Analysis of coal rib fracture depth using numerical modeling and artificial neural network

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Abstract: The failure of coal ribs is a major hazard in underground coal mines. Researchers from the National Institute for Occupational Safety and Health (NIOSH) have been working on the development of an engineering-based rib control method. A user-friendly standalone application, called Design of Rib Support (DORS), is being developed to ease the calculations of rib support. DORS can estimate the Primary Rib Support Density (PRSD, ton/ft^2) for development loading. However, it still needs to take account of another key factor, bolt length, in rib support design. The bolt length can be estimated from the rib fracture depth, and this study focuses on the coal rib fracture depth analysis with numerical modeling and artificial neural network. A total of 331 FLAC3D simulations with different mining scenarios and rib conditions were conducted for this study. Machine learning was then used to predict coal rib fracture depth under different conditions. Based on the numerical simulations, the parameters for mining scenarios and rib conditions were collected as features for machine learning, and coal rib fracture depths were collected as the target to predict. Good data correlation (r-square) was obtained with the use of an artificial neural network. The results from this study will improve the DORS application as a ground control tool for mining engineers.

1. Introduction

The failure of coal pillar ribs is a major hazard in underground coal mines. According to the Mine Safety and Health Administration (MSHA) statistics during the 10-year period between 2010 and 2019, rib-fall accidents contributed to 45.2% of the ground-fall fatalities (Rashed et al. 2022). Extensive studies have been conducted to identify the contributing factors, to develop analysis methods, and to design effective rib support (Bauer and Dolinar 1999; Colwell 2004; Mark et al. 2009; Pappas and Mark 2012; Jones et al. 2014; Zhang et al. 2017; Mohamed et al. 2019, 2020a, 2020b, 2021; Xue and Mohamed 2021). However, rib falls contribute to more fatalities than any other ground falls due to the more challenging conditions such as increasing overburden depth, multiple-seam interactions, thinner coal beds, and thicker partings (Mohamed et al. 2020b). To eliminate the injuries and fatalities due to rib falls in underground coal mines, NIOSH researchers are currently developing an engineering-based rib control method based on the proposed hybrid numerical-empirical approach.

Rib stability can be assessed by determining the load applied to the coal pillar rib and the bearing capacity of the rib. Coal pillar rib rating (CPRR) has been developed to quantify the bearing capacity of coal pillar ribs by considering the influence of various factors on coal pillar rib stability, including coal strength, coal unit thickness, bedding condition, homogeneity, face cleat orientation with respect to entry direction, and various rock parting parameters. CPRR is a rating technique with rating values varying from 1 to 100. A CPRR of 1 represents the weakest coal rib and a CPRR of 100 represents the strongest rib. There are three types of coal ribs observed in underground coal mines: (1) solid coal ribs with or without thin rock partings, (2) coal ribs with in-seam rock partings (greater than 6 in), and (3) coal ribs with a brow. CPRR was first developed for solid coal ribs (Type 1) based on the parametric study on solid coal ribs (Mohamed et al. 2020b). It was then extended to include the analysis of coal ribs with in-seam rock partings (Type 2) (Mohamed et al. 2021). Coal ribs with brows (Type 3) are still being studied.

Overburden depth is a good indicator of the induced load on the ribs. A simple relationship has been established to calculate rib factor of safety (RibFOS) with CPRR and overburden depth. Based on the surveyed data, rib support is necessary to reinforce the failing coal ribs when RibFOS is less than 1.5, and the relationship between RibFOS and PRSD was established to help determine the requirement of rib support density (Mohamed et al. 2021). When a RibFOS less than 1.5 is obtained, the required PRSD can be determined. However, one key parameter is still missing in the rib support design with PRSD. PRSD is calculated with various factors, including anchorage capacity of rib bolt, the number of bolts per vertical bolt row, the bolt spacing between the vertical rows, and mining height. For a determined value, PRSD can be obtained through different combinations of these factors. For example, the bolt spacing or the number of bolts per vertical row can be reduced when longer bolts are used. As a result, the determination of rib bolt length is critical in rib support design after PRSD is determined. In addition, rib bolts should be installed in stable coal mass to reinforce the failing ribs. This indicates that rib bolts should be longer than the rib fracture or softening depth, which represents the minimum length requirement for rib bolts. Therefore, the rib fracture depth analysis provides the logic for the determination of rib bolt length.

In this paper, rib fracture depth was analyzed with numerical simulation and artificial neural networks. First, the development of CPRR, PRSD and DORS was briefly introduced to show the background for rib support design with these new techniques. Second, the approach of using numerical simulations to analyze rib fracture depth was described. It includes the setup of the model, detail of the parametric study, and the method of defining rib fracture depth. After simulations, the parameters potentially affecting rib stability and the associated rib fracture depth were collected to generate a database for input to artificial neural networks. Finally, the data collected from numerical simulations were used to train an artificial neural network, which can be further used to predict the rib fracture depth.

2. Rib support design with CPRR, PRSD, and DORS

The rib support design with CPRR is a hybrid numerical-empirical approach. The numerical approach is mainly used for the development of CPRR to quantify the bearing capacity of coal pillar ribs. A total of 3,048 FLAC3D models have been run with different rib compositions, mining height and overburden depth. RibFOS can be determined for each case and CPRR is calculated from RibFOS and the ratio of in-situ minimum horizontal stress to vertical stress. Based on the calculated CPRRs, the influence of various geological and geometrical factors potentially affecting coal rib stability was quantified through statistical analysis. CPRR can be determined through these measurable parameters in the field rather than by numerical simulations, which are time-consuming and requires expertise. CPRR measures the quality of coal ribs, but not the effect of mining-induced load. However, the statistical analysis shows that there is a simple relationship between CPRR, RibFOS, and overburden depth. Overburden depth is an important factor affecting the induced stress in coal pillar ribs and thus is a good indicator of the stress condition during development. Therefore, RibFOS can be easily determined through CPRR and overburden depth.

For the empirical part, a database has been created from the surveyed coal pillar ribs in underground coal mines, and the purpose is to help define a threshold RibFOS for rib support and determine the rib support density. The sources of the database include the site observation in active underground coal mines in the Eastern United States, MSHA rib fatality reports across the U.S., and published rib data in Australian coal mines. The rib composition, overburden depth, rib support, and rib performance were collected, and CPRR and RibFOS were calculated for each case. Based on the surveyed data, a threshold value of 1.5 was defined for RibFOS to delineate the boundary between support and unsupported ribs in room-and-pillar mines, while all surveyed ribs are supported in longwall mines. In addition, the relationship between RibFOS and PRSD was proposed for room-and-pillar and longwall mines, respectively, based on the surveyed data. PRSD represents the rib support requirements per unit rib area under development loading.

Furthermore, a user-friendly standalone application, called DORS (Design of Rib Support), is being developed by NIOSH researchers to facilitate the calculations of rib support. A snapshot of the application is shown in Fig.1. There are two sections, input and output. In the input section, the user needs to input some information, including site name, rib composition information (number of rib members, lithotype, thickness, strength, and bedding condition), overburden depth, dominant cleat angle with respect to entry direction, study location (pillar side or pillar corner), and mining method (room-and-pillar or longwall). The results are shown in the output section. These include a graphical representation of strength variation of rib composition and the location of weak beddings, a plot of RibFOS versus a wide range of overburden depth showing the RibFOS at the study site, a rib support chart and a report of key parameters (Development rib height, calculated CPRR, calculated RibFOS, Rib support requirement, and PRSD) at the study site. However, it is expected that the researchers will add more features into the DORS application for rib support design, including rib bolt length, the potential for rib brow formation, and rib brow stability. The objective of this paper is to show the calculation of rib bolt length, which is potentially being included in the new version of DORS application.

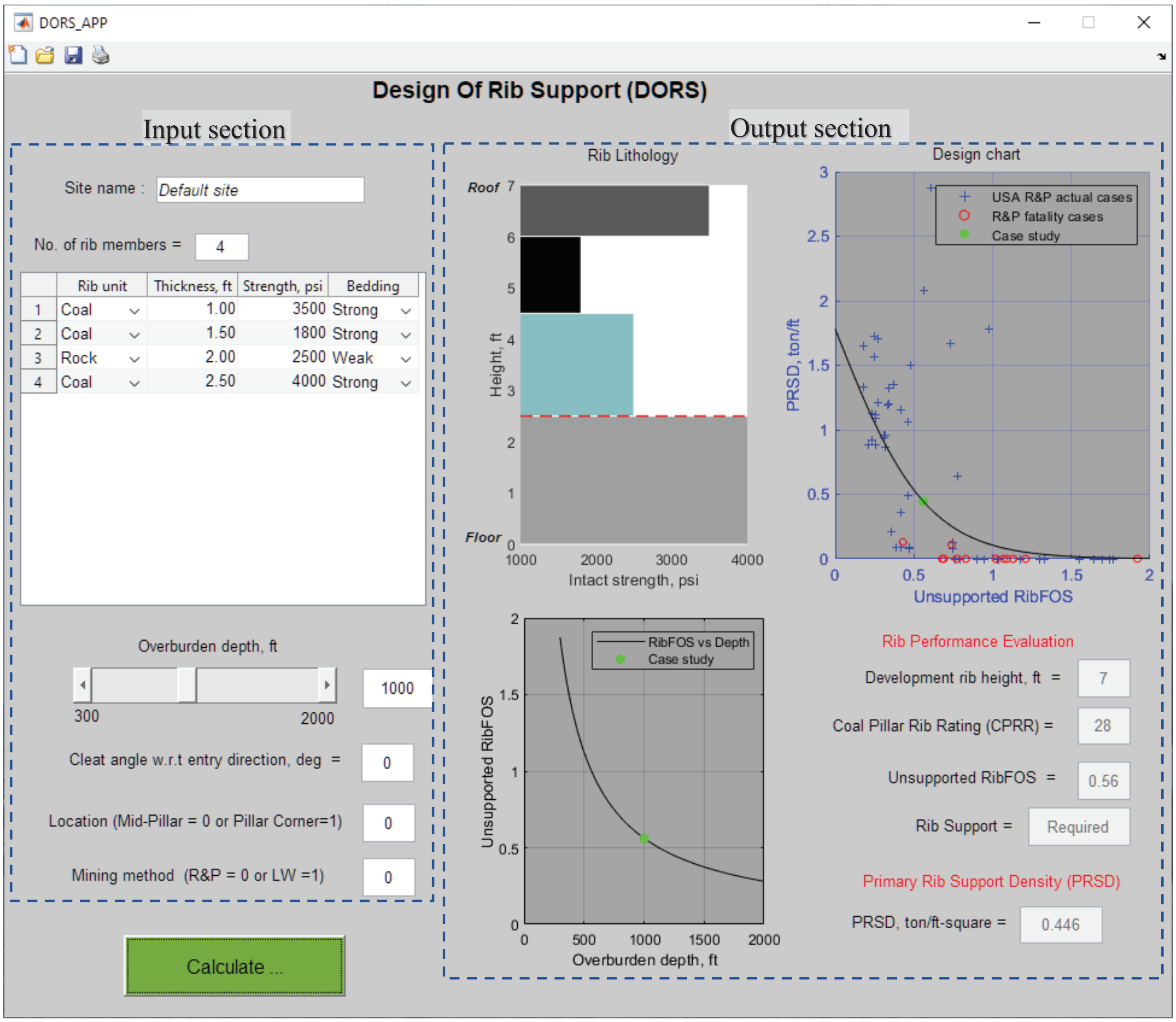

Fig.1. A snapshot of the DORS application (Mohamed et al. 2021).

3. Rib fracture depth analysis with numerical simulation

The rib fracture depth represents the potential depth for rib spalling, and the rib bolts are installed to stabilize the rib that is likely to experience spalling. The rib bolts should be longer than the fracture depth. The methodology of the study is to determine the rib fracture depth for the ribs with different compositions, mining heights, and overburden depths through numerical simulations and to build a neural network model to predict the rib fracture depth. The rib bolt length can then be estimated based on the rib fracture depth prediction.

The plane strain models that have been used in the development of CPRR in previous studies were used for the numerical study on rib fracture depth. The setup of the model is shown in Fig.2. It is assumed that the gateroad in the model is orientated parallel to the maximum horizontal stress and the face cleat orientation is parallel to the gateroad orientation. The roof and floor are elastic. The coal seam, including the rock parting, is represented by the coal mass model. Interfaces were inserted between roof and coal seam and between floor and coal seam. No interface was used within the ribs. The bedding condition can be either weak or strong when there is change in lithotype. For a weak bedding, a thin layer of soft clay with a thickness of 0.05 m (2 inches) was used in the numerical simulations, and relative displacement can easily occur across the bedding.

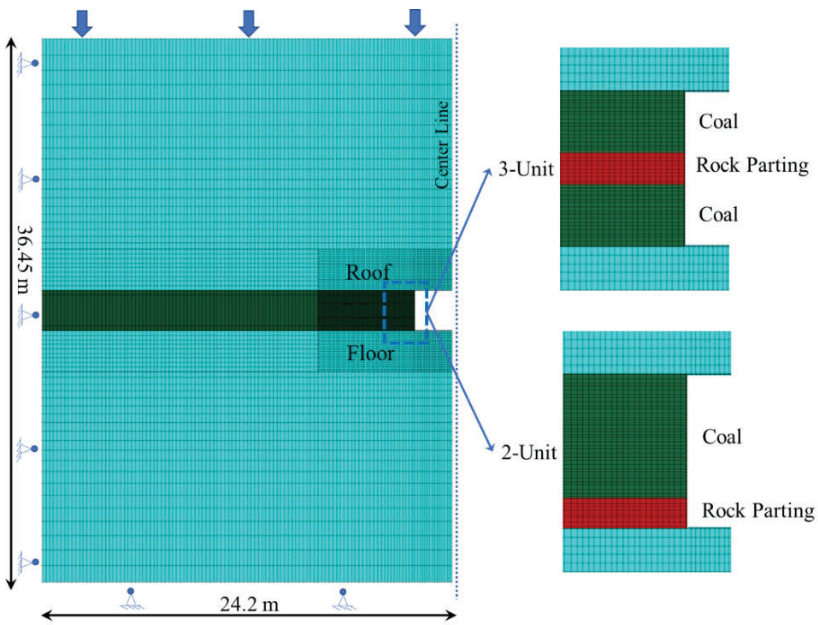

Fig.2. Setup of the plane strain model.

Three coal lithotypes, namely Bright Coal (BC), Banded Bright Coal (BBC) and Dull Coal (DC), were used in the simulations, and there were two types of rock partings, namely Rock-18.1 parting and Rock-38.4 parting, which have an intact rock strength of 18.1 MPa and 38.4 MPa, respectively. The details of the mechanical properties of the coal, rock parting, interfaces, roof, and floor used in the simulations can be found in previous studies (Xue and Mohamed 2021).

A process for simulating the coal rib fracture depth with FLAC3D was developed by Sherizadeh and Sunkpal (2021). The approach is to run the model to equilibrium first, excavate the entry and run the model to equilibrium again, and keep running the model with a FISH function to monitor the rib fracture area every 50,000 steps. The rib fracture area is defined with a lateral displacement value of 5 mm because the value of 5 mm can achieve a good estimate of the fracture zone based on field measurements, observations, and simulation results. As shown in Fig.3, the rib fracture area is represented as the red area, while the rib fracture depth is the maximum depth with a lateral displacement of 5 mm. After equilibrium, the ribs keep moving if the models are kept running, but the rate reduces. The increase in rib displacement is deemed negligible when the increasing rate in the rib fracture area reduces to less than 1.5%. Otherwise, another 50,000 steps would be run until the 1.5% limit is reached.

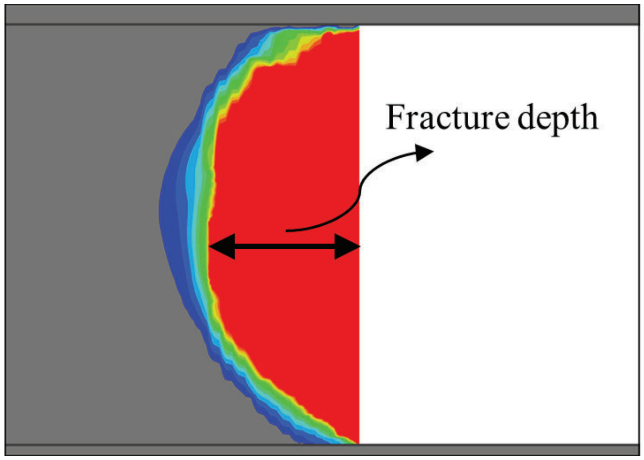

Fig.3. Displacement contour plot of 3.3-m (11-ft) rib of BBC with an overburden depth of 210 m (Sherizadeh and Sunkpal 2021).

The parametric study for rib fracture depth is based on the simulations in a previous study, where a comprehensive parametric study was conducted for the development of CPRR with rock partings (Xue and Mohamed 2021). A total of 1,842 models with different mining scenarios and rib compositions were run, and the RibFOS for each case was determined through the simulations. As discussed earlier, it is recommended to support the ribs with a RibFOS value less than 1.5 in room-and-pillar mines. All the models with a RibFOS less than 1.5 in the previous study were selected for this study. Since all the models were already run to equilibrium condition after excavation, the selected models were run to determine the rib fracture depth based on the proposed method.

In addition, some new cases were added into the parametric study. In the previous study, the range of overburden depth is 91 m (300 ft) to 320 m (1,050 ft). When the coal unit is BBC or DC, most of the coal unit factor of safety (FOS) is larger than 1.5 with the overburden depth range, and there can be very limited data for BBC and DC. A predictive model trained with such an imbalanced dataset may not be able to show good performance when there is BBC or DC in the ribs. It is necessary to include the coal unit with BBC and DC by increasing overburden depth to reduce the FOS. Another two overburden depths of 457 m (1,500 ft) and 610 m (2,000 ft) were included in the parametric study for the situation where BBC or DC are present in the coal ribs. Based on the previous parametric study and the above considerations, a total of 331 models were run for the parametric study to investigate the rib fracture depth.

CPRR is defined as the minimum coal unit rating and the calculation of CPRR focuses on the coal units within one coal pillar rib. Similarly, the rib fracture depth analysis will focus on the coal units. Since the whole rib may consist of multiple coal units, one unit may be stronger than the other one, and different fracture depths can be achieved. The approach focusing on coal units will help determine the fracture depth distribution within the whole rib, which can be further used to predict the potential formation of roof brow.

The box plots of the fracture depth with different coal unit ratings and overburden depths are shown in Fig.4. The coal unit rating quantifies the bearing capacity of the coal unit. Although it does not quantify the displacement of the coal unit, it can be expected that the weaker coal unit will experience more rib displacement. This is because, under the same condition, the weak coal unit is likely to experience a larger extent of failure, and the degradation in stiffness and strength of the failed coal material promotes the movement in the deeper rib area. This can be confirmed from Fig.4 where the mean values of fracture depth decrease with the increasing coal unit rating regardless of the overburden depth. At the same time, overburden depth is a good indicator of the applied load. Fig.4 shows that, regardless of the coal unit rating, coal unit fracture depth increases with the increase in overburden depth.

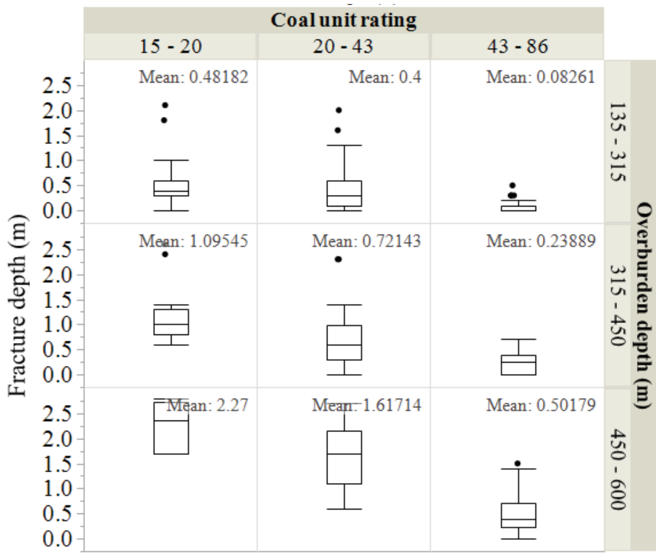

Fig.4. Box plot of fracture depth with different coal unit ratings and overburden depth.

Fig.4 shows that coal unit rating and overburden depth have significant influence on fracture depth. The coal unit FOS can be calculated from coal unit rating and overburden depth, and in such a way, it can combine the influence of these two factors. A scatter plot of fracture depth with coal unit FOS is shown in Fig.5. It can be found that, in general, the fracture depth decreases with the increase in FOS, indicating that the calculated coal unit FOS is a good indicator of fracture depth. However, as shown in Fig.5, the data are scattered along the general trend. If a regression model is built with coal unit FOS only, there can be a large error in the predicted fracture depth. The scatter of the data indicates that there are other factors affecting the fracture depth, and they should be considered in the prediction of the fracture depth. In addition, it is possible that the factors considered in FOS calculation have different influences on the strength calculation (FOS) and displacement calculation (fracture depth). In order to verify this explanation, box plots of fracture depth with varying coal unit thickness are shown in Fig.6. The mean values of the fracture depth keep increasing with the increase in coal unit thickness. This is different from the influence of coal unit thickness on RibFOS where the influence vanishes when the thickness is larger than certain values. The analyses show the necessity to build a predictive model with multiple variables like CPRR. However, it is time-consuming and complex to build such a model to predict the rib fracture depth.

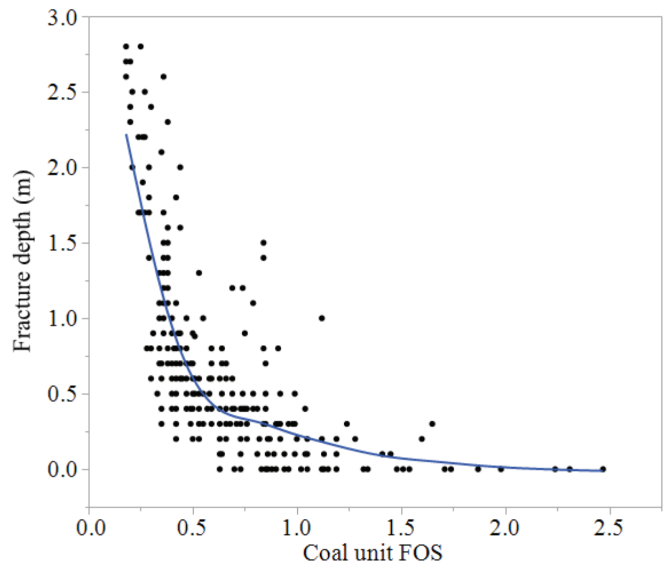

Fig.5. Scatter plot of fracture depth with varying coal unit FOS.

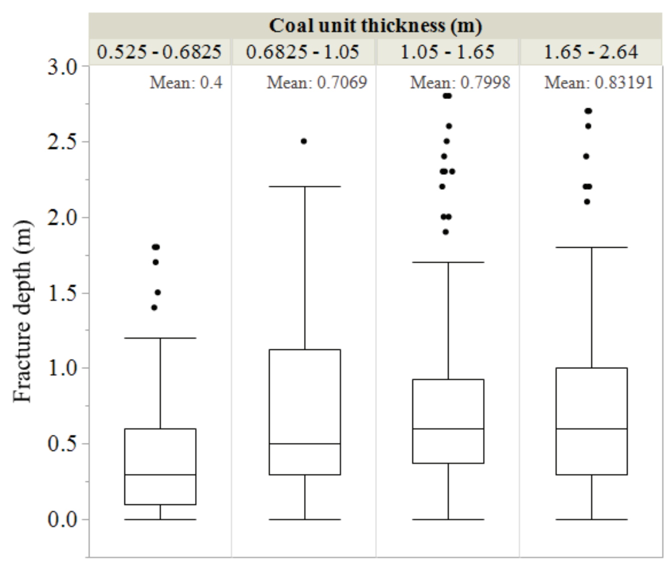

Fig.6. Box plot of fracture depth with varying coal unit thickness.

4. Rib fracture depth prediction with artificial neural network

An alternative approach for rib fracture depth prediction is to build a machine learning model. Machine learning is the field of study that gives computers the ability to learn without being explicitly programmed (Samuel 1959). Machine learning is fundamentally based on statistical methods. The advantage is that machine learning can dig into a large amount of data and help discover patterns that are not immediately apparent (Géron 2017). Machine learning models adaptively improve their performance with increasing training data. Machine learning has been used to address various mining problems, including equipment mechanical failure prediction, production optimization, and ore body delineation (Stewart 2016).

However, there are many machine learning algorithms. Based on the characteristics of the dataset, the algorithm should be able to deal with discrete data and categorical data. On one hand, the parametric study needs to consider the combination of various parameters; a few discrete values were selected for each parameter to control the total number of simulations (Xue and Mohamed 2021). However, the values can have wide ranges when the built model is used to predict fracture depth and therefore the model should be able to interpolate between the discrete values. On the other hand, most of the variables that potentially affect rib fracture depth are numerical. However, some categorial variables should be taken into consideration, such as the bedding condition (clay, interface, or no bedding) above and below the coal unit and the lithotype (rock, roof, or floor) of the upper and lower unit. Based on these characteristics, an artificial neural network is selected to build a machine learning model for the rib fracture depth prediction. Artificial neural networks are computing systems inspired by the information processing and distributed communication nodes in biological neural networks that constitute animal brains. It is based on a collection of connected nodes called artificial neurons. A neural network commonly consists of an input layer, hidden layer(s), and an output layer, and there are various numbers of neurons on each layer (Géron 2017).

A database with multiple features and one target was created in this study from the numerical simulations. The collected data focus on the coal unit within the coal rib, rather than the whole rib. As shown in Fig.7, the coal unit properties, like the unit rating, FOS and thickness, the upper unit properties, and the bottom unit properties, were collected as features. The fracture depth of the coal unit is collected as target. In addition, the categorical data within the database are encoded as numerical with one-hot-encoding so that they can contribute to the fracture depth prediction with the neural network.

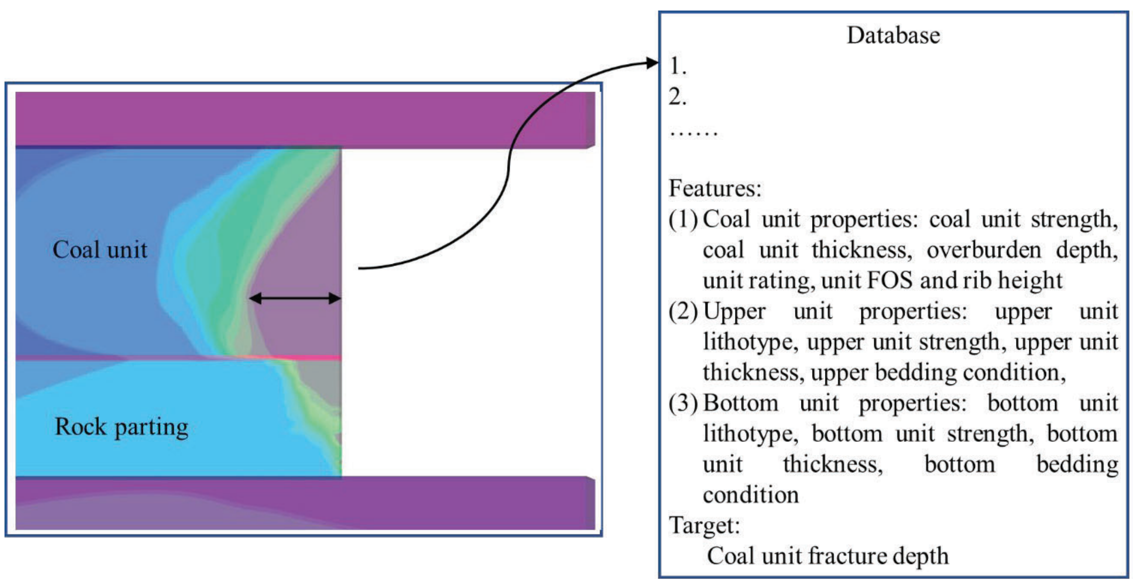

Fig.7. Illustration of data collection to generate the database for the neural network.

It should be noted that the coal unit FOS can be higher than 1.5. Numerical simulations were conducted with a RibFOS less than 1.5 in the parametric study. However, the RibFOS can be calculated from CPRR and overburden depth where the CPRR of the rib is taken as the minimum value of all the coal unit ratings. It indicates that the coal unit ratings can be higher than the CPRR of the rib, and as a result, the coal unit FOS calculated from coal unit rating and overburden depth can be higher than 1.5.

The neural network consists of one input layer, one hidden layer, and one output layer and various numbers of neurons are used on each layer. There are 20 input parameters, and as a result, there are 20 neurons in the input layer. Only one hidden layer is used, and after a few trials, it was determined to use 15 neurons for the hidden layer. The only target for the neural network is the fracture depth determined with a lateral displacement of 5 mm, and there is only one neuron in the output layer.

The performance of the neural network is presented in Fig.8. The model was trained with 80% of the data and was validated with the remaining 20% data. Fig.8 shows that good R-square values were obtained for the training and validation dataset. At the same time, low root mean square errors (RMSE) were obtained for both datasets. The promising results from the neural network make it possible to use the trained model for the prediction of coal unit fracture depth. The trained model can be incorporated into DORS application for coal rib support design.

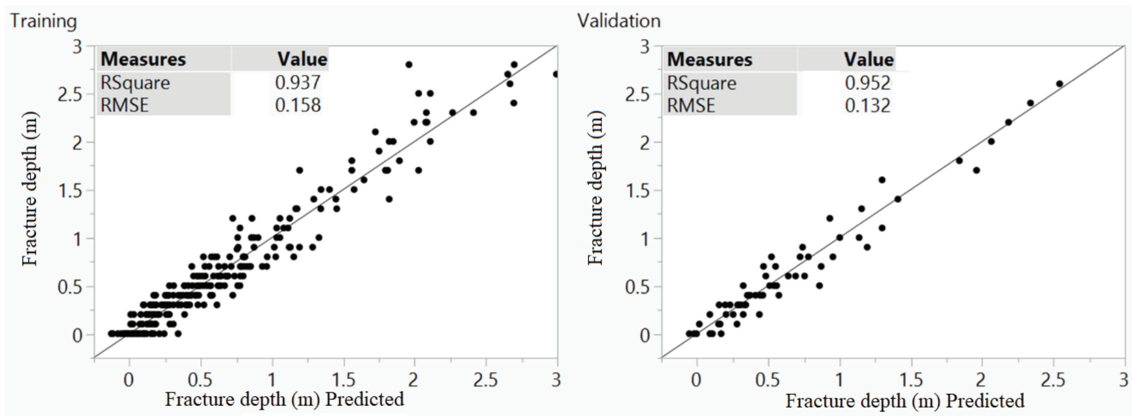

Fig.8. Model performance for training and validation dataset.

5. Conclusions

The failure of coal ribs is a major hazard in underground coal mines. A user-friendly standalone application, called Design of Rib Support (DORS), is being developed for rib support design by NIOSH researchers. The PRSD at development stage can be estimated by the application. However, the rib bolt length, as a key factor for rib support design, still needs to be incorporated in the model. It can be estimated from the rib fracture depth because the rib bolts should be longer than the fracture depth to ensure that the bolts are installed in stable coal mass. In this study, the coal rib fracture depth was analyzed with numerical simulations and artificial neural network.

A parametric study was conducted with numerical simulation to investigate the fracture depth for coal ribs with different coal rib compositions, mining heights, and overburden depths. The results show that the fracture depth increases with increasing overburden depth and decreases with increasing coal unit rating. When the influence of these two factors is combined, the coal unit FOS is shown as a good estimator of the fracture depth. However, the large scatter of the data indicates the necessity to include more variables into the predictive model for rib fracture depth prediction.

An artificial neural network was trained with the data collected from the numerical simulations for the prediction of coal unit fracture depth. The properties of the studied coal unit, the upper unit, and the bottom unit were collected as features, and the target is the fracture depth of the studied coal unit. The features include numerical and categorial data and the categorial data were encoded to be numerical with one-hot-encoding. Good data correlation (r-square) was obtained for both training and validation datasets, indicating promising results for the neural network. The training model shows the potential to be included in the DORS application further enhancing its capability for rib support design. The prediction of coal unit fracture depth will help determine the fracture depth distribution within the whole rib, which can be further used to predict the potential formation of roof brow.

Disclaimer

The findings and conclusions in this report are those of the author(s) and do not necessarily represent the official position of the National Institute for Occupational Safety and Health, Centers for Disease Control and Prevention.

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