Prediction of Disc Cutter Wear using Shield TBM Excavation Data

Yun-Hee Kim\textsuperscript{1)}, Ji-yeon Hong\textsuperscript{2)}, Jae-woo Shin\textsuperscript{2)} and  Bumjoo Kim\textsuperscript{3)}

\textsuperscript{1), 2), 3)} Department of Civil and Environmental Engineering, Dongguk University, 30, Pildong-ro 1-gil, Jung-gu, Seoul, 04620, Republic of Korea

*bkim1@dongguk.edu

ABSTRACT

A disc cutter is an excavation tool on TBM cutterhead that crushes and cuts rock mass while the machine excavates with the rotational movement of the cutterhead and thrust. Disc cutter wear occurs naturally, and disc cutters with abrasion need to be replaced at the proper time, otherwise worn disc cutters influence construction periods and costs, along with management of downtime and excavation efficiency. The most common prediction models for TBM performance and for the disc cutter lifetime are suggested by CSM (Colorado School of Mines) and NTNU (Norwegian University of Science and Technology). However, when a TBM encounters complex and difficult ground conditions in the field, design parameters from existing models correspond less to the values in the field. In this study a series of machine learning models is proposed to predict disc cutter lifetime of a Shield TBM using the excavation (machine) data during operating in response to rock mass. A total of five different machine learning techniques, four types of classification models (i.e., KNN (K-Nearest Neighbor), SVM (Support Vector Machine), DT (Decision Tree), and Staking Ensemble Model) and one artificial neural networks model, were utilized. The KNN model was found to be the best model among the four classification models by producing the highest recall of 81\%. The ANN model was also shown to predict reasonably well the wear rate of disc cutter.

1. INTRODUCTION

Tunnel boring machines (TBM) have been increasingly used due to the growth of urban railway and highway tunnel constructions with the merits of less noise and vibration. The importance of special considerations in the TBM construction, especially in urban area involving soft complex ground conditions, has been reported by many researchers (Kovari and Ramoni, 2006, Wedekin et al., 2012, Jeong et al., 2018). TBM has excavation tools such as disc cutters and cutter bits mounted on the cutter head, used in excavation by crushing and cutting the ground and/or rock by the thrust of the equipment.

\textsuperscript{1)} Ph.D. Candidate
\textsuperscript{2)} Graduate Student
\textsuperscript{3)} Professor
In this process, disc cutter is worn not only normally, but also abnormally, including cracks and falling-off of the disc cutter, depending on ground conditions. The disc cutter wear causes damage to the surrounding disc cutter, increases the thrust and torque of the equipment, and lowers the penetration rate, resulting in the degradation of the excavation efficiency of a TBM. The wear of a disc cutter is triggered by the geological condition of the underground (e.g., rock type including strength, abrasiveness, mineral composition, rock mass including joint system and water content), and by operation of a TBM, and this can be monitored during construction (Frenzel et al, 2008). In abrasive ground containing significant quartz mineral, and mixed ground in which the soil and rock appear together on the face, abnormal wear such as cracking and falling off occurs frequently so that TBM equipment could be stopped by lowered TBM performance.

The most commonly used methods for the prediction of a disc cutter replacement period are the CSM (Colorado School of Mines) model (Rostami, 1997), the Gehring model (Gehring, 1995), and the NTNU (Norwegian University of Science and Technology) model (Bruland, 1998 and Macias, 2016). Existing prediction models have been developed for homogeneous ground or hard rock conditions based on linear cutting tests and excavation data from the field. The prediction of a disc cutter lifetime with these models is not well-fitted in heterogeneous ground or soft soil conditions in urban ground environments. Situations that require unexpected disc cutter replacement occur frequently due to abnormal wear such as uneven wear of the disc cutter or ring breakings in complex ground with a mixture of folds and multiple strata. The numbers of actual disc cutter replacement in the field have more than doubled due to differences in the numbers of disc cutter replacement designed from the NTNU model (Jung et al, 2010). Therefore, to overcome the limitations of the existing disc cutter consumption prediction models and to improve TBM excavation performance in complex/mixed ground, it is necessary to develop a new model that can predict TBM performance and disc cutter replacement cycle in such ground conditions.

In this study, Shield TBM excavation data and characteristics of the ground at the OO~OO high-speed railway construction site was analyzed for development of a new disc cutter wear prediction model. The five data from TBM machines during excavation highly correlated with disc cutter wear were selected and used as input after data pre-processing. After disc cutter wear rates were analyzed by utilizing disc cutter replacement history data, it was applied to a model target. Four classification models and one predictive model were established in the study using machine learning techniques to determine whether the disc cutter needed to be replaced and to predict disc cutter wear, respectively. The classification models were developed by applying KNN, SVM, DT, and ensemble classification methods, staking algorithm in python. An artificial neural networks (ANN) algorithm was used to develop prediction models of disc cutter wear rate. The four classification models and an ANN model were evaluated for entire Shield TBM section and were analyzed for four divided ground conditions, respectively.

2. DATA PREPROCESSING AND MACHINE LEARNING METHODS

For applying data into machine learning algorithms, obtained data should be properly processed. Two data preprocessing methods: min-max scaling methods and Synthetic Minority Over-sampling Technique (SMOTE) and three types of machine
learning algorithms: classification machine learning algorithms, ensemble machine learning algorithms, and artificial neural networks are reviewed in this section.

2.1 Data preprocessing methods

In machine learning, data preprocessing is an initial stage that can improve the performance of models by processing raw data to make it understandable and readable. Among the various data preprocessing methods, the min-max scaling method and the SMOTE technique are applied. The min-max scaling technique rescales the range of features to scale the range in [0,1] to reduce the scale differences among each feature. SMOTE is an oversampling technique in classification problems in order to handle the imbalanced dataset (one class dominates a dataset).

2.2 Classification machine learning algorithms

Three Classification machine learning algorithms were applied: the K-Nearest Neighbors (KNN) algorithm, the Support Vector Machine (SVM) and the Decision Tree (DT). The conceptual figure of each model is presented in Fig.1.

K-Nearest Neighbors (KNN) Algorithm

A non-parametric classification method, the K-Nearest Neighbors (KNN) technique, was first developed by Evelyn Fix and Joseph Hodges in 1951. The KNN model can be used both for classification and regression of target data by using close K-nearest neighbors’ data to target data. When it comes to calculating the distance between target data and nearest data, various distance calculation methods, Euclidean, Correlation, and Minkowski method can be considered. The value of k in the model is also considerable. Both the distance calculation method and k-value affect the model’s performance. The smaller the value of k, the greater the tendency to sensitivity and overfitting of the model, and the larger the value of k, the more tendency to insensitive, over-normalized, and underfitting of the model. The benefit of this algorithm is that there is little effect on error data due to comparison with a relatively small number of data close to the target data, and the drawback of the algorithm time increases the solving the mass data.

Support Vector Machine (SVM) Algorithm

The Support Vector machine (SVM) technique is one of the supervised learning models and is based on the VC theory proposed by Vapnik (1995) and Vapnik and Chervonenkis (1974). The SVM technique is also an algorithm that can be used for classification and regression analysis. Although countless boundaries can divide data into categories for classification analysis, the optimal hyperplane is judged based on the margin, which is the distance between the boundary line and support vector. The support vector refers to the data located closest to the determined hyperplane, and the support vector plays a decisive role in determining the margin. In linear SVM, as the margin increases, the classification error decreases, and the model performance improves. In addition to the linear separation technique provided via SVM, there are RBF (Radial Basis Function) kernels and polynomial kernels that can efficiently perform nonlinear
classification using kernel tricks. The hyperparameters in the SVM are C and gamma. Higher C accepts greater error and higher gamma creates a greater curvature hyperplane.

**Decision Tree (DT) Algorithm**

The decision tree algorithm is a ML algorithm that is intuitively easy to understand and creates a tree-based classification model to automatically find patterns through input/features. As for the decision tree algorithm, various types of algorithms have been proposed by many researchers, and the representative algorithms are AID, CHAID, CART. Decision tree algorithms basically have a common structure, start from the root node, go through the internal node, end at the leaf node, and are classified by a specific separation criterion at each node. The data collected at one end node at the endpoint can be thought of as a group with the same characteristics. Classification or prediction is possible by applying new data to a model constructed using the given data. The hyperparameters that can adjust the model performance are tree depth, maximum features, minimum/maximum leaf of nodes, and minimum samples of splits.

![Decision Tree Diagram](image)

(a) KNN  (b) SVM  (c) DT

Fig. 1 Conceptual diagram of each classification model: (a) KNN, (b) SVM, and (c) DT

**2.3 Staking ensemble algorithm**

The stacking technique is an ensemble model that turns prediction data into training data through individual machine learning algorithms and performs final prediction after learning. This model requires an individual base model and a final meta-model that learns by making the prediction data of the individual base model as training data. As basic models in the Staking model, KNN, Random Forest, Decision Tree, and AdaBoost are introduced, and logistic regression is applied as the final model. The predicted results in each classification are used as input data in logistic regression and predict the result as illustrated in Fig. 2
Artificial Neural Networks (ANN) is a subset of machine learning algorithms based on the concept of the biological neural networks model and recognize the characteristics and patterns of the data by iterative training. An ANN is a multilayer perceptron with multi-hidden layers between the input and output layer and is illustrated in Fig. 3. The input data, which is calculated by the weight and bias in the input layer, goes through the activation function in the hidden layers and is finally converted into output in the output layer. To reduce the difference between the actual and desired outcome, several hidden layers and activation functions can be modified. In this study, ANN is applied to develop the model which can predict disc cutter wear rate by using the MATLAB neural network fitting app. The prediction model evaluates model performance using root mean square error (RMSE) which can evaluate the difference between input and predicted target value.
3. PROJECT OVERVIEW

3.1 Ground Condition

At the 00~00 railway construction site, the total tunnel length is 3,930m, of which the Shield TBM construction section is 1,160m. The 10 samplings and the resistivity survey were carried out to investigate soil/rock conditions and geological profiles. In the laboratory, soil, and rock tests, uniaxial compressive strength, and triaxial compression tests were performed to estimate the type of stratum and soil and rock strength parameters. As shown in the results of the field and lab tests, weathered and sedimentary soil layers formed around the site, with soft and hard rock appearing in some sections. Fig. 4 illustrates four categorized ground conditions; a mixed layer with many weathered rocks, a weathered rock layer, a sedimentary mixed layer mainly composed of soft rock, and a sedimentary layer. The boulders with a diameter of 18-70 cm distributed in the tunnel face at the expected hazard section of the site is presented in Fig. 5.

Fig. 4 Longitudinal geological profile of the 00 tunnel and Shield TBM section
3.2 Shield TBM Equipment Condition

The Shield TBM equipment used in the field is a slurry type shield by Herrenknecht in Germany. The Shield TBM is equipped with a displacement cylinder, articulation cylinder, and drilling line to prevent face plate jamming, correct meandering, secure the ease of curvature construction, and to identify the geological condition in front and reinforce the ground, respectively. These devices were manufactured to cope with the troubles that may occur during the tunneling in mixed ground. Additionally, the Shield TBM is equipped with a bubble chamber to cope with changes in chamber pressure and a crusher for crushing excavated rock or gravel layers to facilitate excavation of the heterogeneous ground. A total of 44 17-inch disc cutters (40 single disc cutters and 4 double disc cutters) and 110 scrapers were installed in the cutterhead. Table 1 describes the main specifications of the Shield TBM equipment and Table 2 presents the configuration of excavation tools (disc cutters and scraper) on the TBM cutterhead.

**Table 1. Major specifications of shield TBM and cutter head**

<table>
<thead>
<tr>
<th>Classification</th>
<th>Specifications</th>
<th>Classification</th>
<th>Specifications</th>
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</thead>
<tbody>
<tr>
<td>Shield Machine</td>
<td></td>
<td>Shield Jack</td>
<td></td>
</tr>
<tr>
<td>Cutter diameter (mm)</td>
<td>8,410</td>
<td>Number (EA)</td>
<td>28</td>
</tr>
<tr>
<td>External diameter (mm)</td>
<td>8,370~8,390</td>
<td>Thrust per jack (kN)</td>
<td>2,124</td>
</tr>
<tr>
<td>Length (mm)</td>
<td>10,500</td>
<td>Total thrust (kN)</td>
<td>59,464</td>
</tr>
<tr>
<td>Main Drive</td>
<td></td>
<td>Maximum tunnel face pressure (bar)</td>
<td>4.5</td>
</tr>
<tr>
<td>Number of motor (EA)</td>
<td>8</td>
<td>Stroke (mm)</td>
<td>2,500</td>
</tr>
<tr>
<td>RPM (rpm)</td>
<td>Max. 3.1</td>
<td>Penetration Rate (mm/min)</td>
<td>50</td>
</tr>
<tr>
<td>Torque (kN·m)</td>
<td>4,680~6,786</td>
<td>Maximum tunnel face pressure (bar)</td>
<td>4.5</td>
</tr>
</tbody>
</table>
Table 2. Major specifications cutter head and disc cutter

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disc cutter diameter</td>
<td>17</td>
</tr>
<tr>
<td>Number of disc cutter</td>
<td>44</td>
</tr>
<tr>
<td>Number of single disc cutter</td>
<td>40</td>
</tr>
<tr>
<td>Number of double disc cutter</td>
<td>4</td>
</tr>
<tr>
<td>Number of scrapper</td>
<td>110</td>
</tr>
<tr>
<td>Disc cutter diameter</td>
<td>17</td>
</tr>
</tbody>
</table>

3.3 Excavation and Cutter Head Intervention data

TBM excavation data, thrust, torque, RPM, and penetration rate from 100 m to 600 m of the TBM excavation length used as input features are shown in Fig. 6 with according to ground types. Although ground conditions during the excavation tunnel have been the most influential factor on disc cutter wear, the only excavation data used for the analysis due to the difficulties of accurately judging ground conditions to the tunnel face. The TBM machine is operated by a skilled expert with the ability to work successfully considering ground conditions. Therefore, in the study, it was judged that the excavation data had sufficient correlating to the ground condition. The detailed analysis of excavation data is delineated further in La et al. (2019). In summary, trust is the most basic standard for judging the strength of the rock and in general, when accounting for increases in rock strength, the operator should use higher thrust. High variability of trust and torque seems to encounter severe change in the ground with the appearance of gravel and boulder layers. In addition, the RPM was operated in a low range of 1 to 2.5, which is also to ensure safe excavation so that construction problems do not occur. The penetration rate (PR) is a principal measure of TBM performance and is calculated by the product of disc cutter press-in depth (mm/rev) and cutter head rotation speed (RPM). Additionally, the rotation distance for each disc cutter was introduced as an input and it was determined that the input is a factor that has a significant influence on disc cutter wear and is calculated using Eq. (1).

\[
RD_i = \frac{D \times 1000}{PR} \times RPM \times 2 \times \pi \times R
\]

where, \( RD_i \) is rotation distance for disc cutter \( i \) (m), \( D \) is excavation distance (m), \( PR \) is penetration rate (mm/min), and \( R \) is the distance from the center of the cutterhead to disc cutter.
Fig. 6 Excavation data from Shield TBM; Thrust, Torque, RPM, and PR in distance
(after La et al., 2019)

A total of 24 TBM machine stopped to exchange worn disc cutters for the entire Shield TBM section, and only the 18 replacement periods were related to the data used in the analysis. During the 18 cutter replacements, 145 disc cutters, 19 disc cutters, and 24 disc cutters were replaced due to normal wear, uneven wear, and cracking or elimination, respectively. Fig. 7 shows that the number of replaced disc cutters in excavation distance and the types of disc cutter wear. Most of the disc cutters were replaced due to normal wear, however, in ground condition 3, many disc cutters were replaced due to the cracking or abnormal wear related to other ground conditions. Disc cutters are installed on cutterhead with different radii, and each disc cutter rotates at a different trajectory during excavation. This is to maximize cutting and energy efficiency. The 40 disc cutters used in the study were divided into five orbits to calculate rotation distance. Fig. 8 illustrates the number of replaced disc cutters in each disc cutter and which disc cutter belongs to the 5 divided trajectories. Disc cutter wear at the replacement time was presumed 100% wear and the disc cutter wear that had no data were linear interpolated. To classify the disc cutter replacement, disc cutter wear over 80% was assumed to be replaced.
4. RESULTS AND DISCUSSION

4.1 Results of classification models

The classification and ensemble models were developed with python and the metrics for evaluating classifiers uses the confusion matrix shown in Table 3 and accuracy, precision, recall, f1-score, AUC, and error rate are given in Eq. (2)-(5).

Accuracy (Eq. (2)) refers to the proportion of accurately predicted data among total data, and it presents to the rate at which the predictive model correctly classifies whether to replace the disc cutter. Precision (Eq. (3)) refers to the rate at which the replacement of the disc cutter occurred when the model predicted that it should be
replaced. Recall (Eq. (4)) is the ratio between the actual disc cutter replacement data and when the predictive model decides to replace and is used as a performance indicator when all positive data needs to be identified and false negatives are not desired. In this study, the recall index was focused to increase the discrimination of disc cutters that are required to be replaced. AUC (Area Under Curve) is between 0.5 and 1 is area under the ROC (Receiver Operating Characteristic) curve. ROC focuses on two indexes that are true positive rate (Recall (Eq. (4))) and false positive rate (Error rate (Eq. (5))).

Table 3. Confusion matrix of binary classification model

<table>
<thead>
<tr>
<th>Actual class</th>
<th>Predicted class</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Replaced (1)</td>
<td>TP (True Positive)</td>
<td>FN (False Negative)</td>
<td></td>
</tr>
<tr>
<td>Unreplaced (0)</td>
<td>FP (False Positive)</td>
<td>TN (True Negative)</td>
<td></td>
</tr>
</tbody>
</table>

Accuracy (%) = \[
\frac{TP + TN}{TP + FP + FN + TN} \times 100
\] (2)

Precision (%) = \[
\frac{TP}{TP + FP} \times 100
\] (3)

Recall (%) = \[
\frac{TP}{TP + FN} \times 100
\] (4)

Error rate (%) = \[
\frac{FP}{FP + TN} \times 100
\] (5)

Table 4 presents the hyperparameters adjusted to have optimum classification models applying to all features through the entire excavation distance. The hyperparameters in the Staking ensemble model uses the same values in each classification models.

Table 4. The hyperparameters used in each optimum classification model

<table>
<thead>
<tr>
<th>Classification model</th>
<th>Hyperparameters used for optimum model</th>
</tr>
</thead>
<tbody>
<tr>
<td>KNN</td>
<td>K-value: 9, Distance method: Euclidean</td>
</tr>
<tr>
<td>SVM</td>
<td>Kernel: RBF, C: 2, Gamma: 0.7, Max iteration: 10000</td>
</tr>
<tr>
<td>DT</td>
<td>Max_depth: 7, Max_leaf_nodes: 10</td>
</tr>
</tbody>
</table>
The model performance results in the entire excavation section data and each ground condition set are shown in Fig. 8. Accuracy, precision, recall, and AUC are the only presented as performance evaluation results. The model performance result of all strata data set in Fig. 8(a) shows the best accuracy in Staking ensemble model and the best recall in KNN model. The KNN model is the most suitable for the entire Shield TBM section in regarding to the index of recall, which is considered more important in the study. The best accuracy and precision in all data sets were shown in Staking ensemble algorithm, and the best in recall in each data set was obtained in the different models. Ground condition 1 and 4 has best recall in SVM model (Fig. 8(b) and 8(c)) and ground condition 2 and 3 has best recall in DT model (Fig. 8(d) and 8(e)). It was confirmed that the more complex and difficult ground condition (ground condition 3), the lower the recall index which can be shown of classification of the disc cutters that require to be replaced.

Fig. 9 Results of the classification models in each different data set; (a) All data, (b) ground condition 1, (c) ground condition 2, (d) ground condition 3, and (e) ground condition 4
4.2 Results of ANN model

The ANN disc cutter wear prediction model was evaluated using the MATLAB neural network fitting application and the coefficient of determination ($R^2$) and the root mean square error (RMSE) function given in Eq. (6) estimate the ANN model. R-squared is a measurement used to explain correlation between one and other factors, with a number close to 1 indicating a strong correlation. RMSE is a standard index to measure model error in predicting quantitative data.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}} \tag{6}$$

where, $x_i$ is the assumed disc cutter wear rate (%), $\hat{x}_i$ is the ANN predicted disc cutter wear rate (%), and $N$ is numbers of data.

Plots the assumed disc cutter wear rate based on actual disc cutter wear and ANN predicted disc cutter wear rate for the entire excavation section data and each ground condition sets are shown in Fig. 10. The plot shown in Fig. 10(a) is the scatter between predicted and assumed values analyzed from the entire excavation section. The distribution in the plot is widely spread from the regression line and RMSE is higher than 20. As expected from the classification results, ground condition 1, which was a more homogeneous condition than the others, obtained the highest R-squared and lowest RMSE among the four ground condition sets (Fig. 10(b)). Ground condition 3 is the most mixed ground found in the site, saw a lot of abnormal wear, and attained the lowest R-squared and highest RMSE among the four ground condition sets (Fig. 10(d)).

KTA (2016) studies the prediction of the Shield TBM performance the condition of passing through the soil or weathered rock layers through the theoretical prediction method with the review of similar cases. In the KTA report, the disc cutter replacement period in the site was predicted using the method proposed by the Japan Shield Construction Estimation Research Group. The number of replacements was predicted as seven in a total section which included no replacement weathered soil layer, 2.4 in bedrock, and 4.1 sedimentary layers. Though the prediction number of disc cutters was seven in total, the number of replacement disc cutters in the field was over 20. In addition, the section where most of the replacement occurred was in ground condition 3, which is the most complex ground.
Fig. 10 Results of the ANN models in each different data set: (a) All data, (b) ground condition 1, (c) ground condition 2, (d) ground condition 3, and (e) ground condition 4
Fig. 11  Comparison between assumed disc cutter wear and ANN predicted disc cutter wear: (a) disc cutter No.9, (b) disc cutter No.19, (c) disc cutter No. 24, (d) disc cutter No.32, and (e) disc cutter No.48.
5. CONCLUSION

This study presented a series of machine learning models developed to predict proper replacement time and wear rate of disc cutters for a Shield TBM tunnel. The findings drawn from this study are as follows:

1. When the data for all ground conditions (i.e., the data for entire excavation section) was incorporated into the four classification models (i.e., KNN, SVM, DT, Staking Ensemble), respectively, the Staking ensemble model was found to show the highest accuracy (84%), whereas the highest value of the recall, a major index representing the performance of a prediction model was obtained for KNN model.
2. For each ground condition, however, the predictive performance was differed by each model. The differences in the model performance may be attributed to different variability and quality of excavation data including different replacement cycles of disc cutters depending on ground conditions.
3. The ANN model predicted the wear rate of disc cutters with the accuracy of the R-squared and RMSE, ranging from 0.4673~0.7195 and 15.1~21, respectively, over different ground conditions, revealing that the more complex the ground, the lower the model performance.

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