# DATA MINING IN FIELD TESTING OF SOIL: NEURAL NETWORKS APPLIED TO RCPTU INTERPRETATION

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## Context of the Study

Field testing of soil is a thriving branch of geomechanics, widely present in both scientific research and practical applications. The problem of measuring certain quantities in the natural environment and translating them into specific information about the granular material is far from trivial. Even the basic question of recognising the type of soil and its spatial location with a satisfying degree of probability remains largely unanswered.

Quick clay is a peculiar glacial marine sediment native to some parts of the Northern Hemisphere (Scandinavia, North America, Siberia) which, while being fairly resistant to loading, is prone to rapid liquefaction once disturbed [6, 7]. Due to several catastrophic events related to failure in quick clay deposits [1], a lot of work is being done to detect areas where quick clays may be found, e.g. the "Mapping of Quick Clay" project by the Swedish Geotechnical Institute [4].

One common method of soil field investigation involves Undrained Cone Penetration Tests (CPTU), where a probe continuously measures three basic parameters while being statically pushed into the soil: cone resistance $q_c\,[Pa]$, sleeve friction $f_s\,[Pa]$ and pore water pressure $u\,[Pa]$. CPTU can be enhanced with additional sensors to measure a fourth quantity: electrical resistivity of soil $R\,[\Omega m]$ (hence RCPTU) – an important parameter for marine sediments [2].

In a single RCPTU test, these four parameters are measured at each depth, up to several dozen meters deep. At each given level, the values of the measured parameters combined together can be used to establish the soil type and its mechanical properties. Such a large quantity of data is difficult to analyze by hand. Until recently, analysis of CPTU tests was mainly based on the experience of researchers supported with classification charts [3, 5], necessarily complemented with physical testing of soil samples collected from certain depths. In this study, a different approach was chosen – to use a data mining technique, namely artificial neural networks [8], to train automata to recognise quick clay layers in RCPTU and CPTU tests. Due to a rigorous training and testing protocol, as well as high quality of the input datasets, this approach proved to be successful.

## Scope of the Study

Three tests sites around Trondheim, Norway were investigated with RCPTU and CPTU probings, as well as traditional drilling and laboratory testing. The results of the laboratory tests were treated as a benchmark, and the RCPTU sounding data from each test site were used to train several generations of neural networks. The trained networks were subsequently tested against each other with an objective to correctly classify soil profiles from sites which had not been used in their training. Some of the networks proved to be more flexible than others, managing to properly recognise soils in each of the three test sites.

In the final phase of the study, the well trained and tested neural networks were applied to a real-case scenario: an imperfect CPTU database with no additional information from laboratory testing. The performance of the neural networks was assessed against the classical approaches incorporating classification charts. The neural networks turned out to be at least on a par with the classical approaches, but also surpassing them in some respects. It is an integral result of neural network operation that the network's performance in a given task, in this case recognising quick clay, is expressed in percentages of certainty. The shapes of these certainty curves give additional insight into the soil structure. The neural networks also skillfully captured transitional zones between different soil types, which are of high importance but are often disregarded in the classical approaches.

## Summary of the Study

Data mining techniques are more and more often used in many fields of research. Their great versatility makes it possible to use them in almost any problem with significant amounts of data. But at the same time, without a thought-out course of investigation and with no scientific rigour, the results obtained might be worthless. In this paper, we present a simple, yet extensive, protocol of training, testing and applying neural networks, which assures high quality of the findings. A similar approach can be followed in other problems, using different computational software or data mining techniques.

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