Proceedings of the 16th International Conference on Soil Mechanics and Geotechnical Engineering

doi:10.3233/978-1-61499-656-9-1067

Three examples of using artificial neural networks in geotechnical engineering

Trois exemples d'utilisation de réseaux neuronaux artificiels en géotechnique

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ABSTRACT
The application of artificial neural networks to geotechnical engineering gives new opportunities to learn from experience and to increase efficiency. This is shown by three examples. In the first example the automatic derivation of improved correlations between parameters of different models is shown. In the second example information from poor field data is extracted, resulting in a reliable prediction when combined with basic expert knowledge. The third example shows how artificial neural networks can be used to improve design and to enable new applications.

RÉSUMÉ
L'application des réseaux neuronaux artificiels (RNA) à la géotechnique donne de nouvelles opportunités pour apprendre à force d'expérience et augmenter l'efficacité. Ceci est illustré par trois exemples. Dans le premier exemple, la dérivation automatique des corrélations améliorées entre les paramètres de différents modèles est présentée. Dans le second exemple, l'information est extraite depuis des champs de données pauvres, ayant comme résultat une prédiction fiable lorsque combinée à une expertise de base. Le troisième exemple illustre comment les RNA peuvent être utilisés pout améliorer la conception et permettre de nouvelles applications.

1 INTRODUCTION

Learning from observations or observed behavior is essential in gaining scientific knowledge, and geotechnical engineering is no different. The observations concerned can be the results of an experiment (either in the field or in the laboratory) or the behaviour of a geotechnical construction. The traditional manner of learning from observations is to try to understand every element of the problem, simplify it by leaving out minor details and to describe it in formulas or numerical models. This makes learning from observations difficult, expensive and time-consuming. This article discusses the use of artificial neural networks (ANNs) to quickly gain knowledge from data by directly using observations, without trying to fully describe the underlying mechanisms.

Three applications of ANNs in the field of geotechnical engineering are discussed, showing the versatility of this technique.

2 ARTIFICIAL NEURAL NETWORKS

First, a brief introduction into the theory of neural networks will be given. A complete discussion on artificial neural networks is beyond the scope of this paper but can be found in Bishop (1995).

Artificial neural networks (ANNs) were developed in the Artificial Intelligence community to simulate the learning abilities of the human brain. By now, the technique has proven to be very useful in other scientific disciplines as well and nowadays it is used in many complex multi-dimensional regression and classification applications.

ANNs are constructed from interconnected 'neurons' or 'nodes'. In each node a numerical transformation is applied to all the input values, then the results are summed thus creating a new output value. The number of nodes, the numerical transformation and the topology of the interconnections define the problem solving capabilities of the ANN. A schematic visualization of a common topology, viz. that of a feed forward backpropagation ANN, is displayed in Fig. 1.

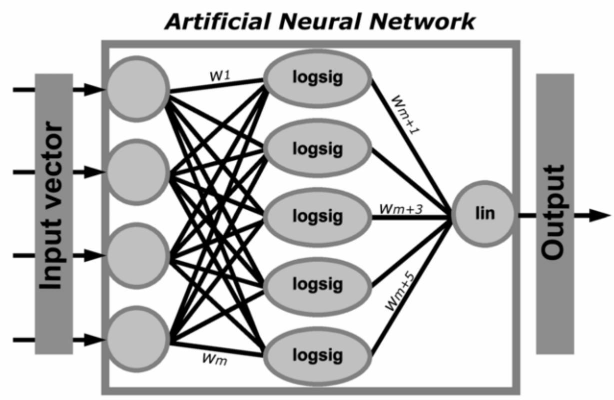

Figure 1. Schematic visualization of a feed forward backpropagation artificial neural network with nonlinear transfer functions in the hidden layer and a linear transfer function in the output layer. By modifying the weights **w** on the connections between the neurons, the network can 'learn' to solve the problem.

ANNs are capable of learning from examples or observations in various ways. For the type of applications described in this paper, feed forward backpropagation neural networks are quite suitable, see e.g. Bishop (1995) or Sarle (2002). McKay (1992) describes learning in these networks as finding 'a set of connections **w** which gives a mapping which fits the training set well, i.e. has small error.' For learning, a set of examples of input and corresponding output are presented to the network. The network will make a prediction of the output for these examples. The errors of these predictions are used to change the weights **w**.

The dataset used in training is often divided in two parts, the training set and the test set. The training set is used to change and improve the network weights as described before. The data in the test set is not directly used in learning, but is used to evaluate how well the network performs on new data. Neural networks can be trained to approximate arbitrarily complex functions, so the test set is required to check the performance of the network.

3 CONVERSION OF MODEL PARAMETERS

The first example is related to the conversion of model parameters of two distinct settlement prediction models.

In the Netherlands, most settlement predictions are carried out using the Koppejan model. This model combines the theory of Terzaghi (1925) for one-dimensional consolidation and the theory of Keverling Buisman (1940) for creep deformation. The basic equation reads:

$$S_t = h\left(\frac{1}{C_p'} + \frac{1}{C_s'}\log\left(\frac{t}{t_0}\right)\right)\ln\left(\frac{p+\delta p}{p}\right) \tag{1}$$

where S_t is the settlement after time t, h is the thickness of the soil layer, C_p' is the primary settlement constant for virgin compression, C_s' is the creep constant for virgin compression, t_0 is the reference time (usually one day), p is the vertical stress in the middle of the layer and δp is the increment of the vertical stress. The model distinguishes between soil behaviour below and above the limit stress, resulting in four model parameters: Cp, Cp', Cs and Cs'. These parameters can be determined from a normal oedometer test.

Major drawbacks of this model are the stress-dependency of the four model parameters, resulting in significant errors at large strains, the overestimation of the creep component in case of multiple load steps and the fact that unloading steps cannot be modelled properly. However, a major advantage of the model is the wide experience with the model within the area of application – with errors up to 30% (and quite often even much more).

A more recent model is the a,b,c-isotache model by Den Haan (1994). Major improvements of this model, compared to the Koppejan model, are the use of natural strain instead of linear strain, the use of intrinsic time instead of an arbitrary reference time, allowing for accurate modelling of loading and unloading, and stress-independency of the model parameters, which still can be determined from an oedometer test. According to this model, the direct strain and the creep strain are given by:

$$\varepsilon_d = a\ln\left(\frac{\sigma_v'}{\sigma_{v0}'}\right) \tag{2}$$

$$\varepsilon_s = (b-a)\ln(\sigma'_v/\sigma'_{v0}) + c\ln(\tau/\tau_0) \tag{3}$$

where ε_d is the strain due to direct compression, ε_s is the strain due to creep, σ_v' is the vertical effective stress, σ_{v0}' is the initial vertical effective stress, τ is the intrinsic time, τ_0 is the initial intrinsic time, and a, b and c are model parameters related to respectively unloading/reloading, virgin loading and creep.

The application of the isotache model has much been hindered by the dominant position of the Koppejan-model. Engineers from daily practice are much more used to the old model and from past experience they often know which parameter values are suitable for a given situation, which is a clear advantage when no laboratory testing has been done yet, or to detect gross errors in laboratory test results. For obtaining accurate settlement predictions, this situation is of course less preferable.

To stimulate the use of the new model, an ANN was trained to convert model parameters from the Koppejan model to the a,b,c-isotache model. This will aid geotechnical engineers who are traditionally reluctant to give up their practical knowledge with the Koppejan model parameters to use this new model more easily.

To find a mapping for Koppejan parameters into a, b and c use was made of a database of 572 oedometer test results, from which both parameter sets were determined. For all tests the saturated volumetric weight γ_w was available as well. This parameter is intuitively expected to be correlated with the model parameters of any settlement model.

To show the possibilities of ANNs, both a neural network approach and a traditional regression approach have been followed in the analysis. Further details are given in Maccabiani (2004).

A traditional two-dimensional regression analysis was carried out to translate the Koppejan parameters for virgin compression into the a,b,c-isotache parameters. Given the differences between both settlement models it is quite probable that the data set is noisy, mainly because of the stress-dependency of the Koppejan parameters. A summary of the best correlations for each parameter is given in Table 1.

Table 1: Performance of traditional regression analysis and ANNs for conversion of settlement model parameters.

Relationship	95% range*	median error	st. dev. error
$a=-0.013*(\gamma_w/9.81)+0.041$	0.0173-0.0275	0.011	0.031
a=b/6.4271	0.0055-0.0478	0.013	0.031
ANN (22 hidden nodes)	0.0108-0.0701	0.012	0.024
$b=1.63*C_p'^{-1.096}$	0.0351-0.3073	0.011	0.036
$b=-0.345*(\gamma_w/9.81)+0.66$	0.0400-0.3000	0.021	0.050
ANN (1 hidden node)	0.0400-0.3107	0.010	0.032
$c=0.28*C_s'^{-0.99}$	0.0013-0.0222	0.0023	0.0047
$c=0.0163*(\gamma_w/9.81)^{-2.85}$	0.0031-0.0152	0.0023	0.0048
c=0.071*b-0.002	0.0004-0.0197	0.0016	0.0052
ANN (7 hidden nodes)	0.0011-0.0226	0.0013	0.0031

* 95% range of a,b,c-parameters. In the original dataset for a 0.0041-0.0921, for b 0.0301-0.3375 and for c 0.0014-0.0207 are found.

From Table 1 it can be seen how noisy this problem actually is: with traditional regression analysis only parameter b can be estimated (from Cp') with an acceptable level of accuracy. For the other parameters, the medians of the errors of the other correlations are in the same order of magnitude as the parameters themselves. The relationships reported in the table only fit the data well after manual removal of about 15 outliers, which were clearly off the trend.

It will be clear that the results from the traditional regression analysis are not very accurate. Furthermore, finding them and testing them against other possible correlations was rather labour-intensive.

In the neural network approach, a more automated procedure was followed to search for a good correlation between these settlement parameters. Basically, it was attempted to find a mapping between C_p',C_s' and γ_w on the one hand and a, b and c on the other hand. Therefore the data set was split in two parts. Randomly, 66 sample cases were chosen from the data set to form the neural network test set. The other 506 samples formed the neural network training set. Given enough degrees of freedom, neural networks can approximate an arbitrarily complex function. The purpose of the test set is to ensure that the neural network model has good generalizing properties and does not just fit the sample data with an unrealistically complex model.

Methods to *a priori* find the optimum number of nodes in the hidden layer have yet to be developed. A routine was written to automatically train different neural networks with 1 to 30 nodes in the hidden layer. The networks were trained using a Bayesian regularization learning algorithm. (McKay, 1992) For each output variable a, b and c the network with the lowest median absolute error in the test set was saved. This process took a few hours on a standard desktop PC and ran fully unsupervised. The topology and the performance of the best networks are given in Table 1.

As can be seen from this table, the prediction accuracy of the neural networks is generally better than that of the traditional regression analyses. In fact, the median values of the prediction errors for parameters b and c and the standard deviations of the errors for all parameters are lower than those of the correlations found by traditional methods. This shows that there is a significant amount of information in the combined input parameters. The outliers mentioned before were not removed from the data set used to train and test the neural networks, which gives an indication of the robustness of neural networks for noisy data.

Using the trained ANN it is easy to draw nomograms. These can be very informative and can show the relationships between the input parameters and output parameter as found for this data set by the neural network. As an example, a nomogram of Cs' versus c, for a value of γ_w of 13 kN/m3 and various values of C_p' is shown in Fig. 2. The unrealistic positive slope for the C_p'=10-line for higher values of C_s' is likely to be caused by a limited amount of training cases in this region of the data space.

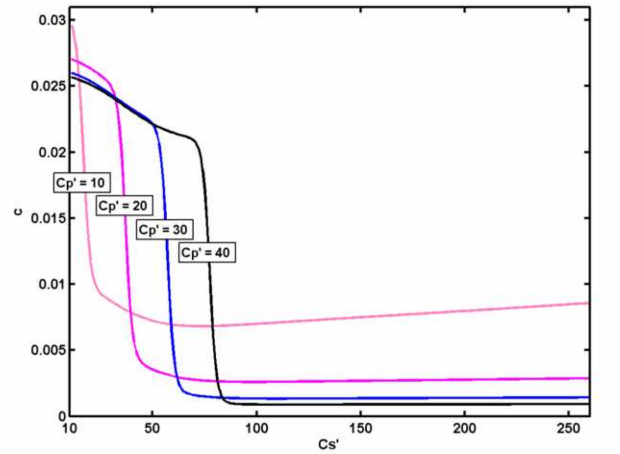

Figure 2. Nomogram of C_s' versus c for different values of C_p' and a constant γ_w of 13 kN/m^3.

4 SAFETY CLASSIFICATION OF DIKES

The second example of the application of ANNs is related to extracting knowledge from sparse historical data.

Fifty years after the 1953 flood disaster which killed 1836 people in the South-Western part of the Netherlands, the question arose whether such a disaster could happen again. Apart from the analyses applying proven techniques, a pilot study using an ANN was started. This pilot study was aimed at investigating whether the available historical data contained relevant information to determine the actual strength of the present dikes, investigating the potential use of an ANN in this respect, and to determine whether the results confirm the idea that the safety of the present dikes in the Eastern Scheldt estuary, which can be closed by a storm surge barrier, is indeed sufficient.

The 1953 storm surge destroyed 47 km of dikes and damaged another 140 km. Although the storm came from the North-west, most of the damage occurred on the South side of the flooded islands, where the dikes were traditionally lower – until this disaster, the Dutch dikes had been 'designed' on the basis of the highest known flood level. Quickly after the storm, much stronger dikes were built, as indicated in Fig. 3. This indicative sketch is also valid along the Eastern Scheldt, although the design conditions for a flood with a probability of 1:4000 per year are comparable to the 1953 flood conditions because of the storm surge barrier which was completed in 1986.

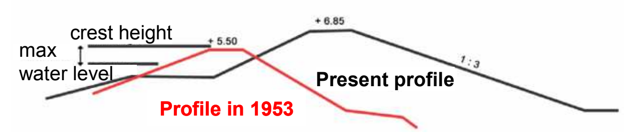

Figure 3. Indicative cross-section of the dikes in the South-Western part of the Netherlands, both in 1953 and at present.

After a thorough analysis of the failed and damaged dikes in the 1950s, it was finally concluded from all observations that in general failure had occurred as a result of wave overtopping and the subsequent weakening of the inner slope (Rijkswaterstaat, 1961). The dikes mainly consisted of sandy clay with little cohesion and a relatively steep slope: between 1:1.5 and 1:2 (vertical:horizontal).

For the present analysis, a total of 90 dikes have been investigated using information from archives. As input parameters the orientation of the dike relative to the wind direction, the height of the crest above the maximum water level, the steepness of the inner slope and the height of the crest above the polder level were used. Data on wave action appeared to be missing almost completely, in spite of the conclusions of the aforementioned analysis. No effort has been made to reconstruct wave data. The degree of damage was chosen as the (single) output parameter. From a traditional analysis no clear distinction can be made between failure and non-failure: in any 2D-graph with two of the input parameters against each other, the data points mix very well. Moreover, the amount of data is rather limited.

The neural network has been trained with 70 cases. The performance has been checked with the remaining 20 cases. In 85% of these cases, the correct output was predicted by the network. In all 20 test cases, the predicted probability of failure varied between 15 and 85 percent. In 8 cases, including the 3 cases which were predicted wrongly, a probability of failure between 40 and 60 percent was predicted. Given the amount and the quality of the data the performance of the ANN can be considered to be good. However, it should also be clear that an ANN is not a panacea.

So far, only true observations from practice have been included. A significant improvement of the results can be achieved by adding expert knowledge. The historical cases have been supplemented with 5 synthetic cases without slope failure for situations with a crest level equal to the polder level (i.e. no slope) and 5 synthetic cases without failure due to wave overtopping with a crest level 10 m higher than the waterlevel.

With this 'expert knowledge', a new analysis has been made for both the situation in 1953 and the present situation along the Eastern Scheldt. The results are depicted in Fig. 4. For the present dikes, it is for at least 70% certain that the current dikes along the Eastern Scheldt are safe for failure of the inner slope due to overtopping of waves during a reoccurrence of the 1953 storm conditions. Details are given in Maccabiani et al. (2003).

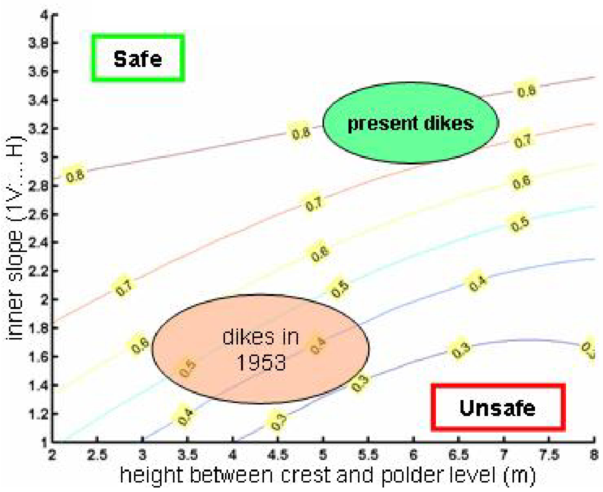

Figure 4. Probability of safety for the dikes along the Eastern Scheldt for the 1953 storm surge conditions.

5 SLOPE STABILITY ANALYSIS

The third example shows the possible use of the speed and model approximation capabilities of neural networks.

In the Netherlands, embankments are of vital importance to protect 60% of the country from flooding. It is enforced by law that the safety of every embankment is evaluated every five years. This requires a significant number of stability calculations, but because the modelling process is time-consuming only a few calculations are made for each embankment, usually considering a worst case scenario in which the most unfavourable subsoil conditions are combined with the most critical geometry on a certain stretch. Essentially, this is an efficiency problem.

This efficiency problem becomes even more pronounced with the design of improvement works for embankments which no longer meet the standards. Ideally, several alternatives need to be checked to find an optimum between construction costs, land use and demolition costs in residential areas. On top of that the stability calculations appear to be rather subjective. Even between experienced geotechnical engineers differences of more than 10% in Bishop's stability factor (Bishop, 1955) have been found for the same case, based on the same subsurface data (Koelewijn, 2002).

An investigation for a faster and more objective slope stability assessment led to a solution where a neural network predicts Bishop's stability factor with 50 input parameters. Seven parameters are used to describe the surface geometry, eight parameters are used to describe the (ground)water conditions and 35 parameters are used to indicate for the upper 20 m of the subsoil below the dike and the upper 15 m behind the dike whether it consists of sand, clay or peat.

The neural network has been trained on 6000 synthetic cases which were created at random for the parameter range as found in practice. The network has been tested with about 3500 cases created similarly, with a median absolute error of a little below 10% in the prediction of Bishop's stability factor. The network was validated with 135 cases taken from daily practice. More details can be found in Maccabiani & Koelewijn (2004).

Because of the high speed and ease with which automation is possible, scenario studies or sensitivity analyses become a trivial task. Once the input data is properly prepared about 5000 calculations can be done in a second on an ordinary desktop PC. With these speeds an early-warning system for flood control that incorporates the strength of dikes becomes feasible, since the strength of the dikes can be assessed for any (expected change in) water level in real-time.

This network has already been used in a real-world application to optimize the design of dike improvements at three different locations. At these locations, the size of the berm on the inner slope had to be increased. With the neural network for each location a nomogram as shown in Fig. 5 could be drawn within seconds and the optimal solution could be determined easily.

At present an improved version of this network is being used to determine safe margins for building activities in the vicinity of 60 km of dikes protecting 150,000 people near Rotterdam. With the neural network, a detailed analysis is possible – otherwise, this would have been too expensive.

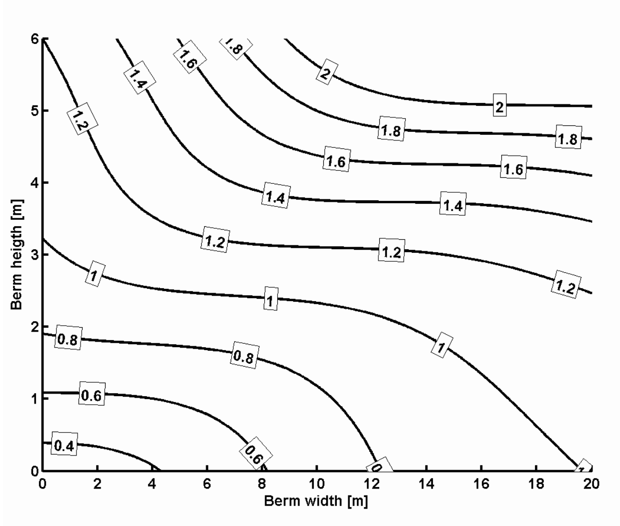

Figure 5. Contour plot of Bishop's safety factor for different values of berm width and berm height. The present situation and three alternatives to arrive at a safety factor of 1.2 are indicated.

6 CONCLUSIONS

The three examples show that the use of artificial neural networks in the field of geotechnical engineering open new possibilities in comparison with the methods which are traditionally used.

The first example shows that better correlations between parameters of different models can be found using an ANN. It is perhaps even more important that these correlations were derived in a fully automated and unsupervised manner. This renders the derivation of correlations in general much more worthwhile. It opens the door to the application of ANNs for highly automated tasks in geotechnical engineering.

The second example shows the possibilities to use ANNs to learn from experience from the past – even if this is not well documented and information on the most important parameters is missing (in this case: subsoil properties and information on the wave conditions). It also indicated the advantages of combining an ANN with expert knowledge.

The third example (again) shows the tremendous increase in efficiency which may be possible using ANNs, without loss of accuracy.

In general, the properties of artificial neural networks are such that several existing tools in geotechnical engineering can be improved dramatically and new applications become viable. The possibility to constantly improve the performance by directly incorporating experience and the enormous calculation speed of a trained network for new cases contribute most to this.

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