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A NOVEL METHODOLOGY TO LOCATE AN ABNORMAL AIRFLOW IN UNDERGROUND MINE VENTILATION NETWORKS

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ABSTRACT

Mine ventilation is one of the most important aspects of mining operations in underground mines. It is critical to maintain and deliver required fresh air to the active areas to reduce the risk of overexposure to hazardous contaminants or explosive atmospheres. An unexpected or unknown event such as roof collapse, unexpected mine door closure/opening, a fire/explosion, or fan malfunction could adversely alter the airflow distribution within the mine ventilation network that could lead to a hazardous underground environment. Knowing the occurrence and location of such an incident is of critical importance. In this study, the authors developed a novel methodology to assist mine operators in quickly identifying the location of any abnormal airflow change within the network using the airflow changes at monitored airways. The concept is based on a direct derivative method developed by the authors. This paper provides the details of the developed method as well as numerical verification examples. The application of this method can benefit mine operators and safety personnel in making better decisions during a mine emergency response operation to mitigate hazardous conditions arising from an unexpected airflow disturbance.

INTRODUCTION

A reliable and stable mine ventilation system is key to the safe and economical operation of underground mines. A mine ventilation system requires routine maintenance to adjust the distribution of airflow to meet the requirements of providing desired fresh air to working places, and removing or diluting hazardous gases, dusts, heat, etc.

Any unplanned flow change event caused by opening/closing a ventilation door or a roof collapse could create a hazardous condition for the miners by putting them at a higher risk of overexposure to a hazardous substance in underground mines. An unplanned airflow change could further jeopardize the response to a fire hazard by altering the flow distribution of fresh air. There is a need for the mine operators to quickly identify the unexpected airflow changes, diagnose the causes, and then resolve the problem.

The study and design of underground ventilation networks has been the subject of research for many decades. One commonly used method of studying a mine ventilation network involving using simulation software is to predict flow distributions with known network properties to gain an understanding of potential ventilation scenarios or to optimize ventilation performance. The network properties include regular airway resistances or friction factors, door/regulator resistances, and fan parameters. Any given ventilation network can be set up using ventilation software such as Ventsim, VnetPC, Vuma, ICAMPS-MineVent. A ventilation network model setup in any software must be calibrated against measurements through ventilation survey practices. Once a network is calibrated and can be relied on for forward simulations of airflow distributions, the same network can be employed to answer other types of questions. One question related to the health and safety of miners is to know the location of an event causing an unexpected abnormal change in the airflow distribution. Identifying the unexpected abnormal airflow change and diagnosing its cause is of importance for mine operators to promptly fix the ventilation problem that will potentially pose hazardous threats to the health and safety of miners. The abnormal event could be either an increase or decrease of airflow recorded at the monitored airways. The objective of this paper is to develop a method to assist mine operators in promptly diagnosing the location of unexpected airflow changes in a mine ventilation network.

NETWORK ANALYSIS

Ventilation network behavior can be characterized by its sensitivity, also known as Jacobian linearization of a network response. A flow resistance change in any airway of a ventilation network can lead to a new airflow distribution. The ratio or partial derivative of flow change in a target airway *j*, referred to as monitored airway, to the resistance change in any other airway *i*, referred as source airway, is taken as the airway sensitivity, $S_{i,j} = \frac{\partial Q_{i,j}}{\partial R_i}$. Consequently, the total flow change in any target airway j caused by resistance change in all other airways can be described as the linearized summation of all partial changes as follows:

$$\Delta Q_j = \sum_i^n \frac{\partial Q_{i,j}}{\partial R_i},\ \ i = 1,2,\ldots,n, j = 1,2,\ldots,m \tag{1}$$

Where Q is the airway flowrate, ***R***, is resistance, ***i*** is the index of ***n*** airways, and ***j*** is the index of ***m*** monitored airways.

From Equation (1), the sensitivity or Jacobian matrix S can be defined in Equation (2).

$$S = \begin{bmatrix} \frac{\partial Q_{1,1}}{\partial R_1} & \cdots & \frac{\partial Q_{1,m}}{\partial R_1} \\ \vdots & \frac{\partial Q_{i,j}}{\partial R_i} & \vdots \\ \frac{\partial Q_{n,1}}{\partial R_n} & \cdots & \frac{\partial Q_{n,m}}{\partial R_1} \end{bmatrix},\ \ i = 1,2,\ldots,n, j = 1,2,\ldots,m \tag{2}$$

Each *i*th row of the sensitivity matrix refers to the sensitivity of all *m* monitored airways with respect to the *i*th airway source airway. Network sensitivity characterizes a ventilation network in terms of how it responds to any changes in any airway resistance leading to a disturbed airflow distribution. Network sensitivity analysis has been used by researchers to develop various tools for calibrating and optimizing a ventilation network [1,2]

Danko et al. [1] present a Jacobian-based network sensitivity matrix together with a least-square-fit numerical algorithm to calibrate the airway resistances across the network. The method uses a Jacobian sensitivity matrix to inverse-calculate the Atkinson friction factors across the model to minimize the root-mean-square (RMS) error between the measured and simulated results. The algorithm requires updating the Jacobian sensitivity matrix, which involves a large number of flow simulations.

Griffith and Stewart [2] further expanded on this method by developing a calibration tool in the Ventsim ventilation simulator allowing the user to automatically calibrate airway resistances using a limited number of surveyed airflows. The tool is a useful option in eliminating the need to manually calibrate a ventilation network. However, the calibration takes long computational time to converge in large networks, which involves updating the Jacobian-based sensitivity matrix of Equation (2) requiring n*m simulations in each update. None of these studies have utilized network sensitivity to back-calculate the location of source airway of an unknown airway resistance change.

In this study, authors have developed a novel methodology to identify the location of the source airway of an unknown abnormal airflow in a ventilation network using the sensitivity matrix in Equation (2). The details of this methodology are provided in the following sections of this paper.

METHODOLOGY

The method of diagnosing the location of the airway causing unexpected airflow changes is built using the sensitivity matrix of the ventilation network of Equation (2). Researchers at NIOSH have developed an efficient method to determine the network sensitivity, *S,* in Equation (2) using only one airflow simulation [3]. The general process of locating the source airway of unexpected airflow changes is to compare the airflow changes at the monitored airways to their sensitivity caused due to the resistance changes in the other airways.

A resistance change, $\partial\mathbf{R}$, in an airway can change the airflow distribution in a ventilation network leading to flow rate changes, **DQ**, in the network airways. Provided that monitored airways for airflow measurement are available, as well as of a significant resistance change in a source airway, it can be shown that the monitored airflow changes can be correlated with the sensitivity of the monitored airways. The airflow change in any of the monitored airways, $\Delta\boldsymbol{Q}_j^S$, is related to the sensitivity, $\boldsymbol{S}$ from Equation (2), through a scale factor:

$$\Delta Q_j^S = S_{i,j} \cdot C_i, , i = 1,2,\ldots,n, j = 1,2,\ldots,m \tag{3}$$

Where $\boldsymbol{S}$ is the sensitivity of the $\boldsymbol{j}$th monitored airway to the $\boldsymbol{i}$th source resistance change, and $\boldsymbol{C}$ is the scale factor corresponding to the $\boldsymbol{i}$th source airway.

In order to determine the airway resistance, change in the network, the Root Mean Squared Error of fit between measured, ΔQ_j^M, and simulated ΔQ_j^S, flow changes at the monitored airways is calculated first for each i^{th} airway in the network.

$$RMSE_i = \sqrt{\left(\Delta Q_j^M - \Delta Q_j^S\right)^2}, i = 1,2,\ldots,n, j = 1,2,\ldots,m \tag{4}$$

Combining Equation (3) and Equation (4) leads to the following.

$$RMSE_i = \sqrt{\left(\Delta Q_j^M - S_{i,j} \cdot C_i\right)^2}, i = 1,2,\ldots,n, j = 1,2,\ldots,m \tag{5}$$

For each potential source airway in the network, a corresponding scale factor is determined by minimizing the corresponding RMSE. It can be shown that the scale factor of any source airway is as follows:

$$C_i = \frac{\sum_j^m \left(\Delta Q_j^M \cdot S_{i,j}\right)}{\sum_j^m \left(S_{i,j}\right)^2}, i = 1,2,\ldots,n, j = 1,2,\ldots,m \tag{6}$$

Using the best scale factor from Equation (6) in Equation (5) ensures minimum RMSE for any source airway. It is assumed that the source airway is the one associated with the minimum RMSE. The application of this method is demonstrated through a numerical example in the next section.

NUMERICAL EXAMPLE SETUP

The numerical example used for testing the proposed methodology is based on the example published in the user manual of NIOSH fire simulation software called MFIRE [4]. The mentioned example is for the Waldo mine ventilation network considered as a well-calibrated model. Figure 1 shows the reconstructed network layout of this example. Matlab software [5] is used as the test platform to run MFIRE simulations and analyze the results. There are a total of 49 airways and 34 junctions in this network. For the purpose of demonstrating, five airways are chosen as monitored airways, also marked in Figure 1. Nine scenarios of source events are planned in this test with each event having increased or decreased resistance in different airways. These scenarios are summarized in Table 1. Application of the developed algorithm in this paper to each scenario leads to the identification of the prescribed source event in each scenario which will be discussed next.

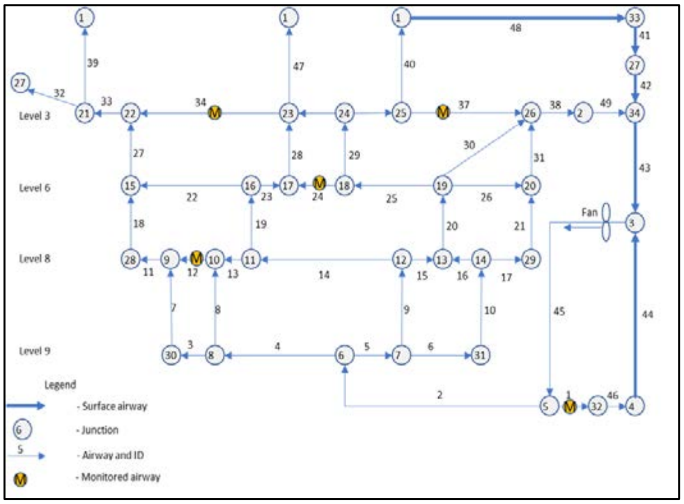

Figure 1. Ventilation network model of Waldo mine (Source: [4]).

Table 1. Event scenarios of resistance changes.

Scenario	Airway ID	Original Resistance [Ns^2/m^8]	New Resistance [Ns^2/m^8]	Resistance Ratio
1	20	0.09	0.91	10
2	21	50.82	5.08	0.1
3	21	50.82	0.51	0.01
4	34	0.92	0.09	0.1
5	34	0.92	9.18	10
6	26	0.52	5.17	10
7	12	0.76	7.56	10
8	8	1.39	0.01	0.01
9	46	55.85	0.56	0.01

RESULTS AND DISCUSSIONS

To demonstrate the performance of the proposed methodology, Scenario #1 is presented in more detail. Scenario #1 involves a resistance change in airway 20 from 0.09 to 0.91, a 10-fold increase. This scenario was examined with the listed monitored airways in Table 2. Figure 2 shows the scaled sensitivity-based airflow changes and the monitored values for this scenario given in Table 2. Figure 3 shows the RMSE of matching the recorded flow changes caused by any potential source airway. The minimum RMSE can be found at the airway 20 that agrees with the designated source airway in this scenario. Identification of multiple airways is done with the buffer selection window at the minimum RMSE. This may lead to multiple airways being identified as the possible source. This can happen if there are airways in series or parallel with the source airway or multiple airways present with RMSE values very close to the minimum RMSE. Therefore, a successful source determination is achieved if the source airway is included together with the identified airways.

Table 2. Event scenarios of airflow changes in m^3/s.

Scenario	Monitored Airway ID				
	1	12	24	34	37
1	0.034	1.171	-2.178	-0.546	1.207
2	-0.002	-0.053	0.129	0.035	-0.106
3	-0.006	-0.118	0.293	0.083	-0.250
4	-0.001	-0.047	-0.349	1.017	-0.229
5	0.002	0.065	0.373	-1.205	0.258
6	0.000	0.008	0.013	-0.008	0.050
7	0.005	-1.727	0.394	0.127	-0.305
8	-0.004	0.538	0.056	0.024	-0.041
9	12.511	-1.244	-0.333	-0.807	-0.154

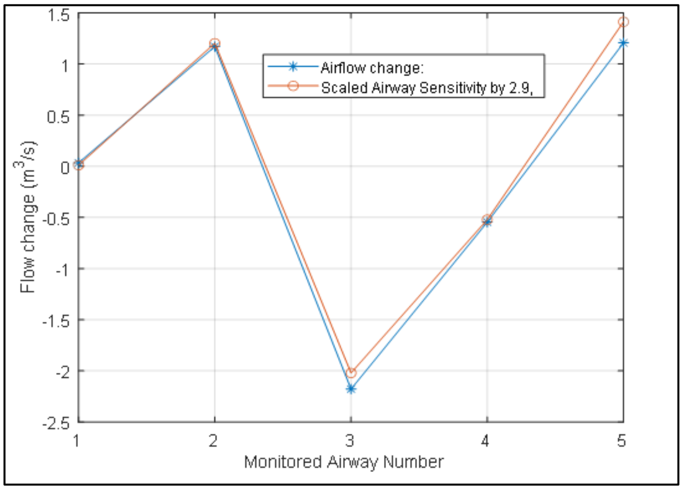

Figure 2. Flow changes at the selected monitored airways corresponding to the minimum RMSE in Scenario #1.

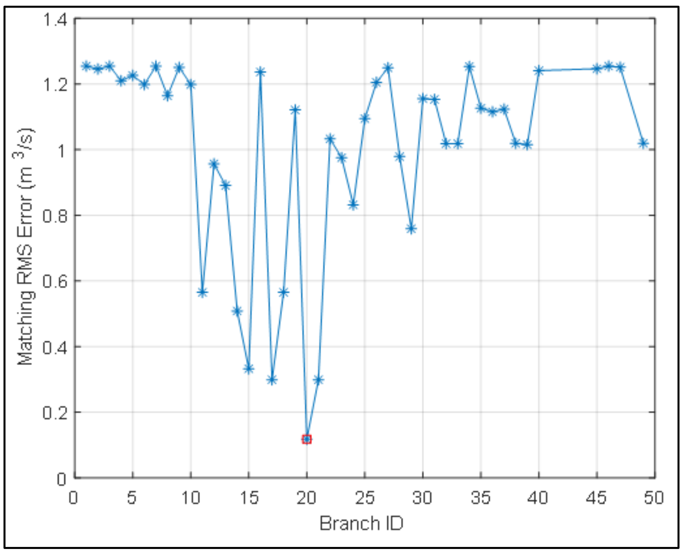

Figure 3. The RMSE of matching airflow changes for every airway.

Performance of the proposed method using the flow changes at the selected monitored airways for all nine scenarios are summarized in Table 3. The identified source airways include the designated actual source airway in each scenario. Every scenario led to successful source determination using the selected monitored airways, indicated as number 1 in the table together with number of identified source airways in each scenario.

Table 3. Performance of the proposed method using the selected monitored airways.

Scenario	Number of identified source airways		
	One Airway	Two Airways	Three Airways
1	1	0	0
2	0	1	0
3	0	1	0
4	1	0	0
5	1	0	0
6	0	0	1
7	0	1	0
8	1	0	0
9	0	1	0

Scenarios #2, #3, #7, and #9 lead to two airways as the source airways. From this group Scenario #2 was examined with the listed monitored airways in Table 2. Figure 4 shows the scaled sensitivity-based airflow changes and the monitored values for this scenario given in Table 2. Figure 5 shows the RMSE of matching the recorded flow changes caused by any potential source airway. In this scenario, airways 21 and 17 are in series connection as shown in Figure 1, and as a result either one can be picked as the source. A successful source determination is achieved if the source airway is included together with the identified airways. The picking of minimum RMS error included a buffer window of 5%.

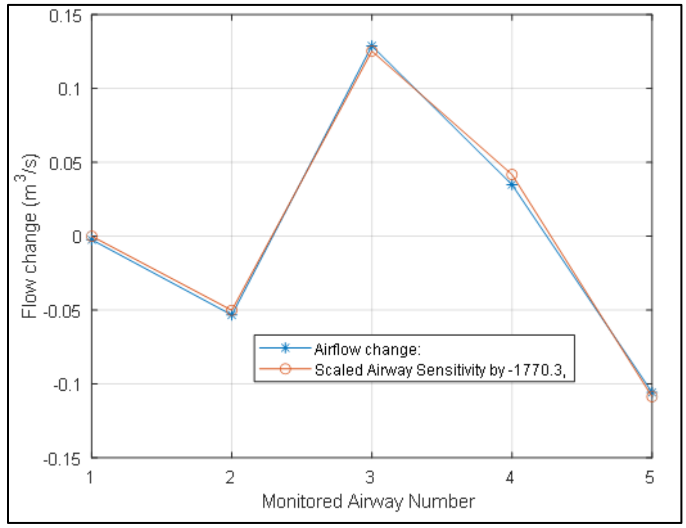

Figure 4. Flow changes at the selected monitored airways corresponding to the minimum RMSE in Scenario #2.

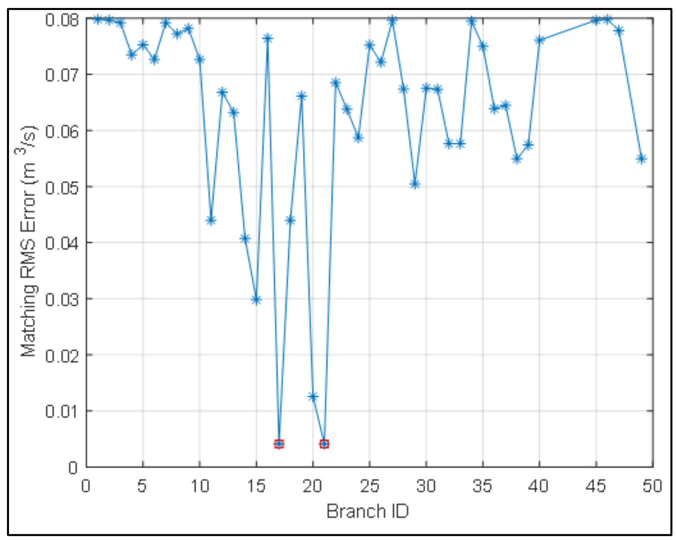

Figure 5. RMSE of matching airflow changes for every airway in Scenario #2.

Scenario #6 presents with 3 airways as potential source airways. Figure 6 shows the scaled sensitivity-based airflow changes and the monitored values for this scenario given in Table 2. Figure 7 shows the RMSE of matching the recorded flow changes caused by any potential source airway. . The identified potential source airways 25, 30, and 31, including the designated source airway 26, are closely connected as shown in Figure 1. This could explain why any of these airways could be a source leading to similar airflow changes in the listed monitored airways.

Although Scenario #9 returns with only two possible source airways with the selected monitored airways but a different set of monitored airways, this could result in more airways being identified as a source which will be addressed later in this section. A limited number of airways identified as a source helps the mine operator by having to check only a few locations to find the source of abnormal airflow.

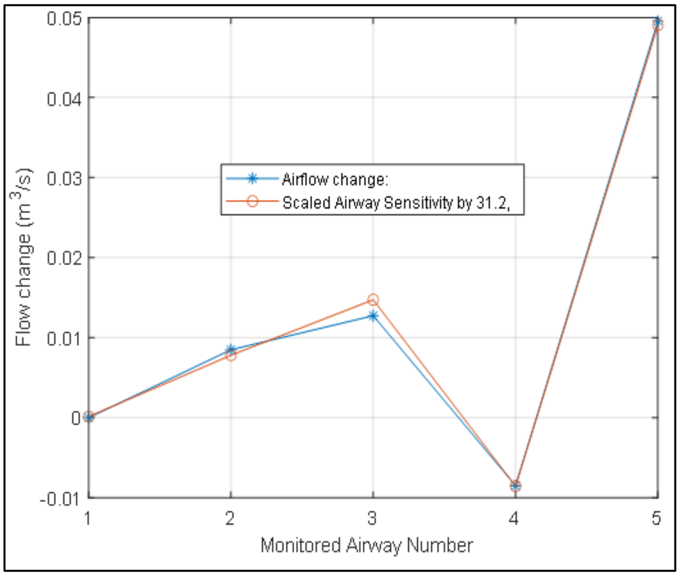

Figure 6. Flow changes at the selected monitored airways corresponding to the minimum RMSE in Scenario #6.

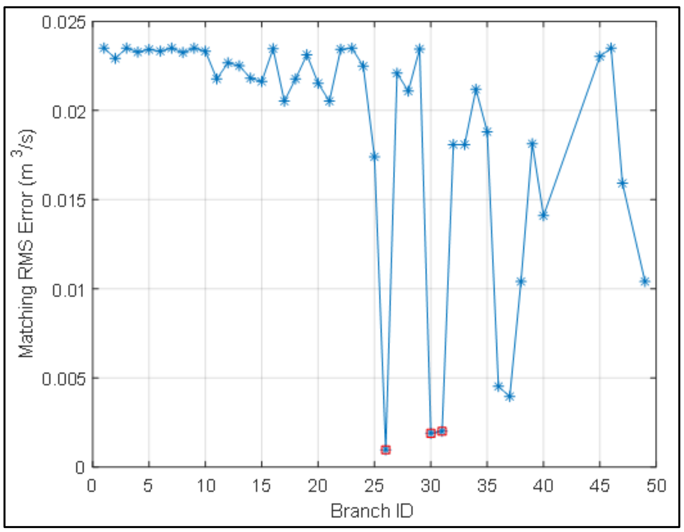

Figure 7. RMSE of matching airflow changes for every airway in Scenario #6.

To further test the proposed methodology, five monitored airways were randomly selected from the full list of airways. We generated 1,000 random realizations of five monitored airways with the goal of identifying the event source location of all 9 scenarios, including the examined Scenario #1.

With the 5% buffer window, only 13 cases or 1.3% of all 1,000 cases did not lead to successful picking of the source airway. In 77% of cases, the identified source can be matched with only one predicted airway . In about 13% of cases, only two airways were picked up by the algorithm, including the source airway. That covers 90% of all 1,000 cases. Additional 6.5% of all cases covers three predicted airways. The success rate, percentage of successful source determination in 1,000 cases, with the use of 5% buffer window is 98.7%. This rate can be improved by increasing the buffer window to 10%, which leads to 99.8% with only 2 failed cases. However, the ambiguity of location determination increases as more potential source airways are returned by the algorithm. About 60% of cases with more than one predicted airway are returned depending on the location of monitored airways.

Scenario #2 is based on a resistance change in airway 21 from 50.82 to 5.08, which is a 10-fold decrease. This scenario was tested with 1,000 random cases of five monitored airways. With the 5% buffer selection window in only 36 cases, 3.6% did not return with successful picking of the source airway. In 87.3% of cases, the identified source can be matched with only two predicted airways, airways 21 and 17 being in series. In about 7.2% of cases, only three airways were picked up by the algorithm, including the source airway. That covers 95% of all 1,000 cases Additional 4.8% covers four or more predicted airways. The success rate with the use of 5% buffer window is 96.4%. This rate can be improved by increasing the buffer window to 10% which leads to 99.1% with only 9 failed cases. However, the ambiguity of location determination increases as more potential source airways are picked—about 20% versus 12% of cases with more than two airways are returned depending on the location of monitored airways.

Scenario #6 is based on a resistance change in airway 26 from 0.52 to 5.17, a 10-fold increase. This scenario was tested with 1,000 cases with five randomly selected monitored airways. The picking of minimum RMS error included a buffer window of 5%. With the 5% buffer selection window with only 38 cases, 3.8% did not return with successful picking of the source airway. In 76.1% of cases, the identified source can be matched with only one predicted airway, airway 26. In about 11.6% of cases, only two airways were picked up by the algorithm, including the source airway. That covers 87.7% of all 1,000 cases, and 12.3% covers three or more predicted airways. The success rate with the use of 5% buffer window is 96.2%. This rate can be improved by increasing the buffer window to 10%, which leads to 98.6% with 14 failed cases. However, as with Scenarios #1 and #2, the ambiguity of location determination increases as more potential source airways are picked. About 36% versus 24% of cases with more than one predicted airway are returned depending on the location of monitored airways.

The remaining scenarios examined in this paper lead to similar results in terms of model accuracy. The performance of the proposed methodology in terms of percentage of successful source identification in 1,000 random realizations of monitored airways, to predict abnormal airflow disturbance caused by a resistance change in any airway of the ventilation network is summarized in Table 4. The model accuracy and total success rate is well over 95% except in Scenario #8. This could be explained by the very low airflow changes detected at the monitored airways. The underlined values indicate the highest percentage of all cases for each scenario corresponding to the highest number of source airways. It is expected that increasing the number of monitored airways can lead to increased model performance. To demonstrate this expectation, the number of monitored airways are increased from 5 to 8 and the model accuracy values are provided in parenthesis in Table 4. As it can be seen the accuracy in each scenario is significantly improved.

Scenario #9 returns four possible source airways for most cases with a different set of monitored airways than the selected ones in Table 2—for example, a set that does not include airway 1 as a monitored airway. The identified source airways 45, 2, 1, and 46 from this scenario are in series or parallel to the airway 1, shown in Figure 1, which leads to the same or similar flow change pattern at the monitored airways.

As described earlier, the accuracy can be improved by increasing the selection buffer windows for minimum RMSE. However, this solution leads to selection of more airways, adding more ambiguity to the source determination. Alternatively, increasing the number of monitored airways seems a logical step in improving the model accuracy.

It can also be observed from the results in Table 4 that Scenarios #6 and #7 return one source airway as opposed to more than one for the selected monitored airways in Table 2. It can be suggested that the methodology could be used to find the most effective monitored airways for locating any possible source airway by checking all the possible combinations of any number of monitored airways. Although this task cannot be done manually, an automated procedure can be used to provide a list of best possible monitored airways for this purpose.

Table 4. Prediction performance of the proposed methodology (%).

Scenario	Total Success Rate	One Airway	Two Airways	Three Airways	Four Airways	More than four Airways
1	98.7(100.0)	77.1(96.9)	12.2(2.0)	6.2(0.5)	1.0(0.3)	2.2(0.3)
2	96.4(99.7)	0.0(0.0)	85.8(97.9)	6.5(1.2)	1.4(0.4)	2.7(0.2)
3	97.8(99.8)	0.0(0.0)	87.5(98.1)	6.0(1.3)	2.2(0.4)	2.1(0.0)
4	98.3(99.9)	78.2(95.0)	13.1(3.1)	2.8(1.2)	1.1(0.2)	3.1(0.4)
5	99.5(100.0)	84.2(96.8)	11.2(2.9)	2.2(0.2)	0.4(0.0)	1.5(0.1)
6	96.2(99.2)	74.9(86.8)	9.6(6.9)	9.3(5.2)	1.1(0.1)	1.3(0.2)
7	99.0(100.0)	74.5(94.4)	6.5(2.1)	3.0(0.6)	5.0(1.6)	10.0(1.3)
8	86.6(97.0)	66.9(90.3)	10.2(5.3)	2.5(0.6)	1.9(0.5)	5.1(0.3)
9	100.0(100.0)	0.0(0.0)	10.8(17.6)	0.0(0.0)	88.8(82.4)	0.4(0.0)

In summary, the total success rate in percentage of 1,000 randomized realizations of the monitored airways distributed within the network example in this paper proves to be high, more than 95% in most scenarios, except in Scenario #8. It is also demonstrated that this success rate can be improved significantly by adding three more monitored airways. It is expected that with real monitored data that includes sensor fluctuation caused by various factors such as sensor error, daily variation caused by atmospheric changes, as well as by the mining operations and movement of equipment in the transport airways, the success rate will suffer. It is the authors' understanding that with enough monitoring stations throughout the mine and proper signal processing and filtering to remove normal operating fluctuation the success rate will remain in the acceptable range.

CONCLUSIONS

A new methodology was presented here as part of an effort to develop a software tool to assist mine operators in identifying the source of any abnormal airflow change within the network using the airflow changes at monitored airways. The concept is based on a direct derivative method developed by the authors.

The new concept was tested using a numerical example and application of 1,000 realizations of monitored airway locations. The new methodology was found to be better than 97% in locating an unknown source airway with flow resistance change in a ventilation network causing an abnormal airflow distribution which could put the miners in work zones at a higher risk of over-exposure to hazardous substances.

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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