Investigation of Dust Emission in Limestone Mines and its Statistical Prediction using Supervised Machine Learning (Regression) Modelling

Pal Rajib[1*], Vardhan Harsha[1], Shanmugam Bharath Kumar[2], Hanumanthappa Harish[3] and Senapati Amrites[1]
1. Department of Mining Engineering, National Institute of Technology Karnataka, Surathkal, Mangaluru-575025, INDIA
2. Department of AI and Robotics, Dayananda Sagar University, Ramanagara-562112, Karnataka, INDIA
3. Department of Mechanical Engineering, RV University, Bengaluru-560059, INDIA
*rajibpaldgms@gmail.com

Abstract
In India, the fugitive dust emissions in the processing plant and mining area of limestone mines are very high. The dust emission of (particulate matter) PM10 and PM2.5 forms an unsafe working environment for workers in processing plant areas and mining areas. The excessive emission of PM10 and PM2.5 will cause lung-related diseases to the workers and the people existing in the adjacent areas of the mine. The dust emission majorly causes air pollution to occur due to the distribution of particulate matter in the work area. This study majorly investigates the dust emission levels of PM10 and PM2.5 in the limestone mine of Kadapa, Andra Prasad, India. The investigation on the dust emission of PM10 and PM2.5 was carried out as per the guidelines of DGMS and MoEF and CC guidelines, with a specific focus on PM10 and PM2.5 particulate matter.

From the study, it was clear that the dust emission levels of PM10 and PM2.5 in the mine area and some parts of the processing area were below the permissible limit of 1200 µg/m³ as per the National Ambient Air Quality Standards (NAAQS, 2009). It was also found that the dust emission levels of PM10 and PM2.5 in the crushing and screening area of the processing plant were above the permissible limit of 1200 µg/m³. Further the statistical prediction model was developed using linear, quadratic and cubic supervised machine learning (regression) modelling. The results indicated that the cubic regression model will provide the accurate prediction of fugitive dust emission with lower error and standard deviation.

Keywords: Dust-emission, Buffer zones, Dust separation systems, Dust emission control, Lime stone mines.

Introduction

In India, the fugitive dust emissions in the processing plant and mining area of Limestone mines are very high. The major composition of limestone is calcite and a kind of calcium carbonate, ($CaCO_3$). This sedimentary rock is produced by living creatures (like shellfish) which are the producers of $CaCO_3$. After the production, it dissolves in seawater and gets deposited as limestone. Some of the mining operations such as blasting, excavation, processing operations and transportation are major contributors to fugitive emissions and air pollution in the work area[1,3,7,14-16].

Both biotic and abiotic elements of the environment are impacted by air pollution. The particulate matter (PM) suspended in the air is majorly composed of calcium, iron, silicon oxides and aluminum. The particulate matter larger than 10µm in diameter settles more quickly than the smaller ones.

The dust emission of (particulate matter) PM10 and PM2.5 forms an unsafe working environment for workers in processing plant areas and mining areas. The excessive emission of PM10 and PM2.5 will cause lung-related diseases to the workers and the people existing in the adjacent areas of the mine. Controlling particulate matter dust emissions is crucial for upholding environmental and worker safety. The Ministry of Environment, Forests and Climate Change (MoEF and CC) requires adherence to the National Ambient Air Quality Standards (NAAQS). The permissible limit of PM10 and PM2.5 should be less than 1200 µg/m³ in order to reduce the negative effects on the environment and human health in mining areas.

Copeland et al[4,5] studied dust suppression in the iron ore pellet plant. The authors majorly focussed on the suppression of fugitive dust emission of PM10. Further, the investigation has provided the optimum curing time of water required for dust suppression. They studied the wettability of airborne dust particles in the taconite pellet plant. The authors majorly focussed on the wettability studies of fugitive dust emission of PM10. Further, the investigation has provided an optimum wettability range for dust suppression. Copeland et al[6] investigated a novel dust tower for testing the dust suppression of airborne dust particles of PM10 during the making process. Further, the investigation has provided the correlation between wetting properties and dust suppression of PM10.

Zhou et al1[7] studied coal dust suppression in the underground mines. The authors majorly focussed on the wettability studies of fugitive dust emission. Further, the investigation has provided an optimum wettability range for dust suppression. Chaulya et al[2,3] studied the fugitive dust emission of PM10 and PM2.5 in iron ore mines. The results showed that the dust control of the environment is crucial in different areas of the mine.

The present study investigates the dust emission of PM2.5 and PM10 in the limestone mine and its statistical prediction using linear, quadratic and cubic supervised machine learning (regression) modeling in mining and plant areas.

Material and Methods

The present study was carried out on the limestone mine of Kadapa, Andra Prasad, Karnataka. Figure 1 shows the view of the working face of the limestone mine. Figure 2 shows that the respirable dust sampler (Ecotech AAS 190) and particulate dust sampler (Ecotech AAS127) are used for testing the fugitive dust samples of PM10 and PM2.5. The oven-dried Glass Microfibre filter paper (8×10") was weighed initially (W1) before sampling. The filter paper was fixed to the equipment as shown in figure 2. Further, the timer of the equipment was set to 8 h (for each shift) and the flow rate was maintained at 1.1 m^3/min. The testing was carried out in different zones of mining areas and processing plant areas. After testing, the filter paper was carried out from the equipment and weighed as W2 after sampling.

Fig. 1: View of the working face of Limestone Mine

Fig. 2: Respirable dust sampler (Ecotech AAS 190) (PM_{10}) and Particulate dust sampler (Ecotech AAS127) ($PM_{2.5}$)

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: In the current work, the PM2.5 and PM10 dust emission of the limestone mine was evaluated. After obtaining the dust emission, the supervised machine learning technique using linear, quadratic and cubic regression prediction models was carried out. The current work results in providing an accurate predictive model of PM10 and PM2.5. Further, the residual analysis was carried out using a probability plot for the validation of the predictive model. So, the current work deals with the statistical evaluation of PM2.5 and PM10 in the processing plant area, mine area and nearby residence area of a limestone mine using a respirable dust sampler (RDS) (Ecotech AAS 190).

Results and Discussion

Investigation of PM2.5 dust emission in Plant location and Mining location and its prediction studies

Table 1
Results of PM2.5 dust emission in Plant location and Mining location

Plant Location			Mining Location		
S.N.	Location (Shift)	Dust Concentration µgm/m³	S.N.	Location (Shift)	Dust Concentration µgm/m³
1	Processing Plant Entrance 2	640.52	1	Over Burden (OB) Excavation (Backfilling) 2	92.17
2	Processing Plant Entrance 1	730.95	2	Over Burden (OB) Excavation (Backfilling) 1	97.15
3	Conveyor 2	845.98	3	Transfer Terminal 2	91.32
4	Conveyor 1	904.56	4	Transfer Terminal 1	96.48
5	Crushing Plant 2	1208.05	5	OB Excavation 2	118.95
6	Crushing Plant 1	1226.26	6	OB Excavation 1	125.51
7	Screening Plant 2	1345.89	7	Nearby School 2	129.84
8	Screening Plant 1	1415.98	8	Nearby School 1	147.62

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

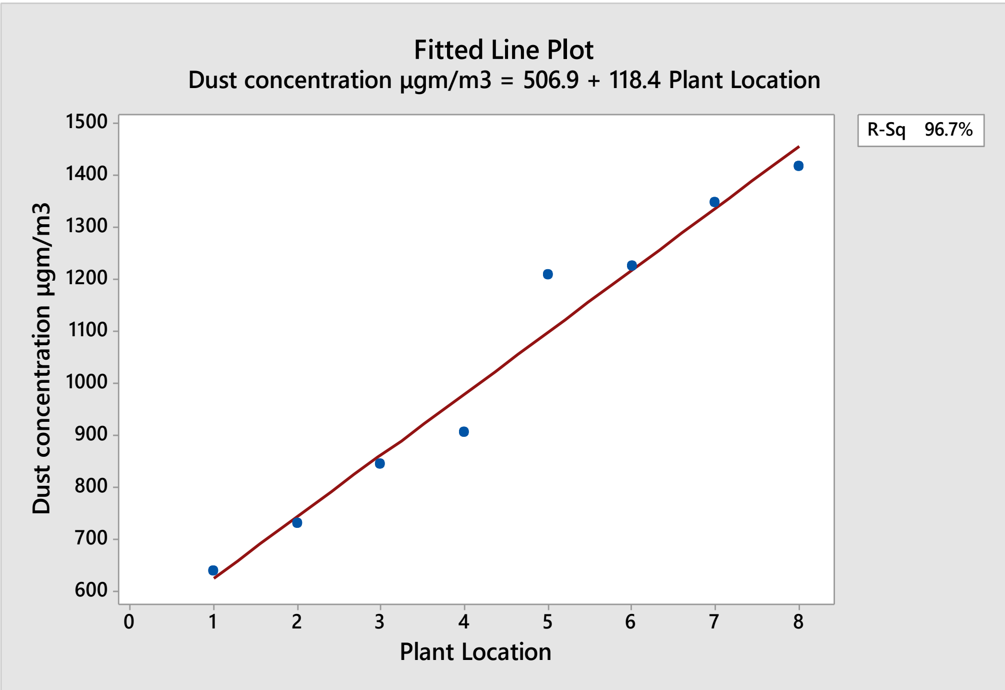

Fig. 3(a)

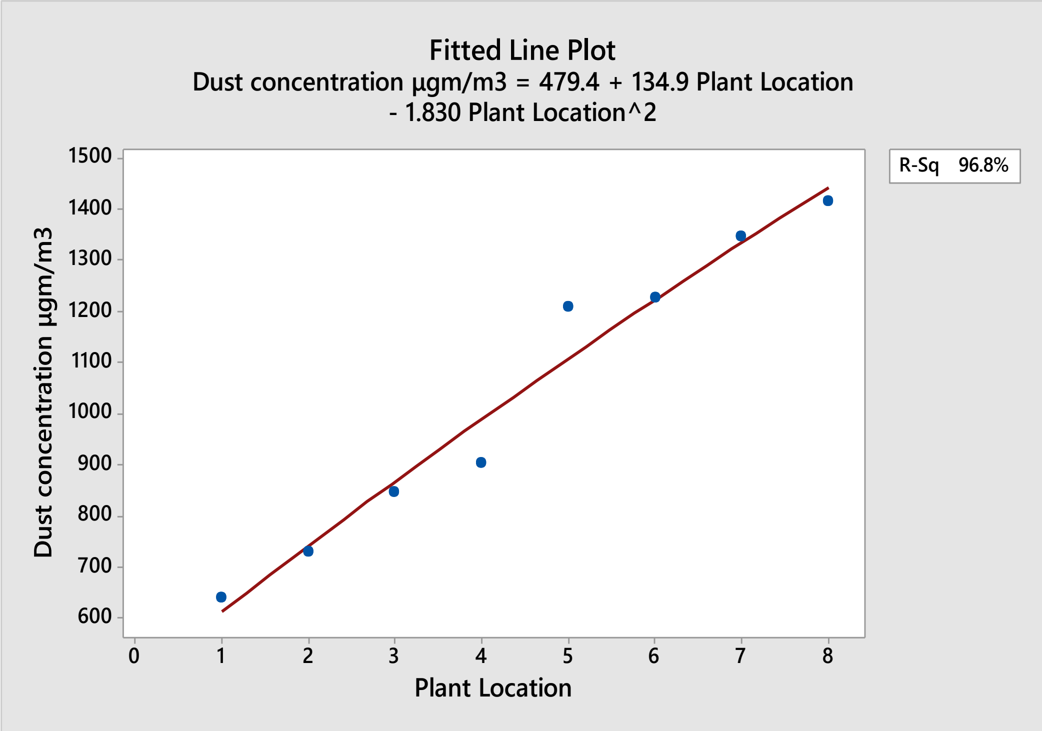

Fig. 3(b)

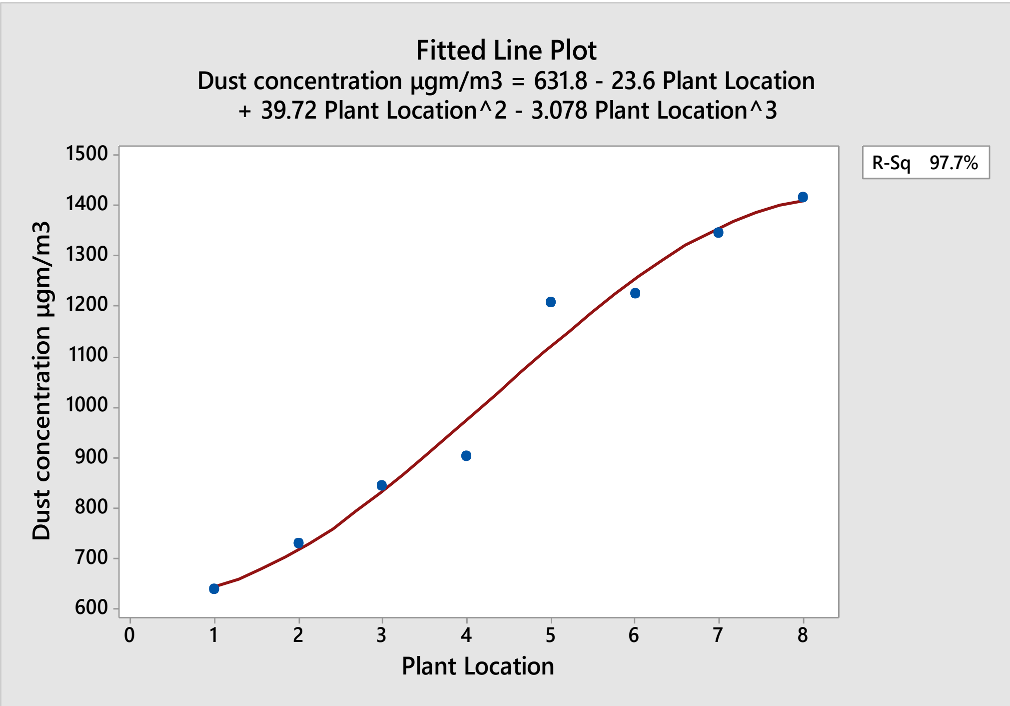

Fig. 3(c)

Figure 3: Prediction results of PM2.5 dust emission in Plant location using (a) Linear, (b) Quadratic and (c) Cubic models

Table 1 shows results of PM2.5 dust emission in plant and mining locations. From table 1, it is clear that the screening and crushing areas of the processing plant have the highest PM2.5 dust emission in the first shift and second shift when compared to other plant locations. This is majorly due to the process of crushing producing more fine dust particles and also screening involves the separation of fine and coarse particles which causes high material movement for stratification[8,10-13]. Because of this process, PM2.5 dust emission is higher for the screening and crushing area compared to other plant locations.

From table 1, it was also clear that all the mine locations have lesser PM2.5 dust emissions when compared to plant locations. Sprinkling of water was carried out more often which reduced the dust dispersion to the environment. Table 1 also demonstrates that the PM2.5 dust emissions in the screening and crushing area of the processing plant exceeded the National Ambient Air Quality Standard, 2009's allowable limit of 1200 μg/m^3.

Figure 3 shows the prediction results of PM2.5 dust emission in plant locations using (a) Linear, (b) Quadratic and (c) Cubic models. From figure 3, it was clear that the regression coefficient (R^2) value of PM2.5 dust emission in the plant location was 96.7%, 96.8% and 97.7% respectively for (a) Linear, (b) Quadratic and (c) Cubic models. This demonstrates that the cubic models are the most accurate in predicting the PM2.5 dust emission test findings at the plant location.

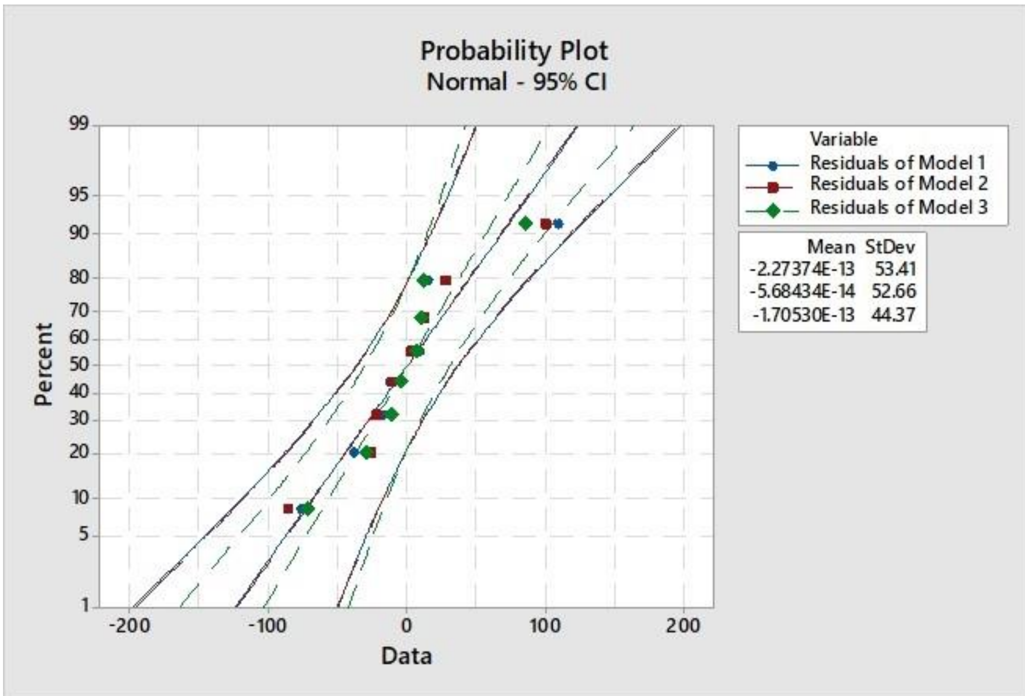

Figure 4: Probability plot of the prediction model of PM2.5 dust emission in Plant location

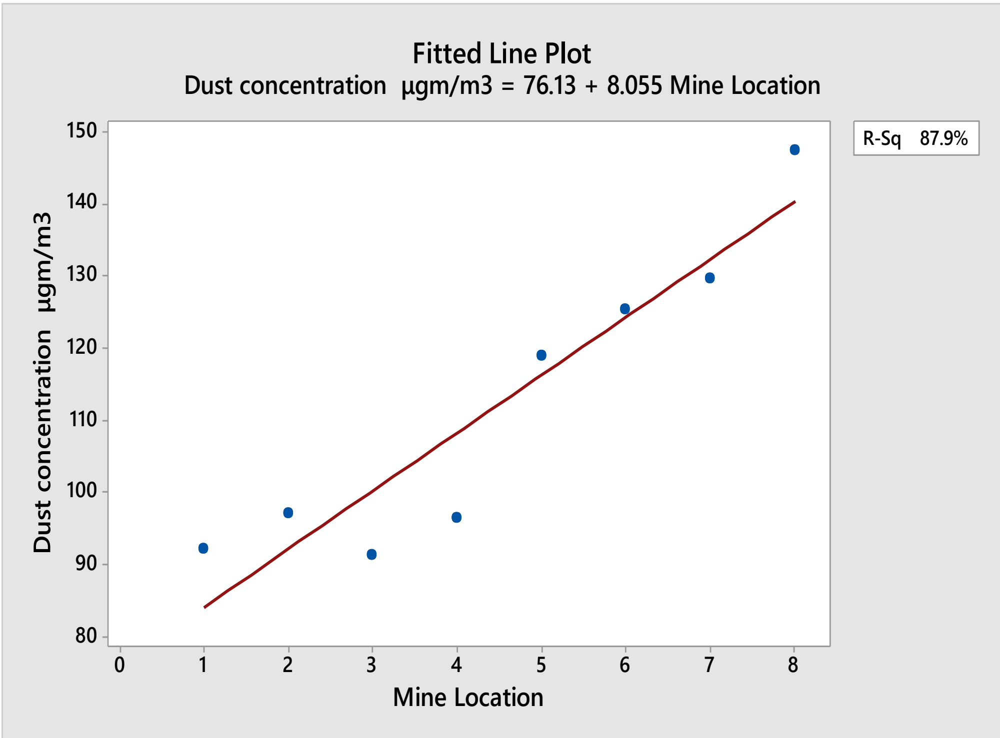

Fig. 5(a)

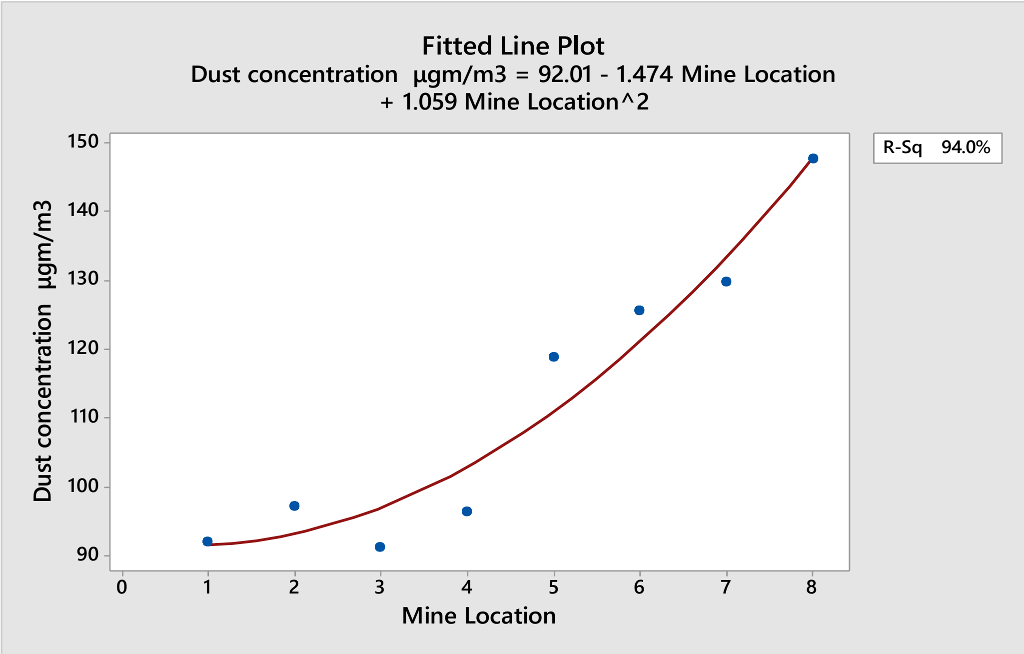

Fig. 5(b)

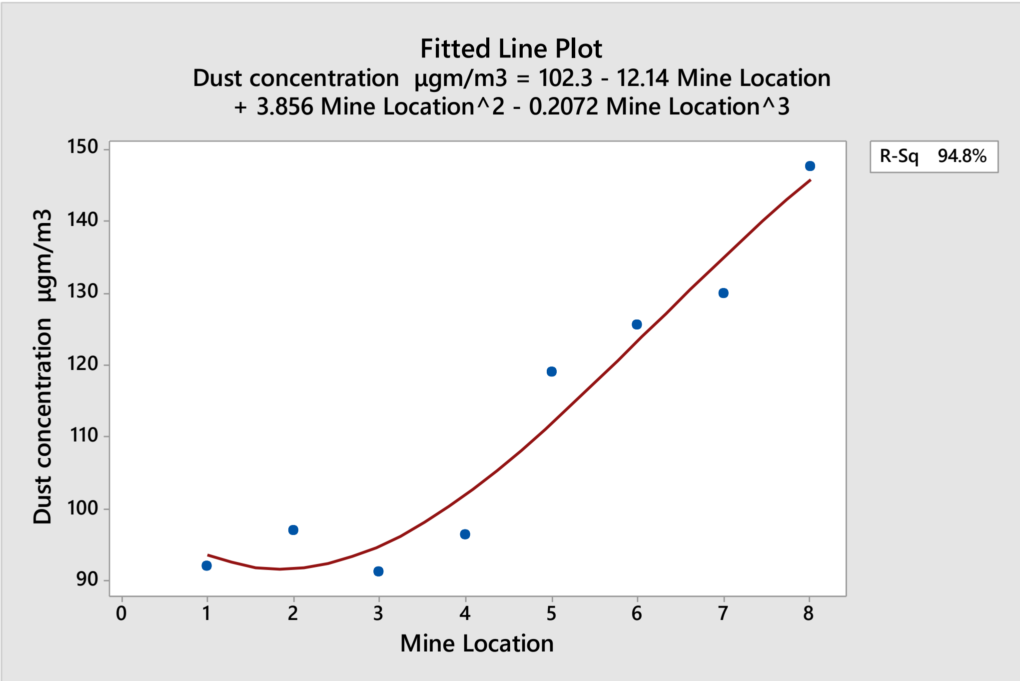

Fig. 5(c)

Figure 5. Prediction results of PM2.5 dust emission in Mining location using (a) Linear, (b) Quadratic and (c) Cubic models

The probability plot of the regression model of PM2.5 dust emissions in plant locations is shown in figure 4. The developed prediction model was validated using the probability plot. It was evident from figure 4 that the cubic model had a lower mean error and standard deviation than the other models. This demonstrates that the best mathematical model for predicting the experimental findings of PM2.5 emission of plant location is the cubic model.

Figure 5 shows the prediction results of PM2.5 dust emission in mining locations using (a) Linear, (b) Quadratic and (c) Cubic models. From figure 5, it was clear that the regression coefficient value of PM2.5 dust emission in mine location was 87.9%, 94.0% and 94.8% respectively for linear, quadratic and cubic models.

Additionally, figure 5 demonstrates that the cubic models are in close relation with the test results of PM2.5 dust emissions at the mining location. Figures 3 and 4 also demonstrate that the best model for predicting PM2.5 dust emissions at mining and plant locations is the cubic model.

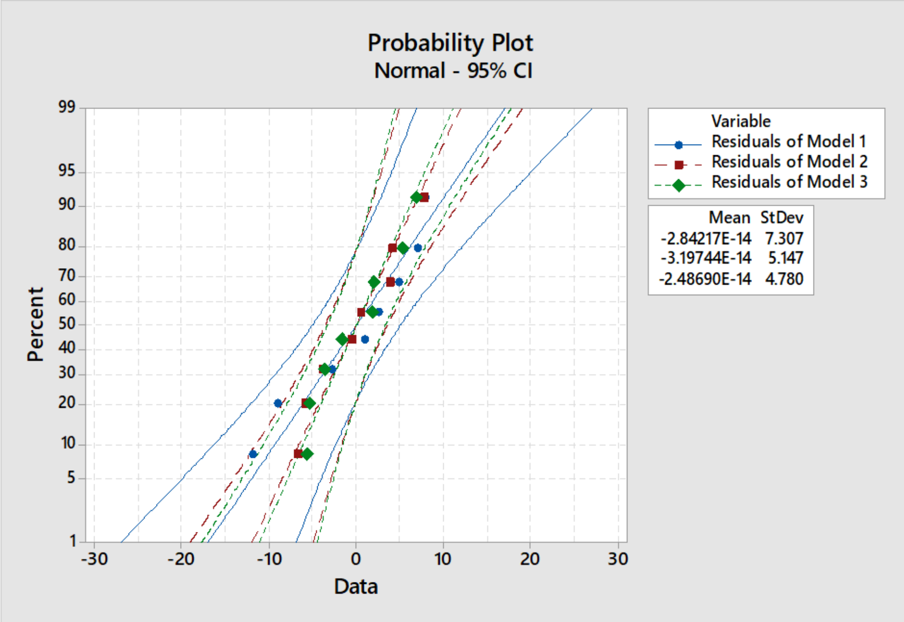

Figure 6: Probability plot of prediction model of PM2.5 dust emission in Mining location

Table 2
Experimental results of PM10 dust emission in Plant location and Mining location

Plant Location			Mining Location		
S.N.	**Location (Shift)**	**Dust Concentration µgm/m³**	**S.N.**	**Location (Shift)**	**Dust Concentration µgm/m³**
1	Processing Plant Entrance 2	743.26	1	Over Burden (OB) Excavation (Backfilling) 2	44.26
2	Processing Plant Entrance 1	796.54	2	Over Burden (OB) Excavation (Backfilling) 1	46.22
3	Conveyor 2	963.14	3	Transfer Terminal 2	95.26
4	Conveyor 1	998.45	4	Transfer Terminal 1	100.26
5	Crushing Plant 2	1265.265	5	OB Excavation 2	136.54
6	Crushing Plant 1	1350.26	6	OB Excavation 1	158.02
7	Screening Plant 2	1364.24	7	Nearby School 2	332.3
8	Screening Plant 1	1454.59	8	Nearby School 1	354.16

Figure 6 shows the probability plot of the regression model of PM2.5 dust emission in the mining 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 figure 6. From figure 6, it was clear that the mean error of the cubic model and standard deviation was lesser when compared to other models. This shows that the cubic model is the most suitable mathematical model for predicting the experimental results of PM2.5 obtained for the mining location.

Investigation of PM10 dust emission in Plant location and Mining location and its prediction studies

Table 2 shows experimental results of PM10 dust emission in plant and mining locations. In comparison to other plant locations, table 2 shows that the screening and crushing area has the largest PM10 dust emissions during the first and second shifts. The machine's emission of fine-sized dust particles was mostly caused by the increased particle dispersion in the atmosphere. So, PM10 dust emission is higher for the screening and crushing area compared to other plant locations.

From table 2, it was also clear that all the mining location has less dust suppression compared with the plant location. There was a higher movement of transportation vehicles which caused the dust particles from the ground to be dispersed in the environment. However, the sprinkling of water at a regular period has reduced the particle dispersion from the ground level.

From table 1, it was also clear that the PM10 dust emission in the plant location of the screening and crushing area was higher than the permissible limit of 1200 µg/m³ as per the National Ambient Air Quality Standard, 2009.

Figure 7 shows the prediction results of PM10 dust emission in plant locations using (a) Linear, (b) Quadratic and (c) Cubic models. From figure 7, it was clear that the regression coefficient (R^2) value of PM10 dust emission in the plant location was 95.7%, 96.3% and 97.6% respectively for (a) Linear, (b) Quadratic and (c) Cubic models. This demonstrates that the cubic models are the most accurate in predicting the PM10 dust emission test findings at the plant location.

The probability plot of the regression model of PM10 dust emissions in plant locations is shown in figure 8. The developed prediction model was validated using the probability plot. It was evident from figure 8 that the cubic model had a lower mean error and standard deviation than the other models. This demonstrates that the best mathematical model for predicting the experimental findings of PM10 emission of plant location is the cubic model.

Figure 9 shows the prediction results of PM10 dust emission in mining locations using (a) Linear, (b) Quadratic and (c) Cubic models. From figure 9, it was clear that the regression coefficient value of PM10 dust emission in mine location was 85.3%, 94.1% and 94.2% respectively for linear, quadratic and cubic models. Additionally, figure 9 demonstrates that the cubic models are in close relation with the test results of PM10 dust emissions at the mining location. Figures 7 and 9 also demonstrate that the best model for predicting PM10 dust emissions at mining and plant locations is the cubic model.

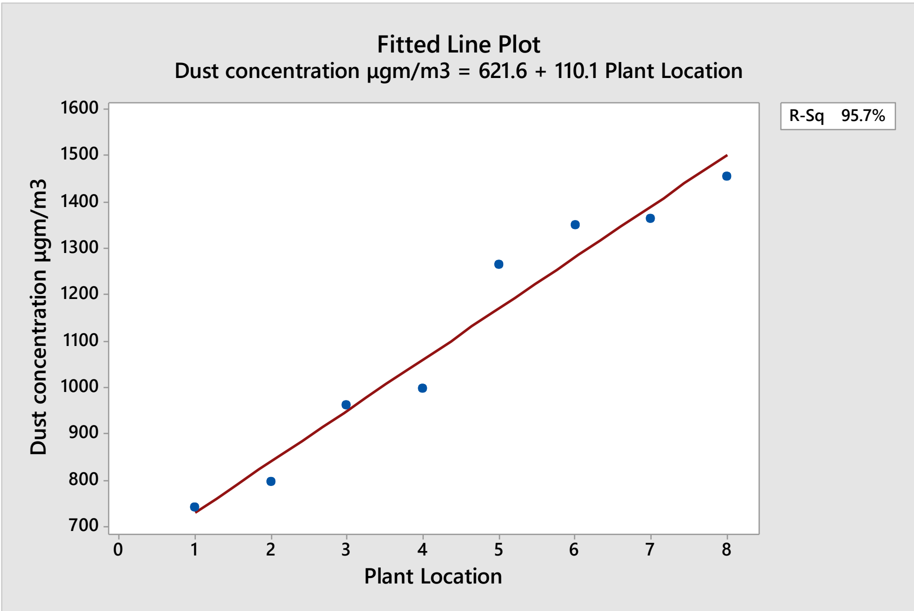

Fig. 7(a)

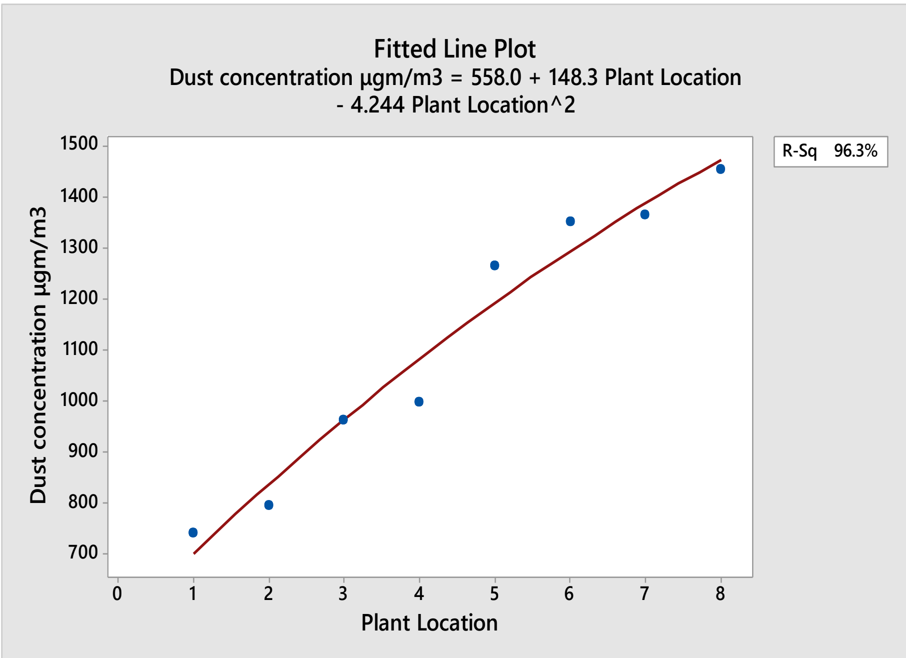

Fig. 7(b)

https://doi.org/10.25303/185da1140125

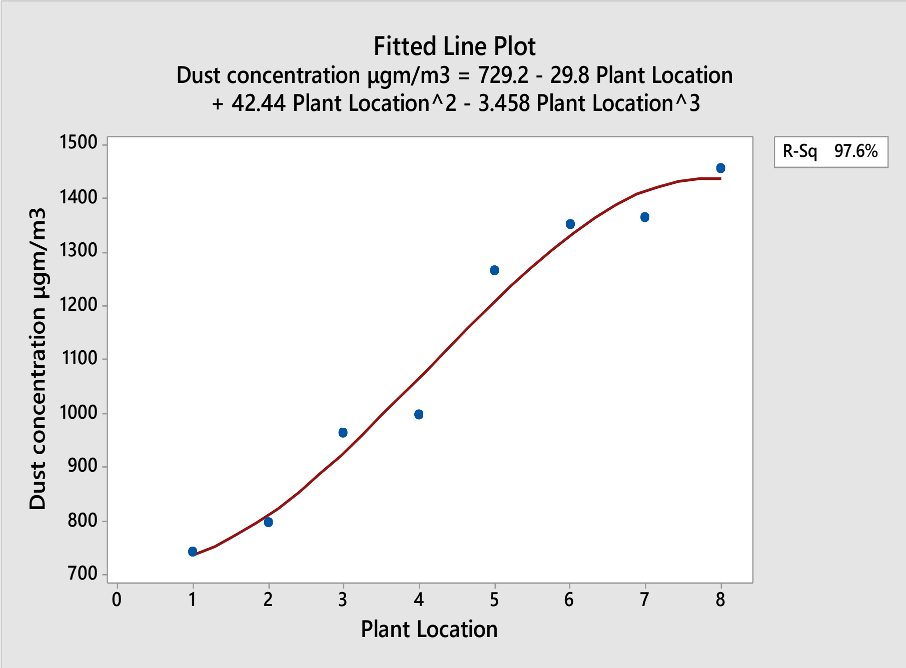

Fig. 7(c)

Figure 7: Prediction results of PM10 dust emission in Plant location using (a) Linear, (b) Quadratic and (c) Cubic models

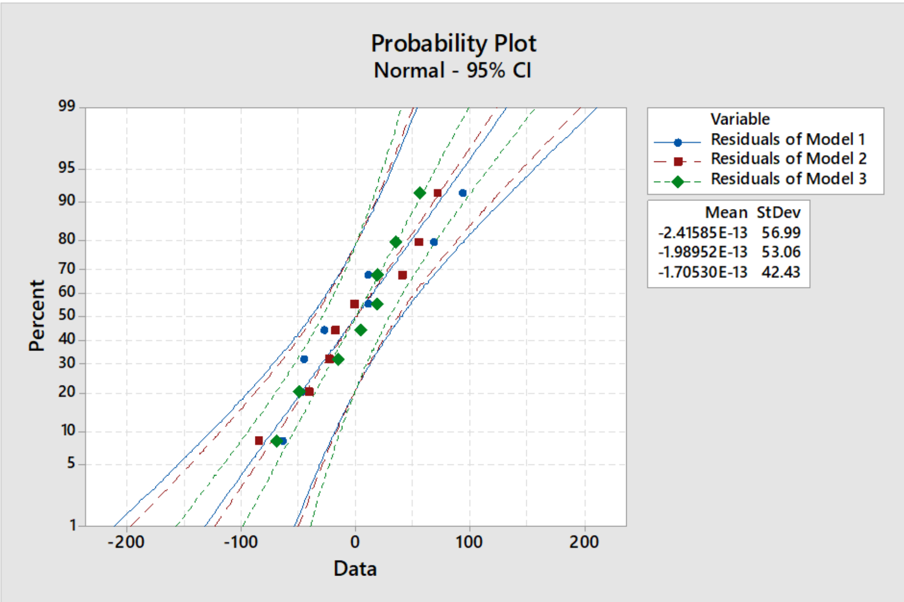

Figure 8: Probability plot of prediction model of PM10 dust emission in Plant location

Figure 11 shows the probability plot of the regression model of PM10 dust emission in the mining 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 figure 11. From figure 11, it was clear that the mean error of the cubic model and standard deviation was lesser when compared to other models. This shows that the cubic model is the most suitable mathematical model for predicting the experimental results of PM10 obtained for the mining location. According to the findings, the cubic regression model was the most effective model for predicting PM2.5 and PM10 dust emissions.

Additionally, the validation results demonstrated that the cubic regression model had a smaller mean error and overall spread of errors. Also, the developed cubic model is the most accurate model with a regression coefficient more than 94%. Additionally, the test results demonstrated that the PM2.5 and PM10 dust emissions from crushing and screening exceed the 2009 National Ambient Air Quality Standard's allowable limit of 1200 µg/m^3. Precautionary steps must therefore be made to avoid increased dust emissions. 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.

Conclusion

The present work aims to test the (Particulate Matter) PM10 and PM2.5 in the mining area and processing plant area of a limestone mine in Andra Pradesh, India using a Respirable Dust Sampler (RDS) (Ecotech AAS 190). The statistical prediction model was developed using linear, quadratic and cubic supervised machine learning (regression) modeling. Furthermore, the statistical prediction model was validated using a probability plot. The mean error and standard deviation were studied for each prediction model. The results showed that PM 2.5 and PM10 dust emissions from screening and crushing areas of the processing plant were over the permissible limit.

The results also showed that PM 2.5 and PM10 dust emissions of all mining locations were within the permissible limit. The prediction results also showed that the cubic regression model is the most suitable mathematical model for predicting the experimental results of PM10 and PM2.5 obtained from the particulate sampler (Ecotech AAS127). Furthermore, the residual analysis using a normal probability plot showed that the cubic model has less error and an overall spread of errors. These validation results show that the cubic model is the most suitable mathematical model for predicting the experimental results of PM10 and PM2.5 obtained from the respective sampler.

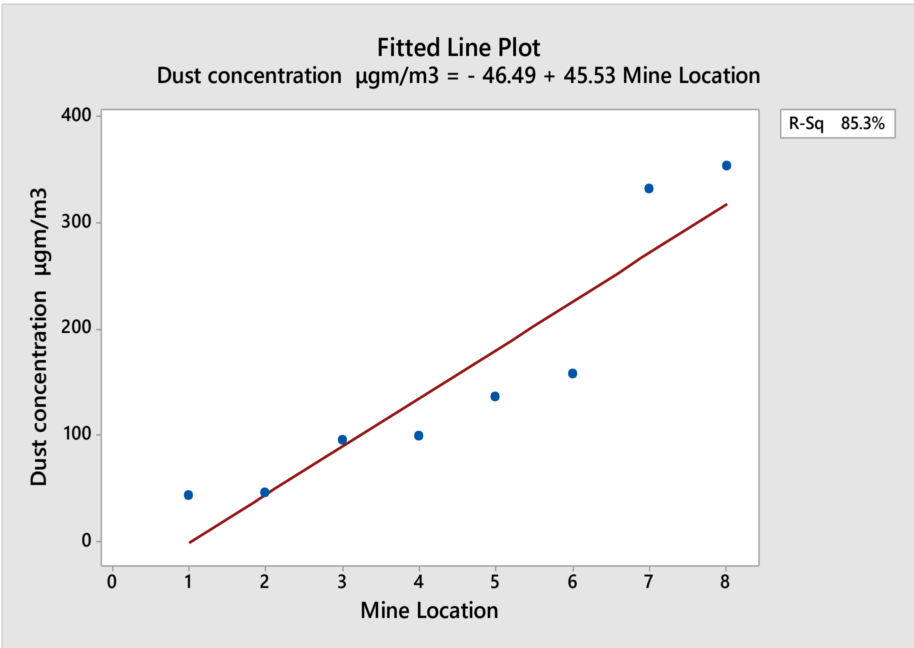

Fig. 9(a)

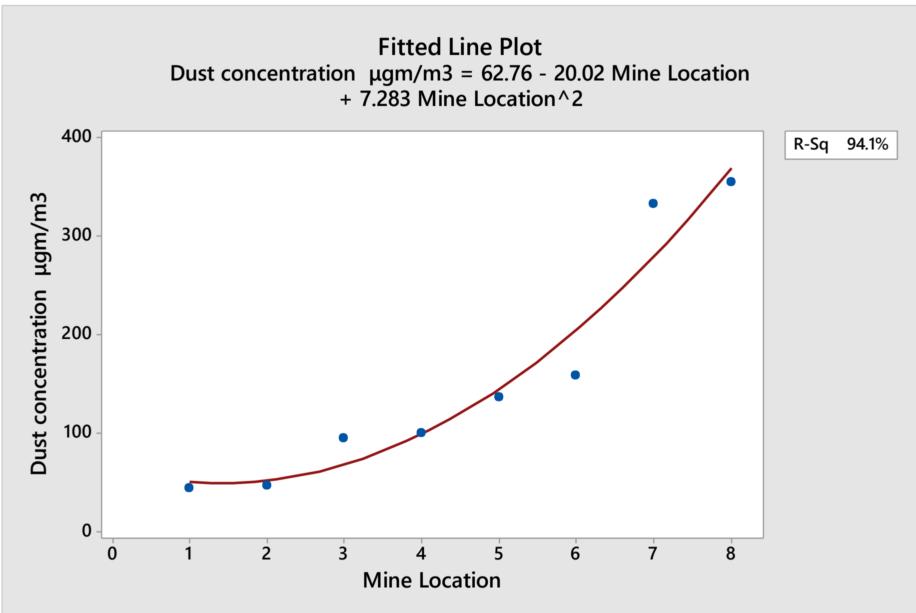

Fig. 9(b)

https://doi.org/10.25303/185da1140125

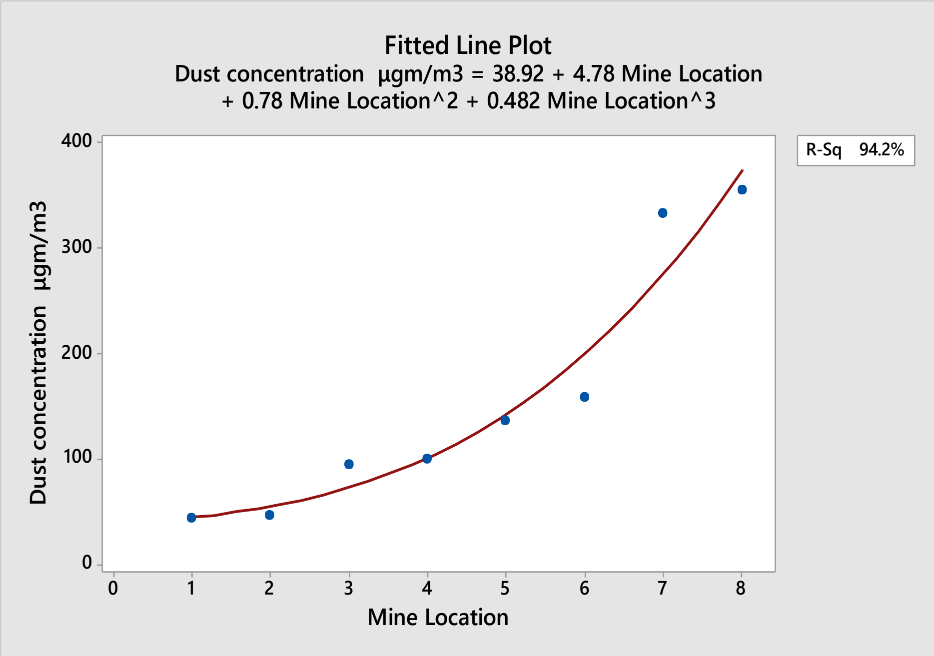

Fig. 9(c)

Figure 9: Prediction results of PM10 dust emission in Mining locations using (a) Linear, (b) Quadratic and (c) Cubic models

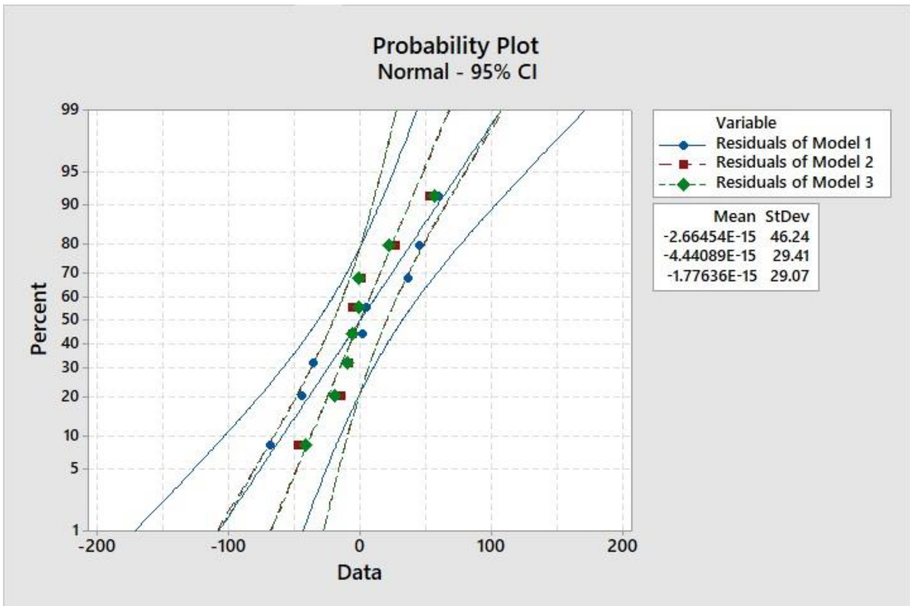

Figure 10: Probability plot of prediction model of PM10 dust emission in Mine location

References

1. Chang P. and Xu G., A review of the health effects and exposure-responsible relationship of diesel particulate matter for underground mines, *Int. J. Mining Science and Technology*, **27(5)**, 831-8 **(2017)**

2. Chaulya S.K., Chowdhury A., Sunil K., Singh R.S., Singh S.K., Singh R.K., Prasad G.M., Mandal S.K. and Banerjee G., Fugitive dust emission control study for a developed smart dry fog system, *Management*, **285**, 112116 **(2021)**

3. Chaulya S.K., Trivedi R., Kumar A., Tiwary R.K., Singh R.S., Pandey P.K. and Kumar R., Air quality modelling for prediction of dust concentrations in iron ore mines of Saranda region, Jharkhand, India, *Atmospheric Pollution Research*, **10(3)**, 675-88 **(2019)**

4. Copeland C.R., Eisele T.C. and Kawatra S.K., Suppression of airborne particulates in iron ore processing facilities, *International Journal of Mineral Processing*, **93(3–4)**, 232-238 **(2009)**

5. Copeland C.R. and Kawatra S.K., Dust suppression in iron ore processing plants, *Mining, Metallurgy & Exploration*, **22**, 177–191 **(2005)**

6. Copeland C.R. and Kawatra S.K., Design of a dust tower for suppression of airborne particulates for iron making, *Minerals Engineering*, **24** ,1459–1466 **(2011)**

7. Guo C., Lv S., Liu Y. and Li Y., Biomarkers for the adverse effects on respiratory system health associated with atmospheric particulate matter exposure, *J. Hazardous Materials*, **421**, 126760 **(2017)**

8. Harish H., Vardhan H., Raj M.G., Kaza M., Sah R., Sinha A. and Kumar S.B., Investigation of iron ores based on the bond grindability test, AIP Conference Proceedings **(2020)**

9. Nie M., Li S., Li X., Bao S., Chen P., Zhang Y., Ding S. and Li J., The Preparation and Dust Suppression Performance Evaluation of Iron Ore Tailing-Based Cementitious Composites, *Molecules*, **29**, 2056 **(2024)**

10. Shanmugam B.K., Harsha V., Raj M.G., Kaza M., Sah R. and Harish H., The screening efficiency of linear vibrating screen - An experimental investigation, AIP Conference Proceedings **(2020)**

11. Shanmugam B.K., Vardhan H., Raj M.G., Kaza M., Sah R. and Harish H., Screening performance of coal of different size fractions with variation in design and operational flexibilities of the new screening machine, *Energy Sources, Part A: Recovery, Utilization and Environmental Effects*, **45(2)**, 4361–4369 **(2019)**

12. Shanmugam B.K., Vardhan H., Raj M.G., Kaza M., Sah R. and Hanumanthappa H., Regression modeling and residual analysis of screening coal in screening machine, *International Journal of Coal Preparation and Utilization*, **42(9)**, 2849–2864 **(2021)**

13. Shanmugam B.K., Vardhan H., Raj M.G., Kaza M., Sah R. and Hanumanthappa H., Application of fractional factorial design for evaluating the separation performance of the screening machine, *International Journal of Coal Preparation and Utilization*, **42(11)**, 3369–3379 **(2021)**

14. Timofeeva S.S. and Murzin M.A., Assessing the environmental risk of mining enterprises by the integral indicator of dust emission, In IOP Conf. Series: Earth and Environmental Science 2020, **408(1)**, 012067 **(2020)**

15. Wang Z., Zhou W., Jiskani I.M., Luo H., Ao Z. and Mvula E.M., Annual dust pollution characteristics and its prevention and control for environmental protection in surface mines, *Science of The Total Environment*, **825**, 153949 **(2022)**

16. Young-Corbett D.E. and Nussbaum M.A., Dust control technology usage patterns in the drywall finishing industry, *J. Occupational and Environmental Hygiene*, **6(6)**, 315-23 **(2009)**

17. Zhou Qun and Qin B., Coal dust suppression based on water mediums: A review of technologies and influencing factors, *Fuel*, **302**, 121196 **(2021)**.

(Received 22nd January 2025, accepted 20th February 2025)