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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). This zones are usually considered to be equal to the combined height of caved and fractured zones above the mined panel in longwall mining. The suitable datasets were collected from the literatures to be used for modeling. The data were used to construct a multilayer perceptron (MLP) network to approximate the unknown nonlinear relationship between the input parameters and HDZ. The proposed MLP model predicted the values in enough agreements with the measured ones by a satisfactory correlation of R^2=0.989. To approve the capability of proposed ANN model, the obtained results are compared to that 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 were compared with the results of available models and the reported in-situ measurements in literatures. Comparative results present a logical agreement between ANN model and available methods. The results remark that the proposed ANN model is a suitable tool in HDZ estimation. At the end of modeling, the parametric study showed that the most effective parameter is the unit weight. The elastic modulus, on the other hand, is the least effective parameter on HDZ in this study.

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

1. Introduction

Longwall mining is the most common underground mining method that is widely used in 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 the overburden strata and to estimate the induced stress of mining. In other words, the main objective of longwall mining is to safely and economically remove coals and minerals from the ground. In this method, the mineral extraction within a panel of large width causes a downward movement of the immediate roof rock strata above the mined panel. Consequently, the roof strata collapse and cave within the excavated area. This process gradually continues and extends upward and causes the disturbed roof strata to become destressed. As a result, the stress due to the 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 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 concerns 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 the process of gradual extension of upward movement have been 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 discussed completely by [1] and [2]. Although physical model and in-situ measurements are of 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 are 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 numerous assumptions that may increase the estimation error.
Considering the abovementioned demerits of 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 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 and designers, as an effective tool for the success of their works. These applications demonstrate that ANNs are efficient in solving the geosciences problems in which many parameters influence the process [7-10]. Unlike these 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 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 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

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perceptron (MLP) neural network was proposed and the obtained results were compared with that of the conventional regression analysis (CRA) method.

2. Height of destressed zone

Having extracted the panel in longwall mining, the immediate roof strata are allowed to move downward. A downward movement of the roof rock disturbs the original natural in-situ stress regime and the hydraulic conductivity in strata. Hence, the roof strata will collapse and fall into the extracted panel space. Depending on the volume expansion of fractured rocks, the movements will gradually influence the rock layers above the immediate roof strata. 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.

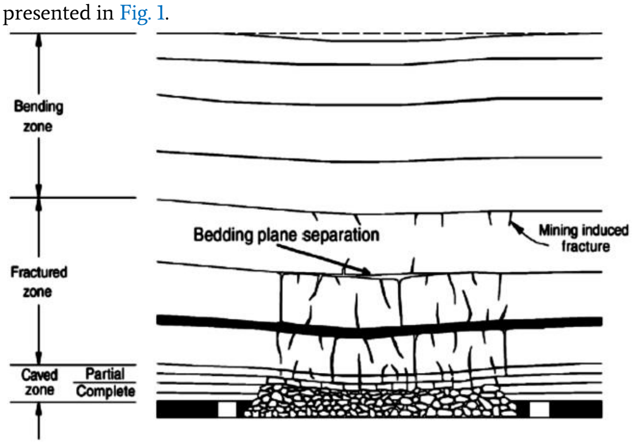

Fig. 1. Zones of overburden movement caused by longwall mining [11].

Since a comprehensive literature review of this work is given by [1] and [2], then only the methods and their resulted data are given here. In overall, in 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 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 described based on the coefficient of the extracted coal seam thickness (h_s).

Table 1. The results of available methods to predict the height of destressed zone as a coefficient of extracted coal seam thickness [2].

Method of appraisal	HDZ ($\times h_s$)
In-situ measurement	2-100
Empirical model	2-105
Analytical model	4.5-48
Numerical model	5.8-47.6
Time-independent Energy model	2.02-57.8

3. Methodology

Artificial neural network (ANN) method was used for 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 output reliable information. 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 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].

Development of the back-propagation networks is composed of three steps including of network architecture defining, training the network and testing. 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 introduced 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 summed 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 jth neuron in hidden layer is connected with a number of inputs as [9, 23]:

$$x_i = (x_1, x_2, x_3, \dots x_n) \tag{1}$$

The net input values in the hidden layer are calculated by

$$\mathrm{Net}_j = \sum_{i=1}^{n} x_i w_{ij} + \theta_j \tag{2}$$

where x_i is the input units, w_{ij} is the weight on the connection of i-th input and j-th neuron, θ_j is the bias neuron and n is the number of input units.

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

$$O_j = f(\mathrm{Net}_j) = \frac{1}{1 + e^{(\mathrm{Net}_j + q_j)}} \tag{3}$$

The total input to the k-th unit is computed by this equation:

$$\mathrm{Net}_k = \sum_{j=1}^{n} w_{jk} O_j + \theta_k \tag{4}$$

Where θ_k is the bias neuron, w_{jk} is the weight between j-th neuron and k-th neuron.

Thus, the total output from kth unit will be:

$$O_k = f(Net_k) \tag{5}$$

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:

$$e_t = t_k - O_k \tag{6}$$

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

The total error function is acquired as follows:

$$E = 0.5\sum_{k=1}^{n}(t_k - O_k)^2 \tag{7}$$

Basically, network training is a process of arriving an optimum weight space for the network. The steepest descent error surface is defined using the following equation:

$$\nabla W_{jk} = -\eta \frac{\delta E}{\delta W_{jk}} \tag{8}$$

where η and E are the learning rate parameter and error function, respectively.

The update of weights for the ($n+1$)-th pattern is:

$$W_{jk}(n+1) = W_{jk}(n) + \nabla W_{jk}(n) \tag{9}$$

Similar logic applies to the connections between hidden and output layers. This procedure is repeated with each pair of training case. Each pass through all training patterns is called a cycle or epoch. The process is then repeated as many epochs as needed until the error is within the user-specified goal [9, 23].

4. Preparing the database for modeling

Providing sufficient number of data is an important stage in ANN modeling. In this study, a vast collection of suitable dataset was prepared from the Iranian coalfields and comprehensive literature surveys and the results are summarized in section 2 based on the researchs conducted by 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 the 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 were 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. Statistical characteristics of the input and output parameters along with their respective symbols are given in Table 2.

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

Type of data	Parameters	Symbols	Max	Min	Variance	Std dev.
Input	Unit weight (KN/m^3)	γ	27.26	20.5	3.75	1.93
	Unconfined compressive strength (MPa)	σ	115	1.85	608.97	24.67
	Poisson ratio (-)	υ	0.3	0.14	0.0015	0.0387
	Overburden depth (m)	H	755	30	28446.67	118.66
	Extracted coal seam thickness (m)	h	6	1.11	1.192	1.092
	Bulking factor (-)	b	1.5	1.07	0.029	0.171
	Elastic modulus (GPa)	E	37.75	0.5	89.15	9.44
Output	Height of destressed zone (m)	HDZ	240	6.6	3818.89	61.79

5. Optimum ANN model for HDZ determination

To obtain an optimum neural network model architecture for HDZ determining, the model architectures were tested with various numbers of hidden layers and nodes, and the parameters were checked with various learning rules, training and transformation functions, learning rates, momentum rates and ANN models to find better values and architecture. The used transformation function was hyperbolic tangent sigmoid function, and the learning rule used for the ANN experiments was the delta rule. Therefore, different types of MLP based networks were 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 was applied in the model as a measure of stopping the training process to prevent overfitting of the proposed model. The model with minimum MSE was selected as the optimum in the present modeling. Accordingly, MSE was 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]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(A_{imeas} - A_{ipred})^2 \tag{10}$$

where A_{imeas} is the i-th measured element, A_{ipred} is the i-th predicted element and n is the number of dataset.

Table 3. Results of some networks with different characteristics for HDZ prediction.

No	Network Architecture	Transfer Function	Training function	MSE
1	7-10-1	LOGSIG	TRAINLM	0.221
2	7-10-1	TANSIG	TRAINGD	0.381
3	7-2-8-1	TANSIG	TRAINGDA	0.0862
4	7-8-2-1	LOGSIG	TRAINLM	0.0721
5	7-7-3-1	TANSIG	TRAINGD	0.0698
6	7-3-7-1	LOGSIG	TRAINGDA	0.0543
7	7-5-5-1	TANSIG	TRAINLM	0.0351
8	7-5-5-1	LOGSIG	TRAINLM	0.0204
9	7-4-6-1	TANSIG	TRAINLM	0.0478
10	7-6-4-1	LOGSIG	TRAINGD	0.0434

As Table 3 indicates, a network with the characteristics shown in row 8 owns 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 was considered as the optimum ANN model to predict the HDZ. Fig. 2 shows a graphical presentation of the suggested MLP network.

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 performance of ANN model. 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 was 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 input data are interred. The rate of changes in the error level during the iterations is shown in Fig. 4. As it can be seen, MSE for training the network starts at a large value of 1.05 and decreases to a smaller value of 0.000056 meaning accurately learning of the network. According to the results, final values of MSE for training, validation and test processes are 5.61×10^{5}, 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 the good 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.

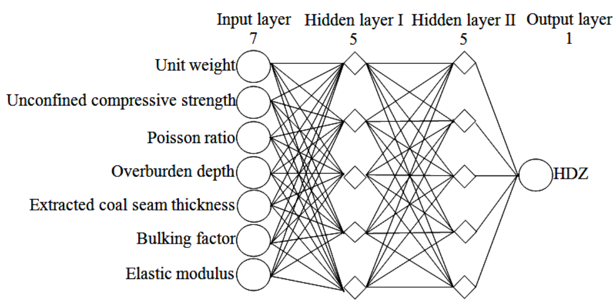

Fig. 2. Structure of suggested MLP model to predict the HDZ.

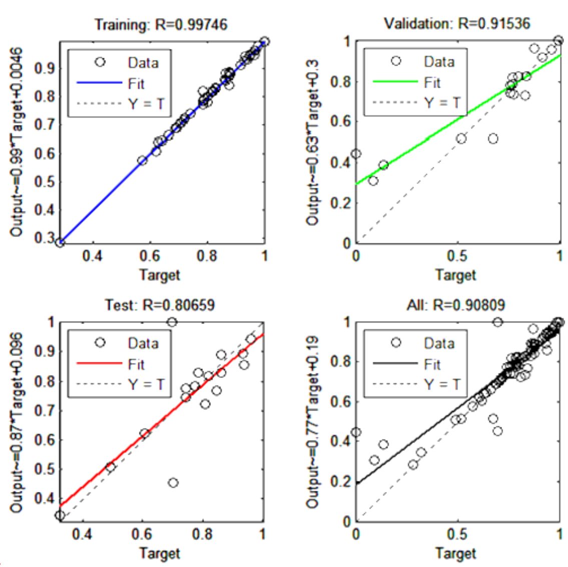

Fig. 3. Results of the optimum MLP model for HDZ prediction (dashed line is for R=1).

6. Conventional regression analysis

Conventional regression analysis (CRA) is a common statistical tool to investigate the relationships between the dependent variables and the known independent variables. This method is carried out based on 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, the relationships between the output (HDZ) and input variables comprising the unit weight, unconfined compressive strength, Poisson ratio, overburden depth, extracted coal seam thickness, bulking factor and elastic modulus are 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:

$$\mathrm{HDZ} = -84.9 + 0.0165\mathrm{H} + 8.8\mathrm{g} - 1.78\mathrm{E} + 53\mathrm{n} - 0.371\mathrm{s} - 30.2\mathrm{b} + 1.13\mathrm{h} \quad (11)$$

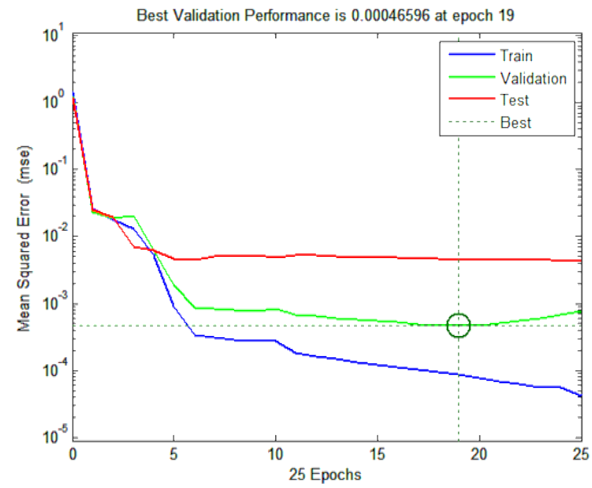

Fig. 4. The best validation performance of model during the training.

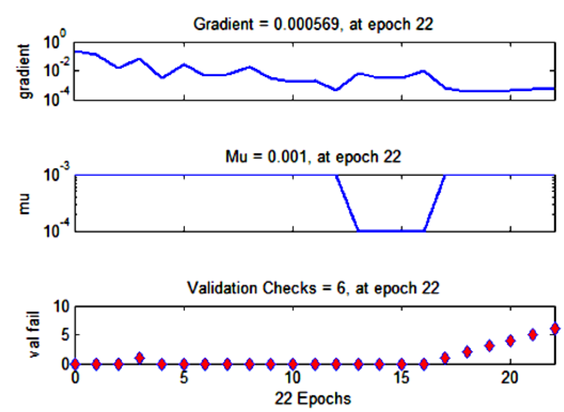

Fig. 5. Change rates of the network parameters for proposed MLP model during the training.

7. Comparative analysis

In this section, first of all, the prediction performance of both ANN and CRA models are assessed and then 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) were employed. The above mentioned performance indices are calculated using the following equations [26,27]:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_{imeas} - A_{ipred})^2} \quad (12)$$

$$\mathrm{VAF} = 100\left(1 - \frac{\mathrm{var}(A_{imeas} - A_{ipred})}{\mathrm{var}(A_{ipred})}\right) \quad (13)$$

$$R^2 = 100\left[\frac{\sum_{i=1}^{n}(A_{ipred} - \bar{A}_{pred})(A_{imeas} - \bar{A}_{meas})}{\sqrt{\sum_{i=1}^{n}(A_{ipred} - \bar{A}_{pred})^2 \sum_{i=1}^{n}(A_{imeas} - \bar{A}_{meas})^2}}\right]^2 \quad (14)$$

$$E_a = \left|A_{imeas} - A_{ipred}\right| \quad (15)$$

$$E_r = \left(\frac{\left|A_{imeas} - A_{ipred}\right|}{A_{imeas}}\right)\times 100 \quad (16)$$

where, A_{imeas} is the ith measured element, A_{ipred} is the ith predicted element, n is the number of dataset, and $\bar{A}_{ipred}$ and $\bar{A}_{imeas}$ 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 the CRA model. Also, the predicted values by MLP model are in good agreement with the measured HDZ. Therefore, one can 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.

Table 4. Performance indices of the proposed models.

Index	MLP Model	CRA Model
R^2	98.96 %	77.39 %
VAF	97.21 %	78.11 %
RMSE	0.0162	2.356
E_a	1.058 m	6.81 m
E_r	2.11 %	12.67 %

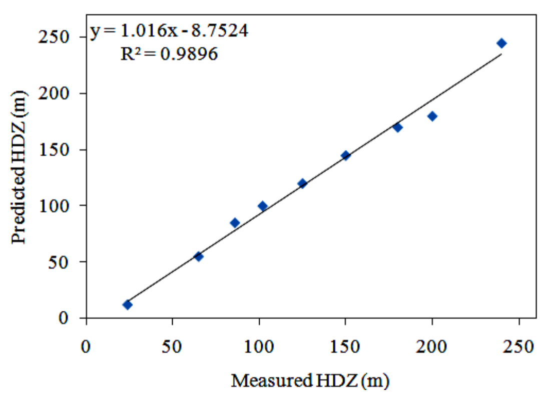

Fig. 6. Determination coefficient obtained for the MLP model.

7.2. Comparison of proposed models with the previous models

As mentioned in section 2, there are several models in the literature to estimate the height of caved fractured/destressed zone that the results of which are summarized in Table 1. Here, the results of proposed models are compared with the results of available models for HDZ prediction. The results obtained from the models werecompared 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 were calculated and are shown in Figs. 9 and 10, respectively. Then, the outputs were compared with the results of available models. Figs 8 and 9 revealed that the MLP model predict HDZ in the ranges of 2.4 to 81.67 times the extracted coal seam thickness, whereas this coefficient is equal to 14-85 in CRA model. Comparing these results with the results of available model in Table 1 showed that the lower limit of MLP model is quite close to the lower limit of empirical model and the in-situ measurements. Also, compared to the other models, the upper limit of this model is closer to the upper limit of empirical model and the in-situ measurements but its upper limit is somewhat closer to the upper limit of empirical model and the in-situ measurements as well as the MLP model. However, the lower limit of CRA model has a high difference with that 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.

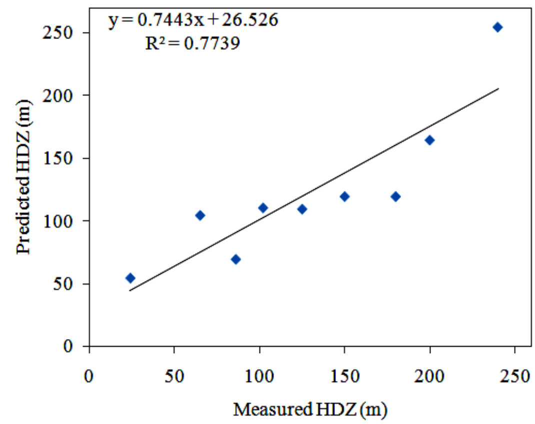

Fig. 7. Determination coefficient obtained for the CRA model.

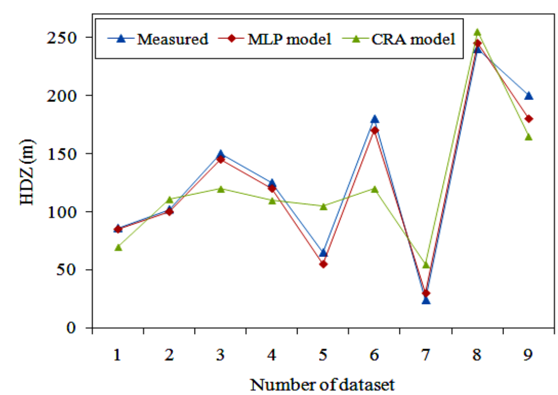

Fig. 8. Comparison of measured and predicted HDZ for different series of dataset.

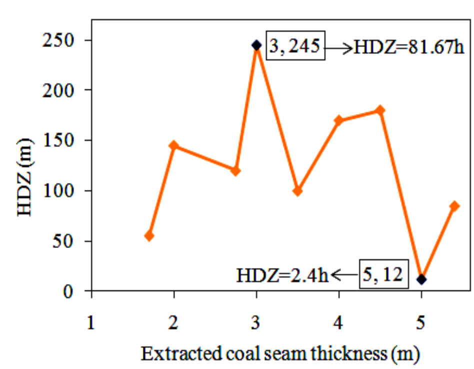

Fig. 9. Relationship between HDZ and extracted coal seam thickness for MLP model.

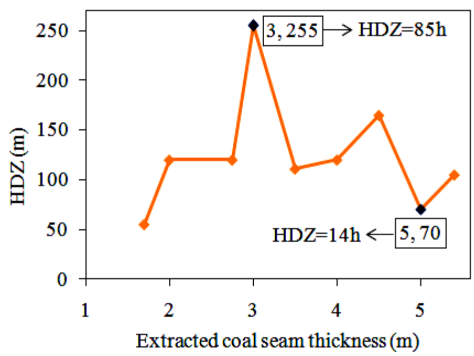

Fig. 10. Relationship between HDZ and extracted coal seam thickness for CRA model.

8. Parametric study

Since the calibration and assessment of the MLP neural network model proved its prediction capability, a parametric study was 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 was 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 the unit weight and elastic modulus of rock mass, respectively.

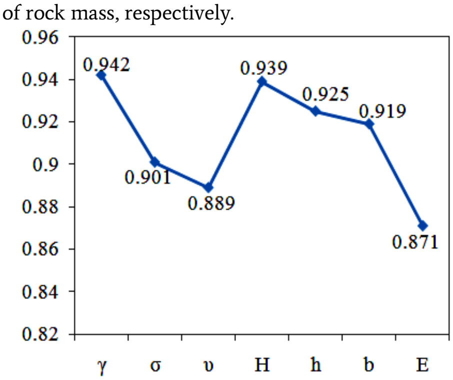

Fig. 11. Relative effects of input parameters on the HDZ

9. Conclusion

In this study, based on the artificial neural network (ANN), a new predictive model was developed for estimation of the height of destressed zone (HDZ) and the obtained results were compared with the results of conventional regression analysis (CRA). Based on the trial and error method, MLP type of feed-forward back-propagation neural network with architecture 9-5-5-1, TRAINLM learning function and LOGSIG transfer function were found to be the optimum networks. To evaluate the performance of the employed models, determination coefficient (R^2), variance account for (VAF), mean absolute error (E_a) and mean relative error (E_r) indices were used. The key results of this study are summarized as follows:

1) For the ANN model, R^2, VAF, RMSE, E_a and E_r were calculated to be 98.96 %, 97.21 %, 0.0162, 1.058 m and 2.11 %, respectively. For the CRA model, the above mentioned indices were 77.39 %, 78.11%, 2.356, 6.81 m and 12.67 %, respectively. It is concluded that the ANN results are in a 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 proves 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 shows that the 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 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 is trained accurately. Therefore, this technique can be successfully utilized to predict the HDZ above the mined panels in longwall mining.

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