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MAINTENANCE, ENGINEERING AND RELIABILITY

Machine learning model for predicting blast fume dilution time in underground working areas

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ABSTRACT

In underground mines, accurate prediction of dilution time is crucial to protect miners from toxic fumes as well as minimize production delays and ventilation costs. Previous researchers have used empirical equations, mine ventilation software, and computational fluid dynamics to calculate dilution time. These traditional methods have high computational cost and design limitations. In this research, machine learning (ML) techniques and data analytics were used to: (i) develop a ML model to predict dilution time based on five on-site blasting and auxiliary ventilation parameters and (ii) determine the order of importance of these parameters. The advantages of using the ML model over the traditional methods are its ability to consider a large number of factors, detect complex nonlinear relationships, and predict the dilution time near-instantaneously. Results show that the normalized artificial neural network has the best prediction capability with an R^2 of 0.987. Among the blasting and ventilation parameters measured, air volumetric flow rate significantly affected the dilution time, followed by duct distance from face and the amount of explosive.

KEYWORDS

Auxiliary ventilation, Computational fluid dynamics (CFD), Data analytics, Machine learning (ML), Underground blasting

RÉSUMÉ

Dans les mines souterraines, il est essentiel de prévoir avec précision le temps de dilution pour protéger les mineurs contre les émanations toxiques et minimiser les retards de production et les coûts de ventilation. Les chercheurs précédents ont utilisé des équations empiriques, un logiciel de ventilation des mines et la dynamique computationnelle des fluides pour calculer le temps de dilution. Ces méthodes traditionnelles ont des coûts de calcul élevés et des limites de conception. Dans le cadre de cette recherche, des techniques d'apprentissage automatique (ML, de l'anglais *machine learning*) et des analyses de données ont été utilisées pour : (i) élaborer un modèle de ML pour prédire le temps de dilution en fonction de cinq paramètres de dynamitage sur place et de ventilation auxiliaire et (ii) déterminer l'ordre d'importance de ces paramètres. Les avantages de l'utilisation du modèle ML par rapport aux méthodes traditionnelles sont sa capacité à considérer un grand nombre de facteurs, à détecter des relations non linéaires complexes et à prédire le temps de dilution presque instantanément. Les résultats montrent que le réseau neuronal artificiel normalisé a la meilleure capacité de prédiction avec un R^2 de 0,987. Parmi les paramètres de dynamitage et de ventilation mesurés, le débit volumétrique de l'air a eu une incidence significative sur le temps de dilution, suivi de la distance du conduit d'aération au dynamitage et de la quantité d'explosif.

MOTS-CLÉS

analyse de données, apprentissage automatique (ML), dynamique computationnelle des fluides (CFD), dynamitage souterrain, ventilation auxiliaire

INTRODUCTION

In most mines, re-entering underground areas affected by blast fumes can be a safety and productivity concern. It is therefore imperative to accurately estimate dilution times. De Souza (2023) discussed management procedures for dilution time that offer safety, efficiency, and economic benefits to mining operations. Traditionally, most underground mines estimate dilution times based on observations and experiences (i.e., professional judgment), which can be inaccurate. Some mines use a theoretical approach; however, they are unable to account for changes in blasting and ventilation conditions (Tiile, 2019). Previous researchers have used empirical equations, mine ventilation software such as VentSim and VnetPC, and computational fluid dynamics (CFD) to calculate dilution times. However, few studies have attempted to predict dilution times using machine learning (ML) models. ML is a semi-automated method to detect patterns in the data. ML algorithms can be applied to a dataset that contains a pattern but that is not programmable or cannot be quantified mathematically. ML models learn to recognize patterns and make decisions with little human involvement. They are used by companies to improve their decision-making and business performance and have led to transformational changes in various industries. The advantage of ML models is their ability to handle complex nonlinear relationships with the large

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number of factors that impact the dilution time. Moreover, a near-instantaneous prediction of dilution time can be made once a ML model is built.

Blast fume behavior in underground mines has been studied by previous researchers using various techniques. De Souza and Katsabanis (1991) conducted extensive experimental testing to develop a mathematical model to predict dilution time in an underground mine. Tiile (2019) estimated safe blast distance and optimal air quantity based on common blasting and ventilation conditions using CFD techniques to simulate blast fume propagation and dilution time. Torno and Toraño (2020) developed CFD models to study the fundamental parameters of dilution. Results were validated and compared with experimental data, showing that CFD can be a powerful tool to analyze dilution of fumes in development blasting. Adhikari et al. (2022) used CFD to investigate fumes trapped in the muckpile in underground development blasting. They showed that, if not properly monitored and controlled, trapped fumes can pose serious health risk to the miners, especially during loading and transportation of the muckpile. Kashnikov and Levin (2017) used ML techniques to define regulator positions using historical data. The ML approach has been shown to aid accurate prediction of several effects of mine blasting events such as ground vibration (Hasanipanah et al., 2015), flyrock (Koopialipoor et al., 2019), airblast (Jahed Armaghani et al., 2018), and fragmentation (Monjezi et al., 2014).

The objectives of this research are to: (i) develop a predictive ML model for dilution time based on five primary on-site ventilation parameters and (ii) determine the order of importance of these parameters. Five common supervised ML algorithms were tested: artificial neural networks (ANNs), decision trees, random forests, K-nearest neighbors, and support vector machines.

ANNs

To model complex patterns and solve prediction problems, ANNs emulate brain neurons. The advantages of using ANNs are their ability to handle large amounts of data, implicitly detect complex nonlinear relationships, and detect interactions among variables. Drawbacks include a lack of understanding of the decision-making process, susceptibility to overfitting, and the empirical nature of model development (Park & Lek, 2016).

An ANN comprises several interconnected neurons. Figure 1 shows a single neuron or processing unit of an ANN. The neuron uses equation 1 to calculate the output (y) from the given inputs (x_i).

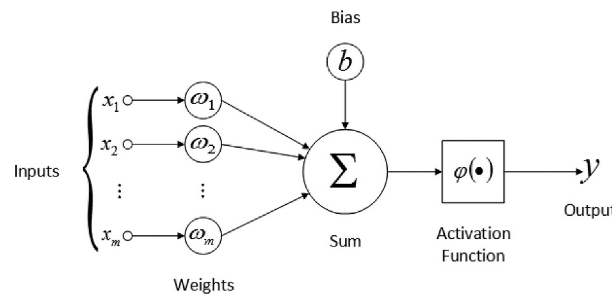

Figure 1. Mathematical model of an artificial neural network (Oliveira et al., 2017)

$$y = \varphi(\Sigma_i(\omega_i x_i) + b) \quad (1)$$

The ω_i are synaptic weights, and b is the bias that increases or decreases the inputs that go to the activation function (φ), which limits the neuron output to a predetermined range.

Decision trees

In decision trees, data are continuously split using if-then-else decision rules. The results are then used to predict the output of a target variable. The advantages of using decision trees are that they are simple to understand and interpret, and it is easy to visualize the explicit representations of decisions and decision-making. Disadvantages include a tendency to overfit data and the unstable nature of decision predictors (De Ville, 2013). The decision tree consists of nodes, branches, and leaf nodes (Figure 2). Each node represents a "test" on an attribute, each branch represents the outcome of the test, and each leaf node represents the final value of the decisions.

Random forest

The random forest is collection of decision trees (Figure 3). The accuracy and problem-solving ability of the algorithm increase with the number of trees in the random forest. The output is generated by averaging the predictions from all decision trees. The advantage of this technique is that it is very stable compared to decision trees. It can handle missing values and nonlinear parameters efficiently. Drawbacks are the long training period and complexity if there are several trees (Great Learning, 2004).

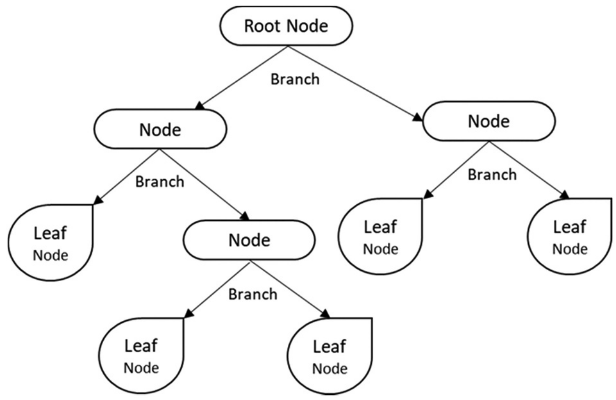

Figure 2. Decision tree structure

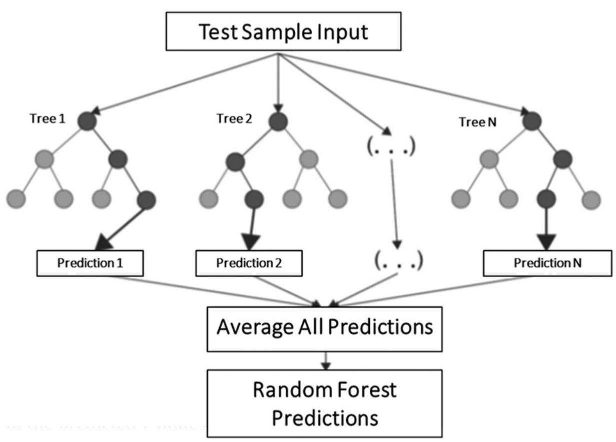

Figure 3. Random forest structure (Bakshi, 2020)

K-nearest neighbor

The K-nearest neighbor algorithm finds the closest data points (neighbors) based on distance metrics such as Euclidean, Manhattan, or Hamming (Figure 4). The predicted value for the test data point is then calculated by averaging the values of its closest neighbors. The advantage of this technique is its simplicity and intuitiveness. Disadvantages include poor performance on imbalanced data and difficulty in choosing the optimal value of K or the number of neighbors to predict the output (Zhang, 2016).

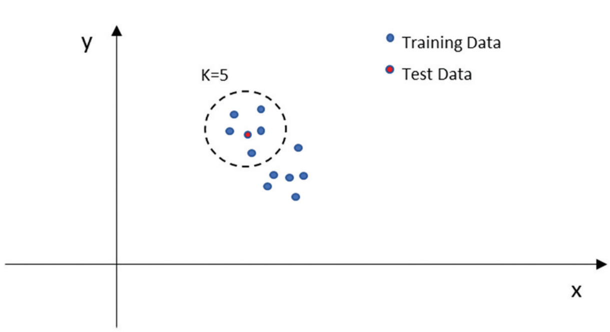

Figure 4. K-nearest neighbor overview

Support vector machine

The support vector machine involves finding a hyperplane using kernel functions to map (separate) *n*-dimensional input data into feature space or independent variables (Figure 5). Support vectors are the data points that influence the position and orientation of the hyperplane. The goal is to maximize the margin between data points and the decision hyperplane, thereby reducing the chances of misclassification. The advantage is an ability to work well with limited datasets, requiring less computational time and high accuracy. The disadvantage is poor performance for large datasets and datasets with noise (Suthaharan, 2016).

METHODS

The accuracy of a given ML model depends on the quantity and quality of the data used to build it. Collecting a large, reliable dataset from the field is not feasible due to variable field conditions and uncertainties in the measurements. Therefore, the data used to train and test the ML models were produced from numerical simulations using CFD. Among the several parameters that affect the dilution time in an auxiliary ventilation system, we chose a commonly used forcing

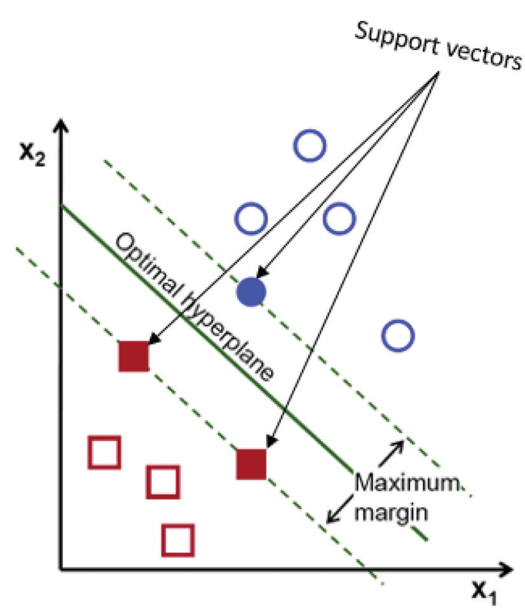

Figure 5. Support vector machine schematic (Dixit, 2020)

ventilation system with five design parameters (independent variables): air volumetric flow rate, duct distance from the face, duct height, horizontal distance from rib, and amount of explosive (Figure 6). The ranges for each independent variable are based on field observations. Spearman's correlation was used to understand the strength of the relationship of each predictor to the response variable (alpha = 0.05).

A high-level overview of the methodology used to predict dilution time is shown in Figure 7. The study was conducted in three phases: CFD analysis, data analysis, and ML modeling.

First, the five independent variables were used to generate the dilution time (dependent variable) using the CFD software tool, scFLOW (Software Cradle, Osaka, Japan). Preprocessing, solver, and postprocessing modules were used to create the geometry model with analysis conditions and to solve and visualize the results.

A total of 62 different field scenarios were simulated in CFD. Next, the datasets were thoroughly explored and analyzed using descriptive statistics summary, Spearman's correlation, and scatterplots. The results from the 62 numerical simulations were divided into training (70%) and testing (30%) datasets. Then, the datasets were subjected to regression analysis to train, test, and validate the supervised ML models using the five algorithms described

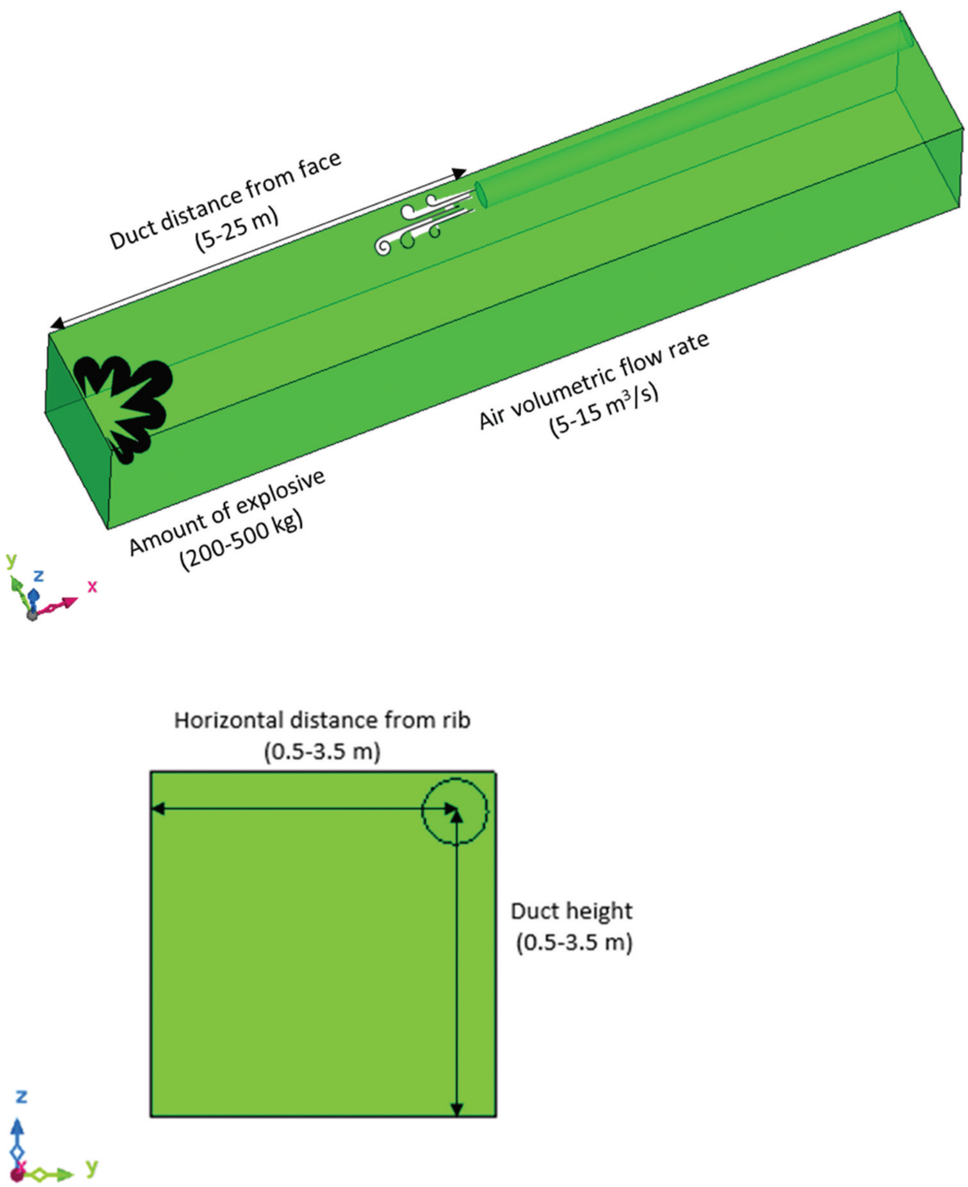

Figure 6. The geometry used in the computational fluid dynamics simulation and the range for each independent variable: isometric (top) and face view (bottom)

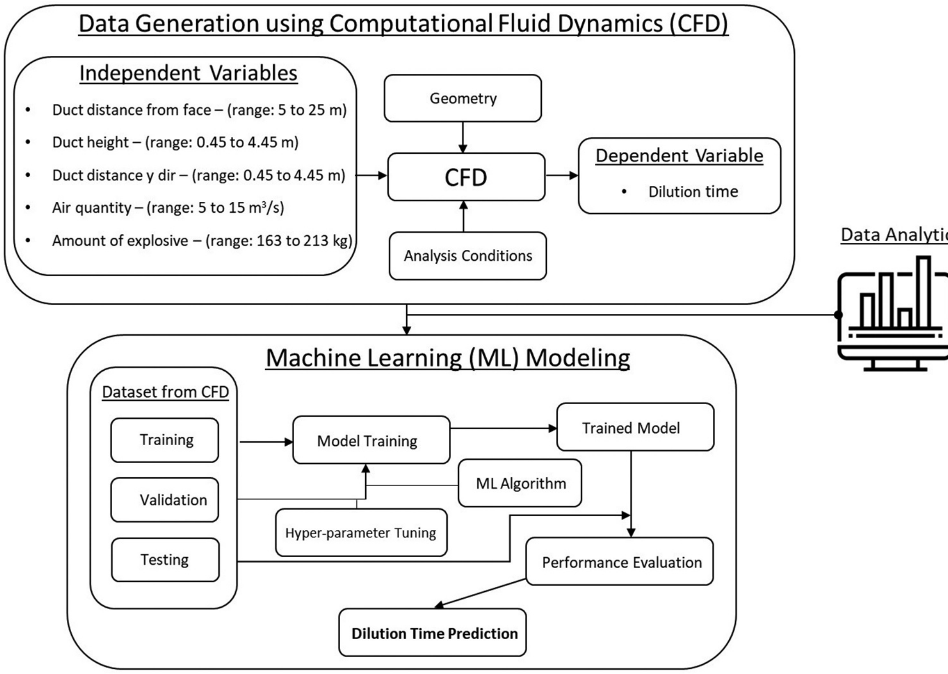

Figure 7. CFD and ML methodology for predicting blast fume dilution time

above. Each of the five algorithms was trained and tested with raw, normalized, and standardized datasets resulting in a total of 15 ML models for performance evaluation.

Variable scaling is important for ML algorithms such as K-nearest neighbors and ANNs, which calculate distances between datapoints to make inferences about the data. If not scaled, the variables with a higher value range influence the output more strongly, resulting in erroneous predictions.

For the ML modeling, different hyperparametric values were tested (available from the primary author upon request), and a fivefold cross-validation method was used to optimize the model hyperparameters and avoiding overfitting. The best sets of hyperparameters were then used for the final model training. Next, the testing datasets were used to evaluate model performance: (i) qualitatively using the plots of predicted vs observed values and (ii) quantitively using the coefficient of determination (R^2), mean absolute error, mean squared error, and root mean squared error scoring functions.

RESULTS AND DISCUSSION

Phase I – CFD analysis

The inlet fresh air diluted the toxic fumes near the face and traveled toward the exit of the drift (Figure 8). The sudden generation of toxic fumes during the blasting operation caused carbon monoxide concentrations to surge (Figure 9). Upon reaching its maximum concentration, the carbon monoxide quickly began to be diluted as it mixed with fresh air blown into the working area through the ventilation duct.

Phase II – data analysis

The dataset obtained from the CFD results was explored, processed, and analyzed. The descriptive statistics of the variables are summarized in Table 1.

The frequency distributions and scatterplots in Figure 11 help to visually validate the correlation trends seen in the heatmap in Figure 10. Although quantitative values of correlation coefficients may not be ascertained from the scatterplots, the positive or negative correlations between the variables can be easily seen.

Phase III: ML modeling

Multiple linear regression

Multiple linear regression was used for explanatory modeling. Equation 2 was deduced from the model and can be used to make estimates with new datasets.

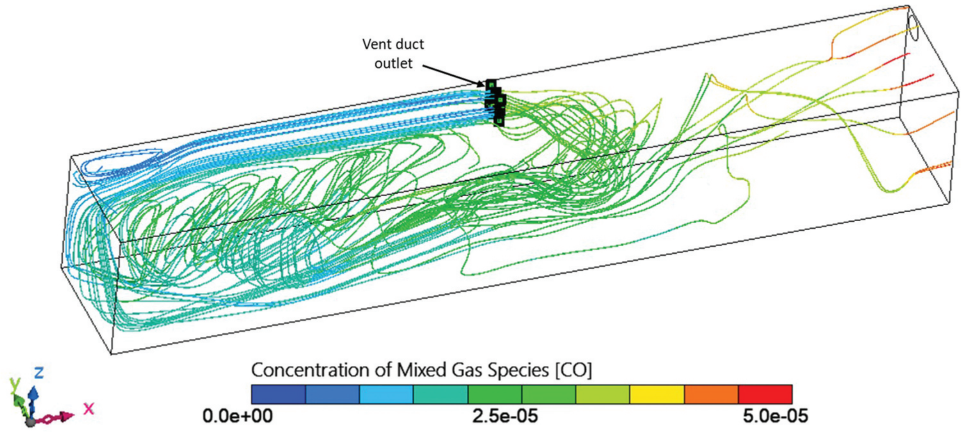

Figure 8. Computational fluid dynamics flow visualization of streamlines (flow trajectories) of carbon monoxide (CO) concentration after 280 s of auxiliary fan start-up

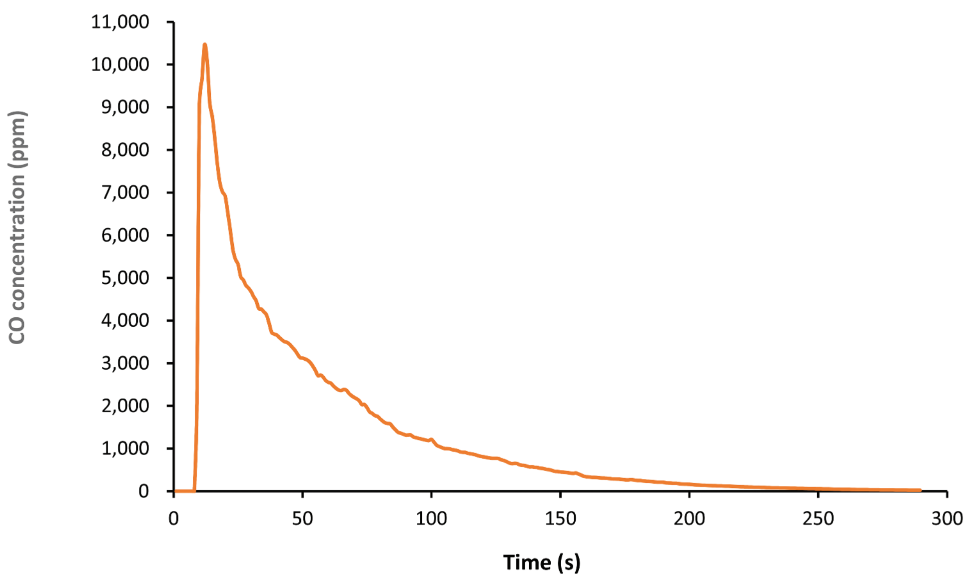

Figure 9. Computational fluid dynamics result showing carbon monoxide (CO) concentration vs time

Table 1. Descriptive statistics for all variables

Variable	Count	Mean	Standard deviation	Minimum	25%	50%	75%	Maximum
Duct distance from face (m)	62	15.00	5.80	5.00	15.00	15.00	15.00	25.00
Duct height (m)	62	4.01	0.72	0.60	4.25	4.25	4.25	4.25
Horizontal distance from rib (m)	62	4.01	0.72	0.60	4.25	4.25	4.25	4.25
Air volumetric flow rate (m^3/s)	62	10.03	3.07	5.00	10.00	10.00	10.00	15.00
Amount of explosive (kg)	62	210.02	53.26	152.00	202.00	202.00	217.25	500.00
Dilution time (s)	62	340.15	142.43	169.30	261.45	296.35	389.20	801.70

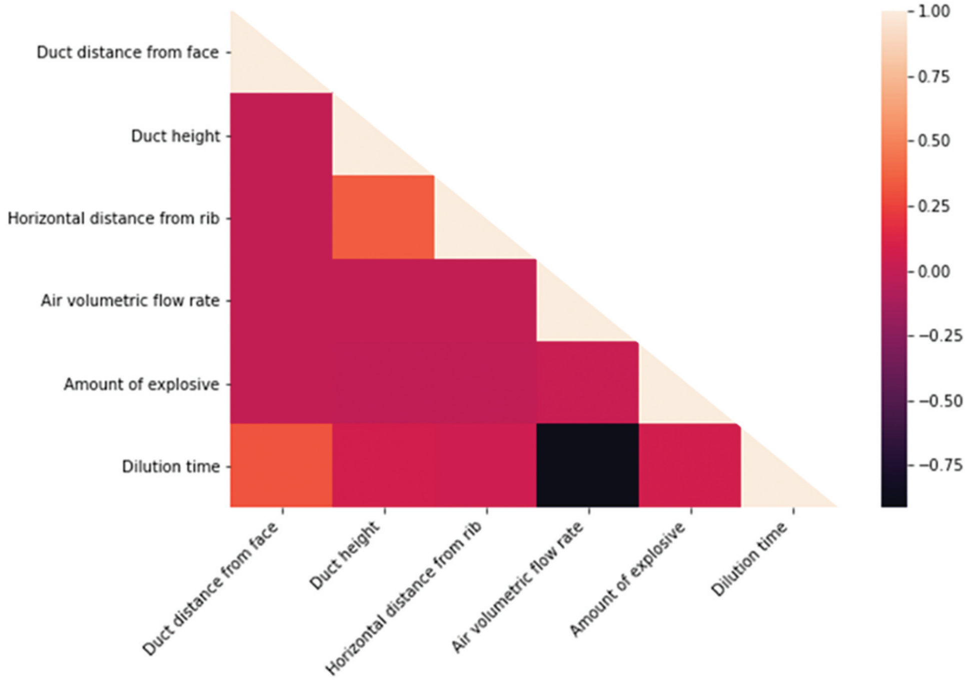

Figure 10. Heatmap of Spearman's correlation between the dependent and independent variables

$$\begin{aligned} \textit{Dilution time}\ (s) = {} & 583.92 \\ & + (5.75 \times \textit{Duct distance from face}\,(m)) \\ & + (14 \times \textit{Duct height}\,(m)) \\ & + \left(\begin{array}{l} 11.29 \times \textit{Horizontal distance} \\ \textit{from rib}\,(m) \end{array} \right) \\ & - \left(\begin{array}{l} 41.71 \times \textit{Air volumetric flow rate} \\ (m^3/s) \end{array} \right) \\ & - (0.06 \times \textit{Amount of explosive}\,(kg)) \end{aligned} \tag{2}$$

Ordinary least squares regression analysis of the five independent variables combined had a goodness of fit (R^2) of 0.87. The independent variable "Duct distance from face" had a weak positive correlation and the "air volumetric flow rate" had a strong negative correlation with dilution time (Figure 10; Table 2). The other three independent variables were not correlated with dilution time.

The residuals for the multiple linear regression model deviated from a normal distribution with a mean of −8.93 and standard deviation of 50.83 (Figure 12). This indicates a problem with linear modeling. Therefore, this study used ML models to better understand the nonlinear relationships and better predict blast fume dilution time.

ML modeling

The performance of the fifteen ML models is shown in Table 3. The cross-validated normalized ANN model performed the best. Second best were both the raw random forest and normalized random forest model. This means that the five independent variables were able to explain 98.7% and 97.6% of variance in the

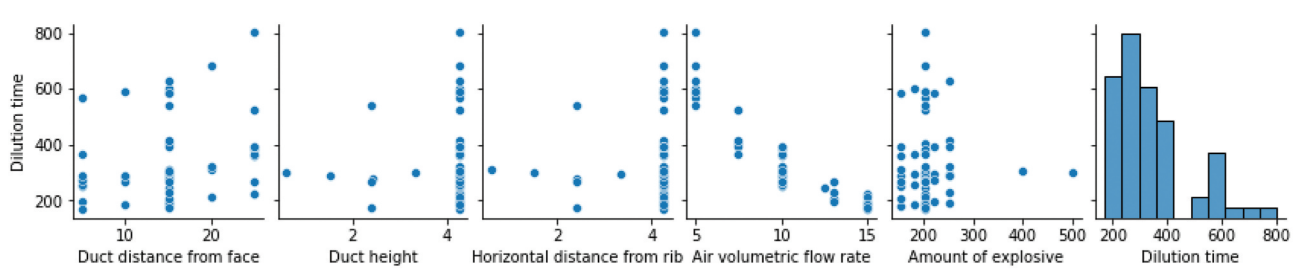

Figure 11. Scatterplot matrix for all variables

Table 2. Correlation coefficients, standard errors, *t* statistics, and *p* values for multiple linear regression of dilution time versus five independent variables

Parameter	Coefficient	Standard error	*t*	*p*>|*t*|	[0.025	0.975]
Duct distance from face (m)	5.753	1.181	4.870	<0.0001	3.387	8.119
Duct height (m)	13.999	9.713	1.441	0.155	−5.459	33.456
Horizontal distance from rib (m)	11.286	9.713	1.162	0.250	−8.172	30.744
Air volumetric flow rate (m3/s)	−41.712	2.233	−18.677	<0.0001	−46.186	−37.238
Amount of explosive (kg)	−0.062	0.129	−0.483	0.631	−0.320	0.196
Constant	583.92	61.758	9.455	0.000	460.21	707.64

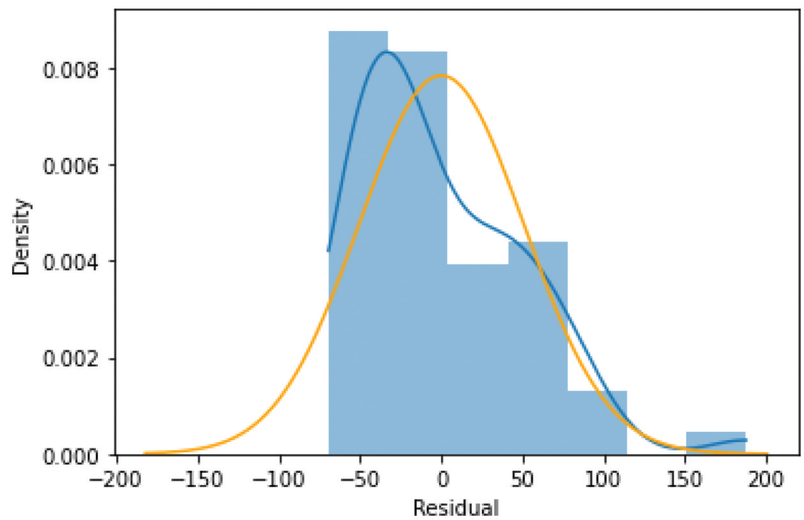

Figure 12. Residuals from multiple linear regression model vs corresponding normal curve

Table 3. Model performance for fifteen machine learning models

Machine learning model	R^2	Mean absolute error	Mean squared error	Root mean squared error
ANN raw	0.869	49.07	3,464.0	58.856
ANN normalized	0.987	14.02	337.85	18.381
ANN standardized	0.012	130.19	26,099.4	161.55
Decision tree raw	0.952	22.69	1,254.8	35.424
Decision tree normalized	0.952	22.69	1,254.8	35.424
Decision tree standardized	0.952	23.47	1,278.1	35.751
Random forest raw	0.976	18.50	630.04	25.101
Random forest normalized	0.976	18.50	630.04	25.101
Random forest standardized	0.975	19.25	665.05	25.789
K-nearest neighbor raw	0.233	117.24	2,0272.3	142.38
K-nearest neighbor normalized	0.842	39.42	4,183.7	64.681
K-nearest neighbor standardized	0.771	42.50	6,035.8	77.690
Support vector machine raw	0.737	55.46	6,953.5	83.387
Support vector machine normalized	0.077	108.60	24,391.5	156.18
Support vector machine standardized	0.654	58.12	9,146.8	95.639

dilution time, respectively, using the normalized ANN, and raw and normalized random forest models during an auxiliary ventilation operation in underground development blasting. These three ML models outperformed the multiple linear regression model (R^2 = 0.87).

According to this analysis, air volumetric flow rate had the greatest influence in terms of predicting dilution time and horizontal distance from rib and duct height had the least (Figure 13). Therefore, to increase the efficiency of an auxiliary ventilation system for a given blast, increasing the air volumetric flow rate, decreasing the duct distance from the face, and limiting the amount of explosives would yield the best results in terms of dilution time.

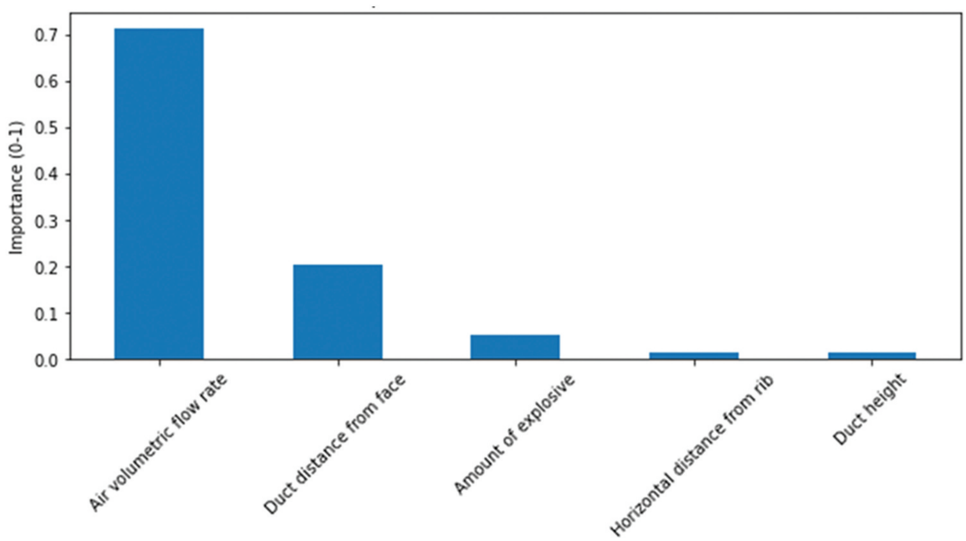

Figure 13. Relative importance of five independent variables in terms of their effect on dilution time

CONCLUSIONS

This paper presents a data-driven approach to predict dilution time based on available and measurable parameters for auxiliary ventilation systems in underground mines. The air volumetric flow rate had the strongest effect on dilution time, followed by duct distance from face and the amount of explosive. Among the 15 ML models developed, the normalized ANN model performed the best ($R^2 = 0.987$). The decision tree and random forest models also performed very well ($R^2 = 0.952–0.976$). Model choice would depend on the user's needs in terms of computational time, linearity of the data, and ability to handle large amounts of data. Unlike CFD models, which are computationally expensive, ML models can instantaneously predict dilution time with high accuracy once the model is built.

While the ML models were built for development blasting with the specific drift dimensions, the same approach can be implemented to predict dilution time at other mine sites. For accurate estimation of the dilution time at a new mine site, the values of the independent variables should be within the range used in the ML model. This study used 62 CFD numerical simulation datasets to predict the dilution time with good performance accuracy. Nonetheless, to further increase model performance and capture the complex nonlinear relationships among the variables, more datasets could be incorporated. Future work will examine other independent variables (e.g., efficiency of detonation and muckpile profile, volume, and porosity) and validation of predicted results with field data.

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DISCLOSURE STATEMENT

The authors declare that there are no competing interests.

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REVIEW STATEMENT

Paper reviewed and approved for publication by the Maintenance, Engineering and Reliability Society of CIM.

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Srivatsan Jayaraman Sridharan is a research scientist at the South Dakota School of Mines. During his PhD, he worked on a number of mine ventilation consultancy projects for the mining companies SAIL and MOIL. He recently completed his PhD dissertation. His research is primarily focused on solving mine ventilation problems using CFD and scale modeling.

Alex Verburg graduated from Iowa State University with a degree in Chemical Engineering in December 2019. He is proficient with Aspen Plus, AutoCAD, COMSOL, and Python.

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