Dynamic prediction of penetration rate based on TBM operational data

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Abstract. In this paper, an artificial neural network-based dynamic prediction model of penetration rate (PR) is proposed. Four tunnel boring machine (TBM) operational parameters, including cutterhead rotational speed (RPM), cutterhead torque (T), total thrust (F), and advance rate (AR) are introduced as input of the network. Their data in the trial excavation phase, are employed to predict the PR in the stable excavation phase. Therefore, the training data will have enough offsets from the test data, and the TBM operators will have sufficient time to either fine-tune the operational parameters or shut off the machine if undesired prediction results come out. To examine the performance of the established model, it is applied to a 20 km water conveyance tunnel. The results show that the network converges fast and steadily with acceptable performance on the test set. The major contribution of this paper is verifying the possibility to estimate the PR based on the historical data of the TBM.

1. Introduction

Hard rock Tunnel Boring Machines (TBMs) are widely applied to mountain tunnel construction since the 19\textsuperscript{th} century, especially to tunnels longer than 2 km [1, 2]. Generally, there are two kinds of hard rock TBMs, one is shielded TBM, and the other is open-type TBM. Shielded TBMs are usually used in fractured rock. Open-type TBMs, however, are frequently adopted when the surrounding rocks are of high quality. TBM penetration rate (PR) as an indicator for timetable planning and estimating the project cost in mechanical tunneling construction is crucial for estimating the performance of a TBM [3]. Therefore, numerous studies have been devoted to establishing a more accurate PR prediction model over the past few decades.

Empirical and theoretical models were proposed based on laboratory tests at first. The Colorado School of Mines model [4-6] and the Norwegian University of Science and Technology model [7] were the most famous ones to estimate the PR. Statistical models based on mathematical rules, and computational models based on machine learning were developed as well [8]. Generalized linear models [9], fuzzy logic models [10, 11], Bayesian inference [12], particle swarm optimization [13],
support vector machine [9, 14-17], k-nearest neighbor [14], random forests [18], gradient boosting [8], and neural networks [8, 16, 19-20] were employed in predicting the PR of TBM. Among them, intact rock properties including uniaxial compressive strength and Brazilian tensile strength, along with rock mass properties, including the number of joint sets, distance between planes of weakness, alpha angle (α), degree of roughness, and rock quality were the most popular inputs. It is evident that these parameters highly depend on the specimen preparation, laboratory tests, and geological survey. Hence, geological uncertainty, experimental errors, and even the number of specimens, which is limited to the costs of drilling, may threaten the performance of the models.

To overcome this limitation, TBM operational parameters were considered in the latest studies. Jing et al. [21] verified that there was a strong relationship between the rock mass properties and the TBM operational parameters. Zhang et al. [22] successfully assessed the rock mass types using cuttinghead speed, cutterhead torque, thrust, and advance rate (AR). Gao et al. [23] forecasted four TBM operational parameters, including the torque, velocity, thrust, and chamber pressure via their records. Zhu et al. [24] tested the efficacy of eight TBM operational parameters on identifying rock mass types. Therefore, it is possible to establish a prediction model for forecasting PR based on the TBM operational data.

The TBM operational data always arrive in a continuous stream, different from the data of the intact rock properties and the rock mass properties [2]. In this case, traditional machine learning models do not work well because each time new data is available, the models are demanded to be retrained on the whole dataset as per the new data. Artificial neural network (ANN) has proved to be a powerful tool to deal with such a problem. Therefore, an ANN-based dynamic prediction model is proposed in this study to estimate the PR via the TBM operational data. The rest of this paper is organized as follows: section 2 introduces the basic concept of the ANN and then shows the layout of the proposed prediction model; section 3 implements the model on a dataset summarized from a water conveyance tunnel in China; and section 4 contains the conclusions of this study.

2. Methodology

2.1. Artificial neural network (ANN)

An ANN is the foundation of artificial intelligence, which is based on a bunch of simple, highly interconnected processing units called neurons [25]. Neurons are connected by weights. The value of the weight controls the strength of the signal between two neurons. Only when the aggregate signal crosses certain threshold, the signal can be transmitted among different neurons. Neurons are organized into layers. Generally, connections are built between layers, while in the same layer, neurons are not connected. Most ANNs arrange their layers in a chain structure with each layer being a function of the layer that precedes it. Layers can be basically divided into three kinds: input, hidden, and output layers. When we feed an input \( x \) into the ANN to produce an output \( \hat{y} \), information travels from the input layer to the hidden layer (if there is one), and to the output layer. This procedure is called feed-forward propagation. On the contrary, the back-propagation algorithm, often simply called backprop, allows the information to flow backward through the network to use the gradient to reduce the cost function and to update the weights \( W \) and bias \( b \) between layers [26]. Given features \( h \), a layer of linear output units produces a vector \( \hat{y} = W^1h + b \). Through this structure, neural networks can approximate most continuous functions to any degree of accuracy by selecting an appropriate number of neuron units and layers [27, 28].

2.2. Architecture of the proposed model

Considering that the TBM operational data stream out from sensors while tunneling, an auto-updating model is required. Usually, streaming data are processed by mini batches. In this study, the batch size of the feed-forward back-propagation ANN is set to 10. The overall network comprises one input layer, two fully connected layers (with eight hidden neurons and a rectified linear unit (ReLU) activation function for each layer), and one output layer. The hyperparameters (\( W \) and \( b \)) of this network are initialized to small random values. Therefore, the first hidden layer is given by:
\( h^{(1)} = g^{(1)} (W^{(1)} x + b^{(1)}) \)  

The second hidden layer is given by:

\[ h^{(2)} = g^{(2)} (W^{(2)} h^{(1)} + b^{(2)}) \]  

The output layer is given by:

\[ P_R = g^{(3)} (W^{(3)} h^{(2)} + b^{(3)}) \]  

The learning rate of the model is set to 0.001 for the ANN and the epochs are 100. The cost function and optimizer of the network are mean squared error and rmsprop, respectively. Figure 1 schematically presents a flowchart of the proposed PR prediction model.

![Figure 1](image.png)

3. Case study

3.1. Dataset and data preprocessing

A water conveyance tunnel in Jilin province, China, was constructed by an open-type gripper TBM of a 7.93 m diameter. The total length of the tunnel was 19,771 m, including 17,488 m constructed by the TBM and 2,283 m constructed by the drill and blast method. During tunneling, there were 199 kinds of operational data automatically collected by the TBM’s data acquisition system. Since the TBM recorded the data on a 10 secs basis, extensive data were collected and readied for processing.

To prepare the data for ANNs' training and testing, the following steps are taken:

**Step 1**: Choosing input features from the operational parameters

Based on [29], cutterhead rotation speed (RPM, rev/min), cutterhead torque (\( T \), kN·m), thrust (\( F \), kN), and advance rate (\( AR \), mm/min) are four crucial parameters for TBM operation, among which the RPM and the AR are manually adjusted while construction, and the applied \( T \) and \( F \) reflect the interaction between the machine and the surrounding rock mass.

**Step 2**: Removing all data points where either RPM, T, F, or AR is equal to zero

As shown in Figure 2, data belonging to downtime phases are equal to zero. Let \( F(X) = f(RPM) \times f(T) \times f(F) \times f(AR) \). According to Equation 4, any \( x \in X \) resulting in \( F(X) = 0 \) is removed from the dataset. Since the tunneling segments are separated by the downtime, 4393 tunneling segments are eventually generated by removing downtime phases.
\[ f(x) = \begin{cases} 0, x = 0 \\ 1, x \neq 0 \end{cases} \] (4)

**Step 3:** Partition the TBM tunneling cycles

A TBM tunneling cycle can be divided into three phases [29], i.e., empty pushing, trial excavation, and stable excavation phases (see Figure 3). Because cutters do not contact the rock wall until the trial excavation phase, only the RPM, T, F, and AR in the trial excavation phase, are employed in this study to predict the mean of the PR in the stable excavation phase. Statistically, a typical trial excavation phase lasts for 120 s. To obtain the prediction results at the very beginning of the trial excavation phase, the means and variances of the data at the first 30 s of the trial excavation phase, are calculated and fed into the prediction model, which ensures that the TBM operators have sufficient time to either fine-tune the operational parameters or shut off the machine if undesired prediction results come out.

**Step 4:** Detecting outliers by three-sigma rule

Since TBM data are automatically collected by sensors, outliers induced by machine failure, or any other problems are inevitable. In this study, three-sigma rule is adopted to remove these outliers as all the selected parameters obey approximate Gaussian distributions [24]. Assume that X is observations, \( \mu \) is the mean of their distribution, and \( \sigma \) is their standard deviation:
P(μ – 3σ ≤ X ≤ μ + 3σ) ≈ 99.73% \hspace{1cm} (5)

Equation 5 implies that about 99.73% of the data should lie within three standard deviations of the mean. In other words, points that fall over three standard deviations from the norm are likely outliers.

**Step 5:** Standardizing features

A normalization method is used to minimize the influence of scales varying between different parameters, which is defined as:

\[ x' = \frac{x - \mu}{\sigma} \hspace{1cm} (6) \]

where \( x \) represents one of the training samples, and \( x' \) is the normalized \( x \).

### 3.2. Experimental results

To ensure a robust generalization, an ANN must perform well not only on the data used for its training but also on new data that it has not seen before. Thus, the dataset is randomly split into two subsets: 80% for training and 20% for test. Mean absolute error (MAE) is adopted in this study to evaluate the performance of the network.

\[ \text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |F(x_i) - y_i| \hspace{1cm} (7) \]

where \( n \) denotes the number of samples, \( F(x_i) \) denotes the prediction value of the \( i \)-th sample, and \( y_i \) denotes the observation value of the \( i \)-th sample. Since MAE calculates the deviations between the prediction value and the observation value, the smaller the MAE, the better is the model’s performance.

The model’s MAE as well as loss over the 100 epochs are given in **Figures 4** and **5**. It can be observed that the model’s MAE sharply falls within the first 20 epochs, then it declines to 0.37 at around 80 epochs. The model’s loss shows the same trend, with the final loss being 0.3. Another thing worth noting is that the training MAE and the test MAE are close, which means that the selected hyperparameters are suitable for the ANN and no over-fitting occurs.

However, the overall MAE and the loss leave room for improvement. One possible way to improve the network is to modify its architecture. Some strategies, such as dropout, L2 regularization, etc. are welcome. More fabulous hidden layers, such as convolution layer, long-short term memory layer, etc. may perform well in this case with suitable hyperparameters.

![Figure 4](image1.png)  ![Figure 5](image2.png)

**Figure 4.** The MAE of the model versus epoch.  **Figure 5.** The loss of the model versus epoch.

### 4. Conclusion

We have proposed an ANN-based dynamic prediction model to estimate the PR of a TBM via the historical data of four TBM operational parameters. The ANN model is composed of four layers, including 1 input layer, 2 hidden layers, and 1 output layer. More specifically, the input layer has eight neurons, which are the means and variances of the cutterhead rotation speed, torque, thrust, and AR in every tunneling segment. There are also eight neurons in each hidden layer, with ReLU as the
activation function. The learning rate, total epochs, batch size, cost function, and optimizer of the ANN are 0.001, 100, 10, mean squared error, and rmsprop, respectively. The output layer has only one neuron that is the PR.

The validity and feasibility of the proposed model are verified by a water conveyance tunnel project in China. The results display that (1) the ANN converges fast and steadily on both the training and test sets; (2) the proposed framework structure performs good exactness and robustness in terms of this database. In a nutshell, this paper manifests the possibility to predict TBM performance via the historical data of the TBM, and ANN is a powerful approach to process massive sensor data and to gain knowledge or rules through experience.

5. References

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