Neural Net Prediction Analysis for Rock Mass Elastic Modulus Based on Joint Fissure Characteristics

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ABSTRACT
Elastic modulus of rock mass is an important mechanics index in critical project. Due to the influence joint fissure characteristics, it can only be get from complicated in situ test or from indirect empirical formula. Basing on qualitative and quantitative data got from in situ investigation, utilizing the neural net's ability of fault tolerance, adaptivity and self-learning, here gives a full set of technological process for rock mass elastic modulus prediction, which can cover the shortages of in situ test and empirical formula method.

Key Words: Joint Fissure Characteristic, Rock Mass Elastic Modulus, Neural Net, Slope

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Introduction
Rock mass is a complex combination of intact rock and joint fissures. Due to the size effect and discontinuity in rock mass, its elastic modulus is obviously smaller than that of corresponding rock mass. For key project construction, rock mass elastic modulus, an important mechanical index, is usually obtained by in-situ test or empirical formula (Wang et al., 2004). It is obvious that the actual rock mass mechanical parameters can be obtained by in-situ test, but time and money constraints its widespread use (Mohammadi and Rahmannejad, 2010; Samui, 2013). Empirical formula method, though simple, fast and convenient, but is often based on one or a few indexes to indirect access to elastic modulus of rock mass and failed to put many related geological factors into consideration. This method has its own limitation (Kou, 2008). For cutting slope rock mass in highway engineering, usually, large amount of valuable test data results directly related to elastic modulus can be obtained in investigation stage, including some quantitative data, such as joint spacing, number of groups, laboratory test parameters, etc., and also some qualitative geological description, such as joint roughness and weathering degree, etc. Usually, the relationship between these factors and elastic modulus of rock mass is difficult to be expressed as a certain quantitative formula, and reduction factor is often introduced to build the link between elastic modulus of rock mass and that of the corresponding rock. Definitely, it must reflect the comprehensively influence of those factors mentioned above. The elastic modulus of rock can get from laboratory experiments; therefore, prediction of rock mass elastic modulus is actually the problem of determining the corresponding reduction coefficient (Li, 2003; Fan et al., 2017).

At first, this paper analyses the main geological factors affecting rock mass elastic modulus. Then, a large number of joints and fissures survey results and experiment date in China water resources and hydropower engineering project, after quantitative or half quantitative processing, were used as sample to make neural network learning and training, to get
the specific inner link between rock mass elastic modulus and the above influencing factors. Finally, a set of rock mass in a highway cut slope is used to verify the research results.

**Basic theory of neural network**

At present, most artificial neural network models are using back-propagation Network (BP Network) and its changing form (Carpenter and Barthelemy, 1994; Fichera and Pagano, 2017; Hu et al., 2016; Ghritlahre and Prasad, 2018; Wang et al., 2016; Isaiah et al., 2017; Liu et al., 2017; Guo and Deng, 2017). The BP Network, a multi-layer network, generalizes W-H learning rules and trains the weight of the differentiable nonlinear functions, and it is mainly applied in function approximation, pattern recognition, classification and data compression (Singh and Borah, 2013; Liu, 2003). This paper applies function approximation that the input vector and corresponding output vector are used to train a network to approximating a function in the process of predicting rock mass mechanics parameters reduction factor in neutral network.

Multi-layer BP network not only has input node and output node, but also has a layer or multi-layer hidden node (Gao et al., 2006; Guo et al., 2003). Its network model structure is shown in the Fig.1 as below.

Neuron in the hidden layer uses the S-type transformation function as the activation function.

\[
f(x) = \frac{1}{1 + e^{-x}}
\]

(1)

Neuron in output layer is a pure linear transformation function. It can be seen that \( f(x) \) is a continuous differentiable function, the first derivative existing. For multi-layer networks, this activation function is divided into regions which are not linear but composed of a nonlinear hyperplane. Therefore, it is a soft and smooth arbitrary interface, and its classification is more precise and reasonable than linear division, and the fault tolerance of this network is better. In addition, since the activation function is continuously differentiable, it can be calculated by using the gradient method strictly, and the analytical formula of its weight correction is very clear. This algorithm is known as error reverse propagation, or BP algorithm (Yang and Wu, 2008).

BP network is the result of the BP algorithm, a kind of supervised learning algorithm, the main ideas as follow: for \( q \) input learning samples: \( P^1, P^2, \ldots, P^q \), and the corresponding output samples are: \( T^1, T^2, \ldots, T^q \). The purpose of learning is to use error produced between the actual output of the network \( A^1, A^2, \ldots, A^q \) and target vector \( T^1, T^2, \ldots, T^q \) to modify its weight to make \( A^i, (l=1, 2, \ldots, q) \) as close as possible to the desired \( T \). That is to say, the error sum of the network output layer is minimized. It gradually approximates the target by continuously calculating the change of network weight and deviation in the direction of decreasing the slope of the error function. The variation of each weight and deviation is proportional to the influence of the network error, and it is transmitted to each layer in a reverse propagation mode (Ravandi et al., 2013).

**Figure 1.** BP network model structure

BP algorithm consists of two parts: forward transmission of information and reverse propagation of error. In the process of forward propagation, the input information is calculated from the input via the hidden layer to the output layer, and the state of each layer of neurons only influences the state of the next layer of neurons. If output layer fails to achieve the expected output, the error variation value of the output layer is to be calculated; and then it turns to propagation, in which the error signal reverses through the access of network along the early path to modify the advise of neurons in each layer value till reaching the expected output. The process above is the BP network training. After completion of the training, the network input is not a vector in the training set, and the network will give the output result in a generalized way, which is the prediction process of the neural network.
Prediction and analysis of rock mass elastic modulus based on neural network

Affecting factor analysis

Among those numerous factors influencing the rock mass elastic modulus, only important factors are taken into consideration in this paper. The weathering degree of rock mass, rock thickness, joint or angle of fissures, joint intensity, the width and roughness of the joint, filling condition, silt content in fillings, rock density, water absorption and the uniaxial compressive strength of the rock, a total of 11 factors are taken as input parameters, the first eight for qualitative factors, the latter three for quantitative factors. The output parameter is the elastic modulus reduction coefficient of rock mass. Since the input parameters of the neural network are all data, the qualitative factors must be quantified by using the scoring method. Based on the experience of engineering practice, the scoring criterions are listed in table 1.

Sample learning and model testing

This paper selects a part of the domestic water resources and hydropower engineering’s data of rock mass to compile the learning samples of neural networks (table 2), a total of 2 hidden layers for neural network, 9 and 4 neurons for each hidden layer respectively, as it shows. After 50,000 iterations, the overall normalization deviation is 0.00049, which achieves the precision requirement.

After the completion of the neural network model, data in table 3 was used to test the accuracy of the neural network. The calculated results are compared with the original field measurement, and the relative deviation of the reduction coefficient is below 18.5%, which meets the general engineering design requirements. Therefore, it proves reasonable and effective to predict the elastic modulus of rock mass by using this neural network model (Messoud et al., 2017).

Results Application

Due to the general characteristics of rock mass mechanics, the neural network prediction model obtained based on the samples obtained from the hydropower engineering samples can also be applied in the rock mass engineering of the highway cutting slope. The elastic modulus of the sandstone rock mass of K138 road in your new highway is expected. According to the geological data, the slope is dip slope of the sandy mudstone in Devonian. The underlying bedrock is mainly composed of medium-thick sandstone, and the interlayer of the thin mudstone, with 20-40° angle of slope. The rock mass is medium-strong weathering, block split or fracture structure, joint development, multi-steep angle, rough surface, most mud filling. According to the indoor experiment results, the sandstone block is 24.5KN/m², the water absorption rate is 1.0, the rock dry compressive strength is 164.4MPa, and the rock elastic modulus is 31.7~48.9GPa.

For simplicity, here take the average value 40.3GPa as the elastic modulus of this rock sample. According to the above information and looking up Table.1 by difference method, we can get the corresponding model inputting parameters, 80, 50, 50, 100, 25, 50, 65, 65, 65, 24.5, 1.0 and 164.4. By the foregoing neural network model, the reduction coefficient gets to be 0.135.
Therefore, the predicted value of rock mass elastic modulus is 0.135*40.3GPa=5.44GPa. According to the quality classification results of engineering rock, the slope rock mass quality is in level IV, reference to hydropower engineering practice summed up experience relationship between rock mass and elastic modulus of rock mass, the elastic modulus of rock mass ranked in this level is usually located between 1~19 GPa. It can be seen that the prediction result of neural network model have good reference value (Mohammed and Ali, 2016).
Conclusions and recommendations

(1) According to the study in this paper, it shows that the method of predicting the elastic modulus reduction factor of cutting slope rock mass formulated by neural networks, based on the qualitative and quantitative rock-joint-fissure data from the sample-collecting site, superiorly combines qualitative description and quantitative index and effectively takes advantage of engineering geology data as well as present achievements in rock test. With exact accuracy, the predicting results obtained through this method are of great value in engineering, and this method will be largely spread in future to make up for the inadequacy of field test and empirical formula.

(2) Due to the characteristics of fault tolerance, adaptability and self-learning ability, neural network model is able to transform a large amount of non-quantitative geological description of rock mass into the initial input parameters involved in neural network arithmetic after certain reasonable conversion, eventually obtaining the comparatively approximating results. Therefore, in addition to the rock mass elastic modulus, the neural network can be used to predict other rock mass mechanical parameters.

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