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UPGRADING THE PREDICTION OF JET GROUTING COLUMN DIAMETER USING DEEP LEARNING WITH AN EMPHASIS ON HIGH ENERGIES

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Abstract

In this article is proposed a new method to estimate the diameter of jet grouting columns. The method uses the largest data collection of column diameters measured to date and includes a large amount of new data that fills the existing gap of data for high injection energies. The dataset was analysed using a deep neural network that took into account the problem's key parameters (i.e. type of soil, soil resistance, type of jet and specific energy in the nozzle). As a result, three different neural networks were selected, one for each type of jet, according to the errors and consistency associated with each. Finally, using the trained networks, a number of design charts were developed to determine the diameter of a jet grouting column as a function of the soil properties and the jet system. These charts allow generating an optimal jet grouting design, improving the prediction of the diameter of jet columns especially in the high energy triple fluid.

Keywords: Jet grouting; ground improvement; column diameter; deep learning; neural networks.

1. Introduction.

Jet grouting [38] is the most powerful, versatile and studied technique among existing ground improvement methods. The technology uses radial fluid injection at very high speeds to erode the ground, partially replacing the eroded material and mixing it with a grouting agent (grout) to create a new material [6,5,22]. Jet grouting has led to wide-ranging applications including foundations, underpinnings, excavation supports, soil improvements, among others [21,19,11].

Currently, there are a large number of jet grouting procedures [8]. However, there are three traditional systems according to the number of fluids injected: single fluid (only grout is injected), double fluid (grout enshrouded by air or water is used) and triple fluid (grout and water enshrouded by air is used) [11,14]. Other systems also exist, such as enhanced triple fluid and superjet grouting, widely used nowadays, which are essentially improvements of the traditional methods [8,37]. The final product obtained with a jet grouting treatment depends on many factors [15], which in turn reside both in the parameters of the system itself (type of jet, injection pressure, flow rate, injected material, lifting and rotational speed of the monitor) and the soil to improve (particle size distribution, density, structure and phreatic level location). According to Modoni et al. [22] the column diameter depends on the jet's capacity to propagate its erosive action at greater distances from the nozzle, which is determined by the combination of the energy given by the injection and the soil's resistance. The way in which the grout interacts with the soil differs depending on the soil's permeability and therefore the fine particle content influences the soil's resistance to erosion, as recognised by Shen et al. [33]. Thus, there are three major types of grout–soil interaction according to the soil's permeability: seepage, sand erosion and clay erosion [22].

Consequently, predicting the diameter of a jet grouting column is a key parameter of major importance in engineering design and it has piqued the interest of many researchers. Atangana Njock et al. [3] reviewed the different existing methods to estimate the diameter of jet grouting columns based on the work published by Ribeiro and Cardoso [27] introducing the methods based on artificial intelligence (AI) as a new category. In this way, they classified the methods to estimate jet grouting column diameters into the following five categories: (1) empirical, (2) conceptual, (3) theoretical, (4) semitheoretical and (5) based on artificial intelligence. The empirical [9] and conceptual methods [23,10,1] are mainly based on single fluid jet, as are most of the theoretical methods [22,36,17], except that of Shen et al. [33]. Among the semitheoretical methods, it should be underlined the work of Flora et al. [15] who collected data from field trials and established what is probably the most widely used jet grouting column estimation method to date for all types of jet grouting. However, the main drawback of this latter work is that the data of only 18 columns were used to validate the method in the triple fluid jet. Methods based on artificial intelligence predict the diameters of new columns using measured column diameter data. A key point to remember is that these methods are dependent on the amount of training data, so the larger the database used, the more accurate the predictions will be. Among these methods, we can highlight that proposed by Tinoco et al. [35] who collected column data mainly from double fluid systems and clayey soils; the authors conclude that the method is only suitable under these conditions and therefore much caution should be taken when applying under different conditions. Ochmański et al. [25] compiled the largest known database to date, with the data of 131 measured diameters of jet grouting columns corresponding to the three jet types (50 single, 43 double and 38 triple). These authors created design charts derived from neural networks that significantly improve the predictions proposed by other authors [32,15] and that are applicable to all types of jet grouting and in all types of soils. Finally, a work based on neural networks [31] should be highlighted, in this case bidirectional long short-term memory networks, based on data from 7 columns, all built with the single fluid jet system and in the same type of soil (pyroclastic soil). The work provides a novel tool to determine the real-time variations in jet grout column diameter with the depth.

Nowadays, due to a lack of reliable methods, uncertainty persists during the design stage regarding the prediction of the final grouted body's diameter. In this sense, analytical methods are unreliable due to the complexity of jet grouting mechanisms [22]. Mathematical models that attempt to emulate the behaviour of the human brain have been developed over several decades. One class of these models are artificial neural networks (ANN) first introduced by McCulloch and Pitts [20]. ANNs have been widely applied to solve and/or understand many geotechnical engineering problems [39,7,34,13,16]. Specifically, ANNs have been used to predict the diameter of jet grouting columns [25,24], offering satisfactory results and even achieving lower levels of prediction errors than other analytical or empirical methods. A neural network having more than one hidden layer is generally referred to as a deep neural network (DNN) [30]. It uses multiple-layer architectures to extract the inherent features of the data from the lowest to the highest layer making it one of the most efficient AI tools for solving very complex problems, being widely used in geotechnical engineering [e.g. 4,18].

In the present study, DNNs were employed to predict jet grouting column diameter based on the problem's key parameters. Prior to the training of the DNN, a comprehensive set of data on jet grouting column diameters was collected. This database included column diameter measurements of all types of jet grouting and soils worldwide, thus, completing previous databases and methods, especially in the triple fluid jet grouting technique high energy range, where most of AI-based studies lack actual diameter data measured, leading to greater uncertainties regarding diameter predictions. It is worth noting that the evolution of this technique has been directed towards the increase of the columns' diameter, particularly for ground improvement works [12], therefore, an enhancement in the prediction of the diameter will lead to more accurate designs. Finally, the performed analysis allowed the plot of design charts to determine the diameter of a jet grouting column based on key input variables.

The paper is organised as follows: Section 2 gives a detailed description of the field data database compiled. The input variables used and the adopted DNNs are addressed in detail in Section 3. Section 4 describes the main results of the analysis and presents the design charts proposed to design jet grouting columns. The main conclusions of the paper are summarised in section 5.

2. Database.

To train the DNN was used a set of test field data in which the diameter of the jet grouting column was measured by different methods (such as visual inspection, sounding pipes or boreholes). The database developed by Ochmański et al. [25] was taken as basis, which in turn complements that elaborated by Flora et al. [15]. This database compiles diameter measurements in columns built in all types of soils and with the three jet grouting techniques. Therefore, it can be considered as a universal database, which can be used as a starting point to cover the objectives of this work. This database was completed with data directly extracted from the scientific literature and other data recovered from the experience of the authors. The data were classified according to the type of jet grouting (single fluid, double fluid or triple fluid). The database also contained data belonging to super jet grouting and other types of high energy jet. These inputs were included as cases corresponding to the triple fluid jet because of their similarities in terms of energy diameter ratio.

Tables S1, S2 and S3 detail all the considered cases, with 89 cases for the single fluid jet, 69 cases for the double fluid jet and 91 cases for the triple fluid jet. It is worth noting that this is the largest jet column diameter database to date, covering all the ranges of energy as well as different types of soils and jet grouting systems. They were compiled from papers published in the scientific literature as well as the authors' technical experience, complementing existing databases. The dataset processed in this work actually represents double the number of records considered in previous works. More specifically, the number of triple fluid system records represents a threefold increase with respect to the amount of data considered in previous works. Additionally, if we focus on the high energy range (E'_n>100 MJ/m), a total of 56 diameter records were used in this work compared to 3 used in previous works.

3. Deep Neural Networks.

3.1. Input variables.

To define the input variables, the same considerations adopted in previous works [e.g. 25,15] were followed and only four input variables were considered: (1) jet grouting injection system, (2) soil type, (3) soil value of the standard penetration test (SPT) and (4) specific energy at the nozzle. Regarding the type of jet grouting, three types were considered (single fluid, double fluid or triple fluid) according to the definitions given in EN:12716 [14]. In relation to the soil type, the data were grouped according to their classification in the standard ASTM:D2487 [2], which divides soils into coarse-grained without fine (less than 5% fine grains), coarse-grained with fine and fine-grained, as stated by different authors [22,32] who demonstrated that erosion mechanisms varied according to the type of soil. The resistance of these three classes of soil to erosion was quantified based on the value of the SPT. In the records where there was no SPT value but resistance to static penetration (q_c), both were correlated following the guidelines given in Schmertmann [29] and Robertson et al. [28]. The last input variable considered was the specific energy at the nozzle (E'_n), which was calculated according to the methods proposed by Flora et al. [15].

3.2. Adopted DNNs.

A DNN with different architectures and parameters was trained for each type of jet grouting. Two scoring indicators, mean absolute percentage error (MAPE) and root mean square error (RMSE), were used to quantify the prediction performance and accuracy of the developed models among the different architecture and parameter options. The sample size of the training and validation sets was determined using the cross-validation technique, considering different fractions (70/30, 75/25, 80/20 and 85/15 and 90/10) and the 80/20 ratio produced the best results. Thus, the available data were divided into two sets, a training set representing 80% of the total data and a validation set representing the remaining 20%. An important issue to bear in mind regards the input variables considered in the analysis: these variables vary in their scales because they measure different quantities. In this way, to improve the predictive power, it is necessary to carry out a feature scaling process. In this case, the data were standardised by removing the mean and scaling to unit variance.

Baseline models of the DNNs were initially built and later optimised through model parameter tuning. There are no established, infallible rules for developing baseline DNN models, and previous experiences clearly demonstrate the importance of empirical testing when it comes to developing neural network models. However, the denominated grid search technique [26] can be used for tuning deep learning models. Therefore, the optimum values of the DNN parameters considered were determined by using a grid search strategy with five-fold cross-validation. Table S4 shows the parameters involved in the grid search along with a brief description.

Once the parameters were chosen, they were refined in their environment in order to maximise each DNN's performance. The final results for each jet grouting type considered are shown in Table 1, and Figure S1 shows a graphical scheme of the neural network adopted in the case of the double fluid.

The process of choosing the architecture and DNN parameters came to an end once the lowest MAPE and RMSE values were found, while constantly checking that the predictions were consistent. During this process, the absence of overfitting was verified by checking the errors gained in the training and validation processes; in all cases, the errors obtained were similar. Learning curves (errors depending on the epochs in the training and validation sets) were inspected to determine the appropriate number of epochs and diagnose the model's performance. These curves also helped us to determine the absence of overfitting in the adopted networks.

Jet type	Hidden layers	Architecture	Activation function	Epochs	Optimizer	Batch size	Learning rate
Single fluid	4	128/64/32/16/1	ReLU	30	Adadelta	10	0.80
Double fluid	3	64/32/16/1	ReLU	70	Adadelta	3	1.05
Triple fluid	5	64/32/16/8/4/1	ReLU	120	Adadelta	3	0.35

Table 1. Summary of the main features of the adopted DNNs.

4. Results: Design charts.

Once the most appropriate network architectures and configurations were selected, their predictions were checked by comparing the measured and predicted diameters with the whole dataset. Figure 1 shows the point clouds of the three types of jet grouting systems considered. Table 2 shows the most significant performance metrics obtained for each type of jet.

Compared to the existing common and universal methods to predict jet column diameters [33,25,15], the present work contributes to a significant improvement mainly for the triple fluid jet. A summary of the metrics obtained in these works are described in Ochmański et al. [25], and the highest performance is found in the study of Ochmański et al. [25], achieving MSE values of 0.007, 0.05 and 0.106 m^2 and MAPE values of 11.93, 12.97 and 15.49%, for the single double and triple jet, respectively. If these results are compared with those shown in Table 2, the present work offers considerable improvements regarding the diameter prediction, mainly for the triple fluid jet.

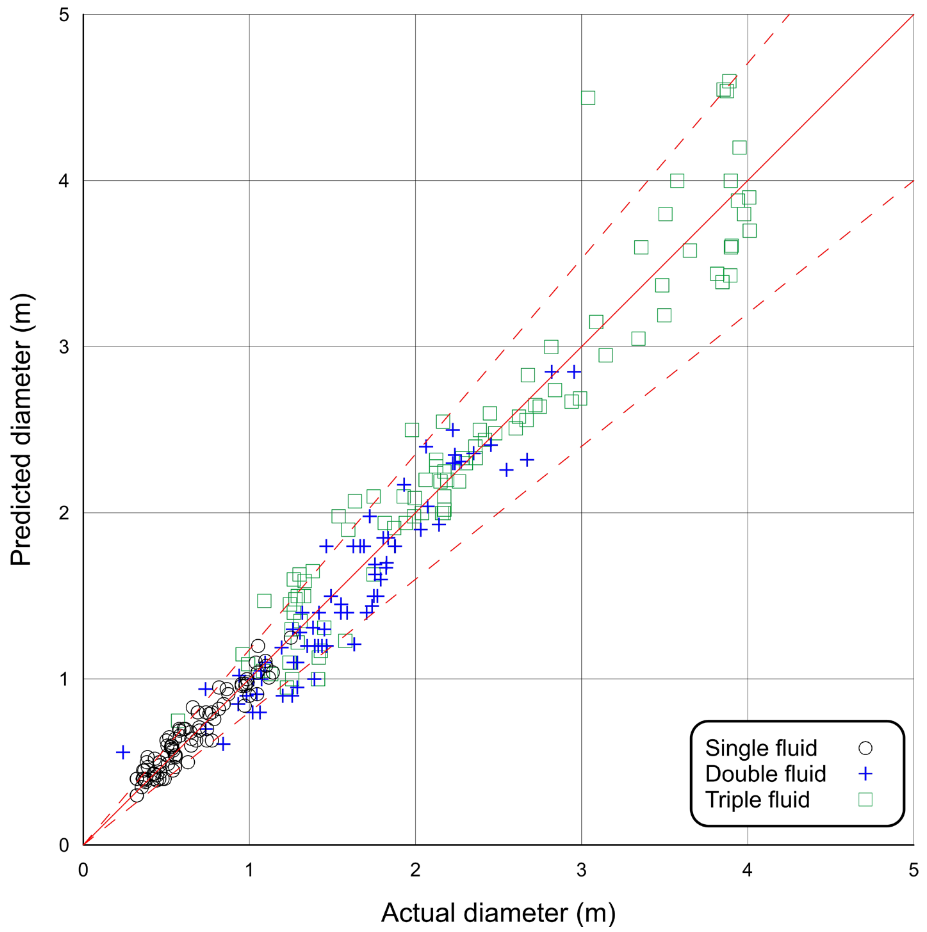

Figure 1. Predicted vs measured jet grouting column diameter for all types of jet grouting considered.

Jet type	R^2	MAPE (%)	MAE (m)	MSE (m^2)
Single fluid	0.91	9.71	0.058	0.005
Double fluid	0.90	12.51	0.157	0.037
Triple fluid	0.91	9.99	0.214	0.087

Table 2. Summary of accuracy parameters of the adopted DNNs. R^2 is the coefficient of determination, MAPE is the mean absolute percentage error, MAE is the mean absolute error and MSE is the mean squared error.

Finally, once the DNNs were trained and tested, they were fed using different input datasets (i.e. SPT blow counts, soil types and energies) strategically prepared to predict the associated diameters. These data were plotted in three main design charts, providing the present work with greater practical usefulness. The proposed design charts are shown in Figures 2, 3 and 4.

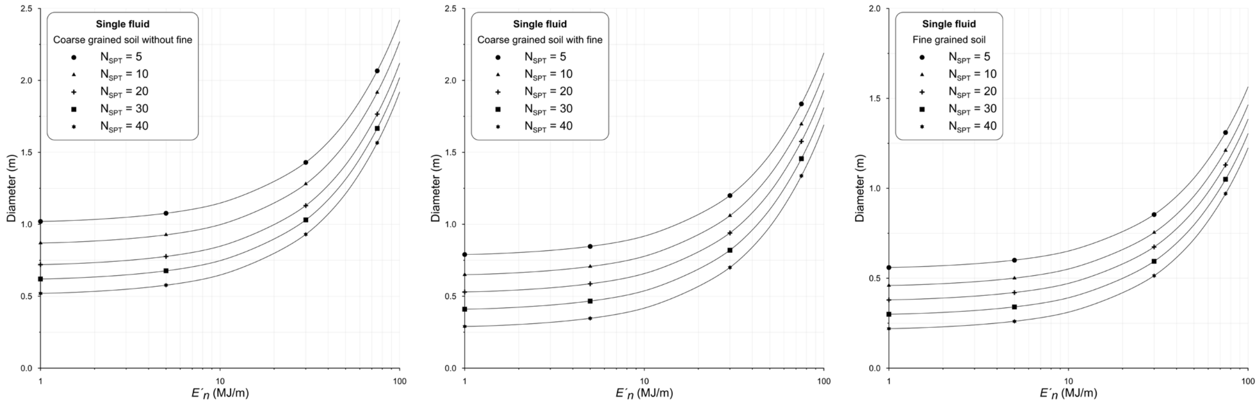

Figure 2. Design charts to predict the column diameter for jet grouting single fluid. From left to right, coarse-grained without fine soils, coarse-grained with fine soils and fine-grained soils.

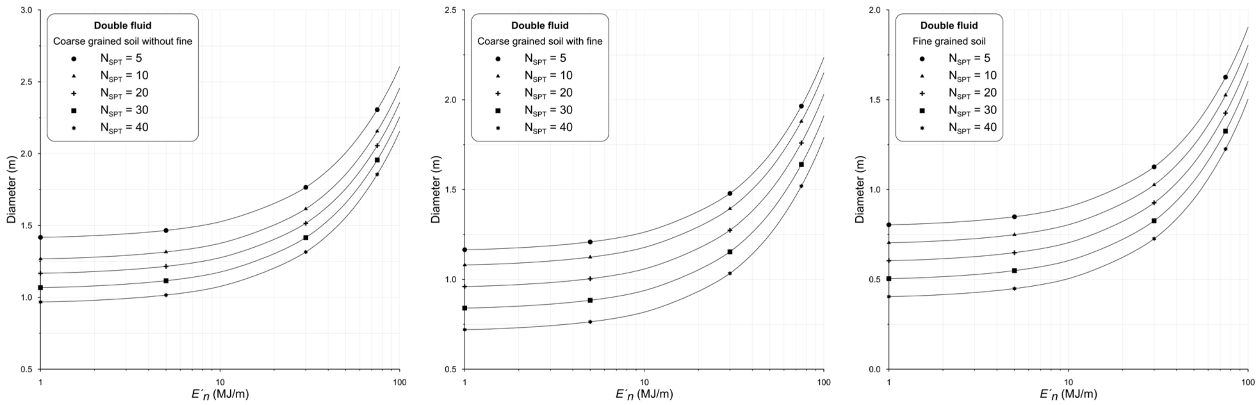

Figure 3. Design charts to predict the column diameter jet grouting double fluid. From left to right, coarse-grained without fine soils, coarse-grained with fine soils and fine-grained soils.

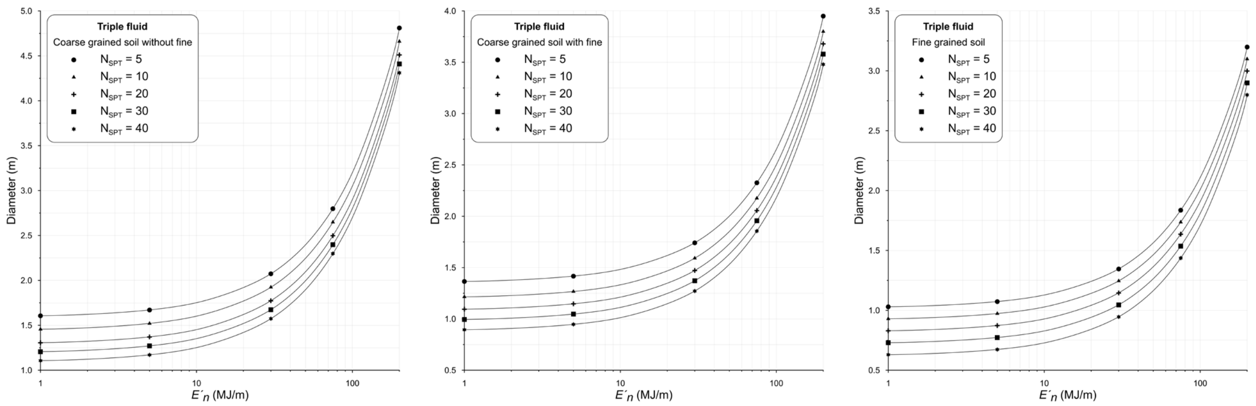

Figure 4. Design charts to predict the column diameter for jet grouting triple fluid. From left to right, coarse-grained without fine soils, coarse-grained with fine soils and fine-grained soils.

When comparing to previously published design charts [e.g. 15,25] some differences are observed and these are manifested more notably in the triple fluid jet, reaching very significant differences (up to 20-30%) in the zone of high energies.

5. Conclusions.

In this paper, deep learning was applied to estimate the diameter of jet grouting columns. To this end, the largest dataset to date of jet grouting column diameter measurements was collected. These data complement existing works, especially regarding the high energy zone of the triple fluid system, which is the most widespread today because the technology's evolution largely focuses on high energies (increases in diameter).

Once the data were collected, the key variable inputs were selected and different DNN configurations (architectures and parameters) were tested in order to select the most appropriate DNNs to explain the problem (those with a lower value in error function and prediction consistency). This process ended with the adoption of three DNNs, one for each type of jet grouting, producing better performance metrics than those offered by existing methods, mainly for the prediction of triple fluid high energy columns diameters.

To improve the practical applications of this work, the trained DNNs were used to plot a series of design charts to allow a quick and easy prediction of a jet grouting column's diameter, based on the specific energy in the nozzle, the type of soil and its strength expressed through the soil SPT value. These charts will contribute to more accurate and reliable designs of jet grouting columns, although the networks trained in this study are likely to be improved in the future as more diameter data are obtained.

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References

1. Arson C, Juge B (2012) A hollow sphere model to dimension soilcrete columns. In: GeoCongress 2012: State of the Art and Practice in Geotechnical Engineering. pp 1006-1015
2. ASTM:D2487 (2011) Standard Practice for Classification of Soils for Engineering Purposes (Unified Soil Classification System). ASTM International, West Conshohocken, PA
3. Atangana Njock PG, Chen J, Modoni G, Arulrajah A, Kim Y-H (2018) A review of jet grouting practice and development. Arabian Journal of Geosciences 11 (16):459
4. Bagińska M, Srokosz PE (2019) The Optimal ANN Model for Predicting Bearing Capacity of Shallow Foundations trained on Scarce Data. KSCE J Civ Eng 23 (1):130-137. doi:10.1007/s12205-018-2636-4
5. Bell A (2012) Geotechnical grouting and soil mixing. In: Chapter 90. ICE Manual of Geotechnical Engineering. Institution of Civil Engineers United Kingdom,
6. Bell F (1993) Engineering treatment of soils. CRC Press,
7. Benali A, Boukhatem B, Hussien MN, Nechnech A, Karray M (2017) Prediction of axial capacity of piles driven in non-cohesive soils based on neural networks approach. Journal of Civil Engineering and Management 23 (3):393-408. doi:10.3846/13923730.2016.1144643
8. Burke GK (2004) Jet Grouting Systems: Advantages and Disadvantages. In: GeoSupport 2004. pp 875-886. doi:doi:10.1061/40713(2004)75
9. Covil CS, Skinner AE (1994) Jet grouting—a review of some of the operating parameters that form the basis of the jet grouting process. In: Grouting in the ground. pp 605-629. doi:10.1680/gitg.19287.0041
10. Croce P, Flora A (2000) Analysis of single-fluid jet grouting. Géotechnique 50 (6):739-748. doi:10.1680/geot.2000.50.6.739
11. Croce P, Flora A, Modoni G (2014) Jet grouting: technology, design and control. CRC Press,
12. Cheng S-H, Liao H-J, Yamazaki J, Wong RK (2017) Evaluation of jet grout column diameters by acoustic monitoring. Canadian Geotechnical Journal 54 (12):1781-1789
13. Díaz E, Brotons V, Tomás R (2018) Use of artificial neural networks to predict 3-D elastic settlement of foundations on soils with inclined bedrock. Soils and Foundations 58 (6):1414-1422. doi:https://doi.org/10.1016/j.sandf.2018.08.001
14. EN:12716 (2001) Execution of Special Geotechnical Works-Jet Grouting. British Standards Institution
15. Flora A, Modoni G, Lirer S, Croce P (2013) The diameter of single, double and triple fluid jet grouting columns: prediction method and field trial results. Géotechnique 63 (11):934-945. doi:10.1680/geot.12.P.062
16. Goh ATC, Zhang RH, Wang W, Wang L, Liu HL, Zhang WG (2020) Numerical study of the effects of groundwater drawdown on ground settlement for excavation in residual soils. Acta Geotechnica 15 (5):1259-1272. doi:10.1007/s11440-019-00843-5
17. Ho CE (2007) Fluid-Soil Interaction Model for Jet Grouting. In: Grouting for Ground Improvement: Innovative Concepts and Applications, vol GSP 168. pp 1-10. doi:10.1061/40912(231)1
18. Koopialipoor M, Tootoonchi H, Jahed Armaghani D, Tonnizam Mohamad E, Hedayat A (2019) Application of deep neural networks in predicting the penetration rate of tunnel boring machines. Bulletin of Engineering Geology and the Environment 78 (8):6347-6360. doi:10.1007/s10064-019-01538-7
19. Lunardi P (1997) Ground improvement by means of jet-grouting. Ground improvement 1 (2):65-85
20. McCulloch WS, Pitts W (1943) A logical calculus of the ideas immanent in nervous activity. The bulletin of mathematical biophysics 5 (4):115-133

21. Modoni G, Bzówka J (2012) Analysis of foundations reinforced with jet grouting. Journal of Geotechnical and Geoenvironmental Engineering 138 (12):1442-1454

22. Modoni G, Croce P, Mongiovì L (2006) Theoretical modelling of jet grouting. Géotechnique 56 (5):335-347. doi:10.1680/geot.2006.56.5.335

23. Mosiici P Jet grouting quality control. In: Grouting in the ground: Proceedings of the conference organized by the Institution of Civil Engineers and held in London on 25–26 November 1992, 1994. Thomas Telford Publishing, pp 227-235

24. Nikbakhtan B, Apel D, Ahangari K (2015) Jet grouting: using artificial neural networks to predict soilcrete column diameter-part II. International Journal of Mining and Mineral Engineering 6 (1):57-71

25. Ochmański M, Modoni G, Bzówka J (2015) Prediction of the diameter of jet grouting columns with artificial neural networks. Soils and Foundations 55 (2):425-436. doi:https://doi.org/10.1016/j.sandf.2015.02.016

26. Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, Blondel M, Prettenhofer P, Weiss R, Dubourg V (2011) Scikit-learn: Machine learning in Python. the Journal of machine Learning research 12:2825-2830

27. Ribeiro D, Cardoso R (2017) A review on models for the prediction of the diameter of jet grouting columns. European Journal of Environmental and Civil Engineering 21 (6):641-669

28. Robertson P, Campanella R, Wightman A (1983) Spt-Cpt Correlations. journal of geotechnical engineering 109 (11):1449-1459

29. Schmertmann JH (1970) Static cone to compute static settlement over sand. Journal of Soil Mechanics & Foundations Division 96 (№ SM3):1011-1043

30. Schmidhuber J (2015) Deep learning in neural networks: An overview. Neural networks 61:85-117

31. Shen S-L, Atangana Njock PG, Zhou A, Lyu H-M (2020) Dynamic prediction of jet grouted column diameter in soft soil using Bi-LSTM deep learning. Acta Geotechnica. doi:10.1007/s11440-020-01005-8

32. Shen S-L, Wang Z-F, Sun W-J, Wang L-B, Horpibulsuk S (2013) A field trial of horizontal jet grouting using the composite-pipe method in the soft deposits of Shanghai. Tunnelling and Underground Space Technology 35:142-151. doi:https://doi.org/10.1016/j.tust.2013.01.003

33. Shen S-L, Wang Z-F, Yang J, Ho C-E (2013) Generalized Approach for Prediction of Jet Grout Column Diameter. Journal of Geotechnical and Geoenvironmental Engineering 139 (12):2060-2069. doi:doi:10.1061/(ASCE)GT.1943-5606.0000932

34. Tarawneh B (2013) Pipe pile setup: Database and prediction model using artificial neural network. Soils and Foundations 53 (4):607-615. doi:http://dx.doi.org/10.1016/j.sandf.2013.06.011

35. Tinoco J, Gomes Correia A, Cortez P (2016) Jet grouting column diameter prediction based on a data-driven approach. European Journal of Environmental and Civil Engineering 22 (3):338-358

36. Wang Z-F, Shen S-L, Yang J (2012) Estimation of the diameter of jet-grouted column based on turbulent kinematic flow theory. In: Grouting and deep mixing 2012. pp 2044-2051

37. Wang Z, Shen S, Ho C, Kim Y (2013) Jet grouting practice: an overview. Geotechnical Engineering Journal of the SEAGS & AGSSEA 44 (4):88-96

38. Yahiro T, Yoshida H Induction grouting method utilizing high speed water jet. In: Proceedings of the Eighth International Conference on Soil Mechanics and Foundation Engineering, 1973. pp 359-362

39. Zounemat-Kermani M, Beheshti A-A, Ataie-Ashtiani B, Sabbagh-Yazdi S-R (2009) Estimation of current-induced scour depth around pile groups using neural network and adaptive neuro-fuzzy inference system. Applied Soft Computing 9 (2):746-755. doi:http://dx.doi.org/10.1016/j.asoc.2008.09.006