Prediction of penetration rate of a small diameter shield TBM based on adaptive neuro-fuzzy inference system and linear regression

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ABSTRACT

Penetration rate of shield TBM is a very important factor used to estimate the construction period and cost. However, the prediction procedure of penetration rate is complicated because there are many factors to consider such as rock mass condition and TBM operating parameters. Therefore, it has become a good alternative to develop a simple prediction model of penetration rate based on some rock mass properties and mechanical measurement data. For this reason, 32 data were collected from the field in this study, and rock quality designation, deformation modulus, Thrust, and revolution per minute were selected as input parameters for model development. Using these variables, two prediction models such as multivariate linear regression and adaptive neuro-fuzzy inference system were developed. In addition, both models were verified and compared by various evaluation indices. The developed two models are expected to be applied for prediction purposes under a similar condition to the field.

Keywords: Shield TBM, multivariate linear regression, Adaptive neuro-fuzzy inference system, Penetration rate

1 INTRODUCTION

Shield TBM, one of the mechanized tunneling, is a full section excavation method propelling forward as supporting with a segment in inner space to prevent a collapse of the surrounding ground by using 'Shield'. A small-diameter shield TBM(<Ø4m) was first used in Korea in 1987 for supplying electric power and telecommunication, and a larger diameter shield TBM has been applied for the purpose of subway construction since the mid-1990s (Lee et al. 2011). Since then, the use of shield TBM has been increased constantly, and it has become important to estimate a construction period and cost.

Penetration rate can be defined as net excavation distance per unit time. It is an important factor in estimating the construction period. However, the process of predicting the penetration rate is complicated because there are many things to consider such as rock mass conditions, TBM operating parameters (Rostami et al. 1996). To overcome this difficulty, empirical models based on database obtained from the field have been proposed by several researchers. Yagiz (2008) developed a multivariate linear regression through the database from the project in New York, Queens Water Tunnel, in which the open TBM(Ø7.06m) was used. Benardos and Kaliampakos (2004) applied the ANN model based on the database from Athene Metro line 3 using EPB type shield TBM(Ø9.48m). Yagiz and Karahan (2011) used particle swarm optimization for Queens Water tunnel to predict the PR. Several techniques such as differential evolution, grey wolf optimization, and hybrid harmony search also were applied (Yagiz and Karahan 2015).

In this study, an appropriate model satisfied with a specific project where a small-diameter(<Ø4m) shield TBM was used, was selected to estimate the penetration rate. To develop the model, data were collected from a field, and key parameters influencing a penetration rate were selected. Using these variables, two predictive models, multivariate linear regression and adaptive neuro-fuzzy inference system (ANFIS) were constructed and, verified and compared by various evaluation indices.

2 SELECTION OF INPUT VARIABLES

Selecting input variables to build a prediction model is important. In general, statistical methods can be used to select variables. It is necessary to select the input variables with high correlation for output variable and consider redundancy between the input variables. However, when considering statistical methods only, important variables for a specific field can be missed. Therefore, in this study, not only statistical methods but also geotechnical characteristics of variables were tried to be considered.

As a preliminary work for selecting variables, 32 data were collected through borehole data and automatically measured mechanical data in the field in Korea. The variables in these data, such as uniaxial compressive strength (UCS), rock quality designation (RQD), rock mass rating (RMR), lugeon, absorption, p wave velocity, s wave velocity, deformation modulus, thrust, revolution per minute (RPM), and torque were obtained as input variables for penetration rate. Table 1 shows descriptive statistics on the collected data. As a first step, the Pearson's correlation coefficient matrix was constructed as shown in Table 2 to determine the degree of correlation between variables. The correlation for penetration rate was -0.636 for thrust, -0.447 for RPM, -

0.340 for RMR, and -0.288 for RQD. The rest of the input variables (lugeon, absorption, torque etc.) did not show any significant correlation. In the relationship between the input variables, the correlation coefficient between RMR and RQD was very large (r=0.969) which represents high redundancy. Also, RQD is the main factor for estimating RMR. Therefore, RMR was excluded under consideration in this study.

In the second step, geotechnical characteristics were considered to select input variables. The strength characteristics for the rock mass is well known to have a major influence on the bore-ability of TBM (Gong et al. 2009), and UCS, p wave velocity, s wave velocity, and deformation modulus can be included in this category. A representative property specifying the strength of rock mass is UCS, which showed a correlation coefficient of 0.853 for p-wave velocity, 0.826 for s-wave velocity and 0.769 for deformation modulus. In this study, non-redundant variables (RQD, Thrust, and RPM) were fixed as input variables and multivariate linear regression analysis was performed for each variable with strength characteristics (Table 3). Thrust was the most significant influence for penetration rate and, followed by RPM. On the other hand, RQD and other properties related to strength characteristics showed a relatively poor correlation with the penetration rate. It can be seen that the penetration rate is influenced by the TBM operating parameters than the rock mass parameters. In Table 3, the correlation coefficients of the four models did not show a significant difference, but the linear regression with deformation modulus had the highest fitness among the four models. Therefore, in this study, thrust, RPM, RQD and deformation modulus for model development were selected as input variables.

3 CONCEPT AND CONSTRUCTION OF MODEL

As mentioned earlier, the problem of predicting penetration rate is complicated and nonlinear because there are many factors to consider such as rock mass condition and TBM operating parameters (Rostami et al. 1996). To overcome this difficulty, ANFIS has been used by some researchers as a popular tool (Grima et al. 2000; salami et al. 2016). The ANFIS is a hybrid system that can satisfy both the learning ability of artificial neural network and the reasoning ability of the fuzzy inference system of the Sugeno type (Takagi and Sugeno, 1985). The fuzzy inference system deals with high-level inference using language information acquired by experts in a specific field and this information is reflected in an activation function called a membership function. But it cannot adapt to the new environment itself. Thus, Jang (1993) developed the ANFIS that adjusts the membership functions effectively through machine learning of neural networks.

The structure of the ANFIS consists of five layers. For simplicity of illustration, it is assumed that it has two input values (x, y) and one output value (f) as shown in Fig. 1. It also uses two if-then rules of Takagi-Sugeno type.

Rule 1: If x *is* A_1 *and* y *is* B_1*, then* $f_1 = p_1x + q_1y + r_1$
Rule 2: If x *is* A_2 *and* y *is* B_2*, then* $f_2 = p_2x + q_2y + r_2$

Layer 1: every node i in this layer is a square node containing a node function

$$O_i^1 = \mu_{A_i}(x) \tag{1}$$

Where x is input to node i, O_i^1 is the activation function of A_i which is called the membership function. It means the degree to which the given x satisfies the quantifier A_i. The membership function used mostly is Gaussian and bell-shaped function with a maximum equal to 1 and a minimum equal to 0. The Gaussian membership function can be expressed as follow

$$\mu_{A_i}(x) = exp\left(-\frac{(x-c_i)^2}{2a_i^2}\right) \tag{2}$$

Where a_i and c_i is a variance and mean value of function respectively. When the values of these parameters change, the shape of Gaussian function also changes. Parameters in this layer are called as '*premise parameters*'.

Layer 2: Every node in this layer is a circle node which multiplies the incoming signals and sends output signals to the next layer.

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(x), \quad i = 1, 2 \tag{3}$$

Each output of the node in this layer represents the firing strength of the if-then rule.

Layer 3: Every node in this layer is a circle node. This ith node computes the ratio of the ith firing strength to the sum of all firing strengths.

$$\overline{w_i} = \frac{w_i}{w_1+w_2}, \quad i = 1, 2 \tag{4}$$

The output in this layer can be referred to as normalized firing strengths.

Layer 4: Every node in this layer is a square node

$$O_i^4 = \overline{w_i}f_i = \overline{w_i}(f_1 = p_ix + q_iy + r_i) \tag{5}$$

Where, p_i, q_i and r_i are the parameter set which called as '*consequent parameters*'.

Layer 5: The single node in the last layer calculates the overall output as the summation of all incoming signals as follow,

$$Overall\ output = O_1^5 = \sum_i \overline{w_i}f_i \tag{6}$$

Unlike ANN learning in a backward direction, the ANFIS proposed by Jang (1993) trains both forward and backward direction. In a forward direction, the parameters of the activation functions called membership functions are fixed, and then the coefficient estimates of the first-order formulas are adjusted by recursive least squares. In a backward direction, coefficients of first-order formulas are fixed first, and the parameters of activation functions are renewed by the gradient descent method. For this reason, ANFIS allows fast convergence and it is also widely used in various field.

In this study, ANFIS and multivariate linear regression were developed, and the data was classified into 80% training and 20% test randomly for performance comparison. 26 data for model training were randomly selected and the rest were used for testing. This procedure was repeated five times, and five ANFIS and multivariate linear regression models were developed. The number of membership functions which is assigned to each input variable and the learning rate were set to 2 and 0.01 respectively by trial and error.

4 PERFORMANCE EVALUATION AND SELECTION OF OPTIMUM MODELS

As mentioned above, five ANFIS and multivariate linear regression models were developed, and each model was validated with training data and test data. The performance of the training data means *good learning* of the model, and the performance for the test data represents *generalization of the model*. In this study, three evaluation indices such as correlation coefficient, root mean square error and variance accounted for were introduced to prevent bias in performance evaluation. Table 4 shows the results of performance evaluation for each model. In these results, the correlation coefficient of ANFIS was slightly larger than the multivariate linear regression for the training data, but there was no significant difference. On the other hand, for test data, ANFIS showed better performance than the multivariate linear regression, and it can be concluded that ANFIS is a more generalized model.

To select the optimal model, a point system was introduced. For example, in Table 4, the correlation coefficient for training data in linear regression gives a higher point in descending order. In the same way, after the calculation is repeated for different performance indices, the 'sum of point' is calculated as a summation of the point for each performance index. Finally, the 'performance point' in Table 5 is computed as the summation of the 'sum of point' of each model (multivariate linear regression, ANFIS) for randomly divided data. As shown in Table 5, the test point for model 5 were calculated as 25 which is higher than that of model 1. Nonetheless, model 1 showed the highest performance point. It is due to the fact that the train point denoting *good learning* for model 5 were less than that of model 1. As a result, linear regression 1 and ANFIS 1 were selected as the best performance models.

5 CONCLUSIONS

Two different models were developed and compared based on the data obtained from the field with shield TBM((<Ø4m). The performance of ANFIS for test data was not noticeable but it was still higher than multivariate linear regression. This seems to be due to the small number of data collected from the field. However, both models derived from this study have a significance in explanatory power. Also, if the data is accumulated continuously, it is expected that there will be a meaningful improvement in performance, especially ANFIS. Lastly, these models will be applicable under similar rock mass condition and shield TBM.

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Table 1. Descriptive statistics for obtained data

	Penetration rate (mm/min)	UCS (MPa)	RQD (%)	RMR (%)	Lugeon -	Absorption -	P wave velocity (m/sec)	S wave velocity (m/sec)	Deformation modulus (MPa)	Thrust (kN)	RPM -	Torque (kN·m)
Mean	36.75	96.2	41.1	50.2	8.3	0.26	4065	2473	38303	4340	7.37	2974
Std.deviation	9.55	47.1	29.0	16.4	25.2	0.16	994	640	17188	1007	1.68	499
Coef. of variance	0.26	0.49	0.71	0.33	3.03	0.61	0.24	0.26	0.45	0.23	0.23	0.17
Skewness	-0.64	0.29	0.59	0.59	4.56	0.99	-0.87	-0.86	0.45	0.44	-0.54	-0.85
Kurtosis	-0.46	0.07	-0.61	-0.43	22.21	-0.38	1.70	1.40	0.52	-0.36	-0.59	1.05
Num. of data	32	32	32	32	32	32	32	32	32	32	32	32

Table 2. correlation coefficient matrix between variables

	Penetration rate	**UCS**	**RQD**	**RMR**	**Lugeon**	**Absorption**	**P wave velocity**	**S wave velocity**	**Deformation modulus**	**Thrust**	**RPM**	**Torque**
Penetration rate	1.00											
UCS	-0.01	1.00										
RQD	-0.29	0.42	1.00									
RMR	-0.34	0.51	0.97	1.00								
Lugeon	0.06	0.04	-0.35	-0.29	1.00							
Absorption	-0.01	-0.76	-0.36	-0.47	0.14	1.00						
P wave velocity	0.06	0.85	0.34	0.42	0.20	-0.62	1.00					
S wave velocity	0.11	0.83	0.26	0.35	0.32	-0.58	0.99	1.00				
Deformation modulus	0.02	0.77	0.37	0.42	0.17	-0.43	0.82	0.83	1.00			
Thrust	-0.64	-0.13	0.19	0.21	-0.03	0.28	-0.25	-0.27	-0.21	1.00		
RPM	-0.45	-0.05	0.45	0.40	-0.31	0.04	-0.14	-0.22	-0.14	0.35	1.00	
Torque	-0.08	0.23	0.36	0.29	0.14	-0.06	0.32	0.32	0.33	0.18	-0.12	1.00

Table 3. Multivariate linear regression for all data

Multiple linear regression	**r (correlation coefficient)**
PR_n = -0.563(thrust_n) -0.217(RPM_n) -0.032(RQD_n) -0.088(UCS_n) +0.975	0.688
PR_n = -0.578(thrust_n) -0.224(RPM_n) -0.025(RQD_n) -0.135(p wave velocity_n) +1.023	0.690
PR_n = -0.574(thrust_n) -0.226(RPM_n) -0.034(RQD_n) -0.111(s wave velocity_n) +1.016	0.689
PR_n = -0.563(thrust_n) -0.237(RPM_n) -0.007(RQD_n) -0.149(deformation modulus_n) +1.009	0.694

(PR_n : normalized penetration rate, thrust_n : normalized thrust, RPM_n : normalized RPM, RQD_n : normalized RQD, UCS_n : normalized UCS, p wave velocity_n : normalized p wave velocty, s wave velocity_n : normalized s wave velocity, deformation modulus_n : normalized deformation modulus)

Table 4. Performance evaluation for each model

Model	**Test**	**r (Correlation coefficient)**	**RMSE**	**VAF**	**Point for r**	**Point for RMSE**	**Point for VAF**	**Sum of Point**
Linear regression 1	Train 1	0.69	0.1797	47.6	2	4	2	8
Linear regression 2	Train 2	0.66	0.1824	43.2	1	1	1	3
Linear regression 3	Train 3	0.69	0.1823	48.0	3	2	3	8
Linear regression 4	Train 4	0.72	0.1763	51.8	5	5	5	15
Linear regression 5	Train 5	0.70	0.1820	49.6	4	3	4	11
ANFIS 1	Train 1	0.74	0.1658	55.4	5	5	4	14
ANFIS 2	Train 2	0.71	0.1696	51.5	1	4	1	6
ANFIS 3	Train 3	0.73	0.1729	53.7	3	3	2	8
ANFIS 4	Train 4	0.73	0.1746	56.2	2	2	5	9
ANFIS 5	Train 5	0.73	0.1749	54.1	4	1	3	8
Linear regression 1	Test 1	0.62	0.2041	52.9	5	3	5	13
Linear regression 2	Test 2	0.48	0.2014	34.4	2	4	4	10
Linear regression 3	Test 3	0.48	0.2049	24.0	3	2	1	6
Linear regression 4	Test 4	0.44	0.2124	26.1	1	1	2	4
Linear regression 5	Test 5	0.54	0.1860	33.7	4	5	3	12
ANFIS 1	Test 1	0.73	0.1781	70.9	4	2	5	11
ANFIS 2	Test 2	0.69	0.1657	61.3	3	4	4	11
ANFIS 3	Test 3	0.68	0.1702	47.9	2	3	2	7
ANFIS 4	Test 4	0.44	0.2119	30.4	1	1	1	3
ANFIS 5	Test 5	0.74	0.1477	55.4	5	5	3	13

Table 5. Calculation of performance point for each model

Model	**Train**	**Test**	**Performance point**
model 1	8+14= 22	13+11=24	8+14+13+11=46
model 2	3+6= 9	10+11=21	3+6+10+11=30
model 3	8+8= 16	6+7=13	8+8+6+7=29
model 4	15+9=24	4+3=7	15+9+4+3=31
model 5	11+8=19	12+13=25	11+8+12+13=44

Fig. 1. ANFIS structure (Jang, 1993)