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ORIGINAL PAPER

Control of Ground Settlements Caused by EPBS Tunneling Using an Intelligent Predictive Model

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Abstract This paper deals with the control of ground surface settlement due to excavation of shallow tunnels. In order to control the settlement, one should be able to predict it, based on the prediction one may consider required preventions and protections. Prediction of surface settlement depends on several parameters and each parameter has an effect on the other. Application of the traditional methods could become impractical as the proposed equations might have low accuracy. To overcome these limitations, intelligent methods could be implemented. The present study aims to develop an intelligent model for prediction of the surface settlement in Shanghai subway line 2 project using adaptive neuro-fuzzy inference system (ANFIS). The results indicated that the proposed model had an appropriate performance. In order to perform sensitivity analysis of the ANFIS model, cosine amplitude method (CAM) was used and according to the results it was found that the operational, geometric and strength parameters had the highest impacts, respectively. Furthermore, amongst the input parameters, the two parameters of grout filling percentage (n) and grouting pressure (P) were identified as the most effective ones. The values of critical settlement were determined based on Rankin's criteria of damage risk assessment to control the ground settlement. Then, the corresponding surface settlement was minimized by changing values of the input parameters. According to the results, control of machine operational factors particularly the n and P parameters had a crucial role in reducing surface settlement and preventing pertinent damages.

Keywords Subway tunnel · Earth pressure balance shield (EPBS) · Ground settlement control · Adaptive neuro-fuzzy inference system (ANFIS) · Cosine amplitude method (CAM)

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Introduction

Most of subway tunnels are constructed in shallow depths and soft grounds found within urban areas. So, it is necessary to protect underground structures and facilities against possible damages resulted from tunnelling operation. Therefore, tunnels should be constructed in such a way to induce minimum deformation in the ground surface, and reduce damages experienced by the surface and subsurface structures [1]. Nowadays, earth pressure balance shield (EPBS) tunneling method is the most common method for tunneling in the soft ground. High flexibility of this method clearly contributes to the stability of the environment around the digging space and largely reduces the settlement. However, application of this method would not guarantee the elimination of ground settlement and requires substantial considerations.

Estimation of the precise amount of settlement plays an important role in safety, design and implementation of tunneling operations. Estimating this parameter helps prevention or control of the probable damages. There are many methods for predicting settlement such as the analytical, empirical, numerical, etc. Ones each of these methods may have some strength and could help in solving the problem but on the other hand, it may have some weaknesses. The most important weakness of the proposed methods is that they fail to consider all the parameters involve in the settlement [2]. In EBP tunneling technique, there are many factors such as the tunnel geometry, ground conditions, and machine operational parameters, which affect the surface settlement. Therefore, it is difficult to predict the settlement only using the traditional method. Chakeri et al. [3] modelled accuracy of the surface settlement of Tehran subway line 7 using the numerical method, whereas, this section of tunnel didn't have acceptable accuracy when implementing by four traditional (empirical and analytical) methods. Numerical methods exhibit good performance concerning the tunneling problems. These methods, contrary to the empirical and analytical ones, consider the effects of a greater number of parameters on the settlement. Nevertheless, these methods also have some limitations. Determination of some of these essential parameters for modelling is difficult and utilizing inaccurate values could result in unreal designs and predictions [4]. In addition, they are highly sensitive to the model's geometric components like model dimensions and configuration, mesh shape etc.

To overcome the above mentioned limitations, intelligent methods have been utilized as they are not limited by the number of input parameters, and are not time and cost consuming, also they have high estimation capability. Many studies have been performed in this respect, too [5–14] and the results have indicated proper performance of these methods. In this study, adaptive neuro-fuzzy inference system (ANFIS) was adopted to predict the maximum surface settlement. ANFIS enjoys the advantages of both neural and fuzzy systems [13]. It is particularly the alternative in cases where the number of available data sets to be used for modeling is low. Most geoscience-related problems do not come with a great deal of available data; and the present research, as well, suffers from such issue, ANFIS is selected to predict the surface settlement in this research.

In spite of numerous advantages provided by the intelligent methods, numerous researches performed on such methods have referred to their pitfalls. The main disadvantage associated with these methods is that they model the settlement without considering the main effective factors. As an example, many researches have ignored the tunnel support parameter. It is clear that a tunnel with no support will induce large deformations in the tunnel making it unstable. Therefore, such main factors, as operational factors should be incorporated in modeling and predicting the surface settlement.

Conducted studies utilizing the intelligent methods have largely focused on the issue of predicting surface settlement so their major output has been a model or an equation for the settlement estimation. In this study, in addition to building a settlement predictive model, attempt is made to consider procedures for settlement control. For this purpose, the most important input parameters were identified utilizing cosine amplitude method (CAM) then attempt is made to minimize the corresponding surface settlement by changing the values of the effective parameters. Various research works done by such persons as Jong and Lee [15] have confirmed the good performance of CAM.

The Criteria of Damage Risk Assessment Due to Ground Surface Settlement

Different researchers have proposed various settlement criteria for damage risk assessment [16–20]. Amongst which Rankin's theory (1998) is the most common criterion. The present study implemented Rankin's criterion. He presented Table 1 for damage risk assessment considering maximum settlement of a structure with single foundation. If the physical damage is less severe to be considered as a criterion, the maximum surface settlement (S_{max}) should be limited to 10–50 mm. Nevertheless, other controlling parameters could be implemented for structures with respect to the application and significance of the buildings. Rankin classifies the causes of damages into two distinct

Table 1 Typical values of maximum surface settlement for damage risk assessment [20]

Risk category	Maximum settlement (mm)	Degree of damage	Description of risk
1	<10	Negligible	Superficial damage unlikely
2	10–50	Slight	Possible superficial damage which is unlikely to have structural significance
3	50–75	Moderate	Expected superficial damage and possible structural damage to buildings, possible damage to relatively rigid pipelines
4	>75	High	Expected structural damage to buildings. Expected damage to rigid pipelines, possible damage to other pipelines

Table 2 Some of technical characteristics of EPBS in project of Shanghai subway line 2

Parameters	Amount
External diameter	6.2 m
Internal diameter	5.5 m
Shield external diameter	6.34 m
Width of lining ring	1.0 m
Shield advancing speed	2.0 m/h
Total thrust of jack	14 m
Shield tail's grouting pressure	0.3 MPa
Shield tail's grouting volume	2.0 m^3/m

groups. First, are the damages of categories 1 and 2 that can occur due to some inherent and natural characteristics of structures, including the shrinkage of concrete or plaster, temperature variations, elastic deformations etc. as well as symmetrical settlements caused by external factors. The second group, include the damages of categories 3 and 4 caused by external factors.

Case Study and Data Bank

The case study of this research is Shanghai subway line 2 project. All required information is gathered from a specific research [21]. The Tunneling Project between Pudong South Road Station and Nanpu Bridge Station was an important component of this project as well as a major project in Shanghai. The tunnel started from the end well west of Pudong South Road Station to the end well east of Nanpu Bridge Station, with a full- up line length of 1997.148 m and a down line length of 1981.960 m. In addition, the soil type in the area was mainly silty clay and the tunnel was constructed using EPBS. The other properties of this project are summarized in Table 2.

EPBS tunneling method, which was initially developed in Japan, has gained popularity for soft ground tunneling [7]. With this technique, the ground movement could theoretically be controlled through balancing the pressure inside the earth pressure chamber relative to the outside ground pressure during excavation. Based on the case history reviews [7, 12], the factors causing settlement can be grouped into three major categories, such as the geometric, strength and operational factors. In this research for each factor some variables are assigned as input parameters, which are given as follows:

1. Geometric factors: Diameter (D) and depth (Z) of tunnel.
2. Strength factors: Cohesion (C), internal friction angle (φ), and modulus of elasticity (E).
3. Operational factors: Penetration rate (V), thrust force (F), grout filling percent (n) and grouting pressure (P).

The amounts of these parameters are shown in Table 3. In general, it can be concluded that all of these nine input parameters play a key role in the development of the ground surface settlement which their significance is briefly expressed as follows:

- By increasing the tunnel diameter (D), the affected area around the face extends making it more difficult to control the convergence. Obviously, if the tunnel depth (Z) is deep enough, the roof falls so that the effects would petered out before reaching the surface. Nevertheless, the effect of tunnel depth on the settlement should always be considered together with that of tunnel diameter [22]. Accordingly, one may use depth to diameter ratio (Z/D) to investigate simultaneously their effects.
- Tunneling in the soft ground requires a higher safety provisions compared to those provided under hard rock conditions. Therefore, it will be very useful to incorporate EPBS approach under such conditions. According to the mentioned issues, the higher the strength of the tunnel encompassing mass, the easier will be the tunneling process leading to lower settlement. Therefore, it is expected that with increase in the cohesion (C), internal friction angle (φ), and modulus of elasticity (E) values, the surface settlement would decrease.
- The EBPS operational factors are the most effective parameters on the surface settlement. The penetration rate (V) reduces the surface settlement to an optimum amount. Excessive amounts cause face support pressure while its reduction causes ground loss. The thrust force (F) is largely associated with penetration rate. Increasing the thrust force to an optimum amount, while jacks are opening, supplies an optimal penetration rate and subsequently decreases surface settlement. Increase of F, while jacks are closing, accelerates the operations and reduces delays in the process of segments installation and, thus, decreases surface settlement.
- Tail void grouting is necessary to prevent ground moving towards the void. Tunneling operations with high grout filling percentage (n) and grouting pressure (P) can considerably reduce settlements developed after the shield passing [7]. The ground volume loss (V_L) is associated with a set of different components which are combined during tunnel excavation. According to Fig. 1, in EPBS excavation, the volume loss occurs at three diverse modes; Volume loss at the tunnel face (V_f), volume loss around shield (V_s) and volume loss in tail void (V_t) [23]. The amount of V_f can be minimized to a large extent by controlling the operational

Table 3 Datasets used for creating intelligent model [21]

No.	D m	Z m	Z/D –	C kPa	φ o	E MPa	F MN	V mm/min	P MPa	n %	S_{max} mm	Data set division
1	6.40	15.50	2.42	12.9	11.8	7.2	13.0	40	0.25	150	52.4	Train
2	6.40	8.40	1.31	11.7	16.4	6.5	14.0	30	0.30	170	53.3	Test
3	6.34	12.00	1.89	12.1	13.7	5.2	14.0	30	0.35	170	55.3	Train
4	6.34	12.00	1.89	12.0	13.7	5.2	14.0	30	0.35	150	57.0	Train
5	6.34	10.50	1.66	11.9	13.8	5.2	14.0	40	0.25	140	62.5	Train
6	6.40	12.00	1.88	34.0	16.6	7.3	16.0	20	0.30	160	70.2	Train
7	6.25	11.80	1.89	12.0	16.6	4.2	16.0	30	0.25	160	79.6	Test
8	6.34	11.80	1.86	12.0	13.6	5.2	14.0	40	0.35	140	79.6	Test
9	6.34	6.10	0.96	11.2	19.5	8.3	14.0	40	0.30	140	84.5	Train
10	6.34	11.20	1.77	11.9	13.8	5.2	14.0	30	0.30	170	89.9	Train
11	6.40	13.80	2.16	36.7	20.7	7.3	31.7	60	0.25	170	7.5	Train
12	6.40	12.00	1.88	15.3	23.9	3.9	31.7	40	0.30	150	7.6	Test
13	6.40	14.50	2.27	43.6	30.0	9.1	31.7	60	0.25	150	8.9	Train
14	6.40	13.30	2.08	28.1	32.8	5.4	31.7	40	0.25	150	9.6	Train
15	6.34	18.20	2.87	214.9	23.8	34.2	20.0	30	0.40	170	10.5	Train
16	6.40	20.60	3.22	201.7	23.5	35.2	30.0	20	0.30	120	11.2	Test
17	6.40	15.00	2.34	312.0	42.1	35.7	30.0	30	0.30	150	14.1	Test
18	6.40	14.20	2.22	32.4	12.4	11.2	31.7	60	0.25	170	14.8	Test
19	6.40	14.50	2.27	34.2	14.5	7.3	31.7	50	0.25	170	16.4	Train
20	6.25	12.00	1.92	340.0	44.9	35.0	33.0	30	0.20	90	16.8	Train
21	6.34	9.87	1.56	112.0	35.2	25.9	31.0	20	0.35	170	17.3	Train
22	6.25	24.00	3.84	240.0	30.1	23.1	33.0	30	0.30	120	19.2	Train
23	6.40	12.00	1.88	12.2	13.1	5.2	14.0	20	0.35	200	20.3	Train
24	6.34	11.90	1.88	11.9	13.8	5.2	14.0	20	0.40	200	21.2	Test
25	6.40	14.50	2.27	32.4	10.7	11.2	31.7	60	0.25	170	22.0	Train
26	6.40	14.50	2.27	34.2	9.2	7.3	31.7	60	0.25	170	22.8	Train
27	6.34	10.60	1.67	18.7	13.5	6.2	14.0	30	0.30	160	26.4	Train
28	6.34	10.90	1.72	11.8	14.4	5.5	14.0	20	0.40	200	27.1	Train
29	6.34	12.70	2.00	12.0	13.4	5.0	14.0	20	0.40	200	32.8	Train
30	6.25	20.00	3.20	30.2	22.8	11.8	23.0	40	0.25	120	34.0	Test
31	6.34	20.00	3.15	10.0	25.0	9.1	10.0	20	0.34	140	35.1	Train
32	6.25	10.40	1.66	30.0	16.5	7.6	16.0	40	0.30	160	35.4	Train
33	6.34	11.40	1.80	11.9	14.1	5.4	14.0	20	0.40	180	38.1	Train
34	6.34	11.90	1.88	11.9	13.8	5.2	14.0	20	0.40	180	38.6	Train
35	6.34	12.00	1.89	15.0	13.7	8.2	14.0	20	0.45	150	40.5	Train
36	6.34	9.40	1.48	32.5	15.5	7.7	15.0	20	0.30	150	40.6	Train
37	6.34	10.40	1.64	11.8	14.7	5.7	14.0	20	0.40	180	40.6	Test
38	6.40	12.00	1.88	11.4	19.2	8.4	12.0	30	0.40	140	42.4	Test
39	6.34	11.80	1.86	12.0	13.8	5.2	31.7	30	0.40	170	45.1	Train
40	6.34	9.78	1.54	11.8	15.2	5.9	14.0	20	0.55	170	47.3	Train
41	6.34	9.78	1.54	11.8	15.2	5.9	14.0	20	0.35	170	47.3	Test

parameters such as face support pressure, penetration rate and thrust force simultaneously. In this case, however, V_s is also partially controlled. The quality of tail voids grouting has a considerable effect on the amount of V_t and surface settlement.

Certainly, there are more parameters contributing to the tunnel settlement; however, they are ignored, as many of them (such as segment thickness and length, shield length, etc.) were constant during the tunneling project.

Maximum Surface Settlement Modelling

Adaptive Neuro-Fuzzy Inference System (ANFIS)

Jang [24] introduced ANFIS, which is a combination of fuzzy logic (FL) and artificial neural network (ANN). All fuzzy systems (FSs) and ANNs have some advantages and disadvantages. FSs can use human language and can use human experiences and expertise of informed individuals. However, they cannot learn. Nevertheless, ANNs can do self-training using data sets. Meanwhile, ANNs are implicit and they are unable to use human language [25]. Therefore, ANFIS takes advantage of both neural and fuzzy systems [26]. According to Fig. 2, ANFIS process is performed through five steps [27]. In fact, training in this system means that nonlinear parameters related to fuzzy membership function of layer one and linear parameters of layer four are determined in a way to obtain a favourable output for an optional input. During the fuzzy-neural process, parameters of membership functions are regulated through a back propagation (BP) algorithm or its combination with the least squares (LS) method, which called hybrid algorithm [27]. The advantage of hybrid method is that it uses BP for parameter associated with input membership function and LS estimation for parameters associated with output membership.

Estimation of Maximum Surface Settlement by ANFIS

In this research, MATLAB software (Ver.: R2015a (8.5.0.197613)) has been used for ANFIS modelling. In order to build the model, it began by normalizing all data into [−1 1] interval, to get the variation ranges of the parameters closer to each other thus improving the model ability to generalize and learn the existing relations between the

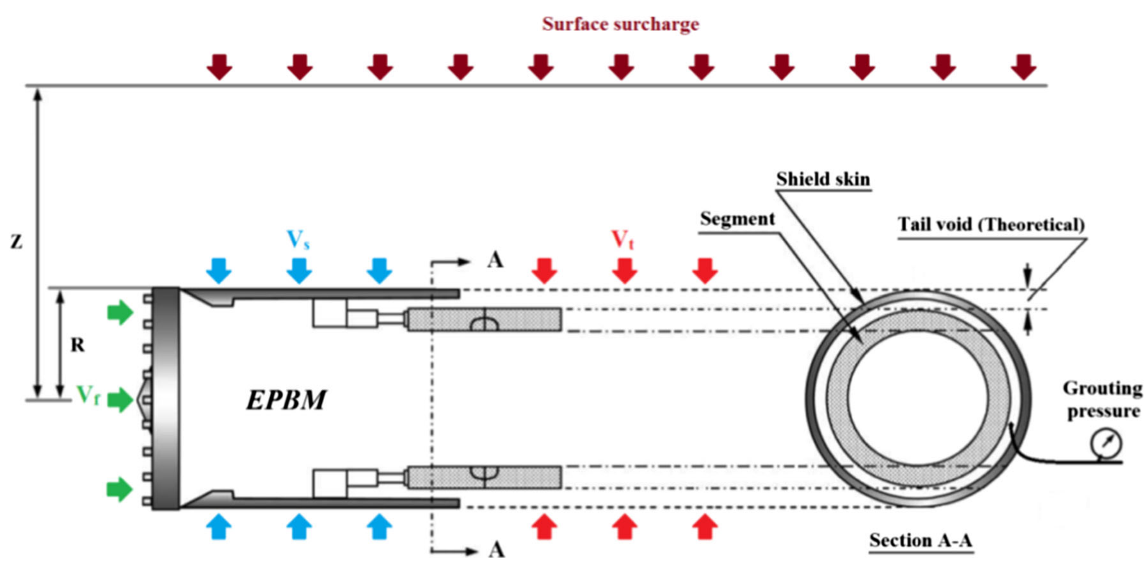

Fig. 1 Schematic diagram of a typical longitudinal section of EPBS with volumes less, tail void, grouting pressure and grout filling [7, 23]

Fig. 2 ANFIS structure [28]

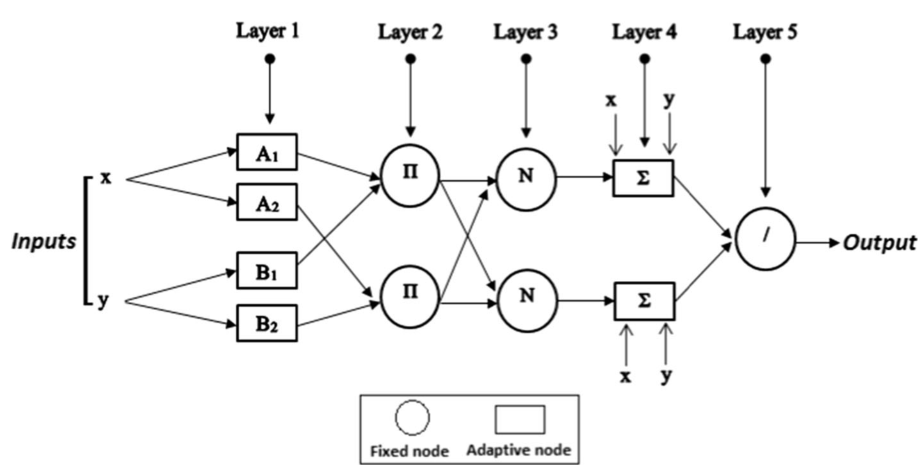

Table 4 Properties of the built ANFIS model for the prediction of maximum surface settlement

Identification method	No. of MF	No. of nude	No. of linear parameters	No. of nonlinear parameters	No. of parameters	No. of fuzzy role
FCM[a]	9	173	81	144	225	9

[a] Fuzzy c-means clustering

parameters. Next, 41 available data sets were randomly divided into two categories of training and testing phases; 29 data sets (about 70%) were considered to build the model and the rest 12 data sets (about 30%) were considered for their evaluation (see data set division in Table 3). The best ANFIS structure was selected by applying the trial-and-error method. The type and number of membership functions (MF), optimization algorithm, epochs, etc. were all optimized via the trial-and-error approach [28]. The built models were evaluated based on the root mean square error (RMSE) values obtained for training and testing phases. The MF and optimization method for all models were Gaussian and hybrid methods, respectively. Other characteristics of the built models are demonstrated in Table 4. Figure 3 depicts the structure of the built ANFIS model.

The RMSE of the model in training and testing phases were equal to 0.064 and 5.046, respectively. Figure 4 shows the coefficient of determination (R^2) of the model and the actual surface settlements versus ANFIS predictions in testing phase. According to the result, it can be inferred that the model developed had a suitable performance and high intelligence.

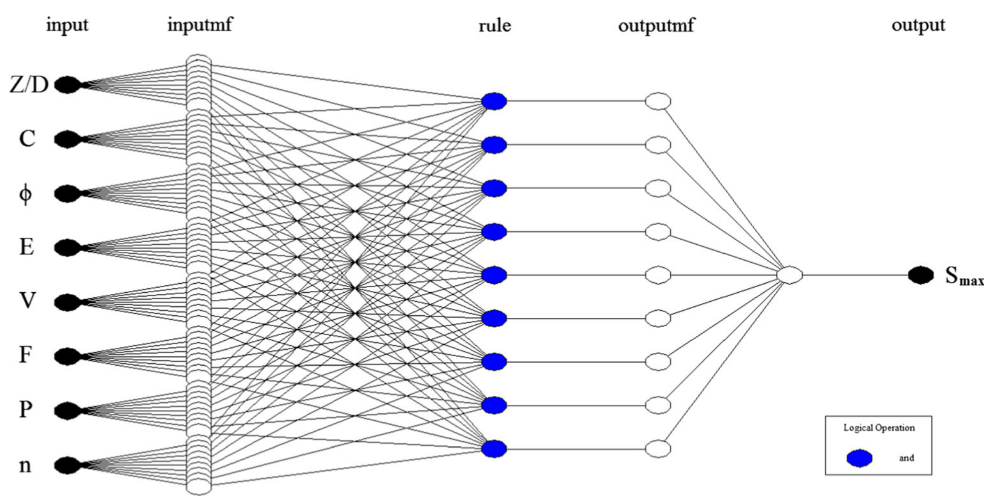

Fig. 3 Built ANFIS model structure to predict maximum surface settlement

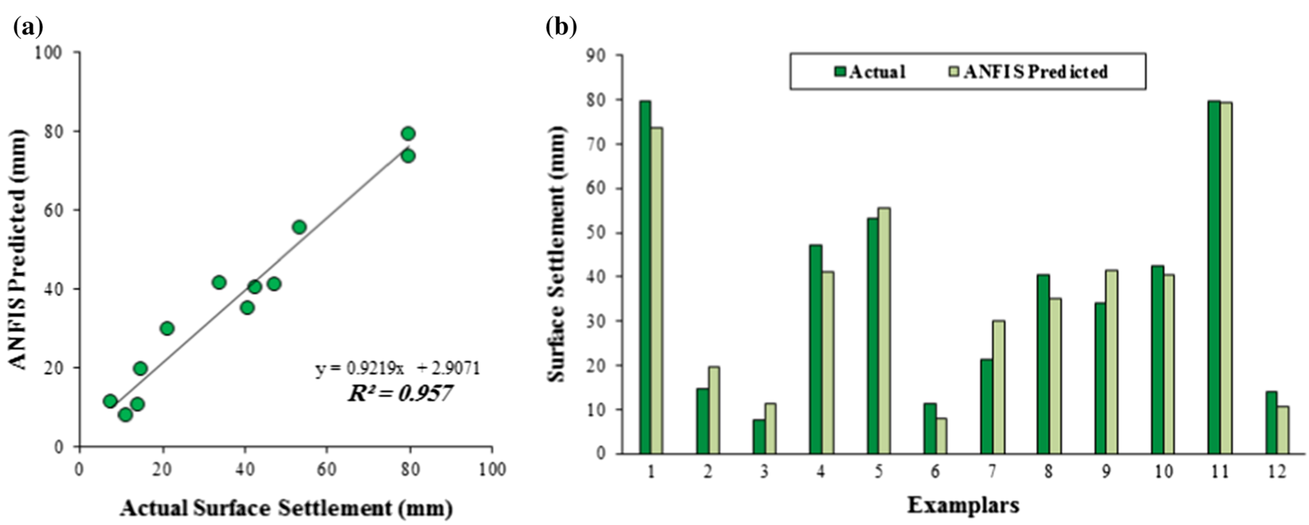

Fig. 4 Coefficient of determination (R^2) of the model and comparison of between actual maximum surface settlements versus model predictions in testing phase

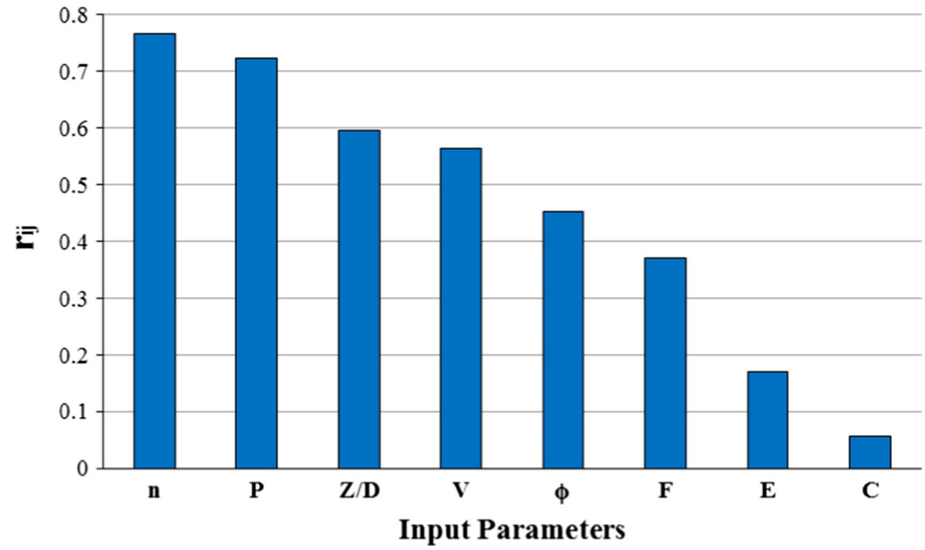

Fig. 5 Strength of relation (r_{ij}) between the maximum surface settlement and input parameters

Sensitivity Analysis by Cosine Amplitude Method (CAM)

In this paper, the cosine amplitude method (CAM) is used to perform the sensitivity analysis of the ANFIS model. As with all the following methods, this similarity metric makes use of a collection of data samples, n data samples in particular. If these data samples are collected, they form a data array, X [29],

$$X = \{x_1, x_2, \ldots, x_n\} \tag{1}$$

Each of the elements, xi, in the data array X is itself a vector of length m, that is,

$$x_i = \{x_{i1}, x_{i2}, \ldots, x_{im}\} \tag{2}$$

Hence, each of the data samples can be thought of as a point in m-dimensional space, where each point needs m coordinates for a complete description. Each element of a relation, r_{ij}, results from a pairwise comparison of two data samples, say x_i and x_j, where the strength of the relationship between data sample xi and data sample x_j is given by the following membership strength:

$$r_{ij} = \frac{\left|\sum_{k=1}^{m} x_{ik}x_{jk}\right|}{\sqrt{\left(\sum_{k=1}^{m} x_{ik}^2\right)\left(\sum_{k=1}^{m} x_{jk}^2\right)}}, \text{ where} \Rightarrow i, j = 1, 2, \ldots, n. \tag{3}$$

Close inspection of Eq. (3) reveals that this method is related to the dot product for the cosine function. When two vectors are collinear, their dot product is unity; when the two vectors are at right angles to one another, their dot product is zero [29].

In order to express the relation between the maximum surface settlement and the input parameters (in testing phase), [1*12] sized matrices were obtained. The matrices so obtained were correlated by means of the Eqs. (1)–(3), and the relation strengths (r_{ij} values) are shown in Fig. 5. According to this figure, the operational parameters of grout filling percentage (n) and grouting pressure (P) were associated with the highest effective value, while the strength parameters of cohesion (C) and modulus of elasticity (E) provided the smallest effective value in the maximum surface settlement (S_{max}). The figure shows the effect of other parameters as well; note the higher effective value of geometric factor (Z/D), rather than that of the strength parameters.

Control of Ground Surface Settlements

As noted earlier, once the ground surface settlement is estimated, the related probable damages could be prevented or controlled, if possible. To this end, it is greatly important to compare the maximum surface settlement with its allowable amount. According to Rankin's criterion (Table 1), the maximum surface settlement values greater than 50.0 mm cause damage risk with a moderate degree. Therefore, this section was an attempt to prevent occurrence of the unallowable settlements (>50.0 mm). 10 data sets in which the surface settlements are greater than 50.0 mm (number 1 to 10) are observed in Table 3.

According to the sensitivity analysis results in the previous section, it was found that the two parameters of n and P had a significant effect on the surface settlement. Thus, implementing appropriate grouting operations can minimize the volume of settlement and volume loss in tail voids (V_t) and reduce the surface settlement. In order to reduce the volume of settlement to an allowable value, the main effective parameters of grout filling percentage (n) and grouting pressure (P) were modified and the corresponding surface settlement was predicted using the proposed ANFIS model.

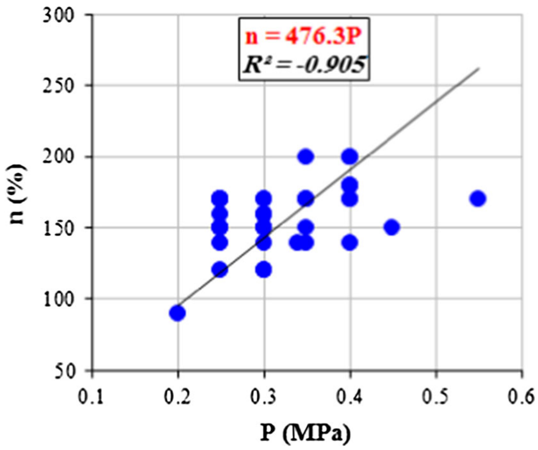

Fig. 6 Relation between grouting pressure (*P*) and grout filling percentage (*n*) parameters

As shown in Fig. 6, there is an entirely direct relationship between the parameters *n* and *P*. As a result, these parameters should be modified simultaneously in the corresponding sensitivity analysis. Hence, the values of *P* and *n* of these 10 categories of data, according to their relationship (Fig. 6) and their maximum values in the present project (Table 3), were increased to an extent that the corresponding surface settlement (predicted by the built ANFIS model) is less than the allowable value. Figure 7 presents the results. For example, the surface settlement of the data category 7, which was measured as 79.6 mm in reality, can eliminate surface settlement by increasing the grouting pressure and changing the *n* value from 140 to 170%.

The interpretation of the results of data category 8 is a bit more complicated. According to the related figure, the surface settlement of this category reached 59.7 mm, which is greater than the allowable settlement, by increasing the *n* value to 200%. Therefore, in order to obtain a surface settlement less than 50.0 mm, the *n* and *P* values should be increased further so that for an *n* value of 220%, the surface settlement reaches its allowable value. The reason why the surface settlement of this data category is more stable than the other categories is related to the insignificant Modulus of Elasticity (*E*) value. To prove this, the value of this parameter was changed in another analysis, though such a change is not possible in practice. By changing the modulus of elasticity (*E*) from its actual value of (4.24 MPa) to a hypothetical value of (5.50 MPa), the predicted settlement reached the allowable value (<50.0 mm) once the (*n*) value increased to 190%. Therefore, the main cause of the continuous settlement at this stage is the excessive deformation of the mass encompassing the tunnel. Since it is not possible to change the geological characteristics, tunneling in such an environment requires in-depth structural design (if possible); otherwise, the only solution is to control the operational parameters (*n*, *P*, etc.).

It is worth noting that the surface settlement of several data categories for a range of *n* values between 170 and 190 percent had an ascending trend, which indicates the excessive complexity and prediction error in this regard.

Conclusions

According to the obtained results it was found that the overall behaviour evaluated by ANFIS method is consistent with that of the actual maximum surface settlement; The R^2 value of the built model was equal to 0.957 in testing phase. This method exhibits the relation between the input parameters and their effects on the output, and has the ability to generalize intelligently the new data.

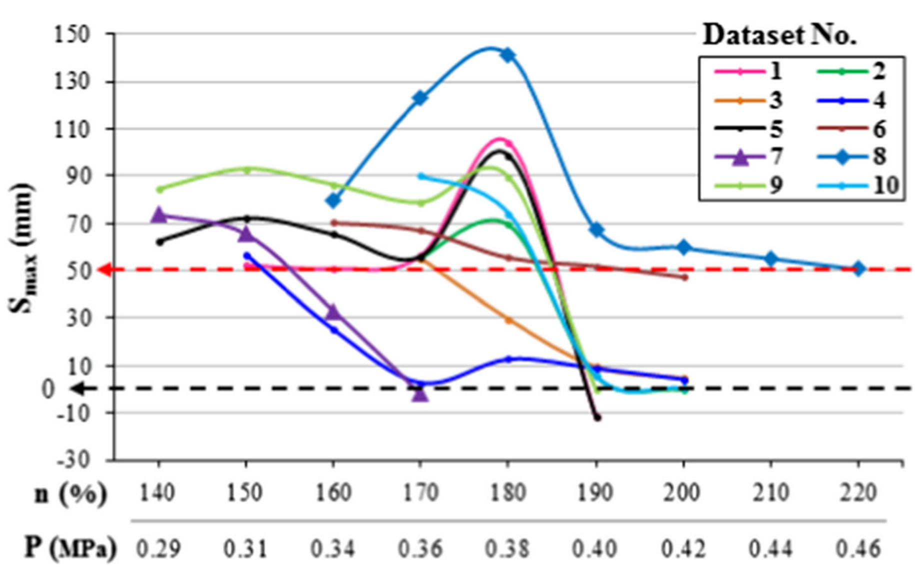

Fig. 7 Sensitivity analysis of maximum surface settlement (S_{max}) relative to the major effective parameters: grouting pressure (*P*) and grout filling percentage (*n*)

In order to introduce the most effective parameter, sensitivity analysis of the ANFIS model was performed by CAM. The results showed that the operational, geometric and strength factors were more important, respectively. Amongst the available variables, grout filling percentage (n) and grouting pressure (P) were the most effective. Therefore, the settlement could greatly be controlled via a proper high quality grouting operation. CAM approach recognized the strength parameters of cohesion (C) and modulus of elasticity (E) as the least effective parameters; this exhibits the advantage of EPBS tunneling method in soft grounds. High flexibility of this method within loose grounds clearly contributes to stability of the environment around the digging space, which greatly reduces the settlement.

To prevent occurrence of the probable damages, the values of unallowable surface settlement (>50.0 mm) were identified based on Rankin's criterion and then the corresponding surface settlement was reduced by increasing the n and P parameters values. The present study exhibited favourable results and showed its effectiveness for most data categories particularly those with favourable geometric and strength parameters. Therefore, it was proved that control of the operational factors had a crucial role in controlling the settlement rate.

Finally, it can be implied that designing deeper tunnels may significantly reduce the effects of roof falls before they reach ground surface. If it is not possible to change the path of tunnel excavation, the surface settlement can be minimized to some extent by controlling the operational parameters especially by implementing appropriate grouting operation.

Face support pressure plays an important role in maintaining the stability of tunnel face and reducing volume loss at the tunnel face (V_f). In the present study, it was not possible to investigate the effect of this parameter due to its absence. Finally, it is recommended to consider the effect of this parameter in prospective research in order to predict, prevent and control surface settlement.

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