Artificial Neural Network to Predict the Surface Maximum Settlement by Shield Tunneling*

Jinli Qiao[1], Jianqin Liu[2,*], Wei Guo[2], and Yitong Zhang[2]

[1] School of Civil Engineering, Hebei University of Technology, Tianjin 300132, China
[2] School of Mechanical Engineering, Tianjin University, Tianjin 300072, China
Tel.: +86 013516187323; Fax: +86 022 27404559
liujianqin@tju.edu.cn

Abstract. Numerous empirical and analytical relations exist between shield tunnel characteristics and surface deformation. Artificial neural networks (ANN) was used to develop predictive relations between the maximum surface settlement and shield tunnel overburdens, shield diameters, thrusts of shield tunneling, advancement rates of shield, fill factors of grouting, cohesive forces, friction angles and compression modules of the soils. So, ANN can become a useful predictive method. With the advantage of ANN in nonlinear problem, the theoretical model to predict the maximum surface settlement is established. The agreement of the measured results with the actual situation of being predicted shows that the proposed model is satisfactory.

Keywords: artificial neural network; the maximum surface settlement; shield tunneling.

1 Introduction

Due to recent city developments with limited available land to build on, more and more public facilities are developed under the ground surface. Construction of shield tunnel excavation process in poor self-formation soils induces generally soil movement, which could seriously affect the stability and integrity of existing structures (pile foundations, buildings, et al). With this tunneling technique, ground movement can be, in theory, controlled by balancing the pressure inside the earth pressure chamber relative to the outside ground pressure during excavation.

To control the ground movement in the design and construction of shield tunnel, we must understand the law of ground movement as much as possible to accurately predict settlement, the settlement range, and analyze the various factors affecting the settlement, but whether it is the internal deformation of the tunnel, or surface deformation corresponding to the top of the tunnel, is a complex nonlinear dynamic systems, and it is difficult to reveal its inherent laws using traditional methods and techniques.

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** Corresponding author.

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Surface settlement caused by shield construction is analyzed using the most construction experience and the settlement slot curve proposed by Peck. Peck [1] basing on statistical analysis of field data of mountain tunnels, artificial tunneling shield machine, and semi-mechanized shield machine, in addition to pneumatic shield construction machines and other engineering methods proposed that the shape of surface settlement trough shield construction is similar to the normal distribution curve in probability theory, and made the settlement formula of various points on the surface settlement tank.

$$\delta(x) = \delta_{\max} \cdot \exp(-\frac{x^2}{2i^2}) \tag{1}$$

Where: $\delta(x)$ is the settlement of the surface point x away from the center; i is the width factor of settlement trough (the distance of tunnel center and settlement curve inflection point); $\delta_{\max}$ is the center's maximum settlement $\delta_{\max} = \frac{vA_c}{2.5i}$; A_c is the area of settlement trough, A is the cross-sectional area of tunnel; v is the loose factor of soil, the general value of 1% ~ 3%.

HS Lang et al measured the ground settlement of the sewage pipes of Taipei City Shield Construction, after the draw, the vast majority of the settlement occurred in the first 4 days after the shield being passed, while the final shape of the settlement trough is similar to Peck curve. In later studies, he has proposed that the curve of longitudinal settlement of earth pressure balance shield changing over time was hyperbolic type[2] .

$$S_{\max} = \frac{t}{a+bt} \tag{2}$$

Where: a, b is parameters related with soil properties shield test being obtained; t is the elapsed time. Surface settlement produced by tunnel construction is affected by many factors; all of this makes the shield-ground interaction complex, mainly include: tunnel overburdens, shield diameters, thrusts of shield tunneling, advancement rates of shield, fill factors of grouting, cohesive forces, friction angles and compression modules of the soils etc.

Empirical methods are still widely used; however, predictions of ground movements based on such methods are insufficient for most practical applications. There are a limited number of analytical and numerical tools that can be used to predict ground deformations, but there is a growing demand for developing practical rational methods for tunnel design. And many researcher have done a lot of theoretical analysis and testing for the surface settlement of shield tunnel and has been a lot of useful results[3-10]， but because of the limited number of measurement and test data and the uncertainty of the relationship between various factors, it is very difficult to fully reflect the regular pattern on the ground settlement. The adjusted network is a good tool for settlement prediction of new tunnels in the same geological environment.

Furthermore, this analysis shows the influence of network training parameters and previous input data treatment on the quality of the adjustment obtained. Significantly enhanced neural network predictive ability was found due to the use of certain data processing techniques. Knowledge acquired was applied to further develop use of this technique for tunnel instrumentation.

2 Artificial Neural Networks

The structure of a neural network, in general, consists of an interconnected group of artificial neurons. These processing units receive the information, apply some simple processing on them and pass them to other neurons. The characteristics of a neural network come from the activation function and connection weights. Since the neural network stores data as patterns in a set of processing elements by adjusting the connection weights, practically, neural networks may be used in nonlinear statistical data modeling, system identification, extraction of complex relationships between inputs and outputs of a system, and for pattern recognition.

The structure of a simple neural network generally contains three layers: input layer, hidden layer, and output layer in Figure 1. Within the ANN training process, the number of hidden layers and the number of nodes in each layer depend on the complexity of the patterns and the nature of the problem to be solved. The training procedure consists of a sequential data feed into the network, followed by the comparative evaluation of the corresponding output provided by the ANN and the actual result. The network adjusts the weighting of the connection links in a continuous effort to produce the results that would best correspond to the training dataset. A complete pass of all the input data through the network consists a training epoch and usually a great number of epochs is required for the residual error to converge below a pre-specified threshold. The testing data set is used to verify the appropriateness of the trained network. Finally, output from other systems or models such as expert systems and statistics need to validate the results from ANN.

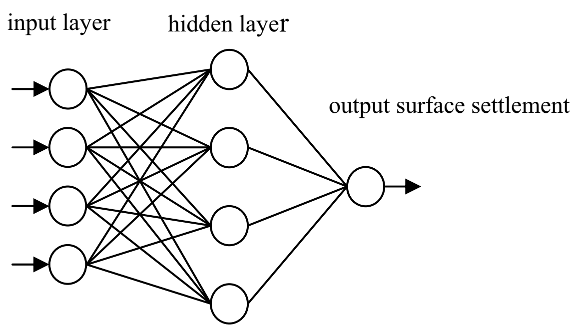

Fig. 1. Neural network architecture

ANN algorithm is summarized as follows:

(1) Using a random number to chose weights and the initial value of thresholds.
(2) The network input sample mode, input mode vector:

$$A_i\left(x_{i1}, x_{i2}, \cdots, x_{ik}\right), i = 1, 2, \cdots, m, \tag{3}$$

Where: m is the number of learning model, k is the number of the input layer neuron; the output vectors of the hope of the corresponding input mode, $Y_n\left(y_1, y_2, \cdots, y_n\right)$ is the output layer neuron number.

(3) The input mode of each unit of the hidden layer:

$$S_i = \sum_{j=1}^{N} \omega_{ij}\alpha_j - \theta_i, \quad j = 1, 2, \cdots, N \cdot \tag{4}$$

Where: ω_{ij} is the right value of the input layer to the middle layer; θ_i is the middle layer neuron threshold, N is the number of middle layer neurons.

(4) As the convergence of the common S-type function is slow, but with the increase in the number of iterations, the error steadily declines. Using improved BP algorithm, application of S-type function is appropriate, so this function S_i is used as the independent variables of S-type (Sigmoid) to calculate output of each hidden layer neuron, S-type function is the following function.

$$f(x) = \frac{1}{1+e^{-x}} \cdot \tag{5}$$

To S_i generation into the $f(x)$:

$$a_i = f(S_i)\frac{1}{1+e^{-\sum_{j=1}^{N}\omega_{ij}x_i - \theta_i}} \cdot \tag{6}$$

(5) Input of each cell of the output layer and the network actual output.

$$b_k = f(\sum_{i=1}^{N} a_i\omega_{ik} - \theta_{bk}) \cdot \tag{7}$$

$$y = f(\sum_{i=1}^{N} b_k\omega_{ky} - \theta_y) \cdot \tag{8}$$

Where: ω_{ik} , ω_{ky} are the connection weights of input layer and middle layer, middle layer and output layer respectively; θ_{bk} , θ_y are the threshold of the middle unit and the output unit respectively; f is the S function.

(6) Calculate the error between the actual output value and hope output value, based on the size of the error adjusts the connection weights output layer to the underlying automatically, that is, propagation process of the errors δ_y in the output layer to the error δ_{bk} of the middle layer. However, the limitations of BP network itself, such as the existence of local minimum problems, slow convergence of learning algorithm, the number of the characteristics of each input sample must be the same and so on, in order to improve its limitations, in this paper, the standard correction formula is basically the introduction of weights momentum term to accelerate the learning rate, to prevent oscillation. Namely:

$$\Delta\omega(t+1) = \eta\frac{\partial E}{\partial\omega} + \alpha\Delta\omega(t) \cdot \tag{9}$$

Where: α is the momentum factor, generally take 0.9 or so.

3 The ANN Model of the Surface Settlement Caused by Shield Excavation

3.1 The Merits of ANN Using for the Surface Settlement

Artificial neural network model, in particular the BP ANN model is applied to the study of surface settlement successfully [11-13]. BP ANN model is superior to traditional methods in some ways, mainly reflected in:

(1) It is well known that surface settlement caused by shield excavation are complex nonlinear systems, because BP ANN model is essentially non-linear fitting, while it is generally better to take into account the non-linear characteristics of the surface settlement caused by shield excavation than the traditional log-linear model;

(2) We can see surface settlement caused by shield excavation has large uncertainty from the measured data, and the measured surface settlements have also a big difference even in the same condition. BP model can maximize to overcome this uncertainty comparing with the certainty of the formula of surface settlement;

(3) In order to make the established formula relatively simple, some minor parameters were removed and retained only the main ones in the traditional model of surface maximum settlement. BP model can regard any number of variables as input parameters, that is a more comprehensive for the parameters affecting the surface maximum settlement caused by shield excavation;

(4) The traditional formula for the surface maximum settlement is established by a limited number of laboratory data and the measured data, its use must be subject to certain limitations. The BP model is established through more information, thus its application is a broader scope. Although the BP model can not be used beyond their scope of learning and training, this problem can be resolved by expanding the scope of training samples.

(5) To the traditional model of surface maximum settlement, the user must have known the surface settlement theory caused by shield excavation, but just understanding the scope of information of BP model of the surface maximum settlement and without surface settlement theory, one can use BP model having established to predict the surface settlement.

3.2 The Factors of the Surface Settlement in ANN Model

Select the nine main factors affecting the surface maximum settlement caused by the shield tunnel construction: 1)tunnel overburdens; 2)shield diameters; 3)thrusts of shield tunneling; 4) advancement rates of shield; 5)fill factors of grouting; 6) Grouting pressure; 7)cohesive forces; 8) friction angles; 9) Compression modules of the soils et al, and establish a network structure including the 9 input units and output units. According to data analysis, input units used: cohesive forces c, friction angles φ, compression modules E_s of the soil, tunnel overburdens H, shield diameters D, grouting pressure P, fill factors of grouting n, thrusts of shield tunneling F, advancement rates of shield. In the surface deformation caused by tunnel construction, the surface maximum settlement is the most concerned, so the output unit used: the surface maximum settlement $S_{\max}$.

3.3 The ANN Model of the Surface Maximum Settlement by Shield Tunneling

Generally, there is no direction and precise method to determine the most appropriate number of neurons for including in each hidden layer in the neural networks. This problem becomes more complicated as the number of hidden layers in the network increases. To establish an optimal network that can be used for predicting the surface maximum settlement, one needs to begin with training and testing the artificial neural networks using a subset of all data sets. In the pilot experiment data set, the samples are divided into a training set and a validation set. Networks with different numbers of hidden nodes will be trained all the way to the convergence of the training samples, measuring their performance with the validation set, and choosing the network that yields the best performance of the validation set. Finally, this selected network model will be used for the whole data set.

Table 1. Samples used for network training

No.	C $/KPa$	φ $/^\circ$	E_s $/MPa$	H $/m$	D $/m$	P $/MPa$	n /%	F $/MN$	v $/mm\cdot\min^{-1}$	$S_{\max}$ $/mm$
1	10.0	25.0	9.12	20	6.34	034	1.4	10.00	20	35.1
2	11.4	19.2	8.42	12	6.4	0.4	1.4	12.00	30	42.4
3	32.5	15.5	7.67	9.4	6.34	0.3	1.5	15.00	20	40.6
4	214.9	23.8	34.2	18.2	6.34	0.4	1.7	20.00	30	10.5
5	12.9	11.8	7.22	15.5	6.4	0.25	1.5	13.00	40	52.4
6	15.0	13.7	8.21	12.0	6.34	0.45	1.5	14.00	20	40.5
7	12.0	16.6	4.24	11.8	6.25	0.25	1.6	16.00	30	79.6
8	11.8	15.2	5.91	9.78	6.34	0.55	1.7	14.00	20	47.3
9	11.7	16.4	6.48	8.4	6.4	0.3	1.7	14.00	30	53.3
10	32.4	10.7	11.17	14.5	6.40	0.25	1.7	31.65	60	22.0
11	312	42.1	35.7	15	6.4	0.30	1.5	30.00	30	14.1
12	11.9	13.8	5.22	11.9	6.34	0.40	2.0	14.00	20	21.2
13	12.1	13.7	5.21	12	6.34	0.35	1.7	14.00	30	55.3
14	201.7	23.5	35.2	20.6	6.40	0.30	1.2	30.00	20	11.2
15	36.7	20.7	7.26	13.8	6.4	0.25	1.7	31.65	60	7.5
16	32.4	12.4	11.17	14.2	6.4	0.25	1.7	31.65	60	14.8
17	43.6	30.0	9.12	14.5	6.4	0.25	1.5	31.65	60	8.9
18	34.2	9.20	7.26	14.5	6.4	0.25	1.7	31.65	60	22.8
19	34.2	14.5	7.26	14.5	6.4	0.25	1.7	31.65	50	16.4
20	340	44.9	35.02	12.0	6.25	0.2	0.9	33.00	30	16.8
21	240	30.1	23.12	24.0	6.25	0.3	1.2	33.00	30	19.2
22	12.0	13.4	5.01	12.7	6.34	0.4	2.0	14.00	20	32.8
23	11.8	14.4	5.53	10.9	6.34	0.4	2.0	14.00	20	27.1
24	11.9	13.8	5.22	11.9	6.34	0.4	1.8	14.00	20	38.6
25	11.9	13.8	5.22	11.2	6.34	0.3	1.7	14.00	30	89.9
26	11.9	13.8	5.22	10.5	6.34	0.25	1.4	14.00	40	62.5
27	12.0	13.7	5.21	12.0	6.34	0.35	1.5	14.00	30	57
28	12.0	13.6	5.2	11.8	6.34	0.35	1.4	14.00	40	79.6
29	11.8	15.2	5.91	9.78	6.34	0.35	1.7	14.00	20	47.3
30	28.1	32.8	5.42	13.3	6.40	0.25	1.5	31.65	40	9.6
31	12.2	13.1	5.2	12	6.4	0.35	2.0	14.00	20	20.3
32	12.0	13.8	5.21	11.8	6.34	0.4	1.7	31.65	30	45.1
33	34.0	16.6	7.26	12	6.4	0.3	1.6	16.00	20	70.2
34	112	35.2	25.9	9.78	6.34	0.35	1.7	31.00	20	17.3
35	30.0	16.5	7.60	10.4	6.25	0.3	1.6	16.00	40	35.4

Table 2. Testing sample for network

No.	C $/KPa$	φ $/^{\circ}$	E_s $/MPa$	H $/m$	D $/m$	P $/MPa$	n $/\%$	F $/MN$	v $/mm \cdot \min^{-1}$
1	11.2	19.5	8.26	6.1	6.34	0.3	1.4	14.00	40
2	11.8	14.7	5.67	10.4	6.34	0.4	1.8	14.00	20
3	11.9	14.1	5.35	11.4	6.34	0.4	1.8	14.00	20
4	30.2	22.8	11.8	20.0	6.25	0.25	1.2	23.00	40
5	15.3	23.9	3.87	12.0	6.4	0.3	1.5	31.65	40
6	18.7	13.5	6.2	10.6	6.34	0.30	1.6	14.00	30

Table 3. Comparison of measured and predicted values

No.	measured $S_{\max}$ $/mm$	predicted $S_{\max}$ $/mm$	Error
1	84.5	81.50	3.55%
2	40.6	41.60	2.46%
3	38.1	39.40	3.41%
4	34.0	36.10	6.18%
5	7.6	7.40	2.63%
6	26.4	25.45	3.59 %

In this paper, the sample data shown in Table 1 are used as a pilot experiment (i.e., for training and validation) and thus for determining the optimal model. The data are fed into the ANN, where the input layer consist 9 input nodes that represent all influencing factors. The process attempts to establish the optimal neural network model and an appropriate number of training epochs for the problem. A validation set shown in

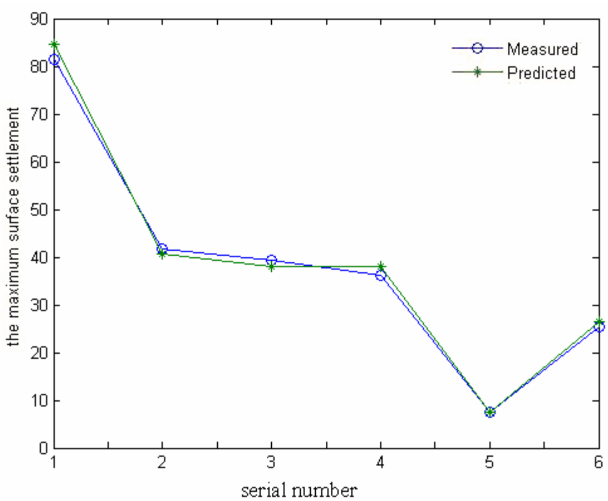

Fig. 2. Performance of neural networks on trained (predicted) and measured data

Table 2. Momentum coefficient is 0.9, steps to take 0.1, after e-learning 2.2665 × 10^5 times, reach the target error of 10^{-5}. The results from testing of validation set are plotted together in Fig. 1. As can be seen, the ANN predictions fit the data in the testing samples.

According to Table 3 and Figure 2, the maximum error of the predicted values and measured values of surface maximum settlement from three testing samples is less than 7%, which shows that the model's predicted performance is satisfactory within the permitted scope of the project.

3.4 Engineering Example

The Tunneling Project between Pudong South Road Station and Nanpu Bridge Station is an important component of Shanghai LRT Line 2 Project as well as a major project in Shanghai. The tunnel starts from the end well west to Pudong South Road Station to the end well east to Nanpu Bridge Station, with the full length of up line 1997.148 m and that of down line1 981.96 m, external diameter 6.2m and inner diameter 5.5 m. The shield eternal diameter is 6.34 m, the width of tunnel lining ring is1m, the shield advancing speed is 2.0m, the total thrust of jack is 14m, the shield tail's grouting pressure is 0.3m, the grout is retarding grout whose intensity in 1d is greater than or equal to the intensity of the surrounding reinforced soil. The shield tail's grouting volume is 2.0m^3/m. The tunnel settlement is expected at the in 1480 EMS-chip cross-section. The depth of the tunnel central axis at 1480 EMS-chip is 22m, overburden thickness 19m, mainly silty clay.

The surface maximum settlement of the 1480 ring predicted by the trained ANN model to is $S_{\max}$ is 16.95mm, compared with the measured maximum surface settlement $S_{\max}$ is 16.20 mm, only has a error of 4.63%.The predictive model performed well and confirmed that artificial neural networks can be successfully used for predicting surface settlements in the project.

4 Conclusions

The ANN system used in this paper demonstrated very satisfactory results in predicting the surface maximum settlement for the case study in question with confidence. The resulting remarks can be drawn hereinafter:

(1) ANN can decrease the errors to permitted targets ,in limited trained times ,by choosing proper self-adapted learning speed and momentum factors.

(2) Through continuous learning, ANN can use a simpler model to accurately predict the surface maximum settlement caused by shield tunnel excavation. This can form a stark contrast with the complex calculations in mechanical system. ANN has a strong anti-interference ability; individual forecasts will not affect the calculation results.

(3) By inputting the factors affecting the surface maximum settlement, the already trained ANN model can then accurately identify the surface maximum subsidence caused by shield tunnel excavation. The more training samples, the closer output gets to the fact.

(4) By analyzing and predicting the surface maximum settlement caused by shield tunnel in Shanghai with the method proposed in this paper, the results are consistent with the engineering practice. This further verifies the correctness of the model. It shows that BP ANN applying to the surface maximum settlement caused by shield tunnel has a broad application prospects.

References

1. Peck, R.B.: Deep excavation sand tunneling in soft ground. In: Proc. 7th Int. Conference on Soil Mechanical and Foundation Engineering, Mexico City, pp. 225–290 (1969)
2. Fang, Y.S., Lin, S.J., Lin, J.S.: Time and settlement in EPB shield tunneling. Tunnels & Tunneling 134(11), 27–28 (1993)
3. Tang, Y., Ye, W., Zhang, Q.-h.: Analysis and research on ground settlement by the shield tunneling in Shanghai (three). Underground Space 15(4), 250–258 (1995)
4. Zhang, Y., Yin, Z., Xu, Y.-f.: Ground surface deformation by shield tunneling. Journal of Rock Mechanics and Engineering 21(3), 388–392 (2002) (in Chinese)
5. Kasper, T., Meschke, G.: On the influence of face pressure, grouting pressure and TBM design in soft ground tunneling. Tunnelling and Underground Space Technology (21), 160–171 (2006)
6. Karakus, M., Fowell, R.J.: Effects of different tunnel face advance excavation on the settlement by FEM. Tunnelling and Underground Space Technology (18), 513–523 (2003)
7. Liu, Z., Wang, M., Dong, X.: Analysis of ground surface settlement by construction with the shield tunneling method. Journal of Rock Mechanics and Engineering 22(8), 1297–1301 (2003) (In Chinese)
8. Huayang, D., Juecheng, Z., Youjian, H.: Testing study on surface displacement of mountainous region with similar material. Journal of Rock Mechanics and Engineering 19(4), 501–504 (2000) (in Chinese)
9. Guoxiang, Z.: Elasto-plastic and stochastic medium method and application in analysis of ground displacement and stress change due to tunnel construction. Journal of Rock Mechanics and Engineering 22(4), 596–600 (2003) (in Chinese)
10. Yi, H.-W., Sun, J.: Mechanism analysis of disturbance caused by shield tunneling on soft clays. Journal of Tongji University (3), 277–281 (2000) (in Chinese)
11. Sun, J., Yuan, J.-r.: Stratum movement and disturbance during the shield tunneling and their intelligent nerve net prediction. Journal of Geotechnical Engineering 23(5), 261–267 (2001)
12. Suwansawat, S., Einstein, H.H.: Artificial neural networks for predicting the maximum surface settlement caused by EPB shield tunneling. Tunnelling and Underground Space Technology (21), 133–150 (2006)
13. Santos Jr., O.J., Celestino, T.B.: Artificial neural networks analysis of São Paulo subway tunnel settlement data. Tunnelling and Underground Space Technology (23), 481–491 (2008)