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A Life Cycle Based Air Quality Modeling and Decision Support System (LCAQMS) for Sustainable Mining Management

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ABSTRACT. Mining activities contribute the high level of air pollution at ground level and have significant environmental impacts. There is an urge to develop an integrated modeling system which helps to analyze these pollutants and their control strategies. Therefore, a new integrated approach is conceptualized as life cycle based air quality modeling system (LCAQMS) for the mining. This paper focuses on incorporating air quality modeling to understand the severity of air pollution in mining and developing an integrated system for mining related decision support with a field application. The system integrates inverse matrix which is used to develop air emission inventory; characterization method to assess the environmental implications; artificial neural network model for carbon footprint analysis; air dispersion modeling to predict the pollutant concentration at receptor level; and multicriteria decision analysis tool to provide air pollution control solutions. The developed LCAQMS method has applied to a copper mining site in the US. Inventory results reveal that NO_X and SO_2 produced more as compared to the other pollutants for this site. The study also helps to quantify the carbon credits for the copper mine. Prediction of the four significant pollutants (PM_{10}, $PM_{2.5}$, SO_2, NO_x) at ground level have been further calculated and validated with observed values at seven different monitoring stations. The modeling results have supported selecting the best alternative management technology for the air pollution control. It indicates that the developed LCAQMS can serve as a useful tool to assess, predict and assist in the selection of environmental mitigation options for mining sites.

Keywords: integrated environmental modeling, air pollution, mining, decision analysis, life cycle, carbon footprints

1. Introduction

Air quality management in the mining industry is a complex task because of a wide range of pollution sources which are highly variable in nature and site-specific. The concerned environmental challenge in the mining sector is vulnerable to the air quality due to the hazardous pollutants (Asif and Chen, 2016). For instance, exceeded limits of nitrogen oxide (NO_x), sulfur oxide (SO_x), particulate matter (PM_{10} and $PM_{2.5}$) and greenhouse gases (GHG) can cause serious health issues (Mining Association Report, 2012). The tracking trends in air emissions provided an indication that NOx and PM_{10} emissions have both increased from 2008 to 2011 in the North America mining and quarrying subsector (CIEEDAC, 2015). The generation of greenhouse gases is inevitable or likely due to consumption of diesel fuel at a larger level. In 2011, the metal mining sector emitted 3500 CO_2 eq. (Kt) of GHG with an increase of 300 Kt (8.5%) as compared to the year 2000 (CIEEDAC, 2015). Of note, emissions increased by 15.7% (3800 Kt) between 2006 and 2008 before increasing again in the years 2012 and 2013 (Asif and Chen, 2016). Hence, poor air quality in mines can lead to occupational illness and death of workers. Sixty-nine mine workers died from occupational diseases including cancer, according to claims accepted by the workplace safety and insurance board (WSIB) of Ontario between 2008 and 2013 (Ontario Ministry of Labor, 2013). 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.

Integrated environmental modeling (IEM) provides a science-based structure to advance and combine the multidiscciplinary knowledge. It provides a platform to assess, investigate, and predict the environmental system and its response to external inputs (Laniak et al., 2013). Because of its broad scope, it brings researchers from multiple disciplines together with decision makers to solve problems. For instance, two approaches have been used to analyze the air quality issue in mining industries. One is life cycle assessment (LCA) approach to develop emission inventory and to analyze environmental impact (Durucan et al., 2006; Norgate and Haque, 2010; Awuah-Offei and Adekpedjou, 2011; Ingwersen, 2011; Norgate and Haque, 2012; Northey et al., 2013; Nuss and Eckelman, 2014). However, the past studies based on LCA modeling in the min-

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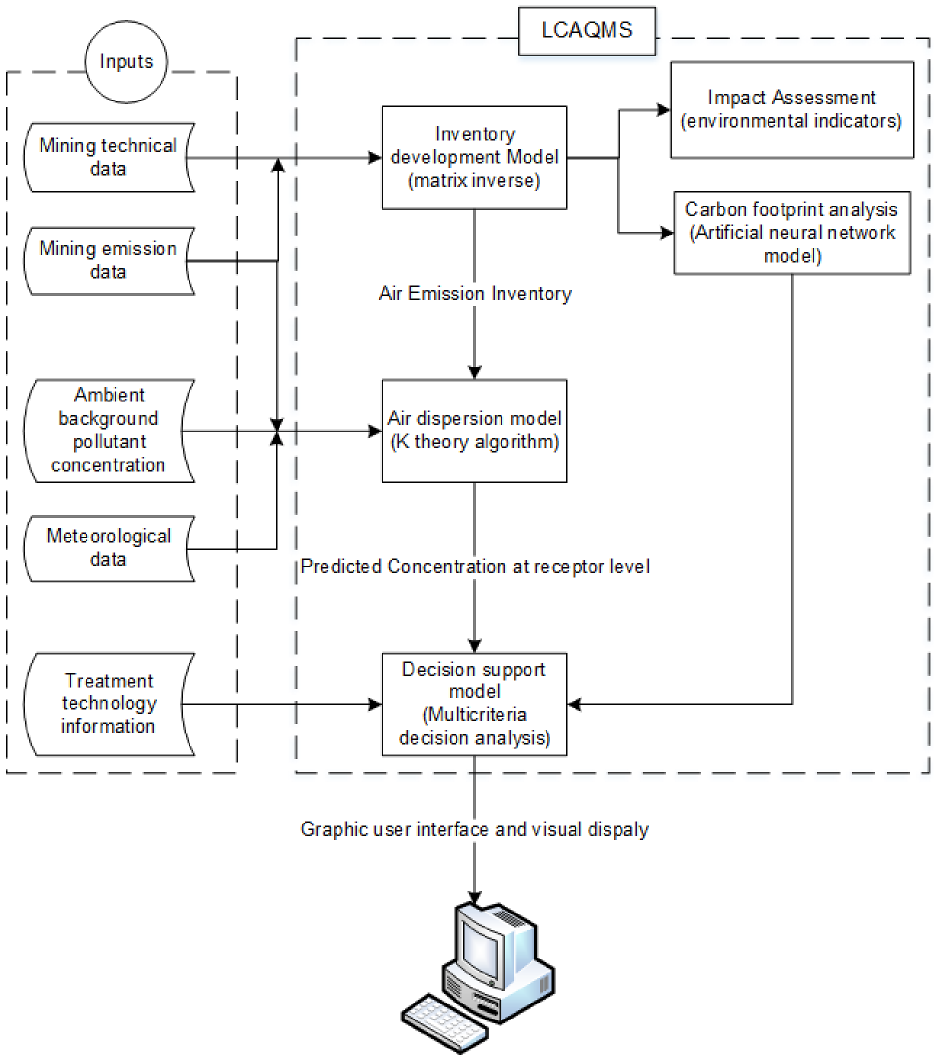

Figure 1. Integrated framework of LCA based integrated air quality modeling system (LCAQMS).

ing sector mostly focused on single variable or point sources such as tailing waste, mine haulage, and are mostly lacking in detailed representation of variables utilized in a linear or non-linear system for flows analysis (Ingwersen, 2011; Awuah-Offei and Adekpedjou, 2011). Another approach is mine targeted air quality modeling to predict concentration of the pollutants (Bhaskar et al., 1989; Reed et al., 2002; Cimorelli et al., 2005; Bonifacio et al., 2013). Numerous air quality models such as box model, Gaussian model, Eulerian model, and Lagrangian model have been reported being applied for the prediction of air quality for the mining industry (Reed et al., 2002). However, all the reported studied have some limitations such as most of the models are mainly centered around the particulate matter and ignore other gaseous air pollutants. The earlier studies also concluded that most air quality models share common assumptions and consequently produced results based on the analysis of the single source at the mining site (Badr and Harion, 2007) and over prediction analysis (Fishwick and Scorgie, 2011; Neshuku, 2012). In this research, both approaches mentioned above have been integrated to assess the air quality and to produce an inventory for the mining system. Moreover, artificial neural network models (ANN) have been considered as efficient tools for predicting the air quality and preparing the data in a systematic way (Gobakis et al., 2011; Cheng et al., 2012; Chan and Jian, 2013). Thus, the present study is used to develop ANN model for predicting carbon footprints and integrate it with other environmental models to enhance the features of the developed system for mining.

The application of IEM is expanding with the emergence of issues related to regional scale, local scale, impacts of air quality, fate and transport of pollutants, and life-cycle analysis (Laniak et al., 2013). However, the application of IEM in the field of mining especially assessing air quality and decision analysis has a great significant. 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 the specified distance far away from the source. Therefore, it is essential to control the air pollution by introducing any promising technology. Thus, 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). Moreover, a massive database is required, and input information for each objective is often represented in qualitative or quantitative form, which is hard to understand and thus intensify the decision-making process (Tesfamariam and Sadiq, 2006). Multiple criteria decision anal-ysis (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 conceptualize the life cycle based air quality model and decision support system and to implement it to the open pit copper mining site for testing the model. The purpose of the model is to combine mining and air dispersion disciplines together by integrating with the field database and mathematical simulations.

2. Methodology and Specification

The mining system is conceptualized in terms of all the potential air pollutants and the mining technical data including meteorological conditions. This conceptualization is reflected in the architecture of framework chosen for the models. LCA based air quality modeling system (LCAQMS) consists of four primary models. These models are comprised of mathematical equations and analytical solutions which help to generate inventory, assess the impacts, predict the air pollutants at ground level, carbon footprint analysis and selection of best alternative technology. Consequently, LCAQMS includes inventory development model, artificial neural network model, air dispersion model and multicriteria decision analysis tool as shown in Figure 1.

2.1. Modeling Approach

Linear/nonlinear, statistical approach, analytical Gaussian based simulation and outranking method are used to develop inventory model, artificial neural network model, air dispersion model and multicriteria decision analysis method respectively.

The study aims to develop the LCA based air quality modeling system (LCAQMS) model which comprises of an inverse matrix as a life cycle assessment (LCA) tool to generate inventory; artificial neural network model to investigate the carbon footprint analysis for the mine in terms of CO_2 equivalent. The mining air dispersion model (MADM) is developed to generate the predicted air pollutants concentration at various receptor levels while considering the deposition effect. Multicriteria decision analysis (MCDA) system is applied to produce weighting index and to provide the best sustainable alternative to control air pollution.

In general, the model aims to provide a user-friendly interface by combining the life cycle based assessment, prediction models, decision-making tools and a database for data storage and management. For verification of the developed system, it is employed to assess the air quality condition in the open pit copper mine.

Available Resources

LCAQMS for the mining is developed using the C sharp programming language in visual studio 2015 and integrated with the inverse matrix and backpropagation artificial neural network (BPANN) model, Gaussian algorithm and visual Preference ranking organization method for enrichment evaluation (PROMETHEE) tool. 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. The algorithm of BPANN model is packaged as a dynamic link library (*.dll) by using the Matlab Compiler. The mining site data and emission inventory from the life cycle modeling are considered as inputs for MADM model. All the equations are solved in excel, and then data is imported to Matlab complier. The input data and all the variables representing alternatives are prepared in the matrix form, and the output can be directly imported to excel as CSV format. However, visual graphs prepared through this tool can be used in raw with little improvement. The contours are prepared using surfer tool. The models have a single graphical user interface and shared data storage as shown in Figure 2.

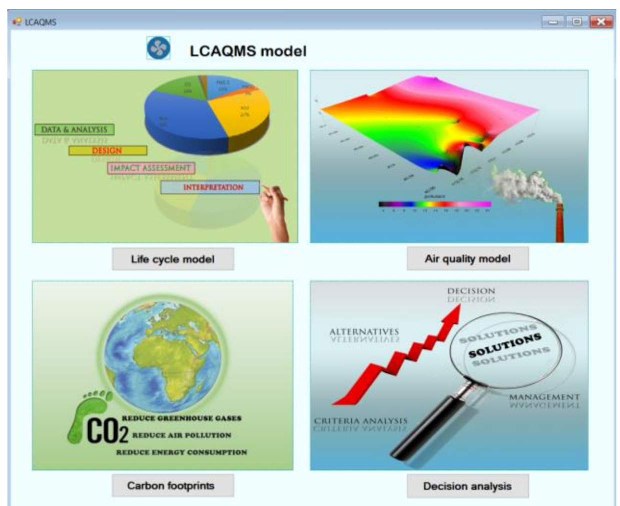

Figure 2. Graphic user interface for the LCAQMS model.

Model Users

Integrated environmental models are usually complex and are often accessible only to experienced modelers. For LCAQMS modeling, the model aims to be easily used by the site and design engineers in the mining industry. The model has been integrated to run with various treatment options for air and different atmospheric conditions relevant to management questions and stakeholder concerns. Other than LCA module the rest of the parts such as air quality and decision analysis are not

Table 1. Input Databases for LCAQMS Simulation

Category	Data	Pollutants/parameters	Description
Technical	Mining activities; infrastructure	Ore removal, drilling, hauling, handling, concentrating, smelting, refining, stockpiling/overburden, tailing and power plants	Technical reports; websites (mine A)
Emissions	Emission data per unit activity (ton/hr)	NOx, SO_2, PM_{10}, $PM_{2.5}$, CO, VOCs, CH_4, Hg, NH_3	Sampling data at source or per unit activity (mine A)
Emissions	National pollution emission inventory for year 2011 ~ 2014 (ton/year)	NOx, SO_2, PM_{10}, $PM_{2.5}$, CO, VOCs	USEPA, 2017a. Air emission inventories. (https://www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data).
Meteorology	Average daily data (2011 ~ 2015)	Wind speed (m/s); temperature (°C); precipitation (mm/hr); frequency of wind direction	NOAA (regional climate center), 2017. Salt Lake City Weather Forecast Office. (http://w2.weather.gov/climate/local_data.php?wfo=slc)
Land use	Digital mapping	Longitude and latitude; terrain type	USGS, 2017. (https://viewer.nationalmap.gov/basic/?basemap=b1&category=ned,nedsrc&title=3DEP%20View)
Air monitoring	Average daily (2011 ~ 2015)	NOx (ppb) based on 1 hr average, SO_2 (ppb) based on 1 hr average, PM_{10} and $PM_{2.5}$ (μg/m^3) based on 24 hrs average	Utah air monitoring programs, 2017. (http://www.airmonitoring.utah.gov/network/Counties.htm)
Greenhouse data	Greenhouse gases facility data Average monthly (2011 ~ 2015)	CO_2, CH_4, N_2O (CO_2 eq. metric tones)	USEPA, 2017b. Greenhouse gases data at facility level. (https://ghgdata.epa.gov/ghgp/main.do)

Table 2. 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 tailing 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: Reduction in 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)

sourced dependent and could be used separately to analyze any kind of local point source air pollution. Model output is then analyzed to provide scientific and visual interpretations for stakeholders, including regional environmental managers.

Spatial and Temporal Scales

Features of LCAQMS includes all the technical data from the mining site and real time atmospheric conditions other than emission data per unit mining activities. The three-dimensional values could be produced by considering x, y, and z directions. Three dimensions LCAQMS model also implies variable grid cells depending on the boundary conditions at the inventory development stage. Moreover, values can be predicted at different distances from $x = 0$ to 30 km depending upon the availability of stability conditions. For vertical height, modeling values can be generated at various points until concentration get sufficiently dispersed or not changed. Usually, the coupling of all the four models increases the computational demand. However, in the inventory model, the input variables are fixed, and other unnecessary parameters are eliminated using cut-off criteria rules in LCA. For carbon footprint analysis, scales require integration with time steps on the order of 8 days for more accurate results. For air dispersion model, daily average data is used along with the local weather station data. Precisely, real-time meteorological data is critical to be used to get the predicted modeled value on the specific day of the month or year.

2.2. Identify Model Structure and Input Values

The parameters and variables are selected from the fields, literature studies, technical reports and mining companies. In the case of open pit metal mining, variables defining the contribution of pollutants are determined by mining corporations and government database. ISO 14040:2006 describes the principles and framework for life cycle assessment (LCA) including life cycle inventory analysis (LCI) phase and life cycle impact assessment (LCIA) phase (Finkbeiner et al., 2006). For this study, the technology matrix for inventory development includs ten variables divided as processing flows [feed (ton/hr), quantity produced (ton/hr) and waste produced (ton/hr)]; technical flows [Area (m^2), 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). The environmental flows comprise of potential pollutants produced and may vary from mine to mine and then compiled in matrix forms (see Appendix Tables A1 ~ A2).

Calculations based on underlying environmental indicators for impact assessment. For example, characterization factors when linked with emission loads (inventory), give results in terms of impact. This relationship is used to determine the midpoint impact analysis in the first module of the model. Because of inherent variability and nature of the processes, only greenhouse gases are used to calculate the carbon credit for the mine using artificial neural network algorithm.

In the proposed mining air dispersion modeling (MADM) approach, there are three components of input database 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, etc. The added parameters are emission rate from the sampling points, stack height, stack diameter, exhaust temperature, exhaust exit velocity and plume rise. These data sets are spatially allocated and stored in the database of MADM in the corresponding compartment and saved as Excel spreadsheet. MADM has been embedded in a Matlab edition 2014a for linear regression. Visual graphs for other results are then plotted in Excel/Sigma plot, and golden software surfer V13 is used to produce contour mapping. Following Table 1 shows different sources of database and their categories used in this study.

For multicriteria decision analysis, all the outputs from MADM and BPANN are carefully evaluated to find the potential air pollution issue in the mine which helps to find the best possible control solutions. Two different groups have been analyzed for ranking to minimize the air contaminants and greenhouse gases (see Table 2). Criteria to evaluate each alternative are identified to ensure the objective of the decision analysis method. The data for each criterion is obtained from literature studies and different mining reports by experts. Existing methods of the mine site A is also included for comparison purpose. The chosen criteria for 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, maximize the future use and minimize the energy/fuel consumption.

Inventory Development Model

This phase of the LCAQMS comprises of two principal activities i.e., identification and quantification by performing inverse matrix method. The life cycle inventory is developed using matrix method by utilizing a system of linear equations. The scope is to include all activities from the stage of the ore extraction to the waste handling. In the first module, all the technical and air emission data are used as input of technology matrix which is used to compute the scalar vector. Consequently, emission load matrix is constructed based on the estimated emissions. The scalar matrix and emission load matrix is multiplied to produce air pollution inventory. In the second module of the model, back propagation algorithm is used in ANN modeling to stimulate CO_2 eq. by utilizing greenhouse emission data (CO_2, CH_4, and N_2O). For assessing other mid-point impacts five 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 (tool for reduction and assessment of chemicals and other environmental impacts) method (USEPA, 2017c). Every method has its impact category and characteristics factor which seeks to establish a linkage between a system and potential impacts. Many characterization factors are established based on the studies conducted in Europe, and only a few are based on worldwide studies such as CML, Recipe, and TRACI. Therefore, selection of method depends upon the relevancy of characterization factors to the site-specific case studies.

The technical, processing and energy flows per unit activity are together considered as an economical flow which is arranged in the technology matrix "*A*" and the environmental flows in the environmental intervention matrix "*B*". In both matrices "*A*" and "*B*", columns represented the processes and rows are the flows. Each process in the matrix is represented by demand vector "*p*" and boundary conditions for the economic flows at the system boundary are expressed by the scaling vector "*α*". Thus, the scaling vector "*α*" can be derived as (Guinee et al., 2010):

$$A\alpha = p \tag{1}$$

$$A^{-1}.\,p = \alpha \Rightarrow \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix}^{-1} \begin{pmatrix} p_1 \\ p_2 \\ p_m \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \\ a_m \end{pmatrix} \tag{2}$$

$$\text{technology matrix. demand vector} = \text{scaling vector}$$

A represents a square matrix, and A^{-1} is the inverse matrix of *A*. Items in the system boundary vector α are the absolute values of the economic flows, which cross the system boundary. Each item in the demand vector *p* is the scaling factor corresponding to the unit process. Then, the final environmenttal load vector β can be obtained by using the environmental intervention matrix "B" as (Cooper, 2003):

$$\beta = B.\alpha \text{ or } \beta = B.(A^{-1} p) \tag{3}$$

The process activities used in the construction of the computational structure of matrix based inventory are divided into ten groups with each 10 × 10 matrix based on their function and availability of data.

Artificial Neural Network Model

Artificial neural networking is a mathematical algorithm that emulates the processes to aid in recognizing pattern and predictions based upon past database. The advantage to using ANN lies 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%). Back-propagation artificial neural network (BPANN) is selected for carbon footprint modeling. Each layer has several neurons which are equal to the number of the inputs and outputs of the system. The architecture of a neural network has layers between the input and the output layers. These layers are considered as hidden layers which allow the network to identify the relevant patterns in the data and to carry out the complex nonlinear mapping between the input and the output variables. The input data, during the training of a network, are propagated in a feed-forward manner to produce output, based on the weights and predefined transfer function. The prediction error is then calculated from the difference between the rendered output and the actual output. The weights of the links could be adjusted to minimize the prediction errors. The network reflects well trained when the sum of all the errors in the system reaches minimum based on trial and error method. Hyperbolic tangent is used as a transfer function of the hidden and output layer neurons. For this study, the architecture 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 i.e., CO_2 equivalent kg. As shown in Figure 3, the input variables are multiplied by the connection weights (w_{ij}) between the input and hidden layer. The weighted signals and bias from the input neurons are summed by the hidden neurons and then projected through a transfer function f_h. The results of the function f_h are weighted by the connection weights (w_{ji}) between the neurons and sent to the output nodes. transfer function f_o is then projected by the output neurons. The output of this neuron is the predicted response $\hat{y}$ (Dieterle, 2003).

Air Dispersion Model

The dispersion of pollutants from various point sources in the mining sector can be determined using simple advection-diffusion equation. A Cartesian coordinate system is used to represent 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):

$$\begin{aligned}&\frac{\partial c}{\partial t} + u\frac{\partial c}{\partial x} + v\frac{\partial c}{\partial y} + w\frac{\partial c}{\partial z} \\ &= \frac{\partial}{\partial x}(k_x\frac{\partial c}{\partial x}) + \frac{\partial}{\partial y}(k_y\frac{\partial c}{\partial y}) + \frac{\partial}{\partial z}(k_z\frac{\partial c}{\partial z}) + R + S\end{aligned} \tag{4}$$

whereas C is the pollutant concentration (g/m^3) at any time t (s) and at any location (x, y, and z); k is the eddy diffusivity coefficient in x (k_x), y (k_y) and z (k_z) direction (m^2/s); u, v, and w are the average wind speed component (m/s); R is the term used for sinks (g/m^3.s) and S used for the sources (g/m^3.s).

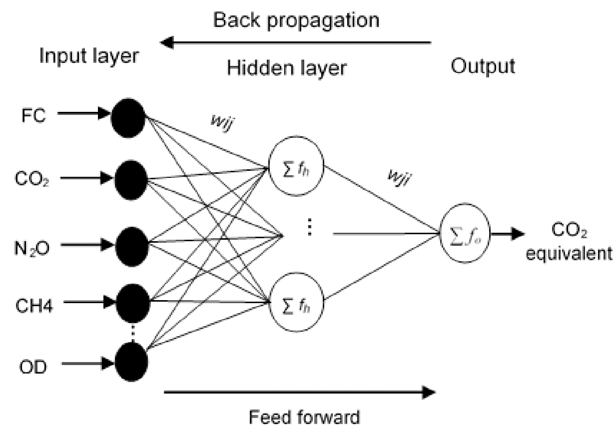

Figure 3. Architecture of feedforward back propagation ANN for carbon footprint prediction for metal mining.

Equation (1) 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 $\partial c/\partial t = 0$; (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, $u(\partial c/\partial x) >> (\partial/\partial x)k_x(\partial c/\partial x)$. Hence, Equation (4) is reduced to the fol-lowing expression:

$$u\frac{\partial c}{\partial x} = \frac{\partial}{\partial y}(k_y\frac{\partial c}{\partial y}) + \frac{\partial}{\partial z}(k_z\frac{\partial c}{\partial z}) \tag{5}$$

Assuming when 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):

$$\sigma^2 x = 2tk_x; \sigma^2 y = 2tk_y; \sigma^2 z = 2tk_z \tag{6}$$

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

$$k_z = Ku_o x \tag{7}$$

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

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

$$C(x,y,z,t) = \sum_{n=i} \frac{E_i}{uh(4\pi t k_y)^{\frac{1}{2}}} exp(\frac{-y^2}{4tk_y}) \\ exp\{\frac{-v_d}{ku_o}(\frac{(Z-H)}{x} - \frac{v_d}{2u})\} \tag{8}$$

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).

Multi-Criteria Decision Analysis System

Preference ranking organization method for enrichment evaluation (PROMETHEE) method comprises of partial ranking and complete ranking. The PROMETHEE II complete ranking is based on a calculation of net outranking flow value (*Phi*) that represents the balance between the positive (Phi^+) and negative (Phi^-) outranking flows. The higher the net flow, the better the alternative (Huang et al., 2011; Yang et al., 2012). Whereas, PROMETHEE I provide a partial ranking of the alternatives. 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. After this, with the help of visual PROMETHEE tool, the partial ranking with PROMETHEE I and the complete ranking with PROMETHEE II along with GAIA (geometrical analysis for interactive decision aid) plane is determined to find the best alternative methods for mining to reduce the impact of air pollution; 4) Finally, the decision-making stage in which the best mining method is selected based on rankings of alternatives. Multicriteria preference index (Π) is expressed as weighted average of the preferred function $p(x_i, x_k)$ (Yang et al., 2012):

$$\prod(x_i, x_k) = \sum_{j=1}^{k} \frac{w_j . P(x_i, x_k)}{w_j} \tag{9}$$

where W_j represents weights of criterion which are determined by analytical hierarchy process (AHP) method using pairwise comparison of each criteria. The method is computed by using super decision tool (https://www.superdecisions.com/).

$\Pi(x_i, x_k)$ represents the degree of preference (P) of the decision making of alternative x_i over alternative x_k. The value of preference index is between 0 and 1:

$\Pi(x_i, x_k) \approx 0$ indicates a weak preference of x_i over alternative x_k for all the criteria,

$\Pi(x_i, x_k) \approx 1$ denotes a strong preference of x_i over alternative x_k for all the criteria

The PROMETHEE method is based on the calculation of positive flow (Phi^+) and negative flow (Phi^-) for each alternative according to the given weight for each criterion. The higher the positive flow ($Phi^+ \rightarrow 1$), the better the alternative. The negative outranking flow expresses how much each alternative is outranked by all the others. The smaller the negative flow ($Phi^- \rightarrow 0$), the better the alternative. The positive and negative flows are expressed as follows:

$$Phi^{+/-} = \sum_{k=1}^{m} \Pi(x_i, x_k) \tag{10}$$

Each criterion is rated based on the scale of 1 to 9, using knowledge of environmental and technical evaluation. Each option based on the preference that has low cost rated as 9 and the high cost rated as 1. For less magnitude of the pollutants emitted rated as 9, otherwise scored 1. The risk is associated with the pathway of the pollutant or the resultant pollutant produced during removal of the target pollutant, may pose a threat to surrounding ecosystem. If this is the case, that alternative would be rated as 1; otherwise rated the higher value up to 9. For long-term performance, an alternative that is more efficient for a long duration is rated as 9, and an alternative that would not be much suitable for the same period is scored as 1. An alternative that has an excellent removal efficiency is rated as 9; otherwise, it is scored less value. If an alternative required less energy to remove pollutant is rated as 9; otherwise, it is rated at a lesser value. An alternative that would increase future use and aesthetic of the site is rated as 9, and vice versa. (See Appendix Table A3 illustrates these criteria and their scoring scale accordingly).

2.3. Selection of Performance Criteria

Performance criteria for such type of environmental models must reflect the overall scope and specific objectives of the modeling activity (Jakeman et al., 2006). There are two important purposes of this proposed integrated system. One is to develop an air quality management tool for mining system which can help to generate mine specific inventory, assess and predict air quality issues which is used to select best treatment method. The second purpose is to analyze new approaches, algorithm and analytical solutions and tested at the mine site for the first time. The simulation modeling results have been compared with the field observations at every stage. Therefore, an agreement between their values and regression analysis is considered as the performance criterion.

3. Case Study

Mine site A is an open pit copper 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 copper smelter, and a copper refinery.

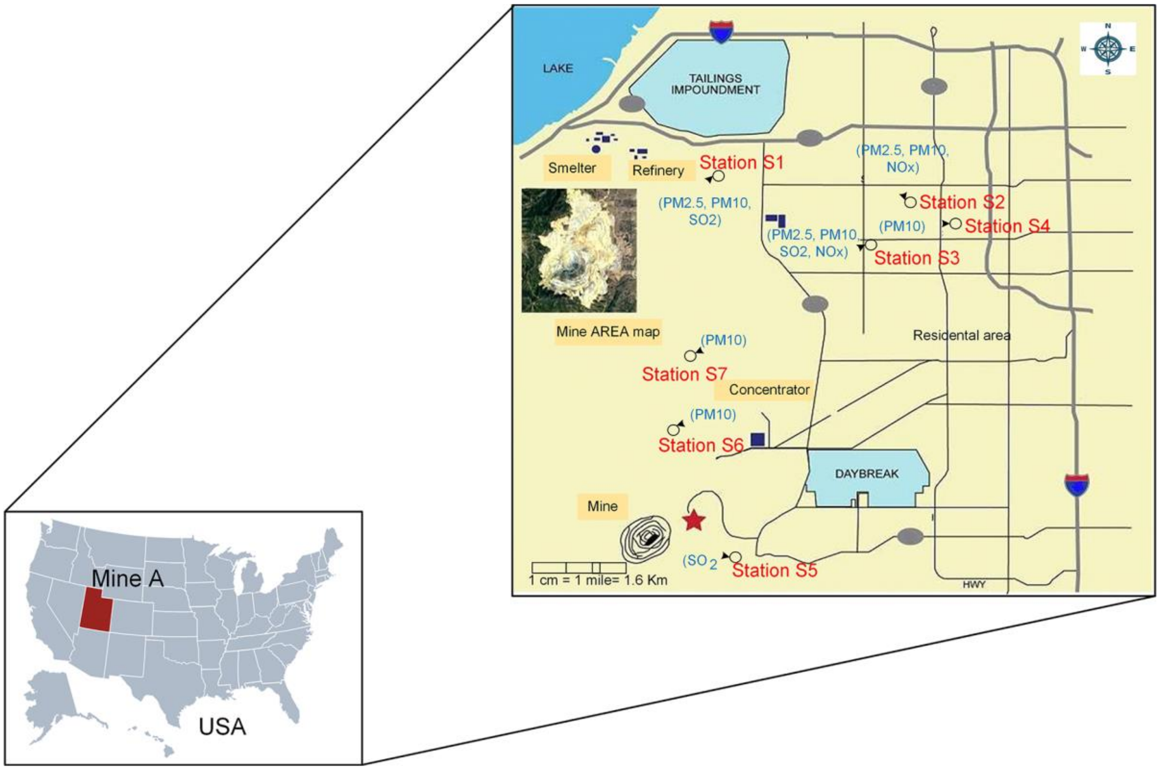

Figure 4. Location of mine and monitoring station.

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) has been examined as shown in Figure 4. The average maximum ambient temperature is 17 ºC. Whereas, average monthly precipitation is 1.54 inches. The mean wind speed is 3.8 m/s. Thus, for each monitoring station, the weather data is separately collected through NOAA regional climate center.

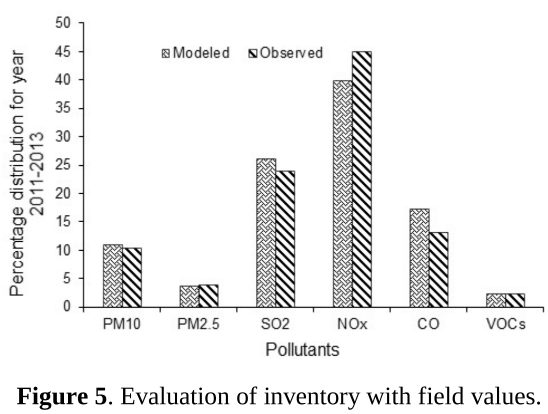

Figure 5. Evaluation of inventory with field values.

3.1. Implementation of LCAQMS Model

Emission Inventory

Air emission inventory were generated by using inverse matrix method. Table 3 shows the analysis results of quantitative inventory obtained through LCA modeling for the year 2011 ~ 2013, illustrating that mine site 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%), $PM_{2.5}$ (3.6%), VOCs (2.3%), NH_3 (0.63%), CH_4 (0.16%) and H_g (.001%). Diesel fuel combustion is one of the major sources of NO_x production. Moreover, oxides of nitrogen can also be generated during smelting and refining processes. Coal power plant is the primary source of SO_2 emissions at the mine site. Most 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 $PM_{2.5}$ are produced mainly from mobile equipment and vehicle exhausts. Whereas, CO is produced due to heavy equipment usage during processing of ore and incomplete combustions. During 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. CH_4 is also considered as a greenhouse gas which may produce because of fuel consumption such as diesel, gasoline, and propane. Though, it is not directly generated due to the mining activities. Usually, the presence of VOCs is more profound during smelting processes of metals. Figure 5 depicts a comparison between modeled values and the observed values gathered through the national monitoring database. For NO_x, there is 11% difference because the obtained values also included the

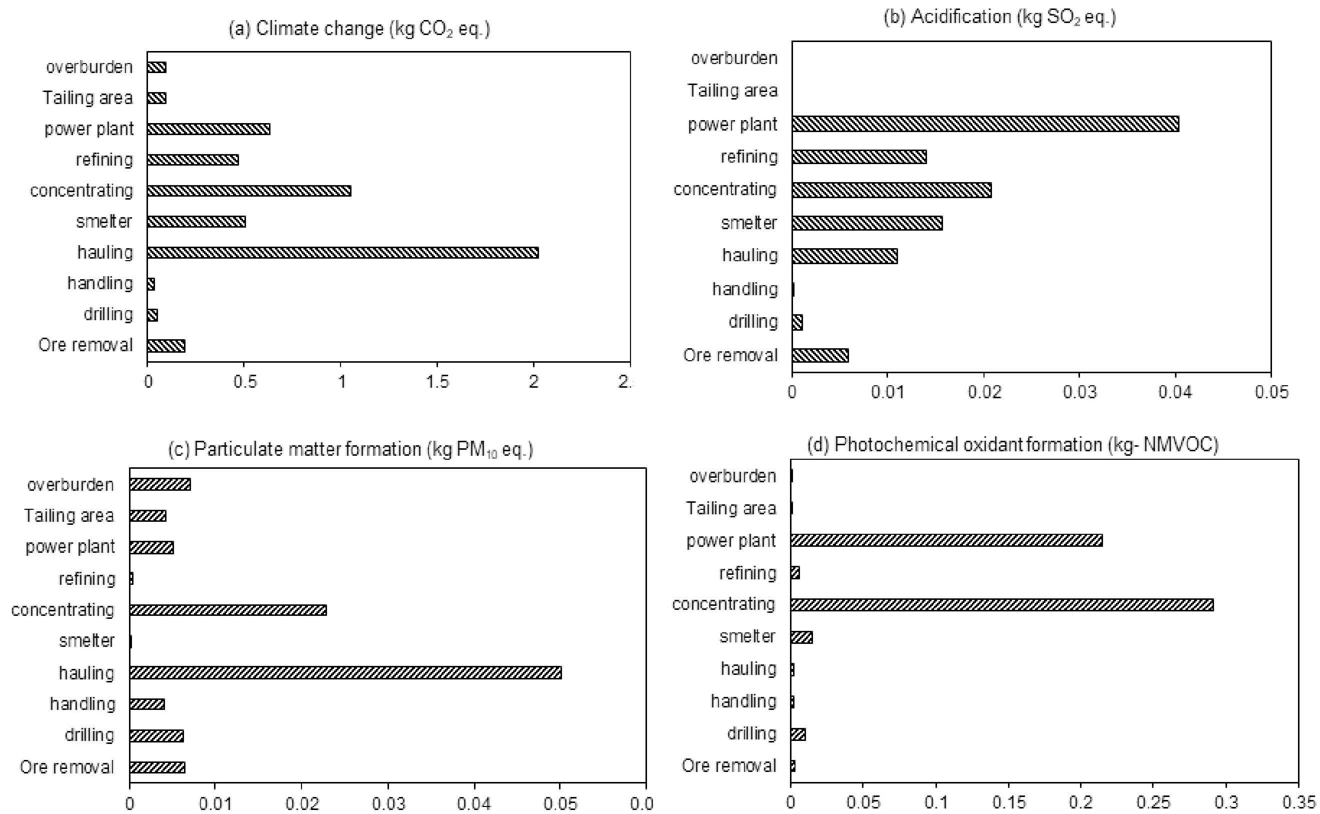

Figure 6. Midpoint impact assessment using TRACI (a) Climate change, (b) Acidification, (c) Particulate matter formation, (d) Photochemical oxidant formation.

power consumption by the laboratory facilities which was not considered during the case study. Same is true for CO. Whereas, for SO_2 modeled value is 7.6% more than observed. The reason behind this is that inlet temperature for concentrator varies which give rise to SO_2 generation. At the time of data collection, a high temperature is considered which ultimately produced the greater amount of SO_2 as compared to the reported observed value which is based on average temperature.

Table 3. LCA Modeling Results of Emission Inventory for Mine site A

Pollutants	Inventory(tons/year)
PM_{10}	1238.4
$PM_{2.5}$	420.5
SO_2	2968.9
NO_x	4551.2
CO	1954.8
CH_4	18.6
Hg	1.49
NH_3	72.8
VOCs	258.5

Impact Category Assessment

Using 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 (see Figure 6). Furthermore, the results were normalized to the midpoint level based on background concentration database available at the Utah monitoring program.

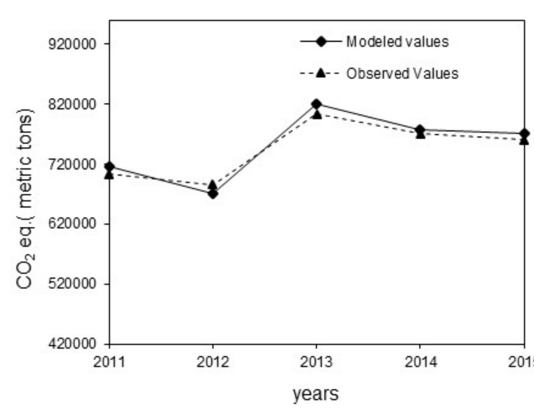

Figure 7. Carbon footprints for mine site A and field comparison.

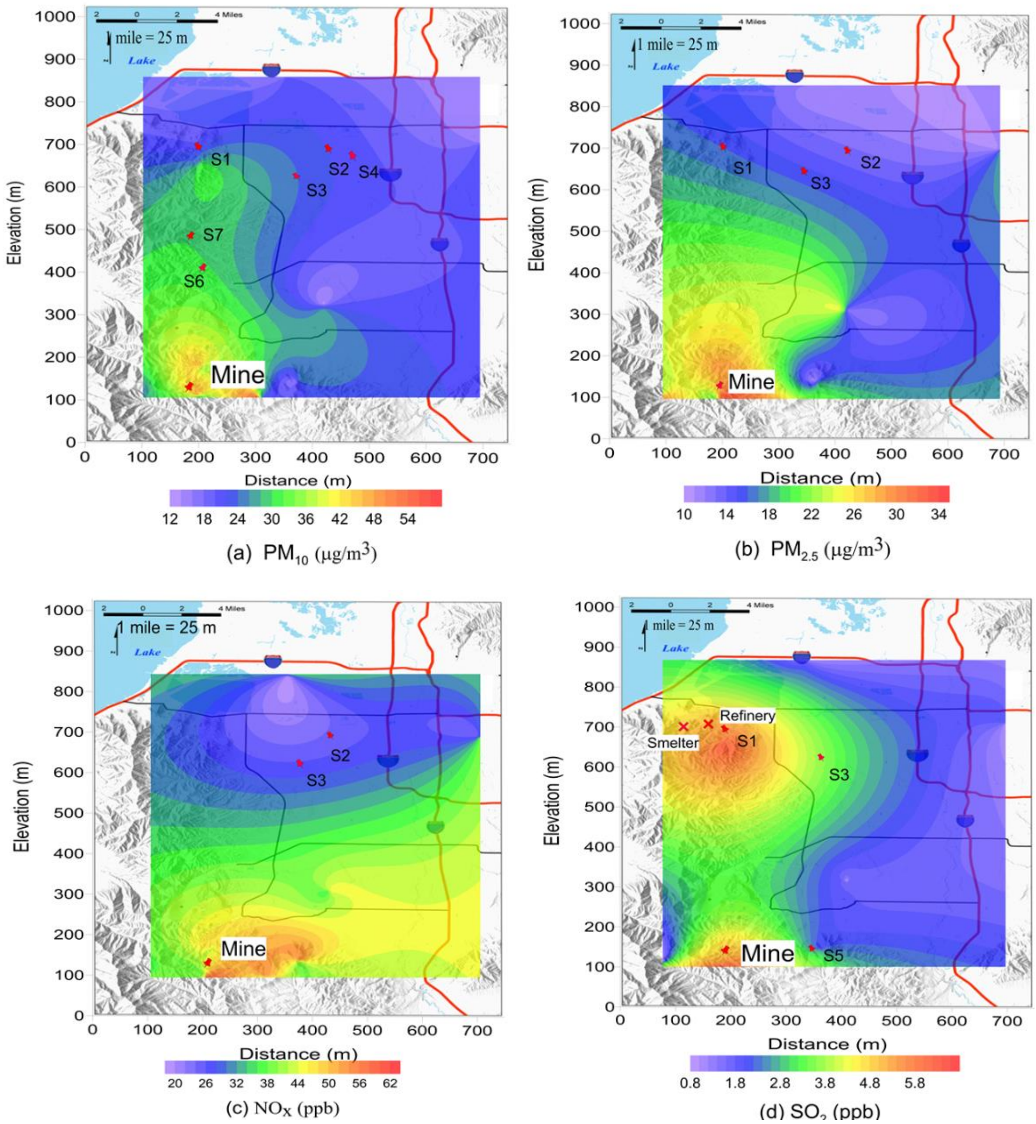

Figure 8. Contour mapping of air quality pollutant concentrations for mine A based on daily average from 2011 to 2015 for (a) PM_{10}; (b) $PM_{2.5}$; (c) NO_x; (d) SO_2.

Carbon Footprint Analysis

Three greenhouse gases (CO_2, CH_4, N_2O) were considered depending upon the availability of data (2011 ~ 2015) and which might directly subsidize to the carbon credit. The input variables subsequently included the stationary fuel combustion sources, coal power plant and adjacent waste landfill site to collect data for CH_4. Different combinations based on various nodes was performed through BPANN model for each scenario. Figure 7 represents the comparison between modeling values of carbon credit for each year with the monitoring values. The trend sharply increased for the year 2013 but then gradually lower for 2014 and 2015.

Prediction of Pollutant at Receptor Level

The predicted concentrations at ground level were determined using the MADM algorithm while considering the dry deposition effect due to gravitational settling. Figure 8 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 traveled as a plume away from the source. For SO_2 maximum concentrations were predicted around the smelter and refinery area of mine site A other than mine pit. The main reason behind this is that the energy source of these units is 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. Thus, all the values met the national ambient air quality standards (NAAQS).

Table 4. Regression Analysis for Pollutants (2011-2015) at Different Monitoring Stations

Station Id	*R^2 for $PM_{2.5}$*					*R^2 for PM_{10}*				
	2011	2012	2013	2014	2015	2011	2012	2013	2014	2015
S1	0.779	0.92	0.93	0.93	0.82	--	0.722	--	--	--
S2	0.68	0.74	--	--	0.89	0.78	0.70	--	--	0.83
S3	--	0.71	0.642	0.775	0.72	0.71	0.74	0.79	--	0.72
S4	--	--	--	--	--	0.94	0.72	0.87	0.77	0.75
S5	--	--	--	--	--	--	--	--	--	--
S6	--	--	--	--	--	0.90	0.91	0.75	0.81	--
S7	--	--	--	--	--	0.79	0.82	0.88	0.91	--
	R^2 for SO_2					*R^2 for NO_2*				
	2011	2012	2013	2014	2015	2011	2012	2013	2014	2015
S1	0.96	0.95	0.84	--	--	--	--	--	--	--
S2	--	--	--	--	--	0.81	0.74	0.79	0.87	--
S3	0.84	0.70	0.71	0.69	0.72	0.74	0.69	0.88	0.71	0.74
S4	--	--	--	--	--	--	--	--	--	--
S5	0.69	0.72	0.70	--	0.84	--	--	--	--	--
S6	--	--	--	--	--	--	--	--	--	--
S7	--	--	--	--	--	--	--	--	--	--

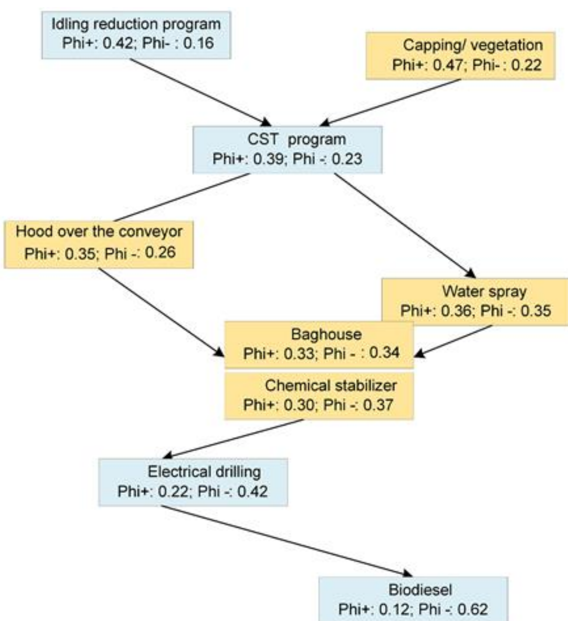

Figure 9. Results of alternatives network analysis using visual PROMETHEE.

Decision Analysis

Figure 9 illustrates the networking of alternatives based on positive and negative flows for mine site A regardless of three different groups. 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, biodiesel method for the reduction of greenhouse gases is considered as a last preferable option as compared to other options. One can also interpret the results as a set of combination of different alternatives as one option. For instance; option 1 is to apply the combination of idling reduction, CST program, capping, hood over the conveyor, bag house and water spraying which could be efficiently used for the removal of pollutants based on the evaluation of seven criteria mentioned in methodology section. This combination of alternatives represented all the two groups and considered as most preferable cost effective option on ranking basis. This option not only controls the dust problem but also reduce the fuel consumption and contribute towards the reduction of carbon footprints. The option 2 is baghouse, water spraying, chemical stabilizer, electrical drilling, and biodiesel. This option is the second preferable combination of different alternatives. 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.

3.2. Validation of Air Quality Model

The MADM simulation is examined and validated by comparing the modeling results with the observations values of monitoring stations (S_1 to S_7) under the same environmental conditions using the average daily data for from the January 2011 to December 2015. Results for $PM_{2.5}$, PM_{10}, SO_2 and NO_x were considered for regression analysis. Since the field values for heavy metals were not available, they were not considered in the model validation. Figure 10 illustrates the comparison of all the observed and modeled values at the monitoring station S_1 for the available pollutants as an example. Similar testing was performed for each monitoring station. Table 4 represents the coefficient of determination (R^2) for all the four pollutants at different monitoring stations. This 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 selected input parameter at various locations.

Table 5. Statistical Evaluation and Comparison among Three Different Air Dispersion Models

Models	*MADM model*		*Ermak model*		*Gaussian plume model*	
	NMSE	COR	NMSE	COR	NMSE	COR
	Indicator for good performance*					
Pollutants	≅ zero	≅ one	≅ zero	≅ one	≅ zero	≅ one
$PM_{2.5}$	0.009	0.95	1.5	0.88	1.9	0.50
PM_{10}	0.001	0.99	0.005	0.95	1.6	0.65
SO_2	0.0007	0.92	0.006	0.98	1.2	0.74
NO_x	0.0005	0.88	0.09	0.80	0.005	0.79

*(Essa et al., 2014)

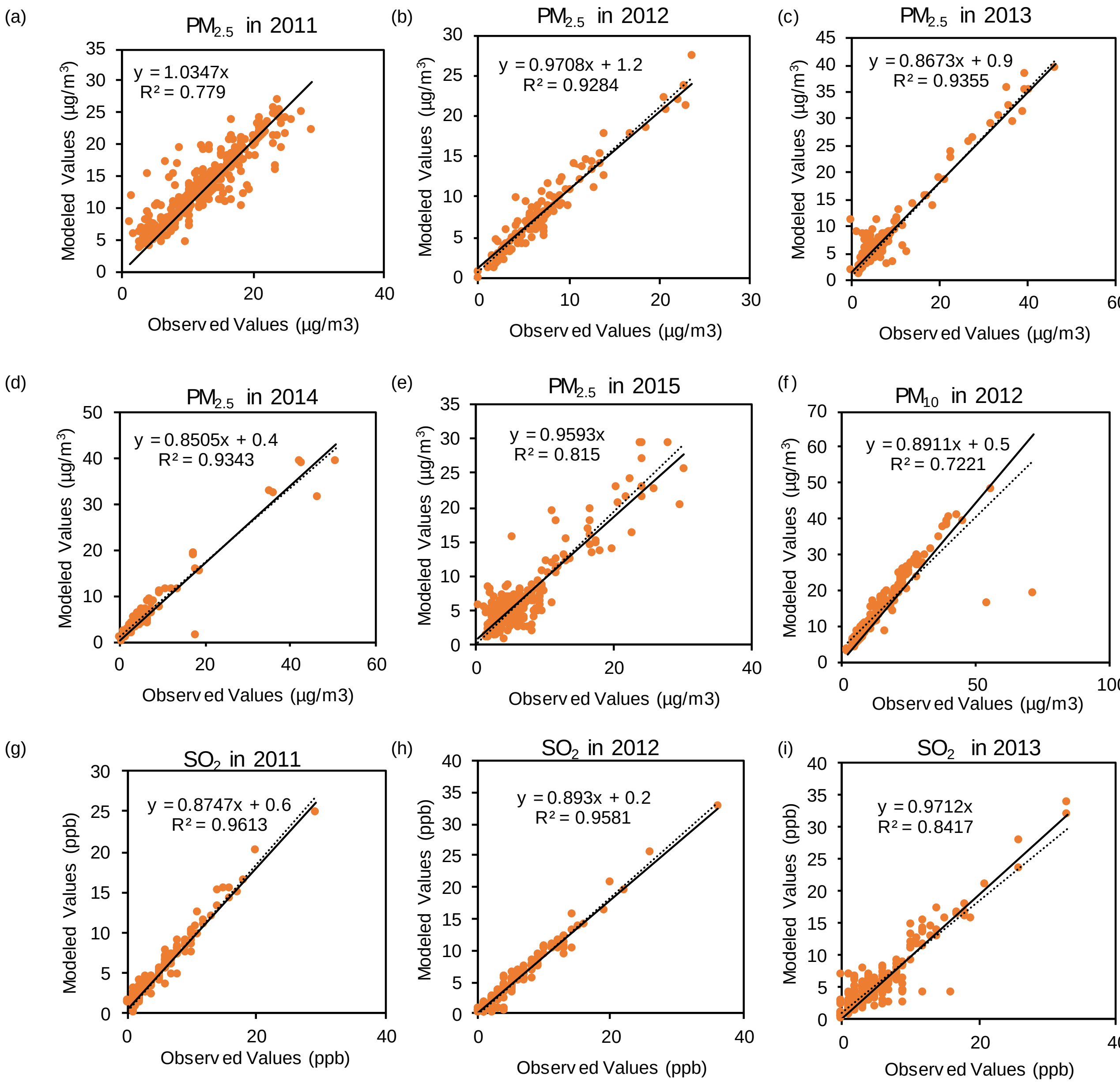

Figure 10. Correlation between modeling and monitoring data for (a) $PM_{2.5}$ at S_1 in 2011, (b) $PM_{2.5}$ at S_1 in 2012, (c) $PM_{2.5}$ at S_1 in 2013, (d) $PM_{2.5}$ at S_1 in 2014, (e) $PM_{2.5}$ at S_1 in 2015, (f) PM_{10} at S_1 in 2012, (g) SO_2at S_1 in 2011, (h) SO_2 at S_1 in 2012, (i) SO_2 at S_1 in 2013.

3.3. Quantification of Uncertainty

The sources of uncertainty in LCAQMS model can be input data, sampling errors, boundary conditions, and missing data.

- Uncertainty in the selection of which variables to include and which to eliminate. The variables included at the stage of inventory development were chosen based on careful analysis and understanding of the mining activities and limited by the availability of input data. Thus, other irrelevant variables were eliminated using cut-off criteria rule in LCA.
- During carbon footprint analysis, a lot of processes, directly and indirectly, contributed towards carbon credits. Artificial neural network algorithm is selected to avoid any uncertainty because of missing values and nonlinear relationships.
- Uncertainty in boundary conditions may affect the analytical solutions. However, for K-theory Gaussian algorithm boundary conditions, assumptions are made based on the past air dispersion models and literature studies.
- The ranking of alternatives is highly influenced by the allocation of weights to criteria as well as alternatives which may contribute to uncertainties. This issue is overcome through calibrating net flow of alternatives by conducting the sensitivity analysis using walking weights as a unique feature in the visual PROMETHEE tool.

4. Discussion

The LCAQMS framework offers a flexible way to store a large quantity of data (e.g., physical environmental and technical data) while preserving their dependability with their corresponding operational processes in the mining system. The model allows the calculation of site-specific LCA impacts based on a real case study and provides a realistic way to allocate environmental burdens as inputs per unit process. It provides the level of details, essential to facilitate the LCA for midpoint 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. Also, this framework helps in a feasibility study of the mining project to find out potential air pollutants and carbon credit. The main aim that motivated the development of MADM method is to provide a reliable yet 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. It extended the tradition Gaussian model to consider point sources, line sources and fugitive emissions with mining emission rate calculations in one model. This approach explicitly shows understanding of the mining system, while successfully involve all the related atmospheric parameters. It allows understanding the effect of physical removal mechanism on the pollutant's load. It is anticipated that the results provided by the MADM help to gain further insight into air quality at mining industry.

The statistical indices of Table 5 point out that a satisfactory agreement was achieved for the MADM method by comparing it with simple Gaussian plume model and Ermak model (Ermak, 1977) using the normalized mean square error (NMSE) and correlation coefficient (COR) (see Appendix Equations A1 ~ A2). Whereas, Ermak model based on the technique of concentration gradient, did not produce the good performance at the downwind distance for $PM_{2.5}$. The NMSE value greater than 1 indicated the over prediction of the $PM_{2.5}$. However, it is noticed that for PM_{10}, SO_2 and NO_x, Ermak model simulates better in contrast to $PM_{2.5}$ modeling. For Gaussian plume model, statistical analysis results show that the modeling results tend to deviate from the actual observed values (NMSE = 1.9 for $PM_{2.5}$; 1.6 for PM_{10}). To encapsulate, overall MADM produced statistically agreeable results in the case of all the four target pollutants.

Furthermore, a multi-criteria decision analysis module in the framework helps to get more quantitative and endpoint modeling results. The model can be used for adaptation of alternative technologies and air pollution control remedies at the mining site which would help in environmental management. Particularly coupling of models within an integrated environment is also a significant contribution to the limited literature available on the integrated environmental modeling system for the mining industry. Although the scope of the present study is limited to the air pollutants for the open pit mining process, the developed approach can be applied to study other mining processes such as underground mining. The customizations just need to be made by including different mining activities during the development of inventory model. For an example, considering the ventilation process as a variable in technical matrix. One of the major limitations of LCAQMS is that it requires a lot of inputs as the requirement of the model.

5. Conclusions

This study is conducted to explore the new integrated life cycle assessment based air quality modeling system (LCAQMS) for the mining sector. The important modules of the model are inventory development, carbon footprint analysis, air quality modeling and decision analysis for effective pollution control. Modeling tools were applied in an open pit copper mine through LCAQMS framework. Based on the inventory results of air emissions developed in the study, it was observed that NO_x and SO_2 were major contributors towards the environmental load. The profound midpoint modeling impacts of copper mines site A were determined using TRACI method. Whereas, BPANN simulation technique was used for carbon footprint analysis of the mine site A. The study confirms that ANN can predict the future concentration based on the past data. Conclusively, this mine was responsible for producing average 0.7 $\times 10^6$ metric tons of CO_2 eq. from the year 2011 to 2015 because of greenhouse gases emissions and fuel consumption during the mining activities. Thus, it is expected that different mines would show different results, due to different operating conditions and emission rates. 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. The MADM was applied for the continuous point sources emission in the mining sector under the neutral conditions. The solution algorithm has been derived by considering the eddy diffusivity depends on the vertical height and as a function of downwind distance. It allows the spatial analyst on local scales by incorporating sampling data collected from the field observation. Air quality profiles of $PM_{2.5}$, PM_{10}, SO_2 and NO_x are presented as a contour mapping for a mine site A. The predicted concentrations have been found in good agreement with the field observations to validate the developed MADM approach. For selecting the best technology based on various selection criteria, PROMETHEE method was used as a multicriteria decision making tool. Hence, showing idling reduction, CST program, capping, hood over the conveyor, bag house and water spraying as the most promising combination of effective treatment methods for the mine site A. 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. 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 cost effective solution for air pollution.

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