

Application of machine learning to determine underground hazard location

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ABSTRACT: Underground mine accidents, such as mine fires, remain a concern for mine operators, posing a health and safety risk to the mine workers. Dealing with an unknown location of an accident underground can be a challenging task, creating a hazardous condition for miners during an evacuation and rescue operation. A timely determination of an underground fire event's location and size is of great importance in reducing the risk of any injuries. Machine learning (ML) has made its way into mining, enabling the development of data-driven predictive models that can be applied to miner's health and safety problems. A new methodology has been developed using the application of a ML technique to characterize underground accidents such as size and location of an underground mine fire using the post-fire airflow data. This paper describes the methodology and its verification through examples. The National Institute for Occupational Safety and Health (NIOSH) is endeavoring to develop workplace solutions to improve detection of and reduce the risk of hazardous conditions. The results demonstrate a promising application of the ML-based models using the airflow monitoring and provide a useful tool for solving the problem of unknown fire location and reducing the risk of hazardous conditions.

1 INTRODUCTION

Mine fires remain a health and safety threat to underground miners despite the decreasing trend in the number of fire-related injuries in mining in the last decade. Mine fires produce significant levels of toxic gases and smoke that can be carried throughout the mine by the airflow through the ventilation network, easily reaching faraway locations from the fire source and increasing the hazard potential for miners (Smith and Litton, 2015). Equipment fires have been recognized as being responsible for most injuries caused by fire in mines during 2000–2013 (Slaughter et al., 2015). To reduce fire-caused injuries in underground mines, it is important to ensure the safety of the underground mine environment during a fire incident. Characterizing an underground mine atmosphere during a fire event was reviewed by Timko and Derick (2006) in terms of methodology, sampling methods, and equations to detect the fire and determine the fuel type.

The mine-wide Atmospheric Monitoring System (AMS) is employed in underground mines for monitoring air quality parameters such as air velocity and methane concentration, as well as detection of a fire. The AMS comprises strategically located environmental and air quality sensors to measure and monitor the atmospheric parameters. The use of an AMS for early warning and fire detection has a significant potential to enhance the safety and well-being of underground miners (Smith and Litton, 2015). The AMS has been used to develop tools to characterize an unknown fire in underground mines (Zhou et al., 2020). The system has also

been used to determine fire location using carbon monoxide (CO) arrival time and concentrations (Bahrami et al., 2019; Bahrami et al., 2020).

Equipment fires can occur both at surface mines and in underground locations. When an equipment fire occurs in an underground mine, the fire could significantly affect the mine ventilation system by a 10-20% apparent change in airway resistance (Gillies and Wu, 2004), and possibly change airflow quantities, airflow directions and unexpectedly contaminate fresh air escape routes. Large-scale test results in the literature show that a typical burning wheel loader can generate a peak heat release rate of about 20 MW, with a carbon monoxide (CO) concentration of 900 ppm and a smoke rollback of over 50 m in the mine entry, posing a severe risk to underground mine workers (Hansen and Ingason, 2013). Unlike the ventilation network in a coal mine, the network in metal/nonmetal mines (MNM) is irregular and complex, often dictated by the complex geology and spatial distribution of the vein/ore deposit forcing the development of many levels to mine steep veins. This complexity is compounded by the frequent usage of booster fans and auxiliary ventilation systems to deliver fresh air to the working faces. Therefore, a need exists for mine operators to have a tool to diagnose the impact of a detected mine fire on a mine's ventilation network.

With advances in sensor technology, automation, and data communication, mining operations are moving toward a digital mine concept, leading to huge amounts of data generated from various sources, including atmospheric monitoring sensors measuring air quality, velocity, and other parameters. Thus, a clearer picture of the mine ventilation system stability emerges. Many mining companies, such as the Barrick Gold Corp. and Newmont Mining Corp. in Nevada, are moving toward a digitally connected workplace for increased efficiency that will lead to increasing profit, decreasing cost, and improved safety (Carter, 2018). A "smart system" of real-time monitoring, together with mine ventilation and fire simulation, can provide a clearer picture of the mine ventilation network's operating health status, as well as its near-future condition in the case of a fire emergency.

Simulation of an underground mine fire using any mine fire simulation software, under the assumption that the location and size of the source is known, requires knowledge of the mine ventilation and fire simulation software. Furthermore, the simulation results must be analyzed to determine the impact of the fire on the ventilation network.

For the above reasons, a strong need exists for a ventilation diagnostic tool, as proposed in this study. The concept of Machine Learning (ML) is a powerful tool for solving complex modeling problems across a broad range of industries. The benefits of this technique are being realized in applications everywhere, including predictive maintenance, health monitoring, financial portfolio forecasting, and advanced driver assistance systems (MathWorks, 2019). Machine learning is based on the simple idea of getting computers to learn and act like humans do—i.e., to improve their learning over time by feeding them data and information (Faggella, 2019). There are many applications of ML and artificial intelligence that address mining problems, including predicting mechanical failures on equipment, production optimization, and ore body delineation (Stewart, 2016).

Machine learning algorithms are considered the next step for digital mine transformation. Some mines have already moved beyond descriptive analytics and visualization platforms and into ML prediction and artificial intelligence (Stewart, 2016). Machine learning has also been used to predict methane concentration around the longwall production area in a coal mine using the monitored sensory data (Sikora and Sikora, 2006). ByungWan, and Rana (2018) developed a smart predictive mine environment index using the measured influential gas concentrations and an Azure ML software. Machine learning has also been used to optimize location and setting of ventilation regulators for desired flow in a mine ventilation network, in lieu of manually adjusting regulators, which could take up to an hour since the ventilation network is slow to respond to the changes (Kashnikov and Levin, 2017). Recently, researchers developed and applied a ML technique to detect a spontaneous combustion fire hazard in underground coal mines using wireless sensor data (Muduli et al., 2019).

An ML-based model, if properly trained, can be used to diagnose impending ventilation issues in response to a mine fire without the need for a lengthy simulation process. The National Institute for Occupational Safety and Health (NIOSH) has developed tools to

characterize an unknown fire source by analyzing the measured data from the AMS installed in a mine (Yuan et al., 2017; Bahrami et al., 2019). The next step in further advancing this tool is to develop a ML-based tool to diagnose the hazard status of a mine ventilation system in response to a mine fire incident.

2 ANALYTICAL FIRE LOCATION MODELS

Locating an underground mine fire and assessing its condition are important for developing firefighting strategies in underground mines. The rescue team can roughly determine where an unknown fire is located and be able to evaluate the conditions based on the reporting of smoke conditions and the feeling of bulkheads for heat (Enright and Ferrier, 2015). The occurrence of an unknown fire can be detected by monitoring the presence of smoke and gases such as carbon monoxide (CO). Currently, the fire location determination is based on the visual reports of smoke or measured hazardous gases, such as CO and nitrogen oxide (NO_x), using hand-held gas sensors. However, with the availability of AMS sensor concentration data of the products of combustion (POC), such as CO, and the arrival times of the POC concentrations exceeding the alarm levels at the triggered sensors, it is possible to automatically determine the airways where the fire is located.

The former U.S. Bureau of Mines (USBM) developed a Fortran code, LMODEL, to calculate the minimum travel time and pathway of the POC from any airway to a smoke detector (Edwards, 1990). The LMODEL does not determine the fire location directly, however, a manual procedure was outlined for the user to determine fire locations from the calculation results (Edwards, 1990). A second fire location code, LFIRE, was developed by researchers at the former USBM Twin Cities Research Center (Laage et al., 1989b; Yang, 1992). This code incorporated matching the POC arrival time patterns, through a root mean square (RMS) error, to automatically determine fire location airways. These codes can lead to more than one airway as the fire location, making the fire location determination somewhat unreliable. Recently, NIOSH researchers developed a new and more accurate fire location determination method that incorporates the POC concentration data, e.g., gradient of CO concentration curve at detection level (Bahrami et al., 2019).

The objective of this paper is to present and demonstrate a new, ML-based technique to determine an unknown fire location based on the application of an ML technique using only the ventilation network airflow response under the influence of an equipment fire source.

3 MACHINE LEARNING-BASED MODEL

The ML-based technique developed in this work is demonstrated using the ventilation network of the Safety Research Coal Mine (SRCM), an underground experimental mine facility located at the Bruceton Campus of the Pittsburgh Mining Research Division (PMRD) of NIOSH. Figure 1 shows the layout of the SRCM facility with the primary airways highlighted.

The SRCM is a room-and-pillar mine with one main return airway in an exhaust ventilation mode bringing fresh air through one main intake airway. A total of 166 airway segments exist in this network. The quantity of the main airflow is controlled by a door at the main return airway. A simplified ventilation network setup is shown in Figure 2. The ventilation model is based on a well-calibrated network from the previous work of NIOSH researchers (Zhou et al., 2019).

This model is converted to an input file that can be used by MFIRE fire simulation software in an automated MATLAB-based data generation. Each airway is labeled by its airway number in the ventilation model, which is also used to identify a fire source location as well as all airflow data in the dataset used for the ML model development. The very low flow-rate airways, shown in light blue in Figure 2, are automatically excluded from the dataset. These airways are typically the ones that are closed off or not practical to be monitored accurately.

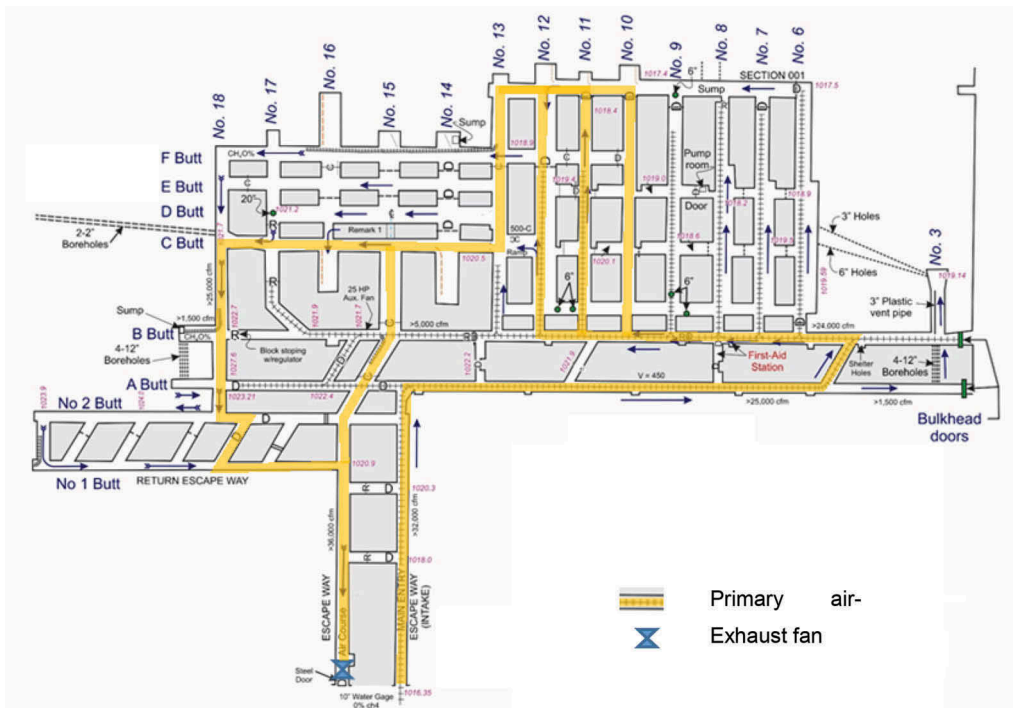


Figure 1. Layout of the Pittsburgh SRCM.

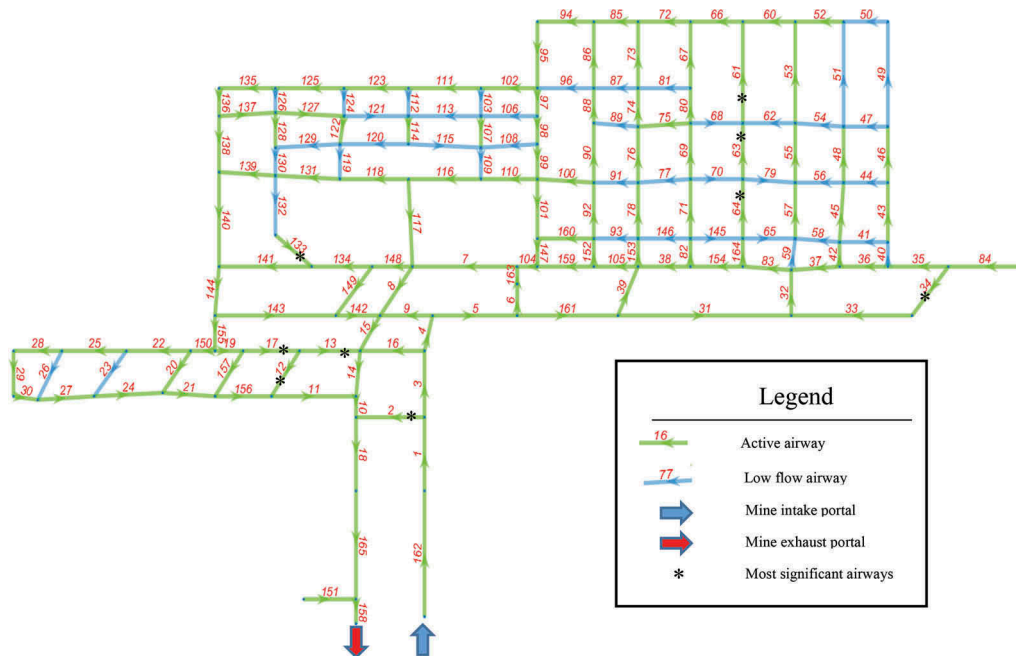


Figure 2. Simplified ventilation network for the SRCM.

The focus of the model is on the active airways with numerically significant airflows, larger than 10 fpm, based on available flow sensor accuracy. After excluding the 42 inactive airways, the remaining 123 active airways are considered in this study as potential fire sources.

The ventilation model input was fed to an automated macro to build a large set of fire scenarios of different fire sizes placed in any airway of the network. For every airway, twenty fire source scenarios were randomly selected from a range of 900 W to 2.6 MW. A total of 200 fire scenarios were generated. A computer workstation with 24 physical cores was employed to run these fire simulations using the MFIRE software. The results of each scenario in terms of airflow distribution in every airway, the fire location airway, and fire size are all recorded in a tabular form with the data for each scenario being placed in one row.

This dataset contains 24,600 rows or records of data. The fire location, in terms of airway ID, is considered categorical response data. With the 123 airway segments, each airway flow data is considered as one predictor or feature, leading to 123 features involved in this dataset.

A ML model relies on the input/output data to learn the underlying physical model behind the data. It is hypothesized that knowing the flow distribution can only lead to one solution in terms of fire location. With this concept in mind, we have developed a ML-based predictive model can use the flow distribution data to determine the fire location causing such flow distribution. In developing any ML-based predictive model, the available dataset is split into a training set and a testing set. In this study, a 70-30 split is considered in which 70 percent of the data records or rows is used to train the model, and 30 percent is used to test the trained model.

Since the response variable is a categorical data, we will be using a suite of different ML algorithms commonly used by other researchers (Zhou et al., 2011; Kumar et al., 2014; Peng et al., 2014; Hasan and Twala, 2015; Chen et al., 2019) and suitable classification algorithms that are available in the MATLAB statistical and machine learning toolbox. The algorithms selected for this activity are listed in Table 1. The approach in this study is to identify the best-performing algorithm available in MATLAB based on its performance in terms of training speed, prediction speed and prediction accuracy.

The “fitctree” function in MATLAB uses binary decision tree for multiclass classification. A decision tree classification method is based on a set of simple rules, such as “if the data value is less than a decision value, classify the data as in one category versus another one.” Decision trees are also nonparametric because they do not require any assumptions about the distribution of the variables in each class. The “fitcknn” function uses the k-nearest neighbor (KNN) classifier. KNN algorithm is a simple, supervised ML algorithm that can be used to solve both classification and regression problems. KNN works by finding the k closest points in data to a query point or set of query points to determine the most frequent label (in the case of classification) or average of the labels (in the case of regression). The “fitcnb” function uses multiclass naive Bayes model. Unlike the k-nearest neighbor and decision trees classification methods, the naive Bayes assumes the data comes from a statistical distribution, and the predictors are independent within each class. The “fitcdiscr” function uses discriminant analysis model. The discriminant analysis method is like the naive Bayes, which assumes the observations in each prediction class can be modeled with a normal probability distribution. However, there is no assumption of statistical independence between predictors. The

Table 1. Selected classification algorithms in MATLAB.

Classification Algorithm in MATLAB	Description
fitctree	Binary decision tree for multiclass classification
Fitcknn(KNN)	k-Nearest Neighbor classifier
fitcnb	Multiclass naive Bayes model
fitcdiscr	Discriminant analysis model
Fitcecoc (SVM)	Multiclass models for Support Vector Machines
fitcensemble	Ensemble of learners for classification

“fitcecoc” uses multiclass models for support vector machines (SVM). A support vector machine classification algorithm classifies data by finding the best boundary that separates all data points. The “fitcensemble” function uses ensemble of learners for classification. A classification ensemble is a predictive model composed of a weighted combination of multiple classification models, in this case decision trees, to increase predictive performance.

The complexity of a ML model depends on the number of its features. It is important to investigate and develop a procedure to automatically determine the most important or influential features correlating to each fire location, while maintaining an acceptable level of prediction accuracy. There are different algorithms available in any ML package that basically accomplish this objective. Typically, features are randomly removed from a given dataset to evaluate how the impact model performs. We use a built-in function to determine the most important airways.

The model performance is determined based on the speed of training and prediction as well as how accurately the trained model predicts the response, and in this case, the fire location. The response variable, fire location, being a multi-class variable with 123 classes, is evaluated against the known class of every scenario.

4 RESULTS AND DISCUSSION

Based on the feature importance function applied to the training dataset, in MATLAB, it was determined that the airflow data from 8 airways can describe 90 percent of the response data variation. These significant airways, which contribute the most to the ML model, are marked with an “*” in Figure 2. Currently, these airways are not monitored as part of the large-scale field test at the SRCM. A future field test will have to be designed to test the predictive models obtained from this study.

Using only the features corresponding with these airways, each algorithm was trained against the training dataset and tested using the testing set. The model performance in terms of prediction accuracy for the suit of selected algorithms is summarized in Table 2. For the training and prediction computer times for each algorithm the KNN algorithm proved to be the fastest algorithm with a training and prediction times of 0.5 and 0.1 seconds, respectively, at least 200 times in comparison with the SVM algorithm with a training and prediction times of 108 and 88 seconds, respectively. According to these results, the best-performing model is built using the KNN algorithm even though the SVM provides slightly more accurate results. Each trained model was also optimized regarding its design or hyper-parameters to achieve the best performance in terms of prediction accuracy.

Employing the KNN algorithm also allowed us to build a predictive model for the fire size using the airflow data of the identified 8 most important airways in the network. The performance of this predictive model is shown in Figure 3 with the R-squared value of 0.94 for the fit between the predicted and the known fire sizes.

Table 2. Model performance in terms of prediction accuracy (%) against the testing dataset.

Classification Algorithm	Number of most important features						
	2	3	4	5	6	7	8
fitctree	69.6	79.9	82.7	83.0	86.9	87.8	88.0
Fitcknn(KNN)	73.0	82.6	85.1	86.4	89.1	90.8	90.8
fitcnb	45.3	56.7	60.4	59.8	62.4	63.6	63.2
fitcdiscr	29.0	37.6	38.3	40.9	42.0	43.6	44.5
Fitcecoc(SVM)	73.3	83.7	88.2	90.6	94.3	94.6	94.7
fitcensemble	72.7	74.5	85.5	86.4	89.6	90.9	90.3

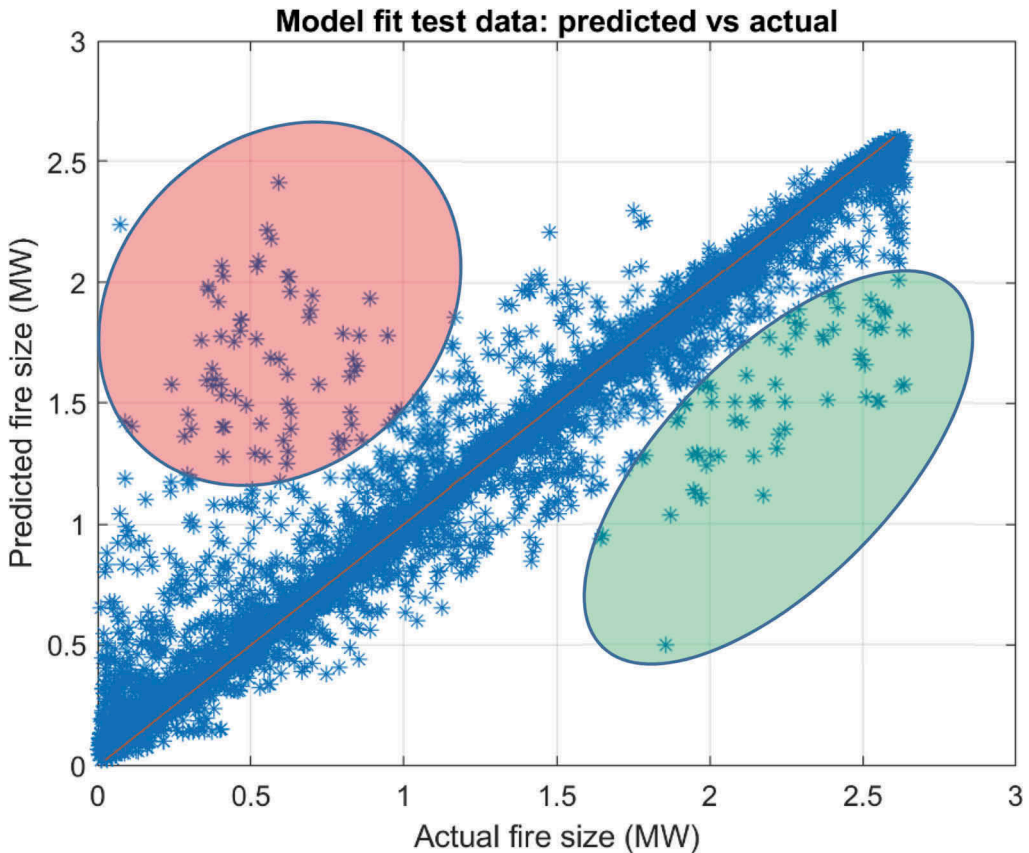


Figure 3. Test performance of the KNN algorithm for fire size prediction.

Despite excellent prediction accuracy, there is a small group of small fire size scenarios, highlighted in light red, that are over estimated. Whereas, another small group of larger fire size scenarios, highlighted in light green, are underestimated. Overestimating a small fire size can be considered a favorable outcome but underestimating a large fire size cannot. Even though the underestimated fire sizes are small, further investigation is needed to examine their locations in the ventilation network. The complexity and size of the ventilation network are not expected to be a problem other than increasing the computation time to build the trained model.

It can be argued that there are still some inaccurate predictions obtained from this model. The authors acknowledge that the prediction performance of the fire location and its size using this ML-based model may be further deteriorated by noise in the data as well as other systemic and man-made changes in the ventilation flow distribution after a fire emergency. However, it is our understanding that the ML-based predictive modeling can be further improved and validated in the field by monitoring significant airways for airflow.

5 CONCLUSIONS

This research supports NIOSH's efforts to develop workplace solutions to improve the detection of hazardous conditions in underground mines. A technique was developed based on an ML-based approach to locate an unknown underground fire as well as its size using the airflow changes caused by the fire. The model developed in this study can predict the location and size of

an unknown fire in an underground mine with reasonable accuracy using the flow data of few critical airways in the network. The accuracy of the developed machine learning-based model is dependent on the continuously calibrated ventilation network. This method provides a useful tool for solving the problem of unknown fire location and reducing the risk of hazardous conditions in underground mines. For the future research, large-scale fire tests will be used to further verify the ML-based fire location method. The information obtained from the ML-based model is not meant to replace the current practices of characterizing underground mine fire.

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. Mention of any company or product does not constitute endorsement by NIOSH.

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