Prediction of surface settlement during shield TBM excavation using extreme learning machine

Dongku Kim[1], H. Lee[1], K. Pham[1], J.-Y. Oh[2], and H. Choi[1]

[1] School of Civil, Environmental and Architectural Engineering, Korea University, Seoul, KS013, Korea.
[2] Infrastructure ENG Team (Underground Civil ENG Group), Samsung C&T, Seoul, KS013, Korea.

ABSTRACT

Tunneling-induced surface settlements in soft ground conditions threaten the stability of nearby structures, especially during subway tunnel excavation in urban areas. Therefore, controlling the surface settlement before excavation is the key to successful tunneling. There have been numerous means for predicting surface settlements during TBM tunneling such as empirical, analytical and numerical approaches. However, these techniques occasionally show poor predicting performance when being applied to actual excavation sites due to complex and unique surface settlement mechanisms. To circumvent limitations of the existing prediction methods, machine learning techniques such as the artificial neural network has been recently introduced. In this paper, the extreme learning machine (ELM), which is an improved version of the artificial neural network, is applied to verify its cost efficient neural network model for the prediction of surface settlements. 14 settlement-inducing features categorized as the tunnel geometry, TBM operating conditions and geological conditions are collected from the Hong Kong shield TBM tunneling site. The performance of ELM is compared with the well-known Levenberg Marquardt and the Bayesian Regularization algorithm for the same single-layered neural network. The obtained results show the significance of performance achieved by the ELM-based prediction of surface settlements.

Keywords: Extreme learning machine; Artificial neural network; Ground settlement prediction; Tunnel excavation; Twin tunnel

1 INTRODUCTION

Ground surface settlements induced by shield tunneling in shallow, soft ground conditions have been a major concern for urban metro tunnel excavation. Settlement-induced vertical and horizontal ground movements cause critical damage to both surface and subsurface infrastructures in highly crowded urban areas. The precise prediction of surface settlements in such conditions remains challenging due to the complex interaction of ground and tunnel excavation. The empirical approaches to the estimation of surface settlements propose empirical formulae, based on an extensive database collected from the preceding tunnel excavation cases, to fit the settlement trough approximately corresponding to the Gaussian or normal distribution curve (Martos, 1958; Peck, 1969; Kimura and Mair, 1981; O'Reilly and New, 1982; Attewell et al., 1986). The analytical approaches adopt well-known mechanical theories for the estimation of surface settlements exclusively for simplified or idealized conditions (Clough and Schmidt, 1981; Sagaseta, 1987; Yi et al., 1993; Lognathan and Poulos, 1998). On the contrary, the numerical approaches such as the finite element method (FEM) and the finite difference method (FDM) take account more complex ground conditions, initial and boundary conditions and time-dependent effects to estimate surface settlements (Leca and New, 2007). Estimating performance of the aforementioned approaches shows intrinsic limitations induced by highly complicated and nonlinear relationship among the settlement inducing factors.

Well known features causing the settlement during TBM excavation are summarized as the face support pressure, excavation method, advance rate, geological condition and tunnel geometry (Suwansawat and Einstein, 2006; Neaupane and Adhikari, 2006; Santos Jr. and Celestino, 2008). Along with the complicated nonlinear relationship among the features, the inherent uniqueness of ground surface settlements tendency of each tunneling site impairs the performance of the classic approaches. To overcome this matter, computational network models such as the artificial neural network and the support vector machine have been suggested to reliably predict surface settlements during shield TBM excavation.

Along with extensive databases collected from electronic sensors instrumented at the excavation site, the recent development of powerful computing systems allows the researchers to develop various network models as a promising prediction tool. One of the most powerful network models is the artificial neural network (ANN). The ANN is a computational network model inspired by the biological signal process of brain cells. Its prediction capability comes from the collective computation power between internal nodes, which enables the network to "self-learn" features of the given database. Since the first development of ANN by Hopfield (1982) and the multiple layer perceptron model of ANN by Rumelhart (1986), development of the backpropagation learning algorithm allows the ANN to be applied in almost all engineering areas.

Even with the ANN's self-learning and non-linear approximation feature, there are some typical disadvantages in the ANN such as the presence of local minima and slow learning convergence due to the intrinsic learning mechanism of the backpropagation algorithm. Being suggested by Huang et al. (2006), the ELM can be a new learning approach for single-hidden-layer feedforward neural networks, which was devised to overcome the ANN's drawbacks. The ELM provides good generalization performance and rapid convergence rate.

2 EXTREME LEARNING MACHINE

The ELM is a single-hidden-layer feedforward network (SLFN) that adopts analytical determination for tuning the hidden neurons (Huang et al., 2006). Compared to traditional neural networks, the ELM algorithm performs significantly faster training task. The traditional learning algorithm iteratively optimizes network parameters by minimizing the cost function with the aid of gradient-based algorithms. In case of the complex neural network structure, the computation process becomes expensive and time consuming. In order to reduce the computational cost and time, the ELM randomly assigns the values of input weights and hidden layer bias, then calculates the system of linear equations for the hidden layer output matrix and output weights. The hidden layer of ELM nonlinearly transforms input data into the ELM feature space, which is a higher dimensional space (Huang et al., 2015). The transformation often allows linear partitioning of the nonlinear input data in the ELM feature space as shown in Figure 1.

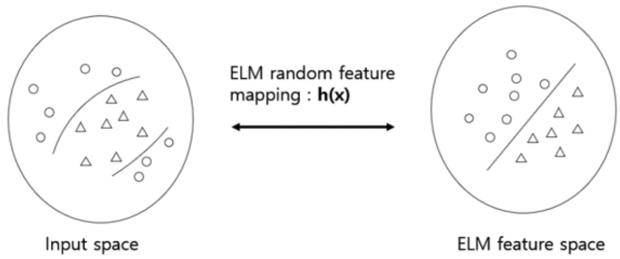


Fig. 1. ELM feature mapping and ELM feature space

3 SITE CONDITION AND DATABASE

3.1 Site condition

The data set, which was collected from slurry shield TBM subway tunnelling site at Hong Kong, was used to verify the performance of implemented neural networks. The tunnel was constructed in the mixed ground condition consisted of alluvial soil, weathered soil and weathered rock. Details of the geological profile at the site, consists of granite, are sorted into layers according to the level of weathering (moderately/completely decomposed granite, MDG/CDG). The surface layer of ground contains alluvium and fill, with the groundwater table around 2.5 m below the ground surface.

The diameter of the excavated tunnel is 7.45 m with the inner segment diameter of 6.8 m. The tunnel depth ranges between 12.6 m and 18.6 m, that is 1.7 ~ 2.5 times of the tunnel diameter. In most sections, the tunnel passes through fill, alluvium and CDG layer, which are weathered rock region.

3.2 Settlement measurements

The measurement of surface settlements along the up-track tunnel was collected from 248 points within the target area. Like other urban area metro tunnels, most of settlement measuring points should be located away from the centerline of the tunnel (i.e., tunnel crown) due to the existing buildings and roads. In this study, settlements within 25.5 m at maximum longitudinal distance were merged into one section, consisting of different numbers of measurements between 1 to 9. The horizontal distance from the centerline for each settlement point was also concerned. The final or maximum settlement was defined as the settlement measurement after two months of excavation to consider the secondary settlement effect. Figure 2 shows the distribution of 69 longitudinal sections along the up-track tunnel defined for this study.

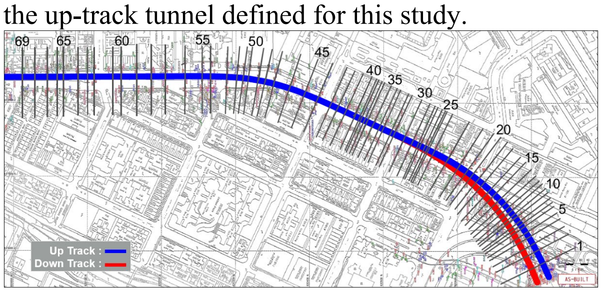


Fig. 2. Distribution of 69 sections along the up-track tunnel

3.3 Network input

For the training phase of network models, settlement-inducing input features are divided into three main categories; tunnel geometry, excavation method and ground geological conditions. The settlement inducing features are chosen based on previous researches with consideration of the degree of influence to the settlement. The chainage length, horizontal distance, soil cover above the tunnel and twin tunnel parameter are chosen as the tunnel geometry features. The twin tunnel parameter corresponds to the distance between the up and down track tunnel, which ranges between 0 and 16.77 m. At the further most point, the distance between the two tunnel is as long as twice of tunnel diameter (2D). Face pressure, advance speed, back grout injection volume and pitching data are selected as the TBM operating data. For the input feature of geological conditions, the soil type at the tunnel crown, springline and invert, and N value were collected.

Soil types around the tunnel were divided into four sections and labeled in numerical values between 1 to 4, in the order of fill, alluvium, CDG and corestone. In addition, the N value at the crown and springline of tunnel were considered to relate with the shear strength of ground formations, which correlates with the ground loss, V_L. All of 13 input features for 248 data sets were collected from the actual measurement at the site. The range of input values is shown in Table 1.

Table 1. Network input database of settlement inducing features

Type	Description
Geometrical	Chainage length
	Horizontal distance
	Soil cover above tunnel
	Twin tunnel parameter
TBM Data	Face pressure
	Advance speed
	Back grout injection volume
	Pitching
Geological conditions	Soil type at tunnel crown
	Soil type at tunnel springline
	Soil type at tunnel invert
	SPT N value at tunnel crown
	SPT N value at tunnel springline

4 NEURAL NETWORK MODELS

The neural network models for settlement predicting are implemented using the Matlab program. Along with the ELM algorithm, two most popular backpropagation neural network training algorithms, i.e. Levenberg Marquardt (LM) and Bayesian Regularization (BR) algorithm, were considered for the purpose of comparison as the same single-layered neural network. In this study, 70% of the input data sets were randomly assigned as the training sets, while the remaining sets were assigned as the testing sets. In case of the LM algorithm, the testing sets were additionally divided into the validation and testing sets equally.

4.1 Model implementation

The prediction performance of neural networks is evaluated based on two statistical evaluation criteria: the root mean square error (RMSE) and coefficient of correlation (R) as given by Equation 1 and 2.

$$\mathrm{RMSE} = \sqrt{\left(\frac{1}{N}\right)\sum_{j=1}^{N}\left(o_j - t_j\right)^2} \quad (1)$$

$$R = \frac{\sum_{j=1}^{N}(t_j - \bar{t})(o_j - \bar{o})}{\sum_{j=1}^{N}\left(t_j - \bar{t}\right)^2 \sum_{j=1}^{N}\left(o_j - \bar{o}\right)^2} \quad (2)$$

where o is the actual value and t is the predicted value, $\bar{o}$ and $\bar{t}$ are the means of actual and predicted values, respectively. N is the number of data sets.

The backpropagation neural networks with the LM and BR training algorithms are implemented. The automatic recommendation tuning parameters were chosen for the best training performance in both algorithms. The optimal hidden node number was determined for each algorithm by the trial-and-error method, ten hidden nodes for both LM and BR respectively. The average performance of the backpropagation neural network algorithm is measured after 20 runs.

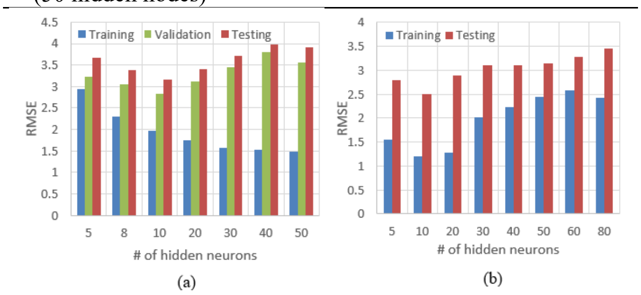
The same SLFN structure was trained using the ELM algorithm. The optimal hidden node number for the ELM prediction model was 50 according to the testing result. The average performance of ELM was measured after running 100 times because of the randomly assigned input weights and hidden bias values. Figure 3 shows the result of parametric analysis for the optimal number of hidden nodes.

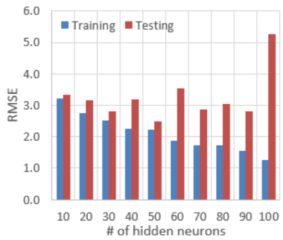
4.2 Performance

The performance indices of the developed neural network models with the optimal hidden-node number are presented in Table 2 indicating that the ELM model has the lowest value of RMSE in the testing datasets. Although the RMSE value of ELM with the training datasets is higher than the other ANN algorithms, the low value of RMSE with the testing datasets indicates that the ELM has better generalization performance than the backpropagation neural networks. Also, the R-value of ELM with the testing datasets shows excellent performance, similar to that of ANN-BR's. The computing time of each run in the ELM was at least 100 times faster than the other two methods, showing the superiority of ELM in both performance and computing time.

Table 2. Performance of ANN-LM, ANN-BR, and ELM models

Predictive model	Train		Test	
	RMSE	R	RMSE	R
ANN-LM (10 hidden nodes)	1.972	0.837	3.166	0.678
ANN-BR (10 hidden nodes)	1.206	0.939	2.510	0.841
ELM (50 hidden nodes)	2.220	0.857	2.496	0.832





(c)

Fig. 3. Performances of neural network models depending on hidden neuron numbers for (a) ANN-LM (b) ANN-BR (c) ELM

5 DISCUSSION AND CONCLUSION

Computer aided analysis such as machine learning techniques helps establish the complex and nonlinear relationship between the excavated TBM tunnel and ground movement. Machine learning-based prediction of surface settlements considers all of the settlement-inducing factors, which have been neglected in previous approaches such as empirical, analytical and numerical methods. Despite wide adaptability of the backpropagation ANN, the high computational cost with time consuming training demand becomes problematic when being applied at actual tunneling sites for the prediction of surface settlements. The ELM successfully complements the shortcomings of the backpropagation ANN, resulting in a lower prediction RMSE value and swift training time.

The testing result of the ELM showed the lowest RMSE value of 2.496, while the ANN-LM and ANN-BR showed the RMSE of 3.166 and 2.510, respectively. The R-value of ELM testing result was 0.832, lower than that of the ANN-BR of 0.841. However, compared to ANN-LM's R-value of 0.678, the R-value of ELM testing is promising enough. Even with high performance, the training of ELM networks was fastest, showing around 100 times faster training process when compared to the ANN-LM.

Some of the issues regarding the ELM algorithm can be summarized as follows; During the training phase of neural network models, the ELM may need higher numbers of hidden neurons due to the random determination of the input weights and hidden biases to obtain good generalization performance. For this matter, there may exist some suboptimal or unnecessary input weights and hidden biases arising in the ELM structure. Further studies on these matters will lead to better performance of prediction of surface settlements using the ELM.

ACKNOWLEDGEMENTS

This research was supported by a grant (Project number: 18NSPS-C149833-01 (Development of safety technology from natural disaster in urban area and urgent rescue technology for social safety through sharing data)) from Infrastructure and Transportation Technology Promotion Research program funded by Ministry of Land, Infrastructure and Transport of Korean government.

REFERENCES

Attewell, P.B., Yeates, J., Selby, A.R., (1986). Soil Movements Induced by Tunnelling and Their Effects On Pipelines and Structures. Blackies and Sons Ltd: London.

Hopfield, J.J., (1982). Neural networks and physical systems with emergent collective properties. Proc. Nat. Acad. Sci 79: 2554-2558.

Huang, G. B., Zhu, Q. Y., and Siew, C. K. (2006). Extreme learning machine: Theory and applications. Neurocomputing 70: 489–501.

Huang, G., Huang, G. B., Song, S., and You, K. (2015). Trends in extreme learning machines: A review. Neural Networks 61: 32–48.

Kimura, T., Mair, R.J., (1981). Centrifugal testing of mode tunnel in soft clay. In: 10th international Conference on Soil Mechanics and Foundation Engineering, Stockholm 1: 319-322.

Leca, E., New, B., (2007). ITA/AITES Report 2006 on Settlements induced by tunneling in Soft Ground. Tunneling and Underground Space Technology 22: 119-149.

Lognathan, B., Poulos, H.G., (1998). Analytical prediction for tunnelling-induced ground movements in clays. ASCE Journal of Geotechnical and Geoenvironmental Engineering 124 (9): 846-856.

Martos, F., (1958). Concerning an approximate equation of the subsidence trough and its time factors. International Strata Control Congress 6: 191-205.

Neaupane, K.M., Adhikari, N.R., (2006). Prediction of tunneling-induced ground movement with the multilayer perceptron. Tunnelling and Underground Space Technology 21: 151-159.

O'Reilly, M.P., New, B.M., (1982). Settlement above tunnels in the United Kingdom their magnitude and prediction. Tunneling: 173-181.

Peck, R.B., (1969). Advantages and limitations of the observational method in applied soil mechanics. Geotechniques 19(2): 171-187.

Rumelhart, D.E., (1986). Learning representations by back-propagating errors. Nature 323: 533-536.

Sagaseta; C., (1987). Analysis of undrained soil deformation due to ground loss. Géotechnique 37 (3): 301-320.

Santos Jr., O. J., Celestino, T. B., (2008). Artificial neural networks analysis of São Paulo subway tunnel settlement data. Tunnelling and Underground Space Technology 23: 481-491.

Suwansawat, S., Einstein, H.H., (2006). Artificial neural networks for predicting the maximum surface settlement caused by EPB shield tunneling. Tunnelling and Underground Space Technology 21(2): 133-150.