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Use of neural networks to predict pile drivability

Utilisation de réseaux neuronaux pour prédire la maniabilité du pieu

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ABSTRACT: At a solar farm site in Australia, piles were installed to support photovoltaic panels across a 200ha area. The original construction methodology assumed piles could be directly driven, however when construction commenced variable ground conditions meant that shallow pile refusal frequently occured. Whilst relationships could be readily identified between driveability and soil strength at specific borehole locations, attempts to extrapolate these predictions across the site via conventional means proved unreliable, and pre-drilling was implemented as a remedial measure at significant budget and time impact to the project. Using commercially available software (NeuralTools 7.5 by Palisade) a neural network was developed to analyse data from the site, allowing for consideration of highly non-linear parameters to predict driveability. Data from early phases of pile installation, along with additional test piles installed adjacent to boreholes was used to train and test a neural network, which was subsequently used to predict zones of likely driveability elsewhere across the site. The neural network predictions were implemented in selected areas of the site, with over 8,000 piles successfully driven. The improved reliability of driving predictions using this method resulted in significant monetary and program benefits by minimising the amount of pre-drilling required. The neural network methodology, whilst computing-power intensive, was demonstrated to be a useful tool in completing a complex multi-variable assessment of driveability.

RÉSUMÉ: Sur un site de ferme solaire en Australie, pieux ont été installées pour supporter des panneaux photovoltaïques sur une surface de 200 hectares. La méthodologie de construction originale supposait que les pieux pouvaient être directement entraînés, mais lorsque la construction commençait, des conditions de sol variables signifiaient que le refus des pieux peu profonds se produisait fréquemment. Bien que les relations entre la maniabilité et la résistance du sol puissent être facilement identifiées sur des sites de forage spécifiques, les tentatives d'extrapolation de ces prévisions sur le site par des moyens conventionnels se sont avérées peu probables. En utilisant un logiciel disponible dans le commerce (NeuralTools 7.5 by Palisade), un réseau neuronal a été développé pour analyser les données du site, ce qui permet de prendre en compte des paramètres hautement non linéaires pour prédire la maniabilité. Les données provenant des premières phases de l'installation des pieux, ainsi que des pieux d'essai supplémentaires installés à proximité des forages, ont été utilisées pour former et tester un réseau neuronal, qui a ensuite été utilisé pour prédire des zones de conduite probables ailleurs sur le site. Les prédictions du réseau neuronal ont été mises en œuvre dans des zones sélectionnées du site, avec plus de 8 000 piles pilotées avec succès. L'amélioration de la fiabilité des prévisions de conduite grâce à cette méthode a permis d'obtenir d'importants avantages monétaires et de programme en minimisant la quantité de pré-forage nécessaire. La méthodologie des réseaux neuronaux, bien que le calcul intensif en énergie, s'est avéré être un outil utile pour mener à bien une évaluation complexe de la capacité de conduite à plusieurs variables.

Keywords: neural networks, pile driving, reliability, renewable energy

1 INTRODUCTION

Installation of driven piles for a solar farm in late 2017 / early 2018 encountered significant construction delays and difficulties when extensive and unexpected shallow refusal of piles occured across the site. A review of ground conditions failed to provide a sufficiently accurate prediction of zones of likely refusal, with pile driveability variable over a scale of metres, compared with borehole information spaced at over 150 m centres. Pile driving hammers and data collected on site was not considered suitable for conventional analysis techniques such as *GRLWEAP*. This paper describes the development and application of an *Artificial Neural Network (ANN)* using available data during construction to overcome this issue and provide a more reliable means of predicting zones of potential driveability across the site.

2 PROJECT DESCRIPTION

2.1 Site description

The site comprises a 200 ha area located near the city of Townsville, in the state of Queensland, Australia. The project comprised the installation of over 60,000 piles to support photovoltaic solar panels, intended to produce up to 148 MW of electricity.

The site was formerly a mango plantation, and was characterised by approximately 50 boreholes drilled to approximately 6 m in depth, with Standard Penetration Testing (SPT) at 1.5 m depth intervals and Dynamic Cone Penetrometer (DCP) testing adjacent to most boreholes. Laboratory testing comprised simple index testing and a limited number of Unconsolidated Undrained triaxial tests. Typically two SPT N values were available in the top 3 m of the soil profile, of interest to the pile installation.

Ground conditions at the site typically comprised alluvial deposits of very stiff to hard silty and sandy clay. In approximately 1/3 of test locations, this material was underlain by medium dense to dense silty and clayey sands from 2 to 3m below ground surface level. At other locations, the very stiff to hard clays persisted to the depth of the borehole. Below 2m in depth, the material was locally cemented in places. The depth and strength of cementation varied between boreholes, without a predictable pattern.

2.2 Piling details

Piles comprised 150 mm steel „H“ piles, installed to target embedments of between 2.3 m to 2.6 m below ground level. Piles were driven using an accelerated driving hammer (Vermeer PD10), emparting nominally 1.3kJ of driving energy. These hammers have a rapid hammer rate of up to 1000 blows per minute and therefore driving was measured by drive time rather than blow count. The actual efficiency of the six hammers used on site was also unknown and the specific hammer details were absent from the *GRLWEAP* database, meaning conventional wave analysis was not possible.

Where piles could not be directly driven, they were installed in a pre-bored hole which was backfilled with stabilised sand. The cost of this pre-boring a pile was in the order of $75 per pile, compared with $40 for a directly driven pile. If pile driving was attempted, but failed, the pile had to be extracted and a pre-bored pile installed. The added cost of this extraction process meant that costs of a failure to drive a pile was considerably more than the aggregate of a driven and a pre-bored pile ($115). Project preferences were to directly drive as many piles as possible. On commencement of construction however, it was found that directly driving piles was unreliable with considerable variability of driving performance occuring for piles only a few metres apart. It was difficult to reliably predict this variability based on ground conditions alone

given that boreholes were spaced at more than 150 m.

Figure 1. Example of variable driven pile length.

Figure 1 gives an indication of the variability of site conditions. The figure shows the variability of finished stick up heights of directly driven piles of between 1.2 m to 2.2 m in close proximity to each other.

As a consequence of this inherit variability and difficulty to predict pile driving performance a decision was made to reset the project baseline from all-driving to all preboring. Thus, any piles which could subsequently be driven were considered to be a saving, rather than business-as-usual, which is important to understand when evaluating the success of the ANN methodology.

3 WHAT IS AN ARTIFICIAL NEURAL NETWORK?

An artificial neural network (ANN) is a computing algorithm which attempts to imitate the way in which the human brain analyses and learns patterns in data to predict outcomes (Rafiq et al, 2003), and „like people, learn by example“ (Awodele and Jegede, 2009).

Several authors (for example Jeng et al, 2003, Shahin et al, 2001) have described the application of neural networks to civil engineering applications, which include the predictions of liquefaction potential, seabed instability, pile capacity, settlement of foundations and deflection of retaining walls.

Lazarevska et al (2014) provide a concise description of the basic architecture of an ANN (in the context of a case study on its use in predicting the performance of concrete structures under fire loading). A typical ANN comprises a number of artificial neurons arranged in layers and interconnected: an input layer, an output layer and some number of hidden layers. The input received by each input layer neuron is multiplied by a weighting coefficient, and then aggregated together and processed through an activation function within the hidden neuron layer(s), before finally being presented to the user as a result or prediction via the neurons in the output layer. Figure 2, extracted from Lazarevska et al (2014), illustrates this process schematically.

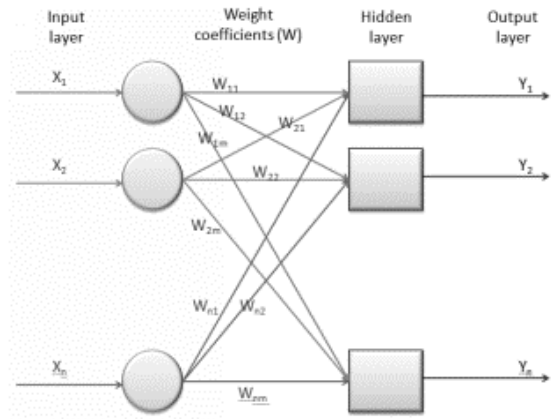

Figure 2. Schematic representation of an ANN (after Lazarevska et al (2014)

Importantly, development of an effective ANN requires the implementation of a *training* phase, where a sample of data with known outcomes is passed through the model, to allow it to *learn*. During this training process, the weight coefficients which relate the neurons to each other are adjusted so as to minimise the error between predictions and known outcomes in the training data set Awodele and Jegede, 2009). Once trained, the model can then be tested against

another known dataset, or used to make predictions for data with unknown outcomes.

Further detailed discussion of how ANN‘s are built and perform is beyond the scope of this paper, but is otherwise described by Rafiq et al (2001), Awodele and Jegede (2009) and others.

4 APPLICATION TO PROJECT SITE

4.1 Selection of site data for model development

At the time of the author‘s intial project involvement, limited data to evaluate pile driveability was available, with relevant production piles concentrated in one part of the site in close proximity to only a few boreholes. As part of a wider redesign and evalation process, installation of test piles was ordered adjacent to 12 boreholes, so that driveability could be compared to borehole data. It was observed that piles could be driven where the uncorrected N value over the top 3.0 m was less than N=42.

Subsequently, at a later project stage, test piles were installed adjacent to a further 11 known borehole locations. Data from these installations yielded similar results.

Whilst an SPT N value of less than 42 appeared indicative of ‘driveable’ conditions, the apparent variability of the ground over smaller distances than the distance between boreholes made predictions away from specific borehole locations difficult. Distance from known borehole locations was therefore an important input parameter to the ANN.

In order to establish and apply the ANN to the site, boreholes where the SPT N value was less than 42 were labelled as “YES” boreholes, and those with SPT N=42 or greater as “NO” boreholes. Following a trial and error process, the following variables were adopted for calibrating the model, considered by the author to provide the ‘best fit’ for the data with as few variables as possible:

- Proximity to nearest borehole;
- Average N value in nearest borehole;
- Maximum N value in nearest borehole;
- Distance to nearest YES borehole;
- Distance to nearest NO borehole.

It is noted that pile driving time may also have been a good indicator of performance, however insufficient good quality data was available for this assessment.

4.2 Software

The ANN was built using proprietary software called *Neural Tools 7.5* (Palisade, 2015), which functions as a plug-in to Microsoft Excel via the *Decision Tools* software suite. Default net configurations (PN/GRN net) and limit on training time (2 hours) were adopted.

4.3 Training

The ANN was *trained* using the results of the initial 12 test piles as well as a selection of a further 81 production piles with good driving and depth of refusal data. Indicative output from the training routine is shown in Figure 3. Whilst limited to “2 hours” trainng time by the software settings, training only took a few seconds.

The training phase suggested that proximty to the nearest „NO“ borehole had the greatest impact on the model‘s result by a significant margin, with the proximity to the nearest „YES“ borehole the next highest. Interestingly, the next most important variable was distance to the nearest borehole, independent of whether this was a YES or NO hole. It is suggested that this is a mathematical fiction arising from the fact that predictions are likely to be more reliable in close proximity to a borehole with known driving characteristics, compared with further away. Obviously then, this variable does not represent an actual phycial property of the ground per se, but rather is more likely a reflection of the

weighting applied internally within the ANN model (Rafiq et al, 2001).

Training	
Number of Cases	93
Training Time	00:00:00
Number of Trials	54
Reason Stopped	Auto-Stopped
% Bad Predictions	1.0753%
Mean Incorrect Probability	2.1436%
Std. Deviation of Incorrect Prob.	9.8626%
Data Set	
Name	Data Set #1
Number of Rows	641
Manual Case Tags	NO
Variable Impact Analysis	
Distance to nearest NO BH	66.4481%
Distance to nearest YES BH	13.9670%
Distance to nearest BH	11.3800%
Nearest BH average N value	5.3107%
Nearest BH max N value	2.8942%

Figure 3. Training phase output

4.4 Testing

The ANN was then *tested* on a further set of 129 production pile results. Results of the testing phase are shown in Figure 4 and Table 1.

Testing	
Number of Cases	129
% Bad Predictions	30.2326%
Mean Incorrect Probability	30.5373%
Std. Deviation of Incorrect Prob.	44.4869%
Data Set	
Name	Testing
Number of Rows	129
Manual Case Tags	NO
Variable Matching	Automatic
Indep. Category Variables Used	None
Indep. Numeric Variables Used	Names from training
Dependent Variable	Category Var. (Driveable?

Figure 4. Testing phase output

Table 1. Testing phase output

Actual classification	Predicted NO	Predicted YES
NO	70	17
YES	22	20

The majority of training piles were production piles located in an area with high rates of refusal, and with proximity to only two boreholes, which is thought to be the reason for the relatively poor correlation of YES predictions. Nevertheless, within the context of the particular project, this was still considered acceptable as the purpose of the model was to select piles to be driven from those where the default option was to pre-bore. Thus incorrectly identifying a pile as undriveble when it might be driveable was not necessarily a concern (and in practice would never be proven, as the piles would have been pre-bored anyway). Incorrectly identifying a pile as driveable (Prediction = YES) but subsequently encountering refusal (Actual = NO) would however add further cost to the project as it would result in an attempted drive, an extraction process and finally a pre-bore and install process, instead of stepping straight to the latter. Thus, of utmost importance in evaluing the ANN data in Table 1 is the 17 piles incorrectly predicted as YES piles when their actual classification was NO, compared with 70 actual NO piles correctly predicted as such. This suggested a nearly 20% chance that a given pile classified as driveable (YES) may actually not be (Actual classification = NO). Put another way, when used as a tool to select piles which might be driveable, the ANN had a predicted failure rate of 1 in 5.

4.5 Prediction and application

The ANN model was used to prepare a map of likely zones of pile driveability, which are shaded black in Figure 5. As the model was developed in parallel with ongoing construction, it was only applied to selected areas predominately to the north and east of the site (top and left of Figure

5), to suit the construction schedule. The areas of predicted driveability were generally centred around borehole locations, reflecting the relatively high weighting of „distance to nearest BH“ as an independant model variable.

The map shown in Figure 5 was used cautiously by the construction team, in light of the relatively high risk of incorrect predictions (1 in 5). Knowing that predictions were likely most reliable towards the centre of the shaded areas (being nearest to a borehole), so far as practical pile driving was commenced towards the centre of these zones, and progressed outwards. Pile driving ceased and pre-boring recommenced as soon as refusal was encountered, in order to minimise extraction and rework costs.

In the areas where the ANN was applied, over 8,000 piles were predicted to be driveable. Of these, fewer than 50 piles refused prematurely. As pile driving ceased as soon as refusal started to occur, reliable statistics on the overall accuracy for predicting actual „NO“ piles were not collected. In some cases, piles were successfully driven in areas beyond those regions of predicted driveability shown in Figure 5, which is not unsurprising given the poor accuracy of predictions related to acutal „YES“ piles. Had more time during the construction process been available, the model could have been updated with results from nearby pile installations, and ‚re-trained‘ accordingly. Nevertheless, the application of the ANN in the manner described resulted in construction savings of over $270,000 AUD compared with the revised baseline costs which assumed that 100% of piles would need to be pre-bored.

5 ASSESSMENT OF TECHNIQUE

5.1 Strengths

As described by Shahin et al (2001), in order to perform a conventional regression analysis, one must first be able to guess the nature of any non-linear relationship between parameters. At the project site, the application of an ANN was able to provide a work-around to the relatively poor understanding of the distribution of hard ground (with N > 42). This meant that valid predictions could be made even without a rigorous understanding of the variability in conditions across the site.

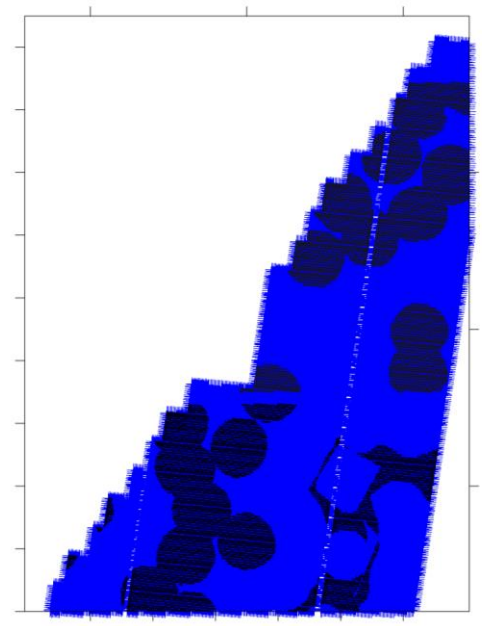

Figure 5. Example testing phase output. Black areas show predicted zones of likely driveability.

Given that available input and „training“ data was limited, the ANN was observed to provide a reasonably good level of accuracy. By contrast, a regression analysis performed on the same dataset, skewed to one part of the site with comparatively few nearby boreholes would likely have resulted in much poorer regression coefficients. The ability to train the model using a limited dataset was considered a significant strength of the approach, consistent with the findings of other authors (for example, Rafiq et al, 2001).

The proprietary software which was used was easy to operate, and the resulting predictions were provided with easy to understand outputs for weighting/influence of variables and likely model accuracy, allowing sense and judgement checks of computed predictions, irrespective of one‘s understanding of the underlying mathematical principles of the ANN methodology itself.

Although not applied in this particular case study site due to the necessary constraints of a live and dynamic project environment, the methodology permits „re-training“ of data sets which can lead to more reliable future outcomes. The ability to do this means that ANN models can be developed progressively over time, with the ability to improve predictions as the model learns patterns in new data.

5.2 Weaknesses

The most significant weakness noted by the author in relation to applying the ANN technique is its „black-box“ approach to data training and prediction of results. As described by other authors (Awondele and Jegede, 2009; Rafiq et al 2001), there is no way of inspecting or scrutinising the underlying equations or mathematical regression used to assess data patterns or determine predictions. Whilst ANN‘s can be useful as demonstrated herein, this weakness limits their application in situations where the model requires significant scrutiny. For example, a 3rd-party review of any such model would be limited to a high-level inspection of training/testing inputs and outputs, rather than a rigorous review of the logic involved in each individual prediction.

The ANN technique was found to be computing-power intensive when applied to this case study. The particular software suite used by the author was limited to 1,000 lines of data per prediction run. Thus, for 60,000 piles, 60 separate analyses had to be run following the training and testing phases, and then compiled into a single database for interpretation and application. It can be reasonably expected that over time these restrictions would diminish as computing power continues to increase.

Finally, and as noted earlier, the technique proved useful where limited data was available and in the absence of easily understood interelationships between independant variables. The model could have been improved if it were possible to obtain data in a more deliberate, methodical manner (rather than relying on available as-built data to train the model). Such a targetted data aquisition program in this instance would have impacted negatively on the project schedule, erasing much of the benefit of applying the technique in the first place. Were more data available in other areas of the site, there is a possibility that conventional regression analyses may also have been more robust. With the benefit of less computational effort and the availability of a interrogable regression equation as output, this may have led to a more favourable project outcome. Nevertheless, within the constrains of available time and data from the project site, the ANN did prove a practical and useful methodology.

6 CONCLUSION

This paper has demonstrated the application of an Artifical Neural Network (ANN) to the prediction of pile driveability at a site with high rates of refusal and difficut to predict variability in driving conditions.

The case study has demonstrated how a relatively small dataset can be used to train and test an ANN which, provided it is applied cautiously, can provide significant cost and program outcomes to a project.

This case study also highlights some limitations of the method, in particular the lack of an interrogable regression equation, and a greater

computing resource required compared to conventional regression. Nevertheless, the model is demonstrated to provide a successful and reliable project outcome.

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