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Research paper

A comparative analysis of artificial neural network predictive and multiple linear regression models for ground settlement during tunnel construction

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Abstract: Ground settlement during and after tunnelling using TBM results in varying dynamic and static load action on the geo-stratum. It is an undesirable effect of tunnel construction causing damage to the surface and subsurface infrastructure, safety risk, and increased construction cost and quality issues. Ground settlement can be influenced by several factors, like method of tunnelling, tunnel geometry, location of tunnelling machine, machine operational parameters, depth & its changes, and mileage of recording point from starting point. In this study, a description and evaluation of the performance of the arti?cial neural network (ANN) was undertaken and a comparison with multiple linear regression (MLR) was carried out on ground settlement prediction. The performance of these models was evaluated using the coefficient of determination R2, root mean square error (RMSE) and mean absolute percentage error (MAPE). For ANN model, the R2, RMSE and MAPE were calculated as 0.9295, 4.2563 and 3.3372, respectively, while for MLR, the R2, RMSE and MAPE, were calculated as 0.5053, 11.2708, 6.3963 respectively. For ground settlement prediction, both ANN and MLR methods were able to predict significantly accurate results. It was further noted that the ANN performance was higher than that of the MLR.

Keywords: tunneling construction, ground settlement, MLR, ANN

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1. Introduction

Tunnel construction is aimed at providing a subsurface throughway for use by military, municipal and mining operatives. Several methods are employed which include drilling, blasting and use of tunnel boring machines (TBM) [1]. However, these operations being destructive in nature tend to cause changes in the natural sub strata setting and changes ground strength leading to settlement. This has adverse impact on existing infrastructure and the cost and safety on the ongoing project. Studies in ground settlement describe settlement as the change in the in-situ ground surface levels [2,3]. The change in settlement at a point may be instant and/or continuous resulting from an impact load, due to stress redistribution with change in pore water and pore air pressure and creep failure of the ground [4].

Different factors have been identified to affect the magnitude of ground settlement during shield tunnel construction. Wang et al. [5] focused on the influence of construction method, depth, location from starting point, geology and hydrogeology influence on settlement. Meng et al. [6] studied the influence of earth pressure balance shield machine control parameters that influence the degree of compression pressure on the surrounding soil. Gong et al. [7] described the failure mechanism and tunnel uplift resistance in soft clay. Fang et al. [8] carried out settlement model tests in sandy soils. Wang et al. [9] described the influence of double layer lining structure on settlement. Li and Yuan [10] presented the impact of a new tunnel construction below an existing double tunnel. In sum, ground settlement can generally be said to be influenced by hydrogeology, geology, construction method, geometry of tunnel, locality to existing tunnel loads or influence of nearby tunnel under construction.

Three methods are applied in settlement prediction, namely, semi-theoretical method [4], numerical analysis method [11], and analytical method [11]. However, the considerations, including inconsistencies in equipment efficiency, ground geology, hydrogeology and human error and their interactions require such applications as the numerical methods – artificial intelligence (AI). AI is an emulation of human thinking process [5]. In spite of the available experience, the research works and empirical data previously established, real time analysis of obtaining conditions and their application is unique for each particular site. The ability for AI to self-learn and self-predict some desired outcomes is the most important characteristic of this approach. AI has been used for classification, optimization and prediction for decision making in a variety of disciplines of operations and research, with great success [5, 12–17]. In addition, artificial neural network (ANN) is one of the most effective methods to predict the deformation and dynamic failure of rock mass [4, 18–20].

The aim of this work is to compare the prediction efficiencies of the ANN models and multiple linear regression (MLR) and for the resultant ground settlement from tunnel construction operation. Using cumulative settlement, settlement, cutter-head mileage, chainage, and depth as the prediction parameters. The case study applies to the field monitoring results for Guangzhou urban rail transit line No. 9.

The prediction performance of the ANN model was shown to be higher compared to MLR model. Both the ANN and MLR methods were able to predict significantly accurate results. The ANN and MLR models achieved are site specific and should be modified accordingly were applied to other sites.

2. Materials and methods

2.1. Artificial neural network

McCulloch and Pitts' pioneering work in the 1940s is widely regarded as the start of the ANN field. The ANN was reported to have been initially used in the late 1950s, following Rosenblatt's discovery of the perceptron network and related learning rule. After subsequent advancements to the basic perceptron network which could only address a limited class of problems, neural networks became popular in the late 1980s and, more recently, in the 1990s [16].

ANNs are information processing structures that are designed to look and function like biological neural tissue. An ANN is a system made up of numerous basic units (called neurons) that are interconnected and function in parallel, sending signals to one another to complete a processing task. The ability of ANNs to imitate the learning process is one of its most notable properties. They are given pairs of input and output signals from which general principles are automatically deduced, allowing the ANN to provide the proper output for a signal that has never been used before (under particular conditions). The importance of quality and quantity of data for training the networks outcomes is pointed out in [19]. Prediction accuracy of ANN based applications in prediction and forecasting is usually higher than 80% as evident in [13, 20]. Neural network models are suitable for parametric modelling and compare favorably with other parametric models such as regression analysis [13, 21].

The disadvantages of ANN include a lack of general procedure, particularly for the selection of its initial weights and other initial parameters for effective application, and the fact that it is best suited for short-term forecasting rather than long-term forecasting, especially for different projects with wide variations in trends. Other learning algorithms and optimization tools can be used to improve ANNs [1, 17, 19]. In this work, the multi-layer networks were utilized in training the network under the supervision of error back-propagation algorithm. To produce an error signal, the network's model output is subtracted from a desired output. This erroneous signal is then sent backwards across the network, in the opposite direction of synaptic connections [13]. To evaluate performance, the coefficient of determination (R2), root mean square error (RMSE) and mean absolute percentage error (MAPE) were utilized [19].

2.2. Multiple linear regression (MLR)

Also known as multiple regression, MLR is a time-honored technique that dates back to Pearson's use of it in 1908. The multiple regression equation can be written as:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon \tag{2.1}$$

where, i is the number of observations, y_i is the i-th dependent variable, x_i is the i-th independent variable, β_0 is the y-intercept (constant term).The regression line intercepts the y-axis, representing the amount of the dependent variable y when all independent variables are equal to zero [3]. β_p is a regression coefficient that represents the amount that the dependent variable y changes when the related independent variables change by one unit. While all the independent variables are constant. Because each data point can differ significantly from the conclusion predicted by the model, the model is not always entirely accurate. To account for such minor fluctuations, the model includes the residual value, ε, which is the difference between the actual and predicted outcomes [22]. The constraint regarding regression techniques is that they are not definite about the underlying causal process, notwithstanding their ability to establish connections [23].

2.3. Case study and model design

The case study was Huadu Automobile City station to Guangzhou Urban Rail Transit line 9, North Railway Station Shield Construction area, over a mileage on the left of Zdk3788.0 to Zdk4078.0. The ground condition is typically limestone area with upper soft and lower hard strata with sections of rock and caves. The shield used is 8.92 m with a total length of 77.35 m. The average torque and thrust are 1647.7 kN·m and 13240.0 kN, respectively. The earth pressure in chamber of TBM (EPCTBM) and ground settlements were recorded at 24-hour intervals every day. The data used in this study is from January to March of 2015. Table 1 below, shows summary of shield machine data and control parameters. The analysis of cumulative settlement was limited to the stated variables above due to, lack of access to data for other influencing factors such as geology, hydrogeology, and shield machine control parameters.

Table 1. Shield machine data and control parameters

Item No.	Description	Details
1	Diameter	5.4 m Inner & 5.7 m Outer diameter of segment
2	Segment ring length	1.5 m
3	EPCTBM	107–171 kPa Variance, plus or minus 5–10 kPa
4	Cutter speed	0.3–3.0 rpm
5	Rotation speed	< 0.8 rpm
6	Torque	< 2000 kN·m
7	Optimum Driving Penetration	1–1.25
8	Grouting Pressure	0.8–0.9 MPa
9	Grouting velocity	30–50 L/min
10	Excavation medium	different soil layers, like sand layer, rock layer, and clay layer

2.4. Parametric analysis

Parametric analysis was carried out by determination of correlation coefficient of key variables using input parameters, such as settlement (A), cutter head mileage (B), chainage (C), tunneling ring number (D), initial depth (E), previous depth (F), and current depth (G).

Cutter head advance rate had the least score of less than 0.05 and hence removed from the parameters as significant variables. An analysis for collinearity was carried out for MLR and three models for prediction of cumulative settlement were modelled. It was observed that chainage and tunnelling ring number had same coefficient of correlation hence chainage was used since it is a direct value obtained from field measurement and not influenced by calculation error or in-situ modifications. Table 2 and Table 3 show performance total

Table 2. Parameter selection and performance ranking

Model No.	Model inputs	R2	MAPE	RMSE	Rank of R2	Rank of MAPE	Rank of RMSE	Final Rank
MLR.TR: 1	A, B, C, E	0.5147	5.8918	12.0412	1	1	2	4
MLR.TR: 2	A, B, C, F	0.4737	6.0777	11.5496	3	2	1	6
MLR.TR: 3	A, B, C, G	0.4894	8.0103	12.2208	2	3	3	8
MLR.TS: 1	A, B, C, E	0.4370	6.9918	14.1412	3	2	3	8
MLR.TS: 2	A, B, C, F	0.4866	11.7795	9.1664	2	3	1	6
MLR.TS: 3	A, B, C, G	0.4980	6.0709	13.8261	1	1	2	4
ANN.TR: 1	A, B, C, E	0.8043	3.6815	6.1825	2	2	2	6
ANN.TR: 2	A, B, C, F	0.8563	1.7735	5.8905	1	1	1	3
ANN.TR: 3	A, B, C, G	0.5486	3.7286	11.7775	3	3	3	9
ANN.TS: 1	A, B, C, E	0.7017	2.4760	9.2807	2	3	2	7
ANN.TS: 2	A, B, C, F	0.8389	1.6291	6.8257	1	1	1	3
ANN.TS: 3	A, B, C, G	0.4495	2.2730	10.1552	3	2	3	8

Note: TS = Training, TR = Testing.

Table 3. Parameter selection and performance total ranking

Model	Total performance rank	Rank	Chosen Model
I	25	2	Model II Settlement, Cutterhead Mileage, Chainage, previous depth
II	18	1	
III	29	3	

ranking for the model iteration of the three models with randomly selected datasets. The determination index, like R2, MAPE and RMSE, were used to rate the performance of each model.

2.5. Data normalization

The data was observed to have varying magnitude, range and units. It was therefore normalized using the equation (2.2) below [12]:

$$y = \frac{y_i + y_{\min}}{y_{\max} - y_{\min}} \tag{2.2}$$

where, y is the input or output variable, y_i is the i-th observed data at i, $y_{\min}$ is the minimum value of the observed data, $y_{\max}$ is the maximum value of the parameter values.

3. Results and discussion

3.1. ANN

The data for settlement, cutter head mileage, chainage, previous depth as the input columns and cumulative ground settlement (H) as the output were divided into training 60%, testing 20% and validation 20% [19, 24, 25]. The default divider and command in MATLAB is used to divide the data into the three sets. The training function used is the Levenberg Marquardt [26].

3.2. Optimum structure of ANN

Trial and error procedure is used to determine the optimum ANN structure based on heuristics proposed by [27]. Minimum of 2 and Maximum of 9 neurons in one hidden layer model based on the study by koopialipoor et al. [24, 27] is considered. Table SM2 in supplementary materials shows proposed Heuristics by researchers for the optimum number of hidden layer neurons [28, 29]. Considering four parameters in this study, 1 hidden layer is considered sufficient for this multiple layer perceptron back propagation ANN, according to [30]. The number of neurons in the hidden layer was obtained after 1000 iterations with randomly selected samples based on a ranking technique by Zorlu et al. [12]. The optimum model is the network with nine neurons in the hidden layer.

Figure 1 shows different frequencies of occurrence for minimum error at locations of hidden neurons. The frequency for each quantity of neurons in the hidden layer is different. This shows that the frequency in this study is dependent on the selected training data. The model with the highest frequency is the $4 \times 9 \times 1$ model. It has above 30 percent of the iterations that is, for more than 300 instances of the 1000 iterations the minimum error will be obtained at the model with nine hidden neurons. Hence, the optimum number of neurons chosen is nine neurons in the hidden layer.

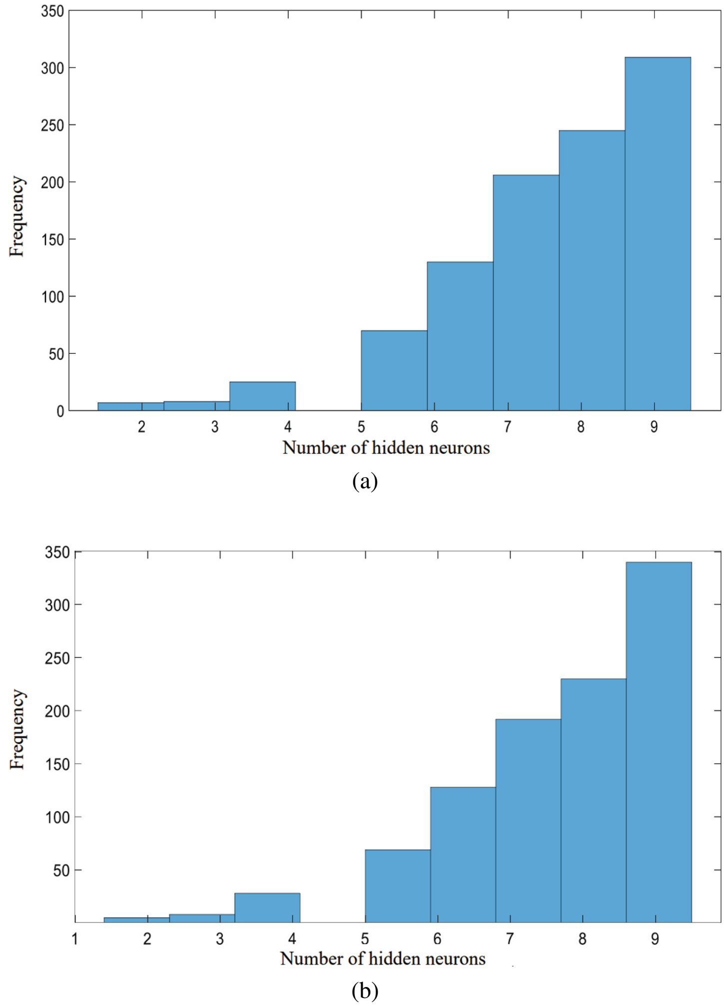


Fig. 1. Histogram of frequency vs number of neurons in hidden layers and hidden layers at minimum RMSE: (a) frequency vs number of hidden neurons; (b) frequency vs number of hidden layers

3.2.1. Transformation function

The chosen ANN of structure $4 \times 9 \times 1$ was subjected to different combinations of transformation functions to determine transfer functions ideal for optimum performance. The tansig, logsig, purelin functions have been widely applied in previous studies in civil engineering and tunnel settlement estimation [13, 31–33]. They have been applied for, input, hidden and output layers. Both tansig-tansig and tansig-purelin gave the same score shown in Table 4. Hence, either can be used. However, tansig-purelin was used due to purelins transfer functions' fast processing power [12].

Table 4. Performance of ANN structure with different transfer functions

Model No.	Description	R2		RMSE		Rank of R2		Rank of RMSE		Total	Rank of total
		Train	Test	Train	Test	Train	Test	Train	Test		
1	Purelin, Purelin	0.5186	0.5158	9.9619	11.0927	8	8	7	9	32	8
2	Purelin, Tansig	0.5870	0.3999	9.9775	9.5522	7	9	8	7	31	7
3	Purelin, Logsig	0.4929	0.5442	10.8230	10.1611	9	7	9	8	33	9
4	Logsig, Purelin	0.9268	0.8524	4.3281	5.5036	4	4	4	4	16	4
5	Logsig, Tansig	0.9650	0.8733	4.0360	6.0588	1	3	3	5	12	3
6	Logsig, Logsig	0.8151	0.8133	6.7568	6.3047	5	5	5	6	21	5
7	Tansig, Tansig	0.9410	0.9188	3.6694	4.6694	3	1	1	2	7	1
8	Tansig, Purelin	0.9560	0.9121	3.7406	4.4529	2	2	2	1	7	1
9	Tansig, Logsig	0.8123	0.8040	7.0237	4.6973	6	6	6	3	21	5

3.2.2. Learning rate and momentum constant

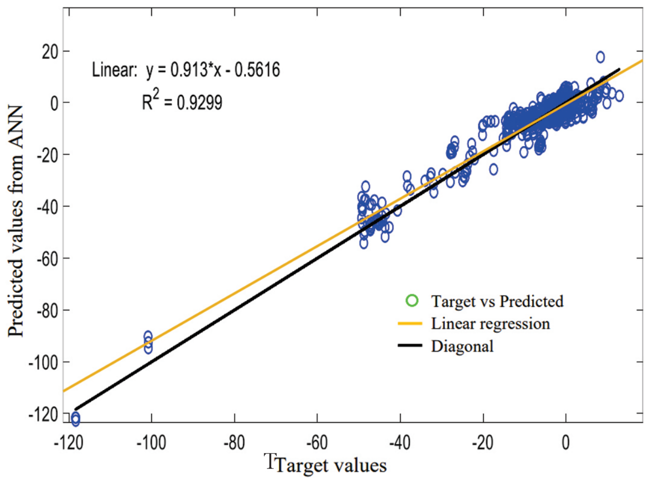
In order to select the optimum learning rate and momentum constant, the model of $4 \times 9 \times 1$ was subjected to 10 constant learning rates and momentum constants obtained from. Table 5 shows proposed heuristics for learning rate and momentum term by various researchers. Using the performance index, RMSE, the performance ranking for the combination of learning rate and moment were plotted. Model No 4 (learning rate, 0.01,

Table 5. Proposed heuristics for learning rate and momentum term by [12, 29, 34–36]

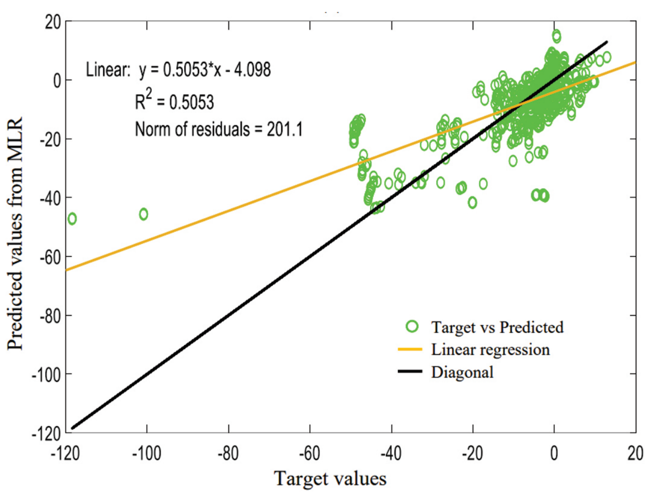
Model No.	Learning rate	Momentum constant	Model No.	Learning rate	Momentum constant
1	0.1	0.3	6	0.15	0.075
2	0.04	0.02	7	0.2	0.6
3	0.05	0.5	8	0.25	0.9
4	0.01	0.00005	9	0.3	0.6
5	0.1	0.9	10	0.5	0.9

Momentum Constant, 0.00005) in Table 5, was observed to perform better with minimum ranking for RMSE. The proposed structure of proposed Artificial Neural Network with 4 inputs, 1 hidden layer, 9 hidden neurons, and 1 output.

MLR analysis is used to correlate the observed cumulative settlement and the predicted results. The basic descriptive statistics of tunnelling data are shown in Table 1. Correlation of predicted and target values of cumulative settlement for the MLR model, for 630 datasets is shown in the supplementary data. The correlation between predicted and target values is shown in Fig. 2, which displays a strong prediction capability.



(a)



(b)

Fig. 2. Comparison between target dataset and predicted values using (a) ANN; (b) MLR

From Fig. 2, the ANN model can attribute the cumulative settlement to the selected variables by 92.95%, while the MLR can attribute the target cumulative settlement to the variables (settlement, cutter-head mileage, chainage, previous depth) by 50.53%.

The MLR regression equation is as follows:

$$Y = 0.66811 + 0.1815A - 0.21644B + 0.40116C + 0.2452F \tag{3.1}$$

In equation (3.1), Y is the cumulative settlement, the values A, B, C, F, are, settlement, cutter head mileage, chainage and previous depth values, respectively. R2, RMSE and MAPE of this model are given in Table 6 and compared to ANN.

Table 6. Comparison of MLR and ANN performance

Item No.	Description	R2	RMSE	MAPE	Rank
1	ANN	0.9295	4.2563	3.3372	1
2	MLR	0.5053	11.2708	6.3963	2

From Table 6, ANN has higher value of R2, and least values of RMSE and MAPE, which can be attributed to ANN models' ability for generalization and learning of non-linear data as an advantage over the MLR. Fig. 3 presents the performance of the ANN and MLR against the target data, from which the ANN model is shown to be more efficient than MLR consistent with previous studies [11, 32].

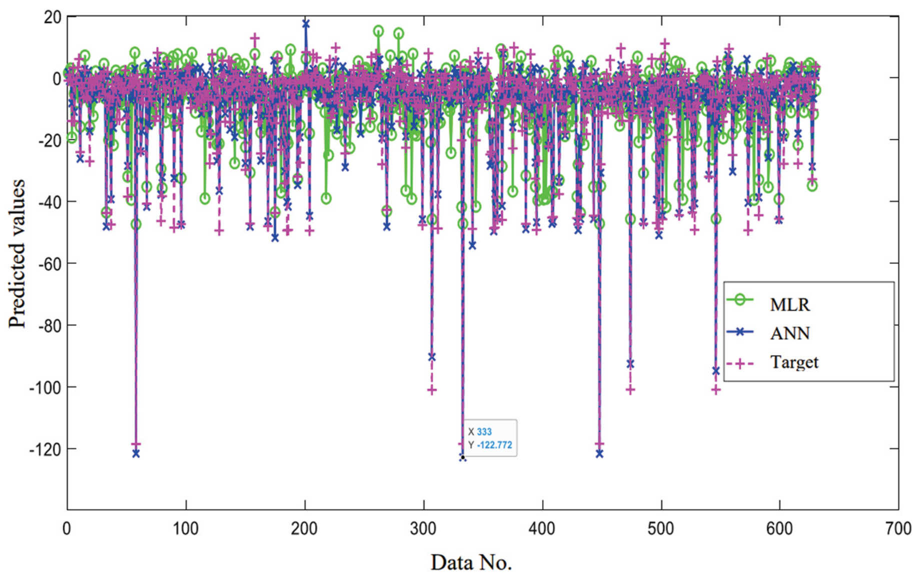


Fig. 3. Comparison between target dataset and predicted values using the ANN and MLR

4. Conclusions

ANN and MLR models were used in this study to forecast the ground settlement caused by shield tunnelling utilizing four effective parameters, settlement, cutter-head mileage, chainage and previous depth. The parameters were employed as input parameters to model cumulative settlement using 630 datasets obtained from Guang-zhou Urban Rail Transit line 9. The following conclusions can be taken from this research:

For an ANN network, four neurons in the input layer, one hidden layer with nine neurons, and one neuron in the output layer were found to be the best ANN structure. The outcome of the model for cumulative settlement prediction revealed that the equation derived from the MLR model did perform well in terms of cumulative settlement prediction, and the target data was within the upper and lower limit of the prediction margin. The prediction performance of the ANNs model was shown to be higher than the MLR model based on the performance indicators. The ANN and MLR models that have been achieved are solely connected to Guangzhou Urban Rail Transit line 9, for the section covered in the period January – March, 2015. These models should be modified in other circumstances other than this shield tunnelling project.

5. Supplementary material

There are three Tables (Table SM1-Table SM4), two figures (Fig. SM1 and Fig. SM2), and computer program in the supplementary material section.

6. Patents

6.1. Acknowledgements

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References

[1] M. Koopialipoor, D.J. Armaghani, M. Haghighi, and E.N. Ghaleini, "A neuro-genetic predictive model to approximate overbreak induced by drilling and blasting operation in tunnels", *Bulletin of Engineering Geology and the Environment*, vol. 78, no. 2, pp. 981–990, 2019, doi: 10.1007/s10064-017-1116-2.

[2] K. Elbaz, S.L. Shen, W.J. Sun, Z.Y. Yin, and A. Zhou, "Prediction model of shield performance during tunneling via incorporating improved particle swarm optimization into ANFIS", *IEEE Access*, vol. 8, pp. 39659–39671, 2020, doi: 10.1109/ACCESS.2020.2974058.

[3] V. Ghiasi and M. Koushki, "Numerical and artificial neural network analyses of ground surface settlement of tunnel in saturated soil", *SN Applied Sciences*, vol. 2, no. 5, 2020, doi: 10.1007/s42452-020-2742-z.

[4] S.G. Ercelebi, H. Copur, and I. Ocak, "Surface settlement predictions for Istanbul Metro tunnels excavated by EPB-TBM", *Environmental Earth Sciences*, vol. 62, no. 2, pp. 357–365, 2011, doi: 10.1007/s12665-010-0530-6.

[5] Z. Wang, W. Yao, Y. Cai, B. Xu, Y. Fu, and G. Wei, "Analysis of ground surface settlement induced by the construction of a large-diameter shallow-buried twin-tunnel in soft ground", *Tunnelling and Underground Space Technology*, vol. 83, pp. 520–532, 2019, doi: 10.1016/j.tust.2018.09.021.

[6] F. Meng, R. Chen, and X. Kang, "Effects of tunneling-induced soil disturbance on the post-construction settlement in structured soft soils", *Tunnelling and Underground Space Technology*, vol. 80, pp. 53–63, 2018, doi: 10.1016/j.tust.2018.06.007.

[7] Q. Gong, Y. Zhao, J. Zhou, and S. Zhou, "Uplift resistance and progressive failure mechanisms of metro shield tunnel in soft clay", *Tunnelling and Underground Space Technology*, vol. 82, pp. 222–234, 2018, doi: 10.1016/j.tust.2018.08.038.

[8] Y. Fang, Z. Chen, L. Tao, J. Cui, and Q. Yan, "Model tests on longitudinal surface settlement caused by shield tunnelling in sandy soil", *Sustainable Cities and Society*, vol. 47, art. no. 101504, 2019, doi: 10.1016/j.scs.2019.101504.

[9] S. Wang, L. Ruan, X. Shen, and W. Dong, "Investigation of the mechanical properties of double lining structure of shield tunnel with different joint surface", *Tunnelling and Underground Space Technology*, vol. 90, pp. 404–419, 2019, doi: 10.1016/j.tust.2019.04.011.

[10] X.G. Li and D.J. Yuan, "Response of a double-decked metro tunnel to shield driving of twin closely under-crossing tunnels", *Tunnelling and Underground Space Technology*, vol. 28, no. 1, pp. 18–30, 2012, doi: 10.1016/ j.tust.2011.08.005.

[11] J. Dalong, S. Xiang, and Y. Dajun, "Theoretical analysis of three-dimensional ground displacements induced by shield tunneling", *Applied Mathematical Modelling*, vol. 79, pp. 85–105, 2020, doi: 10.1016/j.apm.2019.10.014.

[12] K. Zorlu, C. Gokceoglu, F. Ocakoglu, H.A. Nefeslioglu, and S. Acikalin, "Prediction of uniaxial compressive strength of sandstones using petrography-based models", *Engineering Geology*, vol. 96, no. 3–4, pp. 141–158, 2008, doi: 10.1016/j.enggeo.2007.10.009.

[13] M. Esmaeili, M. Osanloo, F. Rashidinejad, A.A. Bazzazi, and M. Taji, "Multiple regression, ANN and ANFIS models for prediction of backbreak in the open pit blasting", *Engineering with Computers*, vol. 30, no. 4, pp. 549–558, 2014, doi: 10.1007/s00366-012-0298-2.

[14] K. Dobosz and W. Duch, "Understanding neurodynamical systems via Fuzzy Symbolic Dynamics", *Neural Networks*, vol. 23, no. 4, pp. 487–496, 2010, doi: 10.1016/j.neunet.2009.12.005.

[15] A. Mukherjee and J.M. Deshpande, "Application of artificial neural networks in structural design expert systems", *Computers and Structures*, vol. 54, no. 3, pp. 367–375, 1995, doi: 10.1016/0045-7949(94)00342-Z.

[16] J. Lai, J. Qiu, Z. Feng, J. Chen, and H. Fan, "Prediction of soil deformation in tunnelling using artificial neural networks", *Computational Intelligence and Neuroscience*, vol, 2016, art. no. 6708183, 2016, doi: 10.1155/2016/6708183.

[17] S. Janani, R. Thenmozhi, and L. S. Jayagopal, "Theoretical investigations for the verification of shear centre and deflection of sigma section by back propagation neural network using Python", *Archives of Civil Engineering*, vol. 65, no. 2, pp. 181–192, 2019, doi: 10.2478/ace-2019-0027.

[18] N.S. Fox, "Field model tests for the prediction of foundation settlement", Ph.D. thesis, Iowa State University of Science and Technology, 1966, doi: 10.31274/rtd-180813-4311.

[19] A. Urbanski, S. Ligeza, and M. Drabczyk, "Multi-scale modelling of brick masonry using a numerical homogenisation technique and an artificial neural network", *Archives of Civil Engineering*, vol. 68, no. 4, pp. 179–197, 2022, doi: 10.24425/ace.2022.143033.

[20] A. Pourtaghi and M.A. Lotfollahi-Yaghin, "Wavenet ability assessment in comparison to ANN for predicting the maximum surface settlement caused by tunneling", *Tunnelling and Underground Space Technology*, vol. 28, no. 1, pp. 257–271, 2012, doi: 10.1016/j.tust.2011.11.008.

[21] A. Sayadi, M. Monjezi, N. Talebi, and M. Khandelwal, "A comparative study on the application of various artificial neural networks to simultaneous prediction of rock fragmentation and backbreak", *Journal of Rock Mechanics and Geotechnical Engineering*, vol. 5, no. 4, pp. 318–324, 2013, doi: 10.1016/j.jrmge.2013.05.007.

[22] R.S. Faradonbeh, M. Monjezi, and D.J. Armaghani, "Genetic programing and non-linear multiple regression techniques to predict backbreak in blasting operation", *Engineering with Compute*rs, vol. 32, no. 1, pp. 123–133, 2016, doi: 10.1007/s00366-015-0404-3.

[23] A. Azimian, R. Ajalloeian, and L. Fatehi, "An empirical correlation of uniaxial compressive strength with P-wave velocity and point load strength index on marly rocks using statistical method", *Geotechnical and Geological Engineering*, vol. 32, no. 1, pp. 205–214, 2014, doi: 10.1007/s10706-013-9703-x.

[24] H. Sonmez, C. Gokceoglu, H.A. Nefeslioglu, and A. Kayabasi, "Estimation of rock modulus: For intact rocks with an artificial neural network and for rock masses with a new empirical equation", *International Journal of Rock Mechanics and Mining Sciences*, vol. 43, no. 2, pp. 224–235, 2006, doi: 10.1016/j.ijrmms.2005.06.007.

[25] M. Hassanvand, S. Moradi, M. Fattahi, G. Zargar, and M. Kamari, "Estimation of rock uniaxial compressive strength for an Iranian carbonate oil reservoir: Modeling vs. artificial neural network application", *Petroleum Research*, vol. 3, no. 4, pp. 336–345, 2018, doi: 10.1016/j.ptlrs.2018.08.004.

[26] K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators", *Neural Networks*, vol. 2, no. 5, pp. 359–366, 1989, doi: 10.1016/0893-6080(89)90020-8.

[27] M. Koopialipoor, E.N. Ghaleini, M. Haghighi, S. Kanagarajan, P. Maarefvand, and E.T. Mohamad, "Overbreak prediction and optimization in tunnel using neural network and bee colony techniques", *Engineering with Computers*, vol. 35, no. 4, pp. 1191–1202, 2019, doi: 10.1007/s00366-018-0658-7.

[28] K.M. Oluwasegun, O.A. Ojo, O.T. Ola, A. Birur, J. Cuddy, and K. Chan, "Development of artificial neural network models for predicting weld output parameters in advanced fusion welding of a magnesium alloy", *American Journal of Modeling and Optimization*, vol. 6, no. 1, pp. 18–34, 2018, http://pubs.sciepub.com/ajmo/6/1/2/index.html.

[29] T. Kavzoglu, "An investigation of the design and use of feed-forward artificial neural networks in the classification of remotely sensed images", Ph.D. thesis, University of Nottingham, 2001.

[30] E. Ghasemi, H.B. Amnieh, and R. Bagherpour, "Assessment of backbreak due to blasting operation in open pit mines: a case study", *Environmental Earth Sciences*, vol. 75, no. 7, pp. 1–11, 2016, doi: 10.1007/s12665-016-5354-6.

[31] C.G. Looney, "Advances in feedforward neural networks: demystifying knowledge acquiring black boxes", *IEEE Transactions on Knowledge and Data Engineering*, vol. 8, no. 2, pp. 211–226, 1996, doi: 10.1109/69.494162.

[32] I. Ocak and S.E. Seker, "Calculation of surface settlements caused by EPBM tunneling using artificial neural network, SVM, and Gaussian processes", *Environmental Earth Sciences*, vol. 70, no. 3, pp. 1263–1276, 2013, doi: 10.1007/s12665-012-2214-x.

[33] H. Fattahi and H. Bazdar, "Applying improved artificial neural network models to evaluate drilling rate index", *Tunnelling and Underground Space Technology*, vol. 70, pp. 114–124, 2017, doi: 10.1016/j.tust.2017.07.017.

[34] M. Hasanipanah, R. Naderi, J. Kashir, S.A. Noorani, and A.Q. Zeynali, "Prediction of blast-produced ground vibration using particle swarm optimization", *Engineering with Computers*, vol. 33, no. 2, pp. 173–179, 2017, doi: 10.1007/s00366-016-0462-1.

[35] J.D. Paola and R.A. Schowengerdt, "A detailed comparison of backpropagation neural network and maximum-likelihood classifiers for urban land use classification", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 33, no. 4, pp. 981–996, 1995, doi: 10.1109/36.406684.

[36] J.D. Paola and R.A. Schowengerdt, "The effect of neural-network structure on a multispectral land-use/land-cover classification", *Photogrammetric Engineering and Remote Sensing*, vol. 63, no. 5, pp. 535–544, 1997.

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