IJES *Iranian Journal of Earth Sciences*
Vol. 13, No. 1, 2021, 14-20.

Influence of rock properties on emission rate of Particulates Matter (Pm) during drilling operation in surface mines

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Received 1 December 2019; accepted 3 June 2020

Abstract

The mining process generates significant amount of dust in the form of particulate matters into the atmosphere. Out of different mining process, opencast mining produces more dust than that of underground mining because of exposure in the ambiance. The mining operations are directly or indirectly involved in the production of dust particles. The activities like drilling operation, Blasting and haul road operations produce fugitive dust and causes significant deterioration of mine atmosphere. This fugitive dust consists of particulate matters (PM), which are more harmful to the human respiratory system. The prevention measures is only possible when the actual prediction of emission of those fugitive dust particles are possible. There is several model that predict the emission of the dust particles, but there is very less model to predict fugitive dust produced from a drilling operation in surface mines. In this paper, study was carried out to develop dust prediction model and to assess the influence of rock properties on dust emission. Based on the results obtained the developed model exhibit close proximity of predicted as well as field measured values with a regression coefficient of 0.75. Thus, the development of the model with effective prediction capability is the novelty of this paper. Decrease in dust emission rate was observed with increased moisture content present in drill cuttings, higher compressive strength, and density.

Keywords: *Dust, Emission, ANN, Multiple regression analysis, Rock properties*

1. Introduction

Dust is a major environmental problem during surface mining operations. Presence of dust particles in the surroundings of surface mines not only causes health problems to the workers but also results in poor visibility that may lead to Heavy Earth Moving Machinery (HEMM) accidents. The HEMM accidents may occur frequently due to the continuous deposition of dust produced from mining operations. In surface mining operations, the dust sources are categorized into 3 types namely point sources, line sources and area sources (Thompson and Visser 2007). The point sources comprises drilling, loading/unloading operation while haul roads and unpaved roads comes under line sources and coal stack yard, dump yard etc. are area sources (Jose and Huertas 2012, BPEMD dust control 1998). The elimination of dust produced at mining site due to various activities is not possible but only their reduction is possible up to some extent. The haul road is major contributor of fugitive dust while drilling and blasting is second most contributor of fugitive dust in mining area (Cole and Zapert 1995). The dust produced during drilling operation in the mine area discharged in the atmosphere in a defined flow stream. The discharged dust in the atmosphere comprises variable sized particles which is harmful to nature and human health. Majority of the dust particles lies between PM2.5 and PM10, which are harmful to human health and leads to major respiratory problems (Chakraborty et al. 2001).

Estimation of emission from respective source is an important factor for any kind of dust dispersion models. Initially dust emits from source is mainly depending on various factors like moisture content, rock density, hardness of rock, compressive strength of rock, etc. Moisture content present in rock virtually leads to less particulate emission (Cole and Kerch 1990). In order to develop a good prediction model, good amount of field data is required and it has to be processed. Though there are various methods available, among them Artificial Neural Network (ANN), Multiple Regression Analysis (MRA) and Cluster methods are commonly used in environment related research including dust prediction models (Lal and Tripathy 2012).

The statistical analysis technique such as multiple regression analysis is often used to analyze the correlation between a single dependent variable and several independent variables. The multiple regression analysis is basic technique used to analyses the several research output including environmental prediction problems. This is highly acceptable regression analysis technique used in versatile dependence area. This technique can be used for various air pollution problems like determination of tropospheric ozone, TSP, PM10, PM2.5, etc. (Sousa et al. 2008). Also the multivariate statistical analyses like Cluster Analysis (CA), Principal Component Analysis (PCA) were also used for assessing

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various pollutants from the coal mines (Pandey et al. 2014).
The ANN has become a more research interest from past two decades and is being successfully applied across various problem domains in the areas of medicine, engineering, science and finance. ANNs can identify and learn interrelated patterns between input data and corresponding output data. After training, ANNs can be used to predict output of new input data. Gaussian plume model and ANN gave more accurate values between 400 meters to 2,900 meters. Multivariate analysis is related to examination of more than two variables (Chaloulakou et al. 2003). The most commonly used multivariate statistical model for environmental analysis is Cluster Analysis, Principal Component Analysis, Factor Analysis, Multiple Linear Regression Analysis (Papanastasiou and Kioutsioukis 2007). Stepwise estimation is the most popular sequential approach for variable selection. The approach helps to understand the influence of the independent variable on the statistical model. The model requires the independent variable of great contribution to be added first. These independent variables are selected and inclusion is carried out based on their incremental contribution over variables already available in the equation (Nagesha and Chandar 2015). This technique can be used for various air pollution problems like determination of tropospheric ozone, TSP, PM10, PM2.5, etc. (Pandey et al. 2014).
There are many basic dispersion models used to determine the dust dispersion, like box model, Gaussian model, Eulerian model and Lagrangian model (Collett and Oduyemi 1997). Out of several dispersion models the box model and Gaussian model gained popularity worldwide.
Box model Algorithms - the box algorithms assume the pollutants distributed uniformly in a box as:

$$\left(\frac{dCV}{dt}\right) = eA + uC_{in}WH - uCWH \tag{1}$$

Where,
e = Pollutant emission rate per unit area
C = Homogeneous concentration within the air shed
C_{in} = Homogeneous concentration entering the air shed
V = Volume of the described box
A = Horizontal area of the box
H = Mixing height (m)
U = Wind speed (m/s)
W = Width of the box
The Gaussian model algorithm - the Gaussian model works based on some assumption that the pollutant distributed in normal statistical distribution as:

$$\chi = \left(\frac{Q}{2\times\pi\times u\times\sigma_y\times\sigma_z}\right)\times e^{\left(-0.5\times\left(\frac{y}{\sigma_y}\right)^2\right)}\times e^{\left(-0.5\times\left(\frac{H}{\sigma_z}\right)^2\right)} \tag{2}$$

Where,
χ = Hourly concentration at downwind distance x (μg/m3)
Q = Pollutant emission rate (gm/sec)
u = Mean wind speed (m/s)
H = Stack height (m)
σ_y=Standard deviation of horizontal plume concentration
σ_z = Standard deviation of vertical plume concentration
The ISC3 (Industrial Source Complex) model was used to test three Georgia stone quarries elsewhere (Cole and Zapert 1995). Based on data obtained from U.S. Department of Energy's Hanford, WA, site, an over prediction of particulate concentrations was observed by ISC3 model.
The performance of test of fugitive dust model was carried out to predict the impact of fugitive particulate emissions from a cement plant on a nearby community in Oman on environment and human health (Abdul-Wahab 2005). Some representative data was collected from three existing residential houses near to the cement site. The comparative analysis was carried out between the results obtained from field and the Fugitive Dust Model (FDM). Results showed a slightly compared correlation between FDM model and measured dust concentrations. The prediction of dust emission of Respiratory Particulate Matter (RPM) and Total Suspended Particulate Matter (TSPM) from various activities of the mine was carried out using FDM model (Trivedi et al. 2009). The investigation was carried out in opencast coal project of Western Coalfields Limited in India. The results showed 68 to 92 % correlations of the values of TSPM using FDM model over observed values. Variations between observed values and predicted values of TSPM may be due to non-accountability of emissions from various other sources like non-mining area activities, domestic use of fuels, transportation network, nearby power plant, cement plant, etc.
Trivedi et al. (2009) compared the FDM model predicted values and observed values for drilling, loading, haul road, unloading, stock yard, work shop, exposed work pit surface and over all mine to observe how much quantity dispersed into atmosphere. The emission from each activity was determined by using Gifford and Pasquill formula. The instruments used for experiments are like high volume sampler for SPM and RPM. Sampling time is 24hrs. Results revealed that the highest emission is dispersion from the unloading of overburden material and also the dust generated from mining activities is not much contributing to the atmosphere.
In this paper study was undertaken to develop dust prediction model and to assess the influence of rock properties on dust emission. Extensive field investigations were carried out in four types of rock formations like coal, sandstone, limestone, and granite. Drilling was carried out using four different drill bits. Initially, field data was accessed using Artificial Neural Networks (ANN), and after that, a mathematical model was developed using Multiple Regression Analysis (MRA). The established model validated with field data. Influence of various properties of rock on dust emission

rate studied by comparing them with field emission rate values and model predicted values.

2. Materials and Method

2.1. Materials and Method

Airborne respirable dust monitoring was carried out during a drilling operation in four rock formations (Like Sandstone, Coal, Limestone and granite) using three personal dust samplers and two ambient point samplers. Initially before starting any field investigation, the metrological station was installed in mine premises, and hourly basis readings were collected. Instruments were placed at a distances towards downwind direction during the drilling operation, and initially, one instrument was placed towards the upwind direction to identify the background concentration. The same procedure was followed on each day for monitoring during field studies in all mines. In order to assess the influence of rock properties on dust emission, some rock samples were collected from the field at different locations and tests were conducted in the laboratory to determine required physico-mechanical properties.

A total of sixty samples were collected from four different type rock formations. The emission model was developed by considering 40 samples, which consist of four types of rock formations (in each formation ten samples) were used.

The further developed model was validated with remaining twenty samples collected from four formations. In addition, the influence of various rock properties on emission rate with respect to different types of rocks was determined by considering of ANN, MRA and field data.

2.2. Field Investigations

Field investigations were carried out in total three opencast mines/quarries. Among them one is an opencast coal mine, one limestone mine and last one is granite quarry (Fig 1 and 2). The details of all case studies discussed in brief below.

Fig 1. Personal dust monitor near drilling machine

Fig 2. Ambient point dust monitor near drilling activity in limestone benches

2.3. Determination of Rock Properties

As rock properties play a significant role in emanating the dust during drilling activity, rock samples collected during the field investigations from different locations of the mine. The samples were brought to the laboratory, and required tests were carried out according to International Society for Rock Mechanics (ISRM) suggested methods. The various rock properties like moisture content present in the drill cuttings, Density, Compressive strength and Rebound hardness number determined as per the ISRM standard. Details of the test results are given in respective case study tables.

Density of different rock samples were determined as per ISRM (International Society for Rock Mechanics) suggested method (Part 1-No.2). Tests were conducted in the laboratory, to find the density of a rock sample, initially a container with some amount of water was chosen. The difference of water level was observed by considered the value before and after inserting the rock sample in the container. Mass of the rock sample was also measured before inserting it into the water container. The difference of water level was used to find the volume of rock sample (Fig 3).

Finally, the density of a material was determined by following formula ie. It is the ratio of mass per unit volume. The symbol of Density is ‘ρ’.

$$\rho = \frac{m}{v} \tag{3}$$

Where,
ρ = (rho) is the density (gm/cc)
m = is the mass (gm)
v = is the volume (cc)

The moisture content was determined as per International Society for Rock Mechanics (ISRM) suggested methods. Initially the 50gm sample was placed in a container which is non-corrodible material and its mass was taken (M1). The container with sample was placed in the oven at a temperature of 105ºC for a period of 24 hours. After 24 hours the container and rock sample was taken out and allowed to cool. Finally the dried sample weight along with container weight was determined (M2). The following formula was used to determine the moisture content.

$$Moisture\,Content = \frac{Mass\,of\;\;water\,Content}{Dried\;Sample\,Weight} \times 100 \quad (4)$$

$$Moisture\,Content = \frac{M1 - M2}{M2} \times 100 \quad (5)$$

Fig 3. Experimental set up for to determine density

2.3.1. Case study-1

First Case Study was taken up in mine-1 which is situated in southern India. In this mine, overburden is fragmented using drilling and blasting. 250mm and 150mm diameter blast holes are drilled with wagon drills in sandstone and coal benches respectively. Field studies were carried out in different seasons to monitor dust emission during the drilling operation. The main purpose of sampling in various seasons considered because of different levels of factors like wind speed, temperature, humidity etc. The first phase of field investigations was carried out in summer and post-summer season. Second stage field investigations were carried out during the winter season, i.e., during the November–December. The blast holes were drilled at a penetration rate of 0.28 m/min to 0.33 m/min. Among all the samples collected from mine-1, fifteen samples were collected from coal benches, 15 from sandstone benches for the emission which ranged between 0.051 gm/s and 0.794 gm/s.

2.3.2. Case study-2

The case study-2 was carried out in a limestone mine. The lithology consists of mainly is limestone (Grey color limestone) in this mine. The drills were operated at a penetration rate ranging between 0.13 m/min and 0.25 m/min. Jackhammer drill was also used for drilling for secondary blasting with 32mm diameter. Dust dispersion from this drilling operation was also considered for investigations. In total, fifteen samples were collected from limestone benches for emission, which ranged between 0.102 gm/s and 0.282 gm/s.

2.3.3. Case study-3

Case Study- 3 was taken up in a granite quarry. Field investigations were carried out in March 2016. In this quarry, blast holes were drilled by wagon drills of 115 mm diameter. These drills were operated at a penetration rate ranging between 0.24 and 0.40 m/min. In total, fifteen samples were collected for the dust emission, which ranged between 0.126 gm/s and 0.526 gm/s.

3. Results and analysis

Based on the data generated from the field investigations, a mathematical model is developed to predict the dust emission from the drilling operation. Artificial Neural Networks approach is used to assess the reliability of field data, and a mathematical model is using multi-regression analysis. To develop emission model, 40 sets of filed data (total 70 % of data), which consists four types of rock formations and to validate model 20 sets of data (total 30% of data) is used.

3.1. Dust prediction modeling using Artificial Neural Networks

Artificial Neural Network (ANN) is one of the most powerful analysis tools and has a wide variety of applications in solving many engineering problems including environmental related tasks. The ANN technique was used in Matlab-R13 code software. The Feed Forward Neural Network with back–propagation algorithm was used to train the network. Neural Network Architecture for emission model is 7:10:1:1, which represents there are seven input variables, ten hidden layers, one output layer and one output variable (Fig 4). The network was trained using Back-propagation algorithm such as "Traincgp." 70 % of the data is used for training, and the 30 % of data was used for validation of the network.

Once the particulate matter were predictive models were developed, their performance was evaluated and determined through RMSE (Root Mean Square Error) and R^2 (Regression coefficient). Fig 5 shows the correlation between actual field measured values with predicted values of dust emission. The R^2 value obtained for emission model is 0.98 which exhibit an excellent relationship. It indicates that the field data and the model are very reliable.

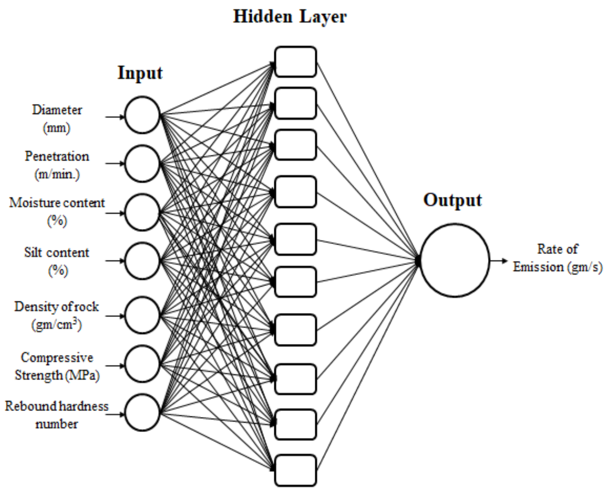

Fig 4. Neural Network Architecture for emission model

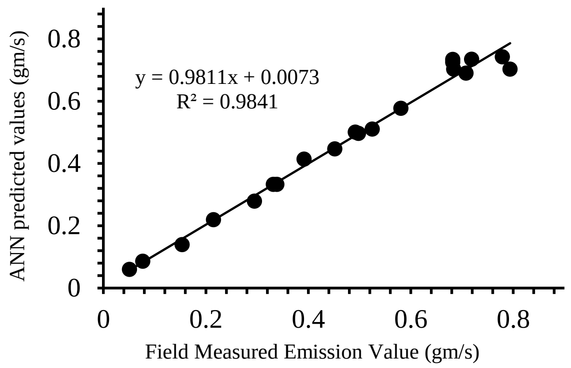

Fig 5. Correlation between of ANN predicted values and field measured dust emission values

3.2 Dust prediction modeling using Multiple Regression Analysis

Multiple regression analysis was used to develop a mathematical model using the same data set. Multiple linear regression models were carried out using 40 data sets while remaining 20 data sets were used for validation. The multiple regression analysis was carried out using SPSS 13.0 software code. In this analysis stepwise regression was adopted to assess the influence of input parameters on output and to develop a mathematical model. Equation 6 represents the developed model to predict dust emission from drilling operation as:

$$E_d = 0.794 + 0.001d - 0.016m + 0.793P + 0.008S - 0.016R - 0.002\sigma_c - 0.0239\rho \qquad (6)$$

Where, E_d is Rate of Emission from drilling (gm/s), m is Moisture content (%), P is Penetration rate (m/min), S is Silt content (%), d is Diameter of drill (mm), R is Rebound hardness number, σ_c is Compressive strength (MPa), ρ is Density of rock (gm/cm^3)

The results obtained from the developed model exhibit more than 91 percent satisfactory results with a standard error of 6 percent. Similarly, the results of F test carried out using ANOVA analysis confirm the validity of the model. Variables in Table 1 are more significant because their probability of 'P' value is less than 0.05.

After assessing developed model through various statistical methods, further to validate the developed model, the plots drawn between actual field measured values with predicted values for dust emission rate. They resulted in regression coefficient (R^2) value of 0.91, which show good correlation (Fig 6), indicating that the developed model with field data is giving better prediction.

Table 1. Coefficients of emission model for estimation of emission rate

Parameters	Regression Coefficients		T-test	Sig.(P)	VIF
	B	Std. Error			
Constant	0.794	0.092	8.673	0.001	---
Diameter (mm)	0.001	0.000	4.176	0.002	2.899
Penetration (m/min.)	0.793	0.193	4.106	0.001	8.895
Moisture content (%)	-0.016	0.002	-7.040	0.001	1.962
Silt content (%)	0.008	0.001	8.062	0.001	5.869
Density of rock (gm/cm^3)	-0.239	0.039	-6.145	0.002	8.589
Compressive Strength (MPa)	-0.002	0.001	-4.190	0.001	10.00
Rebound hardness number	-0.016	0.003	-5.490	0.002	2.539

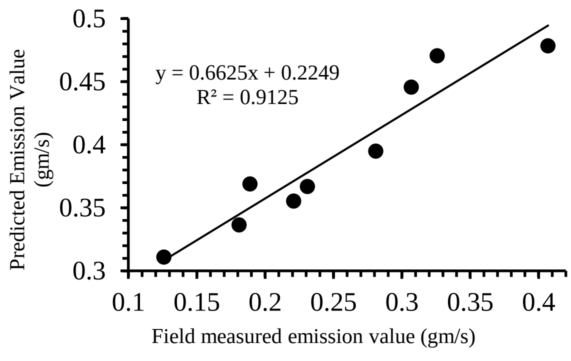

Fig 6. Correlation of model predicted values with field measured values

3.3. Influence of Different Parameters on Emission Rate

The dust emission depends upon various parameters like density, compressive strength, moisture content present in drill cuttings, penetration rate and dill diameter. Influence of multiple parameters on emission rate is assessed using field emission rate and predicted values.

3.3.1. Influence of compressive strength on emission rate

The drill diameter of 150 mm was considered in coal and sandstone benches to assess the influence of compressive strength on emission rate. The properties of the rock samples are included in table 2. The correlation between emission rate and compressive strength is represented in Fig 7. It is observed that, with an increase in compressive strength, the emission rate decreased linearly for coal and sandstone benches. The emission rate varies from 0.33 to 0.29 gm/s at 17 to 27 MPa compressive strength. Reduced emission rate was observed with compressive strength due to the less penetration and less dust emission with increase in strength of the rock. A similar trend was observed between predicted emission rate from ANN and SPSS model and compressive strength.

Table 2. Average values for different properties of Rocks

Sl. No.	Moisture Content (%)	Std. Deviation	Density (gm/cm^3)	Std. Deviation	Compressive Strength (MPa)	Std. Deviation	Type of Rock
1	13.00	4.87	1.25	0.012	17.13	1.25	Coal
2	9.40	4.24	2.30	0.055	44.03	4.09	Sandstone
3	3.09	4.39	2.69	0.033	62.72	3.03	limestone
4	1.10	2.7	2.72	0.060	178.00	7.78	Granite

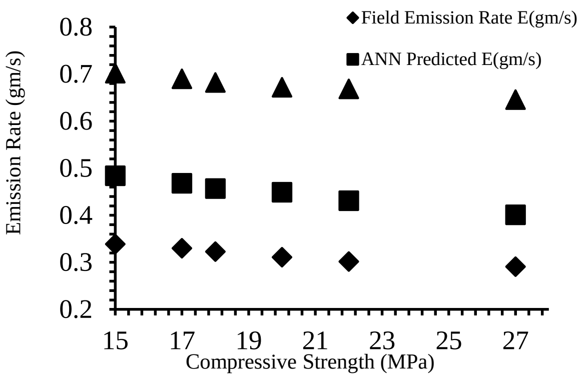

Fig 7. Influence of compressive strength on emission rate

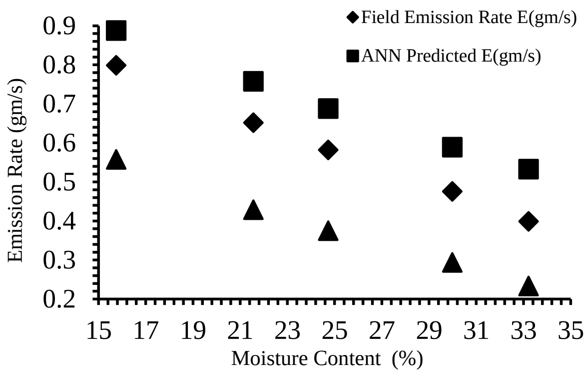

Fig 8. Influence of moisture content on emission rate

3.3.2. Influence of moisture content on emission rate

In order to assess the influence of moisture content on emission rate, moisture content values of sandstone drill cuttings were considered. Moisture content has restraining nature in dust generation and may vary from season to season (Roy et al. 2011). For analysis, the field monitoring data was considered from sandstone benches during summer and rainy season. The plot is drawn between emission rate, and moisture content is shown in Fig 8. It can be observed that, with an increase in moisture content present in drill cuttings, the emission rate decreases linearly, this is because of wet dust tries to settle down quickly at higher density.

3.3.3. Influence of density on emission rate

The density of coal, sandstone, limestone and granite formations and emission rate was mutually correlated and to determine the influence of density values on emission (Fig 9). In general, higher density results in lesser penetration rate, causes lesser dust emission. Decreased emission rate is reported with density in Fig 8. The correlation established by ANN, SPSS and actual field data depicts the similar trend of reduction in emission rate with density.

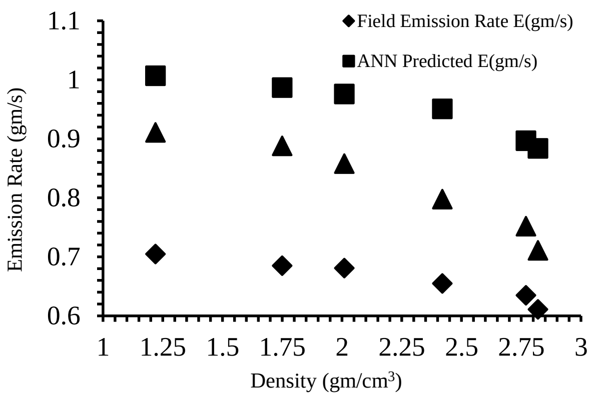

Fig 9. Influence of density on emission rate

4. Conclusions

Drilling and blasting operations are very important operation in any open cast mines, in the mean time both operations introducing enormous amount of particular matters to environment which detracting the ambient. To identify quaintly of emission and at what level of rock properties were influencing for emission rate the present work was carried out. Based on developed model and comparisons of different rock properties with respect to emission some of the conclusion explained below.

The files data generated by monitoring dust emission during drilling was analyzed using Artificial Neural Networks and Multiple Linear Regression (MLR) methods and based on the analysis, the following conclusions are drawn.

- Multi-Layer Perceptron neural network was trained using Traincgp and correlation coefficient (R-square) value between predicted values from ANN method and field measured values is 0.98 for emission model, which shows a very good correlation
- The correlation coefficient (R-square) value between predicted values from SPSS model and field measured values is 0.75 for emission model.
- Based on MLR method, it was observed that emission rate is highly influenced by penetration rate and silt content.
- Results from comparison graphs indicates that with increasing moisture content present in drill cuttings, compressive strength and density the emission rate decreases linearly

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