and as seen asymmetric, and it is thus reason to believe that data sets to the extreme high may be erroneous. For this reason, data sets giving N-values below 13 and above 23 were given additional attention. It was found that the occurrence of these data did not correlate with other extreme variable. For this reason, also these data sets has been disregarded as erroneous, leaving a total of 149 datasets to be further analysed.

Key characteristics of the data are summarized below:

Statistics	Effective Stress, p_o'	Water Content, w	Liquid Limit, LL	Plastic Limit, PL	Undrained Shear Str., Su	Pore press. ratio, B_q	Friction Ratio, R_f	Total Cone Resist., q_T
	kPa	%	%	%	kPa	%	%	MPa
Max	1197	49	73	29	813	0.81	5.0	17.7
Min	11	13	23	13	8	0.16	0.9	0.17
Mode	596	25	41	22	89	0.50	2.70	6.00
Mean	484	25	47	21	261	0.48	2.74	5.50
S. dev.	295	6.8	9.7	3.6	207	0.18	0.83	3.98

Table 2 Key statistics of database

As seen from the table, the statistics on soil sensitivity has not been included, since the method for determination were not consistent throughout the database, and the results were therefore disregarded as unreliable.

Initial correlations between each of the above variables and the cone resistance number, NkT, where then tested, as shown in the following figures, Figure 2 to Figure 5. As seen from these, no consistent correlation can be made.

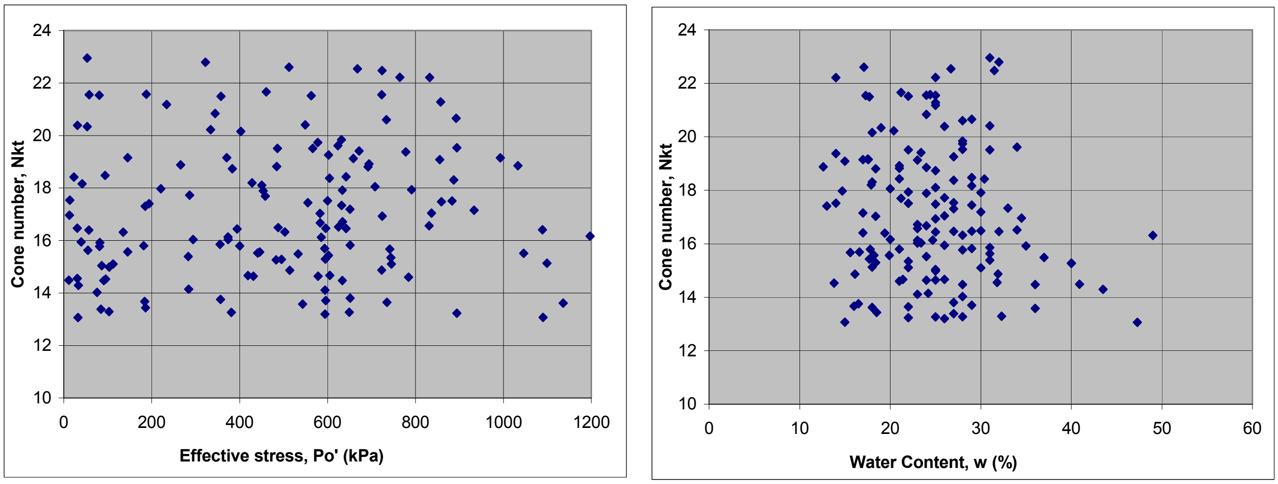


Figure 2 Cone number, N_{kT} versus effective stress and water content

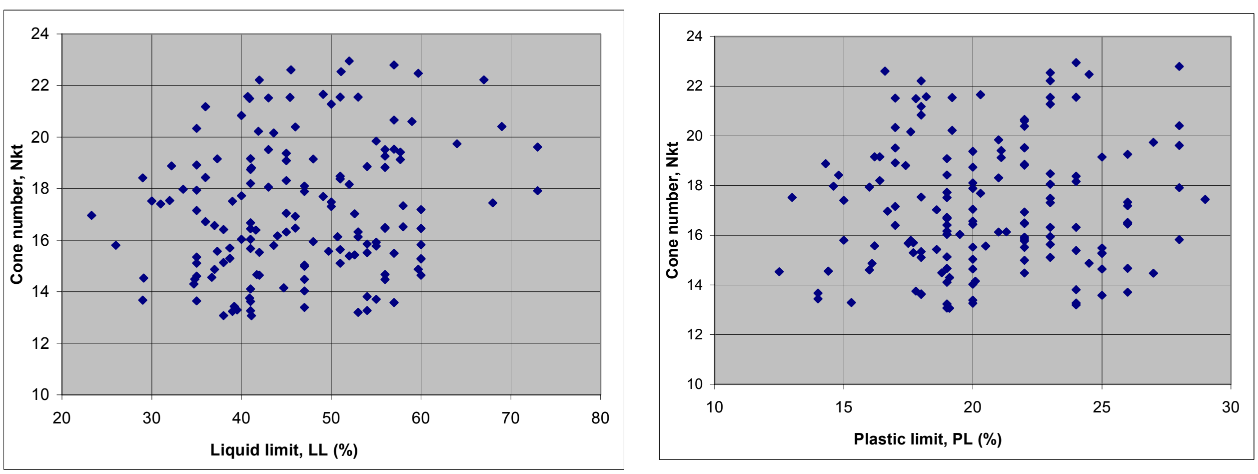
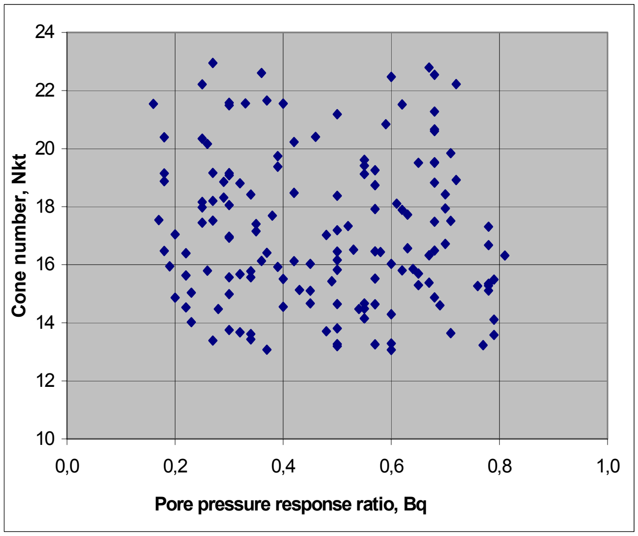


Figure 3 Cone number, N_{kT} versus liquid and plastic limits



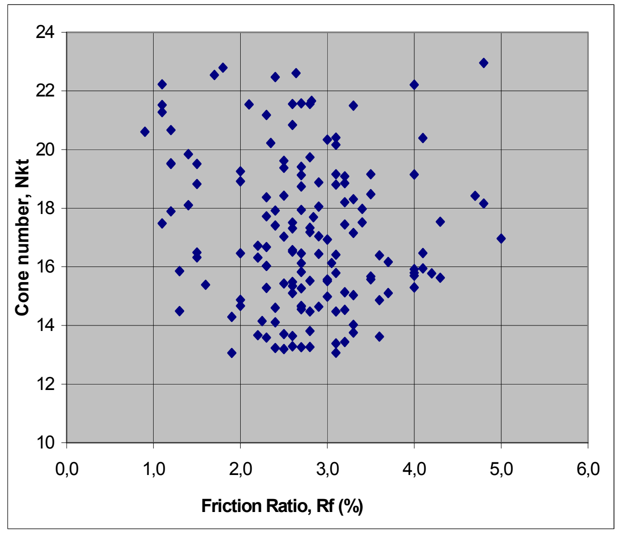


Figure 4 Cone number, N_{kT} versus porepressure response and friction ratio

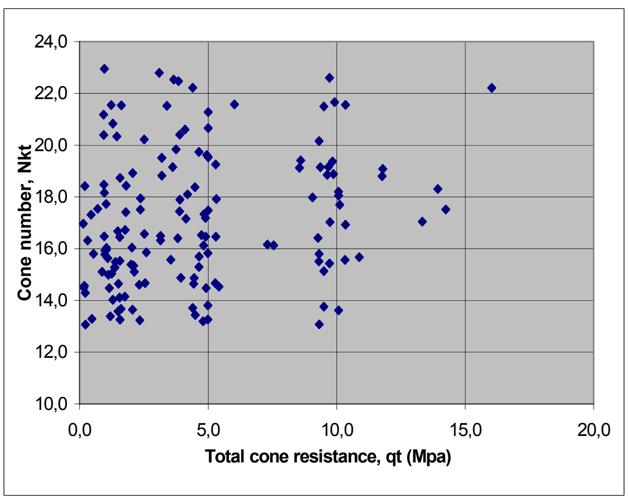


Figure 5 Cone number, N_{kT} versus total cone resistance value

3 ABOUT NEURAL NETWORKS

"Neural networks are computer models that mimic the knowledge acquisition and organisational skills of the human brain. A neural network can be described as computational mechanism able to acquire, represent and compute a mapping from one multivariate space of information to another, giving a set of data representing that mapping", (Goh 1996, Garret 1994).

A neural network consists of a number of interconnected processing elements, commonly referred to as neurons. The neurons are logically arranged into two or more layers, one input layer, one output layer, and one or more intermediate layers, referred to as hidden layers. All neurons in each layer are interconnected to each neuron in the neighbouring layer, and interact with each other via weighted

connections. Number of neurons in the input and output layer represent the number of input and output variables to be included, while number of hidden layers and neurons in each layer is a function of the complexity of problem to be analysed.
The neural network is first trained by the presentation of a series of examples (set of data) where the output value (result) is given in combination with all the different input variables. Through this training process, the network adjusts the weight associated with each connection between two neurons so as to minimise the error between the produced output and the given result. After this training process, the network has stored the relations between the input and output variables, and will then produce results according to this relation.

A further description of the nature of a neural network where also the methodology of the learning process is included is given by Goh (1996), and a thorough description of neural network in general, and the application for use in civil engineering by Flood and Kartam (1994 a and b)

The use of neural networks in geotechnical engineering has been so far only used for limited applications. Recent works are reported by Goh (1995 and 1996) and by Williams et. al. (1995). Goh (1995) investigated the use of neural network in comparison to multiple regression methods for prediction of sand density from CPT records, and the prediction of hydraulic conductivity of compacted clay liners. For both cases, the coefficient of correlation from neural network was higher than from the regression analysis. Goh summarises as follows:

"This study demonstrates the feasibility of using neural networks to capture nonlinear interactions between various soil parameters in a system. A simple back-propagation neural network was used to model two problems involving nonlinear variables. Actual test data were modelled using neural network. After learning from a set of selected patterns, the neural-network models were able to produce reasonably accurate predictions."

In addition to the study above, Goh (1996) have also reported successful use of neural network to predict pile capacity on basis of driveability records, and Williams et. al (1995) reports that "neural network are useful for performing the inversion procedure of SASW (Spectral Analysis of Surface Waves) tests". Finally, Goh et. al. (2005) has demonstrated increased accuracy in prediction of side friction of drilled shafts in clay.

4 TRAINING THE NEURAL NETWORK

In this project, a special hybrid back-propagation model of an artificial neural network has been used. The model utilizes the genetic algorithms search technique and the Bayesian neural network methodology, and is called the Evolutionary Bayesian Back-propagation (EBBP). Further details of the EBBP are described in Chua and Goh, (2003) and Goh et. al. (2005).

The EBBP was used to analyze the inherent relationship between the various soil parameters as given in table, and the cone resistance number, NkT. The EBBP model architecture consists of 7 input nodes, 11 hidden nodes in one hidden layer, and one output node as shown in Figure 6 overleaf.

The database was split into two groups, one for training the network and one for testing the relations. Normally, the training data should be chosen among the data having the highest confidence, in order to establish more reliable correlations. Also, the amount of training data should be significant, for the same reason. Consequently, the data was split under the above conditions, resulting in 100 set of data for training, and 49 for testing.

The results of the EBBP analysis gave a trained network producing the following results in terms of Mean Square Error, MSE, for the training and testing part. In comparison, the reference MSE for the dataset is also calculated based on the difference between a constant N_{kT} value equal to the average value of the dataset and the correct value.

	Mean Square Error, MSE	
	EBBP	Average N_{kT}
Training	1.91	6.74
Testing	3.96	6.31

Table 3 Key statistics of database

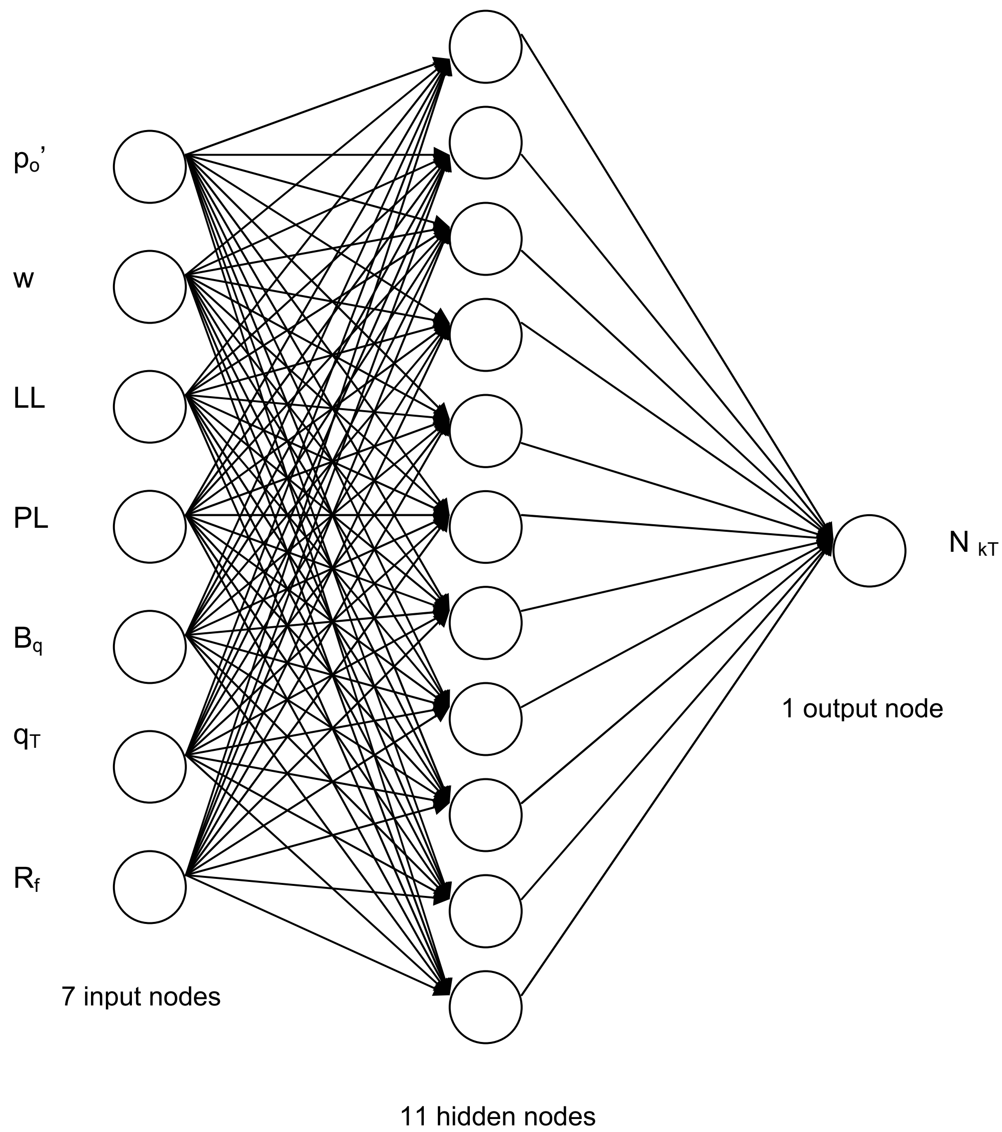


Figure 6 Architecture of the EBBP model

It is seen that the MSE from the trained network is only around 30 % of the value produced if the average N_{kT} is used. For the testing part, the error is somewhat higher, but as described earlier, the confidence level of these data is less than for the training data.

In Figure 7 below is shown the predicted N_{kT} values versus the actual ones for both the training and the testing data.

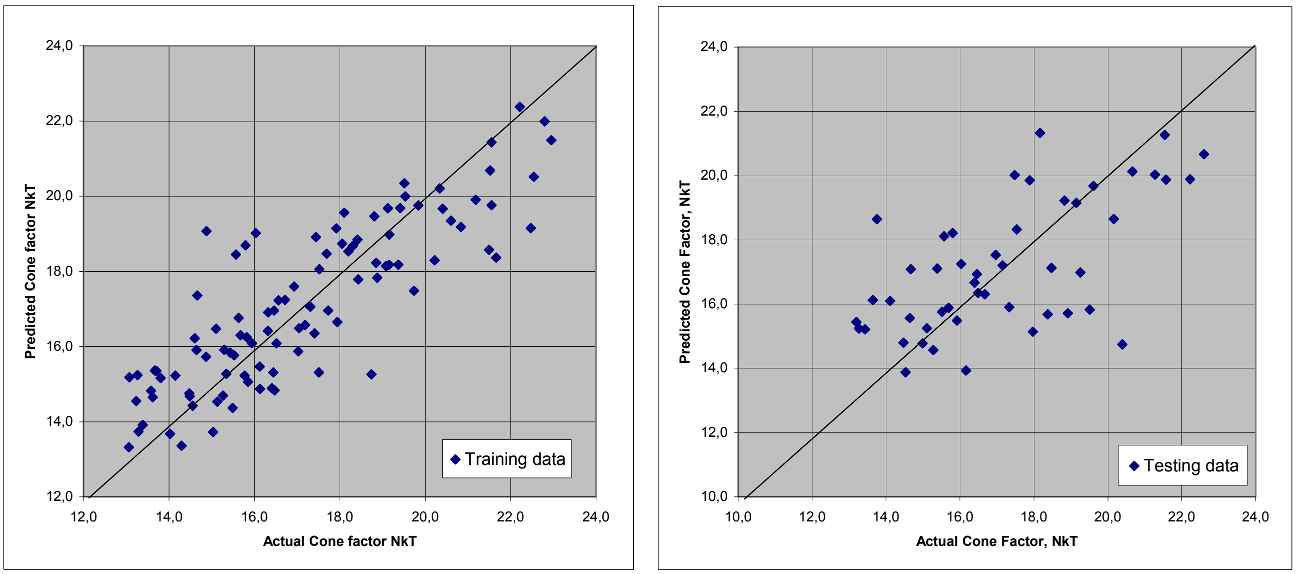


Figure 7 Actual versus predicted N_{kT} from EBBP training and testing data

It is visualized that the trained EBBP model predicts the N_{kT} value very well. It may also be seen that the spread in prediction is somewhat larger from the testing data, and that in particular 2 predictions have large error. If these 2 data is removed from the dataset, the MSE will drop from 3.96 to 2.95. This is then an acceptably low number.

Based on the actual N_{kT} values predicted, the shear strength values have been determined based on equation no (1), and the data have been compared to the measured values from the datasets of the training data as shown in Figure 8.

Again it is seen from the figure that the trained EBBP model predicts the undrained shear strength reliably over the whole strength range, and to a far better accuracy than just if the average N_{kT} value was used.

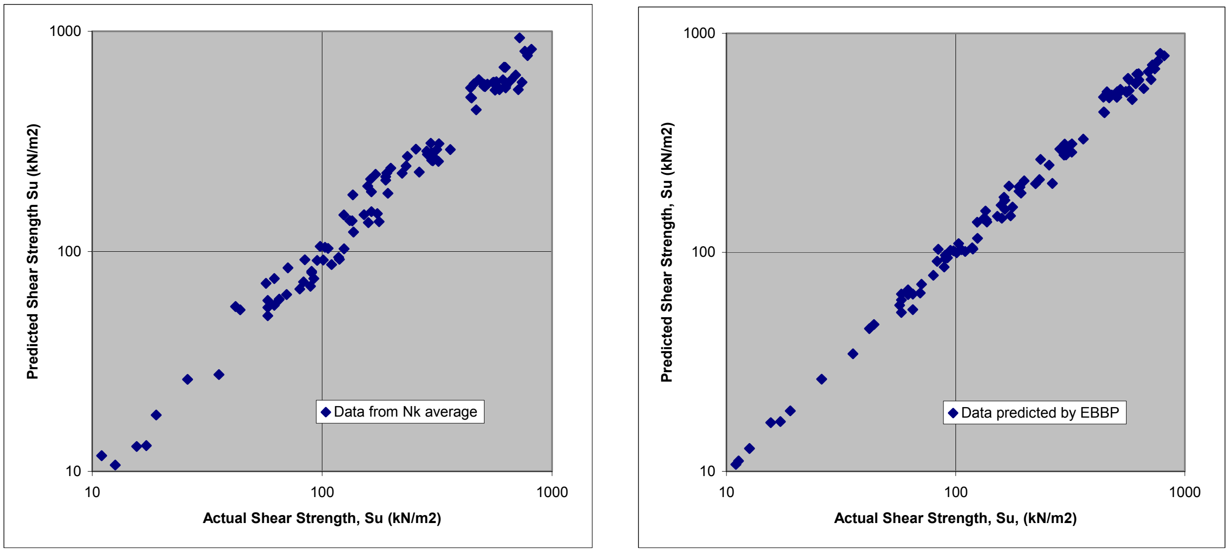


Figure 8 Actual versus predicted Su based on average N_{kT} and from EBBP

The connectivity weights in the learned model and associated to each input parameters reveal their relative importance in influencing the output value. This feature is called automatic relevance determination (ARD). The heavier the ARD the higher is the influence. Figure 9 below shows that all parameters included have important influence in the network model. This fact is rather surprising, and will unfortunately make it difficult to acquire a physical understanding of the learned relations. Also, it may surprisingly be observed that the parameter that has least importance is the pore pressure response B_q. This parameter is among the ones that have been given most importance in empirical relations in the literature.

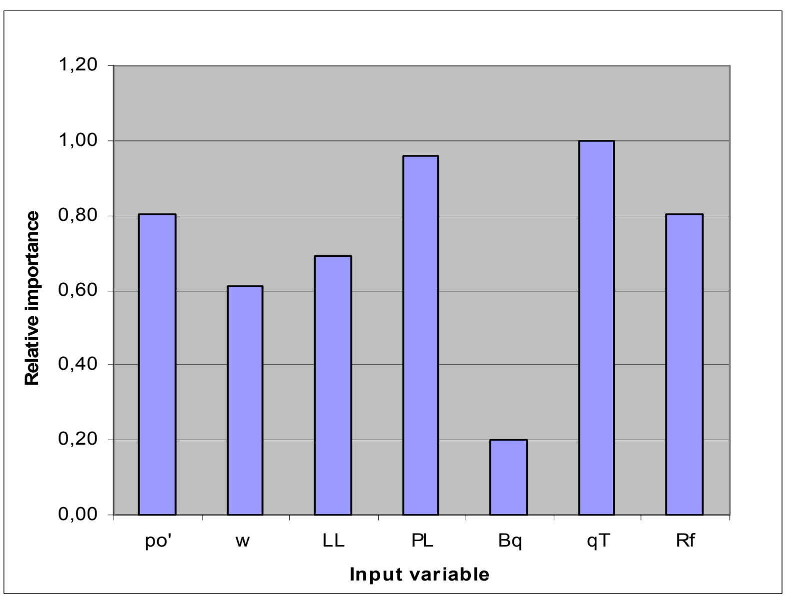


Figure 9 Relative importance of input variables in EBBP model

5 PARAMETRIC STUDIES

Another advantage with EBBP learning is that the every prediction made by the model is associated with standard deviation or error bar based on the data density and inherent error of the input data. This means that the lower the standard deviation, the higher the confidence level for the prediction. This feature is particularly useful when a parametric study is carried out because it tells us the reliability of a relationship interpreted by the EBBP model. In the following, a parametric study of the learned relationship is carried out. However, predictions giving a standard deviation to prediction ratio of higher than 0.25, have been disregarded as non reliable. This situation will occur for many combinations of variables, primarily due to low data density in some areas. Due to this, the correlations is seen to be discontinuous over some ranges of variables

In the following is given a series of figures where the N_{kT} factor is plotted versus the total cone resistance as the main variable, while one other variable is varied, and the 5 remaining variables are kept constant equal to the average value as included in the database.

Note however also that there is a physical minimum limitation in the ratio between q_T and p_o' that will occur for normally consolidated clays. This ratio is found to be around 2.5 for the records in this database. Consequently, when the effective stress p_o' is kept constant of 600 kPa, q_T values of less than 1.5 MPa is not relevant, even though these data points have been plotted.

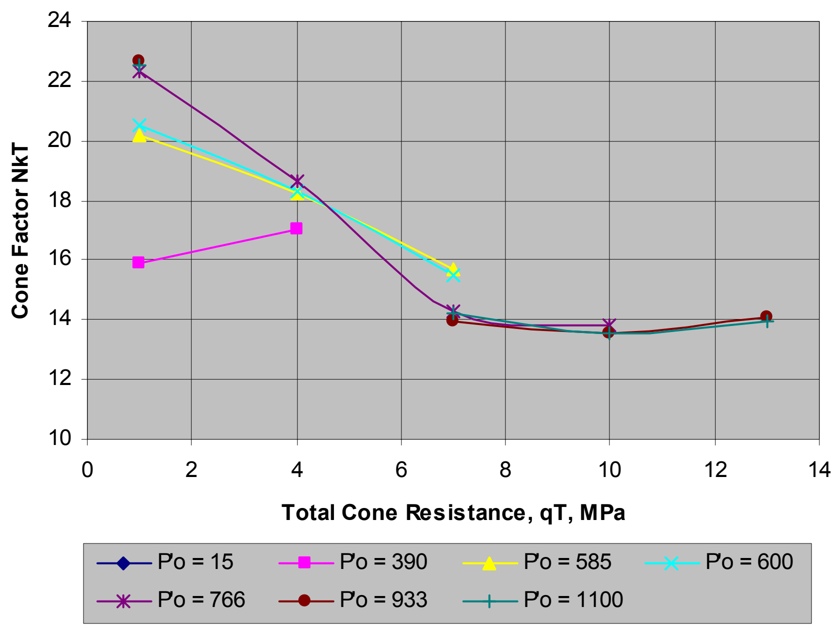


Figure 10 Learned correlation between N_{kT}, q_T, and p_o'

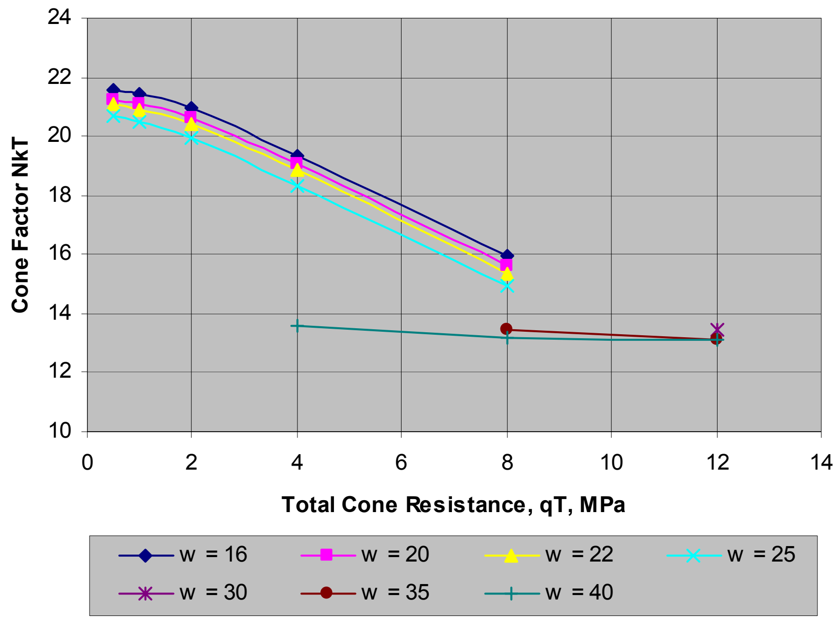


Figure 11 Learned correlation between N_{kT}, q_T, and w

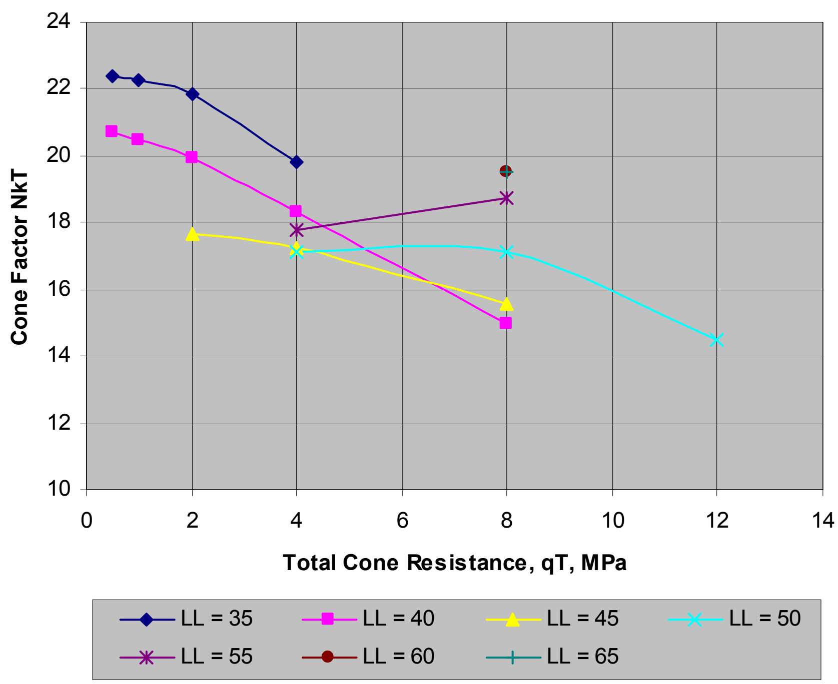


Figure 12 Learned correlation between N_{kT}, q_T, and LL

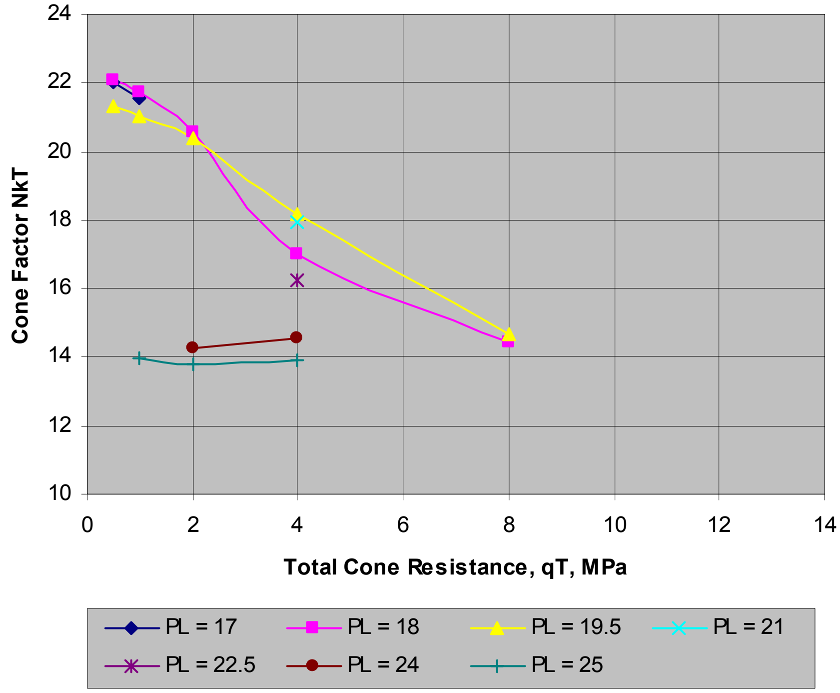


Figure 13 Learned correlation between N_{kT}, q_T, and PL

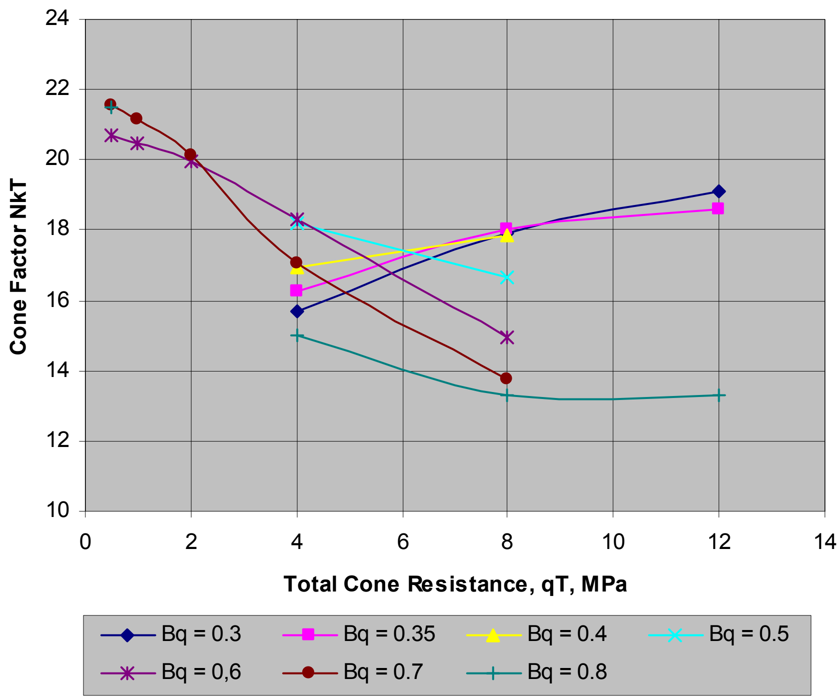


Figure 14 Learned correlation between N_{kT}, q_T, and Bq

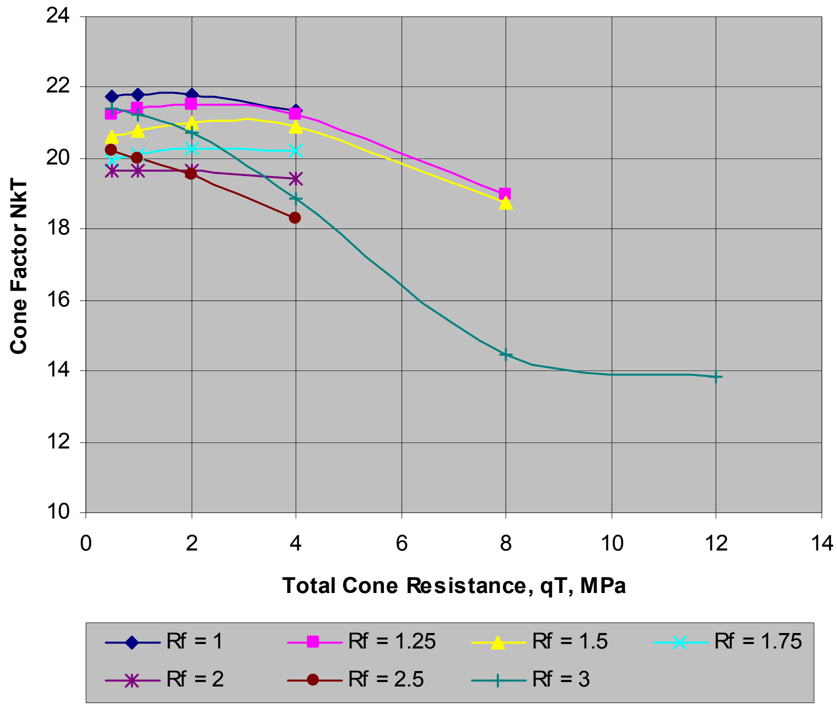


Figure 15 Learned correlation between N_{kT}, q_T, PL and Rf

As seen, the relations are rather complex and not purely logic, but the following trends may be observed:

- There is a clear and consistent trend of falling N_{kT} value with increasing clay strength as measured by the total cone resistance, q_T.
- The NkT value seems to drop with increased effective overburden, but the trend is not consistent.
- The NkT shows a slight drop with increasing water content.
- The NkT value seems to drop with increasing Liquid Limit, but again the trend is not consistent.
- The NkT value seems also to drop with increasing Plastic Limit.
- The NkT value shows a slight reduction with increased friction ratio.

6 CLOSING REMARKS

Use of artificial intelligence like neural network has been proven to be a very efficient tool to establish and explore correlations between various interrelated parameters in a multivariate space. The overall prediction of the cone resistance number, N_{kT}, were found to be done with a mean square error of less than 2. Compared to an average N_{kT} value of 17 to 18, this must be regarded as very accurate.

The predicted N_{kT} value were found to be dependant on a set of variable, but unfortunately, none of these variables can be said to have significant importance over the others. This has made the parametric evaluation of the relative importance far more complicated than expected. However, even though complex relations have been documented, a clear and distinct trend of falling NkT value with increasing cone resistance has been documented.

Considering that a large number of data has been included in the database explored, and that these are assembled from various offshore sites far from each other, the conclusion that the relations are complex and non-obvious, is regarded as an important finding with high reliability. This contradicts many previous empirical correlations that have been published.

It must also be noted that in a multivariate space of many variables, there will exist many local extremes producing low errors between input and output. The search for those is efficiently performed by the EBBP model, but there may still be other extremes not identified, that may give other inter-relations than those included in this report. The likelihood of such existence is larger for systems were many variables are found to have significant importance. The rather complex relations between the variables are a result of the fact that these are found to be of close to equally important.

This project has also demonstrated the general power of back propagating neural networks in the search for correlations within geotechnical engineering. Since the nature of this science is and must be highly empirical, the use of such a tool should be generally promoted. The fact that this project is the first of it's kind to be published in Norway, may be seen as a first step in this direction.

7 ACKNOWLEDGEMENTS

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