NAMVS 2021 – Tukkaraja (Ed.)

Activity-based respirable dust prediction in underground mines using artificial neural network

R. Amoako & A. Brickey
South Dakota School of Mines and Technology, Rapid City, USA

ABSTRACT: Production activities in underground mines generate respirable dust which impacts worker's health and productivity. This underscores the importance of accurately predicting dust concentration towards effecting proactive and timely measures of mitigation. We develop an artificial neural network (ANN) model for an underground metal mine that predicts dust concentration using input parameters that are derived from production activities. The model provides fairly good results, with the prospect of yielding better results with improved data collection. The model produces a correlation of 0.70 between the predicted and actual dust concentration. The work in this paper constitutes the first phase of a larger framework that seeks to manage workers' exposure to respirable dust by incorporating ventilation in short-term production scheduling. In a future work, we seek to incorporate predictions from the ANN model and the impact of conventional dust controls into short-term production schedule optimization as mathematical constraints. This will aid in identifying high dust production activities proactively, and effectively managing available ventilation and dust control measures to enhance miners' safety.

1 INTRODUCTION

Mining operations generate respirable dust which can result in the development of lung diseases, collectively known as pneumoconiosis, in mine workers. Dust may be defined as a solid aerosol particle formed by the mechanical disintegration of a parent material by various processes such as blasting, mucking, crushing, and grinding (Belle, 2004). Dust particles have a size (diameter) range of 1 to 100 μm, and they settle slowly under the influence of gravity (Sellara & Sarver, 2014; WHO, 1999). Dust particles that are 4.0 μm or less in size are known as respirable dust (NIOSH, 2005). When inhaled, respirable dust particles evade the human natural defense mechanisms. Eventually, they get deposited in the lungs where they penetrate past the bronchioles into the gas-exchange region of the lungs. Over the long term, this causes lung diseases with varied health impact ranging from swelling in the lungs to shortness of breath, fatigue, slight fever and chills, scarring of the lung tissues (fibrosis), and death (American Lung Association, n.d.; Mayo Foundation for Medical Education and Research, 2017; NIOSH, 2005). The lung diseases may also increase the risk of other health problems. For instance, silicosis increases the risk of tuberculosis and lung cancer (American Lung Association, n.d.).

In underground metal mining, dust may be generated from production activities such as drilling, blasting, cutting, loading, hauling, and crushing. Underground mine workers can be exposed to dust particles that differ in composition such as crystalline silica, and metals such as lead, cadmium, and arsenic. These constituents make dust a health hazard in underground mines. High levels of dust can reduce visibility and become a safety hazard. The rock geology and production activities determine the type and quantity of dust particles generated. In-place

DOI: 10.1201/9781003188476-42

ventilation and dust control systems influence the amount of dust generated and the fraction that becomes airborne (WHO, 1999).

The concentration of respirable dust generated in underground mining operations is associated with activity type and activity rate, both of which are prime to conventional short-term production scheduling in underground mining. In underground metal mine planning, production scheduling can be defined as the sequencing of mining activities to achieve clearly defined goals in order to generate revenue (Chowdu, 2020). This results in the determination of activity start dates for the operation with a scheduling fidelity corresponding to the desired planning horizon, i.e., long-, medium-, or short-term planning. Long-term production schedules establish the overarching goals, e.g., life-of-mine production and capital project goals, for the operation based on corporate policy (Chowdu, 2020; Chowdu, Nesbitt, Brickey, & Newman, 2020). Medium-term production schedules focus on guiding operations to meet the overall long-term goals and seek to determine activity start dates for a three- to five-year time horizon at monthly or quarterly fidelity. Short-term production schedules inform the day-to-day operations of the mine. They are developed based on the forecast from the medium-term schedule and current operational conditions. Thus, they define an extraction sequence by specifying activity start dates at a finer fidelity, i.e., shift, daily or weekly over a time horizon of one to three months. They focus on the effective utilization of resources, e.g., equipment and labor, to achieve shift, daily, or weekly production targets (Trout, 1997).

We develop an artificial neural network (ANN) model for predicting respirable dust concentration for an underground metal mine with input parameters that are derived from production activities, specifically activity types and activity rates. The work in this paper constitutes the first phase of a larger framework that seeks to manage workers' exposure to respirable dust by incorporating ventilation in short-term production scheduling. In a future work, we seek to incorporate predictions from the model into short-term production schedule optimization as mathematical constraints, along with the resultant dust reduction offered by conventional dust mitigation measures such as ventilation and water sprays. This will help identify high dust production activities proactively and determine how to manage available ventilation and dust control measures to enhance miners' safety while optimizing production.

1.1 *Artificial neural network*

Artificial neural network (ANN) is a machine learning technique that is inspired by the way biological neural system works, such as how the brain processes information. Information processing in ANN involves many highly interconnected processing elements known as neurons that work together to solve specific problems. The learning process involves adjustments to the synaptic connections existing between the neurons (Ertel, 2017; Grosan & Abraham, 2011). In the biological neural system, a neuron consists of a cell body, known as soma, an axon, and dendrites. The axon sends signals, and the dendrites receive these signals. A synapse connects an axon to a dendrite. Depending on the signal it receives, a synapse might increase or decrease electrical potential. An ANN consists of a number of neurons similar to the human biological neurons. These neurons are known as units, and are connected by weighted links that transmit signals from one neuron to the other (Dixon, Ozveren, & Sapulek, 1995; Grosan & Abraham, 2011). The output signal is transmitted through the neuron's outgoing connection, which is analogous to the axon in the biological neuron. The outgoing connection splits into a number of branches that transmit the same signal. The outgoing branches terminate at the incoming connections (analogous to dendrites) of other neurons in the network (Grosan & Abraham, 2011).

An ANN has three types of neurons, and these are known as input, hidden, and output neurons. They are stacked in layers, and receive input from preceding neurons or external sources, and use this to compute an output signal using an activation function. The activation function is a mathematical formula for determining the output of a neuron based on the neuron's weighted inputs. The output signal is then propagated to succeeding neurons. While this is ongoing, the ANN adjusts its weights in order to record an acceptable minimal error between input variables and the final output variable(s) (Krose & van der Smagt, 1996). The complexity of the ANN architecture makes it well suited for solving both linear and nonlinear problems. Advancement in computational power has enhanced its use in the fields of engineering, industrial process control, medicine, risk management, marketing, finance, communication, and transportation.

2 LITERATURE REVIEW

Early epidemiological and pathogenic research has established cumulative exposure to respirable dust as a critical factor in the development of pneumoconiosis, i.e., lung diseases caused by respirable dust (Belle, 2004; Cohen et al., 2016). Duration of exposure and the amount of respirable dust in the mine environment also have significant influence on workers' susceptibility to pneumoconiosis. Belle (2004) reports that the risk of progression to a higher category of pneumoconiosis grows with increasing intensity of exposure (mean dust concentration) and increasing cumulative exposure (intensity x duration). Rossiter (1972) studies the relation between radiological category of pneumoconiosis and dust content of the lung among a mixed group of 221 miners, of whom 76 have progressive massive fibrosis. The author's findings show that the average radiological scores for pneumoconiosis are related, by multiple regression, to the quartz and iron contents of the lungs.

In an experimental study, King, Mohanty, Harrison, & Nagelschmidt (1953) inject different forms of silica, i.e., fused silica, quartz, cristobalite, and tridymite of high purity and equal size distribution, into the lungs of rats. The objective is to study any differences in the rate and severity of pathogenic reactions. Results from the study suggests that the crystal structure of pure silica influences lung tissue reaction. Tridymite produces the most rapid pulmonary fibrosis, followed by cristobalite, quartz, and fused silica in decreasing order of rate of reaction. In a similar study, the injected silica dust produces pathological changes that are more closely related to the mass of the dust than to the total number of particles (Belle, 2004). Meldrum & Howden (2002) establish that the toxicity, i.e., fibrogenic potency, of crystalline silica is variable. The authors cite the following as factors responsible for the variability: polymorphic type of crystalline silica; presence of other minerals; particle number, size, and surface area; and age of rock fragment surface, i.e., freshly fractured surface vs aged surface. The authors assert that the presence of aluminium-containing minerals and the absence of significant exposure to freshly cut surfaces of crystalline silica contribute to low risk estimates for silicosis, a form of pneumoconiosis caused by exposure to silica.

Characterizing the dispersion of dust is an important exercise in mining since it helps to estimate the amount of dust a facility will emit. Conventionally, dust dispersion models for underground mines have been built around one or more of the fundamental equations used in air dispersion modeling, i.e., the Box, Gaussian, Eulerian and the Lagrangian models (Collett & Oduyemi, 1997). In recent years, dust dispersion research has focused on the use of computational fluid dynamics (CFD) to characterize dust emission, deposition and suppression. CFD is a numerical analysis method used to solve fluid-flow problems with the aid of a computer, based on the laws of conservation of mass, momentum, and energy. The method generally follows the Eulerian approach, and can also incorporate the Lagrangian algorithm (NIOSH, 2005).

In more recent times, however, researchers have made attempts to utilize historical data accumulated over the years through dust sampling for machine-learning based prediction. Machine learning offers established algorithms that are able to learn dust dispersion patterns without the need to develop complex dust-specific equations. The objective has been to improve accuracy in the prediction of dust concentration. Grivas & Chaloulakou (2006) and Park et al. (2018) successfully demonstrate the potential of artificial neural network (ANN) as a suitable machine learning technique for evaluating the exposure level of dust. The former focusses on predicting particulate matter concentration in the atmosphere while the latter focusses on particulate matter prediction in subway stations. The authors model the ANN using historical data of variables such as wind speed, ambient temperature, relative humidity, number of subway trains running and ventilation supply.

3 DATA AND METHODOLOGY

We obtain dust sample data from Mine Y, an underground metal mining operation in South America. The data set comprises a total of 214 dust monitoring data points collected from 2017 to 2019 on personnel who are employed in the following jobs: development drilling, production drilling, blasting, loading and haulage. We settle for samples from these personnel since they are directly involved in the underground production activities by virtue of their jobs. Since this number is insufficient for training a machine learning model, we generate artificial data based on the statistical distribution of the samples, and the types of production activities undertaken at the mine. The data set is lognormally distributed with the following parameters: location = -1.327 and scale = 0.957. The minimum and maximum values are 0.02 and 3.8 mg/m^3, respectively, with an eight-hour average permissible exposure limit (PEL) of 3 mg/m^3. For each of the aforementioned job types, we generate a thousand samples, yielding a total of five thousand samples.

Based on the mine planning data from Mine Y, we categorize the production activities into production drilling, development drilling, ore extraction and backfilling activities. Since we are considering activity-based prediction, it is essential to obtain dust samples that are specific to these activities. However, at present, dust sampling in underground mines is generally sampled using a personal dust collection system worn by a miner rather than sampled at the working face of a given activity. To this end, we develop a weighting method that maps the personnel, job-type, samples to production activities in order to obtain representative sample values for each activity type. This involves weighted (fractional) combinations of job-type samples for each activity, based on the fraction of time a given job type lasts during a given activity. This yields a total of four thousand activity-based data points—a thousand for each activity type. Using this new data set, we develop a variety of multi-layer artificial neural network models, and test for the one that most satisfactorily predicts the expected dust concentration for a given production activity. It should be noted that this model is developed with available data with the intent of validating the proposed predictive model to help support and justify the collection of activity-based dust measurements.

3.1 *Feature selection and preprocessing*

With the scope of the study being activity-based dust prediction, we consider features (predictors) that are directly associated with production activities and have direct influence on dust generation. To this end, we consider the four production activity types mentioned in the previous section, i.e., production drilling, development drilling, ore extraction, and backfilling, as features. We also consider activity rate in meters per day (m/day) and activity rate in tonnes per day (t/day) as features, yielding a total of six features. Since a data point (training example) can be associated with only one of the four production activity types, each of these is treated as a binary variable, i.e., they are represented in the model as zeros or ones, while the last two features, i.e., activity rates, are represented as continuous variables. The binary representation enables the model to identify which of the four production activities is associated with a given data point. So, for each data point, only one binary variable will have a value of 1 (turned on) while the others are assigned a zero (turned off). Based on the mine planning data, the activity rates are determined as follows: meters/day is used for development and production drilling, while tons/day is used for development, ore extraction and backfilling activities. We split the data into training, validation, and test sets comprising 2800, 600 and 600 samples, respectively. The data is scaled within the range 0 – 1 since the variables have different orders of magnitude. We employ the MinMaxScaler function of the scikit-learn python library for scaling (Pedregosa et al., 2011).

3.2 *ANN modeling*

Using the Keras python library developed by Chollet (2015), we build a variety of multi-layer ANNs with up to four hidden layers for prediction. In each instance, we conduct hyperparameter tuning to obtain optimal number of neurons (units) for the hidden layers under consideration. In all cases, the input and output layers have fixed neurons, being six and one, respectively. These represent the six input variables (features) and the output parameter (dust concentration), which we seek to predict. Figure 1 is a schematic representation of the ANN architecture we use in this study.

3.2.1 *Hyperparameter tuning*

Hyperparameter tuning is the process of searching for a set of optimal parameters which define the architecture of a machine learning model. These parameters are known as hyperparameters. In this study, we implement hyperparameter tuning to determine the optimal number of neurons for each of the four ANN instances. We do this using the Bayesian optimization object in Keras (Chollet, 2015) on a DELL latitude E6430 computer with a processing speed of 2.6 GHz, and 8 Gb of memory. The process involves iterating over several combinations of neurons for a given instance of hidden layers and returning the combination that yields the best performance. In this study, the iteration occurs over the range of four to two hundred neurons for each hidden layer in each instance. This process can be cumbersome and time consuming when done manually. The use of the Bayesian optimization saves time by automating the search process for the best combination of neurons for a given number of hidden layers. Table 1 shows the results of the hyperparameter tuning. For each instance, we show the optimal number of neurons for the

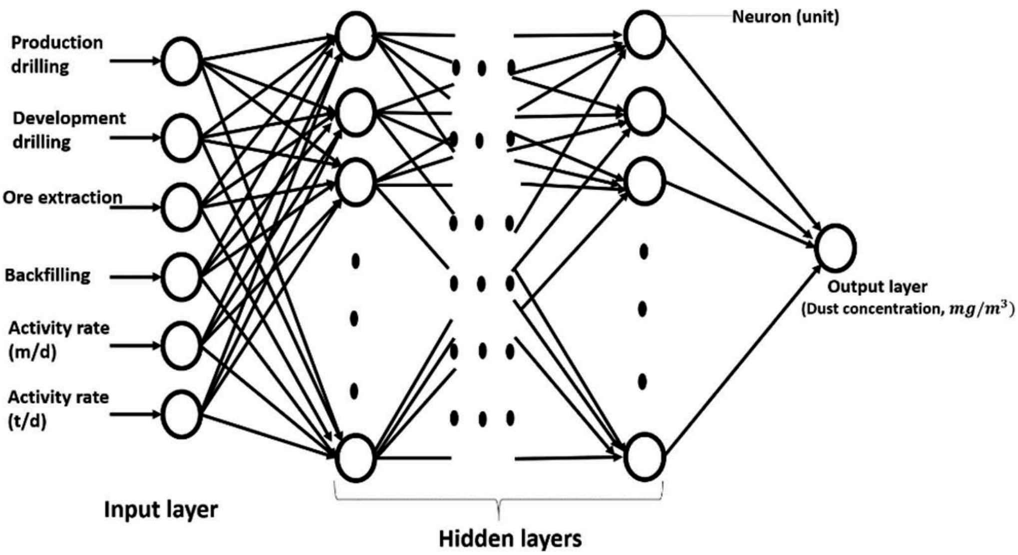

Figure 1. ANN architecture for dust concentration prediction.

Table 1. Optimal neurons for hidden layers.

Number of hidden layers	Optimal neurons for hidden layers
1	120
2	184-66
3	168-BN-DP-60-67
4	101-BN-DP-137-34-121

hidden layers. In the last two configurations of hidden layers, the batch normalization (BN) and dropout (DP) techniques serve to control model overfitting, so as to improve model generalization in respect of unseen, real-world data. The batch normalization technique applies a transformation that maintains the mean output close to zero and the output standard deviation close to one, thereby standardizing the inputs to a given layer (Chollet, 2015). The dropout technique randomly selects neurons that are ignored during training; their contribution to the activation of succeeding neurons is temporarily removed. This is achieved by setting those neurons to zero. The results in Table 1 become the candidate model configurations for subsequent training, validation, and testing.

4 RESULTS AND DISCUSSION

Each of the four models is trained on a total of 2600 dust samples. The training involves running 350 epochs to yield an acceptable reduction in prediction error. To assess model generalization, we proceed with model validation and testing. The validation and testing data sets comprise 600 samples each; these are not used for training. The performance of the model on validation data after training determines if the model requires further tweaking to improve performance. The test set represents unseen, real-world data. Table 2 shows the performance of the models on the training, validation and test sets using the mean square error (MSE) as a metric. The MSE is a statistical metric that provides a means of assessing performance between two or more models. For each model, the MSE measures the average squared difference between the actual and predicted values. A perfect model would yield a MSE of zero, signifying that the actual values are perfectly predicted by the model, i.e., there is no error in prediction. In machine learning, the best performing model among alternatives will be the one with MSE closest to zero. The selection of the final model is based on the MSE values for the test data, i.e., test scores. These scores represent the ability of the models to generalize to unseen, real-world data, i.e., data not included in the modeling process. Subsequently, we choose the four-hidden-layer architecture as the final model since it has the lowest test score (closest to zero).

Figure 2 is a scatter plot for the test data with the threshold limit value superimposed on it. The plot shows how well the predicted dust concentration correlates with the actual concentration. It shows fairly good performance with a correlation (r) of 0.70. The plot also gives a sense of how well the model classifies respirable dust as being above or below threshold. We observe significant underestimation in the lower right quadrant of the plot, and this reflects the imperfection in the data used for modeling, i.e., limited features, insufficient original samples, and lack of direct activity-based data. To this end, we are in continued correspondence with industry partners regarding collection of additional data that corresponds with the different activity types. We expect to have better results with an improved data collection regime. We are also looking at determining additional variables to include as features to help improve model complexity and performance.

Table 2. Model performance based on mean square error.

Model (Hidden layer architecture)	Mean square error (MSE)			Selected model
	Training	Validation	Test	
120	0.00271	0.00340	0.00292	
184-66	0.00266	0.00333	0.00291	
168-BN-DP-60-67	0.00274	0.00349	0.00302	
101-BN-DP-137-34-121	0.00265	0.00342	0.00287	✓

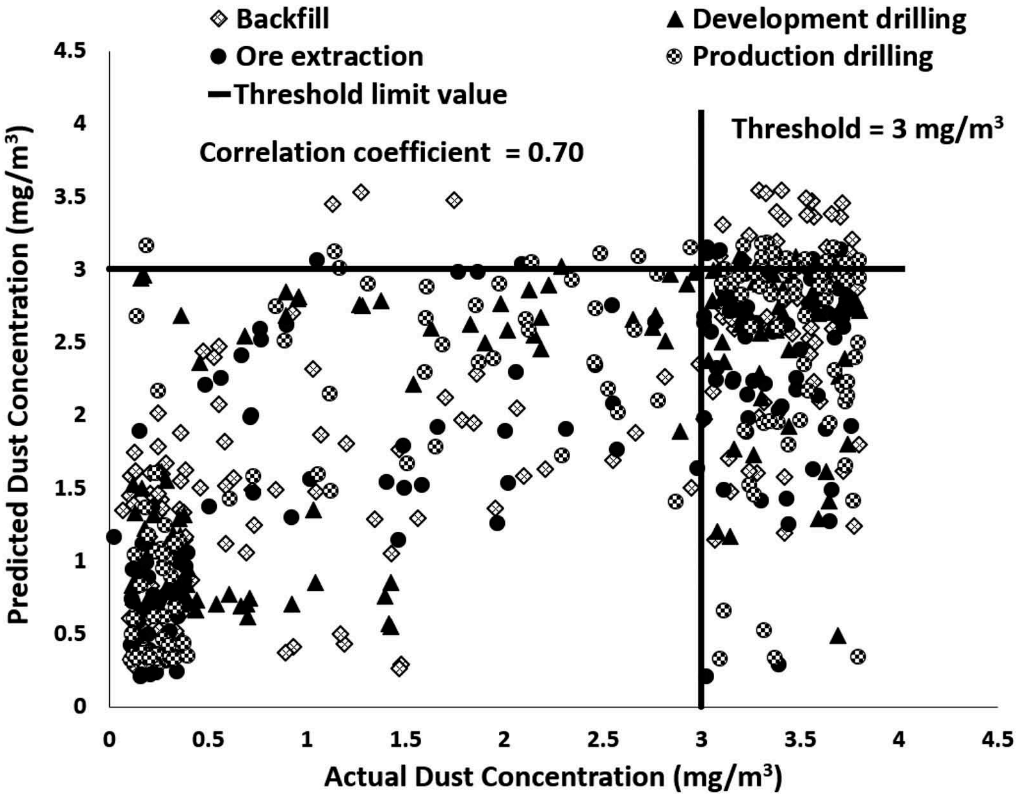

Figure 2. Actual vs predicted values for test data.

This study has shown the potential of using ANN to sufficiently predict respirable dust concentration based on attributes of production activities in underground mines. In the next phase of this project, we will develop mathematical constraints for the predictions from the ANN for all production activities. The constraints will also consider the resultant reduction in concentration offered by existing dust control measures such as ventilation and water sprays. These constraints will then be included in the short-term production schedule optimization. In effect, this will aid planning engineers in proactively determining where further dust mitigation measures are needed, and how to manage dust by effectively utilizing available mitigation resources, e.g., ventilation and water sprays. This will help enhance miners' safety while optimizing production.

5 CONCLUSIONS AND FUTURE WORK

We develop, for an underground metal mine, an artificial neural network model that predicts dust concentration with input parameters that are derived from production activities, specifically activity types and activity rates. Despite the imperfection with the current data set, the model provides fairly good results, with the prospect of yielding better results with improved data collection. The model yields a correlation of 0.70 between the predicted and actual dust concentration. In the future, we seek to improve model performance by determining additional relevant features to include in the model and maintaining correspondence with the case study mine to obtain additional data that corresponds with the different activity types. We also seek to develop appropriate mathematical constraints that will make it possible to include predictions from the artificial neural network, and the resultant reduction in concentration offered by existing dust control measures, e.g., ventilation and water sprays, in the short-term production scheduling process. This will help identify high dust production activities in a proactive manner, and aid planning engineers in managing available ventilation and dust control measures to enhance miners' safety while optimizing production.

ACKNOWLEDGEMENTS

We thank the National Institute for Occupational Safety and Health (NIOSH) for funding this research under grant 0000HCCS-2019-36404.

REFERENCES

American Lung Association. (n.d.). *Learn about silicosis*. Retrieved June 28, 2020, from https://www.lung.org/lung-health-diseases/lung-disease-lookup/silicosis/learn-about-silicosis

Belle, B. K. (2004). *Development of a dust exposure level index (DELI) for South African underground coal mine workers* (PhD thesis). University of Witwatersrand.

Chollet, F. (2015). *Keras: Deep learning for python*. Retrieved from https://github.com/fchollet/keras

Chowdu, A. A. (2020). *Operations research applications in underground mine production scheduling* (PhD dissertation). South Dakota School of Mines and Technology.

Chowdu, A. A., Nesbitt, P., Brickey, A. J., & Newman, A. (2020). Operations research in underground mine planning : A review. *INFORMS Journal on Applied Analytics*. Forthcoming.

Cohen, R. A., Petsonk, E. L., Rose, C., Young, B., Regier, M., Najmuddin, A., … Green, F. H. Y. (2016). Lung pathology in U.S. coal workers with rapidly progressive pneumoconiosis implicates silica and silicates. *American Journal of Respiratory and Critical Care Medicine*, *193*(6), 673–680. https://doi.org/10.1164/rccm.201505-1014OC

Collett, R. S., & Oduyemi, K. (1997). Air quality modelling: A technical review of mathematical approaches. *Meteorological Applications*, *4*(3), 235–246. https://doi.org/10.1017/S1350482797000455

Dixon, D. W., Ozveren, C. S., & Sapulek, A. T. (1995). *The application of neural networks to underground methane prediction*. Proceedings of the 7th US Mine Ventilation Symposium, 49–54.

Ertel, W. (2017). *Introduction to Artificial Intelligence (Undergraduate Topics in Computer Science)* (2nd ed.). Springer.

Grivas, G., & Chaloulakou, A. (2006). Artificial neural network models for prediction of PM10 hourly concentrations, in the Greater Area of Athens, Greece. *Atmospheric Environment*, *40*(7), 1216–1229. https://doi.org/10.1016/j.atmosenv.2005.10.036

Grosan, C., & Abraham, A. (2011). *Intelligent Systems: A Modern Approach* (1st ed.). 10.1007/978-3-642-21004-4

King, E. J., Mohanty, G. P., Harrison, C. V., & Nagelschmidt, G. (1953). The action of different forms of pure silica on the lungs of rats. *British Journal of Industrial Medicine*, *10*, 9–17. https://doi.org/10.1136/oem.10.1.9

Krose, B., & van der Smagt, P. (1996). *An Introduction to Neural Networks* (8th ed.). University of Amsterdam.

Mayo Foundation for Medical Education and Research. (2017). *Bronchitis - Symptoms and causes*. Retrieved June 29, 2020, from https://www.mayoclinic.org/diseases-conditions/bronchitis/symptoms-causes/syc-20355566

Meldrum, M., & Howden, P. (2002). Crystalline silica : Variability in fibrogenic potency. *Annals of Occupational Hygiene*, *46*, 27–30. https://doi.org/10.1093/annhyg/mef624

NIOSH. (2005). *Significant dust dispersion models*. By Reed, W. R. Pittsburgh, PA: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health, DHHS (NIOSH), Publication No. 2005–138, IC. Retrieved from https://www.cdc.gov/niosh/mining//UserFiles/works/pdfs/2005-138.pdf

Park, S., Kim, M., Kim, M., Namgung, H. G., Kim, K. T., Cho, K. H., & Kwon, S. B. (2018). Predicting PM10 concentration in Seoul metropolitan subway stations using artificial neural network (ANN). *Journal of Hazardous Materials*, *341*, 75–82. https://doi.org/10.1016/j.jhazmat.2017.07.050

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., … Duchesnay, E. (2011). Scikit-learn: Machine learning in python. *Journal of Machine Learning Research*, *12*, 2825–2830. https://doi.org/10.1145/2786984.2786995

Rossiter, C. E. (1972). Relation between content and composition of coalworkers' lungs and radiological appearances. *British Journal of Industrial Medicine*, *29*(1), 31–44. https://doi.org/10.1136/oem.29.1.31

Sellara, R., & Sarver, E. (2014). *Characterization of dust in underground coal mines and implications for occupational health*. 2014 SME Annual Meeting and Exhibit: Leadership in Uncertain Times, 294–298. Salt Lake City, UT: SME.

Trout, L. P. (1997). *Formulation and application of new underground mine scheduling models* (PhD thesis). The University of Queensland.

WHO. (1999). *Hazard prevention and control in the work environment: Airborne dust*. Retrieved June 25, 2020, from https://www.who.int/occupational_health/publications/en/oehairbornedust3.pdf

PROCEEDINGS OF THE 18TH NORTH AMERICAN MINE VENTILATION SYMPOSIUM (NAMVS 2021), JUNE 12-17, 2021, RAPID CITY, SOUTH DAKOTA, USA

Mine Ventilation

Editor

Purushotham Tukkaraja, Ph.D., QP

Mining Engineering & Management, South Dakota Mines, Rapid City, SD, USA

CRC Press
Taylor & Francis Group
Boca Raton London New York

CRC Press is an imprint of the
Taylor & Francis Group, an **informa** business

A BALKEMA BOOK

CRC Press/Balkema is an imprint of the Taylor & Francis Group, an informa business

Typeset by Integra Software Services Pvt. Ltd., Pondicherry, India

Library of Congress Cataloging-in-Publication Data

A catalog record has been requested for this book

Published by: CRC Press/Balkema
Schipholweg 107C, 2316 XC Leiden, The Netherlands
e-mail: enquiries@taylorandfrancis.com
www.routledge.com – www.taylorandfrancis.com

ISBN: 978-1-032-03679-3 (Hbk)
ISBN: 978-1-032-03681-6 (Pbk)
ISBN: 978-1-003-18847-6 (eBook)
DOI: 10.1201/9781003188476