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Evaluation of the maximum horizontal displacement around the power station caverns using artificial neural network

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Prediction of the maximum displacement on the sidewalls of the powerhouse is a crucial task in the caverns excavation that depends on the site characteristics including geological and geomechanical parameters. Limitations of the available methods have caused utilizing of new predictive methods. In this research, maximum horizontal displacement around the caverns has been investigated using artificial neural network (ANN), numerical and empirical models for different conditions. The effective parameters including RMR (rock mass rating), overburden depth, coefficient of lateral pressure, pillar width and vertical difference of crown level between two adjacent caverns (powerhouse and transformer) are considered as the input parameters to predict the maximum horizontal displacement. Accordingly, the numerical modeling was utilized to introduce a sufficient database to construct the ANN model. The obtained results from the ANN model were compared with the results of the available numerical and empirical models based on the measured data gathered from different case studies in Iran and other countries. To compare the performance of utilized models, determination coefficient (R^2), variant account for (VAF), mean absolute error (E_a) and mean relative error (E_r) indices between predicted and measured values were calculated. Comparison results showed that based on the geomechanical parameters, the constructed optimum neural network can reliably predict the maximum displacement around the caverns. Finally, the sensitivity analysis of ANN model results shows that overburden depth is recognized as the most effective parameter, whereas tensile strength is the least effective parameter on the maximum displacement around the power station caverns in this study.

1. Introduction

Excavation of underground caverns for variety of applications is dominating worldwide. Prediction of displacement around these structures is a key factor in the performance of the cavern both during and afterwards the excavation. There are various methods including empirical, theoretical and numerical models for prediction of displacement around the underground spaces in the literatures. Among them, numerical methods are widely used for displacements prediction. Zhu et al. (2010) predicted an equation to estimate displacement at the key point on the high sidewall of powerhouse considering spacing between the adjacent caverns by using the Flac3d software. Samadhiya et al. (2004) utilized the 3D finite element modeling for analyzing a powerhouse cavern in an anisotropic rock mass. Yuli et al. (2007) evaluated the stability of an underground powerhouse cavern in a bedded rock formation by the finite element method. Abdollahipour and Rahmannejad (2013) proposed an equation for the prediction of elasto-plastic displacement on the key point sidewall of single caverns using phase2 software. Yazdani et al. (2012) applied displacement-based numerical back analysis to estimate rock mass parameters in the Siah Bisheh powerhouse cavern based on the continuum and discontinuum approaches.

However, in such models there is no a straightforward way for displacements prediction. For example, the numerical models only used for specific case studies and so that; such particular developed model cannot be successfully utilized for other cases. Also, in the empirical models only some of the effective parameters are accounted for maximum displacement determination (Barton, 2002). Considering the above shortcomings of available empirical and numerical methods, new solutions such as artificial neural network (ANN), a branch of artificial intelligence, may suitably cover all of the requirements of displacement prediction around the

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power station caverns. ANNs have emerged as a powerful tool to analyze the mining and geotechnical problems (Kapageridis, 2002; Bizjak and Petkovsek, 2004; Khandelwal et al., 2004). They are capable of learning nonlinear functional mapping and are suitable for adapting the complex functions (Chan et al., 2006). Several researchers have successfully used ANNs for solving the number of tunneling (Santos and Celestino, 2008) and geotechnics related problems (Kapageridis, 2002). Grima et al. (2000) integrated ANN with fuzzy set theory and fuzzy logic to model the TBM advance rate based on the datasets obtained from the rock tunnel projects. Adoko et al. (2013) have predicted tunnel convergence in weak rock using the multivariate adaptive regression spline (MARS) and ANN methods. Azadi et al. (2013) have studied optimum settlement of structure adjacent urban tunnel by utilizing the artificial neural network. Mahdevari and Torabi (2012) applied the ANN model to predict and control of the tunnel convergence.

Considering the above descriptions and limitations of the available models, this paper mainly shows the application of artificial neural network (ANN) technique to predict the maximum displacement around the power station caverns based on the datasets of three rook types under different conditions. To validate the proposed ANN model, its simulation results are compared with the results of the numerical and empirical models on the basis of actual data gathered from different case studies.

2. Artificial neural networks

As the details of Artificial neural networks (ANNs) can be found in the numerous reliable literatures (Kosko, 1994; Haykin, 1999; Ç anakcı et al., 2009; Bhatnagar and Khandelwal, 2012; Rezaei et al., 2012; Majdi and Rezaei, 2013a,b; Sayadi et al., 2014), so it is explained briefly in the following. ANNs are the simplified models of the human brain structure. These techniques have a good potential to map the complex and non-linear relations between input and output variables of a system and so they are commonly used in non-linear engineering problems. Neural network models are actually constructed based on the highly interconnected computing units or neurons which are placed in the successive network layer(s). Generally, a network has three fundamental components including transfer function, network architecture and learning laws that have to be asserted according to the type of problem (Simpson, 1990). A network should be firstly trained before taking new information. Although there exist various types of ANNs, the feed forward back-propagation ANN is the most efficient one. Back-propagation multilayer neural networks consist of at least three layers, i.e., input, hidden, and output layers. The number of hidden layers and the number of respective neurons in each layer depend on the problem complexity; and can be achieved through the trial and error method. The number of input and output neurons are evenly considered as the number of input and output variables of the problem under study (Khoshjavan et al., 2010; Rezaei et al., 2012; Majdi and Rezaei, 2013a,b).

To differentiate between the various processing units, values called biases are set up into the transfer functions. Transfer functions, known as activation functions, are used to transform the weighted sum of all input signals to a neuron and determine the neuron output intensity (Basheer and Hajmeer, 2000). Generally, nonlinear sigmoid (LOGSIG, TANSIG) and linear (POSLIN, PURELIN) functions can be used as transfer functions. The utilization of these transfer functions depends on the purpose of the neural network model. However, the sigmoid type is more efficient (Demuth et al., 1996). In the model training process, data are processed through the input layer to hidden layer until it reaches the output layer (forward pass). At the end, the output is compared with the actual values. The difference between both is propagated back through the network (backward pass) to update the individual weights of the connections and the biases of the individual neurons. The above process is repeated for all the training pairs in the data set until the network error converges to a threshold defined by a corresponding function such as root mean squared error (RMSE) and summed squared error (SSE) indices (Khandelwal and Singh, 2006; Majdi and Rezaei, 2013a,b).

3. Preparing of database

For development of intelligence models such as neural network and fuzzy system, impressive numbers of dataset are required. Therefore, it can be said that data collection is one of the most important stages in the ANN modeling. As the measurement of displacement around the power station caverns is difficult in practice, the numerical modeling is utilized to introduce sufficient database in order to construct an optimum ANN model.

3.1. Data introducing

In this paper, numbers of numerical analyses were executed to predict horizontal displacement around a powerhouse cavern. The 2D finite element program (Phase 2) has been used to simulate the underground power station caverns (Rocscience Inc., 2011). For this purpose, the following simplifications and assumptions have been made:

1. Surrounding rock masses are assumed to be homogeneous, quasi continuous and isotropic.
2. Two minor and major principal stresses act in horizontal and vertical directions.
3. Horse-shoe shape with two cross sections dimension of 33×52 m for powerhouse house and 13×19 m for transformer caverns were selected.
4. Because of too lengthy caverns, plane strain model were applied in modeling.

In this research, effective parameters including RMR, overburden depth of the powerhouse (H_0), coefficient of lateral pressure (K), pillar width (B) and vertical difference of crown level of two adjacent caverns (Z) are considered as the input parameters in numerical analysis. The changing interval of selected parameters is shown in Table 1. Also, the mechanical properties of the surrounding rock mass are presented in Table 2. The aforementioned mechanical properties are RMR, rock mass modulus (E), rock mass Poisson ratio (ν), rock mass compression strength (σ_c), rock mass tension strength (σ_t), rock mass friction angle (φ) and rock mass cohesion (C). These rock mass parameters are obtained using the RocLab program simulation (Hoek et al., 2002). In this simulation, the ground is considered as an elasto-plastic medium obeying Mohr–Coulomb failure criterion.

An expansion factor of 5 with "Box Boundary Type" and gradation factor 0.1 with "Graded Mesh Type" have been used in all phase 2 models. In general, expansion factor or boundary condition coefficient can be automatically defined by the users. External dimensions of the model were determined according to the influence zone of constructions. The influence zone is the area that affected by excavation process. In this analyses expansion factor of 5 is selected based on the trial and error approach. Accordingly, the external dimensions of model are 5 times of cavern width. These boundary condition include fixed X condition in left and right boundaries; and the fixed Y condition in upper and lower boundaries of the model. After establishing the model geometry, mesh can be manually or automatically proceed. Automatically mode is used when the surrounding rock masses of