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Estimating diesel particulate matter using a predictive technique for use in underground metal mine production scheduling

J.A. Buaba & A.J. Brickey
South Dakota Mines, Mining Engineering and Management Department, Rapid City, South Dakota, USA

ABSTRACT: Many underground metal mining operations use diesel-powered equipment which emits diesel particulate matter (DPM) into the atmosphere posing a health and safety hazard to expose mine workers. The United States Environmental Protection Agency (EPA) and National Institute for Occupational Safety and Health (NIOSH) have classified DPM as a possible carcinogen creating greater need to control exposure to DPM in the workplace. Within current underground metal mine planning practices, ventilation requirements are often considered after the production schedule has been developed, leading to operational challenges in managing DPM levels. We present a method of estimating DPM using artificial neural network (ANN) for use in underground production scheduling. By incorporating DPM production from various underground mining activities, the resulting production schedules can help better utilize ventilation and production resources in addition to allowing operations to measure the impacts of various non-ventilation DPM reduction methods, e.g., biofuels, electric equipment. The results here show that there is significant potential in predicting DPM concentrations for underground production activities. This research aims to improve the mine environment by providing a tool to estimate DPM that can be incorporated into the production schedule, thereby influencing strategic and tactical-level planning decisions.

1 INTRODUCTION

Underground metal mining is often conducted through the use of heavy diesel-powered equipment and explosives in tight spaces with limited ventilation. This environment increases the risk of miners being exposed to diesel particulate matter (DPM) and toxic gases. To mitigate this situation, infrastructure, such as a ventilation system, is needed to dilute and flush out these harmful contaminants from the working areas (McPherson, 1993). Diesel-powered equipment emits diesel exhaust (DE) which is a complex mixture of diesel particulate matter (solid fraction) and hydrocarbon gases generated by the incomplete combustion of fuel within an engine. The gaseous components of DE include carbon dioxide, oxygen, nitrogen, water vapor, carbon monoxide, nitrogen compounds (NO and NO_2), sulfur compounds, and numerous hydrocarbons. Some toxic gaseous components are the aldehydes (e.g., formaldehyde, acetaldehyde, acrolein), benzene, 1,3-butadiene, polycyclic aromatic hydrocarbons (PAHs), and nitro-PAHs (EPA, 2002). Solid particles present in DE, i.e., DPM, consists of a center core of elemental carbon (EC) and adsorbed organic compounds (OC) which consist of fine particles (diameter < 2.5 μm) including a subgroup with a large number of ultrafine particles (diameter<0.1μm) making them highly respirable and able to reach deep into the lungs. Within current underground metal mine planning practices, ventilation requirements are often considered after the production schedule has been developed potentially leading to insufficient airflow needed to dilute emissions in underground spaces where diesel-powered equipment operate. This results in high concentration of DPM suspended in the mine atmosphere.

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The International Agency for Research on Cancer (IARC), part of the World Health Organization (WHO), classifies DPM as a potential carcinogen to humans after prolonged exposure which may result in lung cancer among workers with a history of working with diesel engines (Benbrahim-Tallaa et al., 2012). This is a health and safety concern for the mining industry as many operations have a significant reliance on diesel equipment. In January 2001, the Mine Safety and Health Administration (MSHA) enforced rules to limit a worker's exposure to < 160 μg/m^3 of total carbon (TC) over an 8-hour time weighted average (TWA) for metal/nonmetal mines (Bugarski *et al*, 2012). MSHA recommends installation of filters on diesel equipment, use of biofuels, and providing sufficient airflow to dilute pollutants to control exposure to DPM (The Mine Safety and Health Administration, 1997). These strategies tend to be employed as a reactive approach to reducing exposure to DPM when DPM levels are above regulatory limits. To determine compliance, mine operators collect DPM samples for analysis using NIOSH Method 5040: a thermo-optical analysis used to measure carbon-based aerosols by oxidizing elemental and organic carbon to carbon dioxide (NIOSH, 2003)

This paper looks at a proactive approach to estimating DPM production associated with various underground metal mining activities, e.g., *development drilling*, *ore extraction*, for incorporation into the production scheduling process. This will create an ability to evaluate various DPM reduction and elimination methods, e.g., biofuels, electric equipment, and their resulting impact on the production schedule. We develop an artificial neural network (ANN) model, a machine learning technique, to estimate DPM from underground activities using historical DPM monitoring data from a case study mine. Previous research has shown that incorporating ventilation into production scheduling can have a significant impact on mine production schedules (Brickey, 2015; Sharma, 2015; Zhang *et al*, 2017). To this end, we develop an ANN model to estimate DPM production by activity to be incorporated into a production scheduling model with ventilation.

2 AIR QUALITY MODELLING USING MACHINE LEARNING

Machine learning (ML) techniques can identify trends in data without being explicitly programmed. ML techniques, e.g., artificial neural networks (ANNs), have proved to be a suitable tool for modelling particulate concentrations with lesser computational cost (Suleiman *et al*, 2019; Whalley & Zandi, 2016). ANN mimics the web of interconnected neurons in the human brain by using algorithms to recognize relationships in a dataset (Grosan & Abraham, 2011). They are capable of modelling complex and dynamic nonlinear relationships that exist between variables and can be trained to accurately predict new and unseen data. Additionally, ANN models are efficient in handling multivariate inputs and uncertainty (Goyal & Kumar, 2012). The machine learning modelling process involves data preparation, feature selection, model training, testing, and evaluation.

Air quality models have been developed using ANNs to predict air pollutants such as particulate matter (Whalley & Zandi, 2016), ozone (O_3) (Yi & Prybutok, 1996), nitrogen dioxide (NO_2) (Elangasinghe *et al*, 2014) and sulfur dioxide (SO_2) (Chelani *et al*, 2002) in the last two decades. Suleiman (2019) evaluate the effectiveness of particulate reduction scenarios using ML techniques. The author uses traffic flow (number of vehicles), meteorological, and pollutant monitoring data as input variables to predict roadside concentrations of PM_{10}, i.e., particulate matter with diameter < 10μm and $PM_{2.5}$, diameter < 2.5μm. The results show that the predictions from the ML models correlated well with the observed concentrations with an accuracy of about 95%. Yi (1996) develops a neural network model to predict daily maximum ozone levels in urban areas. The author compares the performance of neural network with traditional statistical models such as regression and shows that neural network models are more viable in comparison to statistical methods.

2.1 *Modelling DPM for use in underground production scheduling*

At present, some researchers have used empirical methods to estimate DPM concentrations for underground mines. Haney and Saseen (2000) develop a computer spreadsheet model to estimate DPM levels in underground mines. The authors used in-mine measured DPM concentrations or engine manufacturer's emission data, ventilation, and efficiency of control technology, among others to estimate full shift DPM concentrations. The model was tested with both in-mine DPM (measured) data and laboratory test data in a coal and nonmetal mine. The results showed a difference in the in-mine measured DPM concentration and the laboratory test concentration; the former has lower DPM concentration than the latter. Schnakenberg (2001) used empirical formulas to estimate the average workplace DPM concentration for underground metal and nonmetal mine that used MSHA approved low-emission engines. The author estimated DPM by using as input parameters, the efficiency of exhaust control technology, the particulate index (PI) of MSHA approved engines, ventilation rates for those engines, and general ventilation rates in underground mines.

In our research, we seek to answer the question how we use measured TWA DPM concentration data in the mine planning process to reduce exposure to DPM. We approach this issue by exploring the use of machine learning techniques. Specifically, we are developing methodology that uses artificial neural network and optimization to estimate and integrate data on DPM concentrations from underground activities into a production scheduling model. This study covers the first part of the research thus using artificial neural network to predict DPM concentrations from underground mining activities such as primary development, stope extraction, and production drilling.

Underground metal mine production scheduling consists of determining the start time(s) of mining activities in order to maximize the value of the orebody, while adhering to precedence, activity durations, production, and processing constraints. An underground metal mine is developed by constructing tunnels such as declines, shafts, and drifts to gain access for ore extraction. These activities are collectively called development. When access to the ore is achieved, the orebody is mined either through drilling and blasting or by using a continuous miner depending on the characteristics of the rock and mining method applied. These activities are classified as production. Unit mining operation consist of drilling, blasting, loading, and hauling. Depending on the mining method, the mining process may include backfilling of mined out areas to provide support to adjacent stopes. Each activity is associated with attributes like tonnage, meters, volume, activity duration, and excavation shape and size which are linked by precedence constraints. Resources such as equipment and ventilation are assigned to execute each activity. For instance, a jumbo drill is assigned to development drilling activities and a load-haul-dump (LHD) to material handling activities. While executing these activities, DPM is generated from diesel-powered equipment at or near the working areas. Mining operations schedule production based on activities hence collecting activity-based DPM concentrations will help to incorporate DPM emissions into production scheduling. With ventilation being a limited resource, scheduling activities while including ventilation needs by activities can provide valuable information about how ventilation can impact production and vice versa. Many underground metal mining operations use Deswik (Deswik Mining Consultants Pty Ltd, 2019) for underground production design and scheduling. This software is used by planning engineers to create 3-dimensional models of the mine design and to visualize a schedule using a Gantt-chart style interface.

Currently, DPM concentration is monitored by measuring time-weighted average personal exposure from a DPM sampler placed on a miner for the entire shift. The challenge with using these samples for activity-based DPM estimation is that miners move around the mine hence the DPM concentration recorded may not represent the DPM concentration at the working face related to an activity**.** Yet, this is the DPM data available and we explore its usefulness in this research and with the added objective of justifying the collection of activity-based DPM samples. A typical DPM monitoring data has a record of the personnel monitored, sampling rate, sampling time and the TWA DPM concentration. The personnel monitored provide information on the type of activity being executed at the time of monitoring. We use this information to group the monitored DPM concentrations by activity into development drilling, production drilling, blasting, loading, and hauling. For this project, the underground mining activities are broadly categorized into development drilling, production drilling, ore extraction, and backfill. This research shows the potential of estimating activity-based DPM concentration for use in production scheduling.

3 DATA AND METHODOLOGY

Supervised artificial neural network is applied to DPM monitoring data collected at a case study mine located in South America, to predict DPM concentration from underground activities. DPM samples are collected for analysis to determine compliance with regulations. The data obtained is summarized by personnel monitored, sampling time (in minutes), air sampling rate (in liters/minute), and TWA DPM concentration (in mg/m³). Table 1 shows a sample of the data. Mine planning data was also obtained from the mine, which provides information on the underground mining activities.

3.1 *Data preprocessing*

The dataset comprises of 298 samples collected from 2017 to 2019. We exclude 85 samples (28.52%) from the original data comprising of outliers and samples of personnel not directly associated with the job types under the scope of this study. The remaining 213 samples (71.47% of the original data set) were analyzed in this study. The DPM data is grouped by activity into development drilling, production drilling, blasting, loading, and hauling to represent activity-based DPM concentration produced while executing these activities (see Table 2 below). To obtain sufficient data for training in a machine learning model, we perform statistical analysis to identify the distribution of the data using Minitab (Minitab, 2020). We use this information to generate 1000 random samples for each activity type while not violating

Table 1. Sample DPM monitoring data.

Personnel	Rate (l/min)	Sampling time (min)	TWA DPM concentration (mg/m^3)	TWA Limit (mg/m^3)
Truck operator	3.0	300	0.10	0.16
Scoop operator	3.0	300	0.08	0.16
Jumbo operator	3.5	400	0.31	0.16
Manlift operator	3.5	420	0.18	0.16
Production drill operator	3.5	440	0.09	0.16

Table 2. DPM concentration in mg/m^3 by activity type.

Job Type	Personnel	Number of samples	DPM concentration range (mg/m^3)	Statistical Distribution
Development drilling	Jumbo operator	68	0.00 – 0.38	Lognormal
Production drilling	Production drill operator	11	0.00 – 0.13	Lognormal
Blasting	Manlift and explosive truck operator	30	0.00 – 0.46	Gamma
Loading	Scoop operator	40	0.01 – 0.76	Gamma
Hauling	Truck operator	64	0.00 – 0.24	Gamma

the original data distribution. Table 2 summarize the number of samples, DPM concentration range, and distribution of each activity.

The mine planning data obtained is comprised of more than 4,000 mining activities grouped into four activity types: *production drilling, development, ore extraction,* and *backfill.* We assume that the measured DPM concentration are personal exposure values of operators at the time of executing each activity. For example, with development drilling job type we use DPM concentrations collected from a jumbo operator and so on. The DPM monitoring data is mapped to the mine planning activities using weights which represent the estimated percentage each job type is conducted during a given mine planning activity. This is done to convert the job type samples to activity-based samples. For instance, in mine planning, development activities have both meters to be drilled and tons to be mined attribute. We calculate the DPM concentration for the mine planning development activity by multiplying the weight with the DPM concentration generated from development drilling, blasting, loading, and hauling job types.

3.2 *ANN modelling*

A supervised ANN model is built for the case study mine using 4000 DPM samples. The data is spilt into training, validation and test sets consisting 70%, 15%, and 15% of the DPM samples respectively. The ANN model consists of input, hidden, and output layer neurons which process information sequentially, i.e., from the input layer to the hidden layer and finally to the output layer. The model is trained using the back-propagation algorithm in two major steps: forward and backward passes. In the forward pass, the input variables in the input layer neurons are passed through connecting links of various weights where the input variables are weighted using a linear function (Haykin, 2005). The weighted inputs are passed forward to the hidden layer neurons. The hidden layer estimate values using an activation function and then passes the outputs to the output layer neurons for final estimation. The final output is compared with the target output, i.e., the measured DPM concentration from the original data, to calculate the error in the network. In the backward pass, the error is propagated backwards to adjust the weights such that the error is minimized. This process continues until all the layers are updated (Haykin, 2005). Figure 1 depict a schematic of the ANN architecture.

To predict DPM concentration, a set of predictor variables are selected as input for modelling. We select the activity type, i.e., production drilling, development drilling, ore extraction, and backfill, activity rate in meters/day, and activity rate in tons/day as input parameters to predict DPM generated from activities. We acknowledge that equipment specific data, such as engine load and fuel consumption may improve the estimations, but this information was not available for this case study. The data set is scaled within the range 0 – 1 using the MinMaxScaler function of the Scikit-learn python library (Pedregosa *et al*., 2011). We develop separate, multi-layered ANN models (A, B, C, and D) with one to four hidden layers for prediction using Keras (Keras, 2020). Keras is an open-source software library written in Python for solving machine learning problems with a focus on modern deep learning. Hyperparameter tuning is performed to obtain optimal number of neurons (units) for the hidden layers under consideration. The input and output layers have fixed neurons; six and one, respectively, but varying hidden layers. These represent the six input parameters and the output parameter, i.e., DPM concentration in mg/m^3. Table 3 summarize the results for four scenarios of hidden layers considered. Model D with four hidden layers is selected for modeling DPM concentration. This is based on the mean square error (MSE) test scores, which characterizes the ability of the models to predict unseen, real-world data, i.e., data not included in the modeling process. MSE is the measure of the average error of the predicted and actual values used to evaluate models (Suleiman et al., 2019). The best model has a MSE score closest to zero. Thus, model D is selected as the model for predicting DPM concentration.

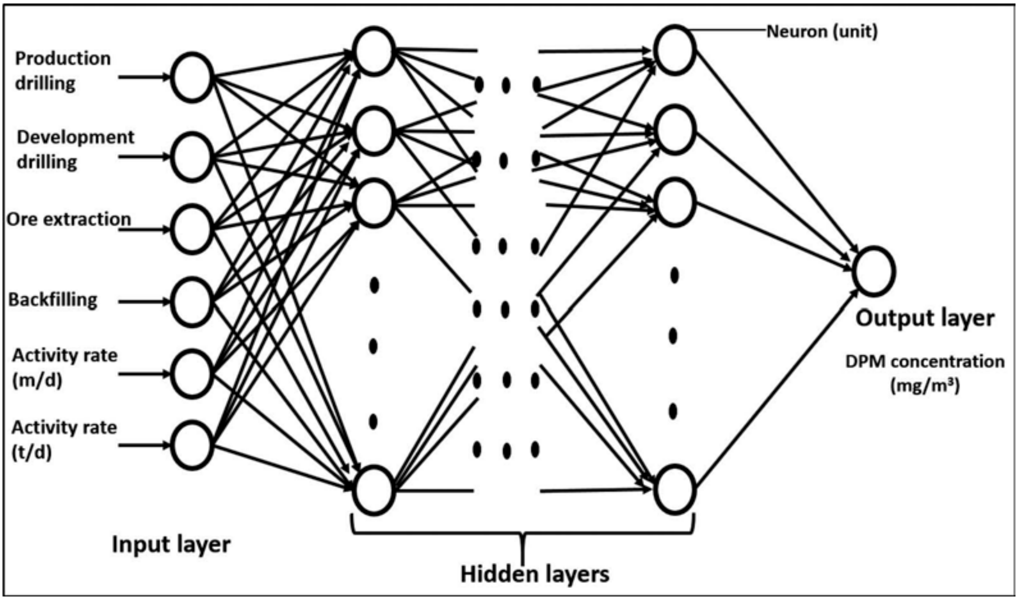

Figure 1. Artificial Neural Network architecture.

Table 3. Model selection with mean square error.

Model ID	Number of Hidden Layers	Optimal Neurons for Hidden Layers	MSE for Test Data
A	1	450	0.0233
B	2	234-287	0.0200
C	3	440-281-402	0.0226
D	**4**	**415-155-18-402**	**0.0198**

4 RESULTS

We develop the DPM estimation model using the selected model D. The model is trained by running 450 iteration on 2800 samples to reduce prediction error. We assess the performance of the model using the validation and test samples. The validation dataset comprises of 600 samples, which are not used in training the model, and is used to evaluate the model to fine-tune the hyperparameters, such as the learning rate. The test dataset (600 samples) is used to provide an unbiased evaluation of the final model fit on unseen, real-world data. It is used once the model is completely trained. Table 4 show the performance of model D on the training, validation, and test data using the mean square error as a performance metric. Model D is able to fit well with unseen data as shown by the MSE values (close to zero).

Figure 2 Is a scatter plot of actual DPM concentration versus the predicted concentration for the test data. The figure shows that the model has some correlation (r = 0.54, MSE =

Table 4. Model D evaluation.

	Mean square root error (MSE)		
	Training	Validation	Test
Model D	0.0176	0.0198	0.0198

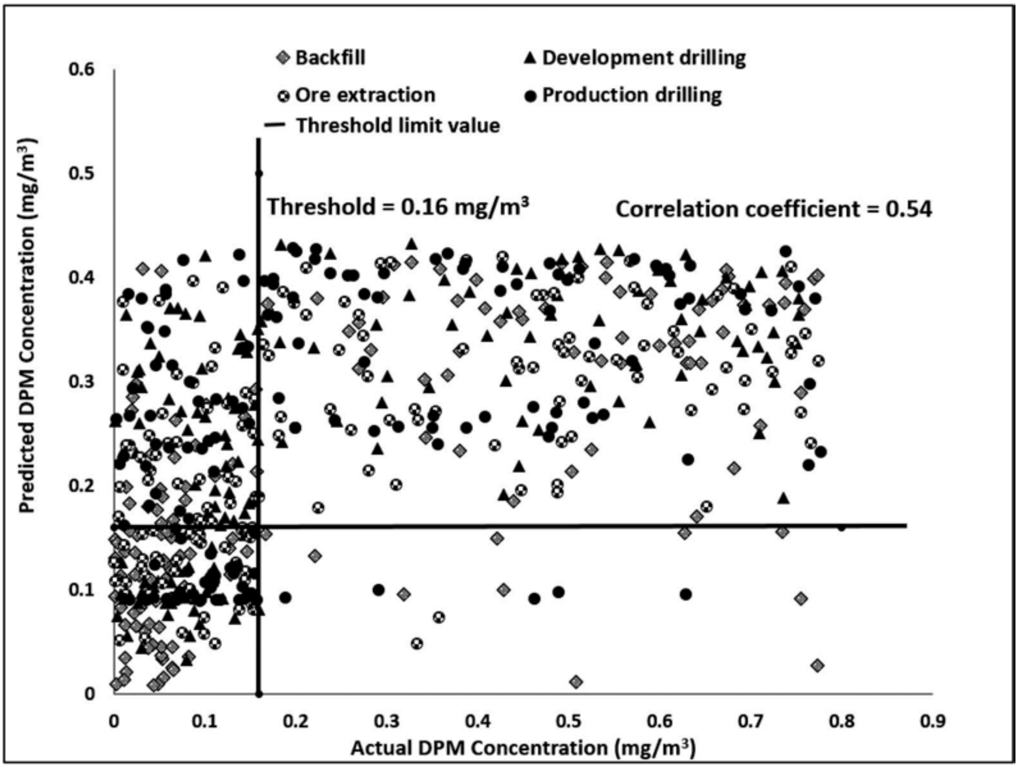

Figure 2. Scatter plot of actual vs predicted DPM concentration for test data.

0.0198) when predicting DPM concentration for the test data. While this correlation is somewhat disappointing, we believe that this shows the estimation method's viability, and that correlation would be significantly improved with activity-based DPM samples and corresponding production data. The actual DPM concentrations vary between 0.00 mg/m^3 to about 0.8 mg/m^3 while the model predicts DPM concentrations between about 0.00 mg/m^3 to 0.43 mg/m^3 for all activity types. This may be as a result of the model's inability to capture the relationship between the input variables and the output resulting in under- and over -estimation of DPM concentration. This can be improved by selecting more features that correlate with DPM concentration. In the meantime, we are in touch with the case study mine to collect activity-based data to improve the model's performance.

5 CONCLUSION

This paper explores the use of artificial neural network for predicting DPM concentration to be used in underground production scheduling. We use historical DPM concentration data collected from a case study mine to train, validate, and test a variety of multilayered ANN models using activity type, i.e., production drilling, development drilling, ore extraction and backfill, activity rate in meters per day, and activity rate in tons per day as input variables. We select the model with the least mean square error (MSE) value as the final model for predicting DPM concentration. The model shows some correlation (r = 0.54, MSE = 0.0198) when predicting DPM concentration for unseen data. Based on the results of this initial analysis, the authors believe that the model can be improved with additional DPM data, e.g., activity-based DPM sampling, and operational data, e.g., equipment performance data, that should assist in correlating DPM data to production activities

We also show the potential of using machine learning, especially artificial neural network, for predicting DPM concentration for use in underground production scheduling. The incorporation of ventilation, as a consumable resource, into the production scheduling process will increase the feasibility of the resulting schedules when compared to those without ventilation capacities as a constraint. Additionally, the model could be used to quantify the impacts on production and potentially justify modifications to the ventilation system required or the impact of various DPM reduction methods.

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Editor

Purushotham Tukkaraja, Ph.D., QP

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

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