Journal of Rock Mechanics and Geotechnical Engineering 9 (2017) 340–349

Contents lists available at ScienceDirect

Journal of Rock Mechanics and Geotechnical Engineering

journal homepage: www.rockgeotech.org

Full Length Article

Application of artificial neural networks for predicting the impact of rolling dynamic compaction using dynamic cone penetrometer test results

R.A.T.M. Ranasinghe*, M.B. Jaksa, Y.L. Kuo, F. Pooya Nejad

School of Civil, Environmental and Mining Engineering, University of Adelaide, Adelaide, Australia

A R T I C L E I N F O

Article history:
Received 12 August 2016
Received in revised form
22 October 2016
Accepted 9 November 2016
Available online 27 February 2017

Keywords:
Rolling dynamic compaction (RDC)
Ground improvement
Artificial neural network (ANN)
Dynamic cone penetration (DCP) test

A B S T R A C T

Rolling dynamic compaction (RDC), which involves the towing of a noncircular module, is now widespread and accepted among many other soil compaction methods. However, to date, there is no accurate method for reliable prediction of the densification of soil and the extent of ground improvement by means of RDC. This study presents the application of artificial neural networks (ANNs) for a priori prediction of the effectiveness of RDC. The models are trained with in situ dynamic cone penetration (DCP) test data obtained from previous civil projects associated with the 4-sided impact roller. The predictions from the ANN models are in good agreement with the measured field data, as indicated by the model correlation coefficient of approximately 0.8. It is concluded that the ANN models developed in this study can be successfully employed to provide more accurate prediction of the performance of the RDC on a range of soil types.

1. Introduction

Soil compaction is one of the major activities in geotechnical engineering applications. Among many other soil compaction methods, rolling dynamic compaction (RDC) is now becoming more widespread and accepted internationally. The RDC technology emerged with the first full-sized impact roller from South Africa for the purpose of improving sites underlain by collapsible sands in 1955 (Avalle, 2004). Over the years, the RDC concept has been refined with updated and improved mechanisms. Since the mid-1980s, impact rollers have been commercially available and are now adopted internationally using module designs incorporating 3, 4 and 5 sides.

The 4-sided impact roller module consists of a steel shell filled with concrete to produce a heavy, solid mass (6–12 tonnes), which is towed within its frame by a 4-wheeled tractor (Fig. 1). When the impact roller traverses the ground, the module rotates eccentrically about its corners and derives its energy from three sources: (1) potential energy from the static self-weight of the module; (2) additional potential energy from being lifted about its corners; and (3) kinetic energy developed from being drawn along the ground at a speed of 9–12 km/h. As a result, the impact roller is capable of imparting a greater amount of compactive effort to the soil, which often leads to a deeper influence depth, i.e. in excess of 3 m below the ground surface in some soils (Avalle, 2006; Jaksa et al., 2012), which is much deeper than 0.3–0.5 m generally achieved using traditional vibratory and static rollers (Clegg and Berrangé, 1971; Clifford, 1976, 1978). Furthermore, it is able to compact thicker lifts, in excess of 500 mm, which is considerably greater than the usual layer thicknesses of 200–500 mm (Avalle, 2006) and can also operate with larger particle sizes.

Moreover, RDC is more efficient since the module traverses the ground at a higher speed, about 9–12 km/h, compared with traditional vibratory rollers which operate at around 4 km/h (Pinard, 1999). This creates approximately two module impacts over the ground each second (Avalle, 2004). Thus, the faster operating speed and deeper compactive effort make this method very effective for bulk earthworks. In addition, it also appears that prudent use of RDC can provide significant cost savings in the civil construction sector. Due to these inherent characteristics of RDC, modern ground improvement specifications often replace or provide an alternative to traditional compaction equipment. It has been demonstrated to be successful in many applications

* Corresponding author.
E-mail address: tharanga.ranasinghe@adelaide.edu.au (R.A.T.M. Ranasinghe).
Peer review under responsibility of Institute of Rock and Soil Mechanics, Chinese Academy of Sciences.

http://dx.doi.org/10.1016/j.jrmge.2016.11.011

Fig. 1. The 4-sided impact roller and tractor.

worldwide, particularly in civil and mining projects, pavement rehabilitation and in the agricultural sector (Avalle, 2004, 2006; Jaksa et al., 2012).

To date, a significant amount of data has been gathered from RDC projects through an extensive number of field and case studies in a variety of ground conditions. However, these data have yet to be examined holistically and there currently exists no method, theoretical or empirical, for determining the improvement in in situ density of the ground at depth as a result of RDC using dynamic cone penetrometer (DCP) test data. The complex nature of the operation of the 4-sided impact roller, as well as the consequent behavior of the ground, has meant that the development of an accurate theoretical model remains elusive. However, recent work by the authors in relation to RDC, as well as by others in the broader geotechnical engineering context (Günaydin, 2009; Isik and Ozden, 2013; Shahin and Jaksa, 2006; Kuo et al., 2009; Pooya Nejad et al., 2009), have demonstrated that artificial intelligence (AI) techniques, such as artificial neural networks (ANNs), show great promise in this regard.

In a recent and separate study by the authors, ANNs have been applied to predict the effectiveness of RDC using cone penetration test (CPT) data in relation to the 4-sided impact roller. The model, based on a multi-layer perceptron (MLP), incorporates 4 input parameters, the depth of measurement (D), the CPT cone tip resistance (q_{ci}) and sleeve friction (f_{si}) prior to compaction, and the number of roller passes (P). The model predicts a single output variable, i.e. the cone tip resistance (q_{cf}) at depth D after the application of P roller passes. The ANN model architecture, hence, consists of 4 input nodes, a single output node, and the optimal model incorporates a single hidden layer with 4 hidden nodes. The authors also translated the ANN model into a tractable equation, which was shown to yield reliable predictions with respect to the validation dataset.

This paper aims to develop an accurate tool for predicting the performance of RDC in a range of ground conditions. Specifically, the tool is based on ANNs using DCP test data (ASTM D6951-03, 2003) obtained from a range of projects associated with the Broons BH-1300, 8-tonne, 4-sided impact roller, as shown in Fig. 1. Whilst the DCP is a less reliable test than the CPT, it is nevertheless used widely in geotechnical engineering practice and a model which provides reliable predictions of RDC performance based on DCP data is likely to be extremely valuable to industry.

2. ANN model development

In recent years, ANNs have been extensively used in modeling a wide range of engineering problems associated with nonlinearity and have demonstrated extremely reliable predictive capability. Unlike statistical modeling, ANN is a data-driven approach and hence does not require prior knowledge of the underlying relationships of the variables (Shahin et al., 2002). Moreover, these nonlinear parametric models are capable of approximating any continuous input–output relationship (Onoda, 1995). A comprehensive description of ANN theory, structure and operation is beyond the scope of the paper, but is readily available in the literature (Hecht-Nielsen, 1989; Fausett, 1994; Ripley, 1994; Shahin, 2016).

In this study, the ANN models for predicting the effectiveness of RDC are developed using the PC-based software NEUFRAME version 4.0 (Neusciences, 2000). As mentioned above, the data used for ANN model calibration and validation incorporate DCP test results obtained from several ground improvement projects using the Broons BH-1300, 4-sided impact roller, which has a static mass of 8 tonnes. The data used in this study are summarized in Table 1. It is important to note that the DCP data are obtained at effectively the same location prior to RDC (i.e. 0 pass) and after several passes of the module (e.g. 10, 20 passes), since it is essential to include both pre- and post-compaction conditions in the ANN model simulations. In total, the database contains 2048 DCP records from 12 projects.

ANN model development is carried out using the process outlined by Maier et al. (2010), including determination of appropriate model inputs/outputs, data division, selection of model architecture, model optimization, validation and measures of performance. This methodology is briefly discussed and contextualized below.

2.1. Selection of appropriate model inputs and outputs

The most common approach for the selection of data inputs in geotechnical engineering is based on the prior knowledge of the system in question and this is also adopted in the present study. Therefore, the input/output variables of the ANN models are chosen in such a manner that they address the main factors that influence RDC behavior. It is identified that the degree of soil compaction depends upon a number of key parameters, including: the geotechnical properties at the time of compaction, such as ground density, moisture content, and soil type; and the amount of energy imparted to the ground during compaction.

As mentioned previously, in this study, the ANN model is based on DCP test results collected from a range of ground improvement projects involving the 4-sided impact roller. The DCP (ASTM D6951-

Table 1
Summary of the database of DCP records.

No.	Project	No. of DCP soundings	Soil type		No. of roller passes
			Primary	Secondary	
1	Arndell Park	23	Clay	Silt	0, 5, 10, 20, 25, 30
2	Banyo	2	Clay	Silt	4, 8, 16
3	Banksmeadow	10	Sand	None	0, 10, 20
4	Ferguson	7	Clay	Silt	5, 10, 15
5	Kununurra	5	Sand	None	0, 5, 10, 20, 25, 30, 40, 50, 60
6	Monarto	6	Sand	Gravel	0, 5, 10, 30
7	Outer Harbor	9	Clay	Silt	0, 6, 12, 18, 24
			Sand	Gravel	
8	Pelican Point	8	Clay	Silt	0, 6, 12, 18
9	Penrith	39	Sand	Clay	0, 2, 4, 6, 10, 20
10	Potts Hill	4	Clay	Silt	0, 10, 20, 30, 40
11	Revesby	4	Clay	Silt	0, 5, 10, 15
			Sand	Clay	
			Sand	None	
12	Whyalla	12	Sand	Gravel	0, 8, 16