New drill-monitoring system evaluates strata strength in real time

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Abstract

The process of roof drilling and bolting is one of the most dangerous jobs in underground mining. In the United States, roof drilling and bolting results in about 1,000 accidents with injuries each year. Researchers from the Spokane Research Laboratory of the National Institute for Occupational Safety and Health are studying the feasibility of using a drill-monitoring system to estimate the strength of successive layers of rock and assess the integrity of a mine roof. Such a system would allow roof drill operators to be warned when a weak layer is being drilled. Using measurements taken during drilling, a neural network can classify mine roof strata in terms of relative strength. The concept has been proven in principle. This research project was undertaken to increase the safety of underground miners, especially those involved in roof bolting. The system should be applicable to the mobile drills now used in underground mines, and the system would likely find wider application as well.

Introduction

The process of roof drilling and bolting is one of the most dangerous jobs in underground mining, resulting in about 1,000 accidents with injuries each year in the United States, according to data compiled by the Mine Safety and Health Administration (MSHA) (Fig. 1). To reduce risks from roof falls, the Spokane Research Laboratory (SRL) of the National Institute for Occupational Safety and Health (NIOSH) is studying the feasibility of using a monitoring system on a roof drill that would assess the integrity of a mine roof. There are two ways in which such a drill monitor would improve safety. First, the monitor would permit an estimate of roof rock strength by layer, allowing for the selection of the appropriate bolt lengths and patterns. This would improve the roof bolting process, making the roof more stable and less likely to fail. Second, the monitor would warn a roof drill operator of weak roof rock in a timely manner, allowing the operator to move to safety. Such a warning could make the difference between life and death for the operator.

Laboratory preparation of customized drill

A full-scale commercial drill (Fig. 2) was customized in the laboratory at SRL to test intelligent drilling systems that would automatically determine the condition of the anchorage strata and optimize drilling efficiency. The basic design of the roof drill was extensively modified by adding the following capabilities:

- sense drilling parameters,
- permit remote control,
- hold specific parameters constant to reduce drilling variability,
- reduce machine vibration and
- drill a straight hole.

Standard 25- or 35-mm- (1.0- or 1.38-in.-) diam fluted vacuum or water-flushed carbide bits can be used, as well as a 25-mm rounded water-flushed diamond bit. For the laboratory tests, a standard 25-mm (1.0-in.) water-flushed carbide drill bit was selected and mounted on a 1.52-m (5-ft) drill rod. The customized drill was used as a test bed for neural net strata characterization, as discussed in this paper.

Drill-monitoring system approach

A functional strata-characterization program was developed to interface with the instrumented rock drill. Torque, rotation rate, thrust, penetration rate and depth of drill-tip penetration are measured and converted to electrical signals by transducers. The information flows through interface boards to a computer with a custom data-acquisition program written in LabView[1], a graphics programming language that includes a graphics display (Fig. 3).

A low-pass filter is necessary to prevent aliasing of an analog signal when it is converted to a digital signal. A multiplexer is often used to reduce system costs, although this is not essential. The signals from the transducers are passed through an analog-to-digital converter to facilitate processing. The data are smoothed by averaging, or other means, and the specific energy of drilling (SED) is computed by means of library functions written in C language. SED is the drilling energy input or the work done per unit volume of rock excavated (Teale, 1965), as determined by

$$e = \frac{F}{A} + \frac{2\pi(WT)}{Au} \qquad (1)$$

where
e is the specific energy of drilling (N/m or Pa),
F is the thrust (N),
A is the area of the drill hole (m^2),
W is the rotation rate (rpm),
T is the torque (N·m) and
u is the penetration rate (m/min).

[1] Mention of specific products or manufacturers does not imply endorsement by NIOSH.

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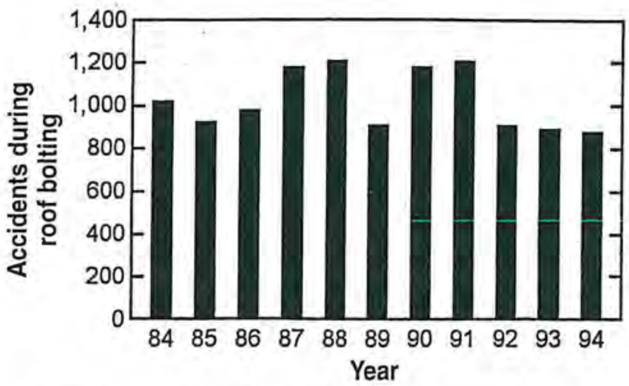

Figure 1 — Accidents during roof bolting.

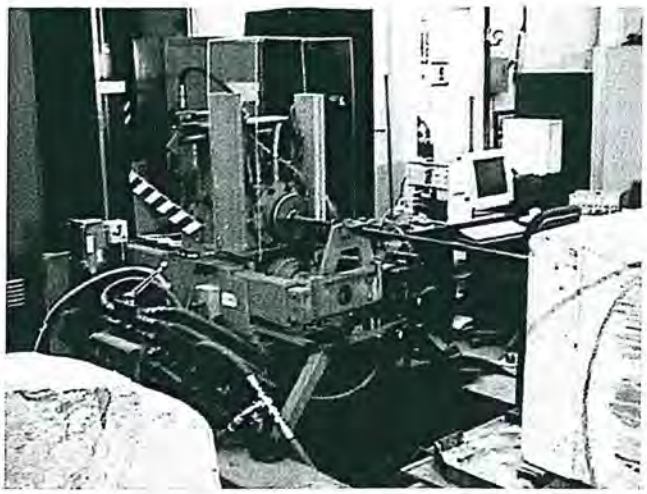

Figure 2 — Laboratory drill.

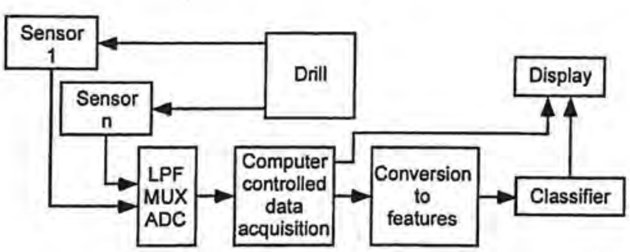

Figure 3 — Drilling data flow (LPF = low-pass filter; MUX = multiplexer; ADC = analog-to-digital converter).

SED includes both translational and rotational work done on the rock. Rotational energy is usually much greater than translational energy. However, if the thrust is zero, there will be no significant penetration of the rock, even if rotational energy is high. SED may be about twice the compressive strength of the material being drilled, although differences in operator use and individual characteristics of the drill and bit may cause SED values to vary. SED is useful for classifying strength if drilling parameters are within the drill's normal operating range. Consequently, it is advisable to monitor drilling parameters to be certain that they are within the normal range of operation. An operator's experience with a particular type of drill and bit can be useful in setting the

Table 1 — Test-drill operating bounds.

Normal drill operation	Depth of bit tip, cm	Torque, N·m	Thrust, N	Rotation rate, rpm	Rate of Penetration, m/min
Lower bound	0	13.56	889.6	100	0.3048
Upper bound	182.9	135.6	13,340	600	3.048

bounds for the normal range of operation. For the test drill, the bounds for the measured parameters of torque, thrust, rotation rate and rate of penetration are shown in Table 1.

SED can be used in combination with penetration rate to provide a minimum set of features for the classifier. Other measurements can be used as supplementary features, if desired. The full set of six parameters (five measurements plus calculated SED) may yield a more robust classifier, but the neural network would be significantly larger. The block diagram for processing drilling data (Fig. 3) shows three major processing steps: data acquisition, conversion to features and use of classifier.

Because 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 of data that corresponds to the layer of material being drilled is converted to suitably scaled features for a neural network classifier. The data can be regarded as flowing past a window. Computations are performed on the subarray of data in the window, with the results being displayed a few seconds afterward. The graphics display, especially the display of estimated strength class vs. depth, results in a significant delay and will require attention when designing a prototype suitable for field use.

Neural network selection

Two commercial neural network packages, EZ-1 (Pryor Knowledge Systems, 1995) and Data Engine (MIT GmbH, 1996a, 1996b), were evaluated.

The EZ-1 is a package of supervised neural network techniques with an accelerator board. The package contains three alternative software programs:

- a probabilistic neural network (Specht, 1988);
- the RCE neural network (Reilly et al., 1982; Reilly and Cooper, 1990), patented as the Self Organizing General Pattern Class Separator and Identifier (Cooper et al., 1982); and
- PRCE, which is a combination of the probabilistic and the RCE methods.

Application problems can be solved by training with known output classes.

Data Engine is a package of unsupervised neural network techniques that contains two alternative software programs:

- Kohonen's self-organizing feature mapping algorithm (Kohonen, 1995) and
- fuzzy cluster means combined with Kohonen's algorithm (Tsao et al., 1994).

Unsupervised neural network techniques have the additional capability of being able to define classes.

As a test, all five alternatives were used to classify geological strata and all appeared to be satisfactory, which is an indication of the significant advances in neural network technology in recent years.

The unsupervised learning algorithm of Kohonen (Kohonen, 1995; MIT GmbH, 1996a) was selected for the crisp classification of layer strength in one of 32 classes. The Data Engine software package was compatible with the LabView software. The competing EZ-1 product with the NESTOR accelerator board processes rapidly, but the software had not been upgraded for the 32-bit address spaces now used in most personal computers.

In the field, rock varies considerably in both composition and strength. Rock strength is often classified in 32 classes (Carmichael, 1982). Field strength values tend to be lower than laboratory values (Heuze, 1980), because a larger volume of rock is likely to have more fractures or joint sets than a laboratory sample (Brady and Brown, 1985). The presence of moisture can also degrade the strength of the rock. Bit geometry and bit sharpness can significantly influence the strength estimate. Thus, an approximation of rock strength is the best that one can do under laboratory circumstances.

Some rock-mass index properties, such as the number of joint sets and the rock quality designation (Franklin et al., 1971), may be computed to give an indication of rock quality for the hole that has been drilled.

A neural network must be trained with known classifications prior to being used to classify new measurements. In the training or learning phase, classification output is compared to known classifications. The error in the output layer must be propagated back through the network to adjust weighting. The use of back-propagation of error in the manner of a steepest descent, as described in Rumelhart and McClelland (1986), was a major step forward in neural-network technology. However, there have been several subsequent modifications and variations on the iterative procedure. For example, some procedures add neurons during the training phase. The iterative process to adjust weights can be done off-line and need not affect the computational time required for classifying in near-real time. The drill bit used in training must be of the same type as the bit used in subsequent drilling. Sharpness of the bit should also be monitored.

Truth-values were obtained to compare measured parameters to known rock type and strength. The training set of features required 32 cases for the 32 classes of strength, so interpolation and extrapolation were required. Although it is more common to scale to a specified range of values, the Kohonen method in Data Engine uses normalized input features set to a mean of zero and standard deviation set to one (MIT GmbH, 1996a, 1996b). The input features, such as penetration rate and SED, are normalized by

$$xp = \frac{(x-\mu)}{\sigma} \qquad (2)$$

where

xp is the normalized value,
x is the input value,
μ is the mean or expected value and
σ is the standard deviation.

A generic artificial neuron is depicted in Fig. 4. Most neural network techniques use an activation function to relate the output of a neuron to the weighted sum of several input numbers. A threshold can be applied to the activation function, which is usually sigmoidal. The Kohonen algorithms are based on competitive learning and do not require the activation function. The weight for each input to a neuron in the artificial neural network is fixed at the conclusion of the training or learning phase, as shown in Fig. 5. The authors recommend that a validation test be performed to demonstrate that the classifications are correct. The neural network can then be used to classify the new input data according to rules frozen into the network, as indicated in Fig. 6. Only the classification process contributes to the computational time of primary concern during drilling.

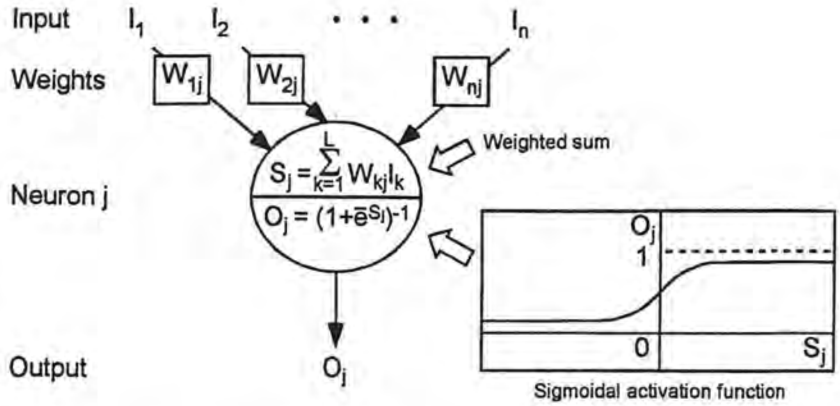

Figure 4 — Example of an artificial neuron.

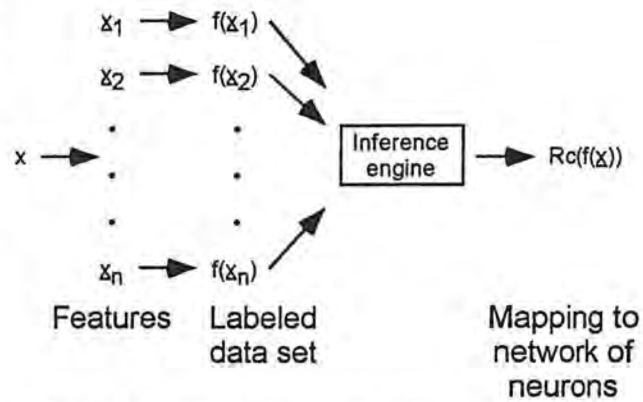

Figure 5 — Neural network training.

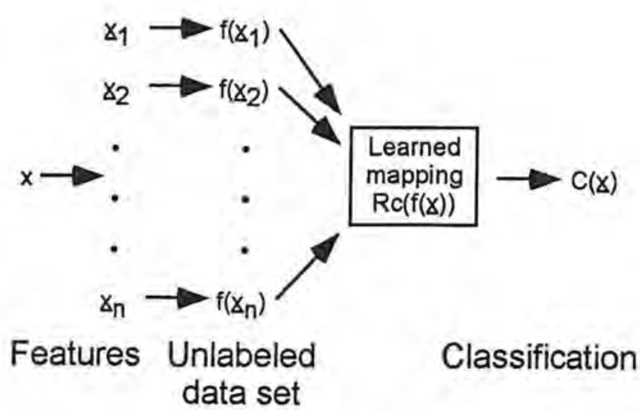

Figure 6 — Neural network classification.

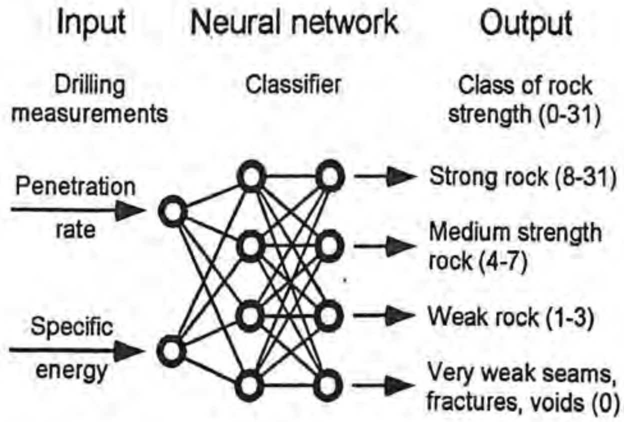

Figure 7 — Mine roof strata characterization.

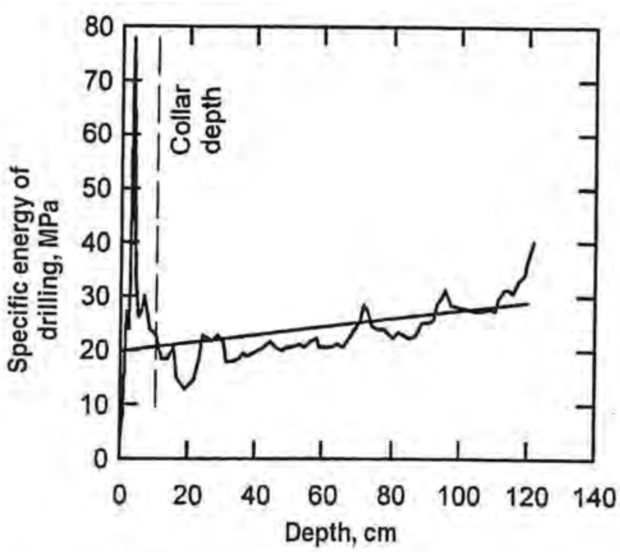

Figure 8 — Specific energy vs. depth.

The conceptual artificial neural network for strata characterization is shown in Fig. 7. The actual network would have many more neurons, from 64 to 384, or even more, depending on the choice of training parameters. Very strong rock would require a different drilling technique, e.g., percussive drilling, rather than rotary drilling. Roller cone bits are regarded as percussive. Consequently, the "very strong" rock category is not depicted. Classifications for the laboratory system were grouped into three color categories to provide visual warnings — red for weak, yellow for medium and green for strong.

A brief investigation of alternate feature vectors was conducted early in the project using data from prior research at SRL and geological classes, as described by King et al. (1993) and King and Signer (1994). 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 SED input can vary from one operator to another, but the penetration rate can help reduce the effect of that variation on the classification. The full set of features — SED, torque, rotation rate, thrust and penetration rate, along with depth as an independent variable — gave a comparable performance at discriminating layers.

The unsupervised method that combined fuzzy clustering with Kohonen's algorithm automatically identified a start-in class, which corresponds to observations made of the drill entering the rock. When the drill bit first enters the rock, visible and audible chatter is common, and noise in the data is high. When the drill tip is at a depth sufficient to quell the start-in 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 because it would be misleading. Although a class must still be labeled, it is impressive that the algorithm could automatically select an appropriate start-in class.

Program software

An overview of the program structure, emphasizing data flow, is presented in Fig. 3. The software for the drilling application consisted of three parts:

- a program written in LabView to control the data-acquisition process and display information;
- a program written in C language to perform the necessary preliminary processing and convert the data into features; and
- the classifier, a neural network created from the Data Engine software package and compatible with LabView.

Some additional routines were created from Data Engine for training and labeling the neural network.

The main graphics language program is rather extensive, requiring more than 600 kbytes of memory. The program for preliminary processing, written in C language, requires only 70 kbytes in the dynamically linked library (dll) version, which is called from the main program as a set of call library functions.

The integration of the classifier with the main graphics language program went off smoothly. However, calling the C language functions from the main program turned out to be more complicated than expected. It was necessary to use several global variables with different names and "exportable wrapper functions" to call the C functions from the main program. A functional laboratory program that interfaced with the transducers on the laboratory drill was used to evaluate the program and refine it for efficient processing.

Laboratory test results and evaluation

Typical drilling data from a borehole were processed. Figure 8 presents SED as a function of the depth of the drill tip. A linear upward trend in the SED is probably caused by friction as the steel drill shaft bends under thrust and rubs in the borehole. Such trends should be removed from the data before classification (Masters, 1993) (Fig. 9). The upper and lower control limits, which are plus or minus two sigma points of the mean as in statistical process control, allow a researcher to distinguish random noise between the control lines from significant differences in rock strength.

Penetration rate is presented as a function of depth in Fig. 10. Penetration rate indicates the results of the drilling process, while specific energy represents work put into the rock. The specific energy input can vary according to the manner of drill operation. The output penetration rate is dependent on the input SED and the resistance of the rock in a given drilling system. Consequently, the combination of penetration rate and SED is expected to reduce the influence of variability on estimated strength. Neither feature is without shortcomings, but together they provide a reliable basis for estimating rock strength. The integration of these two features into a "strength index" is the prime function of the neural network.

The presence of cracks or voids would indicate a weak layer, which would be dangerous in a mine roof. A depth resolution of 2.5 mm (0.1 in.) was selected to detect fractures. A record of the strength estimate for the layers as a function of depth will be retained in a file for viewing after a hole has been drilled. The strength estimate by layer could be useful in selecting appropriate bolt lengths and patterns for roof bolting. The strength estimate may also be useful for the preliminary description of the layer being drilled. It is desirable to monitor and inform the operator when one of the measured variables is out of the normal band of operation, because that would affect the validity of the strength estimate of the layer.

The network was trained on data for which the strength was known and labeled. Data from a typical borehole were placed into one of 32 classes of compressive strength. The resultant strength indices, or classes, are presented as a function of depth in Fig. 11. There are three layers where the strength index drops below four, indicating that those layers are weak and not suitable for anchoring bolts. The deeper layers have a strength index greater than eight, which means they are strong enough to provide a good anchor.

Computational time is a significant consideration for practical implementation. To obtain maximum benefit from the information and provide a timely warning to a drill operator, it is important that the computation be completed within a few seconds after the measurement. An autoregressive integrated moving average (ARIMA) process (Gelb, 1974) with full overlap of the data window was initially used in the smoothing or noise-reduction phase of computation, producing the relatively smooth averaged plot. Although the ARIMA computation worked rather well, as indicated in the smooth plot of strength index vs. depth in Fig. 11, it required about 40 sec to process each window of data. This approach was too slow and was replaced with a simpler averaging computation in a preliminary filter. The nonoverlapping average and new computer hardware enabled researchers to reduce the lag to about 4 sec. The optional trend evaluation from the first to the current data window was retained.

One could also use an autoregressive moving average (ARMA) process if the trend were removed, so that the statistics would be stationary. The ARMA process was also retained as an option with no overlap of the data window, so that computational speed could be maintained. An additional increase in speed by a factor of four was obtained from an upgrade of the computer hardware. The net increase in speed was approximately a factor of ten, resulting in a computational delay of 4 sec or less.

Concrete test blocks containing various types of rock inclusions were designed to simulate changing mine roof conditions. A laboratory test demonstrated the drill's capability of detecting these inclusions (Fig. 12). In this figure, the friction trend has been removed, and noise is evident. If the envelope of high values is viewed, changes in strength are evident. A small change in strength is first indicated at a depth of about 200 mm and a larger change at a depth of about 420 mm. This interval corresponded to the location of the inclusion in the cement block. Detecting an inclusion from a change in the strength was, to the best of the author's knowledge, the first successful demonstration of this capability.

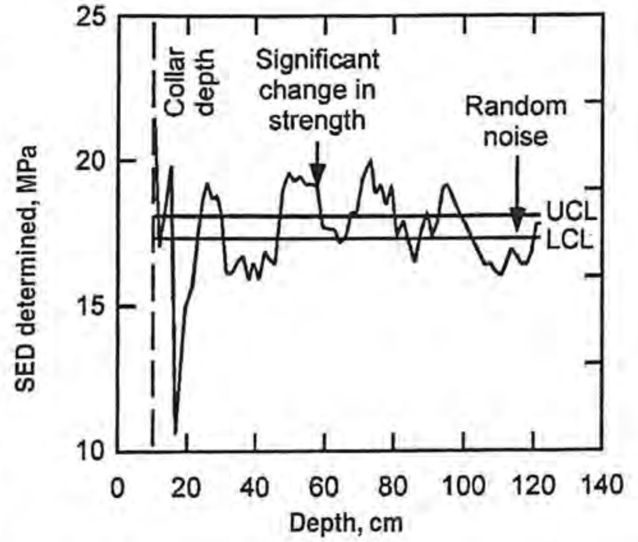

Figure 9 — Detrending (UCL = upper control limit; LCL = lower control limit).

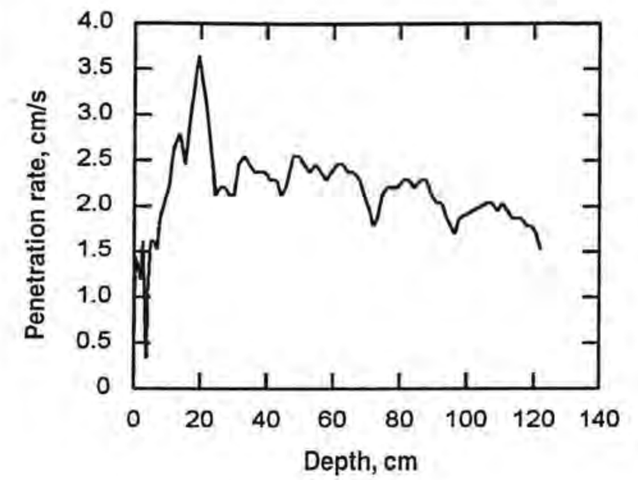

Figure 10 — Penetration rate vs. depth.

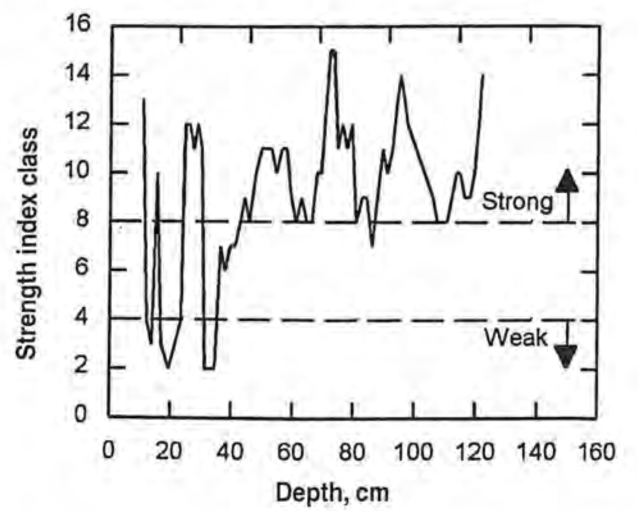

Figure 11 — Strength index vs. depth.

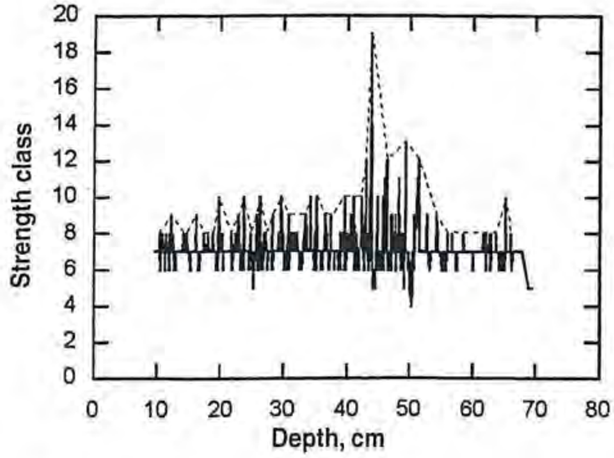

Figure 12 — Detection of inclusion from change in strength.

An important insight gained from the feasibility analysis was that the neural network should be trained with the laboratory data and trained again with the field data. The measured parameters differed for the two situations, especially penetration rate. Rock strength differed as well, but it is advisable to check by training for both situations.

Conclusions

A prototype drill-monitoring system with a strata-strength classifier was developed and demonstrated at SRL. The goal was to characterize the strength of the strata in a timely fashion, so that the information could be used in the field, preferably while drilling is still underway. Drilling measurements for each roof bolt hole can be processed and the essential information displayed for the operator to monitor in near-real time. To do this, it is necessary to measure drilling parameters — torque, rotation rate, thrust, penetration rate and the depth of drill tip penetration — and estimate the strength of the layers being drilled. Neural network technology can classify strata according to its estimated strength.

The Committee on Advanced Drilling Technologies of the National Research Council regards sensing and evaluating rock properties, while drilling as a revolutionary improvement (National Research Council, 1994). Detecting a different layer by the change in rock strength was, to the best of the author's knowledge, the first successful demonstration of this capability. The application of neural-network technology to strength classification of the material being drilled is new, as is estimating the strength of rock layers in near-real time. The concept has been proven in principle, and a patent is pending (Utt, 2000).

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