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# AIR QUALITY MODELING AT SIDCO INDUSTRIAL ESTATE, COIMBATORE USING ANN MODEL

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## ABSTRACT

This study has investigated the potential use of systematic approach to develop Artificial Neural Network (ANN) predicting models for the concentration of pollutants at a specific area in SIDCO, Coimbatore. The goal was to determine the concentration of $PM_{25}$, $PM_{10}$, and TSPM in the atmosphere according to their relationship with the month and pollutant concentration. Four models were run using Artificial Neural Networks, in the first three models, Months (1-12) were considered as input vectors and Concentrations of PM2.5, PM10 and TSPM were considered as targets separately in each model. In the fourth model, Concentrations of particulate matter $PM_{2\cdot5}$, $PM_{10}$ and TSPM were considered as input vectors, and months were considered as targets. Corresponding results were obtained for each model with R value ranges from 0.40302 to 0.9045.The models developed were reprogrammed and trained in such a way to predict the pollutant concentration in a particular month.

**KEYWORDS:** Air Comprises, Mixture Contains a Group, Air Quality Modeling

## INTRODUCTION

Air is one of the essential survival elements of the human life. Air comprises of mixture of gases which is used in breathing and a lot of other activities. The mixture contains a group of gases of nearly constant concentrations and a group with concentrations that are variable in both space and time. By volume, dry air contains 78.09% Nitrogen, 20.95% Oxygen, 0.93% Argon, 0.039% Carbon di-oxide, and small amounts of other gases. Air also contains a variable amount of water vapour, on average around 1%. Air plays a critical part in human's life, that one cannot live without it even for a few minutes. It is necessary to keep the air breathable and safe.

Air Pollution is any undesirable change in the composition of air, or literally the contamination and deterioration of the environment/nature by releasing undesirable constituents in the atmosphere, which are lethal to the human beings and also various forms of life. It disturbs the stability and the ecological balance of the surroundings. It acts as a main reason for various diseases, breath related disorders, lung disorders etc. Major pollution is man-made and few are naturally occurring. Immense growth in the population and in turn phenomenal increase in vehicular traffic, and growth of industries forms a major source of air pollution. Release of undesirable constituents from the industries and vehicles forms the predominant source of pollution. These are termed as pollutants, which can be Particulate Matter $PM_{10}$, $PM_{2.5}$, Gaseous pollutants like $SO_2$, $NO_2$, $NH_3$ and metals like Lead etc. Air comprises of these pollutants generally in certain limits, but once when it is above the limit it causes air pollution. According to National Ambient Air Quality Standards, there are certain tolerance limits for these pollutants, which should not be exceeded. In order to predict the Quality of an air, certain index values can be referred and verified whether the air is clean. Air Quality Index (AQI) or Air Pollution Index is such number which gives the quality of the air. The AQI is commonly used to indicate the severity of pollution.

## MODELLING

A model may be defined as a representation of the reality. The particular representation used in any given case can take a number of forms. Generally, in order to build something huge like a bridge or a fly over or a building, a miniature version of the same will be made as to give a projection of how it will be in the future, it predicts the structure, shape and look of it in a small form giving an insight of how it will be in the future. Similarly, this is applied to mathematics also, this termed as Mathematical Modelling, will predict the future of something representing it in the form of equations or any graphs or charts etc.,

This follows the principle of two variables, dependent and independent variables, i.e., the dependent variables changes according to the independent variables. In the case of air pollution studies, the pollutant concentrations of oxides of sulphur, oxides of nitrogen, particulate matter and meteorological data are the independent variables and AQI is the dependent variable. So, modeling can be done between these and equations stating the behavior can be drawn. On the whole, a mathematical model explains the behavior of something, for instance Air quality using mathematical concepts or equations.

## ARTIFICIAL NEURAL NETWORK

Artificial Neural Network is a tool which mimics the brain, uses the principles that is followed in the brain. It is also called as connectionist architectures, computing paradigms that emulate the basic workings and learning rules of the human brain. The brain is composed of approximately 1011 neurons, connected to roughly 103 other neurons by axons. Neurons are the elements of our nervous system which transmits information from one part to other part. A neuron consists of four elements Dendrites, Soma, Axon, and Synapses. The neurons are interconnected in the layers of the brain where it transmits and deciphers information.

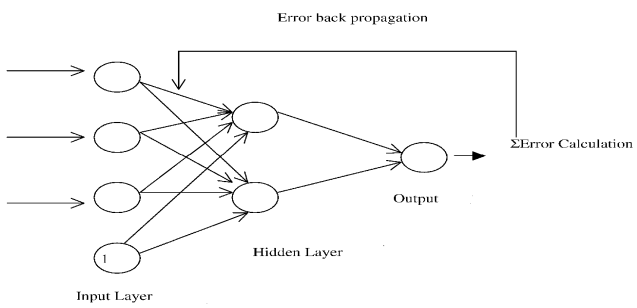


**Figure 1: Neural Network Structure**

Artificial neural networks consists of three layers generally, input layer, hidden layer and the output layer (Figure. 1). The number of layers in the neural networks can vary from a single layer to multiple layers. The layer that gets the inputs from the external environment is called the input layer. The network outputs are generated from the output layer. The hidden layer in the middle consists of neurons, which forms a relationship between the given input and the target and predicts an output, which is again modified using the back propagation algorithm until a satisfactory output is obtained. Weights and bias are assigned which can be changed using trial and error until a satisfactory fit is obtained. Hidden layers are sometimes linked to a black box within which the input data are mapped into outputs utilizing suitable activation functions. Different transfer functions can be used according to the type of data.

Neural networks are trained using various training algorithms where it uses back propagation to assign weights and biases in order to train the network. Levenberg Marquardt back propagation algorithm is the mostly used training function. It is also known as the damped least squares method, is used to solve non-linear least squares problems. The primary application of the algorithm is in the least squares curve fitting problem. Various transfer functions are used in the neural networks according to the type of the data used. Purelin, logsig, tansig and Gaussian are some of the functions which are used as transfer functions.

## OBJECTIVES OF THIS PROJECT

In this paper, emphasis is made on the prediction of levels of air pollution in the Tamil Nadu Small Industries Development Corporation Limited (TANSIDCO) Industrial Cluster, Coimbatore based on the data available for the year 2012.

- To develop models using artificial neural networks for the year 2012.
- **Model 1:** To establish the relationship between PM $_{10}$, PM 2.5 and TSPM with the months for the year 2012.
- **Model 2:** To establish the relationship between PM $_{25}$ and months for the year 2012.
- **Model 3:** To establish the relationship between PM $_{10}$ and months for the year 2012.
- **Model 4:** To establish the relationship between TSPM and months for the year 2012.
- The models developed were to be reprogrammed and trained in such a way to predict the pollutant concentrations in a particular month

## PREDICTION OF PM10 AND TSPM AIR POLLUTION PARAMETERS

Mouhammd Alkasassbeh et al., used Artificial Neural Networks to predict the concentrations of $PMi_0$ and TSPM Air Pollution parameters. A data set collected at Al-Fuhais cement plant for over one-year period (2006, 2007) by eight monitoring stations were used for this study. The ANN models used considered the meteorological parameters: Temperature, Relative Humidity, Wind Speed as inputs and the targets were the concentrations of $PMi_0$ and TSPM. Two Artificial Neural Network based Auto Regressive with external (ANNARX) Input models were used to provide high performance modeling for the $PMi_0$ and the TSPM air pollution parameters. Experimental results showed that the Auto Regressive models can provide good modeling results using a limited number of measurements.

## ARTIFICIAL NEURAL NETWORKS FOR THE IDENTIFICATION OF UNKNOWN AIR POLLUTION SOURCES

S.L. Reich et al., used Artificial Neural Networks which used pattern recognition to identify the unknown air pollution parameters. The problem that is addressed in this paper is the apportionment of a small number of sources from a data set of ambient concentrations of a given pollutant. Three layers feed-forward ANN trained with a back-propagation algorithm were selected. Gaussian dispersion model is used to build the test case. A dataset of hourly meteorological conditions and measured concentrations were taken as the inputs to the network that is wired to recover relevant emission parameters of unknown sources as outputs. The rest of the model data were corrupted adding noise to some meteorological parameters to test the goodness of the method to recover the correct answer. The ANN was applied to predict the 24 hour $SO_2$ concentrations and were compared with the measured concentrations.

Boznar et al., used neural networks to predict short term $SO_2$ concentrations in highly polluted industrial areas of complex terrain around the Slovenian Thermal Power plant at Sostanj, India. Because the classical methods for air pollution modeling, such as dispersion models, were not reliable in topography, neural networks were applied to predict $SO_2$ pollution. There were 37 input variables, including time of day, temperature, wind speed, wind direction, solar radiation, $SO_2$ concentration, relative humidity and emissions. The results were very promising. A multi-layer perceptron with sigmoid transfer function was trained with a back propagation algorithm. Separate networks for different locations were trained because of the micro- climatological situations appearing in the region. The half-hourly concentrations of $SO_2$ were used to train the network. Three stations were observed to examine the ability of the neural network. However, the results for other months or seasons were not tested for the same area. In addition, no statistical validation tests were carried out to observe the performance of the models.

## ASSESSMENT AND PREDICTION OF TROPOSPHERIC OZONE CONCENTRATION LEVELS USING ARTIFICIAL NEURAL NETWORKS

S.A. Abdul-Wahab et al., used Artificial Neural Networks to predict the concentration levels of ozone in the troposphere. The network was trained using summer meteorological and air quality data where the ozone concentrations were the highest. The data were collected from an urban atmosphere. Three neural network models were developed. The first model was used on studying the factors that control the ozone concentrations during a 24-hour period where both daylight and night hours were included. The second model was developed to study the factors that regulate the ozone concentrations during daylight hours at which higher concentrations of ozone were recorded. The third model was developed to predict the daily maximum ozone levels. The predictions of the models were consistent with the measured observations. A partitioning method was used to study the relative percent contribution of each of the input variables. The contribution of meteorology on the ozone concentration variation was found to fall within the range 33.15-40.64%. It was also found that Nitrogen oxide, Sulfur dioxide, relative humidity, non-methane hydrocarbon and Nitrogen dioxide have the most effect on the predicted ozone concentrations. In addition, temperature played an important role while solar radiation had a lower effect than expected. The results of this study indicate that the artificial neural network (ANN) is a promising method for air pollution modeling.

## FORECASTING AIR POLLUTION TIME SERIES USING NEURAL NETWORKS

Harri Niska et al., used neural networks to forecast the Air pollution time series. Genetic algorithm was used for selecting the inputs and designing the high level architecture of a multi-layer perceptron model for forecasting hourly concentrations of Nitrogen dioxide at a busy urban traffic station. The results showed considerable relevance between the observed and the forecasted values. Only two hidden layers were required to get better results.

Benevenuto et al., illustrated the use and some related results of Artificial neural networks for data quality control of environmental time series and for reconstruction of missing data. Artificial neural networks were applied to the short and medium term prediction of air pollutant concentrations in urban areas, interpolating and extrapolating daily maximum temperature, replacing time distribution with spatial distributions. Observed versus Predicted data were compared to test the efficacy of the ANN's in simulating the environmental processes. Their results confirmed ANN's as an improvement of classical models and showed the utility of ANN's for restoration of time series.

## OZONE AND PM10 FORECASTING

Ojha et al., presented a compendium of available methods and software for ozone and PM10 forecasting. Three different methods of Regression analysis, time series analysis and artificial neural networks were discussed in this paper. Lists of available software that can be used as a starting point, for the development of forecasting models were also provided.

Gardner et al., did a case study with the UK data and demonstrated that statistical models of hourly surface ozone concentrations require interactions and non-linear relationships between predictor variables in order to accurately capture the ozone behavior. Comparisons between linear regressions, regression tree and multi-layer perceptron neural network models of hourly surface ozone concentrations quantify these effects. They reported that although multi-layer perceptron models were shown to more accurately capture the underlying relationship between both the meteorological and temporal predictor variables and hourly ozone concentrations, the regression models were seen to be more readily physically interpretable.

Asha Chelani et al., employed Artificial neural networks to predict the concentration of ambient respirable particulate matter ($PM_{10}$) and toxic metals observed in the city of Jaipur, India. A feed-forward network with a back propagation learning algorithm was used to train the neural network to analyze the behavior of the data patterns. The meteorological variables of wind speed, wind direction, relative humidity, temperature and time were taken as input to the network. The results indicated that the network was able to predict the concentrations of $PM_{10}$ and toxic metals accurately.

## ATMOSPHERIC DISPERSION IN COMPLEX TERRAIN

Sarkar and Jaleel presented a comparative study of the predictions of atmospheric dispersion in complex terrain by conventional dispersion models and Artificial neural networks. A multi-layer feed forward back propagation with generalized data rule applied for this study performed better than the mathematical models for all the test data.

## PREDICTION OF GROUND LEVEL AIR POLLUTION

Mahad S. Baawain et al., used a statistical approach to predict the ground level air pollution around an industrial port using Artificial neural networks. A rigorous method of preparing air quality data is proposed to achieve more accurate air pollution prediction models based on artificial neural networks. The models consider the prediction of daily concentrations of various ground level air pollutants, namely CO, $PM_{10}$, $NO_2$, $NO_x$, $H_2S$ and Ozone, which were measured by an ambient air quality monitoring station in Ghadafan village, located 700 m downwind of the emissions of Sohar Industrial port on the Al-Batinah coast of Oman. The training of the models was based on the multi-layer perceptron method with the back propagation algorithm. The results show very good agreement between the actual and predicted concentrations with the $R^2$ value exceeding 0.70. The results also show the importance of temperature in daily variations of ozone, $SO_2$ and $NO_x$, while the wind speed and wind direction play important roles in the daily variations of NO, CO, $NO_2$ and $H_2S$. $PM_{10}$ concentrations were influenced by almost all the measured meteorological parameters.

## SIDCO COIMBATORE STUDY AREA

Artificial Neural Network modeling was done for the Air Quality data which were sampled in SIDCO- Coimbatore. The data consists of the concentrations of Particulate Matter $PMi_0$ and $PM_{25}$ and Total Suspended Particulate Matter, these were taken as inputs. On the other hand, months (112) were given as outputs. In Coimbatore District, Kurichi is located at 10°55'11" N latitude and 76° 57'35"E longitude comprising of Industrial Cluster. This Industrial cluster is located at distance of 7 km from Coimbatore Corporation. In Kurichi, two Industrial estates exist, which are developed by SIDCO and Private. Adjoining to this estate, Tamilnadu Housing Board has constructed Housing units. This Industrial cluster area spreads over an area of about 180 acres. This cluster comes under the administrative jurisdiction of Kurichi Municipality. This industrial cluster is located on the National Highway from Coimbatore to Pollachi.

## SOFTWARE USED

MATLAB 7.12.0.635 (R2011a) software was used for carrying out the Artificial neural networks. Neural network option in the software was used to run the model.

## DATA

Ambient Air Quality data like concentrations of pollutants such as Particulate Matter PM10, PM2.5, and Total Suspended Particulate Matter were obtained from previous experimental studies of Air Quality Monitoring at SIDCO for the year 2012 by Er. R. Chandrasekaran, Assistant Environmental Engineer, Tamil Nadu Pollution Control Board, Coimbatore.

Data preparation is one of the critical and the most important step while modeling through artificial neural networks, because it has an immense impact on the success and the performance of the neural network results. The dataset consisted of the concentrations of the Particulate matter $PM_{10}$, $PM_{25}$ and TSPM for the entire year of 2012. Data preparation was done according to the model which is to be run. Four models were developed for establishing the relationship between the $PM_{10}$, $PM_{25}$ and TSPM with the months. In model I, $PM_{10}$, $PM_{25}$ and TSPM were taken as inputs and months were taken as outputs. In model II, $PM_{25}$ was taken as input and months were taken as outputs. In model III, $PM_{10}$ was taken as input and months were taken as outputs. In model IV, TSPM was taken as input and months were taken as outputs. Table 1 shows the input data and output data used for modeling evenberg-Marquardt back propagation algorithm was used for training the model since it is been recommended as the first choice supervising algorithm. While training with the help of this algorithm, the weights and biases are updated automatically by this algorithm.

**Table 1: Concentrations of Pollutants and Months**

| Months | PM2.5 (µg/M3) | PM10 (µg/M3) | TSPM (µg/M3) |
|---|---|---|---|
| 1 | 19 | 63 | 107 |
| 1 | 28 | 91 | 150 |
| 1 | 19 | 65 | 104 |
| 1 | 26 | 86 | 138 |
| 1 | 37 | 120 | 174 |
| 1 | 39 | 119 | 178 |
| 1 | 25 | 81 | 130 |
| 1 | 29 | 89 | 142 |
| 2 | 49 | 109 | 230 |
| 2 | 59 | 138 | 295 |

**Table 1: Contd.,**

| | | | |
|---|---|---|---|
| 2 | 51 | 112 | 245 |
| 2 | 40 | 92 | 205 |
| 2 | 64 | 121 | 304 |
| 2 | 65 | 123 | 308 |
| 2 | 52 | 122 | 277 |
| 2 | 64 | 148 | 307 |
| 3 | 40 | 92 | 205 |
| 3 | 24 | 79 | 198 |
| 3 | 25 | 78 | 195 |
| 3 | 41 | 97 | 212 |
| 3 | 37 | 119 | 275 |
| 3 | 35 | 196 | 255 |
| 3 | 32 | 94 | 237 |

Levenberg-Marquardt back propagation algorithm was used for training the model since it is been recommended as the first choice supervising algorithm. While training with the help of this algorithm, the weights and biases are updated automatically by this algorithm. Ambient Air Quality data like concentrations of pollutants such as Particulate Matter $PM_{10}$, $PM_{2.5,}$ Total Suspended Particulate Matter and Months were used to run the Artificial neural network. Four models were developed, in which the models used the concentrations of $PM_{10}$, $PM_{2.5}$ and TSPM as inputs and months as outputs.

**Table 2: Predictor Variables Proposed for Each Model**

| Model No. | Model Inputs | Model Targets |
|---|---|---|
| I | $PM_{10}$, $PM_{2.5}$, TSPM | Months |
| II | $PM_{2.5}$ | Months |
| III | $PM_{10}$ | Months |
| IV | TSPM | Months |

## MODEL I

The model was developed to establish a relationship between the months and the different concentrations of $PM_1$o, PM2.5, TSPM. The model was trained with different hidden layers to get considerable $R^2$ value. Figure 3 shows the program used for model I. MODEL II The model was developed to establish a relationship between the months and the different concentrations of PM2.5. Model was trained with different hidden layers to get a considerable $R^2$ value.

## MODEL II

The model was developed to establish a relationship between the months and the different concentrations of $PM_{2.5}$. Model was trained with different hidden layers to get a considerable $R^2$ value.

## MODEL III

This model was developed to establish a relationship between the months and the concentrations of $PMi_0$. The model was trained with different hidden layers to get a considerable $R^2$ value..

## MODEL IV

The model was developed to establish a relationship between the months and the concentrations of TSPM. The model was trained with different hidden layers to get a considerable $R^2$ value. 16. VALIDATION OF THE MODEL Ambient Air Quality data like concentrations of pollutants such as Particulate Matter $PM_{10}$, $PM_{25}$, Total Suspended

Particulate Matter and Months were used to run the Artificial neural network. Four models were developed, in

**Table 3: Predictor Variables for Each Model**

| Model No. | Model Inputs | Model Targets |
|---|---|---|
| I | PM10, PM2.5, TSPM | Months |
| II | PM2.5 | Months |
| III | PM10 | Months |
| IV | TSPM | Months |

which the models used the concentrations of $PM_{10}$, $PM_{25}$ and TSPM as inputs and months as outputs.

## PREDICTIONS FOR MODEL I

Artificial neural network model was run with the concentrations of particulate matter $PM_{10}$, $PM_{2.5}$, TSPM as input and months as the output. Table 4 shows the best architectures for the model, where hidden layers ranging from 2 to 8 were used and the corresponding R-Value was ranging from 0.70756 to 0.9045. The best R-Value was obtained at the hidden layer of 8.

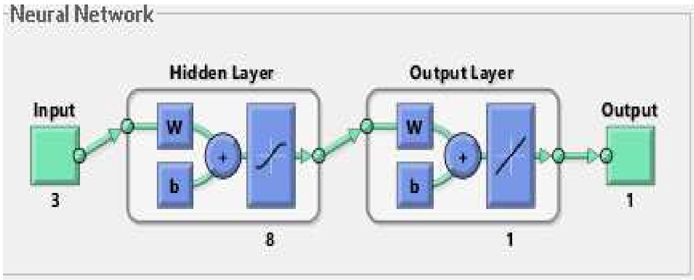


**Figure 2: Neural Network Structure for Model I**

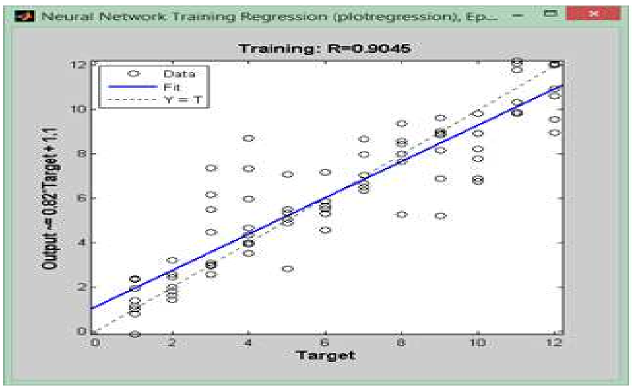


**Figure 3: Regression Plot for Model I**

**Table 4: Best Architectures for Model I**

| Hidden Layers | R- Value |
|---|---|
| 2 | 0.70756 |
| 3 | 0.72881 |
| 4 | 0.79868 |
| 5 | 0.79173 |
| 6 | 0.82897 |
| 7 | 0.88346 |
| 8 | 0.9045 |

## MODEL II

Artificial neural network model was run with the concentrations of PM2.5 as the input and months as the output. Table 5 shows the best architectures for the model, where hidden layers ranging from 2 to 8 were used and the corresponding R-Value was ranging from 0.45041 to 0.83846. The best R-Value was obtained at the hidden layer 5 to Artificial neural network model was run with the concentrations of PM10 as input and months as output. Table 6 shows the best architectures for the model, where hidden layers ranging from 2 to 8 were used and the corresponding R-Value was ranging from 0.40302 to 0.67753. The best R-Value was obtained at the hidden layer of 4 to 8.

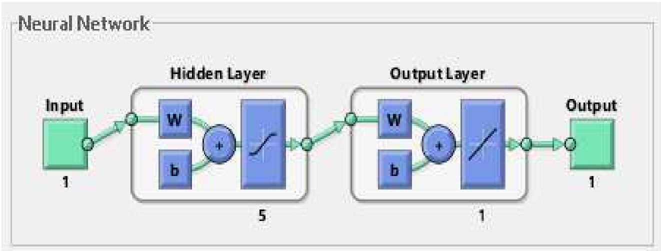


**Figure 4: Neural Network Structure for Model II**

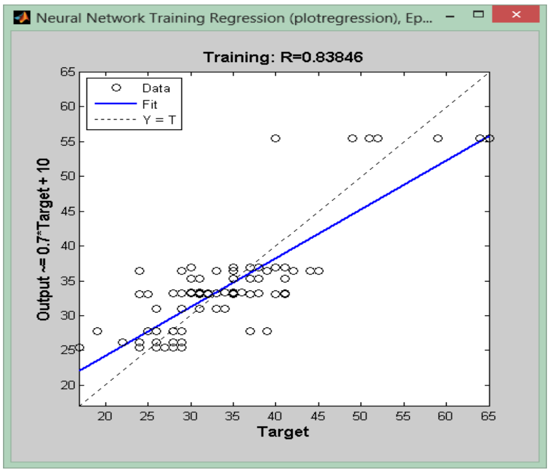


**Figure 5: Regression Plot for Model II**

**Table 5: Best Architectures for Model II**

| Hidden Layers | R- Value |
|---|---|
| 2 | 0.45051 |
| 3 | 0.46954 |
| 4 | 0.46954 |
| 5 | 0.83735 |
| 6 | 0.83735 |
| 7 | 0.83846 |
| 8 | 0.83846 |

## PREDICTIONS FOR MODEL III

Artificial neural network model was run with the concentrations of $PM_{10}$ as input and months as output. Table 6 shows the best architectures for the model, where hidden layers ranging from 2 to 8 were used and the corresponding R-Value was ranging from 0.40302 to 0.67753. The best R-Value was obtained at the hidden layer of 4 to 8.

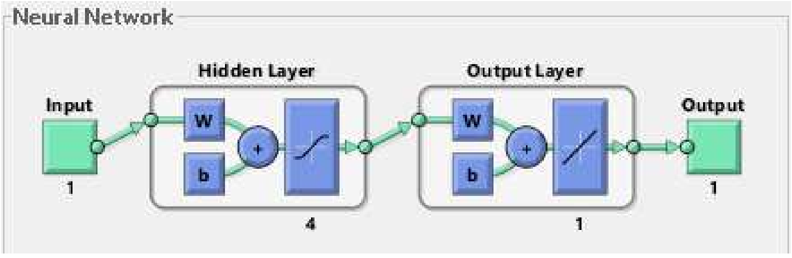


**Figure 6: Neural Network Structure for Model III**

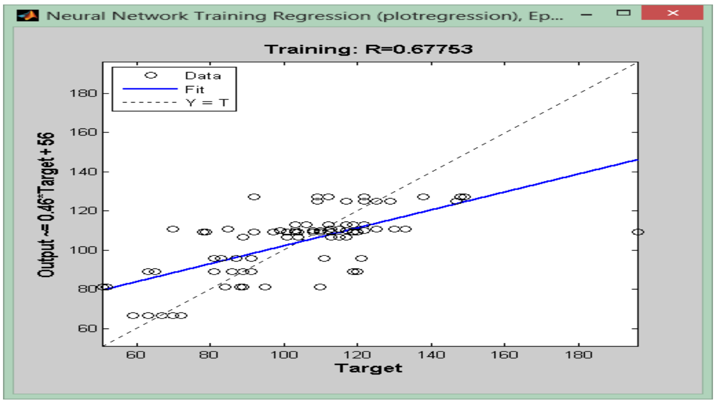


**Figure 7: Regression Plot for Model III**

**Table 6: Best Architectures for Model III**

| Hidden Layers | R- Value |
|---|---|
| 2 | 0.40302 |
| 3 | 0.67463 |
| 4 | 0.67753 |
| 5 | 0.67753 |
| 6 | 0.67753 |
| 7 | 0.67753 |
| 8 | 0.67753 |

## PREDICTIONS FOR MODEL IV

Artificial neural network model was run with concentrations of TSPM as input and month as the output. Table 7 shows the best architectures for the model, where hidden layers ranging from 2 to 8 were used and the corresponding R-Value was ranging from 0.80191 to 0.87119. The best R-Value was obtained at the hidden layer of 6 to 8.

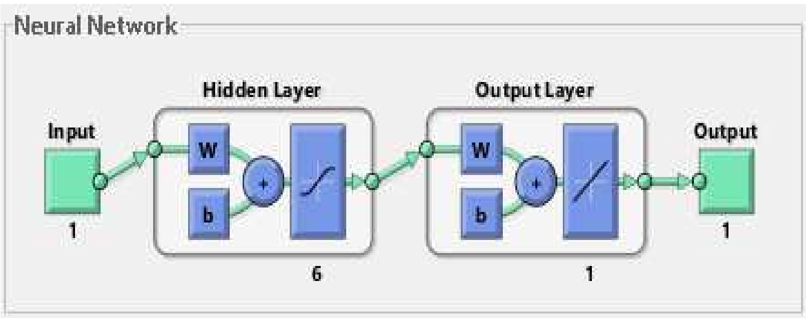


**Figure 8: Neural Network Structure for Model IV**

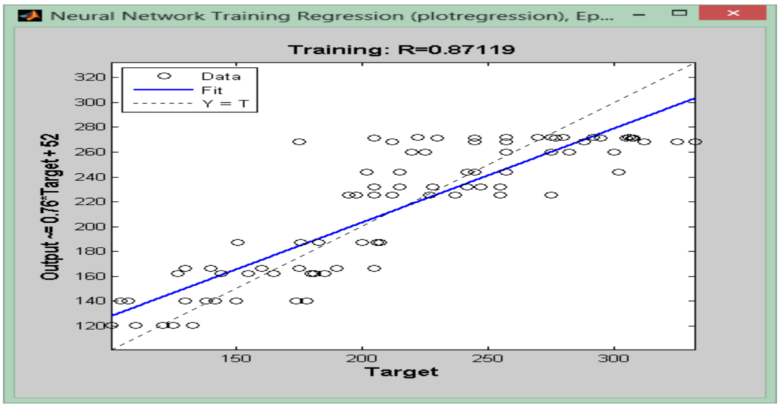


**Figure 9: Regression Plot for Model IV**

**Table 7: Best Architectures for Model IV**

| Hidden Layers | R- Value |
|---|---|
| 2 | 0.80191 |
| 3 | 0.80191 |
| 4 | 0.87066 |
| 5 | 0.87066 |
| 6 | 0.87119 |
| 7 | 0.87119 |
| 8 | 0.87119 |

## CONCLUSIONS

Air pollution models can be a very effective tool in planning strategies for management of local air quality and can provide a rational basis for the control of air pollution. If properly designed and evaluated, air pollution models play a considerable role in any air quality management system. In the present work, the most convincing advantage of ANN model is that this model can be used in two ways, first we can predict the month for a particular concentration of $PM_{25}$, $PM_{10}$, and TSPM. Secondly we can predict the pollutant concentration based on the month.

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