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Predicting the effectiveness of rolling dynamic compaction using genetic programming

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Rolling dynamic compaction (RDC) is a soil compaction method that involves impacting the ground with a non-circular roller. This technique is currently in widespread use internationally and has proven to be suitable for many compaction applications, with improved capabilities over traditional compaction equipment. However, there is still a lack of knowledge about a priori estimation of the effectiveness of RDC on different soil profiles. To this end, the aim of this paper is to develop a reliable predictive tool based on a machine-learning approach: linear genetic programming (LGP). The models are developed from a database of cone penetration test (CPT)-based case histories. It is shown that the developed LGP-based correlations yield accurate predictions for unseen data and, in addition, that the results of a parametric study demonstrate its generalisation capabilities. Furthermore, the selected optimal LGP-based model is found to yield superior performance when compared with an artificial neural network model recently developed by the authors. It is concluded that the LGP-based model developed in this study is capable of providing reliable predictions of the effectiveness of RDC under various ground conditions.

Notation

D	depth of measurement
f_{si}	sleeve friction prior to compaction
P	number of roller passes
q_{cf}	cone tip resistance after compaction
q_{ci}	cone tip resistance prior to compaction

1. Introduction

Rolling dynamic compaction (RDC) is now a well-established method of ground improvement whereby soil densification is achieved by means of high-energy impact blows. RDC employs heavy (6–12 t), non-circular modules (three-, four- and five-sided), which rotate about their corners as they are drawn forward towed behind a tractor (Avalle, 2004b). Thereby, a combination of potential and kinetic energy is derived from the impact mechanism, which provides a series of impact blows as the roller traverses the ground. Consequently, the soil beneath the surface is densified into a state of lower void ratio by expelling the pore air and fluid. However, the major benefit of RDC is its capability of influencing the ground to a greater depth, when compared with conventional static and vibratory compaction, which is more than 1 m beneath the ground surface and sometimes as deep as 3 m in some soils (Avalle and Carter, 2005; Clegg and Berrangé, 1971; Clifford, 1976, 1978; Jaksa *et al.*, 2012). In addition to the greater depth of compaction, RDC is capable of achieving the required density in thicker lifts, which are generally in excess of 500 mm, as compared with traditional layer thicknesses of 200–500 mm (Avalle, 2004b, 2006). Moreover, RDC can operate with larger particle sizes and the surface corrugations produced as a result of its operation provide a measure of interlocking between the adjacent soil layers, which helps to overcome lateral shearing effects. The economics of the use of RDC has also been found to be favourable due to its speed of operation – that is, 9–12 km/h, which is substantially greater than the traditional vibratory roller, which travels at ~4 km/h (Pinard, 1999). These inherent characteristics of RDC make it very effective for many civil, mining and agricultural applications, including pavement rehabilitation; in situ densification of existing fills, such as on brownfield sites and landfills; subgrade proof-rolling (Avalle, 2004a); construction of tailing dams at mine sites (Avalle, 2006); rock demolition in open cut mine waste tips (Scott and Jaksa, 2012); and improvements of existing water storages, channels and embankments (Avalle, 2004b).

To date, RDC has been studied experimentally through a number of field-based case studies. Some of the recent field-based studies that have quantified the effectiveness of the four-sided impact roller are reported by Avalle (2007), Avalle and Carter (2005), Avalle *et al*. (2009), Jaksa *et al*. (2012) and Scott and Jaksa (2014). However, comparatively, there has been very little research directed to date towards the development of a theoretical model for evaluating the effectiveness of RDC and thus, limited published information is available in this regard. Recently, Kuo *et al*. (2013) investigated the influence zone of the impact roller by means of the finite-element (FE) method. In so doing, the FE model was validated against field data obtained by Jaksa *et al*. (2012) and it was shown that RDC was most effective for depths of 0·8–3 m below the surface, where the soil density increases with greater numbers of roller passes. Additionally, in a preliminary parametric study, the authors showed that the most significant factors were soil cohesion, Poisson ratio and shear modulus, as well as the width and mass of the RDC module. However, these field-based studies and the numerical simulations of RDC recorded in the literature to date have limited applicability in practice, especially due to the site-specific nature of their results.

However, until recently, no rational means existed for obtaining an a priori estimation of the degree of densification or the extent of the influence of depth by RDC under different ground conditions; this is now available as a result of work undertaken by the authors, which is discussed below. Indeed, the development of such a reliable theoretical model for prior estimation of the effectiveness of RDC is complex due to the heterogeneous nature of soil and of the various site-specific factors that can potentially affect the improvement process. Consequently, the performance design and application of RDC currently relies heavily on the geotechnical engineer's experience and judgement. Field trials are often carried out on site to ascertain the operational parameters, especially the optimal number of impact roller passes required to achieve the required percentage of maximum dry density.

However, to address this problem, recent studies conducted by the authors in relation to RDC have proposed models by means of the artificial intelligence (AI) technique known as artificial neural networks (ANNs) (Ranasinghe, 2017; Ranasinghe *et al*., 2016). Two distinct ANN models have been developed based on the cone penetration test (CPT) (Ranasinghe, 2017), and the dynamic CPT (Ranasinghe *et al*., 2016). Data and results are obtained from previous ground improvement projects associated with the Broons four-sided 'impact roller'. Except for a few restrictions imposed on model utilisation, they have been shown to be successful in providing reliable predictions of the effectiveness of RDC in various ground conditions. Despite the fact that ANNs provide acceptable performance in many geotechnical engineering applications, they suffer from a few shortcomings. Essentially, ANNs require the network structure and the parameters to be recognised in advance, which usually entails the implementation of somewhat ad-hoc, trial-and-error methods. Moreover, a common criticism levelled at ANNs is their lack of transparency, in that they often fail to explain the underlying physical processes associated with the phenomenon under investigation – in this case, compaction.

This paper investigates the applicability of a relatively new, machine-learning technique called genetic programming (GP) that is reported to overcome many of the shortcomings associated with ANNs and other conventional modelling approaches for the prediction of the effectiveness of RDC. The GP models are developed using a reliable dataset of CPT results that has also been utilised previously for ANN model development by the authors (Ranasinghe, 2017). A comparative study is conducted where the GP- and ANN-based models are compared in terms of a range of performance measures.

2. Genetic programming

Genetic programming (Koza, 1992) is one of the number of approaches based on evolutionary algorithms (EAs) that mimic the concept of Darwin's evolution theory in relation to optimising a solution to a pre-defined problem. Similarly to ANNs, GP is part of the AI class of modelling techniques, which can be considered as an alternative to conventional methods, such as – for example, statistical and FE modelling – due to its ability to approximate any linear/non-linear relationship among a set of observed input and output data in the absence of former knowledge on the underlying mechanisms of the system.

In GP, the individuals in a population are represented as computer programs of variable size and shape (Koza, 1992) that are hierarchically composed of a set of functions and terminals fitted to a particular problem domain. The function set may consist of arithmetic functions (+, −, ×, /), mathematical functions (sin, cos, ln), Boolean logic operators (AND, OR, NOT), logical expressions (IF or THEN), iterative functions (DO, CONTINUE, UNTIL) and/or other user-defined functions (Sette and Boullart, 2001). The terminal set typically comprises input variables attached to the problem domain and pre-specified or randomly generated numeric constants.

2.1 Linear GP

There are several distinct variants of GP, where programs are represented in different forms. Besides the traditional tree-based GP (TGP) approach, these can be either a linear or graphical representation (Banzhaf *et al*., 1998; Poli *et al*., 2007). In linear-based GP variants, there is a clear difference between the genotype and phenotype of an individual

(Alavi and Gandomi, 2012). Moreover, the individuals have a linear string representation, which is decoded and expressed like non-linear entities (Oltean and Grosan, 2003). In the recent past, several linear-based variants of GP have been utilised in civil engineering applications – that is, linear GP (LGP), multi-expression programming, Cartesian GP, gene-expression programming and grammatical evolution (Oltean and Grosan, 2003). However, the emphasis of the present study is placed on LGP.

The main distinguishing feature of LGP over TGP is that LGP evolves programs of an imperative language (e.g. C, C++ or Java) or machine language instead of the standard TGP expressions in a functional programming language (i.e. Lisp) (Brameier and Banzhaf, 2001, 2007). Moreover, the data flow of evolved programs in LGP has a more general register-based graphical representation at the functional level, compared with the rigidly determined tree representation of traditional TGP. A comparison of the typical program structures giving the same end result, produced by LGP and TGP, is presented in Figure 1.

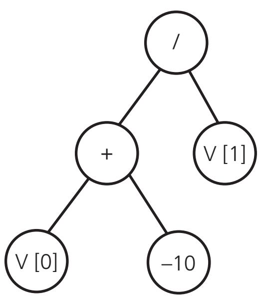
As described earlier, the LGP individuals are evolved either from an imperative programming language (e.g. C, C++ or Java) (Brameier and Banzhaf, 2001, 2007) or a direct machine language (Nordin, 1994). The latter variant is also known as automatic induction of machine code by GP (AIMGP), where the evolved programs are stored as linear strings of native binary machine code (Nordin *et al.*, 1999). In contrast, the individuals in AIMGP are directly executable by the processor (Francone and Deschaine, 2004). AIMGP is found to be more memory efficient and significantly faster than other GP variants because there is no need for an interpreter for the evaluation of individuals (Alavi and Gandomi, 2012; Nordin *et al.*, 1999). As a consequence of these advantages, this study makes use of AIMGP. In the recent past, AIMGP has also been successfully implemented in several applications of LGP in geotechnical engineering. These include estimation of ultimate bearing capacity of shallow footings founded on rock (Alavi and Sadrossadat, 2016), assessment of soil liquefaction (Alavi and Gandomi, 2012), non-linear modelling of soil deformation

```
float DiscipulusCFunction (float v[])
{
 f[0]=0;
 double Input000=v [0];
 double Input001=v [1];

 L0:   f[0]+= v[0];
 L1:   f[0]+=–10;
 L2:   f[0]/=v[1];

 return f[0];
}
```

(a)



(b)

Figure 1. Comparison of the GP structures: (a) LGP and (b) TGP

modulus (Rashed *et al.*, 2012) and soil classification (Heshmati *et al.*, 2008).

2.2 LGP evolutionary algorithm

LGP performs a multi-directional simultaneous search for an optimal solution from a pool of many potential solutions, collectively known as a 'population'. The individuals in the population compete with each other, such that the fittest individuals survive and eventually evolve to do well in the given environment. In general, the basic steps of the LGP EA (Brameier and Banzhaf, 2007) can be summarised as follows.

(*a*) Initialise a population of randomly generated programs and evaluating their fitness.
(*b*) Perform two fitness tournaments with randomly selected programs from the population and select the winning programs.
(*c*) Make temporary copies of the two winning programs.
(*d*) Transform the two winning programs into offspring subjected to genetic operations – that is, crossover and mutation with certain probabilities.
(*e*) Replace the two tournament losing programs with the temporary copies of the winning programs.
(*f*) Repeat steps (*b*)–(*e*) until the termination or convergence criteria are satisfied.

3. LGP-based modelling approach

The following section provides an overview of the data used in the modelling process, followed by a detailed assessment of the methodology adopted in developing the LGP-based models.

3.1 Database and data pre-processing

A comprehensive database containing the results of several field trials undertaken by Broons, as presented in the authors' recent work (Ranasinghe, 2017), is again utilised in the present study. The database comprises in situ soil strength data in the form of CPT results with respect to a varying number of roller passes. CPT results are presented in terms of cone tip resistance (q_c) and sleeve friction (f_s) measurements. It is considered that the differences between the individual measurements obtained at essentially the same location prior to compaction (0 roller passes) and after compaction (10, 20 roller passes etc.) effectively quantify the variation in soil strength and density resulting from RDC. In total, 1977 data records are available after averaging the CPT values over 0·2 m depth intervals from 103 CPT soundings. Further details of the CPT data are given by Ranasinghe (2017).

This study takes into account the fundamental factors that influence ground density improvement by means of soil compaction when deciding the appropriate model inputs and outputs. The input variables used to develop the prediction correlations are: the depth of measurement (D), cone tip resistance (q_{ci}) and sleeve friction (f_{si}) prior to compaction and the number of roller passes (P), while the single output variable is cone tip resistance after compaction (q_{cf}). It is considered that these input variables, either individually or collectively, address the key factors that are the most influential in predicting ground improvement due to the application of RDC. As such, the physical properties of the soil, which include initial density, soil type and moisture content, are accounted for in the CPT data, where the initial density of the ground at a certain depth, D, is indicated by q_{ci}, while the inclusion of f_{si}, together with q_{ci}, provides an indirect and useful representation of soil type in the LGP models through the friction ratio. Moreover, moisture content is considered to be implicitly incorporated in the CPT data, since penetrometer tests, such as the CPT, are themselves affected by the soil moisture at the time of testing. In addition, the amount of energy imparted to the ground during RDC is described in terms of the number of roller passes and accounted for with the parameter P. The density of the ground after the application of P roller passes is effectively captured by the single model output q_{cf}. The ranges of the input and output variables involved in model development are presented in Table 1.

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

Variables	Range
Input	
Depth of measurement, D: m	0·2–4·0
Cone tip resistance prior to compaction, q_{ci}: MPa	0·19–50·65
Sleeve friction prior to compaction, f_{si}: kPa	1·67–473·86
Number of roller passes, P	5–40
Output	
Cone tip resistance after compaction, q_{cf}: MPa	0·17–50·36

Prior to LGP modelling, the available dataset is divided into a series of subsets. In order to conduct a fair comparison between the results obtained herein and those from the previous ANN model (Ranasinghe, 2017), this study utilises the same data subsets employed in the previous ANN model development by the authors. In summary, the entire dataset has been divided into two sets: a modelling dataset (consisting of 1755 records from 91 CPT soundings) and a verification dataset (consisting of 222 records from 12 CPT soundings). The modelling dataset is used to train and validate the LGP models and is adopted in the modelling phase. However, the verification dataset is not a part of the modelling phase in any capacity but is introduced into the selected optimal LGP model in order to further verify its capabilities.

For the LGP analysis, it is necessary to divide the modelling dataset into three subsets: training, testing and validation. The learning subset incorporates 80% of the entire dataset and consists of the training and testing subsets. The programs are genetically evolved and optimised to learn the input/output relationships with respect to the training subset, while the model's generalisation capability is evaluated periodically using the testing subset. Upon the completion of the LGP model calibration, the remaining 20% of the data included in the validation subset is presented to the optimal program as a set of unseen data to assess its performance. However, it is important to ensure that these three subsets are statistically consistent so that they effectively represent the same population, which is the ideal form of data division. It can be seen in Table 2 that the subsets used in this study effectively represent the same population as evidenced by the similar

Table 2. Statistical properties of the data used in the LGP model development

		Statistical parameters				
Variable	Data subset	Mean	SD	Minimum	Maximum	Range
Input						
Depth, D: m	Training	1·95	1·11	0·20	4·00	3·80
	Testing	2·03	1·14	0·20	4·00	3·80
	Validation	2·03	1·14	0·20	4·00	3·80
Cone tip resistance prior to compaction, q_{ci}: MPa	Training	9·33	8·23	0·19	50·65	50·46
	Testing	9·32	8·37	0·30	47·39	47·09
	Validation	9·39	7·83	0·32	47·94	47·63
Sleeve friction prior to compaction, f_{si}: kPa	Training	103·36	71·76	1·67	473·86	472·19
	Testing	99·23	71·29	8·70	441·04	432·34
	Validation	103·54	70·37	7·08	470·29	463·21
Number of roller passes, P	Training	26·59	9·94	5·00	40·00	35·00
	Testing	27·21	9·64	5·00	40·00	35·00
	Validation	26·62	10·30	5·00	40·00	35·00
Output						
Cone tip resistance after compaction, q_{cf}: MPa	Training	10·42	8·30	0·17	50·36	50·20
	Testing	10·50	8·66	0·29	45·12	44·83
	Validation	10·43	8·03	0·39	46·20	45·81

SD, standard deviation

values of mean, standard deviation, minimum, maximum and range.

The entire dataset is rescaled using the min–max normalisation method. Although such data transformation is not strictly necessary, it is usually recommended as it often improves the effectiveness and the performance of the algorithm (Alavi and Gandomi, 2012). Thus, prior to model development, both the input and output variables are rescaled into the range of 0–1 using the following equation

$$x_{\text{scaled}} = \frac{(x_{\text{unscaled}} - x_{\min})}{(x_{\max} - x_{\min})} \tag{1}$$

where $x_{\min}$ and $x_{\max}$ are, respectively, the minimum and maximum values of the x variable with respect to the training dataset, as given in Table 2.

Table 3. Parameter settings for the LGP algorithm

Parameter	Settings
Function set	+, −, ×, /, absolute, square root, trigonometric (sin, cos), exponential
Population size	500, 1000, 2000, 5000, 7500, 10 000
Number of demes	10, 20
Initial program size	80 bytes
Maximum program size	512 bytes
Mutation frequency	50 and 90%
Block mutation frequency	40%
Instruction mutation frequency	30%
Instruction data mutation frequency	30%
Crossover frequency	50 and 95%
Homologous crossover frequency	95%

Table 4. Performance statistics of the optimal LGP model

	Performance criteria		
Data subset	R	RMSE: MPa	MAE: MPa
Training	0·87	4·05	2·72
Testing	0·88	4·08	2·73
Validation	0·87	4·03	2·71

3.2 Model development using LGP

In this study, the commercially available software *Discipulus* version 5.2 (Francone, 2010) is used for the LGP-based model development. This is a supervised learning system, which operates on the basis of the AIMGP platform. It can be considered to be an efficient modelling tool for complex problems, but requires careful consideration in terms of parameter selection.

It has been identified from the literature that the selection of control parameters affects the model's generalisation ability. Therefore, different parameter settings, in terms of population size, crossover rate and mutation rate, are investigated in this study. Most of the other minor parameters are maintained at the values recommended from similar applications (Alavi and Gandomi, 2012; Baykasoğlu *et al.*, 2008; Gandomi *et al.*, 2010; Heshmati *et al.*, 2008). Furthermore, preliminary modelling observations are used when selecting the parameters, as listed in Table 3.

In this study, a relatively large number of LGP projects are carried out with the different parameter combinations discussed above. Furthermore, each parameter combination is tested for five replications to permit different random initial conditions. It is worth mentioning that an LGP project consists of a successively generated series of runs, which may begin

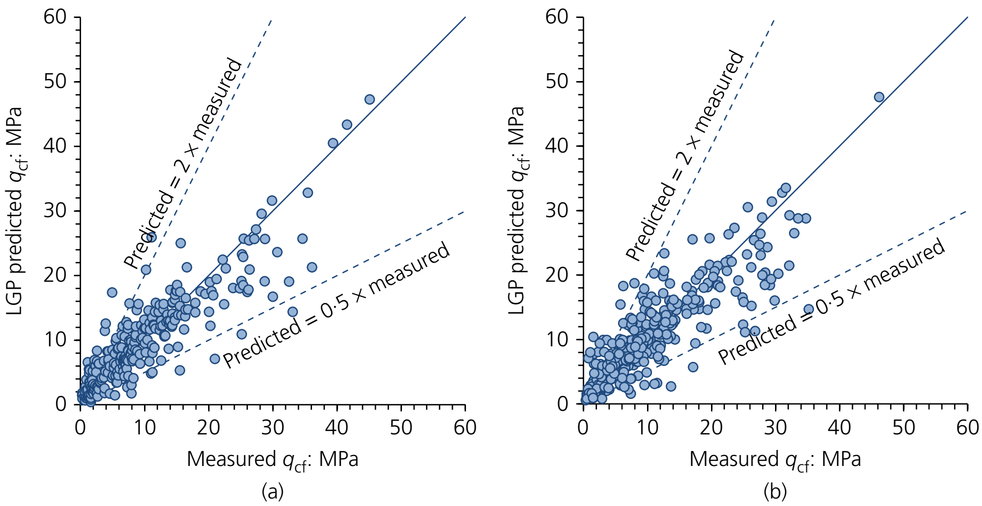


Figure 2. Measured against predicted q_{cf} for the optimum LGP model with respect to: (a) testing and (b) validation datasets

with short runs, and the length of the runs may be permitted to increase as the project continues. This study makes use of mean square error (MSE) as the fitness function, as discussed above, and thus the evolved programs are monitored for minimum error. Each of the LGP projects is given a reasonable time (ranging from a few minutes to 20+ h) to evolve, and the project is terminated when no further improvement in model performance is likely to occur.

The resulting LGP models are evaluated using several performance measures with respect to each of the three data subsets and compared. The criteria used to evaluate the performance of the evolved program models include the coefficient of correlation (*R*), root mean square error (RMSE) and mean absolute error (MAE).

4. Optimal model results

In this section, the details of the optimal LGP-based model are presented along with the performance analysis results. The robustness of the optimal model is investigated using a parametric study, and the details of the sensitivity analysis are presented. In addition, the selected optimal LGP model for predicting the cone tip resistance after compaction (MPa) is presented in computing code in the C language in the Appendix.

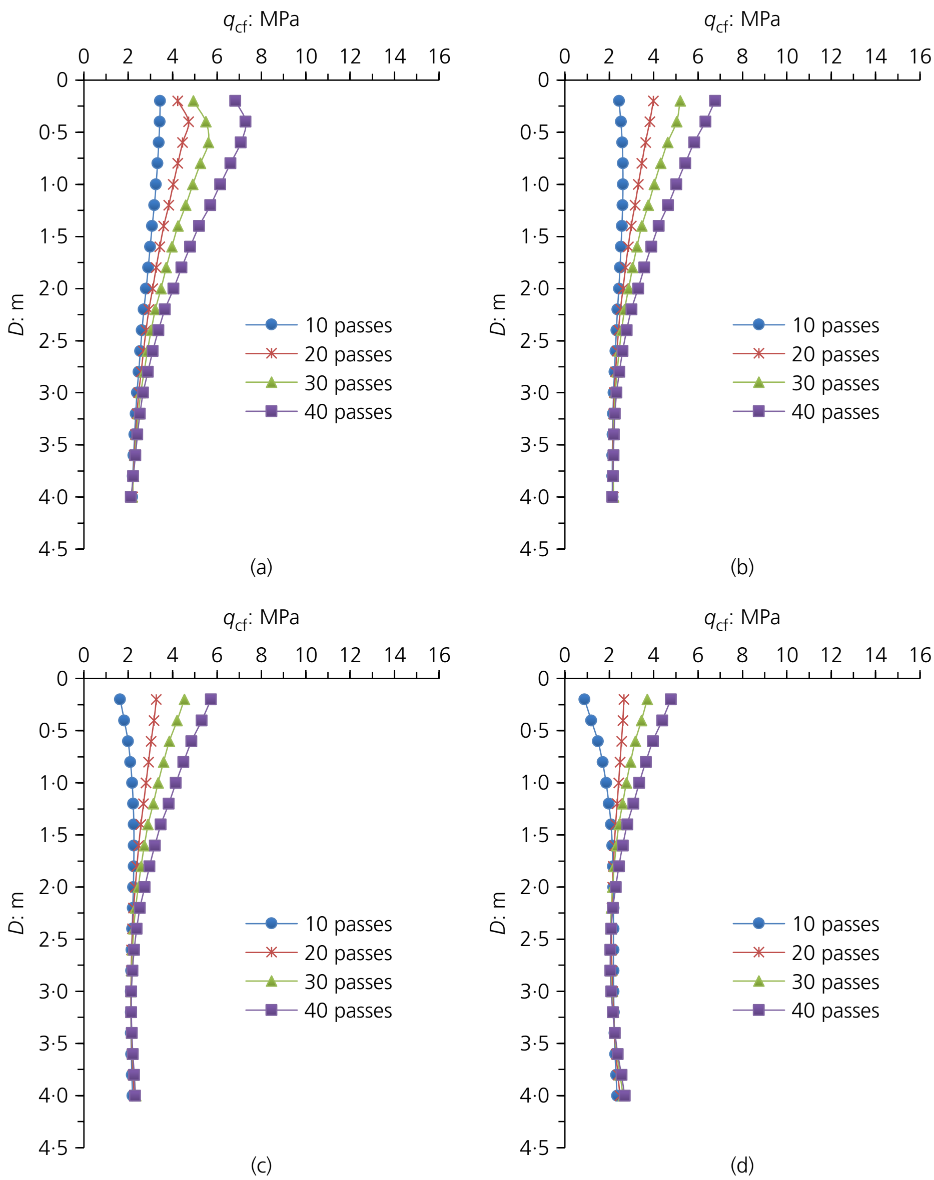


Figure 3. Variation of q_{cf} with different number of roller passes at $q_{ci} = 2$ MPa and: (a) $f_{si} = 50$ kPa, (b) $f_{si} = 100$ kPa, (c) $f_{si} = 150$ kPa, (d) $f_{si} = 200$ kPa

4.1 Performance analysis

In selecting the optimal model, the program models generated from the LGP projects are compared based on the performance measures in terms of *R*, RMSE and MAE, as discussed above. The model yielding the lowest error and highest *R* with respect to the validation data subset is considered to be optimal, and Table 4 presents the statistical performance of the selected optimal LGP model.

It is evident that the selected optimal model is able to predict accurately the target values as evidenced by the high values of *R* and low prediction errors indicated by RMSE and MAE. According to Smith (1986), when $R > 0{\cdot}8$ and the errors are relatively small, there exists a strong correlation between the measured and predicted values. Thus, it can be considered that the optimal LGP model yields reliable estimates of the ground's cone tip resistance due to RDC.

Figure 2 compares the measured and predicted q_{cf} values with respect to the testing and validation set data. It is apparent that the model has learnt the input/output mapping very effectively, which is demonstrated by the very good estimates when

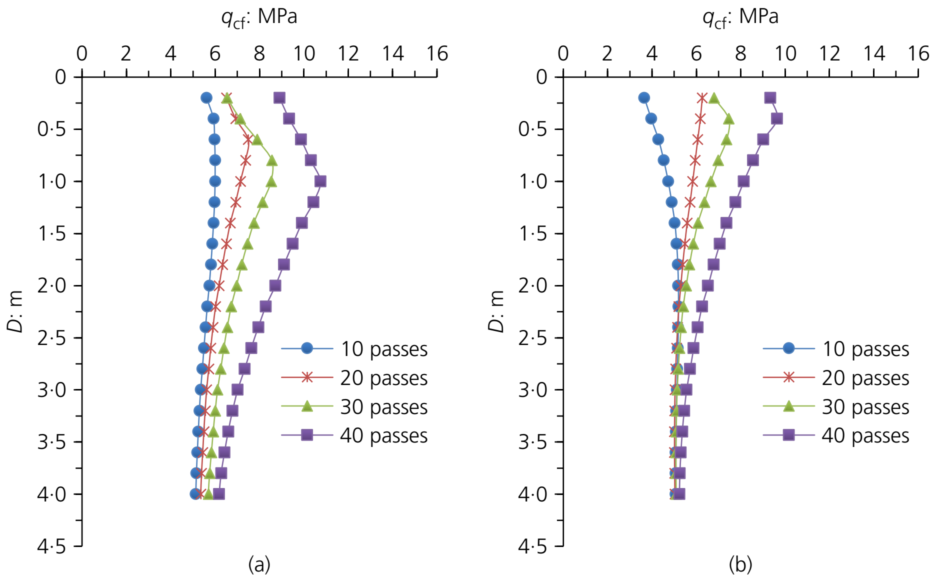


Figure 4. Variation of q_{cf} with different number of roller passes at $q_{ci} = 5$ MPa and: (a) $f_{si} = 100$ kPa and (b) $f_{si} = 200$ kPa

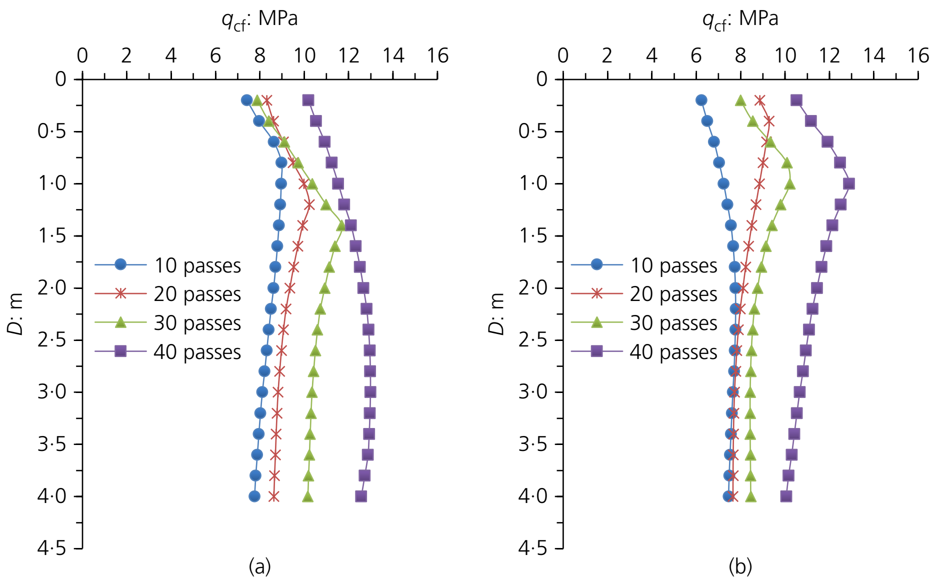


Figure 5. Variation of q_{cf} with different number of roller passes at $q_{ci} = 8$ MPa and: (a) $f_{si} = 100$ kPa and (b) $f_{si} = 200$ kPa

presented with a new set of unseen data. The optimal model predictions are scattered within an envelope of 0·5–2 times the measured values, which can be considered as a reasonable band of accuracy for the ground improvement predictions given the uncertainties involved.

4.2 Parametric study

In order to assess the generalisation ability and the robustness of the selected optimal LGP-based model, a parametric study is conducted, which evaluates the sensitivity of the model output – that is, q_{cf}, to the variations in the input parameters D, q_{ci}, f_{si} and P. This involves investigating the model's response to a hypothetical input dataset, where the input variables are varied one at a time, while all other input variables remain constant at a pre-defined value. It is important to ensure that the variables fluctuate only within the range fixed by the training dataset since the model performs best as an interpolation predictor rather than by extrapolation beyond the calibrated range. In this study, the output, q_{cf}, is examined while the input variables adopt the following values: $q_{ci} = 2$, 5, 8, 10, 15, 20 MPa; $f_{si} = 50$, 100, 150, 200 kPa and the number of roller passes, $P = 10$, 20, 30, 40. Figures 3–8 present the

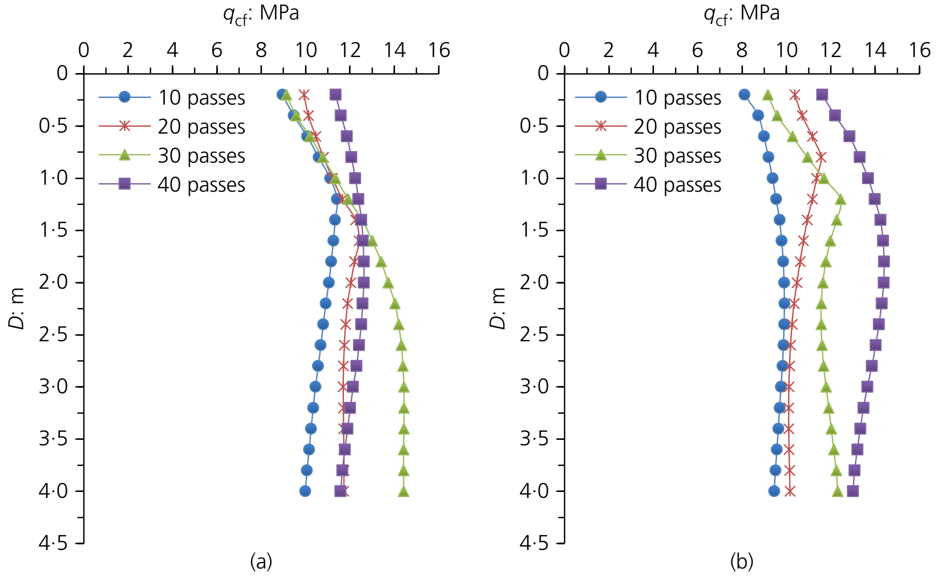


Figure 6. Variation of q_{cf} with different number of roller passes at $q_{ci} = 10$ MPa and: (a) $f_{si} = 100$ kPa and (b) $f_{si} = 200$ kPa

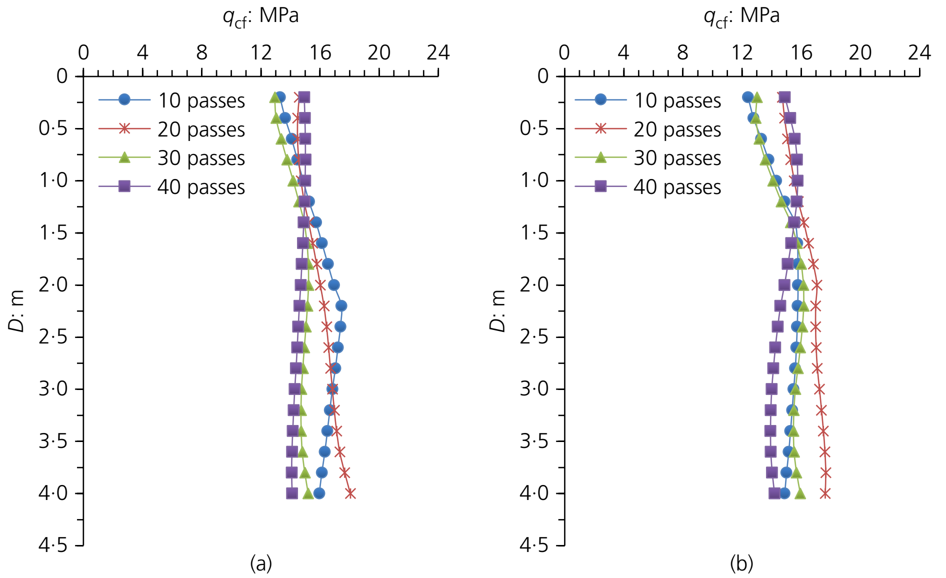


Figure 7. Variation of q_{cf} with different number of roller passes at $q_{ci} = 15$ MPa and: (a) $f_{si} = 100$ kPa and (b) $f_{si} = 200$ kPa

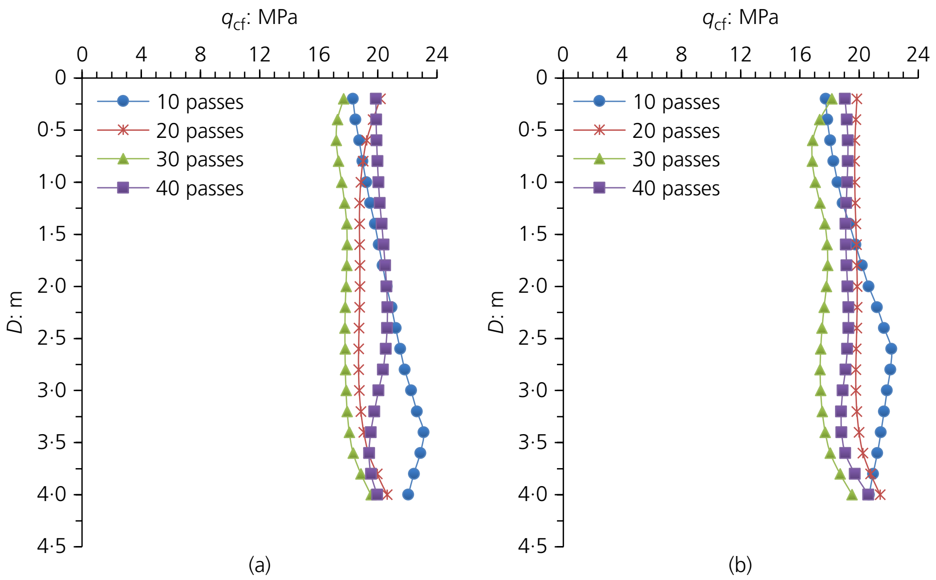


Figure 8. Variation of q_{cf} with different number of roller passes at $q_{ci} = 20$ MPa and: (a) $f_{si} = 100$ kPa and (b) $f_{si} = 200$ kPa

optimal model predictions of q_{cf} with respect to the variations in the input variables.

The results of the parametric study indicate that the soil strength continuously improves with increasing numbers of roller passes at a given location. For instance, in Figure 3(a), it can be observed that q_{cf} consistently rises when the number of roller passes increases systematically from 10 to 40 passes while q_{ci} and f_{si} remain constant at the pre-defined values of 2 MPa and 50 kPa, respectively. A similar trend is also observed when f_{si} is varied between 50 and 200 kPa, while q_{ci} remains constant at 2 MPa (Figures 3(b)–3(d)). Furthermore, the effect of varying q_{ci} is also investigated as illustrated in Figures 3–6. It is evident that when q_{ci} increases from 2 to 10 MPa at a given depth, q_{cf} always improves to a value higher than q_{ci}, consistently indicating some level of ground improvement. However, from Figures 3–6, it is also evident that q_{cf} is less sensitive to variations in f_{si}, as indicated by the modest changes in q_{cf} when f_{si} increases from 50 to 200 kPa, while the other variables remain constant. Nevertheless, it can be concluded that the model predictions are reliable in the sense that the model replicates the expected underlying physical behaviour of RDC compaction and can be considered to be robust.

As can be seen from Figures 3–6, the trends and relationships between the q_{cf} predictions and the variations of the other input parameters are appropriate and conform to the expected behaviour. However, in contrast, the q_{cf} predictions are less satisfactory when the model is exposed to relatively high q_{ci} values. As shown in Figures 7 and 8, the predicted q_{cf} values are negatively correlated with the number of roller passes when q_{ci} is either 15 or 20 MPa. However, from a theoretical perspective, it is difficult to justify the irregular nature of the q_{cf} curves that result from high q_{ci} values and with respect to increasing numbers of roller passes. As such, these figures suggest that the developed LGP model has been unsuccessful in capturing the non-linear relationship between q_{cf} and P appropriately in the presence of higher values of q_{ci} (i.e.

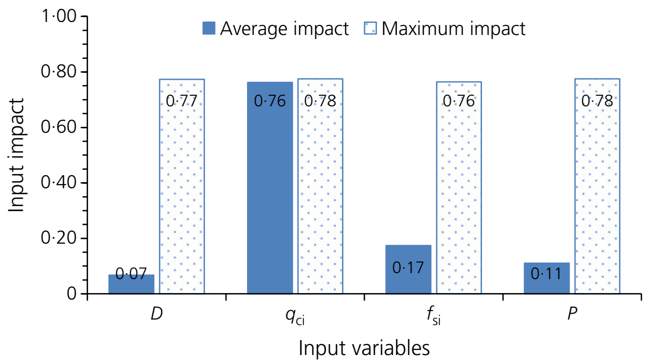


Figure 9. Impact of the input variables on optimal model predictions

Table 5. Comparison of the performance statistics of optimal LGP- and ANN-based models

	Performance criteria					
	R		RMSE: MPa		MAE: MPa	
Data subset	LGP	ANN	LGP	ANN	LGP	ANN
Training	0·87	0·87	4·05	4·19	2·72	2·89
Testing	0·88	0·87	4·08	4·33	2·73	3·03
Validation	0·87	0·86	4·03	4·16	2·71	2·93

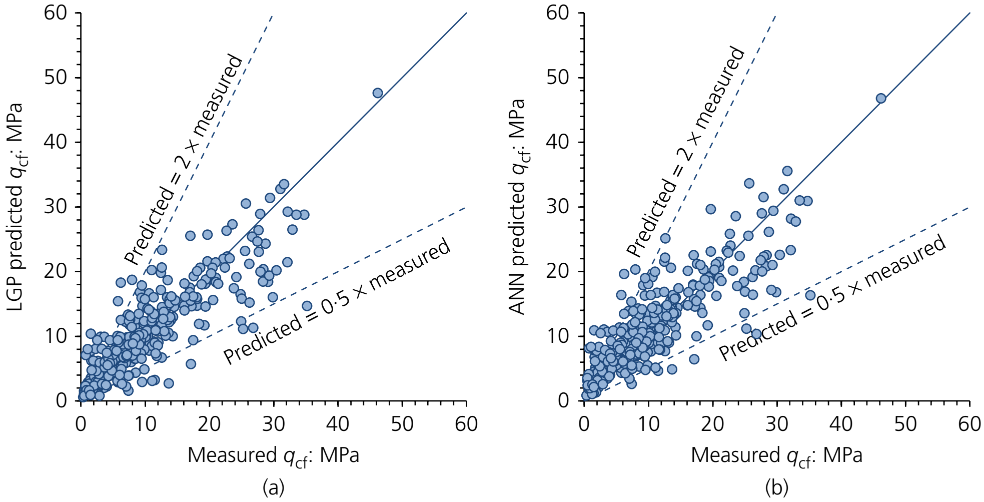


Figure 10. Measured against predicted q_{cf} with respect to validation dataset for: (a) LGP model predictions and (b) ANN model predictions

>10 MPa). This may be attributed to the fact that the LGP model has not been appropriately calibrated for higher values of q_{ci}, which is likely due to the poor representation of such high q_{ci} values in the database. From an examination of the dataset used for the model calibration, it is evident that there is a paucity of such data in the existing CPT database, where the majority of the CPT records (~60%) in the dataset used for the model calibration represent the lower range of q_{ci} – that is, below 10 MPa. This could be attributed to the fact that the RDC in most projects is usually applied to initially loose, but not very dense, ground. As such, the developed LGP model is not well calibrated for the higher values of q_{ci} and therefore, the selected LGP model is suggested to be well suited for the cases with low q_{ci} values – that is, below 10 MPa, where the initial ground condition is loose to medium dense. However, the applicability and the accuracy of the developed model can be further enhanced by incorporating more data from additional RDC-related projects so that it may enhance the generalisation ability of the LGP model into a wider span of q_{ci} values.

4.3 Sensitivity analysis

In this study, a sensitivity analysis is also carried out to investigate the contribution of each input variable to the final model predictions. *Discipulus* is capable of examining the frequency of each input variable appearing in the 30 best selected programs (Francone, 2010). In this LGP-based modelling process, the frequency obtained for all the input variables – that is, D, q_{ci}, f_{si} and P, is equal to 1, which indicates that these variables have been appearing in all of the 30 best programs evolved using LGP. Nonetheless, the average and maximum effect of removing the corresponding variable from the 30 best programs is calculated relative to each input variable, and the results are presented in Figure 9. As can be observed, all the input variables have an almost identical effect on the output if they are removed and, therefore, it is considered that all the selected input variables are highly significant with respect to the q_{cf} predictions. However, as indicated by the average impact measure, q_{ci} has the greatest effect when compared with the other input parameters.

5. Comparative study

In this section, the results obtained from the LGP simulations are compared with those obtained from the ANN-based model recently developed by the authors (Ranasinghe, 2017) using several measures. First, the performances of both models are again evaluated using R, RMSE and MAE, and the results are presented in Table 5. It is observed that, overall, both models exhibit similar performance. Therefore, it can be considered that both models are capable of predicting the target values to a high degree of accuracy, as indicated by the strong

Table 6. Performance statistics of LGP and ANN models with respect to verification data

	R		RMSE: MPa		MAE: MPa	
CPT location	LGP	ANN	LGP	ANN	LGP	ANN
Port Botany – 30	0·96	0·96	4·21	3·63	3·74	3·39
Port Botany – 11	0·86	0·84	3·37	3·65	2·65	2·86
Port Botany – 45	0·96	0·97	7·11	6·06	5·97	5·30
Port Botany – 35	0·71	0·72	3·96	3·75	3·15	2·51
Potts Hill – 37/44	0·27	0·42	2·86	3·15	1·79	2·12
Potts Hill – 27/54	0·51	0·44	1·60	2·23	1·27	1·93
Potts Hill – 24/57	0·58	0·53	2·89	2·88	2·29	2·17
Outer Harbor – EFC 5	0·85	0·84	2·31	3·15	1·89	2·84
Banksmeadow – C3	0·20	0·14	2·47	2·49	1·97	1·90
Cairns – CPT 2	0·54	0·61	4·68	4·26	3·32	2·95
Cairns – CPT 5	0·78	0·79	2·61	2·83	1·53	2·31
Cairns – CPT 8	0·96	0·94	2·02	2·55	1·59	2·27

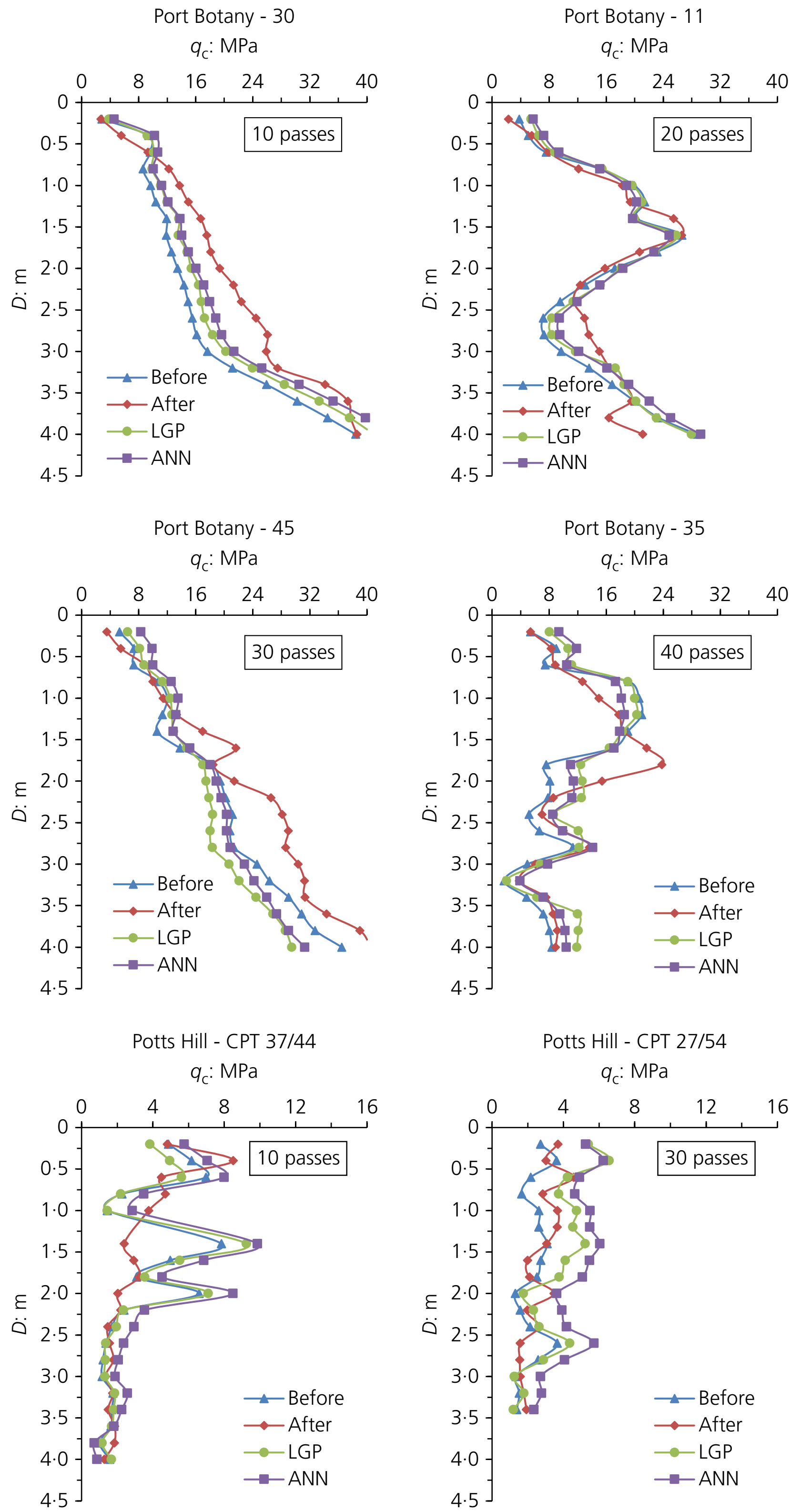


Figure 11. Plots of actual and model predicted CPT results (continued on next page)

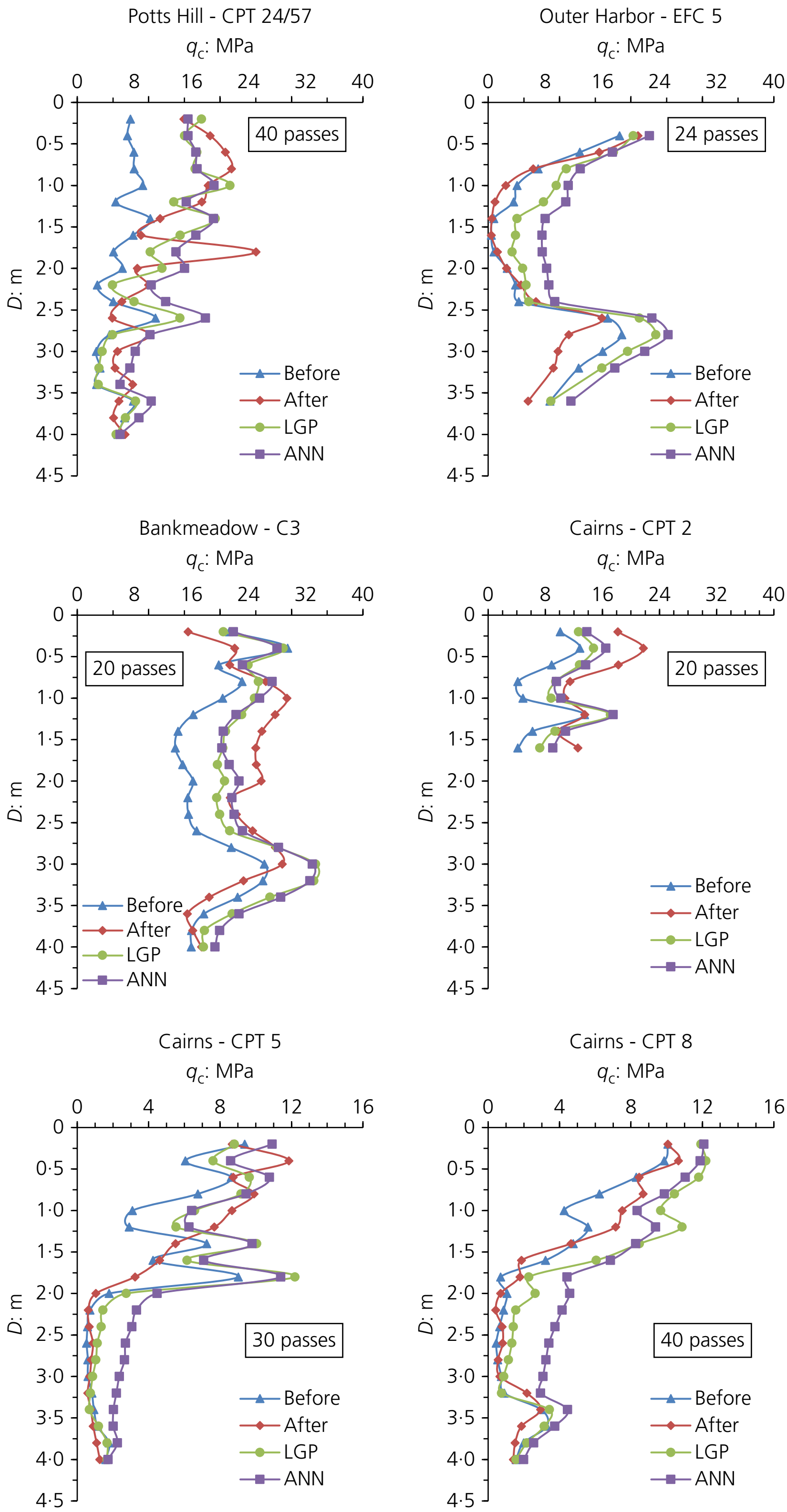


Figure 11. Continued

correlation coefficients – that is, $R > 0{\cdot}8$ (Smith, 1986), together with the relatively low error values with respect to each of the datasets. However, it is evident that the LGP model yields slightly better R values and lower error values compared with the ANN model and thus, the LGP-based model marginally outperforms the ANN model.

Figure 10 compares the measured and predicted q_{cf} values of the optimal LGP and ANN models with respect to the validation set data. It can be clearly seen that there is a minimal scatter given the measured and predicted values are in relatively close agreement. Thus, it is evident that both the models perform very favourably.

Finally, further verification of the LGP-based model's predictive capability is carried out using a completely new, additional dataset, unseen by the model, that lies within the data limits of the LGP model, as explained earlier. The verification dataset was discussed previously in Section 3.1, and further details are given there. The results are summarised in Table 6, together with the corresponding statistics obtained from the ANN model for comparison purposes. In addition, the performances of both the optimal LGP and ANN models, with respect to these additional CPTs, are presented graphically in Figure 11. It is clear that both models perform very favourably with respect to this series of unseen CPT data, although the results in relation to R, RMSE and MAE present a somewhat inconsistent picture, as compared with those obtained thus far. Nevertheless, it can be concluded that the LGP-based model yields marginally superior performance to that of the ANN-based model.

6. Summary and conclusions

This paper presents a unique approach for the prediction of the effectiveness of RDC based on GP. A reliable database consisting of CPT results obtained from several ground improvement projects, associated with the Broons four-sided, 8 t 'impact roller', is utilised for the model development. The emphasis of the present study is placed on a particular variant of GP, namely LGP, which has significant benefits over most other modelling approaches. The models incorporate four input variables: depth (m), cone tip resistance (MPa) and sleeve friction (kPa) prior to compaction and the number of roller passes that, together, are considered to be the most effective in predicting the cone tip resistance after compaction (MPa) as the single model output.

The selected optimal LGP model yields high accuracy in model predictions with a coefficient of correlation (R) of 0·87, an RMSE of 4·03 MPa and an MAE of 2·71 MPa, when assessed using a set of unseen data. The optimal model is evaluated by means of a parametric study and it is apparent that the model is robust and has appropriately captured the input/output non-linear relationships. However, this investigation has revealed that the model performs best with initial cone tip resistance (q_{ci}) values ≤10 MPa. Moreover, the contributions of each of the input variables with respect to model predictions are investigated in a sensitivity analysis and it is observed that each of the input variables is highly relevant to the prediction of cone tip resistance after compaction (q_{cf}). Finally, the LGP simulations are compared with the existing ANN model subjected to several performance measures and both models are compared using a series of unseen CPT data. The results indicate that the LGP-based model marginally outperforms the ANN model and overall produces slightly more accurate predictions.

The LGP approach presented in this paper is considered to be valuable during the pre-planning and pre-design phases. However, it is not expected to replace or undervalue the importance of field trials. It is, nevertheless, a worthwhile additional tool for ground improvement projects involving RDC.

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Appendix

The selected optimal LGP program is represented in a C code as follows.

Note that inputs 000, 001, 002 and 003 represent the depth of measurement (m), initial cone tip resistance (MPa) and sleeve friction (kPa) prior to compaction and the number of roller passes, respectively.

```
float DiscipulusCFunction(float v[])
{
  long double f[8];
  long double tmp=0;
  int cflag=0;
  f[0]=f[1]=f[2]=f[3]=f[4]=f[5]=f[6]=f[7]=0;
  L0:  f[0]+=Input001;
  L1:      f[0]*=0·1595308780670166f;
  L2:      f[0]=sin(f[0]);
  L3:      f[1]+=f[0];
  L4:      f[1]+=f[0];
  L5:      f[0]−=f[0];
  L6:      f[0]=cos(f[0]);
  L7:      f[2]−=f[0];
  L8:      f[0]/=0·6593866348266602f;
  L9:      f[0]−=−0·8144187927246094f;
  L10:      f[0]*=Input003;
```

```
L11:   f[0]−=Input002;
L12:   f[0]+=f[2];
L13:   f[2]*=f[0];
L14:   f[0]/=f[0];
L15:   f[0]+=f[1];
L16:   f[0]*=−0·5910544395446777f;
L17:   f[0]+=f[2];
L18:   f[2]+=f[0];
L19:   f[0]=fabs(f[0]);
L20:   f[3]+=f[0];
L21:   f[0]=cos(f[0]);
L22:   f[0]*=0·4784109592437744f;
L23:   f[3]+=f[0];
L24:   f[0]/=f[0];
L25:   f[2]+=f[0];
L26:   f[0]*=Input000;
L27:   f[2]−=f[0];
L28:   f[0]+=−0·6615190505981445f;
L29:   f[0]*=−0·3511595726013184f;
L30:   f[3]*=f[0];
L31:   f[0]+=Input001;
L32:   f[1]+=f[0];
L33:   f[2]*=f[0];
L34:   f[0]*=f[2];
L35:   f[0]+=f[1];
L36:   f[0]=C_F2XM1;
L37:   f[3]*=f[0];
L38:   f[0]−=f[0];
L39:   f[0]−=f[2];
L40:   f[0]=sin(f[0]);
L41:   f[3]−=f[0];
L42:   f[0]*=f[0];
L43:   f[3]+=f[0];
L44:   f[1]−=f[0];
L45:   f[0]−=Input002;
L46:   f[0]*=0·2955143451690674f;
L47:   f[1]−=f[0];
L48:   f[0]*=f[2];
L49:   f[0]+=Input001;
L50:   f[0]+=f[0];
L51:   f[3]−=f[0];
L52:   f[0]+=Input001;
L53:   f[0]+=f[0];
L54:   f[0]*=Input000;
L55:   f[0]−=f[1];
L56:   f[0]=sin(f[0]);
L57:   f[0]*=f[0];
L58:   f[0]+=Input001;
L59:   f[0]/=0·8695814609527588f;
L60:   f[0]+=Input001;
L61:   f[0]*=Input003;
L62:   f[0]+=Input001;
L63:   f[0]−=Input000;
L64:   f[0]+=Input001;
L65:   f[0]−=Input002;
L66:   f[0]=fabs(f[0]);
L67:   f[3]+=f[0];
L68:   f[0]−=0·2995789051055908f;
L69:   f[0]+=f[1];
L70:   f[0]+=−0·6615190505981445f;
L71:   f[0]*=−0·3288925886154175f;
L72:   f[0]*=0·2570122480392456f;
L73:   f[3]*=f[0];
L74:   f[0]−=f[3];
L75:   f[0]+=Input001;
L76:
  if (!_finite(f[0])) f[0]=0;
  return f[0];
}
```

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