Proceedings of the 11th ANZ Young Geotechnical Professionals Conference – 11YGPC
Queenstown, New Zealand
25 – 28 October 2016

Application of Artificial Intelligence Techniques for Rolling Dynamic Compaction

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ABSTRACT

Rolling dynamic compaction (RDC), involving non-circular modules towed behind a tractor, is now widespread and accepted among many other soil compaction methods. However, to date, there is no accurate method to reliably predict the increase in soil strength after the application of a given number of passes of RDC. This paper presents the application of artificial intelligence (AI) techniques in the form of artificial neural networks (ANNs) and genetic programming (GP) for a priori prediction of the density improvement by means of RDC in a range of ground conditions. These AI-based models are developed by using in situ soil test data, specifically cone penetration test (CPT) and dynamic cone penetration (DCP) test data obtained from several ground improvement projects that employed the 4-sided, 8-tonne 'impact roller'. The predictions of ANN- and GP-based models are compared with the corresponding actual values and they show strong correlations (r > 0.8). Additionally, the robustness of the optimal models is investigated in a parametric study and it is observed that the model predictions are in a good agreement with the expected behaviour of RDC.

Keywords: rolling dynamic compaction, artificial neural networks, genetic programming

1 INTRODUCTION

Impact rolling, generically known as rolling dynamic compaction (RDC), involves heavy (6–12 tonnes) non-circular modules (3-, 4- and 5-sided), which rotate about their corners and fall to the ground when drawn behind a tractor. The square (4-sided) impact rolling module, which is the focus of this study, is shown in Figure 1. RDC is now widespread globally in the construction industry, as this technique provides an alternative to the traditional approaches of ground improvement, with superior compaction capabilities. As such, RDC is effective in that it has a greater influence depth – more than 1 m beneath the ground surface and sometimes as deep as 3 m in some soils (Avalle and Carter, 2005) – compared to conventional static and vibratory compaction, where the influence depths are generally less than 0.5 m (Clifford, 1976). As a result, thicker lifts, in excess of 0.5 m, can be employed, as compared to traditional compaction lifts of approximately 0.3 m, which enhances RDC's cost effectiveness. Moreover, RDC traverses the ground at a speed of 9–12 km/h, which is far more efficient than traditional compaction using a vibratory roller, which travels at a speed of 4 km/h (Pinard, 1999). As a consequence of these improved capabilities, RDC is utilised in many applications worldwide, particularly, (i) in the civil construction industry for in situ densification and subgrade proof-rolling, (ii) in the agricultural sector mainly for the improvement of existing water storages, channels and embankments, (iii) in the mining industry for the construction of tailing dams, rock rubblisation in open cut mine waste tips and the compaction of capping over waste rocks.

Figure 1. The 4-sided 'impact roller' towed behind a tractor

However, to date, there is no reliable method available to predict the effectiveness of RDC in advance. As a result, RDC is often adopted based on experience from previous work undertaken in similar soils and site conditions. In addition, field trials are usually undertaken prior to site works to ascertain the operational parameters, especially the optimal number of roller passes required to achieve the desired percentage of maximum dry density. Therefore, this study aims to develop an accurate and robust tool for predicting the performance of RDC in a range of ground conditions. This research makes use of artificial intelligence (AI) in the form of artificial neural networks (ANNs) and genetic programming (GP), which have also been proven successful in the broader geotechnical engineering context [e.g. (Alavi et al., 2013; Shahin et al., 2005)]. The developed models are validated against a set of unseen data and, in addition, ANN-and GP-based models are compared with each other over a range of performance measures. Additionally, a parametric study is carried out to assess the robustness of the optimal models. It is important to note that these are the very first models that permit a priori prediction of ground improvement as a result of RDC.

2 DATABASE

The data used in this study have been obtained from the results of several field trials undertaken by Broons (SA) Hire, an Australian company operating a range of ground improvement technologies, including RDC. Attention is given to the 4-sided, 8 tonne 'impact roller' (BH-1300). The database is comprised of in situ strength data in the form of cone penetration test (CPT) and dynamic cone penetrometer (DCP) test results with respect to the number of roller passes. In total, the database contains 1,755 records from 91 CPT soundings and 2,048 DCP records from 12 field projects.

In this study, two sets of AI models (i.e. two ANNs and two GP models) have been developed incorporating each of the CPT and DCP datasets for model calibration and validation. The models are developed to predict the degree of density improvement of the ground with respect to the number of roller passes. Therefore, a single output variable of cone tip resistance after compaction, q_{cf} (MPa) is adopted for the CPT models, whilst the average DCP blow count per 300 mm is incorporated in the DCP models. However, it is important that the input variables of these models effectively address the significant factors that influence soil behaviour as a consequence of RDC. Hence, the input and output variables involved in the model development and their ranges are presented in Table 1.

Table 1. Input/output variable ranges used in model development

Data	Model variables		Range
CPT	Input	Depth of measurement, $\boldsymbol{D}$ (m)	0.2 – 4.0
		Cone tip resistance prior to compaction, $\boldsymbol{q_{ci}}$ q⍰ci⍰ (MPa)	0.19 – 50.65
		Sleeve friction prior to compaction, $\boldsymbol{f_{si}}$ (kPa)	1.67 – 473.86
		No. of Roller Passes, $\boldsymbol{P}$	5 – 40
	Output	Cone tip resistance after compaction, $\boldsymbol{q_{cf}}$ (MPa)	0.17 – 50.36
DCP	Input	Soil type	Sand–Clay, Clay–Silt, Sand–None, Sand–Gravel
		Average depth, $\boldsymbol{D}$ (m)	0.15 – 1.95
		Initial no. of roller passes, $\boldsymbol{P_i}$	0 – 50
		Initial DCP count (blows/300 mm)	3 – 65
		Final no. of roller passes, $\boldsymbol{P_f}$	2 – 60
	Output	Final DCP count (blows/300 mm)	2 – 84

3 ARTIFICIAL NEURAL NETWORKS (ANNS)

The ANN concept has emerged from knowledge of the functionality of the human brain and nervous system. ANNs are a data-driven approach and unlike the statistical modelling, they do not require prior knowledge of the underlying relationships among the variables. Besides, the functional relationships between inputs and outputs are learnt by the ANNs from a set of example data.

3.1 Development of ANN models

ANN modelling is carried out using the PC-based software, *Neuframe* version 4.0 (Neuframe, 2000). As described in §2, the model incorporating CPT data consists of 4 inputs along with a single output, whilst the model involving DCP data consists of 5 inputs and a single output. In this study, the crossvalidation technique (Stone, 1974) is used as the stopping criterion, which involves the division of the available dataset into three subsets: training, testing and validation. The training subset is used for model calibration, which involves optimisation of the connection weights in the network. With the testing set, model performance is periodically assessed during training, whereas the network is validated against the independent validation set once the model has been optimised. Data division is carried out in such a way that the training and validation sets contain 80% and 20% of the total data, respectively. The training set is further divided into two subsets; 80% for training and 20% for testing.

In this study, multi-layer perceptron (MLP) models are developed with the use of the back-propagation error method (Rumelhart et al., 1986). The selected MLP architecture is comprised of 3 layers: the input layer, one hidden layer and the output layer. The number of nodes in the input and output layers represent the number of model inputs and outputs and thus, the CPT- and DCP-based models consist of 4 and 5 nodes, respectively in the input layer, whilst both models contain a single node in the output layer. However, the optimisation of the nodes in the hidden layer is crucial so that the structure is neither too complex nor too simple, but appropriate enough to capture accurately the non-linearity of the relationships between the input and output parameters. Therefore, a stepwise, trial-and-error approach is adopted to achieve the optimal network architecture, where a number of ANN models are trained, beginning from the simplest form with a single hidden layer node model and successively increasing the number of nodes. As suggested by Caudill (1988), $2n + 1$ is the upper limit of hidden nodes for a network to map any continuous function, with n being the number of input nodes. Accordingly, the CPT- and DCP-based models are tested to a maximum number of hidden nodes of 9 and 11, respectively. The ANNs, with each trial number of hidden nodes, are initially trained having assigned the default software values to the internal parameters (i.e. learning rate = 0.2, momentum term = 0.8) and the sigmoidal transfer function is used for both the hidden and output layers. However, after determining the best topology, the network with the optimal number of hidden nodes is retrained with different combinations of internal parameters, specifically with different learning rates and momentum terms. After model training, model performance is assessed in terms of the coefficient of correlation (R), root mean square error ($RMSE$) and mean absolute error (MAE).

4 GENETIC PROGRAMMING (GP)

Genetic programming (GP) is an evolutionary computational approach inspired from biological evolution based on Darwinian Theory. The technique was first introduced by Koza (1992) as an extension to the genetic algorithm (GA). In GP, the computer programs are called individuals, which have been made up of a set of functions, variables and constants. In accordance with a GP algorithm, these individuals are automatically evolved into a solution for a given particular problem. In this study, a particular, robust variant of GP, namely linear genetic programming (LGP), is used. In contrast to the conventional tree-based GP approach, the data flow of evolved programs in LGP has a more general, register-based graph representation at the functional level. Additionally, the programs in LGP evolve either in an imperative programming language (e.g. C, C++) (Brameier and Banzhaf, 2007) or directly in machine language (Nordin, 1994). In brief, the LGP algorithm (Brameier and Banzhaf, 2007) involves:

i. *Initialising a population of randomly generated programs and evaluation of their fitness value;*
ii. *Running a tournament and selection of the winning programs;*
iii. In this step, 4 randomly selected programs are subjected to tournament selection, where two programs are selected as the winners based on their fitness.
iv. *Transforming the winner programs*;
v. The two selected winner programs are copied and transformed probabilistically into offsprings subjected to genetic operations; i.e. crossover and mutation.
vi. *Replacing the tournament losing programs with the offspring programs; and*
vii. *Repeating Steps 2 to 4 until the termination or convergence criteria are satisfied.*

4.1 Development of LGP models

LGP modelling utilises the same subsets of CPT and DCP data that are employed in the ANN model development, with the intention of conducting a fair comparison between the model performances. The commercially available software *Discipulus* version 5.2 (Francone, 2010) is used for the necessary computations. The selection of control parameters is considered to be vital in LGP modelling, since it has a direct impact on the model's generalisation capacity. In this modelling, the control parameters are defined in accordance with the recommended values by previous similar LGP applications and also depending on the observations from preliminary runs. As presented in Table 2, several different parameter combinations, in terms of population size, number of demes and crossover rate, are investigated, whilst most of the other minor parameters are set to the software default values.

Table 2. Parameter settings used for the LGP model development

Parameter	Settings
Function set	+, –, ×, /, Absolute, Square Root, Trigonometric (*sin, cos*), Exponential
Population size	500, 1,000, 2,000, 5,000, 7,500, 10,000
Number of demes	10, 20
Program size	Initial = 80 bytes, Maximum = 512 bytes
Mutation frequency	95%
Crossover frequency	50%, 90%

A relatively large number of LGP projects are carried out, where all of the above listed combinations of parameters are tested and replicated 5 times for each setting, in order to address different random initial conditions. Each LGP project is made up of a series of runs, which begins in short and successively progresses in length during the course of a project. Within a run, large numbers of genetic programs are evolved and they are monitored for minimum error, as this study uses the mean square error (*MSE*) as the fitness function. A LGP run is terminated after a reasonable number of generations have evolved without improvement in terms of *MSE*. Finally, a LGP project is terminated given a reasonable time to evolve into an accurate model and when no further improvement in model performance is likely to occur.

5 RESULTS AND DISCUSSION

The following sections summarise the results of the optimal models, along with details of parametric study.

5.1 Performance analysis

The developed ANN- and LGP-based models are evaluated and compared using the performance measures as discussed above; i.e. *R*, *RMSE* and *MAE* with respect to each of the 3 data subsets. In regards to the ANN modelling, with respect to both the CPT and DCP datasets, the models with 4 nodes in the hidden layer were found to be the optimal. The results of these optimal models, along with the optimal LGP results, are presented in Table 3.

Table 3. Comparison of the performance statistics of the optimal ANN- and LGP-based models

Data	Model	*R*			*RMSE*$^+$			*MAE*$^+$		
		T	S	V	T	S	V	T	S	V
CPT	ANN	0.87	0.87	0.86	4.19	4.33	4.16	2.89	3.03	2.93
	LGP	0.87	0.88	0.87	4.05	4.08	4.03	2.72	2.73	2.71
DCP	ANN	0.85	0.83	0.79	6.45	6.52	7.54	4.88	4.74	5.59
	LGP	0.84	0.87	0.81	6.22	5.35	6.80	4.18	3.70	4.74

T: Training, S: Testing, V: Validation
\+ For CPT models units is MPa and for DCP models units is blows/300 mm

As can be observed, the performances of the obtained optimal models, based on the CPT and DCP datasets, are very good given the strong correlation coefficient [i.e. R > 0.8 (Smith, 1993)] and relatively low error values (i.e. *RMSE* and *MAE*). Therefore, it can be concluded that both the ANN and LGP models developed in this study have the capability of predicting the effectiveness of RDC to a high degree of accuracy. Although both the ANN and LGP models exhibit similar performance, it is also apparent that the LGP approach slightly outperforms the ANN technique.

5.2 Parametric study

In order to further explore the accuracy and the validity of the selected optimal models, a parametric study is carried out. The model's generalisation capability is examined so that the model behaviour conforms to the known physical behaviour of the system. This involves investigating the model response to a new set of unseen synthetic input data, where only a single input parameter is varied at a time, while the others are kept constant at a pre-defined value. It is essential that the input variables are varied between the lower and upper bounds of the training dataset, since the ANN- and LGP-based models perform best when interpolating rather than extrapolating.

For the ANN and LGP models incorporating CPT data, the output variable, q_{cf}, is examined, while the input variables of q_{ci}, f_{si}, P and D are varied. For instance, as illustrated in Figures 2 and 3, the predicted value of q_{cf} is studied for both the ANN and LGP models, respectively, by varying the input variables, q_{ci} = 2, 5 MPa, f_{si} = 50, 100 kPa and P = 10, 20, 30, 40. As can be seen, q_{cf} consistently improves as the number of passes, P, increases from 10 to 40, while q_{ci} and f_{si} remain constant at 2 or 5 MPa and 50 or 100 kPa, respectively. This indicates that the soil strength at a particular location is improved beyond the initial strength with successive roller passes. However, when comparing Figure 2(a) and (b) or Figure 3(a) and (b), it is observed that q_{cf} improves only marginally as f_{si} increases from 50 to 100 kPa, while q_{ci} remains constant either at 2 or 5 MPa. Hence, this suggests that f_{si} is less influential on q_{cf}. Nevertheless, it is evident from the parametric study that the distinct non-linear relationship between q_{cf} and P has been appropriately captured by these models.

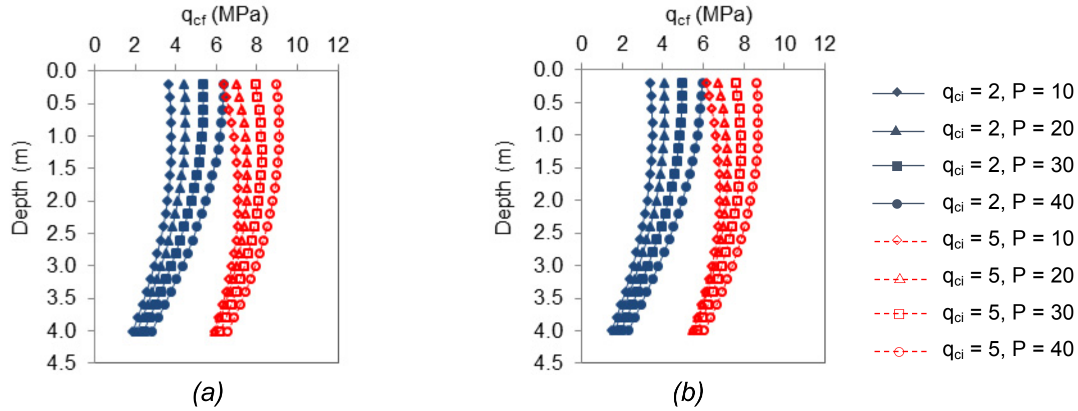

Figure 2. ANN model prediction of q_{cf} for varying q_{ci} (MPa) and number of roller passes, P when: (a) f_{si} = 50 kPa; and (b) f_{si} = 100 kPa

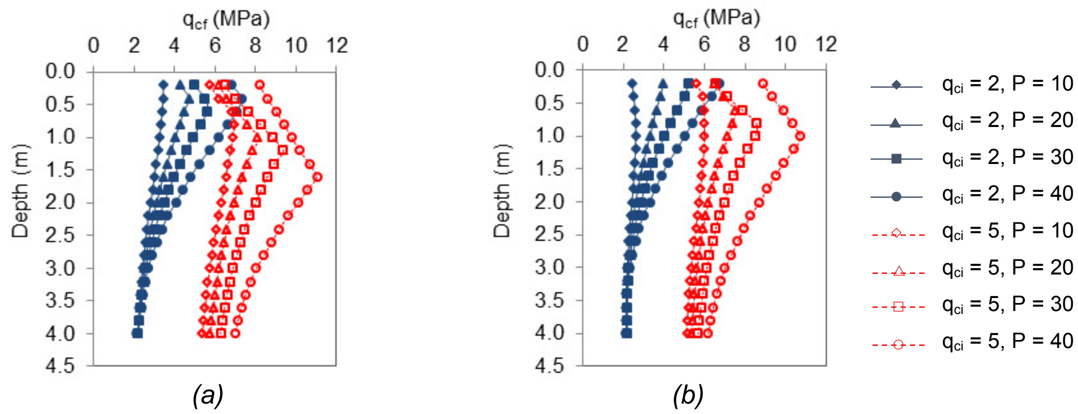

Figure 3. LGP model prediction of q_{cf} for varying q_{ci} (MPa) and number of roller passes, P when: (a) f_{si} = 50 kPa; and (b) f_{si} = 100 kPa

In a similar manner, the optimal ANN- and LGP-based models for DCP data are also investigated in a parametric study. Here, the post-compaction condition of the ground, represented by the final DCP blow count, is predicted from the optimal ANN and LGP models for a given initial DCP blow count (i.e. 5 and 15 blows/300 mm), in each of the different soil types (i.e. Sand–Clay, Clay–Silt, Sand–None and Sand–Gravel) and different numbers of roller passes (i.e. 5, 10, 15, 20, 30, 40). The resulting ANN and LGP model predictions are presented in Figures 4 and 5, respectively. It is observed that the final DCP blow count increases with increasing number of roller passes for a given initial DCP blow count in each of the soil types. It is evident from these results that the ground is significantly improved as a consequence of RDC. Moreover, this confirms the model predictions from the parametric study are in good agreement with the expected behaviour of RDC compaction. Therefore, it can be concluded that the optimal ANN and LGP models are robust when predicting the effectiveness of RDC and thus, they can be used with confidence.

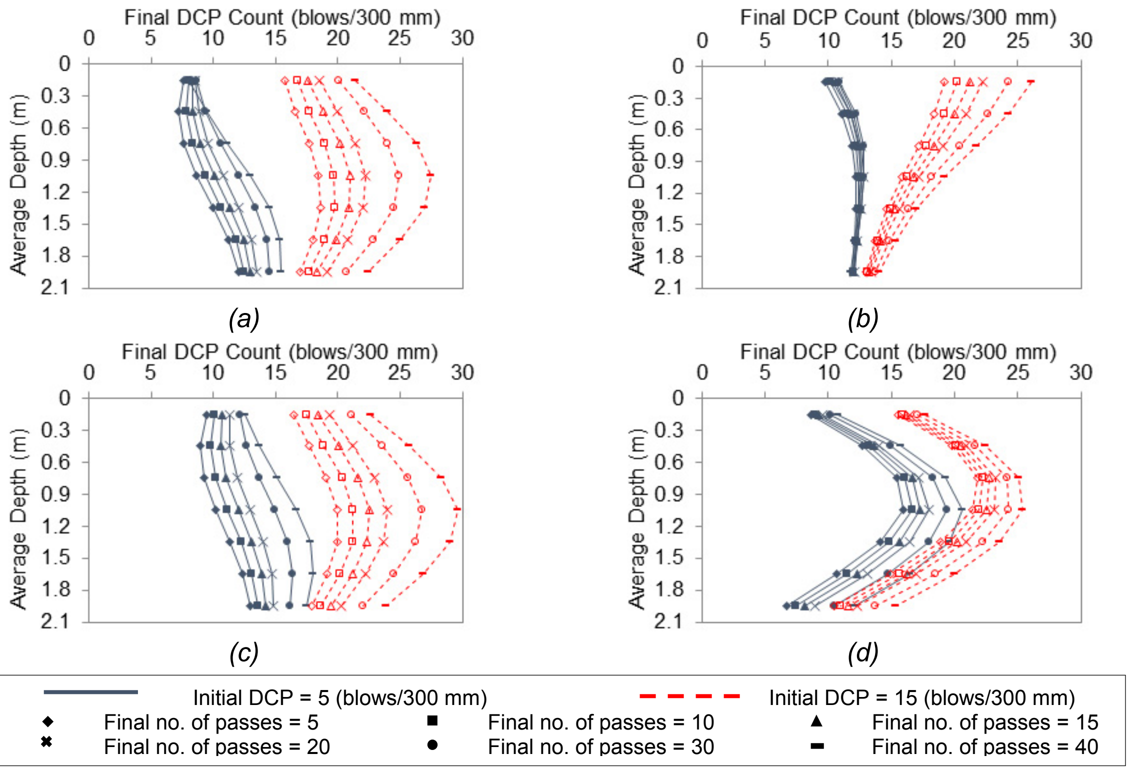

Figure 4. ANN model predictions of final DCP with respect to initial DCP and final number of roller passes in (a) Sand–Clay (b) Clay–Silt (c) Sand–None (d) Sand–Gravel

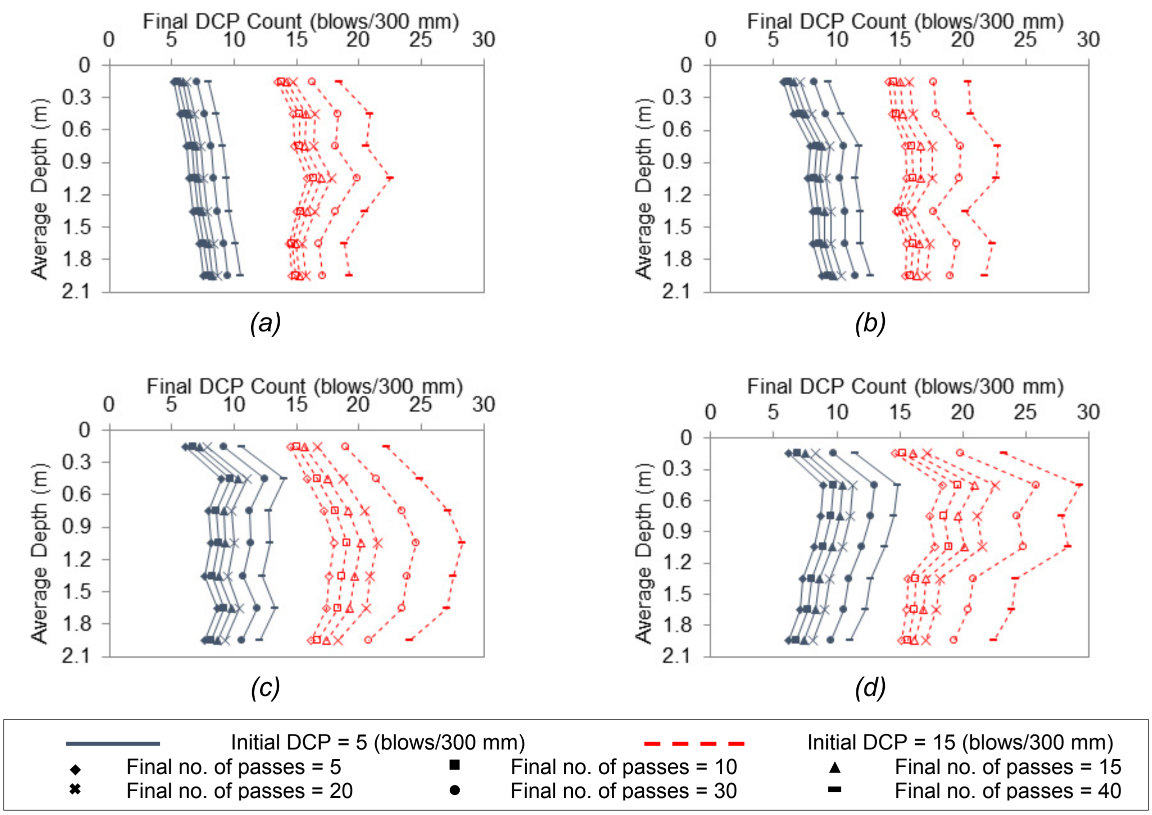

Figure 5. LGP model predictions of final DCP with respect to initial DCP and final number of roller passes in (a) Sand–Clay (b) Clay–Silt (c) Sand–None (d) Sand–Gravel

6 CONCLUSION

This paper investigates the effectiveness of rolling dynamic compaction (RDC) on different soil types and presents novel and unique predictive models based on artificial intelligence (AI) techniques in the form of artificial neural networks (ANNs) and linear genetic programming (LGP). These models incorporate an extensive database of ground density data in terms of cone penetration test (CPT) and dynamic cone penetrometer (DCP) test results associated with the Broons 4-sided, 8 tonne 'impact roller'. A total of 4 models have been developed: two involving ANNs – one for the CPT and the other for the DCP; and two LGP models – again, one for the CPT and the other for the DCP. The resulting optimal ANN- and LGP-based models yield high accuracy of model predictions, with a high coefficient of correlation (R > 0.8) and with lower error values, i.e. root mean square error (*RMSE*) and mean absolute error (*MAE*) when validated against a set of unseen data. The results indicate that the LGP-based models slightly outperform their ANN counterparts and overall produce slightly more accurate predictions. In addition, a parametric study has been carried out to assess the generalisation ability and robustness of these optimal models. The results of the parametric study demonstrate that the response of the models agrees well with the expected physical relationships among the input and output parameters. Therefore, it can be concluded that the developed models are both robust and reliable when forecasting the performance of RDC in various ground conditions. The models developed in this study are intended to provide initial predictions for planning purposes and may replace, or at the very least augment, the necessity for field trials prior to full-scale construction, which in turn contributes to significant cost savings.

7 ACKNOWLEDGEMENTS

This research was supported under Australian Research Council's Discovery Projects funding scheme (project number DP120101761). The authors wish to acknowledge Mr. Stuart Bowes at Broons Hire (SA) Pty Ltd for his kind assistance and continuing support, especially in providing access to the in situ test results upon which the numerical models are based. The authors are also grateful to colleagues Drs. Yin Lik Kuo and Fereydoon Pooya Nejad and Mr. Brendan Scott for their contribution to this work.

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