

INTELLIGENT DRILLING SYSTEM FOR GEOLOGICAL SENSING

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~~Abstract: As an opening is made in rock during mining, the equilibrium of the rock is disturbed, and the rock will tend to deform into the opening. For the safety of miners and equipment and to keep a mine open, the resultant stress and deformation must be controlled, a process known as ground control. The methods or tools used in ground control are called ground support.~~

The most frequently used method of ground support is roof bolting. Many pieces of equipment and installation techniques have been developed to protect and/or remove a bolter operator from the dangers of the immediate bolting area. Unfortunately, removing the operator also removes a valuable source of information on mining conditions. While installing bolts, operators use their senses to determine roof makeup and equipment performance. Remote and automated drills will enable the removal of the operator from this area, but there will still be a need for the information previously supplied by the operator.

~~For these reasons,~~ the U.S. Bureau of Mines is developing ways of detecting changes in rock strata and using this information to control equipment and optimize support selection. One system being developed monitors the drilling operation and uses pattern recognition and analytical formulas to evaluate geologic information so that an expert system can make decisions on support selection. Eventually this information will be used for equipment control, support selection, and input to long-term mine designs.

Introduction

Before any mine opening is made, the rock is in equilibrium. Once an opening is created, however, the rock in the vicinity of the opening is no longer in equilibrium and tends to relieve stress by deforming into the opening. The first step in solving this ground control problem (ground control is a term used to describe the process of supporting or stabilizing the roof, floor, or wall of a mine) is to determine whether ground support is needed, and, if so, what is the best support method. Factors to be considered are safety, economy, and how well the method chosen can be integrated with other mining activities.

Early mining systems used wooden posts to support the roof, but during the past 40 years, roof bolting has become the favored method. Roof bolting offers superior support and reduces congestion in the work area. Nonetheless, while today's roof bolting practices represent a significant improvement over previous methods, placement of ground support is still an arduous and hazardous task.

Installing ground support is dangerous and costly, and disrupts the mining cycle. Today's continuous mining machines (continuous miners) can only advance a short distance before they must be removed to make room for the bolting machine (bolter). Removing the bolter operator from the area being bolted eliminates much of the danger associated with the process but also eliminates a source of information (the operator) about the state of the mine roof. Ultimately, a system that removes the bolter operator from the dangers of the im-

mediate bolting area yet supplies vital information and allows continuous mining of the coal is needed.

One way being considered to accomplish these tasks is to combine a continuous miner and a roof bolter and direct the resulting machine either by remote control or by automated computer control. Because of the very limited space available in a mine entry, a premium will be placed on the size and reliability of such equipment.

Currently, operators use their senses to control equipment and evaluate geological conditions. If the operator is removed from the immediate bolting area, most of the operator's sensory input will be lost.

is discussed that
To prevent a significant decrease in productivity, three problems must be solved. First, we need to develop systems and subsystems that will work in a limited space. Second, we must develop remote or automated controls for these systems. Third, we must find ways of replacing (and even improving upon) the capabilities of a human operator.

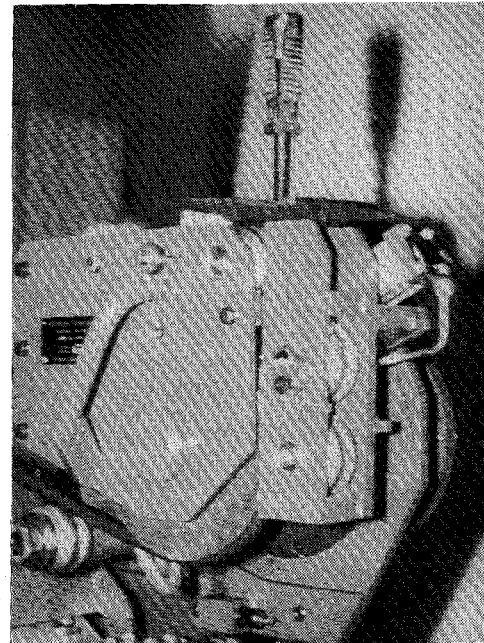


Figure 1. Roof bolt inserter for installing longer-than-seam-height bolts.

Early work by the U.S. Bureau of Mines [1] centered on the development of a roof bolt inserter (RBI), flexible or longer-than-seam height (LTSH) drills, bolting modules, and miner bolters. The RBI (Figure 1) takes a bolt that is longer than the height of the coal seam being mined (or the available working height), bends it approximately 90°, and then inserts the bolt into a previously drilled hole. The flexible drills (Figure 2) are able to drill holes up to 3.66 m long into the mine roof from a working height of 90 cm. Bolting modules are of two different types. First developed were the shorter-than-seam-height (STSH) modules (Figure 3) that

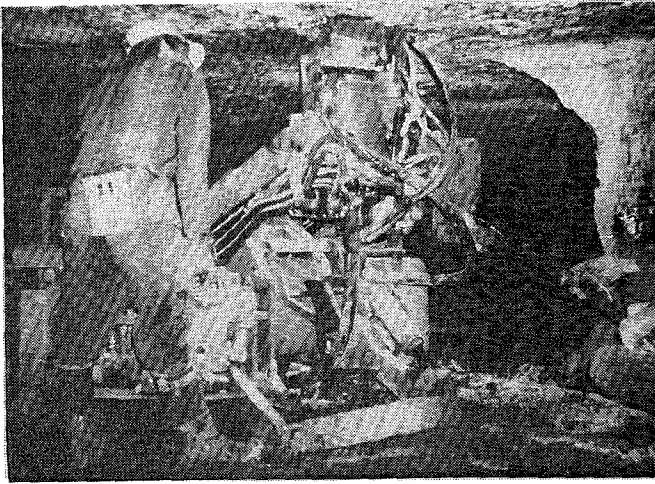


Figure 2. Longer-than-seam-height roof drill during underground tests.

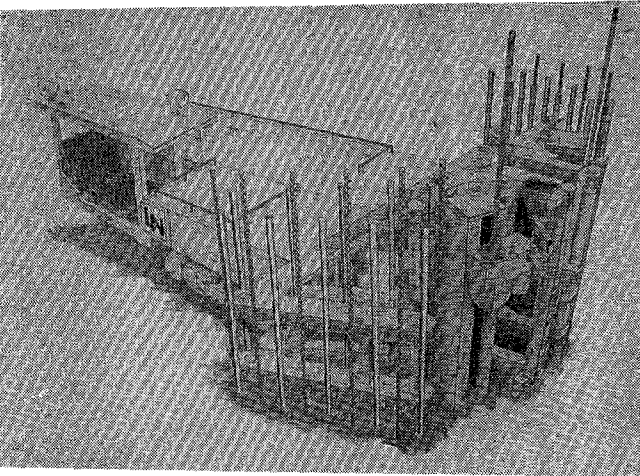


Figure 3. Artist's concept of shorter-than-seam-height bolting module.

are capable of installing bolts shorter than the height of the seam. Second are the LTSH modules that can install bolts that are higher than the mine opening. LTSH modules merged the RBI and LTSH drills. The next development was placing bolting modules on continuous miners, making them into miner-bolters (Figure 4). This allowed a continuous miner to advance without having to withdraw to make room for a bolter.

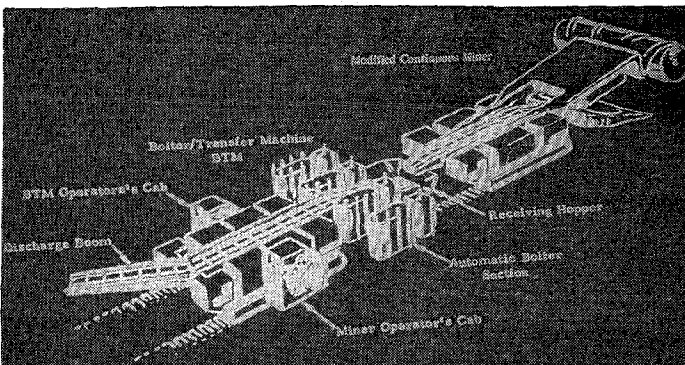


Figure 4. Artist's concept of a miner bolter.

To varying degrees, each of the above systems is successful. However, none of them were sufficiently de-

veloped to be used commercially. Other problems, such as vehicle navigation, control of individual components, and integrated system control, needed to be solved. With regard to the installation of ground support, specific processes needing improvement were drill control, measuring bit sharpness, and the sensing of conditions in the strata being drilled (geologic sensing).

Geologic sensing is considered here to be the detection of the physical characteristics of a rock mass. Using geologic sensing to obtain information about mine strata will be very useful in two ways. First, this information will be used in controlling the drill, and secondly, it will be used in determining optimum roof bolt length and type. Questions such as whether the roof bolt needs to be longer for proper anchorage, whether it should be grouted, and how much the roof bolt should be tensioned are critical for safe and efficient automated placement of ground support.

To effectively utilize geosensing in drilling systems, the Bureau is pursuing two approaches. The first is to develop tools and techniques to collect and display the factors affecting rock and roof stability, e.g., the engineering properties of rock, in situ field stresses, and geological discontinuities, in real time. Given this information, it is possible for geotechnical engineers to formulate hypotheses concerning ground stability.

The second is to increase understanding of the critical precursors to rock mass failure as derived from engineering data collected through geosensing. Several techniques exist to determine these precursors and the quality of the geologic environment surrounding a mine opening. One technique is to transmit a source signal nonintrusively through the rock mass; such a signal is reflected back when it encounters geologic anomalies. Intrusive techniques include collecting core samples and interpreting changes in drilling parameters, which vary with rock type and competency.

Using such techniques, the Bureau has completed a series of field trials that suggest that significant geologic information can be derived from the physical responses of a roof drill during the installation of roof-bolt-type supports. Such information is collected in near real time; rapid data interpretation is possible through the application of rather simple artificial intelligence (AI) software.

Advances in geosensing will greatly improve a miner's ability to gather information on geological parameters rapidly. With the aid of AI, it will be possible to make near real-time interpretations and related decisions.

Smart Drill

Decisions affecting ground control design require detailed knowledge of roof rock geology. This is especially true when weak rock and geologic anomalies are encountered in the roof, and, if not properly supported, can result in roof falls. Roof bolts are placed in underground mine roofs to prevent layers within the rock from separating and falling. The process of roof bolting involves drilling holes into the roof strata and inserting mechanical or resin-grouted roof bolts. An experienced roof bolter operator can often tell by the "sound and feel" of the drill and by observing the rock response to drilling whether layers, fractures, and voids are present, as well as the hardness and type of material being drilled.

To improve worker health and safety, the Bureau is developing a remote-controlled, automated roof-bolting machine that will allow an operator to direct the opera-

tions of the machine from a safe area, even when he or she cannot observe the machine itself. By placing monitoring instruments on the drill of a roof-bolting machine, these "senses" can be regained and even enhanced to collect more precise information about conditions in the immediate roof strata. This machine is referred to as the "smart drill." An artist's concept of a roof bolter with a smart drill system installed is shown in Figure 5.

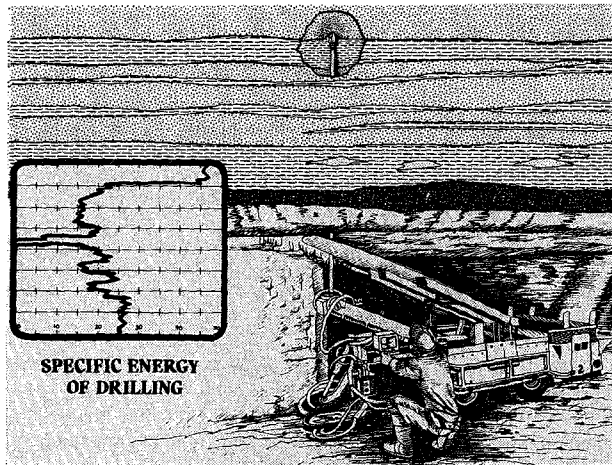


Figure 5. Artist's concept of roof bolter with smart drill system.

The instrumentation system on the roof bolter drill consists of three components. A diagram of this system is shown in Figure 6. The first component, a PC, is used for program development and data retrieval and analyses. The PC is located outside the mine and is not subjected to the adverse conditions underground.

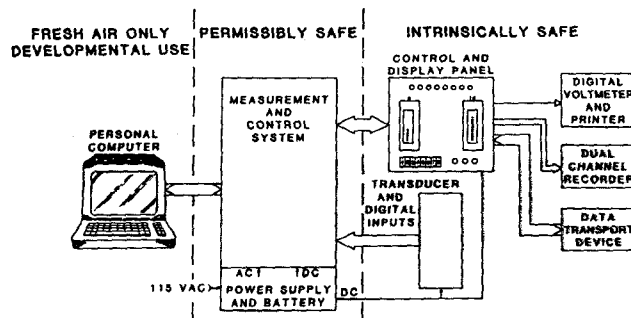


Figure 6. Diagram of roof bolter instrumentation system.

The second component consists of an explosion-proof box that houses the measurement and control systems and other signal-conditioning circuits. All lines running into and out of this box are encased in flexible hose conduit and are protected by barriers to limit the transfer of energy to the transducers of the control panel. The measurement and control section is mounted on the left rear side of the drill in an area previously occupied by the dust collection system, which is not needed because drilling dust is controlled by water flushing.

The third component is a display panel that includes all the external transducer circuits and a data transfer device (DTD). The display panel is mounted on the front of the drilling machine next to the manual control levers, which are used during the drilling and bolting sequence. This location is best to provide maximum visibility and access for the drill operator. The DTD is connected through a short cable to the display panel.

When mounted on the drilling machine, this system provides an operator with near real-time displays of the changes in specific energy of drilling and drill bit position. A microcomputer interprets and analyzes these data, making it possible to identify hazardous roof conditions such as voids, inclusions, and/or changes in strata. Such information can also be downloaded to the DTD and transferred to the surface, where it can be accessed directly with a PC for further analysis.

Research [2] has indicated that there is a correspondence between the specific energy of drilling as a function of torque, thrust, penetration rate, rotation rate, the area of the hole, and the unconfined compressive strength of the drilling medium. To calculate the specific energy of drilling, the following formula is used:

$$e = F/A + 2\pi NT/Au,$$

where e = specific energy of drilling,

F = thrust (N),

A = area of hole (m^2),

N = rotation rate (rpm),

T = torque (J),

and u = penetration rate (m/min).

The specific energy of drilling is defined as the work required to drill through a unit volume of rock. Hence, units are in joules per cubic meter (J/m^3) or newtonmeter per cubic meter (Nm/m^3). This is equivalent to units of unconfined compressive strength defined as Pascals N/m^2 .

Calibration and testing of the smart drill were conducted at the Bureau's Spokane Research Center (SRC). Sandstone test blocks constructed of alternating layers of hard and soft "rock" were cast with voids at specific levels. Cores were taken at the time the blocks were poured to check system calibration. The blocks were used to determine the accuracy of the calculations and the precision with which the specific energy of drilling and bit position could be measured.

Following extensive calibration, initial tests of the drill monitoring and display system showed a definite relationship between the specific energy of drilling and the compressive strength of the medium being drilled.

Field trials were conducted in an underground mine in Utah in two test areas, one in which the predominant roof rock is sandstone and the other in which the rock is mudstone. Figure 7 is a picture of the roof bolter and the smart drill operating in one of the test areas.



Figure 7. Drilling to obtain information on specific energy of drilling.

A pattern of four core holes, each approximately 1.5 m long, was drilled in five locations. Five specific-energy test holes were drilled around each core hole using a template that spaced each test hole 35.6 cm from the core hole. One-hundred specific-energy test holes were drilled in both the sandstone and the mudstone areas (200 holes total), and specimens from 20 core holes were collected from each area (40 cores total) [3].

One-hundred-twenty data records per drill hole were examined, and values were obtained for torque, thrust, rotation rate, penetration rate, position of the drill, and specific energy of drilling. Laboratory tests were conducted to determine the unconfined compressive strengths of the cores. Preliminary results indicated that although average compressive strengths of the sandstone and mudstone were similar, the mudstone showed a greater range of variability than did the sandstone.

Interpretation of Data

Several parallel but independent approaches are being used to analyze and interpret the laboratory and field smart drill test data. The common objective is to correlate the drilling parameter data with actual rock characteristics and rock structure at a specific location. These approaches include use of neural networks and empirical methods to recognize patterns in the data that correlate to rock strength, type, texture, voids, and joints.

The problem with relying only on the specific energy of drilling to identify significant geological features is that data are reduced to a single number. Vital information is lost that might be helpful for detecting geologic features accurately. Therefore, two neural networks were developed that use torque, thrust, revolutions per minute, and penetration rate as input parameters; geological classification is the output. The networks can operate in real time; results from the sandstone section of the mine indicate that drilling data can be correlated with actual rock core samples.

Neural networks and their learning paradigms are modeled after biological nervous systems. These networks form a system of many simple processing elements operating in parallel. The network response is determined by network structure, connection strengths, and the activation function of the processing element. There are many different types of neural networks, and they are used for different purposes. In this work, two types of neural networks were used: a self-organizing or unsupervised learning network and a supervised learning network.

Unsupervised learning refers to the clustering of patterns in feature space. Similar patterns are grouped together, and when a new pattern is introduced, it is compared to the centroid of all the existing clusters to determine the best fit. If the pattern falls outside the bounds of all the cluster spaces, a new cluster is created. The creation and scope of these clusters are governed by a distance function that is measured from the cluster centroid. During this project, several distance functions were evaluated, including Euclidean distance, Minkowski distance, Hamming distance, and Mahalanobis distance. Unsupervised learning is often used when there is inadequate information to create a training set for a supervised learning network, and it is up to the user to determine the relationship of the clusters to the problem.

Supervised learning derives its name from the fact that training data are presented on an input layer and an associated response is presented on an output layer.

In brief, the network uses the back propagation of an error-learning algorithm to adjust the weights of the interconnections to "learn" the correct response to a given input vector. After the network is trained, when an unknown input vector is entered, the output vector represents the network's classification. This classification is a function of how well the training set describes the problem space and the degree of error convergence during the training process.

Neural networks can be used to identify changes in rock features by looking at changes in drill operation as the drill is moved from one location to another. There are several advantages in this type of system. A neural network can be trained to recognize geologic features that are unique to a geographical location. A neural network can process information fast enough to operate in real time with a data acquisition system (DAS). It can identify when the drill is going from one medium to another and detect significant geological features. By storing only these changes of state, the amount of stored data is reduced considerably, which helps to provide "instant" processing of information.

The data used to develop neural networks for this project were from the field test site. Only a core log for a hole drilled in the vicinity of the roof bolt hole was available for classifying and interpreting the drilling data. Geological variations made it difficult to correlate drill parameters to the roof geology directly. It was decided that an unsupervised neural network would be appropriate to pre-process the data to create a labeled dataset for use in training a supervised network.

After several trials, 617 data sets, representing torque, thrust, rpm, and penetration rate for each data collection point along each drill hole, from the sandstone test site were grouped into 6, 9, and 16 different clusters using the Euclidian distance metric (Tables 1 and 2). The number of clusters was determined by the

Table 1. Nine-cluster set.

Cluster No.	Penetration rate, m/min	Thrust, N	Drill speed, rpm	Torque, J	Specific energy MPa
0.....	0.161	1250.4	24.28	3.788	4.72
1.....	.865	3775.7	82.85	20.527	15.21
2.....	1.114	9790.5	426.5	49.148	93.56
3.....	.842	4741.8	402.7	55.738	114.86
4.....	.571	2334.4	428.2	37.868	116.78
5.....	1.092	11876.8	428.9	76.061	141.31
6.....	.857	7655.4	498.3	62.313	158.10
7.....	.318	548.9	416.6	36.444	189.77
8.....	.948	13522.6	439.7	95.192	201.02

Table 2. Sixteen-cluster set.

Cluster No.	Penetration rate, m/min	Thrust, N	Drill speed, rpm	Torque, J	Specific energy MPa
0.....	0.153	1878.9	1.241	0.461	3.72
1.....	.170	622.8	47.32	7.12	9.06
2.....	.865	3776.5	82.85	20.77	15.30
3.....	.814	5088.8	171.3	27.93	33.23
4.....	1.118	9230.1	434.2	46.26	89.15
5.....	1.131	10537.8	438.3	54.46	104.11
6.....	.921	4924.2	395.2	57.00	106.25
7.....	.555	2602.2	438.1	33.60	109.83
8.....	1.174	11649.9	434.8	69.57	124.66
9.....	.651	39350.7	447.6	45.39	130.52
10.....	.767	6556.7	407.4	56.56	131.55
11.....	.839	7757.7	394.8	63.36	132.93
12.....	.529	1443.0	409.5	43.77	136.52
13.....	.947	12646.3	425.7	92.52	189.05
14.....	.287	2958.11	414.5	34.52	197.26
15.....	.912	14016.3	436.3	91.83	201.05

size of the distance metric. These clusters represented features in the roof such as strata changes, cracks, carbonaceous lenses, etc. However, the network of six clusters did not adequately represent the geology because it failed to properly classify bad or unrealistic data, which can result when the drill is spinning without drilling, when drilling the hole is begun, or when there are voltage spikes. Therefore, comparisons were only made for the 9- and 16-set clusters.

The clusters were arranged into a relative strength index based on the calculation of specific energy. The values of specific energy for the 16-set cluster group ranged from 3.72 to 201.1 MPa, while values for unconfined compressive strength from the core samples varied from 87.1 to 177.2 MPa (see Tables 1 and 2). The extremely low values could represent cracks, voids, or weak material that were not possible to measure by core testing.

These cluster groups were then used to train a supervised neural network by associating a input drill vector with a cluster number. The first network consisted of an input layer (torque, thrust, rpm, and penetration rate), two hidden layers of 10 nodes each, and a 16-vector output layer that represented the roof feature space developed from the unsupervised neural network. A logistic activation function was used on both of the hidden layers, whereas linear learning was used on the output layer. Also, the inputs were connected directly to the output layer. The second network was similar to the first except that there was only one hidden layer, nine nodes on the output layer, and no connection between the inputs and outputs.

Figure 8 compares the output of both supervised neural networks and the core log adjacent to the drill holes in the sandstone test section. Directional geological features could not be determined because the core logs were not oriented with respect to the drill holes. The 16-vector output network appears to create too many classes of rock units (overclassify) for the geologic features as compared to the 9-vector output network. Data from the roof area, which is predominately siltstone, was presented to the network, and the resultant classifications are shown in Figure 9. In general, the network appears to have adequately represented the roof; however, more test sites with different geological conditions should be examined in future evaluations.

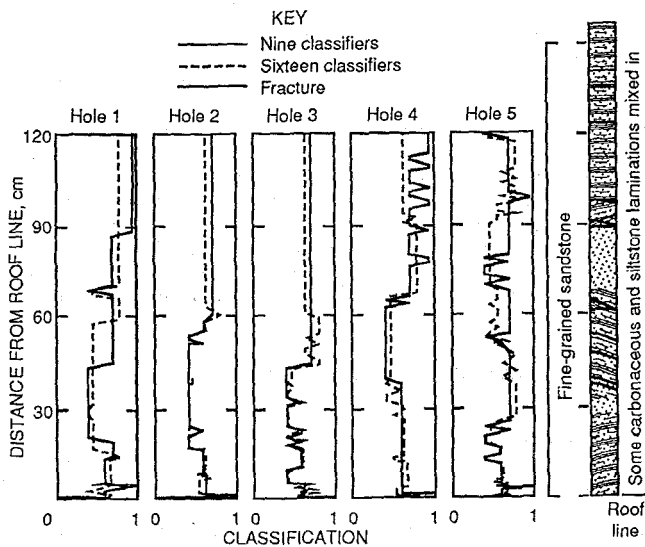


Figure 8. Neural network classifications in sandstone test section.

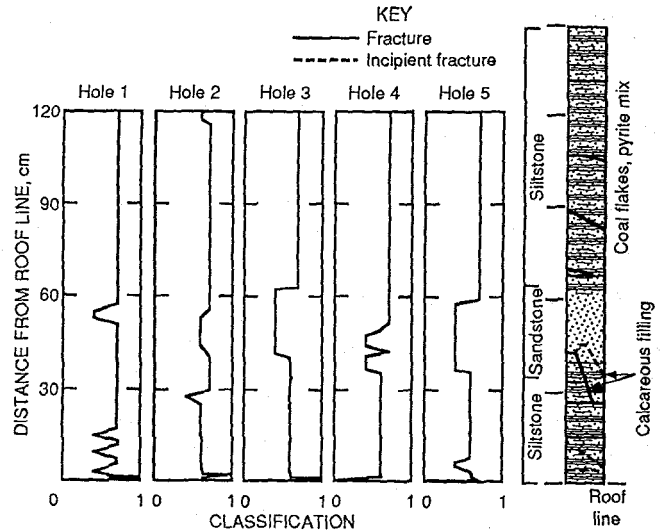


Figure 9. Neural network classification in siltstone test section.

Future Enhancements for Intelligent Drilling

Remote Drilling System

The smart drill concept was modified to include automatic control. The drill consists of a standardized roof drill mounted on a mast. It is powered by a portable hydraulic power pack, and a hydraulic cylinder applies thrust to the drill head. Directional and flow control valves can be operated from a PC. The system has manual override capabilities, so it can be shut down in emergency situations. When completed, an operator will be able to control the drill's torque, thrust, revolutions per minute, and penetration rate remotely [4]. This capability is necessary to hold selected operating parameters constant during drilling trials. In addition, AI control techniques will be used to ensure optimum drilling efficiency in any type of roof strata.

Data Acquisition System

A recently acquired DAS consists of two modules: a medium-speed module and a high-speed one (Figure 10).

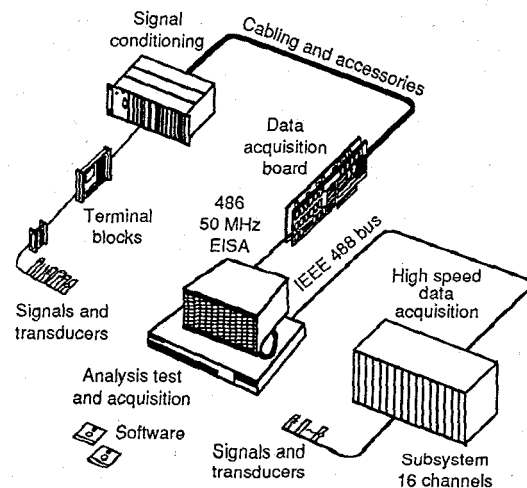


Figure 10. Data acquisition system for model roof drill.

The high-speed module will provide the instantaneous, accurate, time- and phase-coherent, multichannel, high-speed recording capabilities needed for geologic

sensing and subsequent correlation of the specific energy of drilling, drill vibrations, and changes of torque and thrust to rock type.

Traditionally, high-speed digital systems involve multiplex techniques in which several sensors are serviced by one high-speed, analog-to-digital converter. The multiplex approach has several significant disadvantages. It reduces system throughput, requires the use of complex and unique high-speed communications interfaces, and skews inherent interchannel time and phase data. To overcome these problems, an accurate amplifier-per-channel technique with a dedicated high-speed, analog-to-digital converter for each channel has been specified for data acquisition. A key aspect of this system is that it has the capabilities for 16 channels, each with a sampling rate of 250,000 samples per second, and 14-bit resolution for recording parameter changes instantaneously at high speeds.

The medium-speed module will monitor hydraulic pressure, temperature, flow, bit position in the hole, and drill penetration rate. These operating variables may have a significant influence on torque, thrust, rpm, and vibration. The medium-speed DAS will provide a means to increase economically the number of channels needed to acquire these less dynamic parameters, redundancy for the high-speed channels, and the monitoring and feedback signals needed for system control. The medium-speed system will be synchronized with the high-speed system to assure that data are correlatable. The system consists of drill-mounted transducers connected to terminal blocks on a signal-conditioning unit. It has cables leading to an EISA (extended industry standard architecture) DAS board mounted in an EISA 80486/50-MHz PC. The signal analysis software for both systems will be loaded on this computer. The high-speed DAS will also be connected to the PC through an IEEE 488 bus to provide visual data updates to the DAS software at selectable rates. Since the high-speed system has internal data storage, downloading memory will occur over the IEEE 488 bus to a mass memory storage unit after each roof bolt hole has been drilled.

Vibration Analysis

Techniques for analyzing drill bit vibration are being evaluated to determine if vibration analysis can be used to identify the type of strata being drilled. Methods of collecting high-speed vibration data (up to a 250-kHz sampling rate per channel) from rotating drill bits are currently being set up. Sensors will be mounted on a drill steel to measure torque, thrust, and drill vibration. Instantaneous changes in torque and thrust will be measured using strain gauges mounted on the drill steel itself. Vibration will be measured using an accelerometer embedded in the clamp ring housing the transmitter on the drill steel (Figure 11). Software and hardware modifications will be made so that four parallel high-speed inputs (torque, thrust, rpm, and vibration) can be simultaneously sampled and recorded.

Several data-gathering configurations will be investigated to determine which configurations are most sensitive to changes in rock type. Sampling rate, amplitude, frequency content, and antialiasing filter settings will be determined from sensitivity analyses of records collected during drilling test blocks of concrete. Once all the recording parameters are determined, extensive laboratory investigations will be undertaken to determine the validity of the technique. Additional blocks of concrete of varying compressive strengths and textures will be drilled and results analyzed. Optimal data representation schemes will be investigated to maximize the cluster spread and reduce the volume of the data.

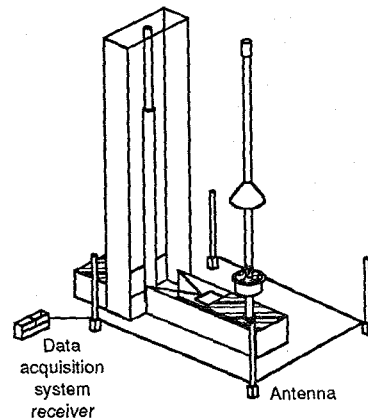


Figure 11. Instrumented drill steel on model drill with radio telemetry to data acquisition system.

Neural Network Analysis

Several neural network architectures will be examined. The architecture must be able to associate drilling data to entry stability and support requirements. Both adaptive resonance theory (ART) and associative memory will be investigated.

ART networks and algorithms maintain the plasticity required to learn new patterns while preventing the modification of patterns that have been learned previously. Much of the emphasis at this stage of the research will be to develop computer codes that will implement the ART structure with the interface on a NEXT computer.

The other area of neural network development is geologic trend prediction. Often ground control problems are related to gradual geologic changes, such as pinchout and rolls. Associative-memory neural networks could be used to look at a progression of drill holes. The information from one drill hole can form one part of a pattern of geologic changes for a set distance. The associative-memory neural network can then categorize the section of mine roof, relate this category to support requirements, and predict geologic changes in the immediate mine roof. This system would give miners a tool to "see" into the mine roof and select supports more accurately.

The existing neural network uses a low-speed DAS and, because it is a prototype, all the processing has been done off line. With an on-line, high-speed DAS, the neural network could be moved to a hardware platform rather than using software. This type of system uses a processor chip for each of the neural network nodes. Weight and bias vectors are encoded on the chip. The advantage of this type of system is speed and a hardware platform that can keep up with the high-speed DAS, depending on the size of the input vector and the number of hidden layers. This would yield finer resolution and increase the effectiveness of detecting voids and cracks.

Emerging and Prospective Applications for Intelligent Drilling

In addition to applying intelligent drilling systems to installation of roof support by conventional means, Bureau researchers are investigating the development of automated roof bolters. In this research, drilling information will be analyzed by AI systems, and decisions will be made automatically as to optimal roof bolt lengths and spacings to match the supports with varying roof geology. By using intelligent drilling and

an automated roof bolting system, not only will roof bolter operators be removed from the hazardous work area, but also knowledge will be captured and made available for decisions related to changing ground conditions.

Intelligent drilling holds great promise for being a low-cost source of geological and rock mechanics data for general use. It may serve as an economical substitute for core drilling and could be widely applied to

mineral and petroleum exploration, civil construction, foundation design, and tunneling.

Considerable interest has been shown in applying intelligent drilling in hostile environments where core drilling would be impracticable, such as underground repositories for radioactive waste, subsurface regions of the moon and Mars, and ocean bottoms. It appears that intelligent drilling for geosensing has a very bright future indeed.

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