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Characterizing Fire in Large Underground Ventilation Networks Using Machine Learning

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ABSTRACT

Underground mine accidents, such as mine fires, remain a health and safety risk to mine workers. Researchers at the National Institute for Occupational Safety and Health (NIOSH) are developing a data-driven, predictive model for characterizing the location and size of unknown underground fires. This study examines applying a machine learning-based model to predict fire size and location in a large underground metal mine based on hypothetical scenarios on the model performance. The results show that the size and location of an unknown fire can be determined with over 80% and 90% accuracy, respectively, and potentially help to reduce the risk of hazardous conditions for emergency response.

INTRODUCTION

Mine fires continue to occur, although at a very low occurrence rate; however, they remain a health and safety risk to both surface and underground mining operations. Smoke and toxic gas are hazardous results of an underground mine fire, which flows to other areas of the mine via the ventilation network [1] posing a higher health and safety risk compared to the surface mine fires. Equipment fires have been recognized as being responsible for most mining injuries during 2000–2013 [2]. To reduce fire-caused injuries in underground mines, it is important to ensure the safety of the underground mine environment during a fire emergency.

In underground mines, an Atmospheric Monitoring System (AMS) is employed to monitor air quality parameters such as air velocity and other gasses concentrations such as methane, CO, and CO2. 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 [1]. The AMS has been used to develop methodologies to characterize an unknown fire in the Safety Research Coal Mine (SRCM) at the Pittsburgh Mining Research Division site and to determine fire location using carbon monoxide (CO) arrival time and concentration [3-5].

An underground mine fire could cause changes in the mine ventilation system by increasing airway resistance by 10%–20% [6], which could lead to changes in airflow quantities and airflow directions. Such changes could unexpectedly contaminate fresh air escape routes. Large-scale test results in the literature show that a typical burning of a wheel loader can generate a peak heat release rate of approximately 20 MW, a CO concentration of 900 ppm, and a smoke rollback of over 50 m in the mine entry that could pose a severe risk to underground mine workers [7].

The ventilation network in metal/nonmetal mines tends to have many airways and is complex with many branching-off zones. This complexity is compounded by using ventilation controls such as doors, regulators, booster fans, and auxiliary fans to deliver fresh air to the working faces. Therefore, there is a need to predict fire size and location within a mine to determine the potential impact of a fire emergency. Such a tool may provide mine operators the ability to evaluate and improve mine ventilation networks to mitigate risk of hazardous exposures to miners, and, to develop improved mine rescue plans for emergency responders.

Successful forward modeling of an underground mine fire scenario using mine fire simulation software requires knowledge about the location and size of the fire source. For these reasons, a ventilation diagnostic methodology is proposed to be used in this study that applies the use of the machine learning (ML) technique that can be considered as reverse modeling to determine the location and size of an underground fire. ML-based methods have been utilized in other industries to perform predictive maintenance, health monitoring, financial portfolio forecasting, and advanced driver assistance systems [8]. The foundation of ML-based modeling is the simple idea of getting computers to learn from data [9]. Many ML and artificial intelligence applications address mining problems, including predicting mechanical failures on equipment, production optimization, and ore body delineation [10]. Moreover, NIOSH researchers conducted machine learning analysis to examine whether a model could be built to assess the likelihood of dynamic ground failure occurrence, leading to seismic events, based on geochemical and petrographic data [11].

An ML-based model, once properly trained using many fire simulations using fire and ventilation software to build the required dataset, can be used to diagnose impending ventilation issues in response to a mine fire without the need for a lengthy simulation process to locate and characterize a fire source. Updating the required dataset will be needed whenever significant changes in the ventilation network occur. NIOSH researchers have previously developed tools to characterize an unknown fire source by analyzing the CO arrival time data from the AMS installed in a mine [12-14].

The objective of this paper is to present and demonstrate the applicability of a previously NIOSH-developed novel methodology [3,15] to characterize an underground mine fire in large ventilation networks. The methodology is based on the application of an ML technique using only the ventilation network airflow response under the influence of a fire source. Previous work [3,15] showed results with reasonable accuracy from the application of this methodology to the SRCM experimental mine at the NIOSH Pittsburgh Mining Research Division.

The evaluation of the performance and efficiency of the developed method when applied to a large ventilation network is the goal of this paper and is presented in the following section.

MACHINE LEARNING-BASED MODEL

The ML-based modeling used in this work has been 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 of NIOSH [3,15].

The selected example mine is a metal mine with multiple zones and several ventilation controls such as main fans, booster fans, doors, and regulators that bring fresh air to the work zones comprising over 4,000 airway segments. The quantity of the airflow distribution is controlled by the ventilation controls. Figure 1 shows the partial layout of the large example mine ventilation network. The complexity of such a model can be seen from the layout, using true 3D coordinates of each airway.

The model was provided in the Ventsim ventilation and fire simulation software which is widely used in metal/nonmetal mines. The model is then imported into MATLAB where a macro-based data generator is used to generate and process data for the ML-based modeling. Each airway is known 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, as nonparticipating airways, are automatically excluded from the dataset. These airways are typically the ones that are dead-end airways or block sections. The focus of the model is on the active airways with numerically significant airflows, larger than 0.05 m/s based on a typical point airflow sensor measurement error.

Furthermore, a continuous airway that has been split into multiple segments for geometry compliance and more realistic visualization can be represented by one of those segments. For consistency, the middle segment airway is selected, rendering the remaining airways along the same continuous path redundant. This will reduce the size of the dataset used in the proposed ML-based model as each remaining airway is a feature considered for fire simulation. After excluding the inactive and redundant airways, the remaining 766 active airways were considered in this study as potential fire sources.

The ventilation model input was fed into a MATLAB macro to build a large set of fire scenarios of different fire sizes placed in any airway of the network. For every airway, 50 fire source scenarios were randomly selected from a range of 6.7 MW to 36.7 MW. The maximum fire size of mine equipment was determined based on the literature available on the heat release rates of equipment tires, diesel fuel, and hydraulic oil, used to estimate the heat release rate (HRR) for wheel loaders and drilling rigs [7,16-17]. For diesel fuel, the total fuel tank capacity is used to estimate the HRR. For a typical wheel loader used in the example mine, the maximum HRR was estimated to be 7–15 MW. For the drilling rig, the maximum HRR was estimated to be in the range of 16–35 MW. A total of 38,300 fire scenarios were generated. A computer workstation with 24 physical cores was used to

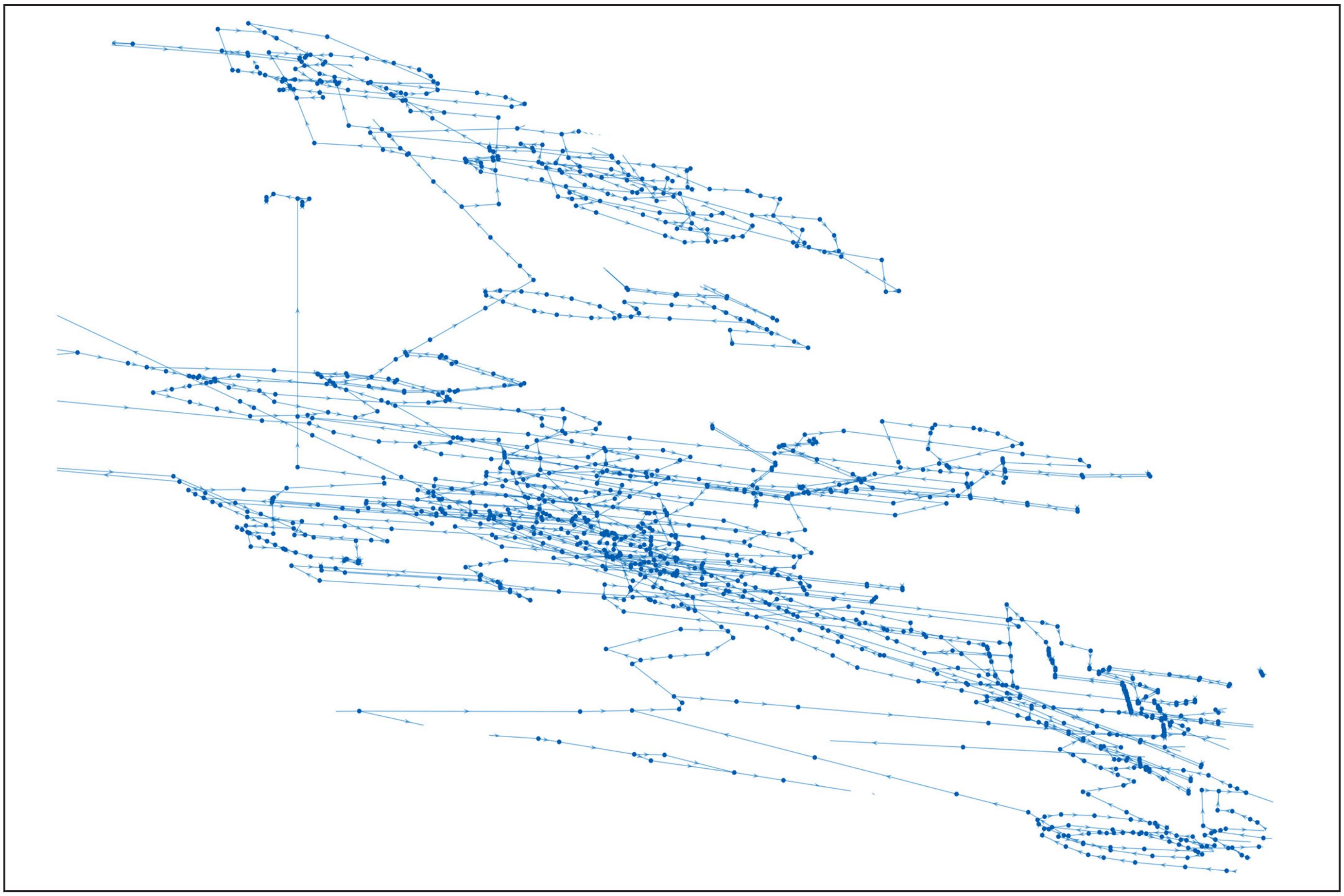

Figure 1. Partial layout of the example mine's ventilation network

run these fire simulations using the Ventsim software [18]. The results of each scenario in terms of airflow distribution in every airway, the fire location airway, and fire size were all recorded in a tabular format to form a dataset with each scenario's data stored in a row.

This dataset contains 38,300 rows or records of data each representing a fire simulation for a fire size in an airway. The fire location, in terms of airway ID, is considered categorical response data. With the 766 airways, each airway flow rate is considered as one predictor or feature, leading to 766 features in this dataset.

An 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 at least one solution in terms of fire location. With this concept in mind, we developed an ML-based predictive model that can use the flow distribution data to determine the fire location causing such flow distribution. The generated dataset was split into a training set (70%) and a testing set (30%). Two different prediction models were considered, one for the fire location and one for fire size. For each model, the training set was used to train the model, and then the test dataset was used to test the trained model and determine the prediction accuracy. The accuracy of the fire location was calculated as the ratio of the number of correctly predicted fire locations to the total number of fire locations.

Since the response variable is categorical data, the suite of ML algorithms in MATLAB was tested. The random forest was chosen from the MATLAB statistical and ML toolbox following the performance of the selected algorithm in previous research by the authors [3]. The fire size is a numeric value, and a regression-based ML algorithm was used to predict the fire size using the changes in the airflow caused by a fire. The model performance is then calculated using the test data set by calculating the R^2, coefficient of determination, between the predicted fire size values and the fire size used in the fire simulation model.

RESULTS AND DISCUSSION

The complexity of an ML model depends on the number of features used. It is important to investigate and develop a procedure to automatically determine the most influencing airways correlated to each fire location while maintaining acceptable prediction accuracy. We used MATLAB's built-in function to determine the most important airways. The importance of an input variable, airway airflow, is calculated by the ML algorithm in terms of its ability to predict the output.

Based on the feature importance function applied to the training dataset in MATLAB, the obtained feature importance of all 766 airways was sorted in ascending order. After that, it was determined how the number of selected features can affect the model performance in predicting the fire location. To accomplish this, the training and testing of the ML-based fire location was repeated for each set of the selected features. Figure 2 shows how the model prediction accuracy improves by increasing the number of used features. Airflow data from the most important seven features/airways lead to about 92% accuracy in fire location prediction. Increasing the number of features to 20 can increase this accuracy to about 96%.

Inspection of the ventilation network and the location of these most significant airways confirms that they are well distributed throughout the ventilation network. This indicates a good representation of strategic airways for monitoring airflow changes during a fire emergency as part of fire characterization for size and location.

A future field test will be needed to test the predictive model obtained from this study in collaboration with the partner mine. The seven important airways needed to achieve over 90% accuracy account for only 1% of the main airways, marked with a circle in Figure 2. Increasing the number of important airways to 20 will increase this percentage to only 3% of total main airways, marked with an arrow in Figure 2.

Model performance is assessed based on the speed of training and prediction and how accurately the trained model predicts the response variable, which in this case is the fire location.

Using only the features corresponding with these seven airways, the selected algorithm was trained against the training dataset using the fire size as the response variable and tested using the testing dataset. The model training with seven features took about 23 seconds. The predicted fire sizes for the test dataset are only using seven features or important airways. The model prediction takes only 1 second. However, preparing the data set which is based on many fire simulations using Ventsim, 83000 simulations in this case, requires a significant amount of computer time but only required whenever the ventilation model is updated.

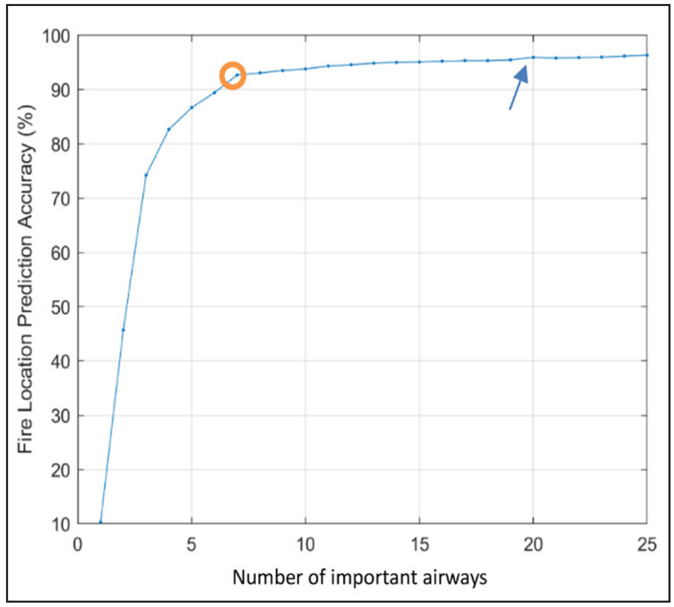

Figure 2. Fire location prediction accuracy as a function of the number of important airways

The performance of the trained fire size model using the seven important airways is shown in Figure 3. Fire size prediction provides an R^2 of 0.88 with seven significant features. In addition to the R^2 performance metric, the average percentage error was calculated as an additional prediction performance metric. The point percentage of predicted values versus actual fire sizes was calculated for each fire scenario and then averaged as an absolute value also led to an average point accuracy percentage of 88%. Adding more features or important airways can improve the fire size prediction slightly by about 2-3 percent.

The ML-based modeling technique used in this study relies on the airflow distribution obtained from the ventilation network. Consequently, the model's performance and accuracy depend on how well the ventilation network is calibrated.

Despite excellent prediction accuracy for such a large network of airways, it can be seen from Figure 3 that smaller fires tend to be overestimated while larger fires tend to be underestimated. However, overestimating a small fire size can be considered a favorable (conservative) outcome. In other words, it would be on the safe side to have a small fire reported as a somewhat larger fire. Additionally, this model does not account for normal operating airflow fluctuations as the model relies on significant changes in the airflow that are larger than the normal operating airflow fluctuations or measurement error.

It can also be seen from the results that the fire location prediction provides better performance with the same

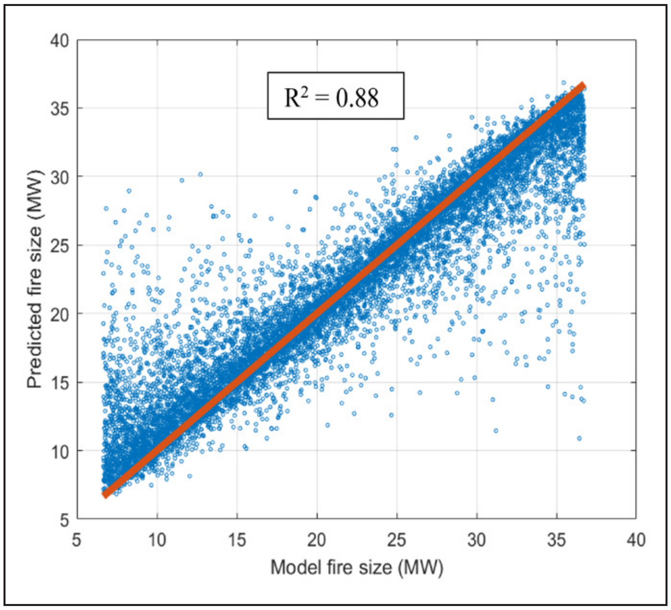

Figure 3. Model performance for fire size on the test dataset using seven important airways

number of used features in comparison with the fire size prediction.

LIMITATIONS

The methodology presented in this paper can be applied to any underground mine operation. However, the results in this paper are only applicable to the example mine presented here. Furthermore, any update by the mine operator in a ventilation network typically results in significantly different airflow distribution and will require the model to be rebuilt. The model does not account for normal operating airflow fluctuations. The results for fire size and location accuracy are specific to the testing of the methodology from hypothetical scenarios generated from machine learning algorithms to evaluate model performance. Further investigation at a field site will be needed to test the predictive model obtained from this study in collaboration with the partner mine.

CONCLUSIONS

This research supports NIOSH's efforts to develop workplace solutions to improve the detection of hazardous conditions in underground mines. A previously developed technique by NISOH based on an ML-based modeling to locate an unknown underground fire and determine its size was successfully applied to a large ventilation network. We achieved reasonably good model prediction performance to locate the fire and its size with over 90% and 80% accuracy, respectively.

The ML-based model only used a small fraction of airways, 20 at most out of 766, to achieve over 90% fire location accuracy.

The accuracy of the developed ML-based model depends on the continuously calibrated ventilation network. This method provides a useful tool for solving the problem of unknown fire locations and reducing the risk of hazardous conditions in underground mines.

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 an endorsement by NIOSH.

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