Geotechnical Aspects of Underground Construction in Soft Ground – Ng, Huang & Liu (eds)

Prediction of surface settlements induced by shield tunneling: An ANFIS model

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ABSTRACT: A new method – fuzzy system combination neural network was used to estimate ground surface settlements. According to the measured data of Shanghai No.2 Subway, and considering various kinds of factors synthetically, an ANFIS fuzzy neural network prediction model was built. Comparing with the prediction results by other three kinds of methods, the validity of the ANFIS fuzzy neural network model was appraised. Confirmed by the instance, ANFIS fuzzy neural network is valuable in predicting ground settlements induced by shield tunneling.

1 INTRODUCTION

Shield tunneling has become one of the most popular methods used in the construction of urban tunnels, such as rapid transit systems and large diameter underground pipelines. However, shield tunneling construction inevitably disturbs the ground and the original stress field of soil, which in turn causes surface settlement that may yield damage of existing adjacent structures and underground facilities. Therefore, it is of significant importance for engineers to accurately predict the surface settlement during the design and construction stages.

Considering the complexity of the problem that involves intricate geological makeup of the ground composed of different materials with varying layer patterns plus different construction methods, it is apparent that using classical method makes it difficult to provide accurate predictions of ground settlement. In addition, it is very difficult to determine input parameters representative of the mixed geological compositions in a prediction model. Therefore, the analytical methods relying on observed data are widely used in investigation of surface settlement. A hybrid intelligent system called ANFIS(Jang 1993) (Adaptive-Network-Based Fuzzy Inference System) combining the ability of a neural network to fuzzy logic have the advantages of both neural networks (e.g. learning abilities, optimization abilities, and connectionist structure) and fuzzy systems (e.g. humanlike 'if-then' rules, and ease of incorporating expert knowledge and judgment available in linguistic terms). Such a hybrid intelligent system holds much potential in prediction. In this paper, a model based on ANFIS is proposed to predict the ground settlement induced by shield tunneling.

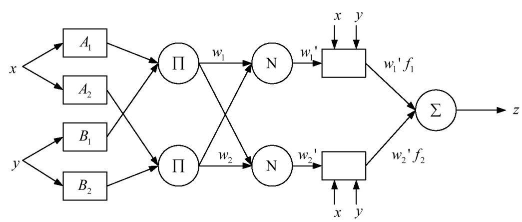

Figure 1. Architecture of ANFIS.

2 DEFINITION OF THE MODEL

2.1 *Brief description on the Adaptive-Network-Based Fuzzy Inference System (ANFIS)*

Both artificial neural network and fuzzy logic are used in ANFIS's architecture (Chang & Lee 2003). The ANFIS is one of the methods to organize the fuzzy inference system with given input-output data pairs. The ANFIS optimizes the parameters of consequent part using least square method and those of premise part using steepest descent method.

For simplicity, we assume the fuzzy inference system under consideration has two inputs (x and y) and one output (z) in the present study. The corresponding ANFIS architecture is shown in Figure 1.

Layer 1: In this layer x and y represent different types of input parameters of the adaptive node i of an adaptive function, and A_i is the linguistic label associated with this node function. Parameters in this layer are referred to as premise parameters.

Layer 2: Every node in this layer is a fixed node labeled Π which multiplies the incoming signals and sends the product out. Each node output represents the firing strength of a rule.

Layer 3: Every node in this layer is a fixed node labeled N. The ith node calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths.

Layer 4: Every node i in this layer is an adaptive node. Parameters in this layer will be referred to as consequent parameters.

Layer 5: The single node in this layer is a fixed node labeled Σ that computes the overall output as the summation of all incoming signals.

The steepest descent method can be applied to find the premise parameters and least square estimate can he applied to optimize the consequent parameters.

2.2 *Input and output parameters*

A relatively too large surface settlement may induce damage or even crash of existing structures. It is therefore very crucial to accurately predict the total surface settlement (the maximum surface settlement after construction) of a point before the shield arrives at this point. It is straightforward to set the total ground surface settlement to be an output variable in a prediction model. In this paper, similar to many other researchers, we choose the total surface settlement 5 meters ahead of the shield face as an output parameter. However, how to choose the input variables depends on the collection of monitored data. Systematic analyses of the measured data show that the disturbed area by shield tunneling of the original stress field of soil is approximately limited in a zone within 15 m from the working point, and almost has no effect on the area out of this zone. M. Karakus's measured data showed also that the maximum settlement is over the tunnel centerline. Considering these two aspects, we choose six parameters, i.e., five total ground surface settlements at the points over the tunnel centerline (i.e., 0, 5, 10, 20 and 30 meters behind the tunnel face) and one of the shield working parameters, the total number of the working cycles of the day, as the inputs.

The investigation in this paper is based on the measured data in the shielding tunnel from Zhongshan Park station to Longdong Road station in the Shanghai No. 2 Subway Tunnel Project. The total length of the tunnel is 1624 m. The earth pressure balance (EPB) shield was used in the project. The outer diameter of the EPB machine is 6340 mm and the length is 6540 mm. The tunnel shield tunneling was started in 18 July, 1997 and completed by 9 November, 1997, and the surface settlements were measured from 21 August. Large numbers of surface settlement markers were installed to measure surface settlements during excavation. The installation of surface settlement markers is described in detail by Sun and Yuan. The soil profile around the tunnel can also be found in the paper. The collected data have formed a database. The database not only allows one to study the behavior of ground movements occurring during excavation, but also becomes a useful source for developing predictive models for the ground settlement. We randomly chose 81 in the database experimental data (from August to October in 1997, see Table 1, detailed list can be found in Tu (2005)) as a training set and 20 data as a validating set (data in November, see Table 2).

Table 1. Samples used for network training.

Serial number	X_1	X_2	X_3	X_4	X_5	X_6	y
1	11.65	24.70	31.60	34.35	34.85	5	21.20
2	1.50	7.65	24.00	36.40	42.29	5	55.25
3	6.80	52.10	72.57	89.67	98.75	8	70.30
...	...						
81	3.75	14.85	38.20	36.85	39.70	6	57.05

Table 2. Samples used for network validation testing.

Serial number	X_1	X_2	X_3	X_4	X_5	X_6	y
1	5.20	20.30	26.75	23.20	9.95	8	40.95
2	−0.05	−1.07	0.35	−2.45	4.95	12	62.45
3	13.07	54.42	82.62	96.60	25.45	11	89.87
4	10.00	27.25	63.00	81.10	91.60	11	53.50
5	14.45	51.30	57.85	74.85	90.52	10	54.50
6	4.75	12.65	28.55	38.11	46.20	4	57.00
7	6.80	52.10	72.57	89.67	98.75	8	83.15
8	3.20	9.75	2.60	1.42	−2.27	11	99.57
9	4.17	7.32	7.32	17.00	44.90	7	41.10
10	14.05	16.15	14.39	22.1	34.50	8	47.22
11	0.95	2.85	16.25	54.45	47.65	12	76.42
12	3.30	15.55	33.30	45.30	52.00	6	53.90
13	1.70	15.60	30.25	47.05	55.40	11	47.30
14	2.95	4.95	13.75	44.15	86.40	10	61.30
15	13.25	43.75	76.30	74.85	68.52	10	56.73
16	3.75	22.02	47.77	66.90	72.75	13	88.15
17	4.57	18.75	46.40	68.75	47.15	7	79.02
18	4.00	11.65	34.05	47.65	77.40	8	61.30
19	0.72	6.92	18.37	43.37	51.65	10	79.60
20	1.90	12.20	30.40	49.65	39.30	11	71.95

Here, X_1, X_2, X_3, X_4, X_5 is total ground surface settlements (unit: mm) at the points over the tunnel centerline (i.e., 0, 5, 10, 20 and 30 meters behind the tunnel face) separately. X_6 is the total number of the working cycles of the day.

2.3 *Data pretreatment*

To speeding calculation, we standardize the original data to have a minimum of 0 and a maximum of 1 by

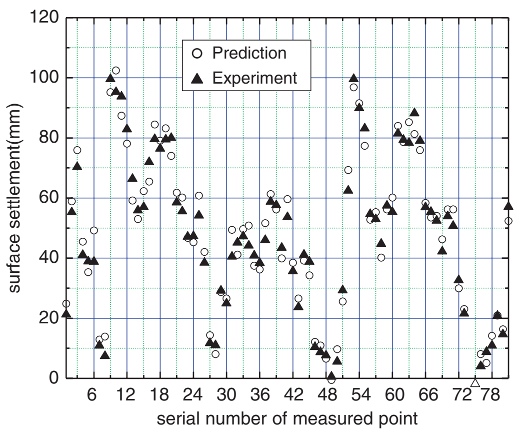

Figure 2. The fitting map of the ANFIS output and the measured data.

Table 3. The comparison of predicted surface settlement and measured settlement.

Serial number	Measured settlement (mm)	Predicted Settlement (mm)	Absolute error (mm)	Relative error %
1	40.95	39.24	1.71	0.042
2	62.45	63.3	−1.15	0.018
3	89.87	92.34	−2.47	0.027
4	53.5	52.46	1.04	0.019
5	54.5	52.59	1.91	0.035
6	57	58.38	−1.38	0.027
7	83.15	81.55	1.6	0.019
8	99.57	103.28	−3.71	0.037
9	41.1	38.25	2.85	0.069
10	47.22	45.39	1.83	0.039
11	76.42	74.23	2.19	0.029
12	53.9	54.96	−1.06	0.02
13	47.3	48.71	−1.41	0.03
14	61.3	62.37	1.07	0.017
15	56.73	54.42	2.31	0.041
16	88.15	86.29	1.86	0.021
17	79.02	80.16	−1.14	0.014
18	61.3	63.91	−2.61	0.043
19	79.6	78.22	1.36	0.017
20	71.95	73.28	−1.33	0.018

linear transformation. It is shown that such a transformation will make the calculation very efficient. The algorithm of the linear transformation is as follows.

The original data of six input variables can be expressed as:

$$S_1 = (X_{1(1)}, X_{1(2)} \ldots X_{1(P)}) , \tag{1}$$

$$S_6 = (X_{6(1)}, X_{6(2)} \ldots X_{6(P)}) .$$

We note that $i = 1, 2, \ldots P$ is the number of samples and totally 81 samples are used in this paper to train the model, i.e., $P = 81$.

We normalize each input datum as

$$X^0_{1(i)} = \frac{X_{1(i)} - \min S_1}{\max S_1 - \min S_1} ,$$

$$\tag{2}$$

$$X^0_{6(i)} = \frac{X_{6(i)} - \min S_6}{\max S_6 - \min S_6} .$$

Then the normalized input data can be expressed as

$$IN_{(i)} = (X^0_{1(i)}, X^0_{2(i)}, \cdots\cdots X^0_{6(i)}) .$$

3 RESULTS AND DISCUSSION

3.1 *Text and indenting*

The present model is realized via a Matlab package of ANFIS. The fitting map of the ANFIS output and the measured data was obtained (Fig. 2). The comparison of predicted surface settlement and measured settlement was also shown in Table 3.

They all show that all the predicted results from the ANFIS model are in good agreement with measured data.

Peck (1969) presented the first available method for estimating the ground settlement due to tunneling and excavation. In his method, charts were developed based on the field data obtained from subway constructions at different places worldwide. The data points, though scattered, revealed the shape of a Gaussian distribution curve. The charts have been widely used for estimating the transverse ground settlement profile caused by tunneling and excavation. Theoretical models based on the combined pi-sigma approach (Gupta & Rao 1994) and BP (Back Propagation) neural network are also used to predict the surface settlement. Due to the limitation of the paper length, we do not discuss them here.

Comparison between the above methods and the ANFIS method is shown in Fig. 3.

It is found that the current prediction is in good agreement with measurement. The maximum error between the model and the testing data is not more than 7%. For comparison, we proposed also the predicted results from two theoretical models based on the BP (Back Propagation) neural network and the combined pi-sigma approach (which are frequently used in predicting the surface settlement), and those from Peck's equation (Fig. 4). We can see from the figure that

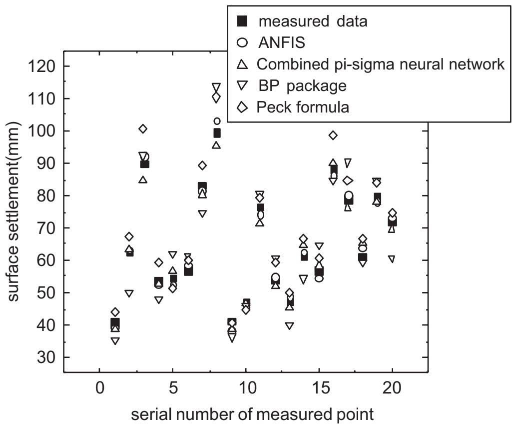

Figure 3. Comparison of predicted results with measured ones.

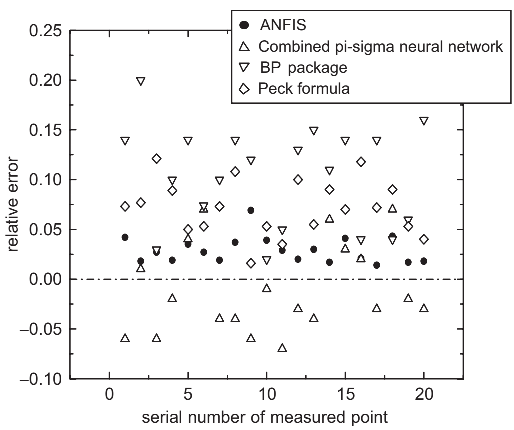

Figure 4. Comparison relative error from ANFIS' to other methods.

the BP neural network has the maximum error among these methods; that the combined pi-sigma approach underestimates but the Peck's formula overestimates the surface settlement.

4 CONCLUSION

This paper has shown the potential for applying fuzzy neural networks to ground surface settlement analysis. five total ground surface settlements at the points over the tunnel centerline (i.e., 0, 5, 10, 20 and 30 meters behind the tunnel face) and one of the shield working parameters, the total number of the working cycles of the day, as input parameters to predict the surface settlement induced by tunnel shield tunneling. The predicted results from the proposed model are in good agreement with field observations and the maximum error between the model and the testing data is not more than 7% in our example. Comparison with some other predicting approach shows that the present model is accurate, steady and efficient.

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