Influence of geological conditions of rock mass ahead of tunnel face on the prediction performance of uniaxial compressive strength prediction model

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Abstract. Accurate and quick prediction of UCS values of rocks ahead of one tunnel provides a reliable guarantee for the safety and economy of tunnel construction. The objective of this paper is to investigate the effect of different rock geological conditions on the prediction performance of the developed genetic algorithm optimization of artificial neural network model when predicting uniaxial compressive strength using measurement-while-drilling data. Firstly, the objective tunnel is divided into four sections based on the geological conditions of the rock mass. Secondly, prediction model for each section is developed. Finally, the prediction accuracy of each section is compared and analysed. The results show that the sections with better geological conditions obtain superior prediction performance. In addition, a larger sample dataset has a positive effect on the prediction performance.

1. Introduction
The measurement of uniaxial compressive strength (UCS) of rocks is one of the key factors affecting the evaluation of geological conditions ahead of a tunnel [1-3]. Accurate and rapid prediction of UCS values of the rocks ahead of the tunnel face can ensure the safety and economy of tunnel construction [1, 2].

The UCS standard test of the rock is directly determined in the laboratory by the measurement of compression characteristics of rock specimen under the axial load. However, this direct laboratory test method is not easy to obtain perfect core samples and is time-consuming and expensive [4, 5]. Some researchers report that due to standard UCS test methods require costly equipment, it is economical and convenient to use the indirect test methods to measure UCS [6-8].

Recently, with the rapid development of measurement-while-drilling (MWD) technology, the evaluation technology of rock mass quality ahead of a tunnel face has been improved [9-12]; Therefore, as long as the original data is properly processed and effectively analyzed, the MWD technology can be regarded as a robust method for detailed characterization of large rock mass. Many scholars have done a lot of research in this field. The original MWD system was developed by Aoki, Shirasagi, Yamamoto, Inou and Nishioka [13]; The geological conditions of different ground depths were evaluated by analyzing the data obtained by drilling in rock with a hydraulic drill. Schunnesson, Pouloupolos, Bastis, Pettersen and Shetty [14] proposed a method to estimate the range of rock strength values based on the MWD hardness parameter index recorded by Atlas Copco software.
Kahraman, Rostami and Naeimipour [15] evaluated the feasibility of estimating UCS, Brazilian tensile strength, point load strength and Schmidt hammer test value by penetration rate parameter. However, limited by the difficulty of efficient analysis and processing of the MWD data, the technology of predicting UCS ahead of a tunnel face using the MWD data has not been effectively applied in the field.

In recent decades, artificial intelligence technologies have been applied to solve geotechnical engineering problems as a powerful tool [16-20]. However, the disadvantages of slow learning speed and easy to fall into local minima exist in the realization of ANN [21, 22]. To solve these problems, optimization algorithms such as genetic algorithm (GA) can be used to enhance the performance of ANN [23-25]. Based on MWD data, Liu, Luan, Zhang, Sakaguchi and Jiang [26] compared and analyzed the performance of regression model, ANN model and hybrid GA-ANN model in predicting UCS. The results show that GA-ANN has better prediction performance, and it validate that MWD data can be used to predict the UCS of the rock ahead of the tunnel. However, the analysis of the influencing factors on the prediction performance still needs further study.

The objective of this paper is to investigate the effect of different rock geological conditions on the prediction performance of the developed hybrid GA-ANN prediction model when predicting UCS using MWD data. Firstly, the objective tunnel is divided into four sections based on the geological conditions of the rock mass. Secondly, GA-ANN prediction model for each section is developed. Finally, the prediction accuracy of each section is compared and analyzed. This study has practical guidance to improve the prediction performance of UCS with MWD data.

2. Data collation and analysis

2.1. Data collation

The Nagasaki Tunnel (east) of the Shinkansen high-speed railroad in Japan, the study subject of this paper, was constructed in 2013 and completed in 2017. The total length of the tunnel is 3.855 km, as shown in Figure 1. During the tunnel excavation, the evaluation of the exposed tunnel face and the construction of the advance tunnel face were carried out. Uniaxial compressive strength (UCS) values and rock quality score (RQS) values for the exposed tunnel face were recorded in the evaluation report. During the drilling construction, the measurement–while–drilling (MWD) data was collected. It should be noted that the UCS values recorded in the evaluation report were obtained by converting the Schmidt hammer rebound values.

![Figure 1. Diagram of the four sections of the new Nagasaki tunnel (east).](image)

2.1.1. RQS. Based on the JH method proposed by Akagi, Sano, Shinji, Nishi and Nakagawa [27], the RQS value is calculated by the summation of 10 individual items including overall state, self-stability, intact rock strength, weathering, joints proportion, spacing of joints, joint aperture, morphology of joints, ground water inflow, and ground water corrosion to assess rock mass quality. Each individual item was assigned a score of 1 to 4 by the field engineer and recorded in the assessment report, depending on the condition of the tunnel faces revealed. A larger value for each item indicates a lower quality item, and vice versa. Therefore, the assessment of the ground water inflow and geological conditions of the tunnel face can be evaluated quantitatively based on the recorded assessment reports. To study the influence of the geological conditions of the rock mass on the predicted performance, the
tunnel was divided into four sections based on the RQS values obtained from the exposed tunnel faces, as shown in Figure 1. The corresponding water inflow, RQS values, and the excellent geological conditions of the four sections are recorded in Table 1. The mileage of sections 1 and 3 are 58K424.4–58K724.3 m and 59K847.3–60K652.1 m, respectively, and the geological conditions are both good and the water inflow are both small, with average RQS values of 23.54 and 21.13, respectively. The mileage of sections 2 and 4 are 59K178.4–59K611.0 m and 61K192.3–61K714.1 m, respectively, and the geological conditions are poor and general, with large water inflow and average RQS values of 25.71 and 24.75, respectively.

Table 1. Comparison of geological conditions for four sections.

| Section   | Mileage            | Water inflow | RQS (Avg.) | Geological Conditions |
|-----------|--------------------|--------------|------------|-----------------------|
| Section 1 | 58K424.4–58K724.3 m| Small        | 23.54      | Good                  |
| Section 2 | 59K178.4–59K611.0 m| Large        | 25.71      | Poor                  |
| Section 3 | 59K847.3–60K652.1 m| Small        | 21.13      | Good                  |
| Section 4 | 61K192.3–61K714.1 m| Large        | 24.75      | General               |

2.1.2. MWD. The collected MWD data include six parameters of the penetration rate (PR), hammer pressure (HP), rotation pressure (RP), feed pressure (FP), hammer frequency (HF) and specific energy (SE). Six MWD parameters and one corresponding UCS parameter are used as input and output of the prediction model respectively, which together form a dataset.

2.2. Statistical analysis

A total of 813 datasets were collected in this study. The number of datasets corresponding to sections 1 to 4 are 302, 60, 273, and 178, respectively. Descriptive statistical was performed on the datasets of each of the four sections, as shown in Table 2. The statistical results show that the distribution of the values of the input and output variables in each zone is wide and variable.

Table 2. Descriptive statistics of datasets for each section.

| Section   | Item    | Parameter | Amount | Avg. | Min. | Max. |
|-----------|---------|-----------|--------|------|------|------|
| Section 1 | Input   | PR        | 302    | 1.24 | 0.15 | 13.30|
|           |         | HP        |        | 14.78| 9.40 | 15.73|
|           |         | RP        |        | 3.80 | 2.10 | 7.70 |
|           |         | FP        |        | 3.58 | 1.59 | 6.30 |
|           |         | HF        |        | 42.07| 9.00 | 56.00|
|           |         | SE        |        | 326.98| 15.10| 1390.40|
|           | Output  | UCS       |        | 25.83| 8.00 | 59.00|
| Section 2 | Input   | PR        | 60     | 1.05 | 0.34 | 2.40 |
|           |         | HP        |        | 13.96| 12.80| 15.10|
|           |         | RP        |        | 3.69 | 2.19 | 5.70 |
|           |         | FP        |        | 3.61 | 2.20 | 7.00 |
|           |         | HF        |        | 36.33| 0.00 | 53.00|
|           |         | SE        |        | 235.54| 105.81| 639.62|
|           | Output  | UCS       |        | 25.23| 19.00| 28.00|
| Section 3 | Input   | PR        | 273    | 0.61 | 0.21 | 4.44 |
|           |         | HP        |        | 14.91| 13.50| 15.70|
|           |         | RP        |        | 5.29 | 2.50 | 8.70 |
|           |         | FP        |        | 4.99 | 2.40 | 8.70 |
|           |         | HF        |        | 21.92| 0.00 | 55.00|
|           |         | SE        |        | 317.38| 56.20| 696.20|
|           | Output  | UCS       |        | 26.56| 16.00| 36.00|
| Section 4 | Input   | PR        | 178    | 0.65 | 0.23 | 2.31 |
|           |         | HP        |        | 14.55| 13.84| 15.50|
|           |         | RP        |        | 6.63 | 3.66 | 12.50|
|           |         | FP        |        | 3.67 | 1.72 | 6.49 |
|           |         | HF        |        | 26.23| 0.00 | 54.96|
|           |         | SE        |        | 205.93| 68.69| 478.40|
In addition, the correlation between input variables was investigated to avoid redundancy of input variable parameters, and the results are shown in Figure 2. If the correlation between two variables is large, then one of the variables needs to be removed. The coefficient of determination \( R^2 \) was used as an index to evaluate the correlation.

For the four sections the \( R^2 \) values between the input variables were less than 0.3 except between PR and SE. Although the \( R^2 \) values between PR and SE corresponding to sections 1 to 4 were 0.33, 0.60, 0.36, and 0.60, respectively, the \( R^2 \) values were still not large. The results indicate that the correlations between the input variables of each section are small and can be used as inputs to the model in their entirety.

![Figure 2](image_url)

**Figure 2.** Correlation statistics among input variables for the four sections. (a) Section 1; (b) Section 2; (c) Section 3; (d) Section 4.

3. Prediction methods and results

3.1. Hybrid genetic algorithm and artificial neural network (GA–ANN)

Genetic algorithms (GA) is a parallel stochastic search optimization method proposed by Professor Holland [28] in 1962, which simulates the theory of genetic and biological evolution in nature. Similar to the biological evolutionary principle of "survival of the fittest" in nature, GA is applied to select individuals in a coded tandem population formed by introducing optimization parameters according to the selected fitness function and through selection, crossover and mutation in genetics. Individuals with good fitness values are retained, and those with poor fitness are eliminated. The new population...
inherits the information from the previous generation and is superior to the previous generation. This cycle is repeated until the conditions are met. The basic operations of the GA are divided into three steps: selection, crossover, and mutation operations. The selection operation is to select individuals from the old population to the new population with a certain probability, and the probability of an individual being selected is related to the fitness value. The better the fitness value of an individual, the higher the probability of being selected. Crossover is the process of selecting two individuals from a population to produce a new superior individual by exchanging and combining two chromosomes. The crossover process is to select any two chromosomes from the population and randomly choose one or more chromosome positions for exchange.

The algorithmic process of genetic algorithm optimization of artificial neural network (GA-ANN) is divided into three main parts: network structure determination, genetic algorithm optimization and neural network prediction. After the structure of the neural network is determined, the length of the individuals of the genetic algorithm is then determined. GA optimizes the weights and thresholds of the ANN. Everyone in the population contains a network ownership value and a threshold value. Individuals calculate individual fitness values by fitness functions, and GA finds the individual corresponding to the optimal fitness value by selection, crossover, and variation operations. In GA-ANN prediction, the optimal individuals obtained by GA are assigned to the initial trial weights and thresholds of ANN, and the regular training and prediction processes are then executed.

### 3.2. Modeling

In this paper, the datasets of each section were divided into training and test datasets in a ratio of 8 to 2. The main parameters of the GA–ANN were determined by the trial-and-error method, as shown in Table 3. Population size, selection method, number of generations, mutation probability, and crossover probability are the main parameters of the GA, which were determined as 500, roulette method, 700, 0.25, and 0.7, respectively. Network structure, activation function, training function, learning rate, and momentum term are the main parameters of the ANN, which were determined as 6–12–1, sigmoid, Levenberg-Marquardt, 0.01, and 0.8, respectively.

#### Table 3. The main parameters of the GA–ANN.

| Algorithm | Parameter                  | Value | Algorithm | Parameter                  | Value             |
|-----------|----------------------------|-------|-----------|----------------------------|------------------|
| GA        | Population size            | 500   | ANN       | Network structure          | 6–12–1           |
|           | Selection method           | Roulette | Activation function | Sigmoid            |
|           | Number of generations      | 700   | ANN       | Training function          | Levenberg-Marquardt |
|           | Mutation probability       | 0.25  | ANN       | Learning rate              | 0.01             |
|           | Crossover probability      | 0.7   | ANN       | Momentum term              | 0.8              |

#### 3.3. Prediction results and discussion

Based on the model developed above, predictions were carried out for each section and the total section with the test datasets, and the final prediction results are recorded to Table 4.

#### Table 4. Comparison of final prediction results.

| Section    | Geological conditions | \( R^2 \) | Training | Test  |
|------------|-----------------------|-----------|----------|-------|
| Section 1  | Good                  | 0.927     | 0.762    |
| Section 2  | Poor                  | 0.617     | 0.548    |
| Section 3  | Good                  | 0.798     | 0.732    |
| Section 4  | Fair                  | 0.710     | 0.273    |
| Total section | -                 | 0.840     | 0.844    |
As described in Section 3.2, the dataset of each section is divided into a training dataset and a test dataset according to a ratio of 8 to 2. For modelling and prediction, the training and test datasets correspond to the training and test stages, respectively, and both stages obtain a set of measured and predicted values. The training value $R^2$ and the test value $R^2$ are calculated from these two sets of measured and predicted values obtained. The final prediction results for each section and all sections are shown in Table 4. It should be noted that the $R^2$ values recorded in Table 4 are the average of 10 prediction results.

The correlation index values of $R^2$ between the measured values of UCS and the average values predicted by the developed GA-ANN model are graphically shown in Figure 3. The comparison between measured UCS and the average values of the predicted UCS with all datasets are shown in Figure 4. The line consisting of the pink dashed line and the solid dots in Figure 4 represents the measured values, and the closer the points of the predicted values of each section are to the measured values indicate the higher prediction accuracy. The results of the comparative analysis showed that the prediction performance of sections 1 and 3 with good geological conditions is better than that of sections 2 and 4 with poor geological conditions for both training and test datasets. The reason for this result is that the better the geological conditions of tunnel face, the more complete the rock mass is, and the MWD data of a single borehole can better reflect the geological conditions of the whole tunnel face. Therefore, it can be concluded that when using hybrid ANN model to predict UCS, its prediction performance is affected by geological conditions of the tunnel face. In addition, the results also showed that the prediction performance of all sections is better than the prediction performance of each single section. This indicates that the number of sample datasets also has an impact on the prediction performance of the prediction model. It can be concluded that higher prediction performance can be obtained with more sample datasets.

![Figure 3](image)

**Figure 3.** Results of the prediction corresponding to the four sections. (a) Training; (b) Test.
4. Conclusion
The measurement of uniaxial compressive strength (UCS) of rocks is one of the key factors affecting the evaluation of geological conditions ahead of a tunnel. Accurate and rapid prediction of UCS values of the rocks ahead of the tunnel face can ensure the safety and economy of tunnel construction. This paper investigated the effect of different rock geological conditions on the prediction performance of the developed genetic algorithm optimization of artificial neural network (GA–ANN) model when predicting uniaxial compressive strength using measurement-while-drilling (MWD) data. The main conclusions obtained are as follows.

1) The comparative results showed that the prediction performance of sections 1 and 3 with good geological conditions is better than that of sections 2 and 4 with poor geological conditions for both training and test datasets. The reason for this result is that the better the geological conditions of tunnel face, the more complete the rock mass is, and the MWD data of a single borehole can better reflect the geological conditions of the whole tunnel face. It can be concluded that when using GA–ANN model to predict UCS, its prediction performance is affected by geological conditions of the tunnel face.

2) The prediction performance of all sections is better than the prediction performance of each single section. This indicates that the number of sample datasets also has an impact on the prediction performance of the prediction model. It can be concluded that a larger sample dataset has a positive effect on the prediction performance.

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