The 2023 World Congress on
Advances in Structural Engineering and Mechanics (ASEM23)
GECE, Seoul, Korea, August 16-18, 2023

A hybrid time series model to predict ground conditions ahead of tunnel face using TBM data

Jee-Hee Jung[1)], *Byung-Kyu Kim[2)], Kang-Hyun Lee[3)], In-Mo Lee[4)]

[1), 3)] Korea Expressway Corporation Research Institute, Hwaseongsi 18489, Korea
[2)] Korea Railroad Research Institute, Uiwangsi 16105, Korea
[4)] School of Civil, Environmental and Architectural Engineering, Korea University, Seoul 02841, Korea
[2)] bkkim86@krri.re.kr

ABSTRACT

This paper presents a time series analysis model that can predict ground types up to ten segment rings ahead of a tunnel face using tunnel boring machine operational data. To achieve this, a hybrid model combining an autoregressive integrated moving average (ARIMA) model and a time delay neural network (TDNN) is proposed. First, the ARIMA model is used to predict machine data ten segment rings ahead of the tunnel face. Then, the predicted machine data is fed into the TDNN to predict ground types ahead of the tunnel face. We achieved a prediction accuracy of approximately 95%, which demonstrates the superiority of the proposed hybrid model.

1. INTRODUCTION

The recent increase in the use of shield tunnel boring machines (TBM) has resulted in a corresponding rise in unexpected accidents at tunneling job sites. Thus, the key issue in tunneling operation is to assess how to reduce these risks in a systematic way (Eftekhari et al. 2018; Chung et al., 2019). To reduce the probability of geological risks during tunneling work using the shield TBM, several methods have been proposed to predict ground conditions ahead of the tunnel face (Lee et al. 2019; Jung et al. 2019). In particular, the method of Jung et al. (2019) uses an artificial neural network (ANN) to predict ground conditions one segment ring ahead of the tunnel face. The main advantage of the developed ANN engine is that only shield TBM operational data is used; no additional testing or measurement is required beyond the machine data. Although this method is applicable in all site conditions, it is limited to predicting

---
[1)] Senior Researcher
[2)] Senior Researcher
[3)] Principal Researcher
[4)] Emeritus Professor

ground conditions one segment ring ahead of the tunnel face. It would be substantially more effective if it is possible to predict ground conditions farther ahead of the tunnel face. Therefore, this study is an extension of the research conducted by Jung et al. (2019) to make it feasible to predict ground conditions up to ten segment rings (rings hereafter) ahead of the tunnel face. To the authors' knowledge, this is the first attempt to predict ground conditions ahead of the tunnel face utilizing only TBM operational data. That is, the predicted ground conditions one ring ahead of the tunnel face provided by Jung et al.'s (2019) ANN could be used as input data for time series analysis reflecting job site characteristics. This study proposes a hybrid model that combines an ARIMA model and a time delay neural network (TDNN), as the latter is well-suited to time pattern recognition. Fig. 1 shows a conceptual diagram of successive steps to utilize the proposed hybrid model.

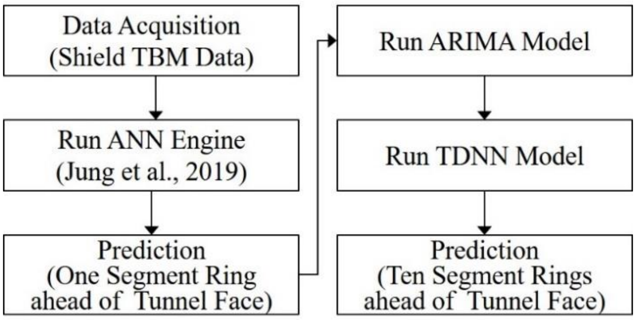

Fig. 1 Conceptual diagram of steps for predicting ground conditions

2. HYBRID TIME SERIES MODEL DEVELOPMENT USING FIELD DATA

2.1 Overview of job sites

The shield TBM operational data were collected from two job sites. An overview of the two job sites is presented in Table 1.

Table 1 Overview of two shield TBM job sites (Jung et al., 2019)

		Site 1	Site 2
Site Location		Country 1	Country 2
Route Length (km)		~2.30	~2.00
Ground Conditions	Classification	Soil, mixed ground (soil + rock), rock	Soil, mixed ground (soil + rock), rock
	Details	Weathered soil, granite	Completely decomposed granite (CDG), CDG with clayey, CDG with corestones, granite
External Diameter (m)		6.35	7.10
Type of TBM		Slurry	Slurry
Quantity of TBMs		3	2

2.2 Ground type classification

The ground type classification method used in this study is based on the method proposed by Jung et al. (2019), as presented in Table 2. The ground was classified into three types, namely relatively hard ground, mixed ground, and relatively soft ground, as explained in Table 2. Type 2 (mixed ground) occurs when a different ground type constitutes more than 25% of the diameter of the cutter head. At and above this threshold, TBM operation is frequently impeded by numerous problems including unbalanced wearing of the disk cutter, loosening of surrounding ground, and sinkholes (Ma et al., 2015).

Table 2 Classification of ground types (Jung at al., 2019)

<table>
<tr><td colspan="2"></td><td>Site 1</td><td>Site 2</td></tr>
<tr><td colspan="2">Site Location</td><td>Country 1</td><td>Country 2</td></tr>
<tr><td colspan="2">Route Length (km)</td><td>~2.30</td><td>~2.00</td></tr>
<tr><td rowspan="2">Ground Conditions</td><td>Classification</td><td>Soil, mixed ground (soil + rock), rock</td><td>Soil, mixed ground (soil + rock), rock</td></tr>
<tr><td>Details</td><td>Weathered soil, granite</td><td>Completely decomposed granite (CDG), CDG with clayey, CDG with corestones, granite</td></tr>
<tr><td colspan="2">External Diameter (m)</td><td>6.35</td><td>7.10</td></tr>
<tr><td colspan="2">Type of TBM</td><td>Slurry</td><td>Slurry</td></tr>
<tr><td colspan="2">Quantity of TBMs</td><td>3</td><td>2</td></tr>
</table>

2.3 ARIMA model for machine data prediction

The Statistical Package for the Social Sciences (SSPS 24) developed by IBM (IBM Corp., 2016a; IBM Corp., 2016b) was used to analyze the normalized machine data to establish the ARIMA model. As described in section 2.2, the three steps proposed by Box and Jenkins (1970) should be performed to develop an ARIMA model.

The stationarity of the normalized machine data should be checked in advance. Thus differencing was performed for all the nine parameters, and the results obtained from first and second-order differencing were compared. Next, the identification process of the ARIMA model was implemented. To do this, the autocorrelation coefficient (AC) and partial autocorrelation coefficient (PAC) of the stationary time series data should be determined and compared. These analyses were performed for all the nine input parameters. As the number of significant spikes was between 1 and 2, the lag values of AR and MA models were assumed to be 1 based on the principle of parsimony. In conclusion, the identified and selected ARIMA (1, 1, 1) and ARIMA (1, 2, 1) models are suitable for predicting machine data ten rings ahead of the tunnel face. Although the 120 cases listed in Table 3 were collected from different locations or different sites and different machines, most of the collected data points passed the model diagnosis steps, making it feasible to use such data in other job sites.

Table 3 Analysis cases

	Site 1						Site 2			
	TBM 1			TBM 3			TBM 1			
Section number	1	2	3	1	2	3	1	2	3	4
Case numbers	1-10	11-20	21-30	31-40	41-50	51-60	61-80	81-90	91-100	101-120
Segment ring numbers	10-55	240-285	830-875	10-55	300-345	805-850	10-105	240-285	400-445	660-760
Number of cases	30			30			60			

2.4 TDNN model for ground type prediction

A TDNN analysis was performed to predict ground types up to ten rings ahead of the tunnel face using the 120 case. This analysis was performed using MATLAB R2016a (Beale et al., 2016; Taylor, 2017). The machine data needed for TDNN analysis were obtained from two sources: measured machine data obtained during tunnel excavation up to the current tunnel face and predicted machine data for the upcoming ten rings ahead of the tunnel face obtained using the ARIMA model. The sequence of TDNN analysis to predict ground types ten rings ahead of the tunnel face is presented as a flow diagram, as shown in Fig. 2.

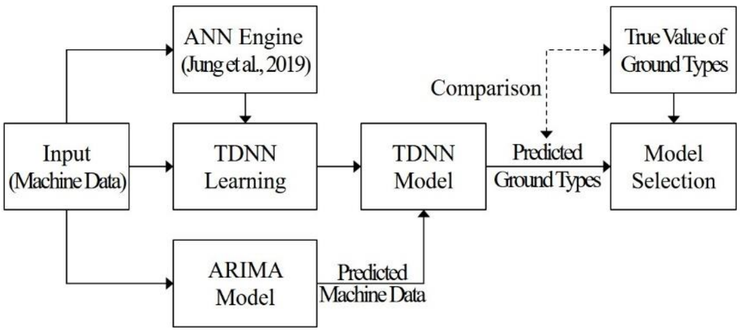

Fig. 2 Sequence of analysis for TDNN engine development

3. MODEL VERIFICATION AND APPLICATION

3.1 Verification of the proposed model

The ground types were predicted up to ten rings ahead of the tunnel face using the developed hybrid time series engine and were compared with the actual ground types observed in-situ for all 120 cases presented in Table 3. Their average prediction accuracies are summarized in Table 4. The table show that the prediction accuracy was higher than 80% in most cases, with an overall average value of 90% or more. This demonstrates that the proposed hybrid time series engine is very effective for ground type predictions up to ten rings ahead of the tunnel face.

Table 4 Comparison of prediction accuracy

	Site 1		Site 2	Sections of frequent ground type variation	All
	TBM 1	TBM 3	TBM 1		
Mean of Prediction Accuracy (%)	92.14	95.36	95.69	83.93	94.74

3.2 Application of the developed engine to a new job

As presented in Table 4, the proposed time series engine demonstrated high prediction accuracy. Accordingly, the developed engine can predict the ground types up to ten rings ahead of the tunnel face in any new job site conditions. To adopt the engine to a new job site, three types of machine data should be inputted—penetration rate, thrust force, and cutter torque—as well as the current ground type. However, as a minimum of twenty data points are required for engine operation, it is only possible to use the engine after twenty rings have already been excavated. After inputting the minimum twenty accumulated machine data points into the engine, calculation is performed automatically, progressing from the normalization stage to prediction of ground types ahead of the tunnel face. Thus, real-time prediction of ground conditions ahead of the tunnel face is possible in any new job site with only few simple settings.

4. CONCLUSIONS

This paper presented a time series analysis model that can predict ground types up to ten segment rings ahead of the tunnel face using TBM operational data. To achieve this, we proposed a hybrid model combining an ARIMA model and a TDNN. First, the ARIMA model was used to predict the machine operational data ten segment rings ahead of the tunnel face. Then, the predicted machine data was fed into the TDNN to predict the ground types ahead of the tunnel face. When applying the TDNN for ground type prediction, it was found that the selected time lag of 1 is reasonable resulting in average prediction accuracy of more than 90% and at least 84% in areas where frequent ground type variations occur. By using the hybrid time series engine proposed in this paper, real-time prediction of the ground conditions up to ten segment rings ahead of the tunnel face is possible in any new job site with only few simple settings, thus reducing geological risks during shield TBM operation.

REFERENCES

Beale, M.H., Hagan, M.T., Demuth, H.B. (2016), Neural Network Toolbox™ User's Guide, Version R2016a. The Math Works, Inc., Natick, MA, USA.

Box, G.E.P., Jenkins, G.M. (1970), Time Series Analysis: Forecasting and Control, Holden-Day, San Francisco, USA.

Chung, H., Lee, I.M., Jung, J.H., Park, J. (2019), “Bayesian Networks-Based Shield TBM Risk Management System: Methodology Development and Application”, KSCE J. of Civ. Eng., **23**(1), 452-465.

Eftekhari, A., Aalianvari, A., Rostami, J. (2018), “Influence of TBM Operational Parameters on Optimized Penetration Rate in Schistose Rocks, A Case Study: Golab Tunnel Lot-1, Iran”, Computers and Concrete, **22**(2), 239-248.

IBM Corp. (2016a), IBM SPSS Forecasting 24, IBM Corp., New York, USA.

IBM Corp. (2016b), IBM SPSS Statistics 24 Algorithms, IBM Corp., New York, USA.

Lee, K.H., Park, J.H., Park, J., Lee, I.M., Lee, S.W. (2019), “Electrical Resistivity Tomography Survey for Prediction of Anomaly in Mechanized Tunneling”, Geomechanics and Engineering, **19**(1), 93-104.

Jung, J.H., Chung, H., Kwon, Y.S., Lee, I.M. (2019), “An ANN to Predict Ground Condition ahead of Tunnel Face using TBM Operational Data”, KSCE J. of Civ. Eng., **23**(7), 3200-3206.

Jung, J.H. (2020), Utilization of Machine Learning Methods to Predict Ground Conditions ahead of Tunnel Face in Shield TBM Method, Doctoral Dissertation, Korea University, Seoul, Korea.

Ma, H., Yin, L., Gong, Q., Wang, J. (2015), “TBM tunneling in mixed-face ground: Problems and solutions”, International J. of Min. Scie. and Tech., **25**(4), 641-647.

Taylor, K. (2017), Deep learning using MATLAB neural network applications, Create Space Independent Publishing Platform, Lavergne, TN, USA.