SELECTING TUNNEL SUPPORT PATTERN BASED ON DRILLING DATA AHEAD OF TUNNEL FACE

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In the construction of mountain tunnels, unexpected events such as geological abrupt change and sudden water inflow often lead to the situation that tunneling construction must be forced to stop. In addition, it is traditional and inefficient to select the supporting pattern by comparing the standard pattern of the design stage with the construction site. In recent years, with the continuous advancement of drilling technology, it is possible to use drilling data to evaluate geological conditions ahead of tunnel face and to select tunnel support pattern effectively. Therefore, it is extremely crucial to effectively evaluate the geological condition ahead of the tunnel face. In this report, In this report, correlation analysis between drilling data and geological conditions and support patterns was carried out. The results show that there is a certain correlation between drilling data and geological conditions and support patterns. Furthermore, the support patterns were selected by using artificial neural network(ANN) based on drilling data, and the optimal ANN model was proposed after verifying the construction site measurement and construction results. The research shows that the method proposed in this report has a great practical significance for the geological condition prediction and evaluation of mountain tunnel and the effective selection of tunnel support patterns.

Key Words : *drilling data, tunnel support pattern, artificial neural network*

1. INTRODCTION

Given a high demand for mountain and underground tunneling systems, tunneling techniques are constantly being optimized. One of the factors affecting the safety, rate and cost of tunneling works is the effectiveness of the selection of tunnel support pattern. This problem has been a subject of numerous experimental studies and theoretical analyses due to the operating aspects involved.

The current technology of selecting support pattern for mountain tunnel site is to select support pattern after comparing with the standard patterns in design stage, combined with geological data ahead of tunnel tunnel face in excavating. In recent years, with the advancement of drilling technology, it is possible to use drilling data of drilling rig to evaluate geological condition ahead of tunnel face[1),2)].

Therefore, in this report, drilling data was considered to be used to explore the relationship between support pattern and geological conditions. In addition, based on drilling data, the selection of the support pattern was performed by using artificial neural network(ANN), and the construction site measurement and construction results were verified.

2. Case description

The data sets used in the study were obtained from new Nagasaki (east) tunnel project in Japan. The new Nagasaki (east) tunnel is located within the Nagasaki City in the southern part of Japan with an East-Westward trend as shown in **Fig. 1**. The tunnel is in the form of Single-Arch with a length of 3.88 km. The

Table 1 Classification number of support patterns.

Class No.	Support pattern	Number of samples
1	II-A(B) II-A(B)B	66514
2	I-2-A(B)	49228
3	I-2-B(B)	75767
4	II-B(B)	81976
5	I-2-B(B)C	35413
6	I-2-B(B)D I-2-B(B)E	9751

Fig.1 Location of new Nagasaki(east) tunnel, Nagasaki, Japan.

approximate project cost is 60 million USD. The project started in 2013 and has finished in 2017. The tunnel was excavated by the New Austrian Tunnelling Method (NATM)[3]. In this tunnel construction, many support patterns were applied, namely I-2-A(RC)(B), I-2-A(B), I-2-A(C), I-2-A(D), I-2-B(B), I-2-B (B) C, I-2- B(B) D [I-2-B (B) E], I-2- B (B) F, II-A-B(B) and II-B(B). Due to the lack of part of the drilling data [corresponding to the tunnel with support patterns I-2-A(RC)(B), I-2-A(C), I-2-A(D) and I-2- B (B) F, totaling about 190 meters] collected from the construction site, the selection of the remaining tunnel support pattern was predicted and analyzed in this study. The support patterns corresponding to the remaining data were divided into six classes according to number of bolts, space of bolts, type and shape of I-beam, initial and secondary lining thickness and eccentric or not, as shown in the example in **Fig. 2**.The classification number of support patterns are shown in **Table 1**.

The hydraulic rotary percussion drill was used for drilling investigation ahead of the tunnel face. The drilling data (the part of the data as shown in **Fig. 3**) obtained from the data collection device include penetration rate (PR), hammer presser (HP), rotation pressure (RP), feed pressure (FP), hammer frequency (HF) and specific energy (SE). Each set of these data and the class number of the corresponding support pattern constitute a data set. The total number of all data sets from 97 drill holes is 318, 649.

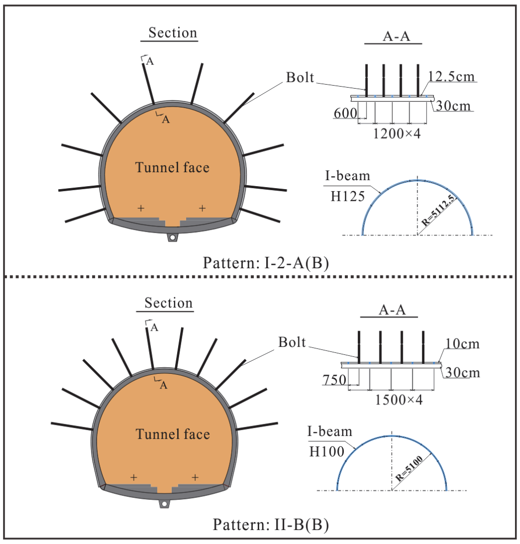

Fig.2 Example of pattern I-2-A(B) and II-B(B).

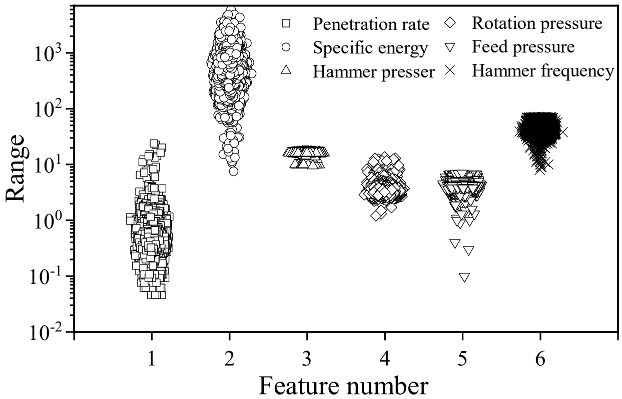

Fig.3 Visualization of drilling data recorded.

3. CORRELATION BETWEEN DRILLING DATA AND MOUNTAIN SHAPE AND SUPPORT PATTERNS

In this study, correlations between drilling data and mountain shape and support patterns were evaluated as shown in **Fig. 4**. The parameter of input energy is a comprehensive parameter of other parameters and was therefore used for evaluation. It should be emphasized that the input energy value used for evaluation is the average value calculated from per 1 meter long drilled hole. The SE is calculated as equations (1) and equations (2):

$$\mathrm{SE} = \frac{E_s f}{vS} \times k \qquad (1)$$

$$E_s = ALN_s \qquad (2)$$

where E_d is SE (J/cm^3), f is hammer frequency (1/min), v is penetration rate (cm/min), S is cross-sectional area of the drill hole(cm^2), K is loss coefficient, E_s is hammer energy (J), A is piston com pression area (cm^2), L is piston stroke(cm), N_s is HP (MPa or

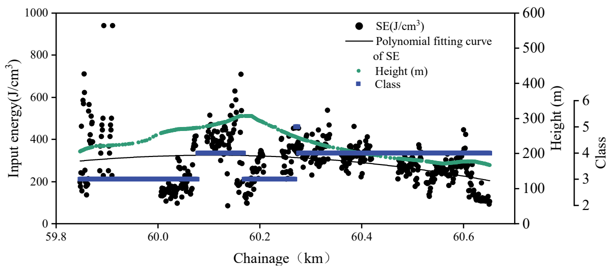

Fig. 4 Comparison of SE with mountain shape and support patterns

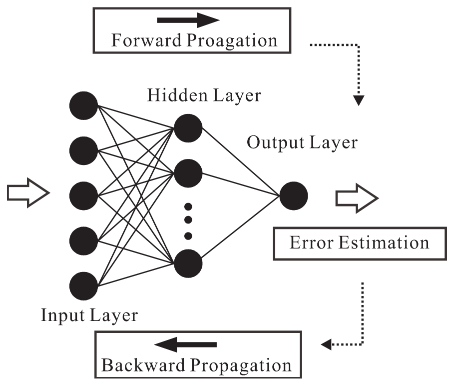

Fig. 5 Structure of BP-ANN model[4].

N/mm^2). As it can be observed from **Fig. 4**, the shape of fitting curve of input energy is similar to that of height line of mountain. In addition, the distribution of input energy and support mode are similar, especially between 60 km and 60.7 km.

4. SELECTION OF SUPPORT PATTERN BY ARTIFICIAL NEURAL NETWORK

In this study, different ANN models were set up applying MATLAB software according to the combination of different training sample size, different network structures and different unmber of feature parameters to search for the most effective ANN architecture. This study used MATLAB software to develop its own code, without using built-in ANN tool of the software. To train ANNs, the most commonly adapted agorihms is the back-propagation(BP)[5]. In this study, BP agorihm was used. **Fig.5** shows the structure of BP-ANN model. In these experiments, learning rate of 0.01 and momentum term of 0.5 were used. Testing and validation of the ANN models were done with date sets shown above. Randomly selected 600 data sets (corresponding to 100 data sets of the remainder of each class) were used in testing stage. Accuracy and computing-time were taken as the performance measures. And, average accuracy (average accuracy = accuracy / 10) and average computing-time (average computing-time = computing-time / 10) were obtained from 10 experiments under the same experimental conditions.

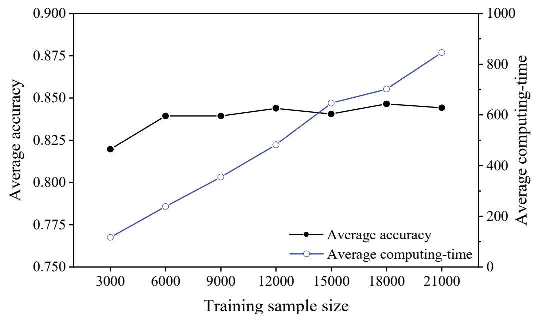

Fig. 6 Variations of the average accuracies and average computing-times with different training sample size.

(1) Training sample size

Fig. 6 shows a graph with variations of the average accuracies and average computing-times with different training sample size. It appears that, for average accuracy, the average accuracies are lower as the number of samples is 3000, and the difference is small when the sample size is 6000, 9000, 12000, 15000, 18000 and 21000. For average computing-time, the larger the sample size, the larger the average time consuming. There is a linear relationship between sample size and average time-consuming.

(2) The number of intput layer nodes

For the number of hidden layers, Kanellopoulos and Wilkinson[6] stated that a second hidden layer is recommended when the output layer of the neural network has 20 (or more) nodes. Garson[7] reported that a single hidden layer is usually sufficient to solve most problems, especially classification issues. Thus, one hidden layer was preferred in this study. For the number of nodes in the input layer, it was equal to 6 (corresponding to the number of feature parameters). For the number of nodes in the output layer, it was also equal to 6 (corresponding to the number of the classes of the support patterns). For average accuracy, as it can be seen from **Fig.7**, the average accutacies of the predicted results of the ANN models increases with the increase of the number of intput layer nodes. The growth curves become horizontal, until the number of nodes equals 30. Moreover, for average computing-time, that the average computing-times increase linearly with the increase of the number of hidden layer nodes. This means that when the number of the hidden layer nodes increases to a certain value, the performance of the network will no longer enhanced.

(3) The number of feature parameters

Fig.8 compares average accuracies for different combinations of the feature parameters. As it can be seen form this figure, the average accuracies increase with the increase of the number of features. The case of 6 features obtains the highest results. The case of

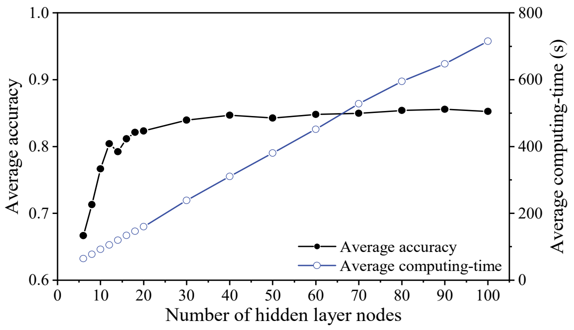

Fig. 7 Variations of the average accuracies and average computing-times with different number of hidden layer nodes.

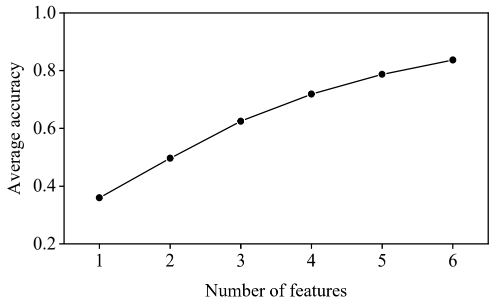

Fig. 8 Average accuracies with different number of features.

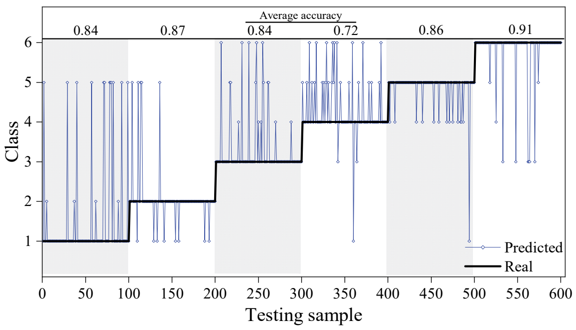

Fig. 9 Classification results of optimal ANN model.

1 feature obtains the worst results. This is due to the significant influence of the number of features on the performance of ANN. Also, as shown in this figure, average computing-time increases with the number of features. The case of 1 feature obtains the minimum value. Additionally, average computing-time value shows that there is on huge difference for 2 features, 3 features, 4 features, 5 features and 6 features.

(4) Optimal model performance

Considering the performance of the ANN models with different hidden layer nodes, different sample sizes and different feature numbers, the model with 30 hidden layer nodes, 6000 training size and 6 features is recommended as the optimal one. Therefore, the average accuracies of the six supporting patterns of 0.84, 0.87, 0.84, 0.72, 0.86 and 0.91 are obtained as shown in **Fig.9**.

5. CONCLUSION

This report analyzes the correlation between the actual tunnel support pattern and the drilling data, and conducts feasibility verification for the reasonable support pattern selection through the ANN. From this study, the following conclusions would be described.

(1) There is a certain correlation between tunnel support pattern and drilling data. Especially, the correlation between input energy parameter and mountain height is high.

(2) Large training sample size, more hidden layer nodes and whole feature prameters can improve the performance of the ANN model, but at the cost of high computing-time.

(3) For this study, it is feasible to select tunnel support pattern by using ANN based on drilling data. In addition, the optimal ANN model is recommended.

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