Experimentation and Statistical Prediction of Dust Emission in Iron Ore Mines using Supervised Machine Learning (Regression) Modelling

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Abstract
In India, the mine area and the processing plant of materials such as iron ore and coal will cause dust emissions. The fugitive dust emission creates a hazardous working environment for the workers. Dust emissions will cause pulmonary-related diseases to the workers and also to the people living in nearby areas of the mine. Environmental effects such as air pollution occur due to the dispersion of particulate matter over the permissible limit in the processing area. This study evaluates dust emission levels and air quality control measures in an iron ore mine (A), Karnataka, India. Fugitive and workplace dust sampling was conducted following DGMS and MoEF and CC guidelines, with a specific focus on PM10 and PM2.5 particulate matter. Measurements revealed that dust concentrations in several mining areas exceeded the permissible limit of 1200 µg/m³ as per the National Ambient Air Quality Standards (NAAQS, 2009).

To analyze and predict these concentrations, supervised machine learning (regression) modeling including linear, polynomial (order 2) and polynomial (order 2) models, was applied. The results indicated that a third-order polynomial regression model provided the best fit for predicting dust concentrations, demonstrating lower error. The study emphasizes the necessity of more robust dust suppression measures including installing a dry fog dust suppression system, to guarantee safe working conditions and adherence to environmental regulations, even in the face of efforts to reduce dust exposure.

Keywords: Dust-emission, Buffer zones, Dust separation systems, Dust emission control, Iron ore mines

Introduction

In India, the mine area and the processing plant of materials such as iron ore and coal will cause dust emissions. Iron is the fourth most abundant material in earth's crust which occurs in sedimentary rocks. It is formed by chemical reactions that combine iron and oxygen in both marine and fresh waters and is transformed into metallic form. In India, iron is one of the most mined elements among the metals accounting for around 6% of the world's total iron production. Most of the iron ore mines exist in forest zones. The activities to extract iron ore include blasting, excavation, loading, dumping, crushing, screening and transportation which emit air pollutants into the environment. Air pollutants resulting from anthropogenic activities affect both biotic and abiotic components of the ecosystem[11].

According to environmental air quality terminology, fugitive dust is the very fine particulate matter (PM) suspended in the air, mainly from the earth's soil. It majorly excludes particulate matter from other typical sources like automobile exhaust. The minerals found in soil, such as calcium, iron, silicon oxides and aluminium, make up the majority of fugitive dust particles. Approximately 50% of fugitive dust particles have a diameter greater than 10 µm and settle faster than the smaller ones[12]. When there is not enough moisture in the ground to hold the soil particles together, fugitive dust forms. This dust then spreads to the above-ground level. After that, particulate matter reaches the atmosphere as a result of wind, moving cars and other activities.

Both natural and artificial soil surfaces are vulnerable to fugitive dust emissions. Inhaling particulate matter (PM) can lead to respiratory infections, chronic lung damage and in rare cases, early death. PM typically enters the respiratory tract and then the lungs. Particles of ≤2.5 µm (PM2.5) are the worst; PM with diameters of ≤10 µm (PM10) can pose health risks to humans[6]. Dust emission in mining operations, particularly in iron ore mines, is a significant environmental and occupational hazard. The mining activities such as drilling, blasting, crushing and transportation of materials generate large quantities of particulate matter (PM), which can adversely affect air quality and pose health risks to workers and nearby communities. The control of dust emissions is critical for maintaining environmental standards and ensuring worker safety[14].

The inhalation of fine particulate matter, particularly PM10 and PM2.5, is associated with a range of respiratory and cardiovascular diseases. A direct correlation between high levels of PM exposure in mining environments and increased incidences of pulmonary diseases among workers emphasized that prolonged exposure to respirable dust in mines can lead to chronic obstructive pulmonary disease (COPD) and silicosis, particularly in environments with elevated free silica content[2].

The regulation of dust emissions in mines is governed by various national and international standards. It provides specific guidelines for permissible exposure limits in Indian mines, while the Ministry of Environment, Forests and

Climate Change (MoEF and CC) mandates compliance with National Ambient Air Quality Standards (NAAQS). The importance of adhering to these regulations is to minimize environmental and health impacts in mining regions[16].

Technological advancements have introduced several dust suppression techniques including water spraying, chemical dust suppressants and dry fog systems. The dry fog dust suppression systems are particularly effective in reducing airborne dust levels in iron ore mines. These systems generate fine water droplets that capture dust particles, preventing them from becoming airborne and further supported the effectiveness of such systems in meeting the NAAQS requirements in heavy-duty mining operations[5,17]. Statistical regression models are widely used for analyzing environmental data and predicting air quality trends. The regression models provide the prediction of PM concentrations, providing insights into the factors influencing dust levels. Extend this approach by incorporating polynomial regression models to capture non-linear relationships in environmental data, offering a more nuanced understanding of dust emission patterns[3].

Several case studies have documented the application of statistical models in evaluating dust emissions in iron ore mines. A comprehensive study on dust generation in an Indian iron ore mine was carried out using regression analysis to identify key predictors of PM10 and PM2.5 levels. Their findings underscored the significance of controlling dust at source points such as crushers and screening plants[1]. The integration of machine learning techniques with traditional statistical models has shown promise in improving the accuracy of air quality predictions. The machine learning algorithms could enhance the predictive power of regression models by accounting for complex interactions between variables. In the context of mining, such models could be used to develop proactive dust management strategies[8].

Implementing dust control measures in mining operations has both environmental and economic implications. The cost-effectiveness of various dust suppression techniques, finding that while initial investments in advanced systems like dry fogging are high, the long-term benefits in terms of reduced health costs and regulatory compliance outweigh these expenses. Effective dust control could enhance the operational efficiency of mining activities by reducing equipment downtime due to dust-related wear and tear[7].

Modeling dust emissions in mining environments present several challenges including the variability in mining activities, weather conditions and the heterogeneity of the particulate matter itself. The limitations of linear regression models in capturing these complexities suggest the need for more sophisticated modeling approaches that incorporate real-time data and adaptive algorithms[4]. Recent advancements in air quality monitoring technologies have enabled more accurate and real-time data collection in mining environments. The role of portable air quality monitors and remote sensing technologies is to improve the spatial and temporal resolution of dust measurements. These advancements support the development of more precise and dynamic regression models for predicting air quality[13].

Seasonal variations can significantly impact dust emissions and dispersion patterns in mining areas. The dust concentrations in Indian iron ore mines were notably higher during the dry season, necessitating season-specific dust control strategies. Nykanen et al[10] recommended adjusting the parameters of regression models to account for these seasonal effects to improve predictive accuracy. Worker training is critical in mitigating the health risks associated with dust exposure in mining environments. There is a need for regular training programs to educate workers on the use of personal protective equipment (PPE) and best practices in dust management. Proper training ensures that dust control measures are effectively implemented at the ground level, reducing the incidence of occupational diseases[9].

The presence of free silica in mining dust is a significant health concern due to its association with silicosis. An assessment of free silica content in Indian iron ore mines found that concentrations often exceeded safe levels, particularly in high-dust areas such as crushers and conveyor belts. The study called for enhanced dust control measures and regular monitoring of silica levels to protect workers' health[15].

The findings from studies on dust emissions and air quality control have important policy implications. There should be stricter enforcement of existing regulations and the introduction of new policies that mandate the use of advanced dust suppression technologies in mining operations. Future research should focus on developing integrated dust management systems that combine real-time monitoring, predictive modeling and automated control measures. This work focuses on the evaluation of dust emission. Air quality control in iron ore mines is crucial for ensuring environmental compliance and protecting worker health. The application of statistical regression modeling, particularly polynomial regression, will be used to find valuable insights into the factors influencing dust levels and the effectiveness of control measures.

Site Description

An iron ore mine A is located in the Bellary district of Karnataka State, having 15°2′00″ and 15°86′30″ N latitude and 76°36′00″ and 76°38′30″ E longitude (Toposheet No. 57A/12 of Survey of India) (Fig. 1). Sampling and monitoring locations of fugitive dust were decided after detailed discussion and consensus with Officials of Mines in predominant downwind directions at a distance of 25±2m from the dust-generating source in crushing and screening plants before installation of the dust suppression system. The monitoring was carried out at nine locations, located at View Point, Plant Bottom, Control Room, Weigh Bridge, Weigh Bridge (Dispatch), Screening Plant, Crushing Plant (Top) and Mining Field Office. Fig. 1a depicts the exact location of the sampling/monitoring sites. Fig 1b. shows wind and temperature data for the sampling period. The predominant wind direction was from NE to SW.

Workplace sampling for air particulate matter (PM2.5/PM10) was carried out at the crushing plant and screening plant inside the shed for three sites each. Ambient particulate matter sampling (PM2.5/PM10) was done at six locations outside the lease boundary. Further, workplace sampling for air particulate matters was carried out for different categories of work personnel for both shifts at different locations inside and outside of the mine lease boundary. Fig. 2 shows the view of the working face of the crusher plant of mine A.

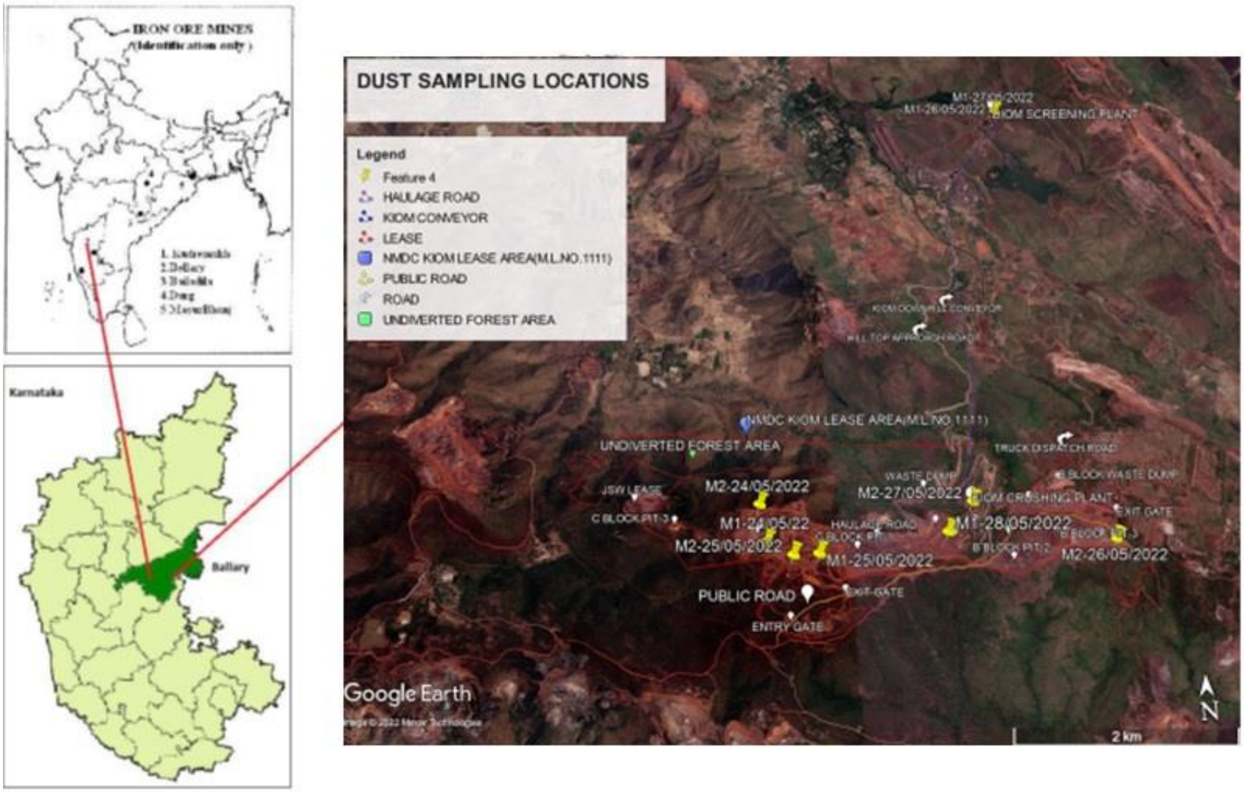

Fig. 1a: Location map of the study area

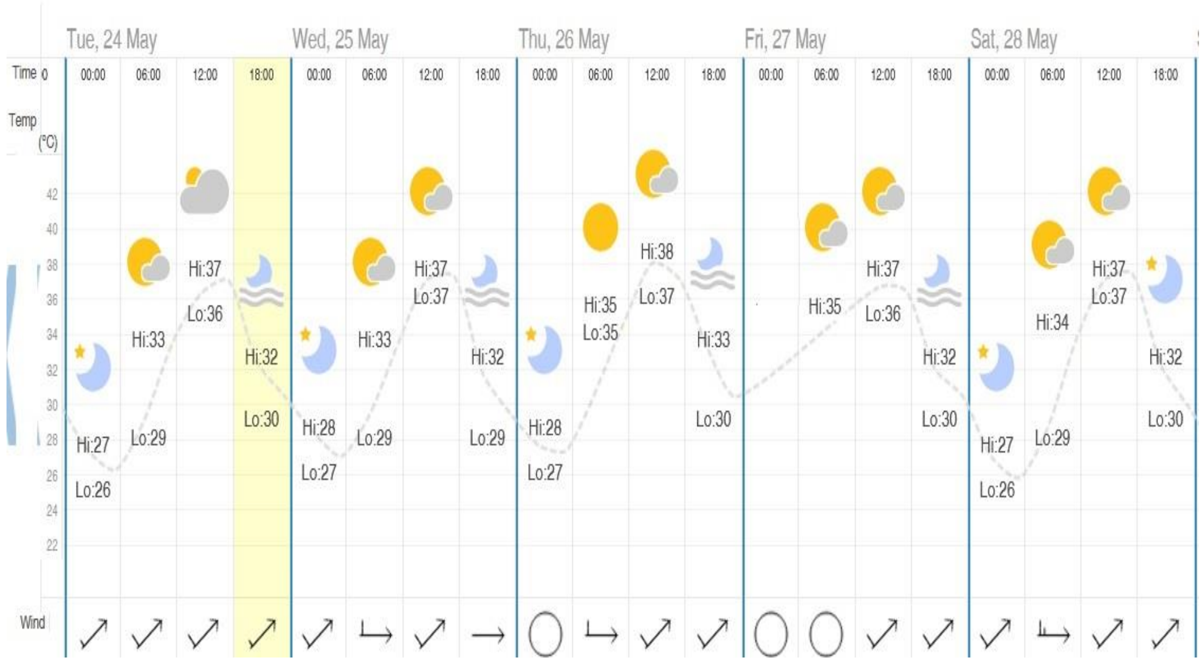

Fig. 1b: Wind and temperature data for the sampling period

Fig. 1: Site description

Fig. 2: View of the working face of the Crusher plant of Mine A

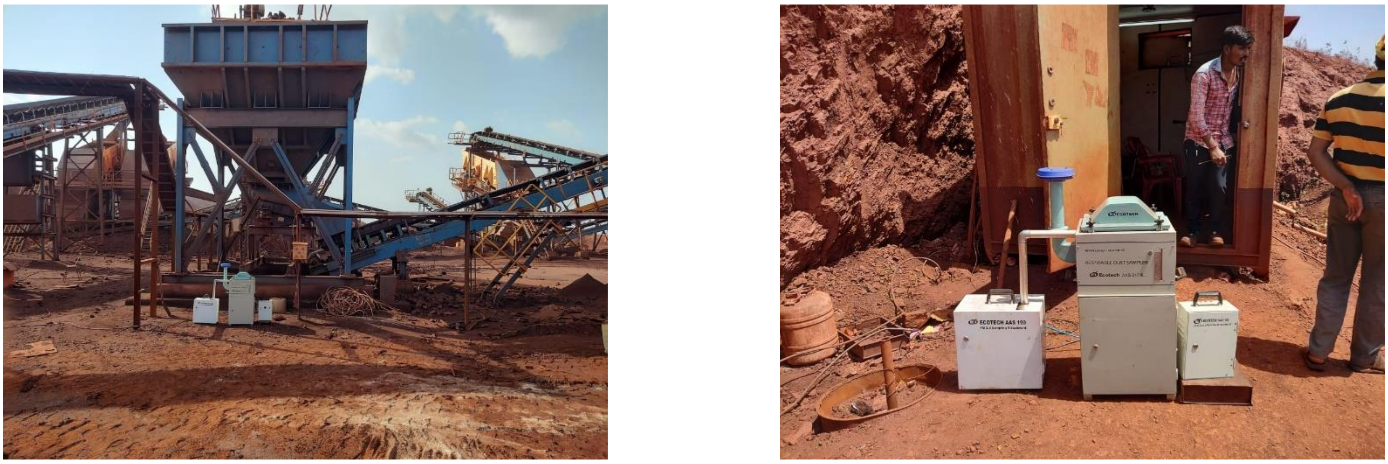

Fig. 3: Dust sampling using a respirable dust sampler (Ecotech AAS 190) (PM10) and Particulate dust sampler (Ecotech AAS127) (PM2.5)

Material and Methods

Sampling and Analysis of Dust: Sampling for fugitive dust monitoring was carried out using a Respirable Dust Sampler (RDS) (Ecotech AAS 190) and a Particulate Sampler (Ecotech AAS127) (Fig. 3). The Glass Microfibre filter paper (8×10”) was oven-dried for 24 h and weighed initially (W1) before sampling. The filter paper was placed safely by unscrewing the plug on the filter assembly. The timer was set for 8 h (for each shift) and the flow rate was adjusted at 1.1 m^3/min. The weight of the dust collected in the cup under cyclone of RDS was added to the weight difference of Whatmann filter paper for the calculation of total suspended particulate matter. Particulate and fine particulate (PM10/PM2.5) sampling was done at a constant flow rate of 1 m^3/h (16.7 litres per minute) with Omni-directional air inlet with PM10 separation by an impactor followed by PM2.5 separation through a 47 mm WINS impactor. A cyclone sampler, which separates the respirable fraction of the particle (about 10 µm and below) from the ambient air drawn through it, was utilized for respirable dust. Larger undesirable particles fall into the grit pot while tiny particles are transported onto the filter paper within the cassette by the design of the cyclone sampler. The cyclone version is not weighed as a unit, in contrast to the Institute of Occupational Medicine (IOM) Sampler cassette/filter paper combo.

Pre- and post-samplings just weigh the filter paper. For optimal functioning, this instrument is kept at a flow rate of 2.2 liters per minute. For optimal functioning, this instrument is kept at a flow rate of 2.2 liters per minute.

Particulate matter was analyzed using standard techniques in accordance with MoEF and CC norms. Field-collected samples were transported to the lab in a plastic zipper and placed in a desiccator for a whole day. An electronic balance with four-digit precision was used to determine the initial weight (W1) and final weight (W2) of the filter paper. Equation 1 is used to determine the dust concentration:

$$\text{Dust concentration} = \frac{W2-W1}{Volume\ of\ air\ passed} \quad (1)$$

Regression modeling and residual analysis of Dust emission: The present work majorly determines the PM10 and PM2.5 dust emission in the iron ore plant. After obtaining the dust emission, the supervised machine learning technique i.e. regression modeling was carried out using linear, polynomial (order 2) and polynomial (order 3) on the results of dust emission. The present work will provide the most suitable regression modeling technique for predicting the dust emission of PM10 and PM2.5. After obtaining the accurate regression model, the residual analysis using a probability plot was carried out to check the error condition for validating the developed regression model.

The present study aims at testing the (Particulate Matter) PM10 and PM2.5 in the mine area, processing plant area and nearby residence area of iron ore mine A using respirable dust sampler (RDS) (Ecotech AAS 190). The statistical regression modeling was carried out on the experimental results using linear, polynomial (order 2) and polynomial (order 3) regression models. Furthermore, the statistical modeling results were validated using residual analysis using a probability plot.

Results and Discussion

Experimental and Statistical studies of PM2.5 dust emission in Plant location and Mining location: Table 1 shows experimental results of PM2.5 dust emission in plant and mining locations. From table 1, it is clear that the screening plant has the highest PM2.5 dust emission in the first shift and second shift when compared to other plant locations. The process of screening involves the separation of fine and coarse particles which causes high material movement for stratification and separation. Because of this process, PM2.5 dust emission is higher for the screening area compared to other plant locations.

Table 1
Experimental results of PM2.5 dust emission in plant location and mining location

Plant Location			Mining Location		
S.N.	**Location name (Shift)**	**Dust Concentration µgm/m³**	**S.N.**	**Location name (Shift)**	**Dust Concentration µgm/m³**
1	CP3 Plant 2	1259.26	1	Weigh Bridge 2 (Dispatch)	6423.68
2	CP3 Plant 1	1378.88	2	Weigh Bridge 1(Dispatch)	8545.23
3	Weigh Bridge 2	1455.91	3	Control Room 2	10662.44
4	Weigh Bridge 1	1623.25	4	Control Room 1	12598.26
5	Crushing Plant 2	2654.22	5	View Point 2	14270.01
6	Crushing Plant 1	2840.39	6	View Point 1	15987.14
7	Screening Plant 2	3567.98	7	Mining Field Office 2	16587.96
8	Screening Plant 1	3710.74	8	Mining Field Office 1	18269.01

*1 and 2 specify the first and second shifts respectively.

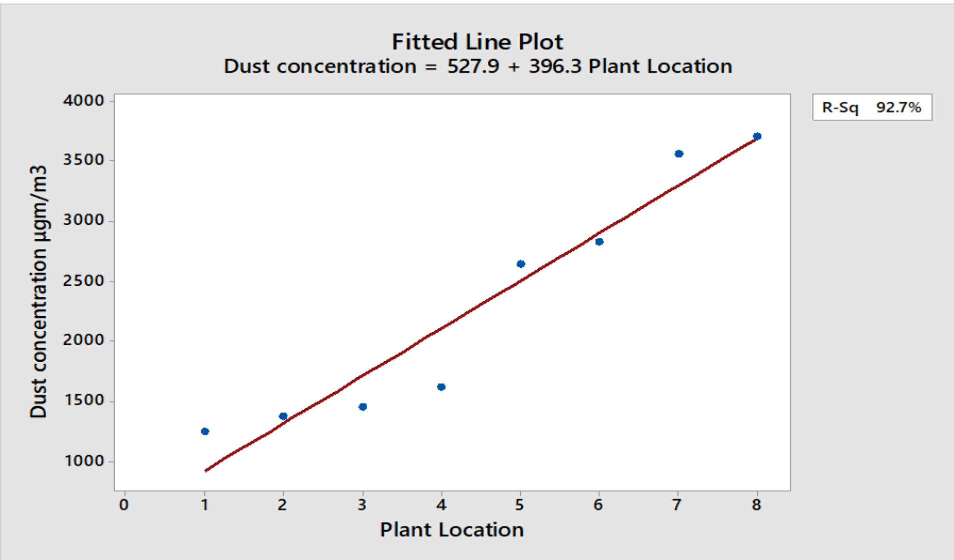

Fig. 4(a)

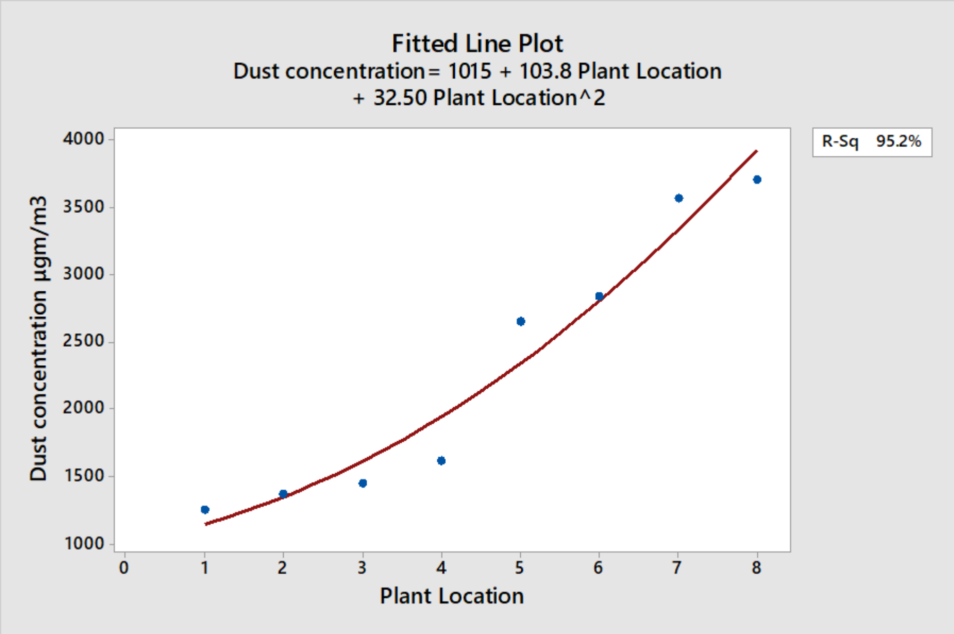

Fig. 4(b)

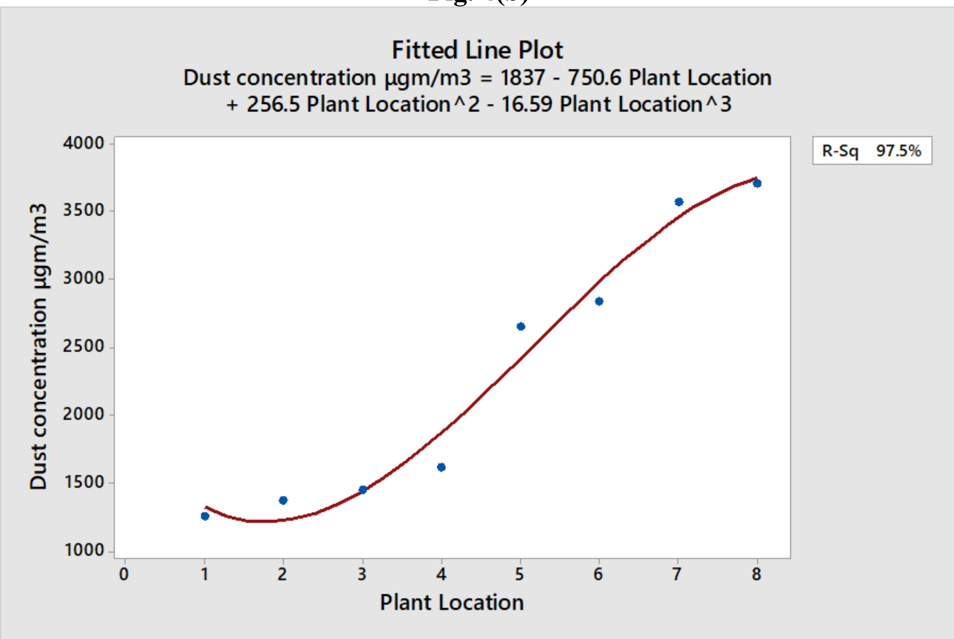

Fig. 4(c)

Fig. 4: Statistical results of PM2.5 dust emission in Plant location using (a) Linear, (b) Polynomial (order 2) and (c) Polynomial (order 3) models

From Table 1, it was also clear that the mining field office area has the highest PM2.5 dust emission when compared to other mining areas. This was majorly due to vehicle movement inside and outside the mine for the transportation of material. This causes high material dispersion in the environment causing the highest PM2.5 dust emission. From table 1, it was also clear that the PM2.5 dust emission in the plant location of screening and crushing area was higher than the permissible limit of 1200 µg/m^3 as per the National Ambient Air Quality Standard, 2009. From table 1, it was also clear that the PM2.5 dust emission in all mining locations was higher than the permissible limit of 1200 µg/m^3 as per the National Ambient Air Quality Standard, 2009.

Fig. 4 shows the statistical results of PM2.5 dust emission in plant locations using (a) Linear, (b) Polynomial (order 2) and (c) Polynomial (order 3). From fig. 4, it was clear that the R2 value of PM2.5 dust emission in the plant location was 92.7%, 95.2% and 97.5% respectively for Linear, polynomial (order 2) and polynomial (order 3) models. This shows that the polynomial (order 3) models have the highest closeness with the experimental results of PM2.5 dust emission in the plant location.

Figure 5 shows the probability plot of the regression model of PM2.5 dust emission in plant locations. After obtaining the accurate regression model for the experimental results of PM2.5 dust emission in plant location, the model was validated using the probability plot as shown in figure 5. From figure 5, It was clear that the mean error of the polynomial model (Order 3) and standard deviation were lesser when compared to other models. This shows that the polynomial model (Order 3) is the most suitable mathematical model for predicting the experimental results of PM2.5 obtained for plant location.

Fig. 6 shows the statistical results of PM2.5 dust emission in mine location using (a) Linear, (b) Polynomial (order 2) and (c) Polynomial (order 3). From fig. 6, it was clear that the R^2 value of PM2.5 dust emission in mine location was 98.9%, 99.8% and 99.8% respectively for linear, polynomial (order 2) and polynomial (order 3) models. Fig. 4 also shows that the polynomial (order 3) models have the highest closeness with the experimental results of PM2.5 dust emission in the mine location. This shows that the polynomial (order 3) model is the most suitable model for predicting PM2.5 dust emission in plant and mine locations.

Fig. 7 shows the probability plot of the regression model of PM2.5 dust emission in the mine location. After obtaining the accurate regression model for the experimental results of PM2.5 dust emission in the mine location, the model was validated using the probability plot as shown in fig. 7. From fig. 7, it was clear that the mean error of the polynomial (Order 3) model and standard deviation were less when compared to other models. This shows that the polynomial (Order 3) model is the most suitable mathematical model for predicting the experimental results of PM2.5 obtained for mine location.

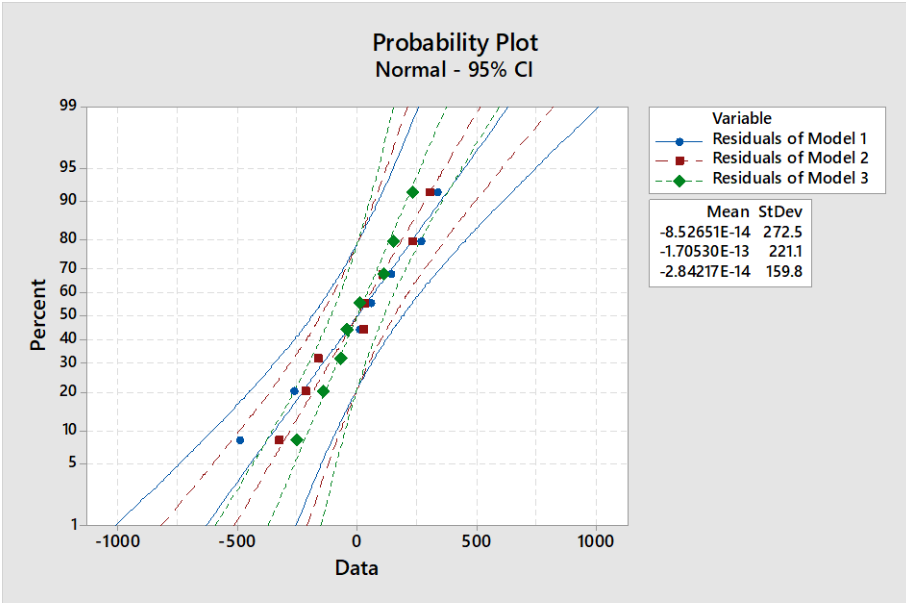

Fig. 5: Probability plot of the regression model of PM2.5 dust emission in Plant location

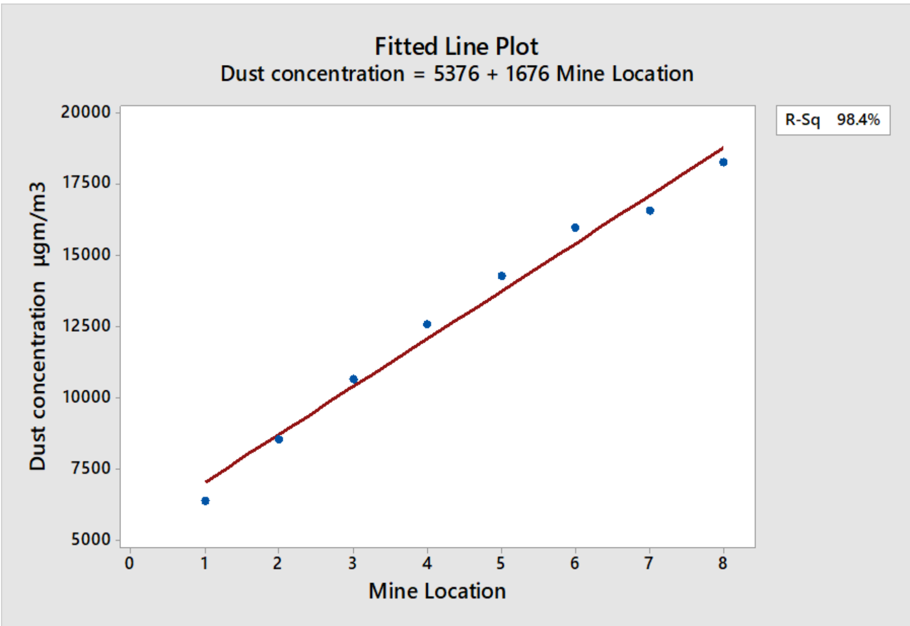

Fig. 6(a)

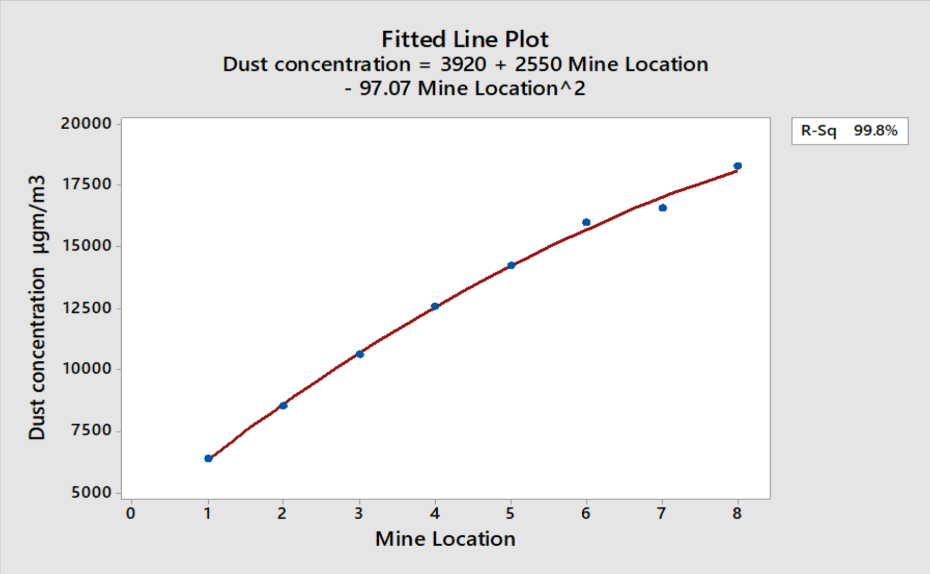

Fig. 6(b)

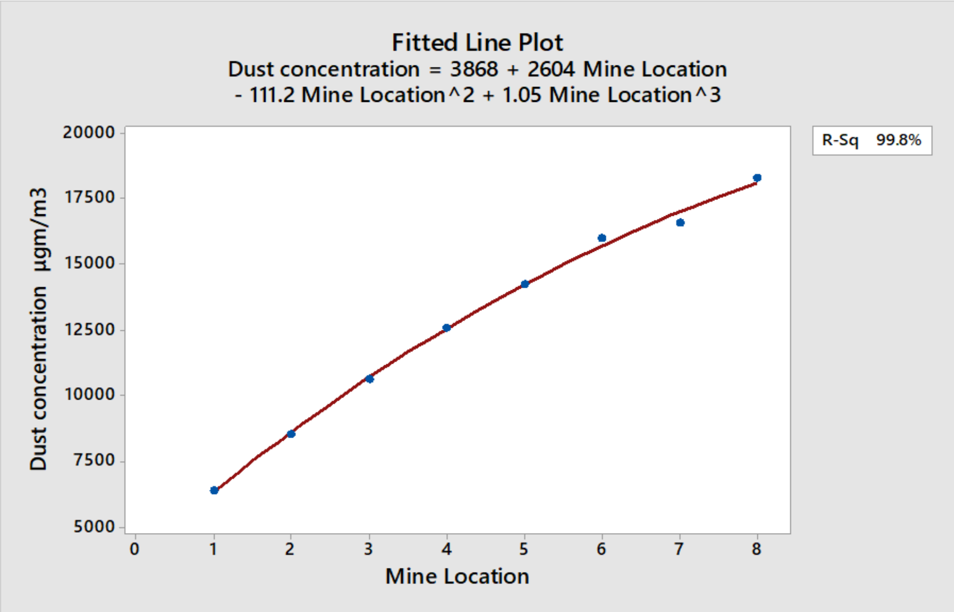

Fig. 6(c)

Fig. 6: Statistical results of PM2.5 dust emission in the Mine location using (a) Linear, (b) Polynomial (order 2) and (c) Polynomial (order 3)

Table 2
Experimental results of PM10 dust emission in plant location and mining location

Plant Location			Mining Location		
S.N.	**Location name (Shift)**	**Dust concentration $\mu gm/m^3$**	**S.N.**	**Location name (Shift)**	**Dust concentration $\mu gm/m^3$**
1	CP3 Plant 2	553.95	1	Weigh Bridge 2 (Dispatch)	1389.14
2	CP3 Plant 1	528.78	2	Weigh Bridge 1(Dispatch)	1331.58
3	Weigh Bridge 2	710.53	3	Control Room 2	1433.31
4	Weigh Bridge 1	780.26	4	Control Room 1	1440.65
5	Crushing Plant 2	840.51	5	View Point 2	1471.86
6	Crushing Plant 1	926.32	6	View Point 1	1624.98
7	Screening Plant 2	1167.89	7	Mining Field Office 2	2065.59
8	Screening Plant 1	1254.77	8	Mining Field Office 1	2296.48

Experimental and Statistical studies of PM10 dust emission in Plant location and Mining location: Table 2 shows experimental results of PM10 dust emission in plant and mining locations. From table 1, it is clear that the screening plant has the highest PM10 dust emission in the first shift and second shift when compared to other plant locations. This was majorly due to the higher particle movement which caused coarse-sized dust particles emitted from the machine. So, PM10 dust emission is higher for the screening area compared to other plant locations.

From table 2, it was also clear that the mining field office area has the highest PM10 dust emission when compared to other mining. This was majorly due to the higher movement of transportation vehicles which caused the dust particles from the ground to be dispersed in the environment causing the highest PM10 dust emission. From table 1, it was also clear that the PM10 dust emission in the plant location of the screening area (shift 1) was higher than the permissible limit of 1200 μg/m^3 as per the National Ambient Air Quality Standard, 2009. From table 1, it was also clear that the PM10 dust emission in all mining locations was higher than the permissible limit of 1200 μg/m^3 as per the National Ambient Air Quality Standard, 2009.

Fig. 8 shows the statistical results of PM10 dust emission in plant locations using (a) Linear, (b) Polynomial (order 2) and (c) Polynomial (order 3). From fig. 8, it was clear that the R2 value of PM2.5 dust emission in mine location was 95.1%, 97.3% and 97.3% respectively for Linear, Polynomial (order 2) and Polynomial (order 3) models.

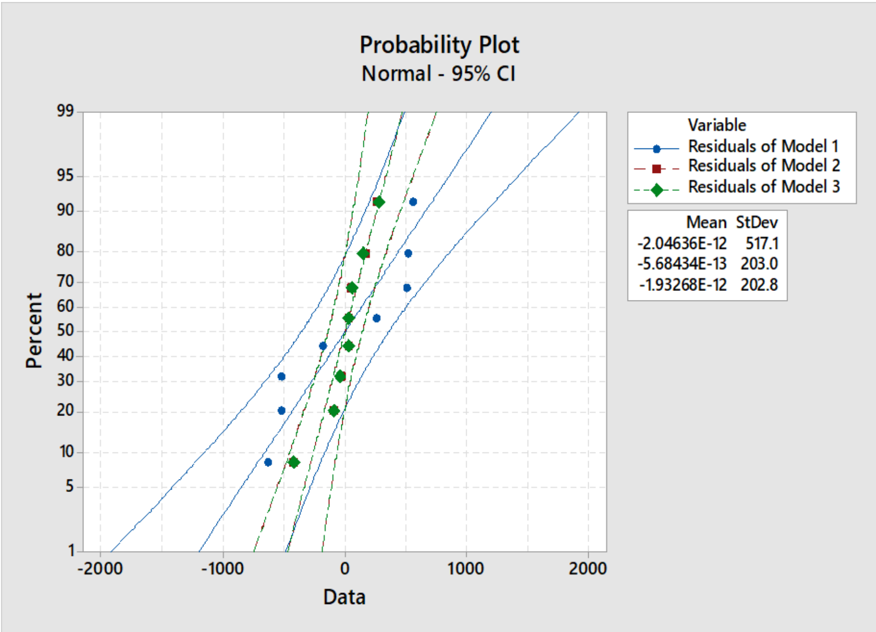

Fig. 7: Probability plot of Polynomial (order 3) model of PM2.5 dust emission in Mine location

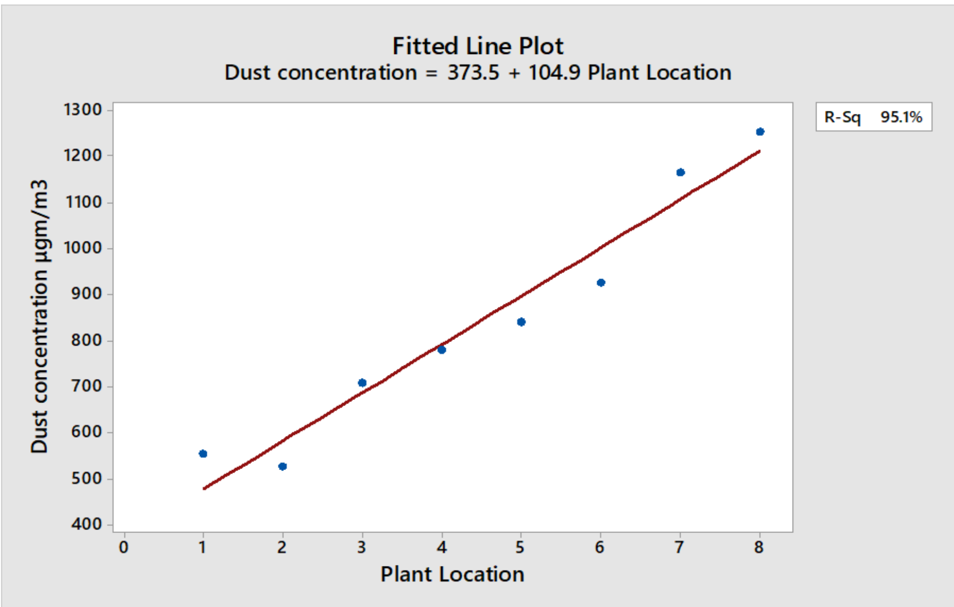

Fig. 8(a)

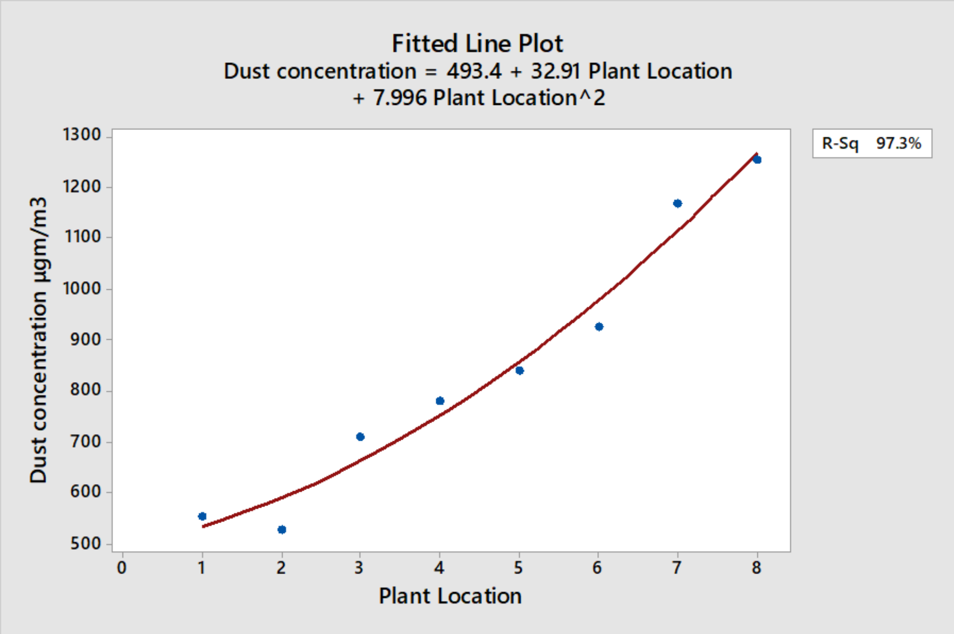

Fig. 8(b)

Fig. 8(c)

Fig. 8: Statistical results of PM10 dust emission in Plant location using (a) Linear, (b) Polynomial (order 2) and (c) Polynomial (order 3)

Fig. 8 also shows that the polynomial (order 3) models have the highest closeness with the experimental results of PM2.5 dust emission in the mine location. This shows that the polynomial (order 3) model is the most suitable model for predicting PM2.5 dust emission in plant and mine locations. Fig. 9 shows the probability plot of the regression model of PM10 dust emission in plant locations. After obtaining the accurate regression model for the experimental results of PM10 dust emission in plant location, the model was validated using the probability plot as shown in fig. 9. From fig. 9, it was clear that the mean error of the polynomial model (Order 3) was lesser when compared to other models. The standard deviation which shows the spread of overall error was lesser for the polynomial (Order 3) model. This shows that the polynomial model (Order 3) is the most suitable mathematical model for predicting the experimental results of PM10 obtained for plant location.

Fig. 10 shows the statistical results of PM10 dust emission in mine location using (a) Linear, (b) Polynomial (order 2) and (c) Polynomial (order 3). From fig. 10, it was clear that the R^2 value of PM2.5 dust emission in mine location was 76.4%, 96.5% and 97.2% respectively for Linear, Polynomial (order 2) and Polynomial (order 3) models. Fig. 10 also shows that the Polynomial (order 3) models have the highest closeness with the experimental results of PM2.5

dust emission in the mine location. This shows that the polynomial (order 3) model is the most suitable model for predicting PM2.5 dust emission in the plant and mine locations.

Fig. 11 shows the probability plot of the regression model of PM10 dust emission in the mine location. After obtaining the accurate regression model for the experimental results of PM10 dust emission in the mine location, the model was validated using the probability plot as shown in fig. 11. From fig. 11, it was clear that the mean error of the polynomial model (Order 3) was lesser when compared to other models. This shows that the polynomial model (Order 3) is the most suitable mathematical model for predicting the experimental results of PM10 obtained for mine location.

From the results, it was clear that the polynomial (Order 3) regression model was best suitable prediction model for predicting PM2.5 and PM10 dust emission. Further, the validation results showed the spread of error and mean error were less for the polynomial (Order 3) regression model. The R^2 value of more than 97% shows the highest effectiveness of the developed mathematical model with test results.

Further, the experimental results show that PM2.5 and PM10 dust emission for some parts of the plant area and all parts of the mining area were higher than the permissible limit of 1200 μg/m^3 as per the National Ambient Air Quality Standard, 2009. So, precautionary measures need to be taken to prevent higher dust emissions.

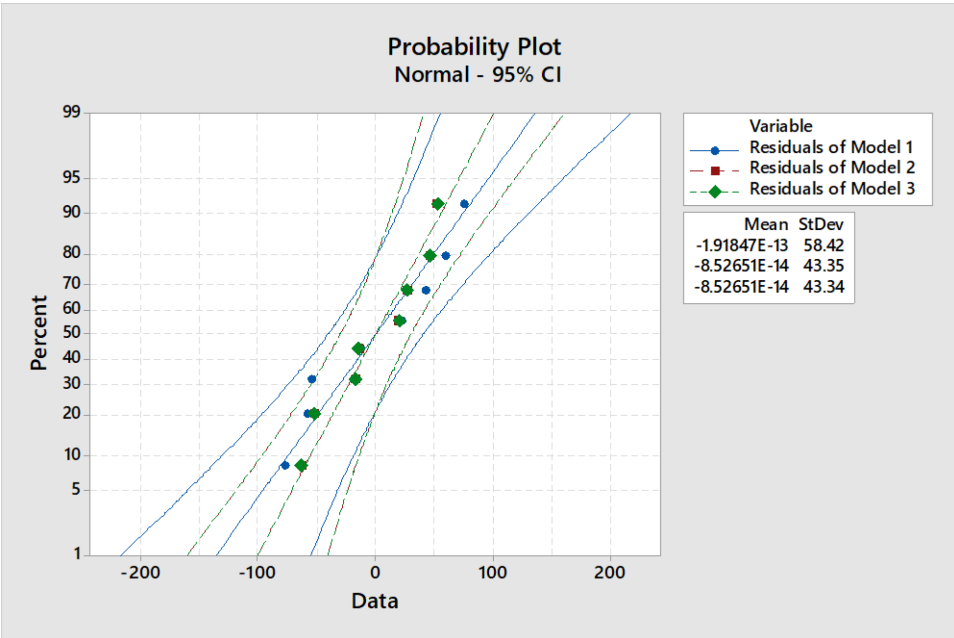

Fig. 9: Probability plot of Polynomial (order 3) model of PM10 dust emission in Plant location

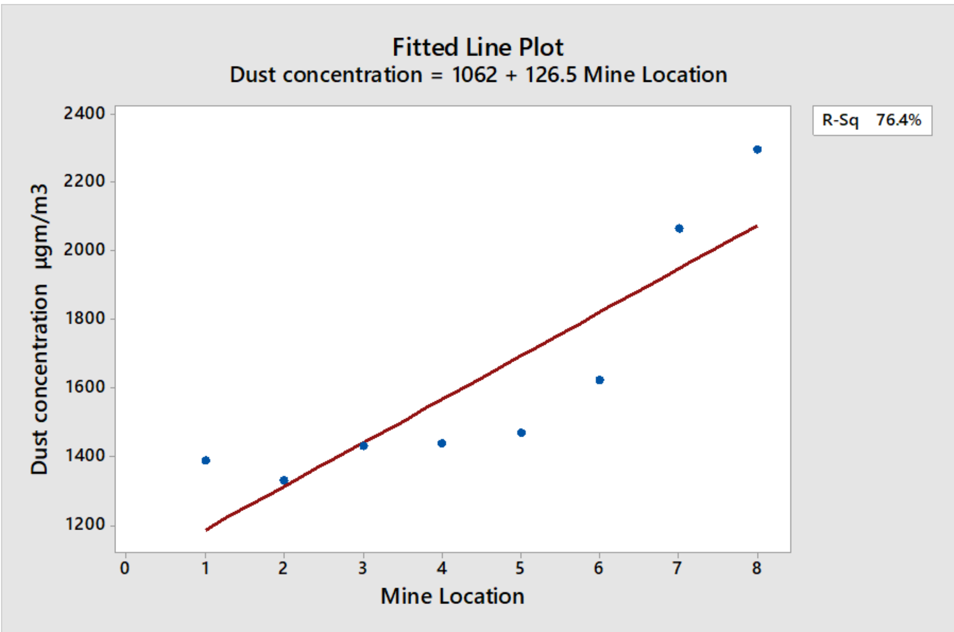

Fig. 10(a)

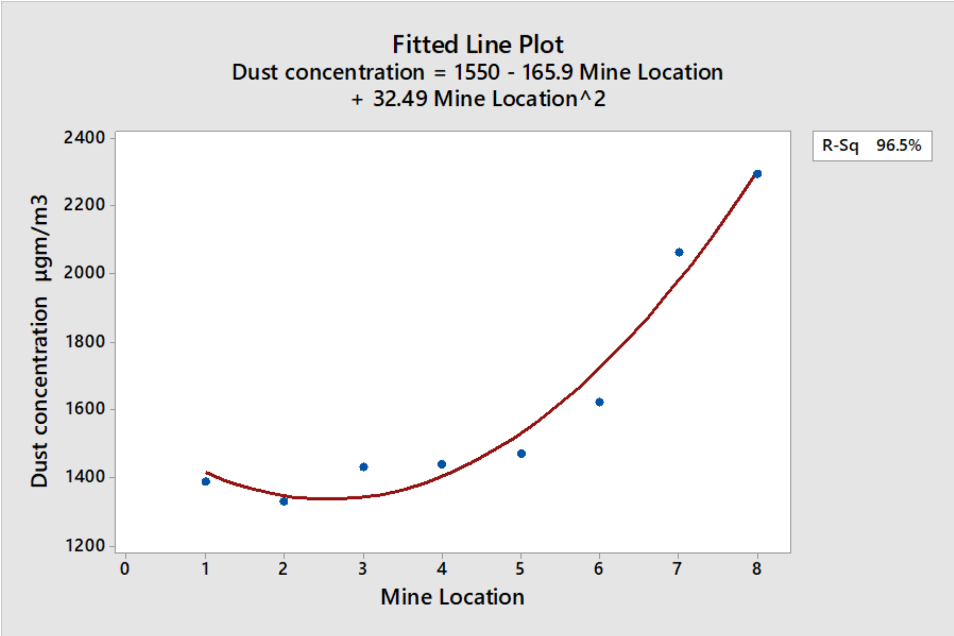

Fig. 10(b)

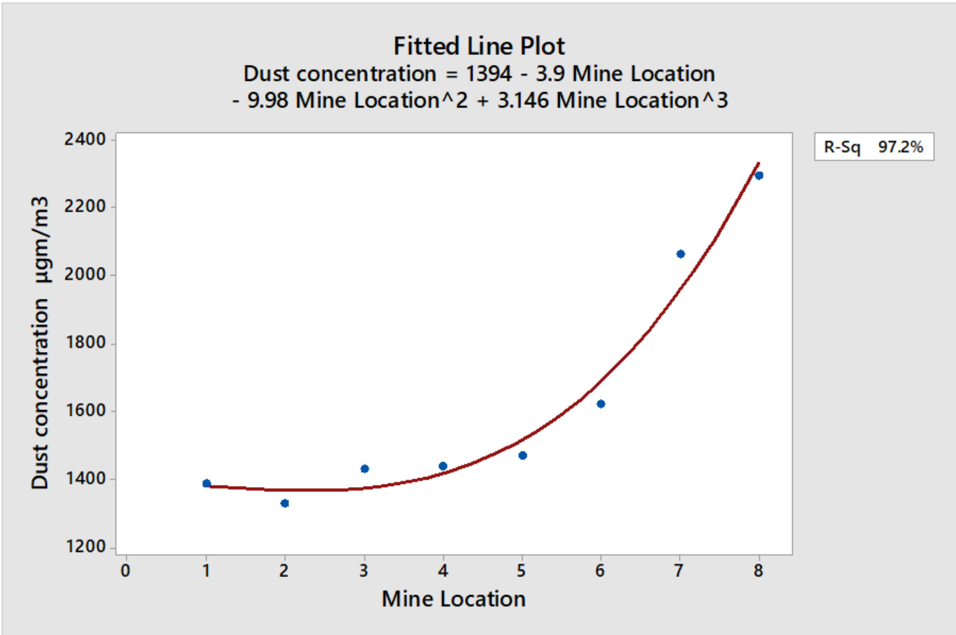

Fig. 10(c)

Fig 10: Statistical results of PM10 dust emission in the Mine location using (a) Linear, (b) Polynomial (order 2) and (c) Polynomial (order 3)

Conclusion

The present work aims at testing the Particulate Matter PM10 and PM2.5 in the mine area, processing plant area and nearby residence area of iron ore mine A using respirable dust sampler (RDS) (Ecotech AAS 190). The statistical regression modeling was carried out using linear, polynomial (order 2) and polynomial (order 3) regression models. Furthermore, the statistical modeling results will be subjected to residual analysis using a probability plot. The mean error will be studied for each regression model. The results showed that in some of the areas, the dust suppression was over the permissible limit.

The results also showed that the PM2.5 near the minefield office was around 18269.01µg/m^3 (first shift) and 16587.96 µg/m^3 (Second shift). The results also showed that the PM10 near the weigh bridge control room was around 2065.59 µg/m^3 (first shift) and 2296.48 µg/m^3 (Second shift). The results of PM10 and PM2.5 are beyond the permissible limit of 1200 µg/m^3. The regression results also showed that the polynomial regression model of order 3 is the most suitable mathematical model for the experimental results of PM10 and PM2.5 obtained from the particulate sampler (Ecotech AAS127).

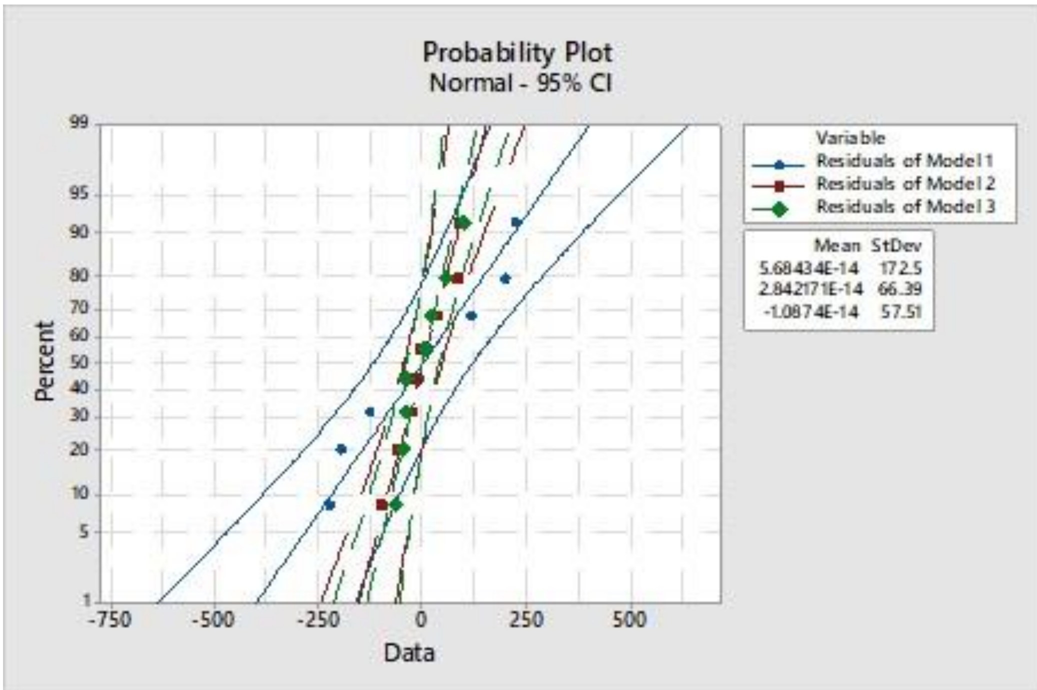

Fig. 11: Probability plot of Polynomial (order 3) model of PM10 dust emission in Mine location

Furthermore, the residual analysis using a normal probability plot showed that the polynomial model (Order 3) has less error. This shows that the polynomial model (Order 3) is the most suitable mathematical model for predicting the experimental results of PM10 and PM2.5 obtained from the respective sampler.

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(Received 21st November 2024, accepted 25th December 2024)