for, excess fines generation in comminution, flotation sliming, gangue acid consumption and heap blinding in leaching, and other mineralogical problems in mineral processing and extractive metallurgy.

Conclusions

Based on the results of this pilot study, hyperspectral imaging shows considerable promise for mapping the distribution of minerals in mining, metallurgical and geological environments. It is not a replacement for laboratory-based analysis of geometallurgical samples or for standard geological mapping, but it can be a useful complement to both. Hyperspectral imaging is capable of more spatially comprehensive coverage than blast-hole sampling and can identify clays and other minerals not distinguishable with standard geological field methods. The main current obstacle to routine deployment of hyperspectral imaging in geometallurgy is the large size of datasets and the long time required to convert raw spectral data into geo-registered mineral maps checked against ground-truth data. Both of these are areas of ongoing and future research at the University of Arizona. ■

References

A list of all references is available in the full-text paper.

Identifying risk factors from MSHA accidents and injury data using logistic regression

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To read the full text of this paper (free for SME members), see the beginning of this section for step-by-step instructions.

Special Extended Abstract

This study applies a machine-learning technique known as multiclass logistic regression on a 10-year injury dataset from the U.S. Mine Safety and Health Administration (MSHA) to determine miners' susceptibility to injury and to help identify significant risk factors associated with different classes of injury. The analysis identifies specific risk factors that influence a mineworker's susceptibility to a given class of injury: nonfatal with no days lost or restricted activity; nonfatal with days lost and/or days of restricted work activity; and fatal and total permanent or partial permanent disability. These factors include miner's age, mine type (coal versus noncoal), experience on the current job (years), shift start time, employment type (operator versus contractor), mining district and type of accident. The results of the analysis indicate that a miner's experience on the job (the number of years worked in a current job) is a significant risk to injury occurrence, even for those with decades of total mining experience.

Background

Mineworkers are exposed to a variety of hazards within the mining environment. These hazards include rock falls, equipment malfunctions, fires, explosions and harmful gases, which make miners susceptible to mine accidents. In recent decades, mine safety has become an integral part of the mining industry culture through increased safety training and hazard recognition. At present, MSHA enforces the health and safety rules outlined in the Federal Mine Safety and Health Act of 1977, as amended by the MINER Act of 2006. The U.S. National Institute for Occupational Safety and Health (NIOSH) works to develop innovative safety solutions through the provision of research grants with the focus of reducing safety and health-related accidents. Between research-focused NIOSH and regulation enforcement by MSHA, the United States has seen a steady decline in mine-related accidents. Many mining companies have set the goal of achieving zero harm. To this end, researchers have analyzed accidents and injury data with a goal of mitigating mine accident and injury occurrence using a variety of statistical, quantitative and novel methods, including machine learning. Machine learning is a branch of artificial intelligence that allows computer systems to improve their performance at a task through experience (learning) for the purpose of predicting future outcomes. In this study, we apply a machine-learning technique known as the multiclass logistic regression to a 10-year (2008 to 2017) injury dataset from MSHA to (1) determine a miner's susceptibility to a class of injury given characteristics such as age, mining experience, and work location and (2) identify the various risk factors associated with each class of injury to help identify potential risk factors associated with different classes of injury. The multiclass logistic regression is well suited for predicting the outcome of a dependent categorical variable (such as degree of injury) using a set of independent variables (such as age, mining experience and work location).

Methodology

This study examines injured miners involved in a single accident while working on a mine site. The following injuries fall within the scope of this study: fatal, permanent total or permanent partial disability, nonfatal with days lost only, nonfatal with days lost and days of restricted work activity, nonfatal with restricted work activity only, and nonfatal with no days lost or restricted activity. To achieve statistical relevance, we aggregate these degrees of injury into three classes: (1) fatal and total permanent or partial permanent disability (FP), (2) nonfatal with days lost and/or days of restricted work activity (DLR) and (3) nonfatal with no days lost or restricted activity (NDLR). Aggregating the injuries provides sufficient data to enable validation of the model at a 95 percent confidence level. We conduct statistical tests—chi-square contingency, correlation and multicollinearity—to determine which independent variables to consider for modeling. These independent variables serve as inputs to the logistic regression model while the dependent variable (degree of injury) serves as the output.

Results

From the model, we determine which independent variables have had significant impact on injury occurrence over the period under study. These variables are classified as risk factors and include miner's age, mine type (coal versus noncoal), experience on the current job (years), shift start time, employment type (operator versus contractor), mining district and accident type.

The output of the model also presents interactions among the three injury classes as follows: nonfatal with days lost and/or days of restricted work activity (DLR) versus nonfatal with no days lost or restricted activity (NDLR), and fatal and total permanent or partial permanent disability (FP) versus nonfatal with no days lost or restricted activity (NDLR). Thus, we set NDLR as a reference response variable to enable assessment of the relative impact the various predictors have on the injury classes. This is useful for assessing a miner's susceptibility to a class of injury given characteristics such as age, experience on the job, mine type and accident type suffered. For instance, Fig. 1a shows that susceptibility to DLR generally decreases with increase in experience on the job, while Fig. 1b shows that susceptibility to both DLR and FP generally increases with an increase in age. Table 1 is a summary of the most susceptible groups of miners in respect of DLR and FP. From the foregoing, we observe that a miner's experience on the job—that is, the number of years worked in a current job—is a significant risk to injury occurrence, even for older miners who might have decades of total mining experience.

Conclusions

We apply the multiclass logistic regression on MSHA accidents and injury data to identify risk factors and miner's susceptibility to injury. We observe that regardless of the overall mining experience of a miner, the initial year in a new position incurs the highest DLR risk. The multiclass logistic regression proves to be a tool that can be used beyond basic statistics in providing robust mine accident and injury analysis. Using this tool, safety managers can identify areas that need prioritized training or attention. Periodic analysis with this tool and taking pragmatic measures thereafter will promote a strong safety culture and risk mitigation in the mine environment.

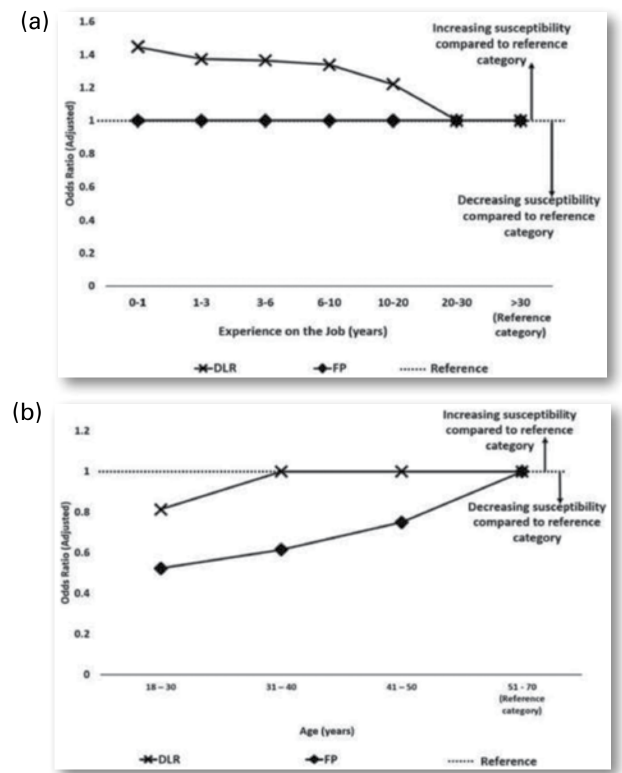

Fig. 1 Risk profile for (a) experience on the job and (b) age.

References

A list of all references is available in the full-text paper.

Table 1 — Most susceptible categories.

Predictor	DLR	FP
District	Northeast	*
Experience on the job (years)	0–1	*
Shift start time	Shift 2 (peak start time, 3 pm)	*
Age (years)	51–70	51–70
Employment type	Operator	Contractor
Mine type	Noncoal	*
Accident type	Slip or fall	Powered haulage

*Implies all categories of the predictor have equivalent injury susceptibility.