Application of adaptive neuro-fuzzy inference system (ANFIS) for slope and pillar stability assessment

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Abstract. This study seeks to apply ANFIS model for stability assessment of surface and underground excavation. Two cases of stability assessment for highway slope and underground rib-pillar mining were performed. This paper presents more than one practical approaches in ANFIS simulation for slope and pillar stability assessment. The most important factors to achieve good performance of ANFIS in this study are types of membership function, number of membership function and number of input variable. The results show that the simulation based on those important factors can reach proper error checking. Considering error checking of the model, type and number of MF simulations can show the best result by comparing more than one simulation. Excellent performance of the 4 (four) input variables in slope case and 3 (three) input variables in pillar case provides valuable information for stability assessment using ANFIS.

1. Introduction
Slope and pillar stability is a technical problem that affects many things in mining field project. Forecasting and pre-project stability assessment will give reference information to the project designer. It is related to the excavation geometry and amount of production. Stability assessment of existing slopes and pillars can provide a reference for designer to avoid unwanted accidents. For this reason, many of stability analysis methods have been applied to solve the problem of stability assessment. The methods that have been widely known are analytical, numerical, empirical, probability and observational methods. Since the problem of uncertainty in the field has become more and more complicated, ANFIS has been proposed to assess the stability problem.

ANFIS and other artificial intelligence techniques have been widely used in recent years to assess surface and underground excavation. Chen et al employed the ANFIS model to predict the stability of epimetamorphic rock slopes. ANFIS model applied 41 data pair for training and 5 input variables of rock properties and slope geometry. Gaussian type of MF and hybrid learning rule of ANFIS model produced a good testing error of prediction [1]. Fattahi performed prediction of slope stability using ANFIS-SCM (subtractive clustering method). It shows effective result than multiple linear regression prediction approaches [2]. Silva et al. applied fuzzy logic approach to assessing failure risk in earth dams. They performed the fuzzy fication of geotechnical variables related to the shear strength of soils (in a simpler way than when using conventional probabilistic methods), and also to use the current
methods of slope stability analysis to obtain factors of safety expressed as fuzzy numbers [3]. Adoko and Wu stated that the use of Fuzzy Inference Systems in geotechnical engineering was in two fundamental conditions. First; epistemic uncertainty (lack of information, updated data unavailable and impreciseness) were handled successfully as well as expert knowledge and linguistic variables which were very important for some decision-making process. Secondly, fuzzy systems models were proved to be a good tool for prediction mainly when neural network or genetic algorithms were combined with [4].

Assessment of underground excavation using ANFIS and other artificial intelligence techniques also has been widely used by researchers. Salimi et al. evaluated the applicability of the ANFIS model on a limited data set of hard rock Tunnel Boring Machine (TBM) performance [5]. The result shows that the prediction performance of the Support Vector Regression (SVR) model is slightly better than ANFIS. Lai et al. summarized the study of Qu; about the prediction of ground settlement during shield tunneling using an Artificial Neural Networks (ANN). In the study; cohesion, angle of internal friction, compressive modulus of soil, earth covering thickness, diameter of TBM, grouting pressure, grouting filling ration, shield jacking force and shield tunneling rate were applied as the input variable to predict the maximum surface settlement. It can be concluded that the prediction model can obtain high-precision results [6]. Fattahi et al. performed assessment of damaged zone around underground spaces using ANFIS model [5]. In its study; Three ANFIS models of grid partitioning (GP), subtractive clustering method (SCM) and fuzzy c-means clustering method (FCM) were implemented. A comparison was made between these three models, and the results show the superiority of the ANFIS-SCM model to predict the problem under consideration [7].

ANFIS (Adaptive-Network-based Fuzzy Inference System) is a fuzzy inference system implemented in the framework of adaptive networks. By using a hybrid learning procedure, the proposed ANFIS can construct an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs [8]. The essential part of neuro-fuzzy synergisms comes from a common framework called adaptive networks which unifies both neural networks and fuzzy models. The fuzzy models under the framework of adaptive networks are called ANFIS, which possess certain advantages over neural networks [9]. There are several features that enable ANFIS to achieve great success. ANFIS refines fuzzy IF-THEN rules to describe the behavior of a complex system and does not require prior human expertise. In application for real problem, ANFIS is easy to implement, and it enables fast and accurate learning. ANFIS model offers desired data set, greater choice of membership functions to use, strong generalization abilities, excellent and explanation facilities through fuzzy rules. ANFIS is also easy to incorporate both linguistic and numeric knowledge for problem-solving [10].

Since increasing the uncertainties of field problem for stability assessment, ANFIS becomes part of alternatives to be applied. The simulation of ANFIS model using limited variable is needed to perform to anticipate limited data condition in field and laboratory projects. Building ANFIS using more than one type of membership functions (MF) and choosing different type and number of variables can provide alternatives for comparison. This paper presents slope and pillar stability assessment using the learning ability of ANFIS.

### 2. Method

This study presents two cases of stability assessment using ANFIS model both in surface and underground excavation. The first case is slope stability in which the data was collected from Chen et al. [1]. The data was based on a detailed investigation of 53 slopes in the vicinity of Kaili-Sansui highway in epimetamorphic rock region, at Guizhou Province of China. The second case is underground mining pillar stability [11]. Pillar case histories were collected from thirteen different mines. All of the pillars within the database are open stope rib pillars. Application of ANFIS to assess those two cases was performed by dividing the data into two sets, namely training and checking data set. Training data set was used to build ANFIS training of the case. Checking data set was used to know the reliability of ANFIS training instability prediction/stability assessment. Error testing for data
checking represents the ability of ANFIS models/training to assess stability. The smaller the error checking, the better the stability assessment produced. It means the higher the level of reliability of the model.

2.1. Data collection for slopes
Data from highway slope as reported by Chen et al. was used for applying the ANFIS model. Slopes data was divided into two parts, 41 for training data set and 12 for checking data set [1]. Descriptive statistics and checking data sets for slopes can be seen in Table 1 and Table 2.

Table 1. Descriptive statistics for slope data

| Input variable       | Training data set | Checking data set |
|---------------------|-------------------|------------------|
|                     | Min   | Max   | Mean  | Min   | Max   | Mean  |
| Bulk density (kN/m³)| 20    | 27.4  | 23.8  | 19.6  | 26.5  | 24.3  |
| Height (m)          | 10    | 99    | 46.5  | 30    | 68    | 46.3  |
| Inclination (°)     | 10    | 50    | 32.5  | 20    | 50    | 33.3  |
| Cohesion (kPa)      | 6.5   | 44    | 33    | 15.4  | 43.8  | 35.7  |
| Internal friction angle (°) | 19 | 38 | 29.4 | 21 | 38 | 31.8 |

2.2. Data collection for pillars
Data of underground mining pillar under consideration is presented in Hudyma (1998) as is quoted by Lunder (1994). This study takes stable and failed pillars cases from the data. Thirty training data set and eight checking data set were applied in the model [11] shown in Table 3 and Table 4.

Table 2. Checking data ANFIS for slope

| Code | Bulk density (kN/m³) | Height (m) | Inclination (°) | Cohesion (kPa) | Internal friction angle (°) | Slope stability |
|------|----------------------|------------|-----------------|----------------|-----------------------------|-----------------|
| 1    | 19.6                 | 58         | 40              | 29.6           | 23                          | 0               |
| 2    | 25.4                 | 35         | 20              | 33             | 33                          | 1               |
| 3    | 22.4                 | 50         | 50              | 29.3           | 26                          | 0               |
| 4    | 26.2                 | 30         | 35              | 41.5           | 36                          | 1               |
| 5    | 26.2                 | 36         | 23              | 42.3           | 36                          | 1               |
| 6    | 25.6                 | 32         | 30              | 39.8           | 36                          | 1               |
| 7    | 25.6                 | 60         | 35              | 36.8           | 34                          | 1               |
| 8    | 26.2                 | 37         | 30              | 42.8           | 37                          | 1               |
| 9    | 26.2                 | 68         | 35              | 43.8           | 38                          | 1               |
| 10   | 20.6                 | 42         | 30              | 32.4           | 26                          | 0               |
| 11   | 26.5                 | 54         | 42              | 41.8           | 36                          | 1               |
| 12   | 20.8                 | 53         | 30              | 15.4           | 21                          | 0               |

Table 3. Descriptive statistics for pillar data

| Input variable       | Training data set | Checking data set |
|---------------------|-------------------|------------------|
|                     | Min   | Max   | Mean  | Min   | Max   | Mean  |
| Pillar ratio        | 0.31  | 4.5   | 1     | 0.5   | 2.2   | 1     |
| Estimated pillar (Mpa) | 26  | 102   | 44    | 26    | 75    | 52    |
| Pillar width (m)    | 9     | 45    | 22    | 11    | 33    | 22    |
| Stope height (m)    | 34    | 170   | 92    | 50    | 135   | 86    |
| Pillar height (m)   | 4     | 53    | 23    | 11    | 40    | 27    |
Table 4. Checking data ANFIS for pillar

| NO | Pillar ratio | Estimated pillar (Mpa) | Pillar width (m) | Step height (m) | Pillar height (m) | Depth (m) | Extra ratio | CSIR (RMR) | UCS (Mpa) | Pillar stability |
|----|--------------|------------------------|------------------|----------------|------------------|------------|-------------|-------------|-----------|-----------------|
| 1  | 0.55         | 69                     | 11               | 50             | 20               | 1000       | 0.5         | 64          | 121       | 0               |
| 2  | 2.18         | 66                     | 24               | 90             | 11               | 870        | 0.59        | 75          | 148       | 1               |
| 3  | 0.68         | 38                     | 27               | 120            | 40               | 300        | 0.68        | 71          | 176       | 0               |
| 4  | 0.75         | 57                     | 30               | 105            | 40               | 300        | 0.84        | 71          | 176       | 0               |
| 5  | 1.25         | 33                     | 15               | 135            | 12               | 210        | 0.75        | 71          | 176       | 1               |
| 6  | 0.54         | 26                     | 21               | 75             | 39               | 210        | 0.63        | 71          | 176       | 1               |
| 7  | 1.43         | 75                     | 33               | 55             | 23               | 620        | 0.25        | 78          | 316       | 1               |
| 8  | 0.50         | 49                     | 14               | 60             | 28               | 340        | 0.7         | 68          | 90        | 0               |

2.3. Applications of the ANFIS method

ANFIS model was applied for slope and pillar stability cases. This study presents more than one practical approach/simulation in term of input variable and type of membership function (MF) in the model. A different number of input variables was used in each case. Less number of variables was applied as a comparison to the sufficient number of data conditions. It represents limited data in the field and laboratory test. Analysis and discussion were performed to understand the result of ANFIS model. The grid partition method was utilized to generate the training structure, and the hybrid learning rule was employed in the learning procedure. The output variables represent the stability of the slopes and pillars, 1 for stable and 0 for failed. Data were divided into two separate sets that are training data set and checking data set. Checking data set was applied in the process to know the accuracy and the effectiveness of the trained ANFIS model.

3. Result and Discussion

3.1. Slope stability case

Based on the same data which used by Chen et al., this paper presents some different practical approaches in term of the input variable, type of membership function and number of membership function in the model. In the work of Chen et al. the data was analyzed using ANFIS. It only used five input variables and the Gaussian membership function. It means usability of 4 input variables was not performed. In this study, the architecture of ANFIS model applied 5 and 4 input variables. Each input variable has two and three membership functions of Triangular and Trapezoidal-shaped type [1]. Result of ANFIS model for slope stability case is shown in Table 5.

According to Table 5, 5 input variables were applied in ANFIS1 (simulation 1.1 – 1.4). Training and testing error of every type and number of MF is also presented in Table 5. Resulted from this model, most significant testing error has resulted from Triangular-shaped type of MF with 2*2*2*2*2 number of MF. The smallest testing error was resulted from Triangular-shaped type of MF, with 3*3*3*3*3 number of MF. In this model, 3*3*3*3*3 number of MF gives less error testing.

Reducing the number of input variables was conducted in ANFIS2 model (simulation 1.5 – 1.8). It was performed to know the effect on testing error if bulk density is not used as the input variable. Numerical attributes for output were the same with ANFIS1, 1 for stable and 0 for failed. Result of the ANFIS2 in term of training and testing error of every type and number of MF is presented in Table 5.
According to Table 5, Triangular-shaped with 3*3*3*3 number of MF has the most significant testing error. While Trapezoidal-shaped with 2*2*2*2 numbers of MF has the smallest testing error.

Table 5 shows that the number of input variables, type, and number of MF reports different result for error checking of ANFIS. In case of 5 variables, for Triangular-shaped type of MF, an increase in the number of MF produced significant differences (improve to better value) in error checking data. Triangular-shaped type of MF with number of MF 2*2*2*2*2 produced error of 2.393, significant if compared with error value resulted from number of MF 3*3*3*3*3. Trapezoidal-shaped type of MF reported that an increase in the number of MF produced no significant different value of error checking. A different result was reported for 4 variables case. Smaller error checking has resulted from less number of MF. Triangular-shaped type of MF with number of MF 2*2*2*2 produced error of 0.164, number of MF 3*3*3*3 produced error of 0.376. Trapezoidal-shaped type of MF with number of MF 2*2*2*2 produced error of 0.095, number of MF 3*3*3*3 produced error of 0.151.

The results of these tests indicate that the most critical factors in achieving excellent performance are type of MF, number of MF and number of input variable. Every addition for number of MF not automatically give good error result. Evaluation of the model based on error checking plays an important rule. Type and number of MF which produces smallest error checking are chosen as the best model. More than one ANFIS simulation give alternatives to produce the best performance of ANFIS simulation, and it can be used to assess the slope stability under consideration.

### Table 5. The ANFIS structure information for slope stability case

| Number of trial simulation | 1.1 | 1.2 | 1.3 | 1.4 | 1.5 | 1.6 | 1.7 | 1.8 |
|----------------------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Number of input            |     |     |     |     |     |     |     |     |
| Input combination          | 5   | 4   |     |     |     |     |     |     |
| Number of membership      | 2*2*2  | 3*3*3  | 2*2*2  | 3*3*3  | 2*2*2*2  | 3*3*3*3  | 2*2*2*2  | 3*3*3*3  |
| Functions (MF)             | *3*3  | *3*3  | *3*3  | *3*3  | *3*3  | *3*3  | *3*3  | *3*3  |
| Type of membership        | Triangular | Trapezoidal | Triangular | Trapezoidal | Triangular | Trapezoidal | Triangular | Trapezoidal |
| Function                  |     |     |     |     |     |     |     |     |
| Training data set         | 41  | 41  |     |     |     |     |     |     |
| Checking data set         | 12  | 12  |     |     |     |     |     |     |
| Epoch number              | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Number of fuzzy rules     | 32  | 243 | 32  | 243 | 16  | 81  | 16  | 81  |
| Error training            | 0.0187 | 0.000011 | 0.0007 | 0.0002 | 0.122 | 0.0013 | 0.061 | 0.042 |
| Average testing error     | 2.393 | 0.017 | 0.069 | 0.056 | 0.164 | 0.376 | 0.095 | 0.151 |

The results show that 53 data sets in which 80% data for training and 20% data for testing are reliable to be applied in the ANFIS model. Those amounts of data set are a powerful tool for modeling the problem of slope stability in rock mechanics engineering issues. This result gives valuable information to face the next problem of slopes stability particularly in amount of data set issues. The amount of data in the field can be more or less than 53 data, but through the selection of type and number of MF, as shown by this study, the excellent performance of ANFIS can be produced.

Reducing the number of input variables can produce good error value. It indicates that involvement less number of input variables (4 input variables) based on the selection of type and number of MF still can obtain a proper error checking. It gives valuable information related to utilization of those 4 variables in different cases. Those 4 input variables are height, inclination, cohesion, and internal...
friction angle. The last two variables are soil and rock properties that basically can be determined through direct shear test (widely known kind of test) in the laboratory.

3.2. Pillar stability case

Eight and 3 input variables were applied in the ANFIS model for pillar stability case. Each input variable has two and or three membership functions of Triangular and Trapezoidal-shaped type of MF.

The grid partition method was utilized to generate the training structure, and the hybrid learning rule was employed in the learning procedure. Result of ANFIS model for pillar stability case (ANFIS3 and ANFIS4) is shown in Table 6. ANFIS3, simulation 2.1 – 2.4, applied 8 input variables. Training and testing error of every type and number of MF is also presented in Table 6. From the simulation result, the biggest testing error has resulted from Trapezoidal-shaped type of MF with 2*2*2*2*2*2*2*2 number of MF for input variable. The smallest testing error has also resulted from Trapezoidal-shaped type of MF with 2*2*3*2*2 *2*2*3 number of MF for input variable.

ANFIS4, simulation 2.5 – 2.8, applied 3 input variables, it was performed to know the effect on testing error. The number of training and checking data sets used the same approach with ANFIS3. Three input variables represent the limited data condition in the field. Data acquisition is strongly related to site-specific. It is not probable to get all of variables which were applied in ANFIS3 in every project. Applying 3 (three) input variables gives an alternative approach to face the problem of limited data condition in field project.

Table 6. The ANFIS structure information for pillar stability case

| Number of trial simulation | 2.1 | 2.2 | 2.3 | 2.4 | 2.5 | 2.6 | 2.7 | 2.8 |
|----------------------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Number of input            | 8   |     |     |     |     |     |     |     |
| Input combination          | Estimated pillar, Pillar width, Stope height, Pillar height, Depth, Extra ratio, CSIR (RMR) and UCS | Pillar Ratio (Pillar width/Pillar height), Estimated pillar and UCS |
| Number of membership functions membership type | 2*2*2*2 | 2*2*3*2 | 2*2*2*2 | 2*2*3*2 | 2*2*2*2 | 2*2*3*2 | 3*3*3 | 2*2*2 | 3*3*3 |
| Training data set          | Triangular | Trapezoidal | Triangular | Trapezoidal |
| Checking data set          | 30   | 30   | 8    | 8    |
| Epoch number               | 100  | 100  | 50   | 50   | 100  | 100  | 100  | 100  |
| Number of fuzzy rules      | 256  | 256  | 576  | 576  | 8    | 27   | 8    | 27   |
| Error training             | 0.0004 | 0.0002 | 0.00003 | 0.00003 | 0.282 | 0.159 | 0.312 | 0.194 |
| Average testing error      | 0.549 | 0.552 | 0.627 | 0.448 | 0.329 | 1.489 | 0.427 | 1.156 |

The ANFIS simulations based on the number of input variable, type and number of MF report different result for error checking. In case of 8 variables, for Triangular-shaped type of MF, an increase in the number of MF produced no differences in error checking. Error difference between two models of Trapezoidal-shaped (simulation 2.3 and 2.4) was found, but it was not large enough. Three input variables simulation showed the result that less number of MF gave more good error checking value. The results show that the simulation-based on number of variables, type, and number of MF can give the chance to reach proper error checking. The results of simulation 2.1 – 2.4 indicate that a slight
change in number of MF will not have much effect on the error checking. While changing all number of MF, simulation 2.5-2.8, can give the significance different in error checking. Every addition for number of MF and number of input variables is not automatically produced good error result. Excellent performance of the 3 input variables in the model provides valuable information. Three input variables in the pillar case gave more good error result than 8 input variables. It can be stated that implementation 3 input variables based on selection of type and number of MF can give better error value.

4. Conclusion
This study shows that the ANFIS model can be performed as a powerful tool for modeling some problems involved in slope and pillar stability issue. The most important factors in achieving excellent performance of ANFIS are type of MF, number of MF and number of input variables. The results show that simulation of type and number of MF can give the chance to reach proper error checking. Every addition and change for number and type of MF not automatically give good error result. Considering error checking as a basis for evaluation, type and number of MF simulations can show the best results by comparing more than one simulation. Involvement of less number input variable based on selection of type and number of MF still can obtain a proper error checking. Proper performance of the 4 input variables in slope case and 3 input variables in pillar case provides valuable information for stability assessment using ANFIS. Four input variables in the slope case still can produce good error result. Three input variables in the pillar case gave more good error result than 8 input variables. It should be stated that the implementation of 4 and 3 input variables applied in the ANFIS model based on selection of type and number of MF can give excellent and better error value.

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