Determination of the height of destressed zone above the mined panel: An ANN model

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ABSTRACT

The paper describes an artificial neural network (ANN) model to predict the height of destressed zone (HDZ) which is taken as equivalent to the combined height of caved and fractured zones above the mined panel in longwall mining. For this, the suitable datasets have been collected from the literatures and prepared for modeling. The data were used to construct a multi-layer perceptron (MLP) network to approximate the unknown nonlinear relationship between the input parameters and HDZ. The MLP proposed model predicted values in enough agreements with the measured ones in a satisfactory correlation, in which, a high conformity (R²=0.989) was observed. To approve the capability of proposed ANN model, the obtained results are compared to the results of the conventional regression analysis (CRA) method. The calculated performance evaluation indices show the higher level of accuracy of the proposed ANN model compared to CRA. For further evaluation, the ANN model results are compared with the results of available models and in-situ measurements reported in literatures. Comparative results present a logical agreement between ANN model and available methods. Obtained results remark that the proposed ANN model is a suitable tool in HDZ estimation. At the end of modeling, the parametric study shows that the most effective parameter is unit weight whereas elastic modulus is the least effective parameter on the HDZ in this study.

Keywords: Height of destressed zone; Artificial neural network; Conventional regression analysis; Parametric study

1. Introduction

Longwall mining is the most important underground mining method that widely used in a large scale. This method involves the complete removal of large rectangular panels of coal seams and minerals. The key problem of longwall mining is to control overburden strata and estimation of induced stress due to mining. In other words, the main objective of longwall mining is to removal coals and minerals from the ground in a safely and economically way. In this method, the mineral extraction within a large panel width causes a downward movement of the immediate roof rock strata above the mined panel. Consequently, the roof strata collapse and cave within the goaf area. This process continues and gradually extends upward and causes the disturbed roof strata to become destressed. As a result, the stress due to overburden weight above the destressed zone (DZ) will be transferred towards the surrounding gates and pillars as well as to the front abutment. Generally, the height of disturbed or the height of destressed zone (HDZ) area above the mined panel depend on the many parameters such as overburden depth, extracted ore thickness or mining height, panel width, the roof rock strata strength properties, bulking factor and so on [1-4].

A principle concern of longwall mining researchers is to establish a suitable approach to evaluate the panel roof strata behaviour during and after the panel extraction. Because of this, Failure mechanisms and breakage characteristics of mined panel roof strata and process of gradual extension of upward movement are considerably investigated by many investigators [1, 2]. Accordingly, there are several methods to evaluate the progressive fracturing and caving of panel roof rock strata including in-situ measurement and physical, empirical, numerical and analytical modeling that are referred completely by [1] and [2]. Although physical model and in-situ measurements are the high-precision methods but they are time consuming and expensive due to intrinsic complication of the implementation. Empirical methods cannot be competent for all cases because they have been generally constructed based on the data extracted from a specific case study with a particular characteristic [5]. Numerical modeling is a common used method in estimation of the roof rock strata fracturing and caving...
processes. However, this method requires a large number of input parameters, may need to be approximated or assumed [6]. Among the aforementioned methods, analytical modeling is a simple and inexpensive method but it is also based on the numerous assumptions that may increase the estimation error.

Considering the abovementioned demerits of the available methods for estimation of the failure mechanism of the roof rock strata above the mined panel, adopting other alternatives to overcome these problems is seems to be necessary. Intelligence predictive systems can be the appropriate approaches in this regard. The artificial neural networks (ANNs) are considered to be one of the most suitable tools to solve the complex systems. Due to its multidisciplinary nature, ANNs are becoming popular among researchers, planners, designers, etc., as an effective tool for the success of their works. These applications demonstrate that ANNs are efficient in solving problems in geosciences which many parameters influence the process [7-10]. Unlike the abovementioned available methods, the influence of all effective parameters can be simultaneously considered in determining the height of destressed zone. In this research, the height of destressed zone (HDZ) is considered as the combination of the height of the caved and the fractured zones in the roof rock strata above the mined panel. For proper evaluation of the amount of transferrable loads towards the adjacent access tunnels and to the intervening barrier pillars, the height of destressed zone (HDZ) must be estimated accordingly. Therefore, the main objective of this paper is to offer a reliable solution to the problem of HDZ estimation. For this purpose, a multilayer perceptron (MLP) neural network has been proposed and the obtained results are compared with the results of the conventional regression analysis (CRA) method.

2. Height of destressed zone

By extracted of the panel in longwall mining, the immediate roof strata are allowed to move downward. A downward movement of the roof rock causes the disturbing of strata the original natural in-situ stress regime and the hydraulic conductivity. Hence the roof strata will collapse and fall into the extracted panel space. Depending up on the volume expansion of the fractured rocks, the movements will gradually influence the rock layers above the immediate roof strata. The downward movement of the roof strata then gradually extends upwards and will cause the disturbed roof strata to become destressed [1, 2].

Height of destressed zone is the most important factor in determining the transferred loads towards the front abutments and panel rib-sides in which the gates and pillars are situated. In general, there are three distinct zones of movement in the roof rock strata above the longwall panels including caved, fractured and bending continuous deformation zones that are shown in Fig. 1 [11]. As previously mentioned, the height of destressed zone is considered as the combination of the height of caved and fractured zones that are clearly presented in Fig 1.

Since a comprehensive literature review of this work is given by [1] and [2] in detail then only the methods and their resulted data are given here. Rounding up the abovementioned comprehensive literature review, there are various empirical, mathematical, numerical and physical models as well as in-situ measurements to predict the height of caved and fractured/destressed zones. Results of as in-situ measurements, analytical, numerical and empirical models presented by different researchers to calculate the height of destressed zone in addition to the results of energy model proposed by Rezaei et al. [2] are shown in Table 1. In this Table, the results (height of destressed zone) are determined based on the coefficient of the extracted coal seam thickness (hd).

<table>
<thead>
<tr>
<th>Method of appraisal</th>
<th>HDZ (×105)</th>
</tr>
</thead>
<tbody>
<tr>
<td>In-situ measurement</td>
<td>2-100</td>
</tr>
<tr>
<td>Empirical model</td>
<td>2.105</td>
</tr>
<tr>
<td>Analytical model</td>
<td>4.5-48</td>
</tr>
<tr>
<td>Numerical model</td>
<td>5.8-476</td>
</tr>
<tr>
<td>Time-independent Energy model</td>
<td>202-578</td>
</tr>
</tbody>
</table>

3. Methodology

As mentioned before, artificial neural network (ANN) method is used to modeling in this research. The basic concept of ANNs can be found in numerous literatures [12-24]. Therefore, only the methodology and the procedure of modeling are described here. In ANN models, training of the network must be implemented before expecting any reliable information out of it. Feed-forward back-propagation algorithm is one of the most efficient approaches, compared to various available algorithms for training the neural networks. Back-propagation (BP) algorithms are capable in solving of complex problems that makes them so popular. Back-propagation multilayer neural networks consist of at least three different layers including input, hidden, and output layers. Each layer consists of a number of elementary processing units, called neurons and each neuron is connected to the next layer through weights. For example, neurons in the input layer will send their outputs as input to neurons in the hidden layer. This process is continued to output layer of the system. Number of hidden layers and respective neurons depend on the complexity of problem being studied [9, 21].

Developing of the back-propagation networks composed of three steps including of network architecture defining, training the network and testing of it. Feed-forward networks often have one or two hidden layers of sigmoid neurons followed by an output layer of linear neurons as shown in Fig 2. To differentiate between the various processing units, values called biases are set up into the transfer functions. All neurons in the back-propagation network are associated with a bias neuron and a transfer function, except for the input layer. Transfer functions are used to filter the weighted sum of all input signals to a neuron and determine the neuron output strength. The bias is much like a weight, except that it has a constant input of 1, while the transfer function shifts the summed signals received from this neuron. The most commonly used transformation functions in ANN modeling are logistic sigmoid (LogSig) and hyperbolic tangent sigmoid (TanSig) functions [9, 13].

In the training stage, data are processed through the input layer, the hidden layer and so on until it reaches the output layer (forward pass). In this layer, the output is compared to 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 [22]. The input and output data are mainly represented as vectors called training pairs. 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) or sumed squared error (SSE). Considering the number of neurons in the hidden layers, it can be said that insufficient neurons can cause “underfitting”, whereas excessive neurons can result in “overfitting”. In the underfitting, the requisite accuracy of the modeling is not achieved, whereas in the overfitting, the
network performance would not be real because instead of realizing relationship between the patterns, network just remembers the patterns [9, 22].

The process of reaching the final result is important in neural network modeling which is outlined here. The \( k \)th neuron in hidden layer is connected with a number of inputs as [9, 23]:

\[
x_k = (x_{1k}, x_{2k}, x_{3k}, \ldots, x_{nk})
\]

The net input values in the hidden layer are calculated by

\[
Net_j = \sum_{i=1}^{n} w_{ij}x_i + \theta_j
\]

where \( x_i \) is the input units, \( w_{ij} \) is the weight on the connection of \( i \)th input and \( k \)th neuron, \( \theta_j \) is the bias neuron and \( n \) is the number of input units.

Considering the Eq. (2) and by the convenient transfer function, logarithmic sigmoid function, the net output from hidden layer is calculated as follows:

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

The total input to the \( k \)th unit is computed by this equation:

\[
Net_k = \sum_{j=1}^{m} w_{kj}O_j + \theta_k
\]

Where \( \theta_k \) is the bias neuron, \( w_{kj} \) is the weight between \( j \)th neuron in hidden layer and \( k \)th neuron.

Thus, the total output from \( k \)th unit will be:

\[
O_k = f(Net_k)
\]

During the learning process, the network is presented with a pair of patterns, an input pattern and a corresponding output pattern. The network computes its own output pattern using its weights and thresholds. Now, the actual output is compared with the desired output. Hence, the error for any output in layer \( k \) is calculated by this equation:

\[
e_k = t_k - O_k
\]

where \( t_k \) and \( O_k \) are the desired output and the actual output, respectively.

The total error function is acquired as follows:

\[
E = 0.5 \sum_{k=1}^{n} (t_k - O_k)^2
\]

### Table 2. Characteristic and symbols of input and output parameters used in the modelling.

<table>
<thead>
<tr>
<th>Type of data</th>
<th>Parameters</th>
<th>Symbols</th>
<th>Max</th>
<th>Min</th>
<th>Variance</th>
<th>Std dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input</td>
<td>Unit weight (KN/m²)</td>
<td>y</td>
<td>27.26</td>
<td>205</td>
<td>3.75</td>
<td>193</td>
</tr>
<tr>
<td></td>
<td>Unconfined compressive strength (MPa)</td>
<td>σ</td>
<td>115</td>
<td>1.85</td>
<td>608.97</td>
<td>24.67</td>
</tr>
<tr>
<td></td>
<td>Poisson ratio (·)</td>
<td>v</td>
<td>0.3</td>
<td>0.14</td>
<td>0.0015</td>
<td>0.0387</td>
</tr>
<tr>
<td></td>
<td>Overburden depth (m)</td>
<td>H</td>
<td>755</td>
<td>30</td>
<td>284466.7</td>
<td>118.66</td>
</tr>
<tr>
<td></td>
<td>Extracted coal seam thickness (m)</td>
<td>h</td>
<td>6</td>
<td>1.11</td>
<td>1192</td>
<td>1.092</td>
</tr>
<tr>
<td></td>
<td>Bulking factor (·)</td>
<td>b</td>
<td>1.5</td>
<td>1.07</td>
<td>0.029</td>
<td>0.171</td>
</tr>
<tr>
<td></td>
<td>Elastic modulus (GPa)</td>
<td>E</td>
<td>3775</td>
<td>0.5</td>
<td>8915</td>
<td>944.4</td>
</tr>
<tr>
<td>Output</td>
<td>Height of destressed zone (m)</td>
<td>HDZ</td>
<td>240</td>
<td>6.6</td>
<td>3818.89</td>
<td>61.79</td>
</tr>
</tbody>
</table>

### 5. Optimum ANN model for HDZ determination

To obtain an optimum neural network model architecture for HDZ determining, the model architectures is tested with various numbers of hidden layers and nodes, and the parameters are checked with various learning rules, training and transformation functions, learning rates, momentum rates and ANN models to find better values and architecture. The transformation function used is hyperbolic tangent sigmoid function, and the learning rule used for the ANN experiments is the delta rule. Therefore, different types of MLP based networks are examined based on the trial and error method in MATLAB software environment. For this purpose, the mean sum of squares of the network errors (MSE) which is a typical performance function usually used for training feed-forward ANNs is applied in the model as a measure of stopping the training process to prevent overfitting of the proposed model. The model with minimum MSE is selected as the optimum in the present modeling. Accordingly, MSE has been calculated for different types of the ANN models including models with one and two hidden layers having different number of neurons and other outlined characteristics and the obtained results are shown in Table 3. The MSE index is calculated by this equation [24]:

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (A_{\text{meas}} - A_{\text{pred}})^2
\]

where \( A_{\text{meas}} \) is the \( i \)th measured element, \( A_{\text{pred}} \) is the \( i \)th predicted element and \( n \) is the number of dataset.

**4. Preparing of database for modeling**

Providing sufficient number of data is one of the most important stages in ANN modeling. In this study, a vast collection of suitable dataset was prepared from the Iranian coalfields and comprehensive literature surveys that its results summarized in section 2 based on the researches conducted by the authors [1, 2]. For predicting the height of destressed zone using ANN and CRA models, 7 parameters comprising of overburden depth, extracted coal seam thickness, and unit weight, elastic modulus, Poisson ratio, unconfined compressive strength, bulking factor of rock mass were considered as input parameters. The average values of roof strata characteristics are being used for the input values. About 45 series of datasets have been collected for modeling in this research. To train and construct the models, prepared datasets have been divided into two groups of training and testing. Eighty percent (80%) of the datasets were utilized in training the ANN model and constructing the regression analysis and the rest 20% were used for testing the optimum models. It should be noted that a sorting method was utilized in selecting datasets for testing. These datasets are not utilized in training stage but kept only for testing and evaluating the models. The statistical characteristics of the input and output parameters along with their respective symbols are given Table 2.
As Table 3 indicates, a network with the characteristics shown in row 8 has got the minimum MSE. Accordingly, a feed-forward back-propagation MLP neural network with architecture 7-5-5-1, training function of trainlm Levenberg-Marquardt and LOGSIG transfer function is considered as the optimum ANN model to predict the HDZ. Fig. 2 shows a graphical presentation of the suggested MLP network.

<table>
<thead>
<tr>
<th>No</th>
<th>Network Architecture</th>
<th>Transfer Function</th>
<th>Training function</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7-10-1</td>
<td>LOGSIG</td>
<td>TRAINLM</td>
<td>0.221</td>
</tr>
<tr>
<td>2</td>
<td>7-10-1</td>
<td>TANSIG</td>
<td>TRAINGD</td>
<td>0.361</td>
</tr>
<tr>
<td>3</td>
<td>7-2-8-1</td>
<td>TANSIG</td>
<td>TRAINGD</td>
<td>0.0862</td>
</tr>
<tr>
<td>4</td>
<td>7-8-2-1</td>
<td>LOGSIG</td>
<td>TRAINLM</td>
<td>0.0721</td>
</tr>
<tr>
<td>5</td>
<td>7-7-3-1</td>
<td>TANSIG</td>
<td>TRAINGD</td>
<td>0.0698</td>
</tr>
<tr>
<td>6</td>
<td>7-3-7-1</td>
<td>LOGSIG</td>
<td>TRAINGD</td>
<td>0.0543</td>
</tr>
<tr>
<td>7</td>
<td>7-5-5-1</td>
<td>TANSIG</td>
<td>TRAINLM</td>
<td>0.0151</td>
</tr>
<tr>
<td>8</td>
<td>7-5-5-1</td>
<td>LOGSIG</td>
<td>TRAINLM</td>
<td>0.0204</td>
</tr>
<tr>
<td>9</td>
<td>7-4-6-1</td>
<td>TANSIG</td>
<td>TRAINLM</td>
<td>0.0478</td>
</tr>
<tr>
<td>10</td>
<td>7-6-4-1</td>
<td>LOGSIG</td>
<td>TRAINGD</td>
<td>0.0434</td>
</tr>
</tbody>
</table>

To test and validate the optimum ANN model, about 20% of datasets were chosen randomly. These data were not used in network training. The results of the network are presented in this section to demonstrate the ANN model’s performance. Correlation coefficient between the predicted and measured values of HDZ is taken as the network performance measure. The prediction was based on the input datasets which has been discussed in the previous section. Fig. 3 showed the results of the optimum MLP model in terms of correlation coefficient (R) for training, validation and testing processes as well as the overall data. The model outputs (predicted HDZ) are plotted against the targets (measured HDZ). The best fit line is represented by a solid line. As seen, maximum values of R for training, validation, test and overall data are obtained 0.99, 0.91, 0.80 and 0.90, respectively, which indicates a high conformity between predicted and measured HDZ values. The trained MLP network is capable of a proper output whenever suitable inputs data are interred. The rate of changes in the error level during the iterations is shown in Fig. 4. As it can be seen, the MSE for training the network starts at a large value of 1.05 and decreases to a smaller value of 0.000056 that means the accurately learning of the network. According to the results, final values of MSE for training, validation and test processes are $5.61 \times 10^{-6}$, 0.00098 and 0.0071, respectively. As it can be seen from Fig. 4, by using the magnifying MSE curve during the training of the model, the best validation performance obtained at epoch 19 and the value of MSE is 0.0046 which shows a good level of performance of the model. Moreover, the change rates of the gradient, momentum rate and validation check for proposed MLP neural network model during learning are also presented in Fig. 5.

6. Conventional regression analysis

Conventional regression analysis (CRA) is a common statistical tool to investigate relationships between the dependent variables and the known independent variables. This method is carried out based on some experimental data. In other words, CRA can predict the output variables based on the corresponding input variables [25-27]. In this research, based on the CRA method, relationships between the output (HDZ) and input variables comprising of unit weight, unconfined compressive strength, Poisson ratio, overburden depth, extracted coal seam thickness, bulking factor and elastic modulus have been discussed. To generate the statistical relation on the basis of the same database as considered for training the MLP model, a Minitab16 statistical software package was used. Accordingly, the relation between independent variables (inputs) and dependent variable (HDZ) obtained as follows:

$$HDZ = -84.9 + 0.0165H + 8.87Y - 1.78E + 53\nu - 0.37\gamma + 30.2b + 1.13h$$ (11)

Fig. 2. Structure of suggested MLP model to predict the HDZ.

Fig. 3. Results of the optimum MLP model for HDZ prediction (dashed line is for R=1).

Fig. 4. The best validation performance of model during the training.
7. Comparative analysis

In this section, the prediction performance of both ANN and CRA models are firstly assessed and compared with the real values based on the statistical evaluation performance indices. Then, the proposed models results are compared with the results of previous models of HDZ prediction in terms of the coefficient of the extracted coal seam thickness.

7.1. Comparison of MLP and CRA models

To compare the results of the proposed models, root mean square error (RMSE), determination coefficient (R²), variant account for (VAF), mean absolute error (Ea) and mean relative error (Er) have been employed. The above mentioned performance indices are calculated using the following equations [26,27]:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\tilde{A}_{\text{meas}_i} - \tilde{A}_{\text{pred}_i})^2}
\]

\[
VAF = 100 \left(1 - \frac{\text{var}(\tilde{A}_{\text{meas}}) - \text{var}(\tilde{A}_{\text{pred}})}{\text{var}(\tilde{A}_{\text{meas}})}\right)
\]

\[
R^2 = \left[\frac{\sum_{i=1}^{n}(\tilde{A}_{\text{meas}_i} - \bar{A}_{\text{meas}})(\tilde{A}_{\text{meas}_i} - \bar{A}_{\text{pred}})}{\sum_{i=1}^{n}(\tilde{A}_{\text{meas}_i} - \bar{A}_{\text{meas}})^2}\right]^2
\]

\[
E_a = \left|\frac{\tilde{A}_{\text{meas}_i} - \tilde{A}_{\text{pred}_i}}{\tilde{A}_{\text{meas}_i}}\right| \times 100
\]

\[
E_r = \left|\frac{\tilde{A}_{\text{meas}_i} - \tilde{A}_{\text{pred}_i}}{\bar{A}_{\text{meas}} - \bar{A}_{\text{pred}}}\right| \times 100
\]

where, \(\tilde{A}_{\text{meas}_i}\) is the ith measured element, \(\tilde{A}_{\text{pred}_i}\) is the ith predicted element, \(n\) is the number of dataset, and \(\bar{A}_{\text{meas}}\) and \(\bar{A}_{\text{pred}}\) are the average of prediction and measured sets, respectively.

The values of models performance indices are calculated and presented in Table 4. This evaluation is based on the testing datasets (9 series) that were not incorporated in training and developing of the models. Also, determinate coefficient between the measured and predicted HDZ values obtained from MLP and CRA models are indicated in Figs. 6 and 7, respectively. Furthermore, Fig 8 illustrates measured values of HDZ as well as the values resulted from the MLP and CRA models for testing data. Considering the above comparisons, the performance of MLP model is much better than CRA model. Also, the predicted values by MLP model are in good agreement with the measured HDZ. Therefore, one conclude that the proposed ANN neural network can properly utilized to predict the height of destressed zone above the mined panel in underground longwall mining.

7.2. Comparison of proposed models with the previous models

As mentioned in section 2, there are several models to estimate the height of caved fractured/destressed zone in literature that their results are summarized in Table 1. Here, the results of proposed models are compared with the results of available models for HDZ prediction. Models obtained results are compared in terms of the coefficients of extracted coal seam thickness (h). For this purpose, the relationships between extracted coal seam thickness and predicted HDZ values resulted from MLP and CRA models are firstly calculated and shown in
Figs. 9 and 10, respectively. Then, the outputs are compared with the results of available models. It can be concluded from Figs. 8 and 9 that the MLP model predict HDZ in the ranges of 24 to 81.67 times the extracted coal seam thickness, whereas this coefficient is equal to 14-85 in CRA model. Comparison these results with the results of available model in Table 1 showed that lower limit of MLP model is quite close to the lower limit of empirical model and in-situ measurements. Also, the upper limit of this model is closer to the upper limit of empirical model and in-situ measurements compared to the other models but its upper limit is somewhat closer to the upper limit of empirical model and in-situ measurements as well as the MLP model. However, the lower limit of CRA model has the high difference with those of the other models. As it is seen from these comparisons, there is a good agreement between the MLP model and with the previous models especially with in-situ measurements. Accordingly, this technique can be successfully used to predict the HDZ above the mined panel in longwall mining to cover the related difficulties in this regard.

8. Parametric study

Since the calibration and assessment of the MLP neural network model are proved its prediction capability, a parametric study is conducted to evaluate the impact of the input parameters on the height of destressed zone (HDZ). For this purpose, the relative influence of each input variable on the HDZ is achieved by varying the desired parameter and keeping fixed values for the other input variables. The larger absolute value showed the higher effect of the corresponding input variable on the output. Accordingly, the relative effects of input parameters on the HDZ are shown in Fig. 11. As shown, the most and least effective parameters on the HDZ are unit weight and elastic modulus of rock mass, respectively.

9. Conclusion

In this study, a new predictive model based on the artificial neural network (ANN) has been developed for estimation of the height of destressed zone (HDZ) and obtained results are compared with the results of conventional regression analysis (CRA). Based on the trial and method error, MLP type of feed-forward back-propagation neural network with architecture 9:5:5:1, TRAINLM learning function and LOGSIG transfer function was found to be the optimum network. To evaluate the performance of the employed models, determination coefficient (R²), variance account for (VAF), mean absolute error (Ea), and mean relative error (Er) indices were used. The key results of this study are summarized as follows:

1- For the ANN model, R², VAF, RMSE, Ea, and Er were calculated 98.96 %, 97.21 %, 0.0162, 1.058 m, and 2.11 %, respectively. For the CRA model, the above mentioned indices were determined as much as 77.39 %, 78.11 %, 2.356, 6.81 m and 12.67 %, respectively. It was concluded that the ANN results are in a very close agreement with the measured values as compared to the CRA predictions.

2- Comparative analysis between the proposed models and available models for HDZ prediction was proved that the results of ANN model are in accordance with the results of previous models especially with the in-situ measurements and empirical models.

3- The parametric study of ANN result showed that rock mass unit weight and rock mass elastic modulus are the most and least effective variables on HDZ, respectively.

4- The key advantage of the proposed ANN model compared to the previous conventional models is that the possible effective parameters on the HDZ can be taken into account.

5- With regard to the aforementioned achieved results, it is concluded that the ANN model possesses a good capability in predicting the HDZ and provides a reliable result whenever it trained accurately. Therefore, this technique can be successfully utilized to predict the HDZ above the mined panels in longwall mining.

REFERENCES


