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Optimization of Air Pollution Control Model for Mining

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***Abstract*—**The sustainable measures on air quality management are recognized as one of the most serious environmental concerns in the mining region. The mining operations emit various types of pollutants which have significant impacts on the environment. This study presents a stochastic control strategy by developing the air pollution control model to achieve a cost-effective solution. The optimization method is formulated to predict the cost of treatment using linear programming with an objective function and multi-constraints. The constraints mainly focus on two factors which are: production of metal should not exceed the available resources, and air quality should meet the standard criteria of the pollutant. The applicability of this model is explored through a case study of an open pit metal mine, Utah, USA. This method simultaneously uses meteorological data as a dispersion transfer function to support the practical local conditions. The probabilistic analysis and the uncertainties in the meteorological conditions are accomplished by Monte Carlo simulation. Reasonable results have been obtained to select the optimized treatment technology for $PM_{2.5}$, PM_{10}, NO_x, and SO_2. Additional comparison analysis shows that baghouse is the least cost option as compared to electrostatic precipitator and wet scrubbers for particulate matter, whereas non-selective catalytical reduction and dry-flue gas desulfurization are suitable for NO_x and SO_2 reduction respectively. Thus, this model can aid planners to reduce these pollutants at a marginal cost by suggesting control pollution devices, while accounting for dynamic meteorological conditions and mining activities.

***Keywords*—**Air pollution, linear programming, mining, optimization, treatment technologies.

I. Introduction

THE rapid increase in economic growth of mining industries is accompanied by the emission of substantial quantities of air pollutants. Major air pollutants during construction and operational phase of the mining are particulate matter (PM_{10} and $PM_{2.5}$), NO_x and SO_2. Particulate emissions are primarily associated with fugitive dust that comes from the usage of heavy equipment such as haul truck, windblown dust from mineral stockpiles, drilling, loading and blasting activities [1]. In addition, many reagents used in processes of mining can responsible for air pollutants such as SO_2 may produce during the process of cyanide destruction and fuel consumption. Fuel combustion is also responsible for the release of nitrogen oxide (NO_x). At both workplace and residential areas, these airborne particles are adversely affecting the health by contributing to illnesses such as damaging the lungs, respiratory tract and causing skin diseases by absorbing into the skin [2]. There are strict rules for health and safety of workers by the Canada government, especially those working in the mining sector [3].

With increasing environmental awareness, more and more mining companies are showing their interest to address the air quality problems to identify appropriate corrective measures to improve the environmental sustainability of their processes. Two approaches have been used to analyze this issue. One is the direct application of abatement technology to reduce the air pollution, based on the quantities of pollutant's concentration in the effluent stream. The second approach is to develop a decision tool to control air pollution and effective management in a stochastic manner. Many control technologies have been widely studied and practically used in the mining sector based on the environmental protection agency (EPA) guidelines, such as desulfurization of fuel, electrostatic precipitators, and baghouse to reduce particulate matter, etc. [4]. However, in this study, the focus is on the second approach, as this strategy complements the first approach by including treatment options while, minimizing economic resources for their implementation. The recent advances in optimization theory and its applications have enabled the decision makers to develop the systematic tools to control environmental problems by using mathematical programming techniques. Shaban et al. developed a mixed-integer linear programming (MILP) model to optimize the set of control options to achieve a certain pollution reduction criterion based on the available maximum budget in urea plant [5]. Grandinetti et al. developed a multi-objective linear programming model to identify the best available technologies (BATs) in a manufacturing industry [6]. Ren et al. studied a multi-objective approach based on linear programming (LP) for the design of a distributed energy system that minimizes the energy cost and CO_2 emissions [7]. Cristóbal et al. used mixed integer non-linear programming for the optimal design of pollution control devices in coal-fired plants [8]. Chen et al. developed robust fuzzy linear programming for coal-burning power plants and the kilns to suggest total suspended particulates (TSP) pollution control technique [9]. Thus, simplification is motivated by the numerical difficulties associated with the optimization of nonlinear models, which are more difficult to handle than linear programming formulations. The complexity simulation is another major limitation of multi-objective functions using non-linear programming.

The most significant part of the optimization model is to seek the objective which helps to evaluate control treatment methods. Most of the studies consider the least cost control strategy which reflects the overall cost of the techniques [10],

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whereas the total cost of the treatment comprises of direct cost and indirect cost. The direct cost includes equipment cost, installation, operating cost, maintenance, and utilities (electricity, power). The indirect cost comprises of overhead, tax, insurance, administration, recovery cost and labor cost [4]. Furthermore, each planning strategy can also be classified into two ways. 1) The open-loop control; 2) closed-loop control [11]. In open-loop control, the objective is determined based on an initial state of the system and any expected inputs can be predetermined and not altered during the simulation whereas, a closed-loop determines at each time during the development of the system by comparing the actual and the desired output of the system. Both play an important role in the air pollution control strategy. Nevertheless, open-loop control is more flexible with day to day or yearly changing weather conditions and closed-loop control is suitable for emergency control procedures such as smog alerts [11]. Thus, in this study, an open-loop control strategy is planned.

Long-term air pollution control planning generally includes the consideration of planning objective, cost analysis, system synergies, various technologies and generation of optimal solutions to achieve a balance of technical and economic feasibility to improve the environmental quality. Past studies mostly include pollutant emissions and ignore the dispersion of pollutant and meteorological variabilities [12], whereas the pollutant concentration at downwind distance depends on not only the source emission but also dynamic meteorological conditions of that area. To overcome this issue, dispersion transfer function (DTE) could be integrated into a model as one of the constraints [9]. The transfer coefficient or DTE can be determined by modifying the Gaussian model. The simple Gaussian air dispersion model includes several determinative parameters related to meteorological conditions including wind speed and direction, vertical and horizontal dispersion coefficients and topographical site conditions.

The objective of this study is to develop an optimization model based on linear programming for mining-air pollution control planning called as *air pollution control model (APCM)*. For this purpose, an open-loop control strategy is planned to determine the minimum cost of the treatment while considering the availability of resources and air quality as the two main constraints. Moreover, the paper integrates the air dispersion Gaussian model as a transfer function in the air quality constraint to consider the basic meteorological parameters. The uncertainties of the meteorological conditions are analyzed by Monte Carlo simulation.

II. Methodology

A. Development of Air Pollution Control Model (APCM)

To determine the best treatment technology for air pollutants, various control emissions technologies are employed. The emission of the pollutant (p) should not exceed the limitation air quality criteria at the optimum cost while the production of metal does not exceed the available resources. The emission of the pollutant is summarized through various mining activities ($i_{1\text{-}10}$) based on average yearly contribution. The mining activities included in this research are mining pit, hauling, crushing and conveying, milling and grinding unit, a processing unit, tailing area, power plant, and stockpiling area.

To solve the complex problems, there are certain assumptions which must be made to relate the appropriate variables. It is assumed that: 1. There is certain number of source activities instead of a single point source. For each type of source (i :1-n), they have the same pollutant's concentration limitation and cost of treatment equipment. 2. The optimized model is simulated for a specified period with the subject to change in direct and indirect costing value in future. 3. The limitation of concentration of a pollutant is determined based on the national ambient air quality standards (NAAQS). 4. The treatment technologies should be listed down and identified.

The optimum problem of minimizing the treatment cost can be conceptualized using open-loop control framework of linear programming as shown in Fig. 1. The objective function is then solved in Excel solver by running the model every time for different pollutants and various controlling technologies.

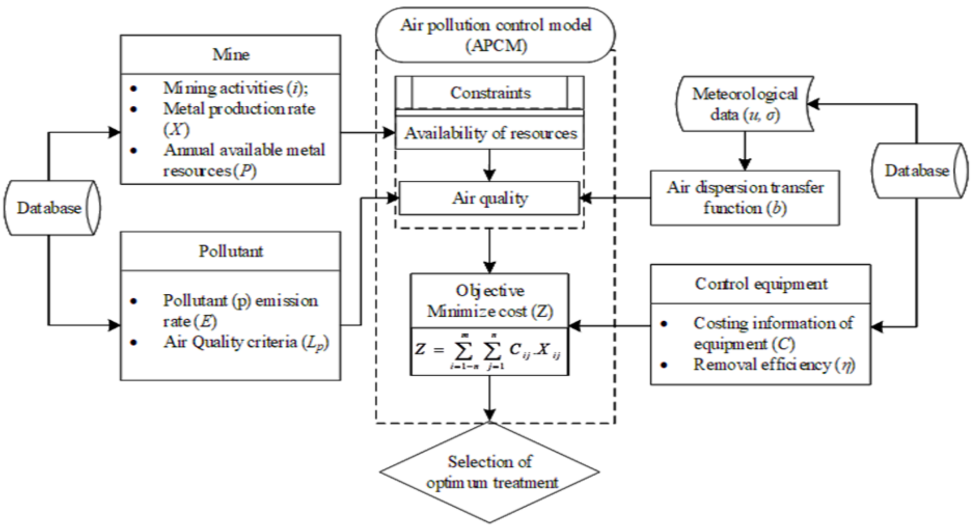

Fig. 1 Open-loop control framework to conceptualize APCM for optimum treatment

The mathematical model is formulated as follows:

B. Objective

The objective is to minimize the treatment cost Z (\$/yr). The model includes m mining activities and n treatment methods and expressed as follows:

$$Z = \sum_{i=1-n}^{m} \sum_{j=1}^{n} C_{ij} . X_{ij} \tag{1}$$

whereas C =Total cost of treatment j of pollutant p for activity i per production of metal (\$/production), X = Metal produced after controlled treatment option j at source i (tonnes/year).

The total cost of any treatment j included direct cost as well as indirect cost and expressed as follows

$$C = DC + IC \tag{2}$$

DC = Direct cost of treatment including purchased cost, installment cost and operating cost, IC = Indirect cost of treatment includes maintenance cost, labor cost.

C. Constraints

1. Availability of Resources

A monetary benefit of optimizing the effective treatment strategy could equally provide an information about the metal production depending upon the resources available. This constraint helps decision makers to evaluate the treatment options according to the production from each mining activity. If the production after treatment exceeded the annual resources, then the benefit of selecting the suitable technology is not feasible. Thus, one of the most policy-relevant features and constraints is not to exceed the available resources.

$$\sum_{j=1}^{n} a_{ij} . X_{ij} \leq P \tag{3}$$

P= The annual available resources of metal (tonnes). The coefficient a_{ij} is equal to 1 if control j is applicable or feasible at source i and 0 if not suitable for the pollutant whereas

$$X_{ij} \geq 0 \tag{4}$$

2. Air Quality

This constraint represents the air quality and pollutant concentration relationship.

(a) Air pollutant DTF is formulated by using Gaussian air quality dispersion model. As, in this study, it is assumed that distribution of air pollutants dispersion is along the centerline. Thus, the DTF b (sec/m^3) is expressed as:

$$b = \sum_{i}^{m} \frac{1}{\Pi u \sigma_y \sigma_z} \cdot \exp\left(-\frac{y^2}{2\sigma_y{}^2} - \frac{H^2}{2\sigma_z{}^2}\right) \tag{5}$$

whereas u is the average wind speed (m/sec), H is the effective height (m) from source "i", y is the distance from the centerline (m), σ_y and σ_z are standard deviations of dispersion in x and y-direction (m). Thus, (5) has the following form to be used in the air quality constraint:

$$C = Ei\ b\ X \tag{6}$$

whereas C is the pollutant concentration at the certain downwind distance (µg/m^3) and Ei is the emission rate (kg/tonn). Moreover, b and E are considered as technology coefficients in air quality constraint and X is the unknown variable.

(b) The constraint of air quality is formulated as follows:

$$\sum_{i=1-n}^{m} \sum_{j=1}^{n} (1-\eta_j).E_{ijp}.\ b_{ij}\ .\ X_{ij} \geq L_p \tag{7}$$

where η is the efficiency of control method j at source i. The emission rate of pollutant p from source i with control j is E_{ijp}, whereas L_p is the standard criteria for each pollutant p.

D. Case Study

Mine A is an open pit mine located in the Utah county, USA comprises of approximately 900 ha area. Processing facilities included a concentrator, a 175-megawatt (MW) coal-fired power plant, a smelter, and a refinery. For this study, air emissions during copper production are considered. Five years' average daily data from the year 2011 to 2015 is collected. The average maximum ambient temperature is 17 ^{o}C. The mean wind speed is 3.4 m/s. The weather data are separately collected through NOAA regional climate center as well Airport weather station (W1). The pollutants data are collected from the four-monitoring station (S1 to S4) as shown in Fig. 2.

III. Input for Optimization Model

Table I summarizes all the important parameters used as inputs for the optimization model. The production capacity of the mine and availability of resources as copper production values are mentioned in Table I, which are average values for the year of 2011-2015 whereas, the unknown variable is X which is copper production from each mining activity after applying control strategy. Furthermore, emission of the pollutants is obtained from the life cycle inventories and reports of mine A. The major pollutants included in this study are PM_{10}, $PM_{2.5}$, NO_X and SO_2.

Particulate controls are mainly collectors (cyclones), electrostatic precipitators, baghouse or wet scrubbers. Mechanical collectors are used to controlling larger diameter particulate in a pre-control capacity whereas, electrostatic precipitators are used mostly in high emission rate applications such as coal-fired power plants [13]. Baghouses (fabric filters) cover a wide range from large scale to very small emission sources. Moreover, filter size varies depending on particulate loading, temperature and moisture content. Wet scrubbers are generally effective for large-particulate emission sources [14]. NO_x can be controlled by selective non-catalytic reduction (SNCR), which involves the injection of ammonia or urea into the exit air stream to react with NO_x to form nitrogen and water. Without the benefit of a catalyst, the reaction temperature is very high (1,400 to 1,500 °F), which makes SNCR only effective in a relatively high, narrow temperature range. Selective catalytic reduction (SCR) is one of the most effective NO_x controls for combustion sources. The catalyst allows an efficient reaction to take place at lower temperatures; typically, 500–900 °F, depending on the type of catalyst [15]. Whereas, a flue gas desulfurization (FGD) system is based on an alkaline reagent. The purpose of using these reagents is to absorb SO_2 in the effluent stream and produce by products such as calcium sulfate and sodium compound. These solid sulfate compounds are then removed from the air stream using equipment installed at downstream. FGD technologies are further classified as wet and dry based on the reagent used during the application. Wet regenerable FGD systems are more efficient because of 95-98% SO_2 control capability [16].

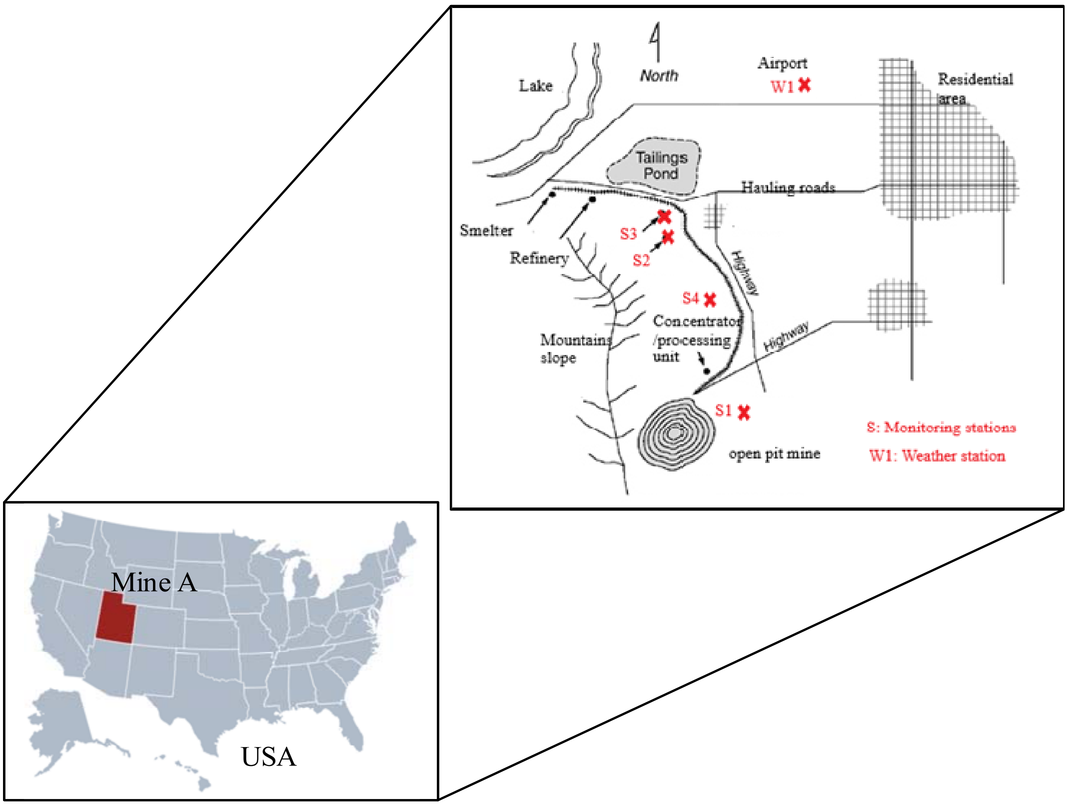

Fig. 2 Location of mine and monitoring station

TABLE I
INPUTS FOR OPTIMAL MODEL

Input parameters	Values
The annual production rate of mine (10^5. tonnes/yr)	2.55
Grade of copper mine (g/tonnes)	0.97
Total production of copper (tonnes. 10^5)	2.68
Emission of $PM_{2.5}$ produced (10^4. kg/yr)	7.74
Emission of PM_{10} produced (10^4. kg/yr)	6.50
Emission of NOx produced (10^4. kg/yr)	1.26
Emission of SO_2 produced (10^4. kg/yr)	3.78

Table II represents the costing information of various identified air pollution control equipment. The direct and indirect costing is obtained which can be added using (2) to find out the total cost of the specific option. Moreover, removal efficiency range is provided in Table II, which was applied as (1- η) to obtain the reduction of emission (E) after treatment of pollutant and used in (7).

TABLE II
ECONOMIC INPUTS FOR AIR POLLUTION CONTROL TECHNOLOGY

Air pollution control equipment	Removal efficiency (%) [4]	Direct cost ($).$10^3$ (*DC*)	Indirect cost ($). 10^3 (*IC*)
Wet Scrubbers (WS)	96	159	103
Electrostatic precipitator (Ep)	99	221	202
Bag house (BH)	95	56	29
Selective catalytic reduction (SCR)	85	8.490/ton	3.540/ton
Non-selective catalytic reduction (NSCR)	65	3.130/ton	2.545/ton
Low NOx burner (LNB)	55	1.170/ton	2.400/ton
Flue gas recirculation (FGR)	60	1.370/ton	0.450/ton
Dry flue gas desulfurization (FGD-dry)	94	6300	1250
Wet flue gas desulfurization (FGD-wet)	98	7760	5600
Dust suppressant-Magnesium chloride (DS)	85	$0.37/(10^3.yd^3)$	$0.12/(10^3.yd^3)$

IV. Monte Carlo Simulation

Random variables related to meteorological parameters and emission rates of pollutant both were considered. Fig. 3 illustrates the probability analysis of wind speed (m/s) using Monte Carlo method. Fig. 3 represents the histogram of wind speed showing an average of 3.4 m/s. The random normal distribution method was used to statistically determine the maximum probability of all outcome to be used as input in the optimization model. A similar method could be used to evaluate the uncertainty in other parameters such as emission rate of the pollutants. Fig. 4 illustrates the percentage distribution of the atmospheric stability of this area depending upon the local weather condition and solar isolation method using Pasquill–Turner method scheme. This method distributes the atmospheric stability into seven distinct categories instead of six (from A to G or 1 to 7) by using radiation index and wind speed [17], [18].

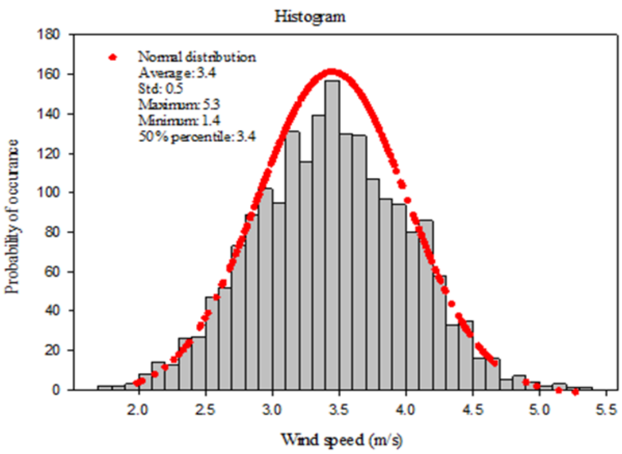

Fig. 3 Monte Carlo simulation of wind speed

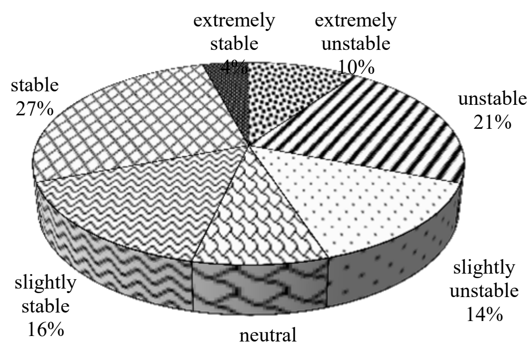

Fig. 4 Percentage distribution of stability classification

The results reveal that the stable condition (class F) appears most of the time of the year based on the percentage relative frequency distribution. Whereas, unstable (class B) is the second dominant condition (21%) followed by slightly stable (16%) and slightly unstable (14%) patterns as shown in Fig. 4. Thus, the values of standard deviation (σ_y and σ_z) in transfer function are based on the stability percentage occurrence.

V. Results and Discussion

A. Optimization Least Cost Treatment Analysis

For each pollutant, different set of treatment options were planned to determine the best cost-effective solution. For each alternative of air pollution control method, the model was run separately for each pollutant based on a single objective function. The selected treatment technologies in this study for $PM_{2.5}$ and PM_{10} are the same, as both are the particulate matter and can be removed by using the similar method. Table III illustrates that electrostatic precipitator option is costly among other methods to treat the particulate matter. The reason behind this is obvious that removal efficiency is highest which is 99% in comparison to other technologies whereas, the low cost option with a good removal efficiency is baghouse. It is interesting to note that dust suppressant (magnesium chloride) is cheapest among all with the removal efficiency of 85 %. In the mining sector, dust suppressants are used more frequently. However, it can only be applied to some of the activities such as hauling roads, stockpiling area, grinding area and where there are chances of wind blow the dust. All the three other options which are baghouse, wet scrubbers and electrostatic precipitators can be installed in terms of units whereas, for dust, suppressants can be applied only in terms of quantity per area. Fig. 5 (a) represents net annual treatment cost of individual as well as combined treatments for the particulate matter (PM). It is worth noting that the combined cost of baghouse and dust suppressant is less than electrostatic precipitator. The combined treatments can be analyzed by using coefficient a_{ij}=1 in (3).

For NO_x, the comparison was made among the four most profound treatment methods. The order obtained depending upon the cost, removal efficiency and air quality is as follows:

SCR>NSCR>FGR>LNB

SCR has a very high cost of treatment than NSCR. Although the main process and concept of both these methods are similar, the catalysts are required for SCR which is responsible for increasing its operating cost. Fig. 5 (b) represents that NSCR has higher treatment cost as compared to FGR, while both have removal efficiency range from 60-65%. The selection of these options totally depends on the type of mining activity. In the case study, that coal power plant is used to fulfill the energy or electricity demand of this mine. To remove the sulfur dioxide, flue gas desulfurization was selected for analysis. To determine the least cost option, a comparison was made between wet and dry flue gas desulfurization. The results show that wet option is most costly as compared to other options.

B. Analysis of Pollutant after Treatment

After selecting the least cost-effective solution for each pollutant, the final concentration after treatment is analyzed using (6). Table IV represents the concentration of pollutants using simple Gaussian model and compared it national ambient air quality standard (NAAQS) of the pollutants and concentration after treatment. It is noteworthy that $PM_{2.5}$,

PM_{10} and NO_x are above the air quality criteria values and need treatment. Whereas, SO_2 is already under the limits and do not need any kind of treatment. It is clearly noticed that after treatment the reduced concentration of $PM_{2.5}$ is 1.813 μg/m^3, PM_{10} is 13.1 μg/m^3, NOx is 11.34 ppb and SO_2 is .003 ppb. The values of NAAQs are also included in the model by using "L_p" variable in air quality constraint. Thus, all the values after treatment met the criteria. The results of Table IV are directly related to DTF. It concludes that not only costing of equipment and their removal efficiency are important but also air quality criteria and production rate of the metal are significant for optimizing the control strategy.

TABLE III
OPTIMIZATION ANALYSIS OF AIR POLLUTION CONTROL TECHNOLOGY

Pollutants	Treatment options	Optimum Cost ($). 10^3
$PM_{2.5}$ and PM_{10}	1. Baghouse (BH)	567
	2. Wet scrubber (WS)	656.5
	3. Electro precipitator (EP)	1377
	4. Dust suppressant (DS)	100.98
NO_x	1. Selective catalytic reduction (SCR)	2079
	2. Non-selective catalytic reduction (NSCR)	923.93
	3. Flue gas recirculation (FGR)	239.76
	4. Low NOx burner (LNB)	170
SO_2	1. Dry flue gas desulfurization (FGD-dry)	7290
	2. Wet flue gas desulfurization (FGD-wet)	13230

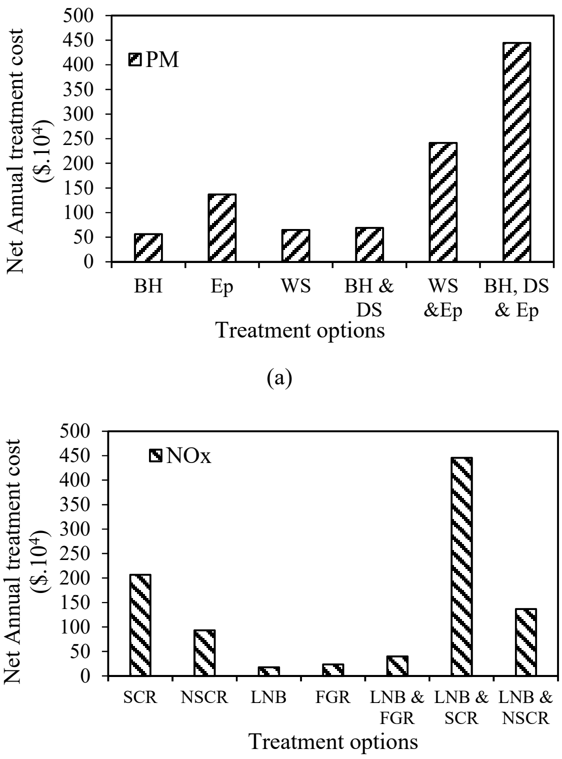

Fig. 5 Scenario analysis of various treatment combinations (a) PM, (b) NOx

TABLE IV
AVERAGE POLLUTANT CONCENTRATION WITH AND WITHOUT TREATMENT

Pollutants	Before treatment	NAAQS [19]	Optimized Treatment	After treatment
$PM_{2.5}$ (μg/m^3)	16.5	15 (μg/m^3) (annual)	BH and DS	1.813
PM_{10} (μg/m^3)	72.21	150 (μg/m^3) (24 hr)	BH and DS	13.1
NO_x (ppb)	62	53 ppb (annual)	NSCR	11.34
SO_2 (ppb)	5.8	75 ppb (annual)	FGD-dry	.003

C. Comparison of Control Cost and Production

APCM model is solved for the case study to meet both production and emission control requirements. Fig. 6 depicts relation of copper production and control cost of pollutants. Four different solutions are identified to treat particulate matter and NOx together as one option. These options are selected based on the least cost option from each set of pollutant treatment. For example, option 1 comprises of baghouse for particulates and flue gas recirculation for NOx with the total cost of 88 10^4 \$ and production of 1.2 x10^5 tonnes/yr. The option 2 comprises of a combination of baghouse and dust suppressants for particulate matter and flue gas recirculation along with low NOx burner with the total cost of 109 (10^4 \$). This option is able to produce 1.3 x 10^5 (tonnes/yr). Whereas, option 3 includes baghouse for particulate matter with the non-selective catalytic reduction for NOx with the production of 1.47 x 10^5 tonnes/yr the cost of 149 x10^4 \$. The last option considered for comparison includes baghouse and dust suppressants for particulate matter and non-selective catalytic reduction for NOx. The option 4 is like option 3 with the addition of dust suppressants and able to produce 1.36 times more copper at the cost of 162 x10^4 \$.

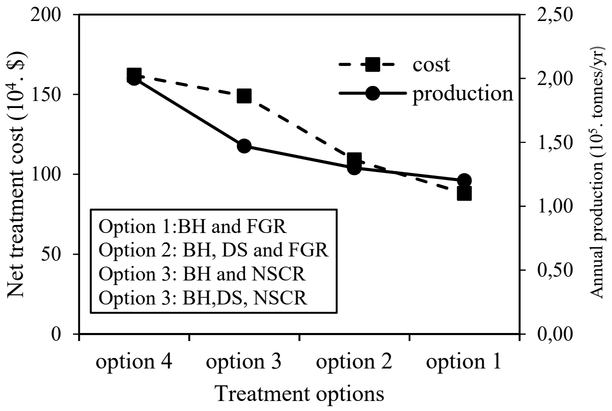

Fig. 6 Correlation of control cost with annual production

If the planner strategized to select only on cost basis then option 1 is the minimum cost solution. If both production and cost of treatment must be evaluated then option 3 and 4 can be considered.

VI. CONCLUSION

In this study, an optimization APCM for multi-pollutants dispersion from the mining sector has been presented. The model is based on a linear algorithm to achieve a single objective by determining the least cost option among various treatment technologies. Various simulation runs were conducted for each pollutant and every treatment option. The approach also considered the prescribed national air quality standard and availability of resources, which are incorporated as constraints. The effect of meteorological parameters such as wind speed, atmospheric stability, and the temperature was introduced as DTF. A general Gaussian air dispersion model was applied to determine the concentration after considering the treatment effect. The emission rate of pollutants from various mining activities helps to determine the concentration at downwind location, while incorporation real time meteorological data. Moreover, the uncertainties in certain meteorological parameters such as wind speed and atmospheric stability were overcome through probability analysis by using Monte Carlo method. In conclusion, the model can be used as a decision tool for planners to select the sustainable and cost- effective technology to control air pollution.

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