



Life Cycle Based Air Pollution Analysis and Management for Open Pit Mining

Zunaira Asif* and Zhi Chen

Concordia University, Montreal, QC, Canada

Abstract. Mining activities are responsible for deteriorating the air quality at local or receptor level. In this paper, a life cycle based air quality modeling system (LCAQMS) for the mining is proposed. The aim of the model is to integrate different environmental models for understanding the impact of mining activities and THE effect of various atmospheric factors toward the vulnerability of air quality. The system is based on a life cycle assessment model, artificial neural network model, air dispersion model, and multicriteria decision model which is used to develop air emission inventory, carbon footprint analysis, prediction of the pollutant concentration, and air pollution control solutions respectively. The model is applied to the open pit copper mine, USA. The results reveal that NO_x (39.6%), SO_2 (25.8%), CO (17%), PM_{10} (10.7%), and $\text{PM}_{2.5}$ (3.6%) are the profound pollutants produced during copper mining. The study also helps to analyze the environmental impacts based on various indicators such as acidification and climate change. Prediction of pollutants at ground level have been determined and further validated with field data at different monitoring stations. Thus, the LCAQMS can serve as a mine-targeted air pollution model which helps to assess and predict the air quality with the selection of a cost-effective solution for air pollution.

Keywords. *air pollution, mining, decision analysis, life cycle, carbon footprints*

*Correspondence:
zunairabilal1@gmail.com

1. Introduction

Air quality management in the mining industry is a complex task, mainly due to the wide range of sources, and the fact that these sources are highly variable in nature, difficult to measure, and site-specific in terms of energy consumption and pit area. The concerned environmental challenge in the mining sector is vulnerability to the air quality due to the hazardous pollutants (Asif and Chen, 2016). For instance, nitrogen oxide (NO_x), sulfur oxide (SO_x), and particulate matter (PM_{10} and $\text{PM}_{2.5}$) from various activities of mine and greenhouse gas (GHG) emissions (Mining Association Report, 2012). With increasing environmental awareness, more and more mining companies are showing their interest to address the air quality problems and carbon credit and to identify appropriate corrective measures to improve the environmental sustainability of their processes.

Over the last few years, many researchers studied to develop inventories by the help of life cycle assessment (LCA) modeling in the metal mining industry (Awuah-Offei and Adekpedjou, 2011; Durucan et al., 2006; Ingwersen, 2011; Norgate and Haque, 2010; Norgate and Haque, 2012; Northey et al., 2013; Nuss and Eckelman, 2014). Thus, it is significant to include maximum dependent variables which are directly responsible for environmental burden in mining industry. To strengthen the assessment in the complex mining system, an improved and integrated approach to quantify the greenhouse gases and carbon footprint based on life cycle thinking needs to be developed and implemented. Thus, the artificial neural network models (ANN) are capable to reflect the underlying linear and nonlinear relationship amongst the air pollution data and further predict the future concentration based on training of the past data. In recent years, the

application of ANN models has been applied successfully to assess the air quality (Chan and Jian, 2013; Cheng et al., 2012). Moreover, it seems to be a worthy choice because it shows remarkable performance while dealing with complex interactions within the given input parameters (Gobakis et al., 2011). However, very limited work is available in field of metal mining. Considering this fact, the present study conceived the possibility to predict the carbon footprint analysis in terms of CO₂ equivalent (eq.) emission as the midpoint impact analysis with varying greenhouse gases.

Mining operations obtain air quality permits prior to starting any new project, construction or expansion. This can involve prediction of pollutant concentration emitting due to existing various mining operations. In the past, numerous air quality models such as the box model, Gaussian model, the Eulerian model, and the Lagrangian model have been reported to be used for the prediction of air quality for the mining industry (Reed, 2002). The methods mentioned above have some limitations when applied to the mining system. For air quality assessment, the traditional mathematical models do not incorporate emission rates from various mining activities; these methods are incapable of handling uncertainties introduced by complex mining system. Most of the studies, such as dust propagation, are only based on modeling of single pollutant and ignore other pollutants like greenhouse gases and heavy metals. Most of the models ignore the deposition and settling of the particles. Therefore, mining industry needs a model that can accurately predict the pollutants (Bonifacio et al., 2013). In general, Gaussian-based models are easier to implement with relatively fewer requirements for the meteorological data and computational effort. Despite the usefulness of above mentioned model, there is a quest continue to contribute more in the field of mining with the advanced Gaussian algorithms.

Air quality deterioration has been increasingly drawing researchers' attention over the past few decades due to its close relation to the health of the workers as well as the surrounding communities. Secondly, air is the only medium which can take pollutants to a certain distance far away

from the source. Air pollution control technologies in the mining industry are categorized into source control and alternative solutions. However, selecting the suitable optimal technology for a mine site is a critical task. Because most environmental decision making (i.e., the selection process) involves multiple criteria and conflicting objectives (e.g., minimizing pollution and cost while maximizing production) (Kiker et al., 2005; Sadiq and Tesfamariam, 2009). Multiple criteria decision analysis (MCDA) methods deal with such problems whose alternatives are predefined and multiple criteria-based ranking to evaluate the alternatives (Sadiq and Tesfamariam, 2009).

The objective of this paper is to develop a life cycle based air quality modeling system for open pit mining and integration with the field data.

2. Research Methodology

LCA-based air quality modeling system (LCAQMS) consists of four primary models including a life cycle model, artificial neural network model, air dispersion model, and multicriteria decision analysis as shown in Figure 1. These models are comprised of mathematical equations and analytical solutions.

The main framework is divided into four parts: (1) quantitative analysis and impact assessment which comprises of a life cycle assessment model and artificial neural network model to generate inventory along with environmental impact assessment and carbon footprint analysis for the mine in terms of CO₂ equivalent respectively, (2) air quality assessment and prediction module which consists of the mining air dispersion model (MADM) to generate the predicted air pollutants concentration at various receptor levels while considering the deposition effect, (3) selection of treatment method which comprises of multicriteria decision analysis (MCDA) system to produce weighting index and to provide the best sustainable alternative to control air pollution, and (4) interpretation and visualization is the final user interface phase of the system. LCAQMS for the mining is developed using the C# programming language in Visual Studio 2015. The original data are processed through the MATLAB

that represents the algorithms of the models, and the results of the models are subsequently displayed and stored in Excel files. However, visual graphs prepared through this tool can be used in raw with little improvement. The models have a single graphical user interface and shared data storage.

2.1 Life Cycle Assessment (LCA) Model

The life cycle inventory is developed using an inverse matrix method by utilizing a linear system.

The goal and scope of LCA in this study is to include all the activities responsible for potential pollutants. In the first step, all the technical data are used as input of technology matrix which is used to compute the scalar vector. Consequently, an emission load matrix is constructed based on the estimated emissions. The scalar matrix and emission load matrix is multiplied to produce an air pollution inventory.

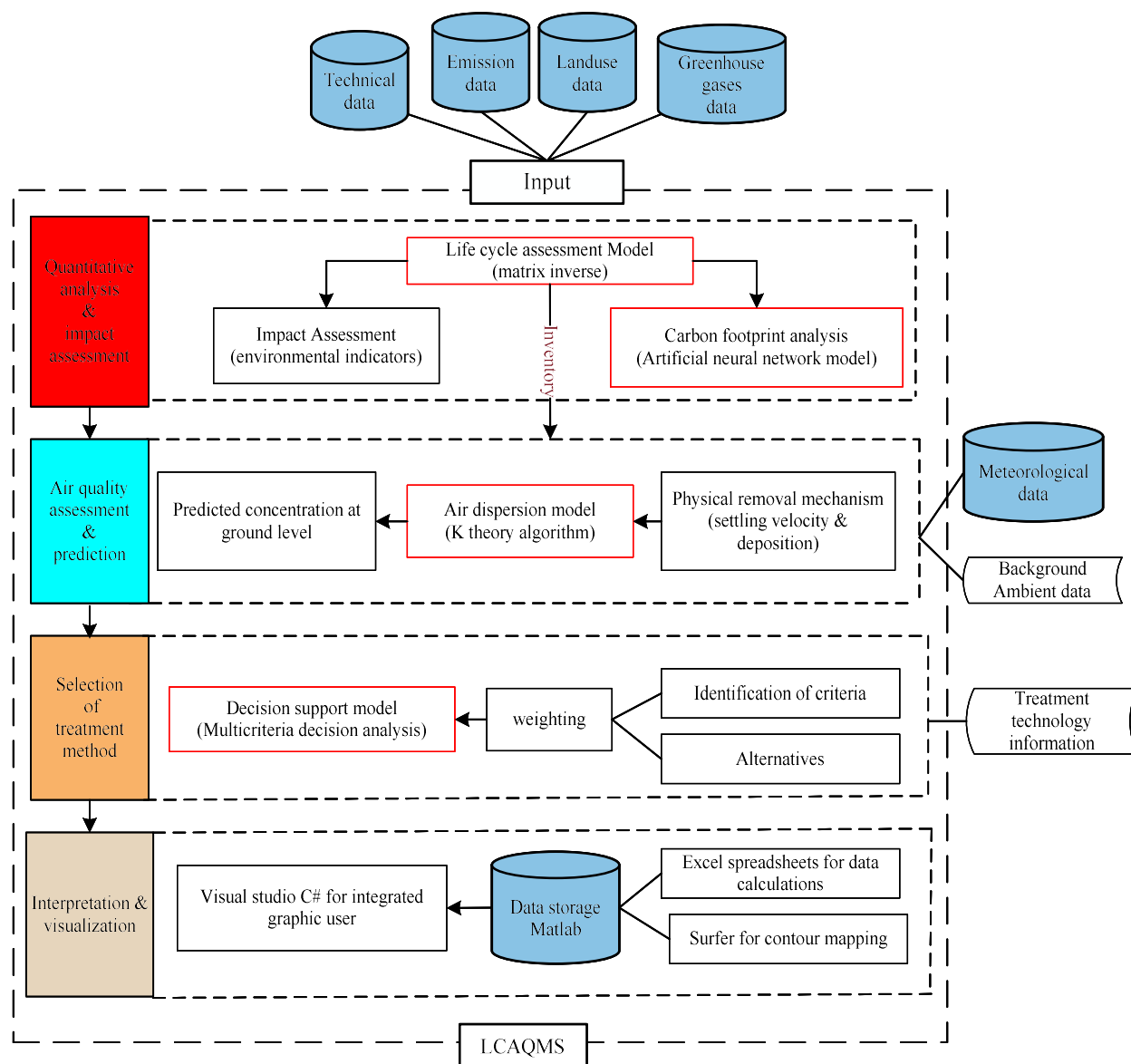


Figure 1: Conceptualized framework of LCA based air quality modeling system (LCAQMS)

The technical data of the mine is represented as technology matrix "A" and all the air pollutants emission data is represented as environmental intervention matrix "B". In both matrices A and B, columns represent the processes and rows are the flows. Each process in the matrix is represented by demand vector "p" and boundary conditions for the flows at the system boundary are expressed by the scaling vector "α". Thus, the scaling vector α can be derived as (Guinee et al., 2011):

$$A\alpha = p \quad [1]$$

$$A^{-1} \cdot p = \alpha \Rightarrow$$

$$\begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \dots & a_{mn} \end{pmatrix} \begin{pmatrix} p_1 \\ p_2 \\ p_m \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_m \end{pmatrix} \quad [2]$$

technology matrix . demand vector = scaling vector

A represents a square matrix, and A^{-1} is the inverse matrix of A. Then, the final environmental load vector β can be obtained by using the environmental intervention matrix B as (Cooper, 2003):

$$\beta = B \cdot \alpha \quad [3]$$

For assessing other midpoint impacts various environmental indicators are used depending upon the type of potential pollutant produced. Mainly climate change, acidification, photochemical oxidant formation, and particulate matter formation are used for characterization of data by using TRACI method (It is a tool which provides characterization factors for impact assessment based on global warming potential).

2.2 Artificial Neural Network Model

Artificial neural networking is a mathematical algorithm which assist in recognizing pattern and predictions based upon the past database. The advantage to using ANN lie in their capacity to solve linear and nonlinear problems. For this study, the dataset has been divided as training dataset (70%), testing dataset (15%) and validation dataset (15%) based on random selection. Back-propagation artificial neural network

(BPANN) is selected for carbon footprint modeling. For this study, the model mainly consists of four input variables (x) such as fuel consumption (x_1), CO_2 (x_2), N_2O (x_3), CH_4 (x_4) and operating hours of equipment (x_5) depending upon the site conditions and database and one output: CO_2 equivalent kg.

2.3 Air Dispersion Model

The dispersion of pollutants from various point sources in the mining sector can be determined using a simple advection-diffusion equation. A Cartesian coordinate system is used to represent the x, y, and z-axis in the direction of the wind (constant), along with the crosswind direction and in the vertical direction respectively. The governing equation for the pollutant transport is expressed as follows (Essa et al., 2014):

$$\frac{\partial c}{\partial t} + u \frac{\partial c}{\partial x} + v \frac{\partial c}{\partial y} + w \frac{\partial c}{\partial z} = \frac{\partial}{\partial x} \left(k_x \frac{\partial c}{\partial x} \right) + \frac{\partial}{\partial y} \left(k_y \frac{\partial c}{\partial y} \right) + \frac{\partial}{\partial z} \left(k_z \frac{\partial c}{\partial z} \right) + R + S \quad [4]$$

whereas C is the pollutant concentration (g/m^3) at any time t (sec) and at any location (x, y, z); k is the eddy diffusivity coefficient in x (k_x), y (k_y) and z (k_z) direction ($m^2.s^{-1}$); u , v , and w are the average wind speed component (m/s); R is the term used for sinks (g/m^3s); and S used for the sources (g/m^3s). Equation 4 can be solved by considering some assumptions such as (i) neglecting the sources and sinks for the current situation thus, $S=0$; $R=0$; (ii) at steady state $\frac{\partial c}{\partial t} = 0$;

(iii) the wind is blowing in x direction only so $v=w=0$; (iv) transport of contamination in x direction is outweighed due to the wind as compared to eddy flux in the same direction,

$$u \frac{\partial c}{\partial x} \gg \frac{\partial}{\partial x} \left(k_x \frac{\partial c}{\partial x} \right) \quad \text{Hence, reduced to}$$

$$u \frac{\partial c}{\partial x} = \frac{\partial}{\partial y} \left(k_y \frac{\partial c}{\partial y} \right) + \frac{\partial}{\partial z} \left(k_z \frac{\partial c}{\partial z} \right)$$

Assuming that the plume is released from the source considering the same coordinates system, then coefficients of eddy diffusivity can be calculated by using standard deviation as follows (Rao, 2007):

$$\sigma^2 x = 2 t k_x; \sigma^2 y = 2 t k_y; \sigma^2 z = 2 t k_z \quad [5]$$

In order to observe the contamination at the receptor site, downwind distance x is considered, and eddy diffusivity can be written as:

$$k_z = K u_o x \quad [6]$$

whereas K is von Karman constant with a constant value of 0.4; u_o is the frictional velocity (m/sec; mostly taken as 0.1 of wind speed).

The following expression is used to predict air quality at receptor level including dry deposition (V_d m/sec) based on the separable variable k-theory Gaussian algorithm to get the final analytical solution for mining activities.

$$C(x, y, z, t) = \sum_{n=i} \frac{E_i}{u h (4 \pi t k_y)^{\frac{1}{2}}} \exp\left(\frac{-y^2}{4 t k_y}\right) \exp\left\{\frac{-v_d}{k u_o} \left(\frac{(Z-H)}{x} - \frac{v_d}{2u}\right)\right\} \quad [7]$$

where H is the plume rise (m), and Z is the mixing height (m). E is the emission rate per unit mining activity "i" (g/s).

2.4 Multi-Criteria Decision Analysis (MCDA) System

MCDA technique is used to provide a structural approach to a decision-making process. This technique enables systematic analysis and modeling of preferences with the aim of providing help and guidance to decision makers in identifying their most desired solution. The selected approach consists of four primary stages: (1) identification of alternative methods considered as actions in the context of objective of the study at the data gathering stage; (2) defining the criteria and assigning values which assist in evaluating the options; (3) analysis of data by determining the preference functions and parameters, and (4) the decision-making stage in which the best cost-effective method is selected based on rankings of alternatives. Generally, the MCDA problem for sustainable solution involves "m" alternatives evaluated on "n" criteria. The grouped decision matrix can be expressed as follows (Yang et al., 2012):

Criteria	C_1	C_2 C_n
Weights	W_1	W_2 W_n
Alternatives	A_1	A_2 A_n

[8]

$$\begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{bmatrix} \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$$

where x_{mn} is the evaluation given to alternative A_m with respect to criterion m , W_n is the weight of criteria n , n is the number of criteria, and m is the number of alternatives.

3. Case Study

Mine A is an open pit copper mine located in Utah County, USA. Processing facilities included a concentrator, a 175-megawatt (MW) coal-fired power plant, a copper smelter, and a copper refinery. The operation produced approximately 300,000 tons of refined copper per year plus significant quantities of other metals such as gold. For this study, air emissions during copper production is considered. Five years' average daily data from the year 2011 to 2015 is collected. For validation, seven monitoring stations (S1 to S7) have been examined.

The parameters and variables were selected from the field, technical reports, and correspondence of the mining company. The technology matrix included 10 variables divided as processing flows [feed(ton/hr), quantity produced (ton/hr) and waste produced (ton/hr)]; technical flows [Area (m²), capacity of unit (Mt), frequency of activity per shift (number), truck trips per shift (number) and operating hours per shift (hr)] and energy flows [fuel consumption (L/hr) and energy consumption (Kwh/t)]. Moreover, emission data from various mining activities were included.

For the input of mining air dispersion model (MADM), three kinds of input database were used including geographic, meteorological, and air emission inventory from the LCA output as shown in Figure 1. The geographic database included digital maps, land usage data, elevation

dataset, surface roughness length, and processed into gridded surface within the modeling domain. Whereas, meteorological data included the wind speed, direction of the wind, ambient temperature, precipitation rate, stability class, and so on.

For multicriteria decision analysis, two different categories have been analyzed for ranking to minimize the air contaminants and greenhouse gases (see Table 1). Criteria to evaluate each alternative were identified and data for each criterion was obtained from different mining reports by experts. The chosen criteria for the decision system are minimize the air pollution, minimize the cost, maximize the extraction rate or efficiency, maximize the sustainable performance, minimize the risk associated with the pollutants, minimize the quantity required for chemicals and application rate in context of dust suppressants, and maximize the future use and minimize the energy consumption.

4. Results

4.1 Life Cycle Assessment

An air emission inventory was generated by using the inverse matrix method. Figure 2 shows the percentage distribution of the pollutant's inventory results for the year 2011–2013, illustrating that mine "A" contributed a maximum amount of NO_x (39.6 % mostly NO_2) and SO_2 (25.8%). Thus, the rest of the environmental load was because of CO (17 %), PM_{10} (10.7 %), $\text{PM}_{2.5}$ (3.6 %), VOCs (2.3%), NH_3 (0.63%), CH_4 (0.16%), and Hg (.001%). Diesel fuel combustion is one of the major sources of NO_x production. During the smelting and refining process, nitrogen oxide is produced. The coal power plant is the primary source of SO_2 emissions at the mine site. Most of the particulate matter is generated from natural activities at a mining site such as heavy machinery, bulldozing, blasting, and hauling of trucks on unpaved roads. Moreover, PM_{10} is also emitted when the wind blows over different types of stockpiles. PM_{10} and $\text{PM}_{2.5}$ are produced mainly from mobile equipment and vehicle exhausts.

Table 1

Identification of alternatives to minimize air pollution

Treatment methods	Removal efficiencies	References
Category 1: Air pollution control alternatives		
Bag house	99% of captured pollutants	(Driussi and Jansz, 2006)
Hood over the conveyor belt	99-100%	(Cecala et al., 2012)
Capping of waste by vegetation	75%	(Sheoran et al., 2013)
Chemical stabilizer for haul roads	85%	(Dwayne and Regensburg, 2001)
Water spraying	50-75%	(Prostański, 2013)
Category 2: Minimization fuel consumption to reduce greenhouse gases		
Biodiesel (blended form)	98%±11% of CO	(Bugarski et al., 2014)
Idling reduction using routing systems and real time GPS	15 % reduction in GHGs (total)	(Vivaldini et al., 2012)
Concentrated solar thermal technologies (CST)	15 % reduction in GHGs (overall mine)	(Eglinton et al., 2013)
Electric drilling as existing system	42 % reduction of fuel from stationary fuel combustion	Mine A, USA

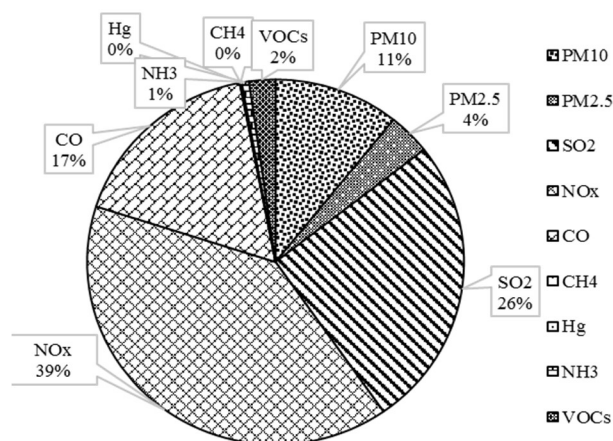


Figure 2: Percentage distribution of air pollutants inventory for mine A

Whereas, CO is produced due to heavy equipment usage during the processing of ore and incomplete combustions. During the data collection, it was found that landfill methane gas is being utilized for the refinery process from an adjacent municipal waste dump to replace natural gas used to heat the electrolyte. CH₄ is also considered as a greenhouse gas which may be produced due to fuel consumption such as diesel, gasoline, and propane; although it is not directly generated due to the mining activities. Usually, the presence of VOCs is more profound during the smelting processes of metals.

Using the TRACI method, the impacts of the same mine were calculated, based on the four selected environmental indicators which are climate change, acidification, particulate matter formation, and photochemical oxidant formation. The results imply that it is possible to attribute the calculated environmental impact to each mining activity included within the boundary conditions and trace it back to the unit process(es) that generated them. As an example, climate change and acidification are presented in Figure 3. Furthermore, the results were normalized to the midpoint level based on background concentration database available at the air monitoring program.

4.2 Carbon Footprints

The contribution of three greenhouse gases (CO₂, CH₄, N₂O) were analyzed along with the fuel consumption and operating duration which is directly subsidize to the carbon credit. The sources subsequently included the stationary fuel combustion sources, coal power plant, and adjacent waste landfill site to collect data for CH₄. Different combinations based on various nodes was performed through the artificial neural network model for each scenario. Figure 4 represents the modeled average value of carbon credit for each year for mine A and then compared it with the monitoring values for the same year. The trend sharply increased for the year 2013 but then gradually lowered for 2014 and 2015.

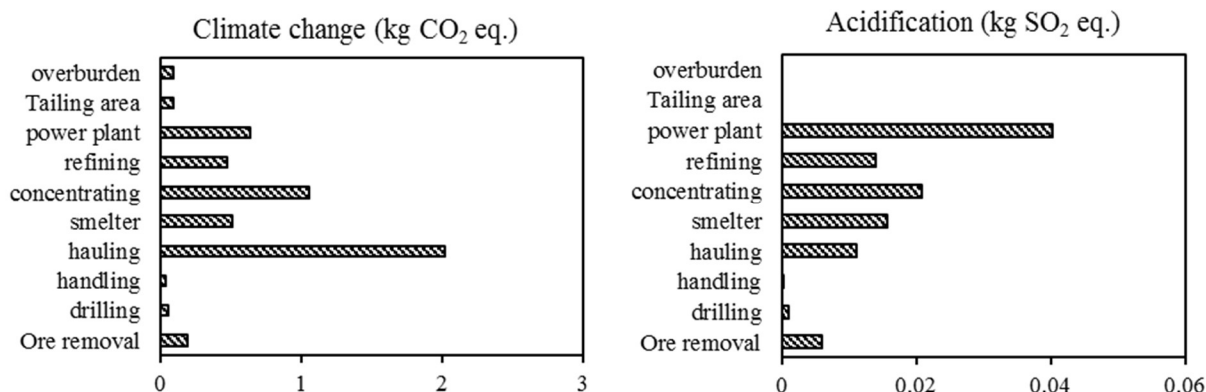


Figure 3: Midpoint impact assessment using TRACI

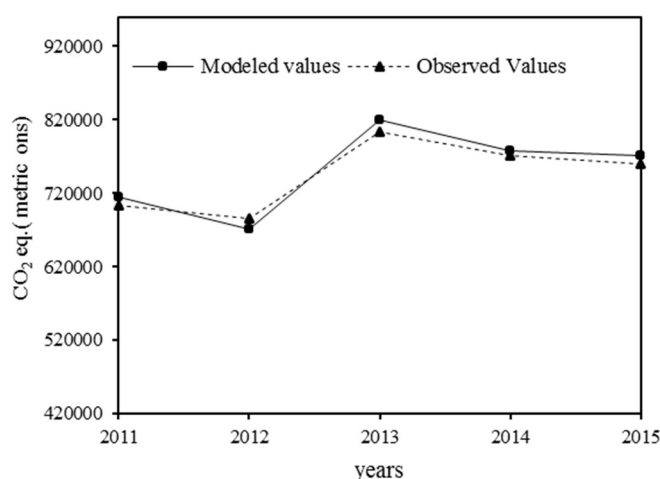


Figure 4: Carbon footprints for mine A and field comparison

4.3 Air Dispersion Analysis

The predicted concentrations at ground level were determined using the MADM algorithm while considering the dry deposition effect due to gravitational settling. Figure 5 shows the contour map representing elevation values at y-axis and distances interval at x-axis. Maximum values for $PM_{2.5}$ and PM_{10} were observed at the mining site. The predicted concentration gradually reduced as it traveled as a plume away from the source. For SO_2 , maximum concentrations were predicted around the smelter and refinery area of mine A other than the mine pit. The main reason behind this is that the energy source of these units is the coal power plant. Moreover, it is interesting to observe that NO_x was found from 44 to 60 ppb not only around and at the mining site but also near the mine pit. It is noticeable that NO_x is high in this area due to transportation activities during hauling and other mobility of the equipment and other incomplete combustion of engines.

4.4 Decision Analysis

Among the air pollution control alternatives, the preferred option based on the seven criteria is capping/vegetation followed by hood over the conveyor, water spraying, bag house, and chemical stabilization. The analysis results show that to minimize the carbon footprints by controlling fuel consumption, idling reduction is the dominated preference followed by CST program as an alternative. Table 2 illustrates the alternatives based on positive flows (Φ^+) and negative flows (Φ^-) for mine A regardless of two different categories which are air pollutants and minimization fuel consumption to reduce greenhouse gases. More inclined toward the positive flow, it would be better if the solution is based on the selected criteria. If all the options are considered as one group to fulfil the objectives of this study then in this situation, capping of vegetation along with the combination of idling reduction and CST program are dominated alternatives. Whereas, the biodiesel method for the reduction of greenhouse gases is considered as a last preferable option as compared to other options. In conclusion, the good networking also assists in selecting suitable technologies as a common set to implement a plan to control the air pollution at the mine site effectively.

Table 2

Results of alternatives analysis using MCD

Alternatives	Φ^+	Φ^-
Idling reduction program	0.42	0.16
Capping/Vegetation	0.47	0.22
CST program	0.39	0.23
Hood over the conveyor	0.35	0.26
Water spray	0.36	0.35
Bag House	0.33	0.34
Chemical stabilizer	0.30	0.37
Electrical drilling	0.22	0.42
Biodiesel	0.12	0.62

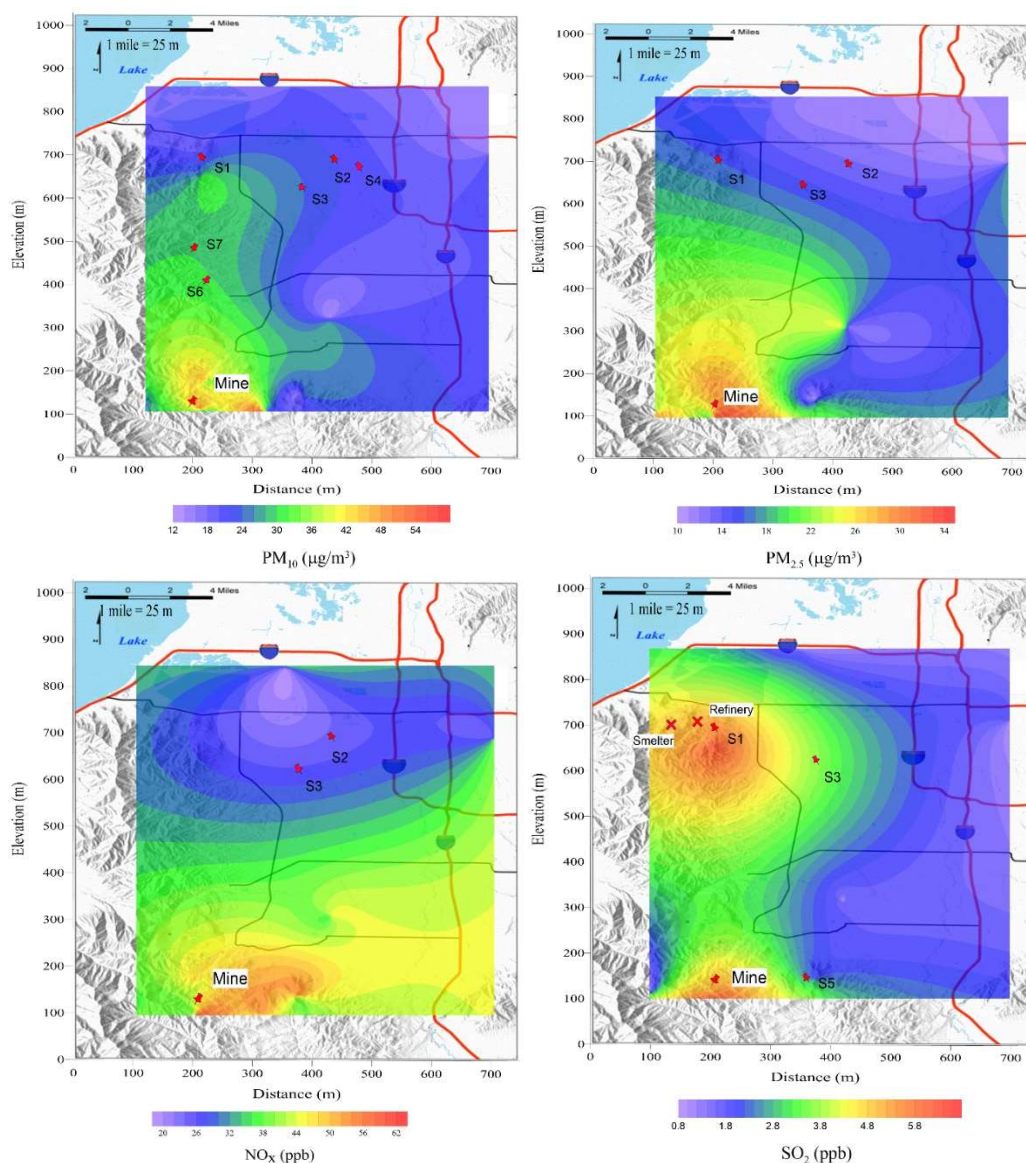


Figure 5: Contour mapping of Air quality pollutant concentrations for mine A based on daily average from 2011 to 2015 for PM₁₀; PM_{2.5}; NO_x; SO₂

5. Discussion

The LCAQMS allows the calculation of site-specific LCA impacts based on a field data and provides a realistic way to allocate environmental burdens. It provides the level of details, essential to facilitate the LCA for impact categories. LCAQMS application reveals that by developing inventory, assessing midpoint impact, and analyzing carbon footprint, it could be useful as an assessment tool based on life cycle approach for further investigation of air pollution. The main aim that motivated the development of the

MADM method is to provide a simple air quality model that would provide predicted concentration profiles for pollutants through the advanced Gaussian algorithm which can be easily applied to the mining sites.

The MADM simulation is examined and validated by comparing the modeling results with the observations values of monitoring stations (S1 to S7) under the same environmental conditions using the average daily data from January 2011 to December 2015. Figure 6 illustrates the comparison of all the observed and modeled values

at the monitoring station S1 for the available pollutants as an example. For NO_x , S3 data is considered as there were no observing data available at S1. Similar testing was performed for each monitoring station. It is noteworthy that 24-hour daily maximum standards were used for comparison for $\text{PM}_{2.5}$ and PM_{10} . Whereas, 1-hour daily maximum values were used for SO_2 and NO_x . Thus, all the values met the national ambient air quality standards (NAAQS). Only a few samples in the case of $\text{PM}_{2.5}$ exceeded the standard. Results for $\text{PM}_{2.5}$, PM_{10} , SO_2 , and NO_x were

considered for regression analysis. Table 3 represents the coefficient of determination (R^2) for all the four pollutants at different monitoring stations based on average values from the year 2011 to 2015. These results indicate that the MADM model can satisfactorily reproduce the variations of particulate matter and gaseous particles (SO_2 and NO_x). Moreover, the correlation value shows that model could generate predicted results using a selected input parameter at various locations.

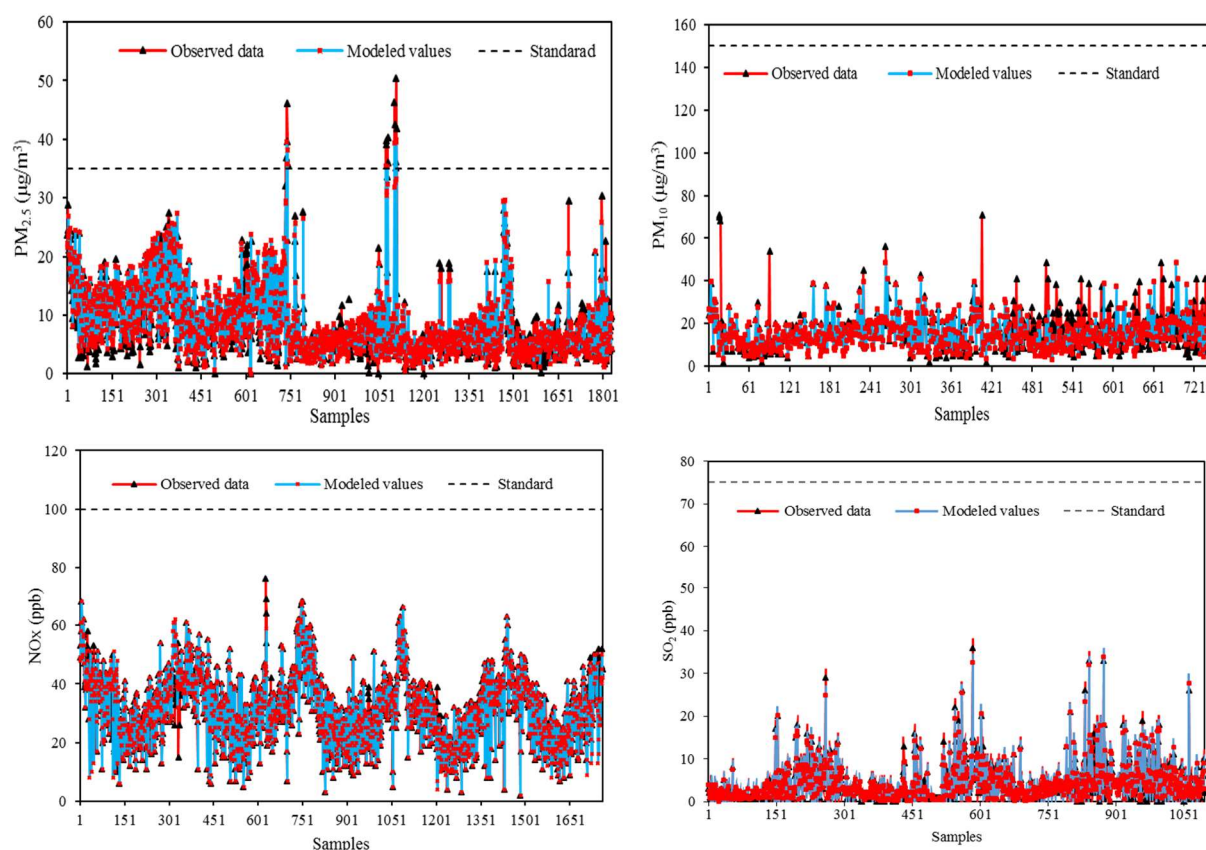


Figure 6: Correlation between modeling and monitoring data with standards for $\text{PM}_{2.5}$ at S₁ (2011-2015); PM_{10} at S₁ (2012-2014); NO_x at S3 (2011-2015); SO_2 at S₁ (2011-2013)

Table 3

Regression analysis (R^2) for pollutants at different monitoring stations

Station Id	PM _{2.5}	PM ₁₀	SO ₂	NO _x
S1	0.87	0.79	0.92	--
S2	0.77	0.78	--	0.81
S3	0.71	0.74	0.73	0.75
S4	--	0.81	--	--
S5	--	--	0.74	--
S6	--	0.84	--	--
S7	--	0.85	--	--

6. Conclusion

This study was conducted to explore the new integrated life cycle assessment-based air quality modeling system (LCAQMS) for the open pit mining. Inventory development, carbon footprint analysis, air quality modeling, and a decision of the best treatment technology to minimize air pollution are the key features of this system. Based on the inventory results of air emissions

developed in the copper mine study, it was observed that NO_x and SO₂ were major contributors towards the environmental load. The profound midpoint modeling impacts of copper mine A were determined using the TRACI method. Whereas, the BPANN simulation technique was used for carbon footprint analysis of mine A. Conclusively, this mine was responsible for producing an average 0.7×10^6 metric tons of CO₂ eq. from the year 2011 to 2015 because of greenhouse gases emissions and fuel consumption during the mining activities. Mining air dispersion model (MADM) has been developed for the modeling of air emissions by considering various mining activities, emission rates, particle settling, and deposition. For selecting the best technology based on various selection criteria, the MCDA method was used. The model can be used for the environmental assessment by generating its air pollution inventory, prediction of air quality at receptor level based on different mining activities and atmospheric conditions, and management scenarios. Thereby it enables to improve the environmental performance and helps to select the best optimum cost-effective solution for treatment of air pollution.

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