Neural Network Technology for Strata Strength Characterization

Walter K. Utt, Spokane Research Laboratory,
National Institute for Occupational Safety and Health, Spokane, WA
wau0@cdc.gov

Abstract

The process of drilling and bolting the roof is currently one of the most dangerous jobs in underground mining, resulting in about 1,000 accidents with injuries each year in the United States. To increase the safety of underground miners, researchers from the Spokane Research Laboratory of the National Institute for Occupational Safety and Health are applying neural network technology to the classification of mine roof strata in terms of relative strength. In this project, the feasibility of using a monitoring system on a roof drill to assess the integrity of a mine roof and warn a roof drill operator when a weak layer is encountered is being studied. Using measurements taken while a layer is being drilled, one can convert the data to suitably scaled features and classify the strength of the layer with a neural network. The feasibility of using a drill monitoring system to estimate the strength of successive layers of rock was demonstrated in the laboratory.

Introduction

The Spokane Research Laboratory (SRL) of the National Institute for Occupational Safety and Health (NIOSH) conducts research to improve the safety of miners. Roof falls in underground mines have caused many fatalities in the past. To reduce the risk of deaths and injuries from roof falls, 1- to 3-m-long bolts are used to reinforce the rock. However, the process of drilling and bolting the roof is currently one of the most dangerous jobs in underground mining and according to data compiled by the Mine Safety and Health Administration, resulted in about 1,000 accidents with injuries a year between 1984 and 1994 in the United States. By using a monitoring system on a roof drill to assess the integrity of a mine roof, a roof drill operator could be warned when a weak layer is encountered. Such a warning could make the difference between life and death for the operator.

A cross section of a typical mine roof and various types of roof support, including bolts, are shown in figure 1. Neural

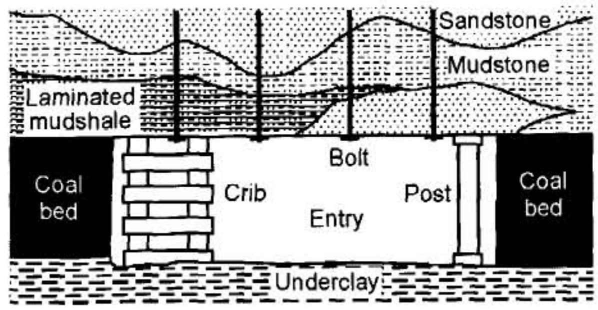

Figure 1.—Cross section of coal mine roof and support types.

network technology is being applied to the classification of mine roof strata in terms of relative strength. That is, measurements taken while a layer is being drilled can be used to compute the specific energy input and convert these data to suitably scaled features. A neural network can then be used to classify the strength of the layer.

Method

A functional strata characterization program has been developed. The program is designed to interface with an instrumented rock drill. Torque, rotation rate, thrust, penetration rate, and depth of the drill tip are measured and converted to electrical signals by transducers. This information flows through interface boards to a computer with a custom data acquisition program that includes a graphics display (figure 2).

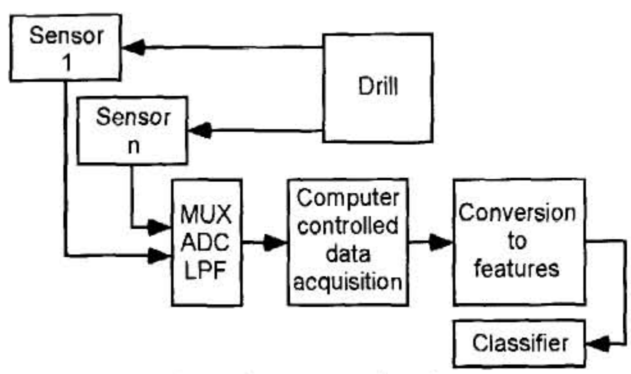

Figure 2.—Drilling data flow

The data are smoothed by averaging, and the specific energy of drilling (SED) is computed. SED is the drilling energy input or work done per unit volume of rock excavated [1].

The SED includes both rotational and translational energy. Rotational energy is usually much larger than translational energy. However, if thrust is zero, there will be no significant penetration, even if the rotational energy input is high. SED usually ranges from equivalence to about twice the compressive strength of the material being drilled and is a useful feature for strength classification if drilling parameters are within the normal operating range. Consequently, it is advisable to monitor initial measurements to be certain they are within the normal range of operation. The SED can be used in combination with penetration rate to provide a minimum set of features for the classifier. The other measurements can be used as supplementary features, if desired. The computer program block shown in figure 2 consists of three major parts: data acquisition, conversion to features, and the classifier.

Since strength is to be evaluated while drilling is still underway, it is necessary to process a subset of data corresponding to each layer. A subarray that corresponds to the layer of material being drilled is converted to suitably scaled features for a neural network classifier. A pipeline processing system is an appropriate concept for processing the data while drilling through successive layers. The laboratory prototype was designed to be consistent with pipeline processing. However, the graphic display results in a delay, which will require attention in the design of a prototype suitable for field use.

Two commercial neural network packages (EZ-1 and Data Engine) were obtained and evaluated. The EZ-1 [2] is a package of supervised neural network techniques with an accelerator board. The package contains three alternative software programs. These are—

1. A probabilistic neural network [3],
2. The RCE system (Reilly, Cooper, Elbaum), patented as the Self Organizing General Pattern Class Separator and Identifier [4], and
3. PRCE, which is a combination of the probabilistic and the RCE programs.

The Data Engine [5] is a package of unsupervised neural network techniques that contains two alternative software programs.

4. Kohonen's self-organizing feature mapping algorithm [6] and
5. Fuzzy cluster means combined with Kohonen's algorithm [7].

All five alternatives appeared to be satisfactory, which is an indication of the significant advances in neural network technology in recent years. Due primarily to compatibility considerations, the learning algorithm of Kohonen (alternative 4) [5] was selected for the crisp classification of layer strength. Naturally occurring rock varies considerably in both composition and strength. Rock strength is often classified in 32 classes [8], which is adequate for our proposes. The neural network was trained with data of known classifications prior to using it to classify new measurements. The conceptual network is shown in figure 3. The actual network would, of course, have many more neurons. Classification output was monitored on a computer graphics display. For signalling a warning, the classifications were grouped into three color categories, red for weak, yellow for medium, and green for strong.

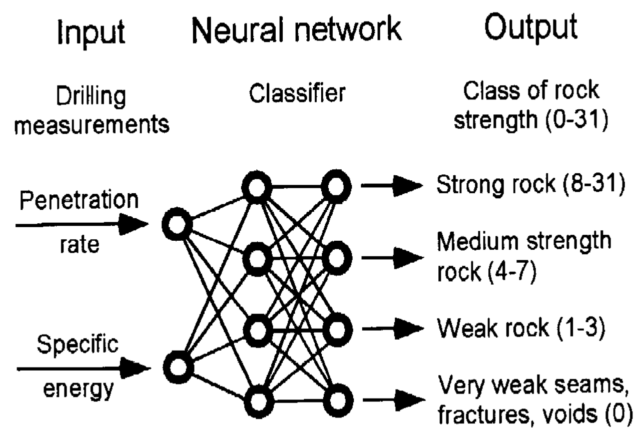

Figure 3.—Mine roof strata characterization

A brief investigation of alternate feature vectors was conducted early in the project using data from prior research at NIOSH/SRL and geological classes in the manner of King and Signer [9]. After a neural network was trained on some of the existing data files, it was used to classify data from another file and was found to be successful in discriminating layers. The two features, SED and penetration rate, were found to be satisfactory for classifying different layers into the proper geological classes. The full set of five features (SED, torque, rotation rate, thrust, and penetration rate) gave comparable performance at discriminating layers.

The fuzzy clustering algorithm (alternative 5) automatically identified a start-in class, which corresponds to observations made of the drill entering the rock. When the drill first enters the rock, there is a lot of chatter, and the data are very noisy. When the drill tip is at a depth sufficient to quell the chatter, it is said to have established a collar. In fact, the data obtained prior to reaching the collar depth should not be used in the strength classification, since it would be misleading.

Results

A prototype drill monitoring system with a strata strength classifier was developed in the laboratory. Drilling measurements for each roof bolt hole can be processed and the essential information displayed for the operator to monitor in near-real-time. A file of selected information for each borehole can be stored for later retrieval. Prior experience told us that the drilling data are likely to be noisy. Consequently, measurements will be processed in subsets, which will allow the use of statistics, smoothing, and conversion into features for each layer. The features must be scaled properly for use in the neural network classifier, so it was necessary to write a program to convert raw data into suitably scaled features. That program was written in C language. Classifying each layer drilled according to estimated strength is a new capability.

Typical drilling data from a borehole were processed. SED is presented as a function of the depth of the drill tip in figure 4. The spurious peak would not be used in estimating rock strength. The data collected before the collar depth is reached (10 cm) would not be used in the classifier to estimate rock strength. There is a linear upward trend in the SED that is probably caused by friction. The steel drill shaft bends under thrust and rubs in the borehole. It is recommended that such trends should be removed from the data before classification [10]. Penetration rate is presented as a function of depth in figure 5. The penetration rate iindicates the results of the drilling process, while SED represents work put into the rock. Neither feature is without shortcomings, but together they provide a reliable representation of the strength of the rock.

The network was trained on data for which the strength was known and labeled accordingly. Data from a typical borehole were placed into one of 32 classes of compressive strength. The strength index class is presented as a function of depth in figure 6. There are three layers where the strength index drops below 4, indicating that those layers are weak and not suitable for anchoring. The deeper layers have a strength index greater than 8, which means they are strong enough to provide a good anchor. If an estimate of compressive strength is required, it can be obtained. For example, the index value of 4 corresponds to 31,030 ±3,447 kPa. However, the strength index class is adequate for our purpose. The strength classification is both feasible and useful.

Conclusions

The feasibility of using a drill monitoring system to estimate the strength of successive layers of roof rock while drilling is still underway was demonstrated in the laboratory. This system should be applicable in all underground mines. There is considerable interest in developing a field prototype, and

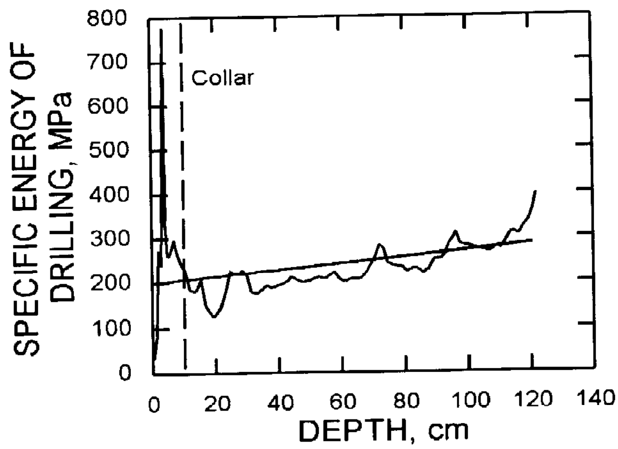

Figure 4.—Specific energy versus depth

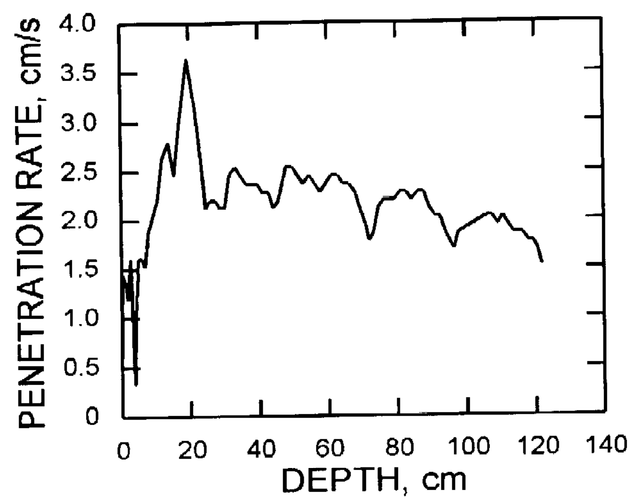

Figure 5.—Penetration rate versus depth

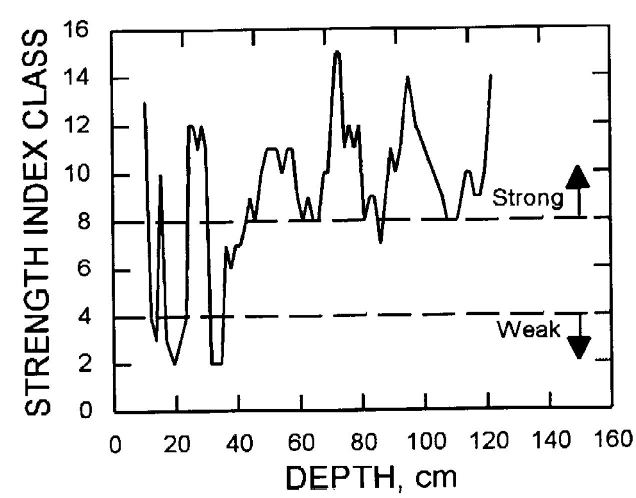

Figure 6.—Strength index versus depth

two research and development team s have already expressed interest in applying and extending the system. The technology could be extended to other rotary drilling applications, such as drilling holes for blasting in mining and construction, since rock strength is an important consideration in efficient blasting. The application of neural network technology to strength classification of the material being drilled is new, as is estimating the strength index class in near-real-time.

References

1. Teale, R. (1995). The Concept of Specific Energy In Rock Drilling. *Int. J. Rock Mech. Min. Sci. & Geo. Abs.*, Vol. 2, pp. 57-73.

2. Pryor Knowledge Systems, Inc. (1995?). EZ-1 Neural Network System-Basic. Bloomfield Hills, MI. 74 pp.

3. Specht, Donald F. (1988). Probabilistic Neural Networks for Classification, Mapping, or Associative Memory. In *Proceedings IEEE Second International Conference on Neural Networks* (San Diego, CA). Vol. 1, pp. 525-532.

4. Reilly, D. L., L. N. Cooper, and C. Elbaum (1982). A Neural Model for Category Learning. *Biol. Cybernetics*, Vol. 45, pp. 35-41.

5. MIT GmbH (1996). Data Engine V.i. Data Mining by Intelligent Data Analysis. Part I: Basics, 81 pp.; Part II: User Manual, Function Reference, and Tutorials, 262 pp. Aachen, Germany.

6. Kohonen, T. (1995). *Self-Organizing Maps*. Springer-Verlag, New York, NY, 362 pp.

7. Tsao, E.C-K., J. C. Bezdek, and N. R. Pal (1982). Fuzzy Kohonen Clustering Networks. *Pattern Recognition*, Vol. 27, No. 5, pp. 757-764.

8. Carmichael, R. S. (1982). *Handbook of Physical Properties of Rocks*, Vol. 2. CRC Press, Boca Raton, FL, 306 pp.

9. King, Roger L., and Stephen P. Signer (1994). Using Artificial Neural Networks for Feature Detection in Coal Mine Roofs. In *Computer Methods and Advances in Geomechanics. Proceedings of the Eighth International Conference on Computer Methods and Advances in Geomechanics*, ed. by H. J. Siriwardane and M. M. Zaman (Morgantown, WV, May 22-28, 1994). Vol. 3, Balkema, Rotterdam, pp. 1853-1857.

10. Masters, Timothy (1993). *Practical Neural Network Recipes in C++*. Academic Press, San Diego, CA, 493 pp.