# DEVELOPMENT OF AN ARTIFICIAL NEURAL NETWORK MODEL ON DUST PROPAGATION IN A SURFACE MINE AND KNOWLEDGE EXTRACTION FROM THE MODEL

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## 1.0 Introduction

Air borne dust is emitted from various sources within a surface mine. Dispersion of air borne particulate matter is controlled by the general meteorological conditions like wind speed, temperature profile, relative humidity, mining activity level and geo mining conditions. Propagation and dispersion of airborne dust, within a surface mine, is a complex phenomenon. Explicit knowledge on propagation of dust, emitted from multiple sources, within a surface mine and the explanatory variables involved in this phenomenon is largely absent. Precise knowledge on dust emission is prerequisite for using available mathematical models. Also, in case of statistical analysis, knowledge on auto correlation between the variables is essential.

Artificial neural network (ANN) mimics human brain. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. A neural network consists of a large number of nodes (or neuron) arranged in form of input, and an output layers, with number of hidden layers in between these layers. ANN is an adoptive system that changes its architecture based on information that flows through the system

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during the learning phase. The modeling process recognizes relationship or pattern between input and output variables using a supervised feed forward network trained with standard gradient descent back propagation algorithms along with the least squares types of method. Training of the network is a process of learning when the error of the calculated or predicted output. in relation to the actual output is back propagated to adjust all weights and bias values. If average error is within a prescribed tolerance, the training is stopped, the weights are locked and the network is ready for use.

In this paper an ANN model is built by using meteorological data and several data on mining parameters collected from different operating opencast coal mines. It is stated before that knowledgebase about dust propagation and generation is imprecise. Therefore, an attempt has been made to extract knowledge from the ANN model by sensitivity analysis using 3 D plots. The paper is structured as follows. With a brief introduction on dust dispersion in ambient atmosphere of a surface mine a conceptual framework on ANN is developed. Next, an ANN model is built using several input variables. Finally, sensitivity analysis is done and 3D plots are drawn to extract knowledge, from the model about the complex phenomenon of dust dispersal, in a surface mine.

**2.0 Conceptual framework for Artificial Neural Network (ANN)**

ANN is a non-linear self adaptive approach (Girish .K., 2007, Sarle, 1994). ANN research falls mainly into three categories: the biological-neural network itself, computer network structure development, and applications in various scientific and engineering problems. ANN is represented by a set of nodes and arrows (Fig1). In general, the preparation of a neural network requires a forward model for computing a training set and test data set and a neural network training procedure. A successful pattern classification methodology depends heavily on the particular choice of the features used for development of an ANN architecture. (Sahin et al, 2011). Hornik et al. (1989) stated that ANN can act as universal approximations of non-linear functions. ANN is a tool either where no precise theoretical model is available, or when uncertainty in input parameters to complex systems, for example, ecological or environmental systems, complicates deterministic modeling (Huang and Foo, 2002; Lee et al., 2002; Scardi, 2001). Empirical air pollution forecasting systems can be developed using ANN approach (Gardner and Dorling, 1998; Jorquera et al., 1998).

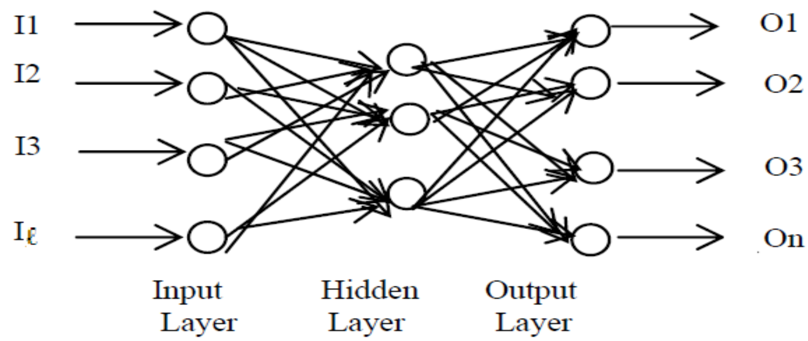


Fig. 1 **Feed forward back-propagation neural network**

$SO_2$ and $PM_{10}$ concentrations can be predicted using ANN. (Boznar et al., 1993; Mok and Tam, 1998; Saral and Ertürk, 2003; Chelani et al., 2002; Onat et al., 2004; Sahin et al., 2005, Yildirim and Bayramoğlu, 2006).Gardner and Dorling (1998) have published a comprehensive review of studies using an ANN approach for environmental air pollution modeling. Kukkonen et al. (2003) have studied five neural network (NN) models, a linear statistical model and a deterministic modeling system for the prediction of urban $NO_2$ and $PM_{10}$ concentrations.( Sahin et al. 2004) used a multi-layer neural network model to predict daily CO concentrations, using meteorological variables, in the European side of Istanbul, Turkey. Kurt et al. (2008) also developed an online air pollution forecasting system in Istanbul using NN. Another NN model developed by Saral and Ertürk (2003) also used to predict regional $SO_2$ concentration. Nagendra and Khare (2006) studied the usefulness of NN in understanding the relationship between traffic parameters and $NO_2$ concentrations. Recently, several researchers used NN techniques to predict airborne particulate matter concentrations (Ordieres et al. (2005) Hooyberghs et al. (2005), Perez and Reyes (2006) and Slini et al. (2006)). All these studies reported that ANN can be used to develop efficient air-quality analysis models. ANN can capture nonlinear relationships; their performance is superior when compared to statistical methods such as multiple linear regressions. (.Weizhen Lu et al., 2002). ANN is applied to predict surface $O_3$ concentration (Ruiz-Suarez and Mayora, 1994; Yi and Prybutok, 1996; Comrie, 1997). More recently MLP (Multilayer perception) models were used to predict the concentrations of other common air pollutants (Chelani et al., 2002). In China, ANN applications to environmental issues also have received growing attention (e.g., Liu et al., 2000; Hao et al., 2000). Neural networks capable of modeling non-linear relationships between input and output variables are often used in forecasting variables in complex environmental systems (Gardner & Dorling, 1998). ANN is useful in the situations, where underlying processes / relationships may display chaotic properties. Chaloulakou et al (2003) made a comparative study between multiple regression models and feed forward artificial neural network with respect to their predictive potential for $PM_{10}$ Geeta Varkey et. al (2004) discussed how an ANN can be used to derive suspended matter from the spectral values of beam alternation coefficients Bindulal and G. Pathak (2006) have used artificial neural network for the prediction of SPM in different coal mine area.

## 3.0 Data and method

The mining companies, as per statutory norms, maintain quarterly record of meteorological data and particulate matter concentration, at strategic locations, within a surface mine. Model input variables are various meteorological parameters, areas of mine facilities like railway siding , waste dumping yards , coal handling plants , excavation areas , coal production, overburden removal rate and vegetation cover between the dust emitting source and the monitoring stations . Air quality data, collected from an opencast mine in Orissa is used to develop ANN model and create 3D shaded plots of few model input variables. Descriptive statistics of the input variables is given in Table 1.

**Table No 1**

| Variables | Observation | Mean | Std. Dev. | Minimum value | Maximum value |
|---|---|---|---|---|---|
| **Vegetative cover index** | 160 | 0.56 | 0.198 | 0.1 | 0.8 |
| **Avg. Relative Humidity (%)** | 160 | 58.12 | 23.29 | 14.5 | 91.5 |
| **Mean Wind Speed(m/sec)** | 160 | 2.96 | 2.62 | 0 | 11 |
| **Avg. Temperature( ° C)** | 160 | 28.09 | 5.05 | 16.4 | 37.4 |
| **Rainfall mm** | 160 | 2.43 | 5.91 | 0 | 28 |
| **Siding ($m^2$)** | 160 | 737.5 | 260.32 | 400 | 1200 |

| | | | | | |
|---|---|---|---|---|---|
| **CHP ($m^2$)** | 160 | 1337.5 | 1290.45 | 400 | 4000 |
| **Excavation Area ($m^2$)** | 160 | 1287.5 | 882.30 | 600 | 3000 |
| **Dump ($m^2$)** | 160 | 812.5 | 232.23 | 600 | 1200 |
| **Distance (m)** | 160 | 2287.5 | 973.15 | 500 | 3000 |
| **Coal production ( tonne /day)** | 160 | 67040.28 | 9867.73 | 50000 | 87000 |
| **Overburden removed ($m^3$/day)** | 160 | 22699.5 | 5077.271 | 12000 | 34880 |

**Source Environmental report available at mines**

**Table No 2**

Data description on dust concentrations measured at various strategic points, within the mine, is shown in Table 2

| Variables | Observation | Mean value | Standard Deviation | Minimum Value | Maximum Value |
|---|---|---|---|---|---|
| **Suspended particulate matter** | 160 | 269.68 | 150.36 | 165 | 579 |

## 4.0 ANN model

The model is developed by training the network with input and output data. The normal approach is to split the sample into training and testing dataset . The training data set is used to develop the model , while test data is used to examine the performnance of the model in forcasting SPM concentration. The network is trained in a supervised manner with back propagation algorithm , that is, multilayered feed forward network. At the start of the modelling process training data is preprocessed training data set by normalising input and output data so that they fall within interval (-1,1). To create a ANN nwtwork there are eleven variables with five node in the first layer and one node in the second layer. Transfer function in the first layer is tansigmoidal and second layer is purelin . The network is trained up to maximum epoch of 1000 and error goal is set at 1e-7. Post processing of the trained is done by performing a linear regression between each element of the network response and the corresponding actual output . The model is developed by using nueural network toolbox in MATLAB 7.0

**5.0 Results**

Testing data is used to examine prediction capability of the ANN model . Thirty percent of the input data is used for testing purpose. The correlation coeficent is 98% , which implies that 98% of the test data can be explained by the ANN model. The model is thus robust . Figure 1 shows minor deviations between the actual output and predicted values . The two graphs ( Figure 1 & 2) show that the model is now ready for further naalysis .

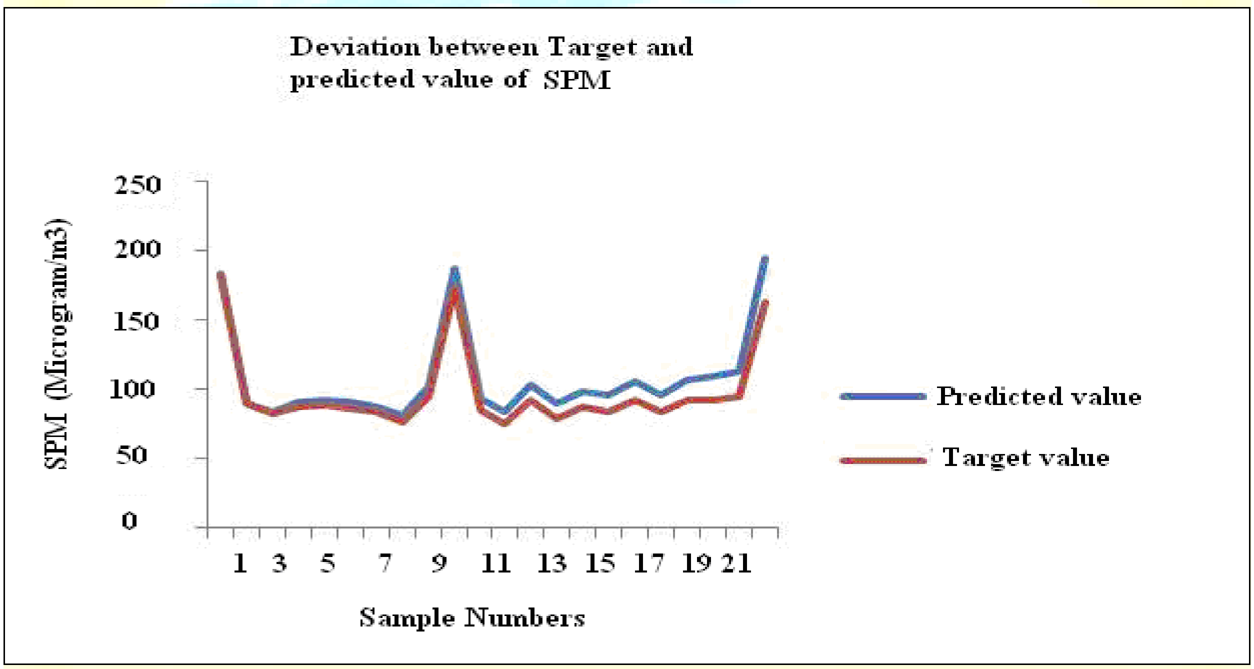


**Fig 2 Figure showing deviation between target and predicted value of SPM.**

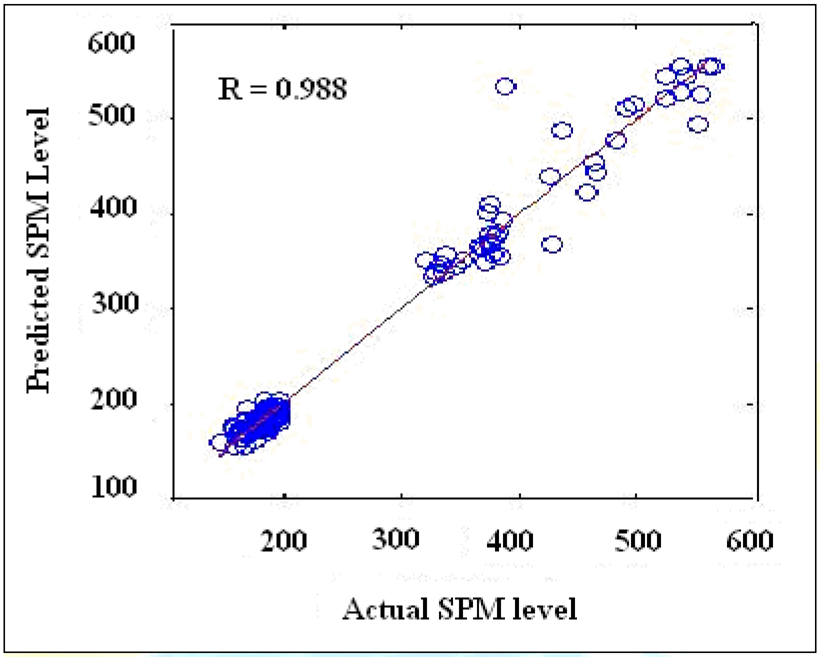


**Fig. 3 Figure showing predicted and actual SPM level**

## 6.0 Sensitivity analysis

In a mine there are multiple sources of fugitive dust emission. Dust propagation and emission depend both on meteorological parameters of the ambient environment and level of mining activities in the mine. Thus dust propagation in a surface mine is a complex phenomenon involving myriad factors whose interrelationships are not clearly understood. Specific knowledge on dust propagation, its explanatory variables and their interrelationships are prerequisites for building mathematical and statistical models. Artificial neural network can be applied for model building where precise knowledge on a particular phenomenon is not available. Figures 4-7 present sensitivity analysis on dust concentration and different variables that are used as model inputs.

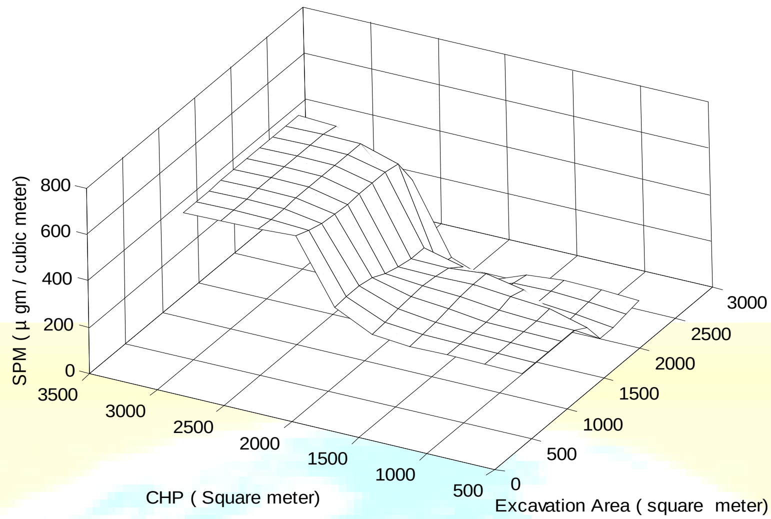


**Fig. 4**

In figure 4 a 3 D plot is drawn using CHP area and mine excavation areas as two input variables and model output SPM. By making one variable constant, say along 500 square meter line of excavation area, the variation in SPM generation along this fixed line of excavation area is solely due to increasing CHP area. The following conclusions can be drawn from this result.

1. By making excavation area constant there is significant increase in SPM level by changing area of CHP area.
2. By making CHP area fixed there is no significant increase in SPM with changes in excavation area.
3. CHP area is a major explanatory variable. Therefore, SPM emission is highly sensitive to CHP area

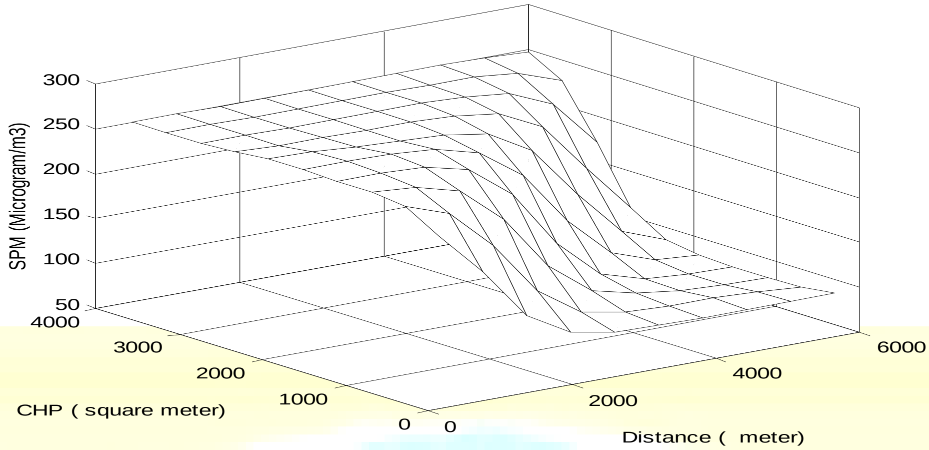


**Fig 5**

From the above figure (Fig 5) the following knowledge is extracted.

1. Sampling points are located at certain distances from the active mining zone. With distance remaining constant SPM level will increase with changes in CHP size.

2. If CHP area is unchanged, there is only marginal increase in SPM level with changes in distance of sampling point from the dust emitting source.

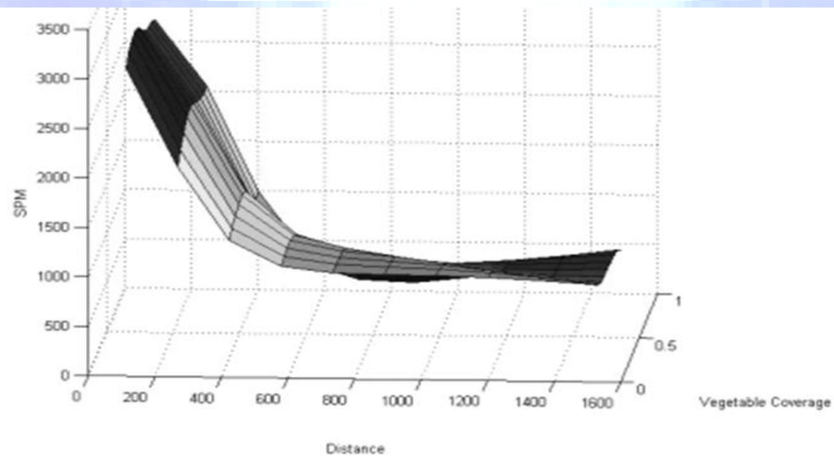


**Fig 6**

Significant amount of SPM can be arrested in the intervening vegetative cover between the sampling station and active mining zone. Vegetative cover is expressed on a numeric scale of 0 to 1. Score is assigned based on the subjective judgment of the project team on the extent of existing vegetative cover between the active mining zone and the sampling point. A thick vegetative cover can be assigned a maximum score 1. On a constant vegetative cover line, say 0.5, SPM level increases with reducing distance ( Fig.6). At constant distance line SPM value remains unchanged with changing vegetative cover. Therefore, vegetative cover adjacent to the active mining zone is not effective in bringing down spm concentration.

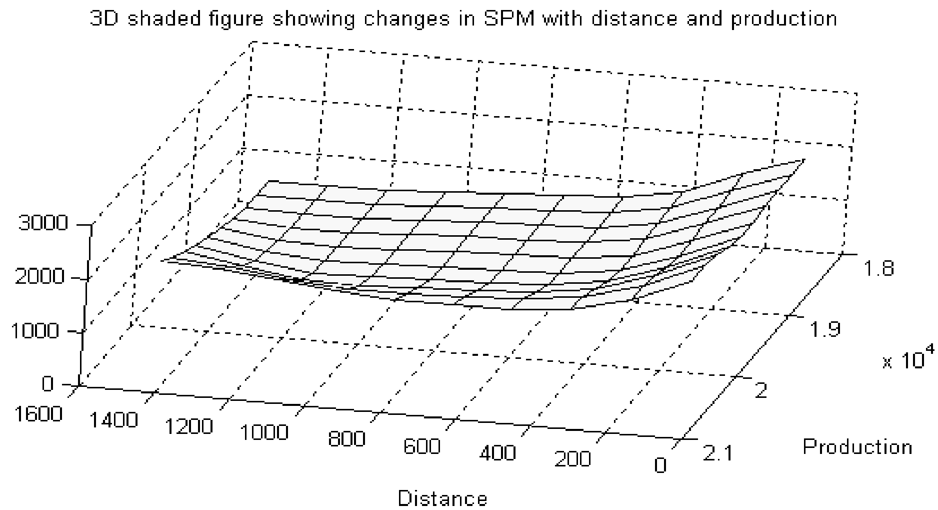


**Fig 7**

In this 3D shaded figure 7 it is also shown that distance of sampling point is the dominant factor of dust concentration inspite of small range of production fluctuations.

Few examples of 3D plots and sensitivity analysis are shown above. Sensitivity analysis using 3 D plots, as discussed above, can thus be used to extract knowledge about a complex system on which understanding is implicit.

## 7.0 Conclusion

In this paper applicability of ANN models to predict SPM concentration at surface mines, using local meteorological data, is examined. Air Quality Modeling, using the soft computing techniques, is an emerging area of research in environmental sciences. ANN model appears to be a useful tool for prediction of SPM level of the surrounding ambient environment at a surface limestone mine. The model can be trained under different site- specific mining condition. So far, not much work has been done on SPM modeling and knowledge extraction under Indian mining areas using soft computing approach, this paper is a small step in that direction.

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