A Novel A-CNN Method for TBM Utilization Factor Estimation

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Abstract. Utilization factor is one of the most important performance indicators of TBM, which affects the construction period and cost of the tunnel. However, there are few models to evaluate the utilization factor based on geological conditions and operational parameters. In this paper, a novel A-CNN neural network architecture for TBM utilization factor estimation is proposed. Firstly, the input dimension is expanded by a full-connected neural network. Secondly, a convolutional neural network is designed and added behind the expanded input to extract relevant features. Finally, a regressor is designed to build the mapping relationship between the extracted features and the utilization factor. The data collected from a Singapore tunnel project was utilized to verify the proposed method. The results show that the $R^2$ of the proposed method on the test set is 0.521, which is 52.33%, 15.60%, 34.10%, and 9.40% higher than the KNN-based, SVR-based, RF-based, and DNN-based methods, respectively. Therefore, the proposed method can estimate the TBM utilization factor more accurately.

Keywords: EPB; utilization factor estimation; deep learning; A-CNN

1. Introduction

Tunnel boring machine (TBM) is widely used in urban underground space development due to its advantages of fast excavation speed, high construction quality and little disturbance to the surrounding environment, etc. [1,2]. However, its performance is greatly affected by geological conditions. Meanwhile, the operation of the driver will also affect the performance of the machine.

There are four performance indicators of TBM, i.e. tunneling speed (or penetration rate), utilization factor, advance rate and cutter life [3]. The advance rate is the product of the utilization factor and the tunneling speed. These indicators represent the net tunneling speed of the TBM, the ratio of the tunneling time to the entire construction time, the gross tunneling speed and the cutter consumption, respectively. Currently, the researches on TBM performance are mainly focused on tunneling speed prediction [4] and cutter wear estimation [5], and little attentions are paid to utilization factor. An important reason is that there are many influencing factors, which bring challenges to the accurate evaluation of utilization factor. However, if the estimation of utilization factor is not accurate, even if the tunneling speed is estimated more accurately, we cannot get an accurate advance rate.

The entire construction time of a TBM includes time for tunneling, step change, support or assembly, cutter inspection and replacement, and equipment maintenance, etc. Statistics show that the utilization factor in TBM construction projects is generally 5% to 65%, and it varies greatly in different projects [3]. Alber and Rühl [6] indicated that geological conditions had a great impact on the utilization factor, because the surrounding rock with poor integrity would increase the additional support time, while the rock with strong abrasiveness would accelerate the cutter wear, thus increasing...
the time for cutter inspection and replacement. Bieniawski et al. [7] discussed the impact of contractors and on-site construction personnel’s experience on the utilization factor, and pointed out that lack of experience may lead to a 10% reduction in utilization factor. From the above qualitative analysis, we can conclude that the operational parameters, geological conditions and on-site management have a great impact on the utilization factor.

The CSM model and the NTNU model are the most classic utilization factor prediction models. They evaluate the utilization factor by allocating the downtime of TBM into different activities [8]. However, the two models established in the early years are not much able to meet the current needs. Simoes et al. [9] used machine diameter, RMR, groundwater inflow and RQD to predict the TBM utilization factor by using fuzzy logic method, and its RMSE on the test set was 0.0315. Farrokh [10] developed a hard rock TBM downtime prediction model based on the statistical analysis of on-site data from 89 tunnels, and it used a series of charts and formulas to predict the downtime of each process. Noori et al. [11] established utilization factor prediction models by using the multiple linear regression (MLR), artificial neural network (ANN) and artificial neural network-particle swarm optimization (ANN-PSO), respectively.

Existing researches generally predict or estimate the utilization factor of the whole tunnel before construction, so as to provide guidance for machine selection, construction time evaluation and construction management optimization. In this study, the estimation of the utilization factor is refined to each tunneling cycle. A TBM utilization factor estimation model is established based on a novel A-CNN architecture, which takes the operational parameters, loads and geological type of a tunneling cycle as the input. This model can lay a foundation for the optimization of operational parameters under different geological types, and thus it is valuable for engineering practice.

2. Project Description
The project is part of the Thomson Line in Singapore, and the studied section is approximately 710 m with stacked twin bored tunnels, as shown in figure 1. The two tunnels were excavated by earth pressure balanced shield machines (EPBs) of the same model. The ring or tunneling cycle numbers of the tunnels were from 1 to 502, and the length of one tunneling cycle was about 1.4 m. Field investigations were conducted before the tunnel excavation to obtain an overview of the geology along the tunnel. The ground condition consisted of 4 m to 15 m thick Fill layer overlying the Marine Clay and Fluvial Clay, which was then underlain by Old Alluvium and Jurong Formation. Besides, Fort Canning Boulder Bed (FCBB) was generally below the Marine Clay and Fluvial Clay. There are fifteen boreholes along the tunnel alignment, and their geological types and ring numbers are listed in table 1.

![Figure 1](image-url)
Table 1. Geological information of fifteen boreholes.

| Borehole NO. | Upper Tunnel | Lower Tunnel |
|--------------|--------------|--------------|
|              | Ring NO.     | geological formation | Ring NO. | geological formation |
| 1            | 500          | Jurong Formation (V) | 500      | Jurong Formation (IV) |
| 2            | 388          | Jurong Formation (V) | 388      | Jurong Formation (V) |
| 3            | 302          | Jurong Formation (IV) | 302      | Jurong Formation (II&IV) |
| 4            | 265          | Jurong Formation (V) | 265      | Jurong Formation (III&V) |
| 5            | 229          | Jurong Formation (V) | 229      | Jurong Formation (III&IV) |
| 6            | 202          | Jurong Formation (IV) | 202      | Jurong Formation (IV) |
| 7            | 192          | Jurong Formation (V) | 192      | Jurong Formation (IV) |
| 8            | 137          | FCBB          | 137      | FCBB          |
| 9            | 123          | FCBB          | 123      | ——            |
| 10           | 119          | FCBB          | 119      | FCBB          |
| 11           | 117          | FCBB          | 117      | FCBB          |
| 12           | 98           | Fluvial Clay  | 98       | FCBB          |
| 13           | 96           | Fluvial Clay  | 96       | FCBB          |
| 14           | 63           | Marine Clay   | 64       | Composite geology |
| 15           | 44           | Marine Clay   | 44       | Composite geology |

EPB collected 1446 parameters every 5s, including the thrust, torque, tunneling speed, and cutterhead speed, etc. A complete tunneling cycle generally includes the tunneling phase, waiting phase, and stopping phase. Among them, the waiting phase is generally waiting for the muck truck, and the stopping phase is generally used for assembling segments or supporting, as well as equipment maintenance and cutter replacement. Figure 2 shows the changes in the utilization factor of each ring. It can be seen that the utilization factor fluctuates between 0 and 70%. The average utilization factors of the upper and lower tunnel are 41.5% and 37.1%, respectively. The excessively low utilization factor is mainly caused by the equipment failure. While the high utilization factor is mainly caused by the long tunneling time, that is, the tunneling speed is too low. Due to the great contingency of equipment failure, and the main purpose of this paper is to study the influence of geological conditions and operational parameters on the utilization factor, the excessively low utilization factor is regarded as outlier and deleted.

Figure 2. Utilization factor of each ring of the upper and lower tunnels.

3. The Proposed A-CNN Method

In this study, we consider using deep learning to establish the mapping model between loads, operational parameters, geological type and utilization factor, because it has strong mapping expression ability and has many successful applications in engineering fields [12]. Among the many deep learning methods, the convolutional neural network (CNN) and its variants are the most widely used. In general, they outperform other traditional machine learning methods and deep neural network
(DNN) by introducing the local receptive fields and shared weights strategies. However, in our research, the input dimension is 9, which cannot support the CNN to perform more convolutional and pooling operations, and the expressive ability of the model is severely limited. To solve this problem, a novel A-CNN architecture is proposed, which is a combination of traditional artificial neural network (ANN) and CNN.

Figure 3 shows the architecture of the proposed A-CNN model. Firstly, a fully-connected neural network is used to expand the dimension of input. Then, a convolutional module is designed and connected to the expanded input to extract relevant features. Finally, a simple regressor is applied to establish the mapping relationship between the extracted features and the utilization factor. The notation “16@64×1 (k=5, s=2, ‘same’)” represents that the convolutional layer has extracted 16 feature maps (each map has 64 features), and the kernel size is 5, the stride is 2 with zero-padding. While the notation “16@30×1 (p=5, s=2, ‘valid’)” represents that the pooling layer has extracted 16 feature maps (each map has 30 features), and the pool size is 5, the stride is 2 without zero-padding.

4. Validation and Analysis

4.1. Dataset Construction
There are five geological formations corresponding to fifteen boreholes of the upper tunnel, i.e. Jurong Formation (IV), Jurong Formation (IV), FCBB, Fluvial Clay and Marine Clay. Their geological types were set to 0, 1, 2, 3 and 4, respectively. Then, the digital was converted to a vector. The data from the upper tunnel was used to construct the training set, and the data from the lower tunnel was used to construct the test set. For a sample, its input features were the normalized average values of thrust, torque, cutterhead speed, and tunneling speed in a ring, and its target variable was the utilization factor. In addition, geological type in vector form was also added to the input features. However, there was an extreme imbalance in the amount of machine data and geological data. The training set had only 15 samples, while the test set had 9 samples. Obviously, it’s challenging to build a powful model with such a small number of samples.

Fortunately, the authors established a geological formation recognition model in a paper recently.
submitted [13], and achieved good results in both the upper and lower tunnels of this project. By using this geological formation recognition model, we could predict the geological formations of many tunneling rings with a high degree of confidence, thereby augmenting the existing training set. Finally, the sample size of the new training set was expanded to 268. And a part of samples were randomly selected from the new training set to form the validation set. The details of the constructed datasets are shown in Table 2.

### Table 2. Details of the datasets.

| Dataset   | Tunnel | Sample size | Input (9×1)                                      | Output (1×1)       |
|-----------|--------|-------------|-------------------------------------------------|-------------------|
| training set | upper | 241         | thrust, torque, cutterhead speed,                | utilization factor |
| validation set | upper | 27          | tunneling speed,                                |                   |
| test set   | lower  | 9           | geological type (vector)                        |                   |

#### 4.2. Results and Discussion

In this study, the mean square error (MSE) and coefficient of determination (R²) are used to evaluate the performance of the established utilization factor estimation models.

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2
\]

\[
R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y}_m)^2}
\]

where \(N\) is the sample size, \(y_i\) is the true value of the target variable, \(\hat{y}_i\) is the predicted value of \(y_i\). \(\bar{y}_m\) is the average value of \(y_i\).

To prove the effectiveness and superiority of the proposed method, some commonly adopted machine learning methods, such as k-nearest neighbors (KNN), support vector regression (SVR), random forest (RF), and deep neural network (DNN), are also applied for modeling. Table 3 shows the performances of all comparative methods on the validation set and test set, and the key parameters of these models are also listed in the table. It can be seen that the RF-based method performs best on the validation set, and its MSE and \(R^2\) on the validation set are 0.0042 and 0.758, respectively. While the proposed method outperforms other comparative methods on the test set, and its MSE and \(R^2\) on the test set are 0.0064 and 0.521, respectively. Although the RF-based method and KNN-based method perform better than the proposed method on the validation set, their performances on the test set are poor. In addition, the performance of the DNN-based method on the test set is much better than other machine learning methods. Figure 4 illustrates the prediction results of all methods on the validation set and test set.

It is worth noting that even with the proposed method, the prediction results on the validation set and the test set are not very consistent with the true values. This may be because the augmented dataset is not perfect. In addition, the utilization factor is not only affected by geological conditions and operational parameters, but also by other factors, such as the level of on-site management and the spare parts supply capacity.

### Table 3. Performances of all comparative methods on the validation set and test set.

| Method   | Key parameters | Validation set | Test set |
|----------|----------------|----------------|----------|
|          |                | MSE | \(R^2\) | MSE | \(R^2\) |
| KNN      | n_neighbors=11 | 0.0052 | 0.696 | 0.0137 | -0.023 |
| SVR      | kernel: rbf, C=1000, gama=0.13, max_depth=3, max_features=7, n_estimators=35 | 0.0071 | 0.586 | 0.0085 | 0.365 |
| RF       |                | 0.0042 | 0.758 | 0.0109 | 0.180 |
| DNN      | 100-20-Dropout(0.5) | 0.0072 | 0.581 | 0.0076 | 0.427 |
| Proposed | shown in figure 3 | 0.0065 | 0.620 | 0.0064 | 0.521 |
5. Conclusions
In this work, a novel A-CNN architecture is designed to estimate the TBM utilization factor of each tunneling cycle, which takes loads, operational parameters and geological types the TBM encountered as input. The architecture is a combination of traditional ANN and CNN. Firstly, a fully-connected neural network is utilized to expand the input dimension, which helps to carry out the convolutional and pooling operations. Then, taking the expanded input as input, a CNN module is designed to extract relevant features more accurately. Finally, a simple regressor is added behind the CNN module to establish the mapping relationship between the extracted features and the utilization factor. On-site data collected from stacked twin bored tunnels of Singapore was utilized to verify the effectiveness of the proposed method. Moreover, to prove the superiority of A-CNN, commonly adopted KNN, SVR, RF, and DNN are also applied for modeling. The results demonstrate that the A-CNN outperforms other comparative methods. Its MSE and R² on the validation set and test set are 0.0065, 0.620 and 0.0064, 0.521, respectively. Specifically, its R² on the test set is 52.33%, 15.60%, 34.10%, and 9.40% higher than the KNN-based, SVR-based, RF-based, and DNN-based methods, respectively. Therefore, the proposed A-CNN can estimate the TBM utilization factor more accurately, which can lay a foundation for the optimization of operational parameters under different geological types.

Acknowledgements
This research was supported by the National Key R&D Program of China (Grant No. 2018YFB1702503), the Shanghai Municipal Science and Technology Major Project (Grant No. 2021SHZDZX0102), and the State Key Laboratory of Mechanical System and Vibration (Grant No. MSVZD202103).

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