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Prediction of No2, So2and Pm10concentrations in Ambient Air Using Artificial Neural Networks and ANFIS

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Abstract: **-- Atmospheric pollution is currently one of the most important environmental problems at the global scale. Several forecasting models have been developed with the aim of obtaining the concentrations of atmospheric pollutants. Artificial Intelligence models have been widely used for the prediction of air pollutants, especially the Artificial Neural Networks (ANNs) and Adaptive Network Based Fuzzy Inference System (ANFIS). Study area chosen for the present work is Sanathnagar, Punjagutta, Hyderabad Central University and Pashamylaram areas in Hyderabad, Telangana. The present study includes application of Artificial Neural Networks for the prediction of air pollutant concentrations of NO2, SO2 and PM10 of all selected study areas by using meteorological parameters as inputs. The models are developed based on trial and error method by choosing various number of neurons and number of hidden layers. The best performing network was sought by experimenting combinations of number of neurons and number of hidden layers with respect to Coefficient of Correlation and RMSE (Root Mean square Error).In the present study Adaptive Network based Fuzzy Inference System was also developed for the prediction of NO2, SO2 and PM10 of all selected study areas by using meteorological parameters as inputs.**

***Keywords*:** **ANFIS, ANN, Correlation, Meteorological, Prediction, RMSE.**

I. INTRODUCTION

AIR POLUTION

Indian Standards Institute define air pollution as, "Air pollution is the presence of ambient atmosphere or substances generally resulting from the activity of man in sufficient concentration present for a sufficient time and under circumstances which interfere significantly with the comfort, health or welfare of persons or with the full use or enjoyment of property". An air pollutant is a substance in the air that can have adverse effects on humans and the ecosystem. The substance can be solid particles,

AIR QUALITY PREDICTION

Air quality prediction helps significantly in the management of our environment. Air quality forecasting tools are necessary to take precautionary measures to reduce the effect of a predicted pollution peak on the surrounding population and ecosystem. Long-term air pollution control is needed to prevent the situation from becoming worse in the long run. On the other hand, short term forecasting is required to take preventive and evasive action during an episode of air borne pollution.

Air pollution is becoming an environmental threat with the increase in Industrialization and Urbanization. The air quality is becoming essential both for the environment as well to the society. Hence, the present paper focuses on a comprehensive review on existing air quality forecasting techniques through soft computing.

AIR QUALITY PREDICTION TOOLS

The various types of soft computing techniques of Artificial Intelligence for the prediction of air pollutants are Artificial Neural Networks (ANN), Support Vector Machines (SVM), Fuzzy Logic (FL), Hidden Markov Model (HMM), Genetic Algorithm (GA), Adaptive network based fuzzy inference system(ANFIS). ANN and ANFIS are the most tools in the prediction of air pollutants. (Niharika et al.,2014) commonly used.

II. STUDY AREA

Rapid urban sprawl of Hyderabad city during the recent decades is one of the major factors for air pollution. The major sources of air pollution are vehicular emissions, large scale construction activities, fugitive dust, industries, bio-mass burning, fuel adulteration and traffic congestion. Vehicular pollution is mainly due to two stroke engines, poor fuel

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quality, inadequate maintenance, congested traffic, poor road conditions and traffic management system.

The present public transportation is inadequate & poor and usage of individual vehicles is also a major contributor to the pollution. The vehicular pollution has grown at an alarming rate due to urbanization and has become a serious problem. The main pollutants from automobile are hydrocarbons, lead, benzene, carbon monoxide, sulfur dioxide, Nitrogen dioxide and particulate matter. The Telangana State Pollution Control Board has wide network of air quality monitoring stations in Hyderabad area. In the Present Study four different significant stations were selected as study area and is presented in Table1.

Table 1. Study Area Specifications

S.NO.	NAME OF THE STATION	SIGNIFICANCE OF THE STATION
1	Sanathnagar	Centre of the city and Balanagar IDA
2	Punjagutta	Highly traffic density zone
3	Hyderabad Central University, Gachibowli	Downstream of industrial area and sensitive zone
4	Pashamylaram	Industrial Area

III. METHODOLOGY

The Methodology of Present Study is followed as per the schematic diagram shown in the Figure 1.

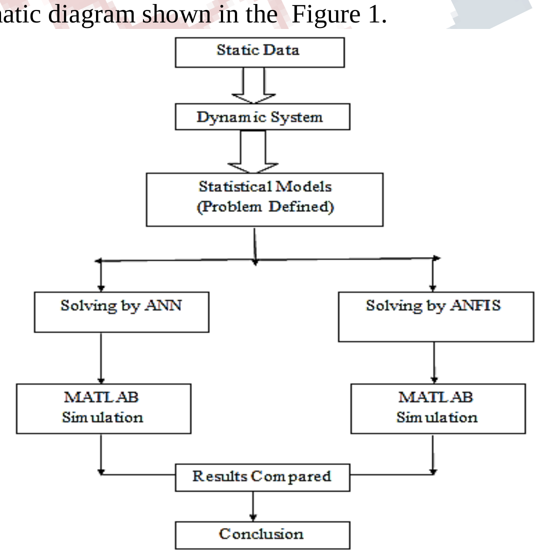

Figure 1. Flow Diagram of the Methodology Followed for the Prediction of Air Pollutants

Methodology of ANN

In this study, a multilayer Feed-Forward Back propagation type of ANN was considered to Predict NO_2, SO_2 and PM_{10} Concentrations in the ambient air. In a Feed-Forward Back propagation network, the input quantities are fed into input layer neurons, which in turn pass them onto hidden layer neurons after multiplying by a weight. The weights are adaptive coefficients within the network that determine the intensity of the input signal. A hidden layer neuron adds up the weighted input received from each input neuron, associates it with a bias, and then passes the result on through a nonlinear transfer function. The output neurons do the same operation as that of a hidden neuron. The bias neurons are connected to the all neurons in the next hidden and output layer neurons to improve the convergence properties of the network. The network is first trained before its application to the problem. In the training process, the target output at each output neuron is compared with the network output and the difference or error is minimized by adjusting the weights and biases through a training algorithm. The R^2 value (Coefficient of determination), it denotes the level of correlation between the Observed and Predicted Concentrations and it is preferred due to comparability with conventional studies. The best performing network was sought by experimenting combinations of number of neurons and number of hidden layers. Air quality forecasting model is developed using Artificial Neural Network. Air Quality prediction model for air pollutants such as NO_2, SO_2 and PM_{10} was developed using Neural Network. MATLAB 2011a Software was used for Artificial Neural Network model development modeling. The training parameters were changed for the best and optimized results, they were changed according to hit and trial method. During the training of the neural network different training functions were used and also the number of hidden layers along with the number of neurons was varied in order to get back the optimized model for the air pollutants prediction.

Normalization of Data

Ideally a system designer wants the same range of values for each input feature in order to minimize bias within the neural network for one feature over another. Data normalization can also speed up training time by starting the training process for each feature within same scale. It is useful for modeling applications where the inputs are generally on widely different scales. The normalized data is determined by min-max normalization which is expressed as

$$X = (x_i - x_{min})/(x_{max} - x_{min})$$

Where

X = normalized value
x = input parameter
x_{max} = maximum value among input parameters

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Validation

Out of whole set of 4 years data 15% is chosen for the validation purpose. For the best Neural Networks drawn by training and testing the data, validation is applied. However, there are still many hard handle problems with the Artificial Neural Networks.

1. Back Propagation algorithm convergence in accordance with the direction of the mean square error gradient descent, there are many local and global minimum mean square error gradient, which makes neural network is easy to fall into local minimum (local minima).
2. Back Propagation learning algorithm convergence rate is very slow, and may waste a lot of time.
3. The selection of the number of hidden nodes of the network is still a lack of unified and complete theoretical guidance.
4. Generalization ability of the learning network is poor.

To overcome the above stated problems considering vagueness and complexity of the problem ANFIS Model is considered.

PHASE II

Methodology of ANFIS

The ANFIS System is as shown in the Figure 2.

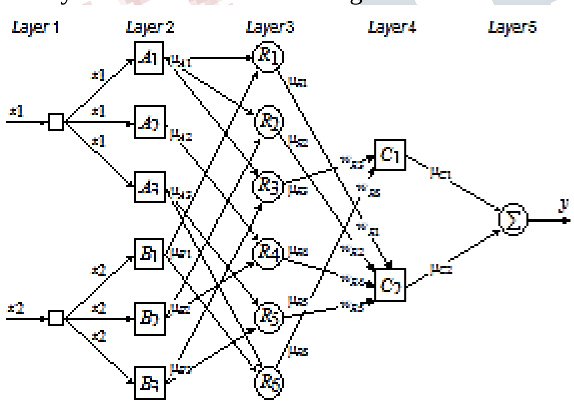

Figure 2. ANFIS System

Each layer in the ANFIS System is associated with a particular step in the fuzzy inference process.

Layer 1 is the Input layer: Each neuron in this layer transmits external crisp signals directly to the next layer

Layer 2 is the Fuzzification layer: Neurons in this layer represent fuzzy sets used in the antecedents of fuzzy rules. A Fuzzification neuron receives a crisp input and determines the degree to which this input belongs to the neuron's fuzzy set.

Layer 3 is the Fuzzy Rule Layer: Each neuron in this layer corresponds to a single fuzzy rule. A fuzzy rule neuron receives inputs from the Fuzzification neurons that represent fuzzy sets in the rule antecedents.

Layer 4 is the Output Membership Layer: Neurons in this layer represent fuzzy sets used in the consequent of fuzzy rules.

Layer 5 is the Defuzzification Layer: Each neuron in this layer represents a single output of the Neuro Fuzzy system. It takes the output fuzzy sets clipped by the respective integrated firing strengths and combines them into a single fuzzy set.

COLLECTION OF DATA

The hourly concentrations of air pollutants like Nitrogen Dioxide(NO_2), Sulfur Dioxide (SO_2) & Suspended Particulate Matter (PM10) and hourly Meteorological Parameters like Atmospheric Temperature (AT), Wind Speed (WS), Wind Direction (WD), Relative Humidity (RH), Solar Radiation (SR), and Atmospheric Pressure (AP) were collected for the Study area for the period (2012-2015) from TSPCB.

IV. RESULTS AND DISCUSSIONS

RESULTS OF ARTIFICIAL NEURAL NETWORKS

Artificial Neural Network model is developed to predict NO_2, SO_2 and PM_{10} taking the meteorological parameters such as atmospheric temperature, wind speed, wind direction, relative humidity, pressure and solar radiation as inputs. Predicted Values of NO_2, SO_2 and PM_{10} for four stations (Sanathnagar, Punjagutta, HCU and Pashamylaram) are shown in the Table 2, 3 & 4 respectively.

Table 2. Typical Layout Showing Predicted Monthly Mean Values of NO_2 (in µg/m3)

MONTHS	Sanathnagar	Punjagutta	HCU	Pashamylaram
January	40.1	45	45.2	55.3
February	39	49	32	54.2
March	54	70	41	49.3
April	39	15.1	32.3	48
May	11	14	27.3	35.2
June	17	12.9	13.4	15.3
July	18,2	14.2	13.4	8.9
August	23.6	20.2	14.3	17.8
September	28.9	24.9	15.2	23.9
October	29.1	22.4	14.7	43.9
November	58	44.2	20.2	26.3
December	54.1	45.0	44.9	37.3

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Table 3.Typical Layout showing Predicted Monthly Mean Values of SO_2 (in µg/m3)

MONTHS	Sanathnagar	Punjagutta	HCU	Pashamylaram
January	12	13	10.23	13.2
February	8.1	29.2	4.1	19.1
March	10.9	28.0	10.8	16.2
April	8.8	10.2	8.4	10.1
May	10	15.4	3.1	9.6
June	3.1	6.9	2.1	4.6
July	5.1	5.2	2.5	4.8
August	6.3	5.0	2.0	6.4
September	5.2	14.9	2.1	5.3
October	5.9	28	3.0	20.2
November	16	36.0	2.7	9.3
December	15	27.2	4.9	7.6

Table 4. Typical Layout Showing Predicted Monthly Mean Values of PM_{10}(in µg/m3)

MONTHS	Sanathnagar	Punjagutta	HCU	Pashamylaram
January	109	88	81.7	108
February	93	82	80.2	97
March	94	100	112	94
April	79	89	89.8	82
May	77	79	73	105
June	38	53	37.2	49
July	36	36	32.1	35
August	30	38	27	38
September	38	44	46.3	45
October	41	75	40.2	67
November	92	80	87.2	89
December	93	89	133	102

Several networks are developed for each station. The best neural networks have been proposed among all the trained networks. The best neural network is chosen in such a way that the R^2 value of the network should be >0.9. From the above tabular columns the best network models proposed for prediction of NO_2, SO_2 and PM_{10} are given in Tables 5, 6 and 7 respectively. The Correlation values of these proposed models are good.

Table 5. Proposed Model for Prediction of NO_2

Station Name	NO_2 Concentrations				
	Network	Training	Validation	Testing	Overall
Sanathnagar	6-9-50-1	0.931	0.931	0.930	0.933
Punjagutta	6-7-70-1	0.939	0.937	0.963	0.946
HCU	6-7-75-1	0.955	0.956	0.957	0.935
Pashamylaram	6-10-55-1	0.953	0.954	0.943	0.951

Table 6. Proposed Model for Prediction of SO_2

Station Name	SO_2 Concentrations				
	Network	Training	Validation	Testing	Overall
Sanathnagar	6-10-72-1	0.962	0.943	0. 955	0.957
Punjagutta	6-10-80-1	0.972	0.962	0.988	0.961
HCU	6-10-61-1	0.958	0.972	0.985	0.978
Pashamylaram	6-10-25-1	0.948	0.968	0.968	0.967

Table 7. Proposed Model for Prediction of PM_{10}

Station Name	PM_{10} Concentrations				
	Network	Training	Validation	Testing	Overall
Sanathnagar	6-10-50-1	0.965	0.942	0.952	0.959
Punjagutta	6-10-70-1	0.955	0.979	0.967	0.956
HCU	6-10-68-1	0.969	0.938	0.946	0.939
Pashamylaram	6-10-55-1	0.945	0.955	0.951	0.938

Figure 9, 10, 11 and 12 shows the training performance of the four Stations.

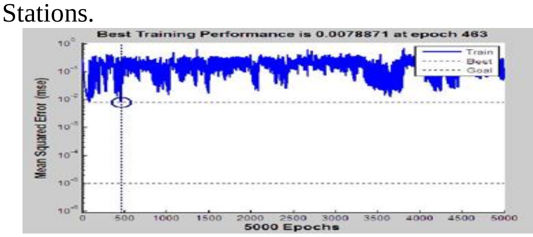

Figure 9. Training Performance as different Hidden Neurons Chose for Training Network for Sanathnagar Station Data

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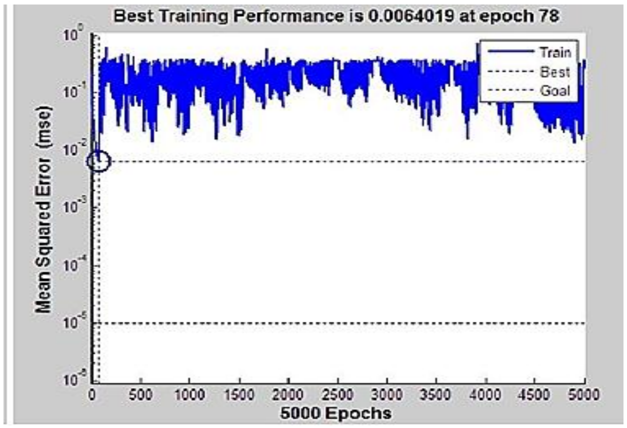

Figure 10.Training Performance as different Hidden Neurons Chose for Training Network for HCU Station Data

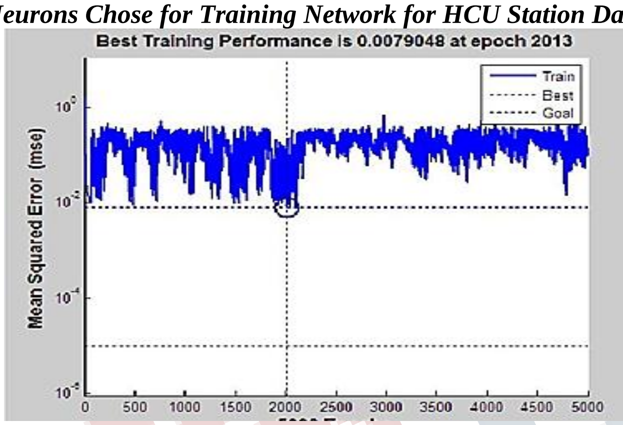

Figure 11. Training Performance as Different Hidden Neurons Chose for Training Network for Punjagutta Station Data.

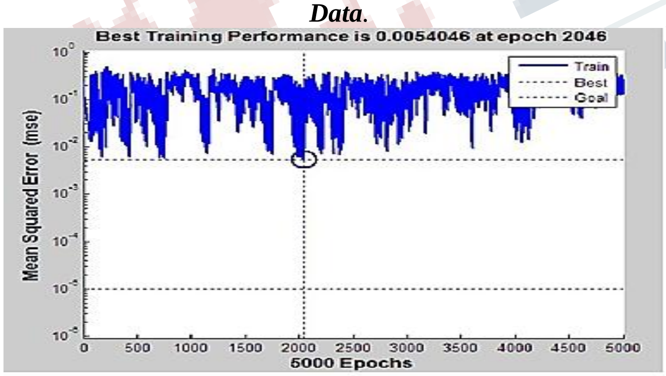

Figure 12. Training Performance as Different Hidden Neurons Chose for Training Network for Pashamylaram Station Data.

V. RESULTS OF ANFIS

ANFIS Model is developed to predict NO_2, SO_2 and PM_{10} by taking the Meteorological Parameters such as Atmospheric Temperature, Wind Speed, Wind Direction, Relative Humidity, Pressure and Solar Radiation as inputs.

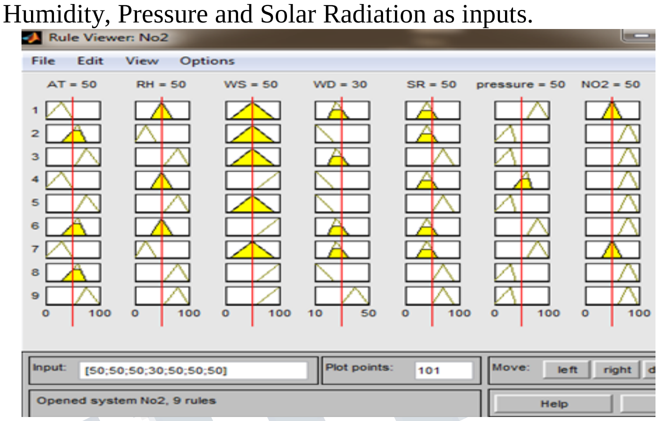

Figure 13 (a) Rule viewer for the prediction of NO_2

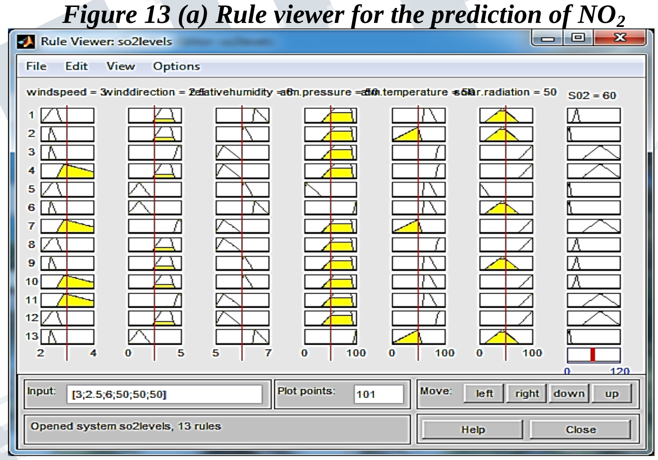

Figure 13 (b) Rule Viewer for the Prediction of SO2

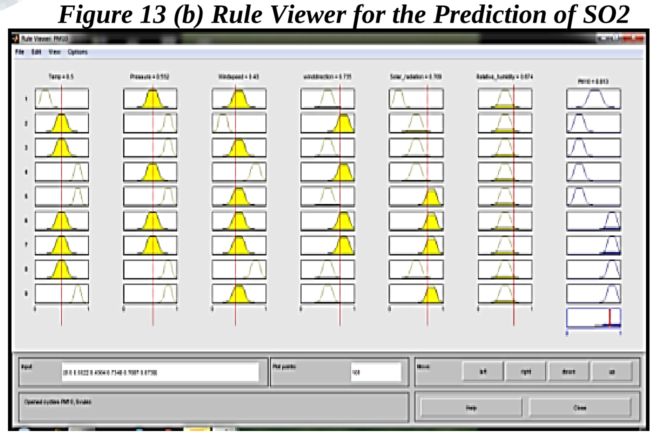

Figure 13 (c) Rule Viewer for the Prediction of PM_{10}

Surface Viewer for NO_2 is as shown in the Figure 14 (a) and Surface Viewer for SO_2 is as shown in the Figure 14 (b).In the above 3D surface plots the blue color surface indicates the low

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surface roughness values i.e. the better surface finish can be obtained. The yellow color surface indicates the high surface roughness values.

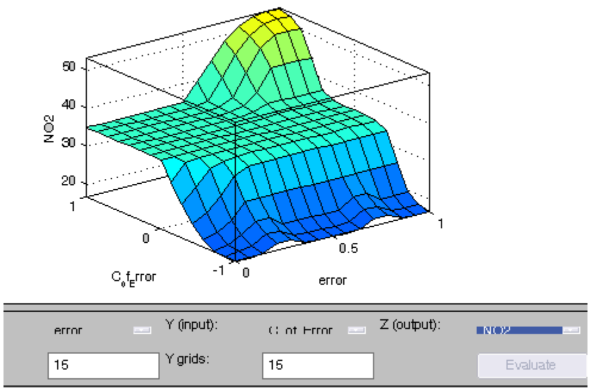

Figure 14 (a) Surface Viewer for NO_2

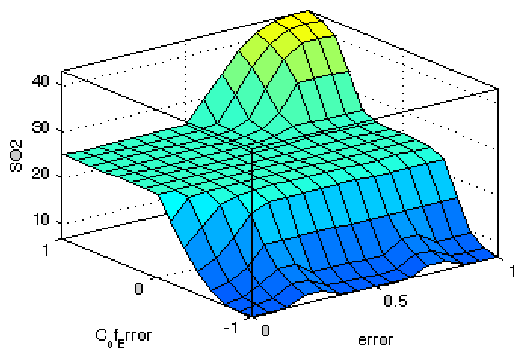

Figure 14 (b) Surface Viewer for SO_2

Normalized Values of Observed and Predicted Concentrations of NO_2 , SO_2 and PM_{10} using ANFIS Modeling for four stations are shown in the Table 8,9,10 and 11.

Table 8 Typical Layout Showing Predicted Monthly Mean Values of NO_2 (in µg/m3)

MONTHS	**Sanathnagar**	**Punjagutta**	**HCU**	**Pashamylaram**
January	43.2	51	55.4	50.9
February	43.7	49.1	34	59.5
March	51	70	43	56
April	42.9	23	36	53
May	16	25	29	41
June	13	22	21.2	20.1
July	17.3	21.2	19.4	13.2
August	23.9	27	23.1	22.1
September	29.1	29	25.3	27.2
October	30.9	50.2	32.1	51.1
November	56	56	34.1	30.1
December	44.1	50	56	42

Table 9 Typical Layout Showing Predicted Monthly Mean Values of SO_2 (in µg/m3)

MONTHS	**Sanathnagar**	**Punjagtta**	**HCU**	**Pashamylaram**
January	16.7	17.2	18.5	16
February	14.3	28.8	10.3	23
March	15.2	26.4	18	20.5
April	13.3	15.4	15.2	14.3
May	14	15.9	8.2	13.1
June	7.2	18.7	6.4	6.9
July	9.3	9.6	3.3	7.4
August	10.3	8.1	4	9.2
September	10.7	21	3.1	7.3
October	9.9	34.5	9.3	25
November	20.2	36.5	7	13.2
December	21.8	28	6.5	11.1

Table 10. Typical Layout of Predicted Monthly Mean Values of PM10 (in µg/m3)

MONTHS	**Sanathnagar**	**Punjagtta**	**HCU**	**Pashamylaram**
January	97	138	89.3	182
February	93	162	79	164
March	97	145	111	143
April	92.1	119	97	114
May	84.7	120	67	103
June	46	57	44.1	55
July	42.1	47.9	32.2	44
August	42	49.2	25.4	55
September	43	57.4	44	56

October	40.9	91	39	109
November	107	117	86	98
December	106	113	115	111.1

Table 11. Proposed Model for Prediction NO2, SO2 and PM10 using ANFIS

S. No	Station Name	Membership Function	Concentrations		
			NO2	SO2	PM10
1	Sanathnagar	Gbell	0.972	0.976	0.962
2	Punjagutta		0.954	0.980	0.952
3	Hcu		0.946	0.977	0.965
4	Pashamylaram		0.973	0.968	0.954

The ANFIS model provided better prediction capabilities than Artificial Neural Networks model because they generally offer the ability to model more complex nonlinearities and interactions. The Adaptive Neuro Fuzzy-Inference System gives closed correlation with experimental values.

RESULTS OF CORRELATION

Both the Correlation methods were performed for the concentrations of pollutants for Sanathnagar station for the year 2016 and the results are as follows.

Results of Pearson's correlation formula

In this method, correlation was performed in two steps.

I. Between the pollutants concentrations and the meteorological parameters
II. Between the Predicted and observed values of pollutants concentrations.

STEP-1

The Pearson's correlation between pollutants (NO2, SO2 & PM10) and meteorological parameters were carried out and results are shown in Table 12,13 and 14.

Table 12. Correlation coefficients between NO_2 and Meteorological parameters

	NO_2	WS	WD	AT	RH	SR	AP
NO_2	1.00						
WS	0.14	1.00					
WD	-0.21	-0.27	1.00				
AT	0.46	0.14	0.24	1.00			
RH	0.28	-0.17	-0.18	-0.97	1.00		
SR	0.59	-0.22	0.46	0.77	-0.63	1.00	
AP	-0.16	-0.05	0.44	0.41	-0.37	0.66	1.00

Table 13. Correlation coefficients between SO_2 and Meteorological parameters

	SO_2	WS	WD	AT	RH	SR	AP
SO_2	1.00						
WS	0.39	1.00					
WD	0.36	-0.27	1.00				
AT	0.65	0.14	0.24	1.00			
RH	-0.62	-0.17	-0.18	-0.97	1.00		
SR	0.48	-0.22	0.46	0.77	-0.63	1.00	
AP	0.44	-0.05	0.44	0.41	-0.37	0.66	1.00

Table 14. Correlation coefficients between PM_{10} and Meteorological parameters

	PM_{10}	WS	WD	AT	RH	SR	AP
PM_{10}	1.00						
WS	-0.40	1.00					
WD	0.30	-0.27	1.00				
AT	-0.49	0.14	0.24	1.00			
RH	0.62	-0.17	-0.18	-0.97	1.00		
SR	0.06	-0.22	0.46	0.77	-0.63	1.00	
AP	0.15	-0.05	0.44	0.41	-0.37	0.60	1.00

Pearson correlation coefficients are calculated between all pollutants and of each pollutant with all meteorological parameters using the standardized data.

STEP-2

In second step, R^2(Coefficient of determination) was performed for the pollutant concentrations for the year 2016 for Sanathnagar station and the results are as follows.

Nitrogen Dioxide (NO_2)

Comparison was done for the results of NO_2 concentrations using ANN and ANFIS of Sanathnagar Station for the year 2016 (shown in the Table 15

Table 15. Comparison between Observed and Predicted NO2 values of ANN and ANFIS

Month	Observed Values	Predicted Values using ANN	Predicted Values using ANFIS
January	44.0	40.1	43.2
February	42.4	39	43.7

March	50.2	54	51
April	41.4	39	42.9
May	14.9	11	16
June	14.2	17	13
July	16.3	18.2	17.3
August	22.8	23.6	23.9
September	28.3	28.9	29.1
October	29.8	29.1	30.5
November	55	58	56
December	53	54.1	44.1

Regression graph is plotted between Observed and Predicted values of ANN is as shown in the Figure 15 (a)

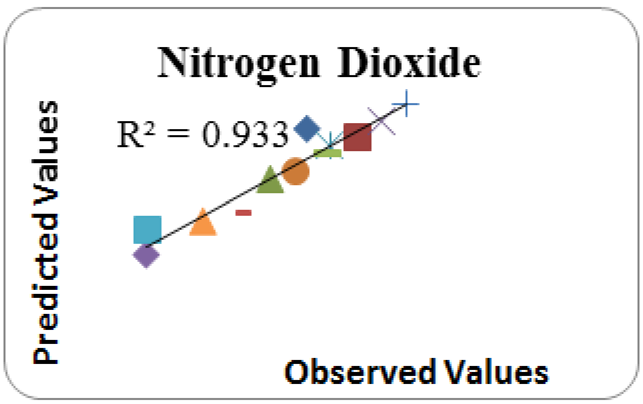

Figure 15 (a) Regression Graph between Observed and Predicted Values of NO2 for ANN

A Regression graph is plotted between Observed and Predicted values of NO2 using ANFIS is shown in the Figure 15 (b)

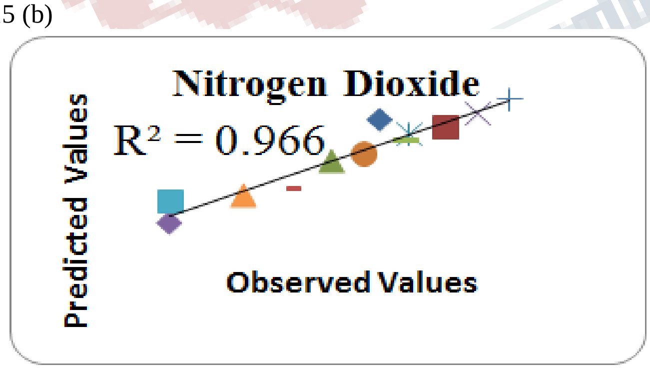

Figure 15 (b) Regression Graph Plotted between Observed and Predicted Values of NO2 Using ANFI

From the fig 15 (a)In ANN, Coefficient of determination for NO2 is 0.933 and from the fig 15(b) In ANFIS, Coefficient of determination for NO2 is 0.966.

Sulfur Dioxide (NO2)

Comparison was done for the results of SO2 concentrations using ANN and ANFIS of Sanathnagar Station for the year 2016 (shown in the Table 16).

Table 16. Comparison between Observed and Predicted Values of SO2 Using ANN and ANFIS

Months (2016)	Observed Values(Target)	Predicted Values Using ANN	Predicted Values Using ANFIS
January	15.2	12	16.7
February	13.2	8.1	14.3
March	14.2	10.9	15.2
April	12.2	8.8	13.3
May	13.2	10	14
June	6.3	3.1	7.2
July	8.9	5.1	9.3
August	9.7	6.3	10.2
September	9.5	5.2	10.7
October	8.9	5.9	9.9
November	19.5	16	20.2
December	20.7	15	21.8

A Regression graph is plotted between Observed and Predicted values of SO2 using ANN is shown in the Figure 16 (a)

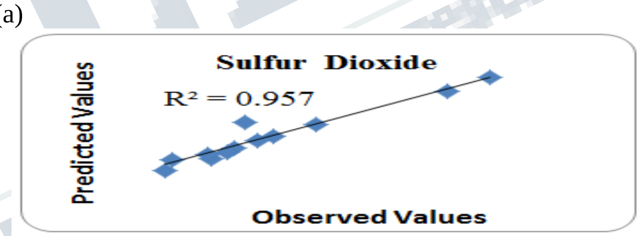

Figure 16 (a) Regression Graph Plotted between Observed and Predicted Values of SO2 Using ANN

A Regression graph is plotted between Observed and Predicted values of SO2 using ANFIS is shown in the Figure 16(b)

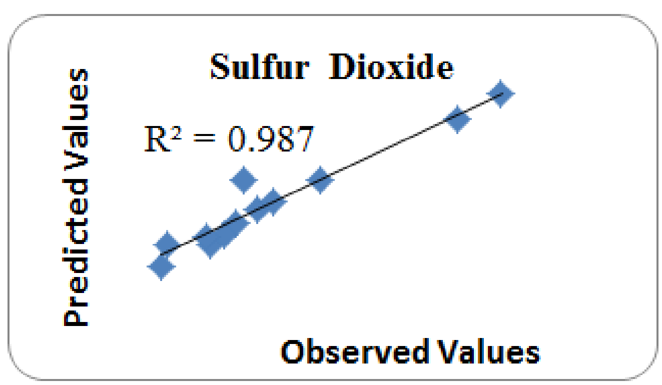

Figure 16 (b) Regression Graph Plotted between Observed and Predicted Values of SO2 Using ANFIS

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From the fig 16 (a)In ANN, Coefficient of determination for SO2 is 0.957 and from the fig 16 (b) In ANFIS, Coefficient of determination for SO2 is 0.987.

Suspended Particulate Matter (NO2)

Comparison was done for the results of SO2 concentrations using ANN and ANFIS of Sanathnagar Station for the year 2016 (shown in the Table 17).

Table 17. Comparison between Observed and Predicted Values of PM10 Using ANN and ANFIS

Months(2016)	Observed Values(Target)	Predicted Values Using ANN	Predicted Values Using ANFIS
January	98.7	109	97
February	94.6	93	93
March	95.3	94	97
April	91	79	92.1
May	83.2	77	84.7
June	47.3	38	46
July	42.2	36	42.1
August	40	30	42
September	42.8	38	43
October	41.2	41	40.9
November	105	92	107
December	107	93	106

Regression graph is plotted between Observed and Predicted values of PM10 using ANN is shown in the Figure 17 (a).

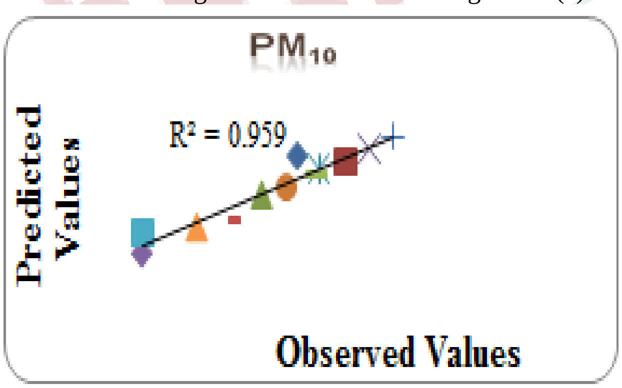

Figure 17 (a) Regression Graph Plotted between Observed and Predicted Values of PM10 Using ANN

A Regression graph is plotted between Observed and Predicted values of PM10 using ANFIS is as shown in the Figure 17 (b)

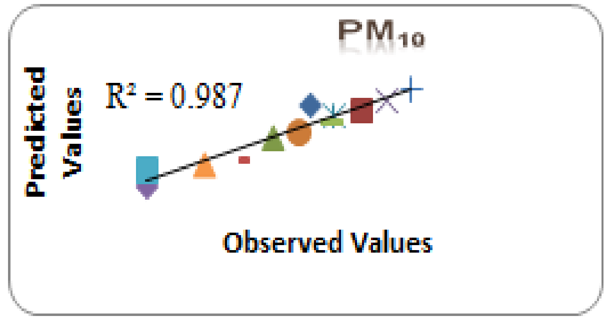

Figure 17 (b) Regression Graph Plotted between Observed and Predicted Values of PM10 Using ANFIS

From the fig 17 (a) In ANN, Coefficient of determination for PM10 is 0.959 and from the fig 17 (b) In ANFIS, Coefficient of determination for PM10 is 0.987.

Results of Root Mean Square Equation (RMSE)

The RMSE is a frequently used measure of the differences between values predicted by a model and the values actually observed. It represents the sample standard deviation of the didderences between predicted values and observed values. The values are shown in the following Tables 18 and 19.

Table 18. Proposed Model for the RMSE Prediction (ANN)

S.NO	STATION	NO2	SO2	PM10
1	Sanathnagar	0.0134	0.0142	0.0145
2	Punjagutta	0.0166	0.0164	0.0123
3	Hcu	0.0102	0.0155	0.0176
4	Pashamylaram	0.0132	0.0109	0.0186

Table 19. Proposed Model for the RMSE Prediction (ANFIS)

S.NO	STATION	NO2	SO2	PM10
1	Sanathnagar	0.0123	0.0156	0.0109
2	Punjagutta	0.0145	0.0134	0.0176
3	Hcu	0.0172	0.0138	0.0182
4	Pashamylaram	0.0128	0.0165	0.0178

RMSE value of zero indicates a perfect fit. From the Table 4.18 and 4.19 the values obtained are nearer to zero. The lower the RMSE, the more accurate is the prediction. The best fit between observed and calculated values, will have RMSE equals to zero

V. CONCLUSIONS OF THE PRESENT STUDY

• Models are developed to predict monthly mean concentrations of NO2, SO2 and PM10 using Artificial Neural Networks and ANFIS for four stations (Sanathnagar, Punjaguta, Hcu and Pashamylaram) for the year 2016.
• The simulation results of neural network show the training algorithm performs well in the process of convergence

characteristics and improve the convergence rate, a satisfactory approximation.

• For the prediction of NO2 for Sanathnagar, Punjagutta, HCU and Pashamylaram using ANN, the R2 value obtained are 0.931,0.939,0.955,0.953 and R2 value for the same using ANFIS are 0.972,0.954,0.946,0.973.

• For the prediction of SO2 for Sanathnagar, Punjagutta, HCU and Pashamlaram using ANN, the R2 value obtained are 0.943,0.969,0.972,0.968 and R2 value for the Prediction using ANFIS are 0.976,0.980,0.977,0.968.

• For the prediction of PM10 for Sanathnagar, Punjagutta, HCU and Pashamylaram using ANN, the R2 value obtained are 0.942,0.967,0.938,0.945 whereas R2 value using ANFIS are 0.962,0.952,0.965,0.954.

• The Concentrations of NO2, SO2 and PM10 using ANN and ANFIS are predicted and compared with observed concentrations of Sanathnagar station data and regression analysis is carried out

• Computational efforts can be reduced in ANFIS where as compared to ANN Model since ANFIS is a logic based model.

• The present study has indicated that ANFIS model provided a well suited method and gave promising results for modeling of highly non-linear air pollution problem in urban and industrialized areas.

• Hence, we conclude that by using the ANFIS system we can predict the air pollutants more accurately with less consumption of time and less computational efforts as compared to Artificial Neural Networks.

• The research study has conclusively demonstrated the utility of soft computing techniques with focus on ANFIS in air quality management.

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