International Journal of Civil
Engineering (IJCE)
ISSN(P): 2278-9987; ISSN(E): 2278-9995
Special Edition, Nov 2016; 11-20

International Academy of Science, Engineering and Technology
Connecting Researchers; Nurturing Innovations

PREDICTION OF NO_2 AND O_3 CONCENTRATIONS IN AMBIENT AIR USING ARTIFICIAL NEURAL NETWORKS AND NEURO FUZZY FOR HYDERABAD

M. SAFIYA BANU[1] & N. MUNILAKSHMI[2]

[1]M.Tech Scholar, Department of Civil Engineering, Sri Venkateswara University College of Engineering, Andhra Pradesh, India

[2]Assistant Professor, Department of Civil Engineering, Sri Venkateswara University College of Engineering, Andhra Pradesh, India

ABSTRACT

In the present study an Artificial Neural Networks (ANNs) models are developed to predict NO_2 and O_3 concentrations for Hyderabad. The meteorological variables like wind speed, wind direction, temperature, relative humidity and atmospheric pressure are used as input variables. The best performing network was sought with respect to Coefficient of correlation. Fuzzy Inference system was proposed to predict the NO_2 and O_3 concentrations. A Mamdani-type fuzzy inference system (FIS) was developed in the IF-THEN rules format. The product (*prod*) and the centre of gravity (centroid) methods were performed as the inference operator and defuzzification methods, respectively, for the proposed FIS. The results obtained using Neuro-Fuzzy were compared with the outputs of an Artificial Neural Networks model. The correlation coefficient between observed and predicted concentrations are in the range of 0.966 to 0.985.The evaluation of models results shows that the degree of success in NO_2 and O_3 concentration are seems to be good.

KEYWORDS: Artificial Neural Networks and Neuro-Fuzzy

INTRODUCTION

Air pollution is a major threat to health and is generated by rapid urbanization, population growth and industrialization. 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. Atmospheric pollution is currently one of the most important environmental problems at the global scale. It has a significant impact on human health. The air quality in cities varies depending on the degree of industrialization, population density, traffic density, topographical characteristics and meteorological variables. The global and regional variations in the climate together with the topographical conditions of the studied area, affect the transport and dispersion of pollutants. In Industrialized cities, the pollutants emitted by the industrial areas have the most significant effect in environmental pollution. 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 (concentrations or criteria pollutant levels), specially the artificial neural networks (ANNs) and Fuzzy Logics (FL). These models have proven to be suitable for the prediction of air pollutants, especially in cities where there are monitoring networks to measure the pollutant concentrations and the meteorological variables. Study area chosen for the present work is

Hyderabad. The hourly concentrations of air pollutants like Nitrogen Dioxide (NO_2) and Ozone (O_3) hourly meteorological parameters like Wind Speed (WS), Wind Direction (WD), Relative Humidity (RH), Solar Radiation (SR), Atmospheric Temperature (AT) and Atmospheric Pressure (AP) were collected simultaneously from different Ambient Air Quality Stations established by the Andhra Pradesh Pollution Control Board at Hyderabad (2010 – 2014).

In a developing country like India vehicular pollution is no loner intangible threat. It contributes to a shocking 64% of the total pollution in Delhi, 52% in Mumbai and 30% in Calcutta. In Indian urban life style, the atmosphere at traffic junctions and intersections of any urban center receive maximum input of traffic exhausts pollutants and thereby they are converted into localized high pollution episodes. NO_2 is of great concern and the major source of NO_2 are automobiles.

Neuro-Fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human like reasoning style of fuzzy systems with the learning and connectionist structure of Neural Networks.

Neuro fuzzy modeling is considered to be an excellent predictive and data analysis tool for air quality forecasting. It involves two techniques Neural Networks and Fuzzy Logic which are many times applied together for solving engineering problems where the classic techniques do not supply an easy and accurate solution. The Neuro-Fuzzy term means a type of system characterized for a similar structure of a fuzzy controller where the fuzzy sets and rules are adjusted using neural networks tuning techniques in an iterative way with data vectors (input and output system data). Such systems show two distinct ways of behavior.

In the past several studies has been done to predict the pollutant concentration by using meteorological parameters by using various statistical tools among that Artificial Neural Networks is one of the most used tool for the prediction. *Boznar et al (1993)* 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. *Dhirendra Mishra and Pramila Goyal(2015)* developed the artificial intelligence based Neuro-Fuzzy (NF) model was proposed for air quality forecasting and the concentration of Nitrogen Dioxide (NO_2) pollutant was analyzed with the available meteorological concentrations. *Padma (2014)* predicted the Air Quality Using HYBRID Soft Computing Techniques by using hybrid soft computing technique, a cost effective technique superior to traditional statistical methods, with good accuracy of approximately 98%.

Neural networks (NNs) [1], [2] are appropriate for air quality modeling due to their ability to learn, generalize and model non-linear relations. Another important quality of NNs, except their ability to learn based on finding dependencies in training data and representing those in synapse weights, is the ability to generalize gained knowledge. Fuzzy systems allow expressing object

PROBLEM FORMULATION

The prediction problem has been formulated as follows:

- For given measured readings of NO_2 emissions at measured values of temperature, wind speed, and wind direction in industrial and dense traffic areas; what will be the predicted emission values of NO_2 at urban areas?
- For given measured readings of NO_2 emissions at measured values of temperature, wind speed, and wind direction in industrial and dense traffic areas; what will be the predicted emission values of O_3 at urban areas?

Due to the complex relation between inputs and outputs, neural net stands as a reliable mapping tool for this application. The proposed neural net first prediction scheme takes industrial area readings (NO_2, temperature T, winds speed WS and wind direction WD) as input values and computes NO_2 estimates for urban areas. The second prediction scheme computes estimates of O_3 levels as output values based on NO_2, temperature, wind speed, wind direction input values. The neural net schemes are reconfigured to provide category or class (safe, acceptable, not acceptable, and dangerous) for output (NO_2 or O_3) levels.

The neural net forecasting scheme works in two sequential modes of operation [4, 5, 6, 7]. The first mode is learning under supervision, and the second mode is autonomous operation and testing.

ARTIFICIAL NEURAL NETWORKS

The neural networks try to shape the biological functions of the human brain. This leads to the idealization of the neurons as discrete units of distributed processing. Its local or global connections inside of a net also are idealized, thus leading to the capacity of the nervous system in assimilating, learning or to foresee reactions or decisions to be taken. W. S. McCulloch, W. Pits, described the first Neural Network model and F. Rosenblatt (Perceptron) and B. Widrow (Adaline) develop the first training algorithm. The main characteristic of the neural networks is the fact that these structures can learn with examples (training vectors, input and output samples of the system). The neural networks modifies its internal structure and the weights of the connections between its artificial neurons to make the mapping, with a level of acceptable error for the application, of the relation input/output that represent the behavior of the modeled system. The advantages of the neural networks are: learning capacity; generalization capacity; robustness in relation to disturbances. And its disadvantages are: impossible interpretation of the functionality; difficulty in determining the number of layers and number of neurons.

In the present study, a multilayer Feed- Forward Back propagation type of ANN was considered to forecast ambient air NO_2 and O_3 concentrations.

FUZZY SYSTEMS

Fuzzy systems propose a mathematic calculus to translate the subjective human knowledge of the real processes. This is a way to manipulate practical knowledge with some level of uncertainty. The fuzzy sets theory was initiated by Lofti Zadeh [16], in 1965. The behavior of such systems is described through a set of fuzzy rules, like:

IF <premise> THEN <consequent> that uses linguistics variables with symbolic terms. Each term represents a fuzzy set. The terms of the input space (typically 5-7 for each linguistic variable) compose the fuzzy partition. The fuzzy inference mechanism consists of three stages: in the first stage, the values of the numerical inputs are mapped by a function according to a degree of compatibility of the respective fuzzy sets, this operation can be called fuzzyfication. In the second stage, the fuzzy system processes the rules in accordance with the firing strengths of the inputs. In the third stage, the resultant fuzzy values are transformed again into numerical values; this operation can be called defuzzyfication. Essentially, this procedure makes possible the use fuzzy categories in representation of words and abstracts ideas of the human beings in the description of the decision taking procedure. The advantages of the fuzzy systems are: capacity to represent inherent uncertainties of the human knowledge with linguistic variables; simple interaction of the expert of the domain with the engineer designer of the system; easy interpretation of the results, because of the natural rules representation; easy extension of the base of knowledge through the addition of new rules; robustness in relation of the possible disturbances in the system. And its disadvantages are: incapable to generalize, or either, it only answers to what is written in its rule base; not robust in relation the topological changes of the system, such changes would demand alterations in the rule base; depends on the existence of a inference logical rules.

NEURO FUZZY SYSTEMS

Since the moment that fuzzy systems become popular in industrial application, the community perceived that the development of a fuzzy system with good performance is not an easy task. The problem of finding membership functions and appropriate rules is frequently a tiring process of attempt and error. This lead to the idea of applying learning algorithms to the fuzzy systems. The neural networks, that have efficient learning algorithms, had been presented as an alternative to automate or to support the development of tuning fuzzy systems. The first studies of the neuro-fuzzy systems date of the beginning of the 90's decade, with Jang, Lin and Lee in 1991, Berenji in 1992 and Nauck from 1993, etc. The majority of the first applications were in process control. Gradually, its application spread for all the areas of the knowledge like, data analysis, data classification, imperfections detection and support to decision-making, etc. Neural networks and fuzzy systems can be combined to join its advantages and to cure its individual illness. Neural networks introduce its computational characteristics of learning in the fuzzy systems and receive from them the interpretation and clarity of systems representation. Thus, the disadvantages of the fuzzy systems are compensated by the capacities of the neural networks. These techniques are complementary, which justifies its use together.

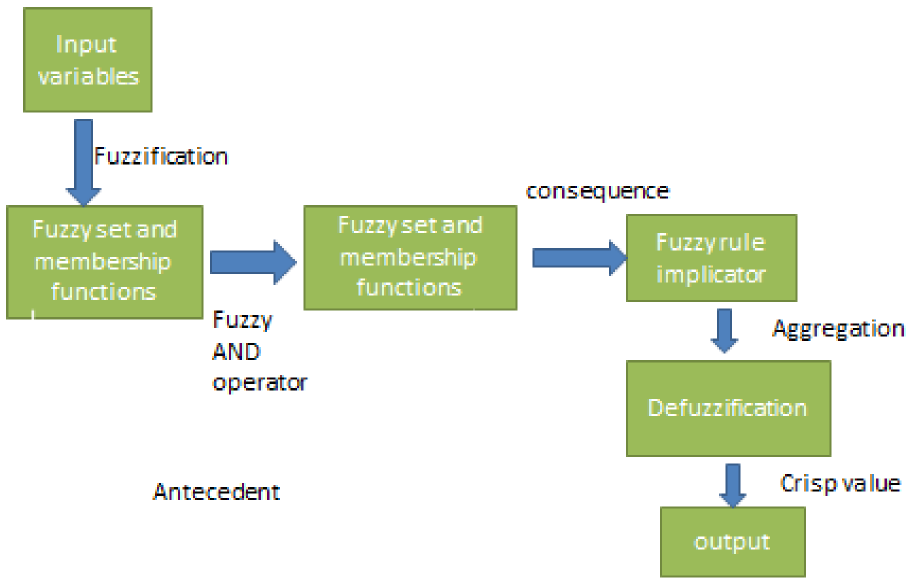

Figure 1: Block Diagram of Fuzzy Logic Modeling

MODELS OF FUZZY NEURAL SYSTEMS

In response to linguistic statements, the fuzzy interface block provides an input vector to a multi-layer neural network. The neural network can be adapted (trained) to yield desired command outputs or decisions as shown in Figure (2). Figure (3) shows the second model of fuzzy neural system. Figure (4) shows the SimuLink Model of fuzzy Logic Controller

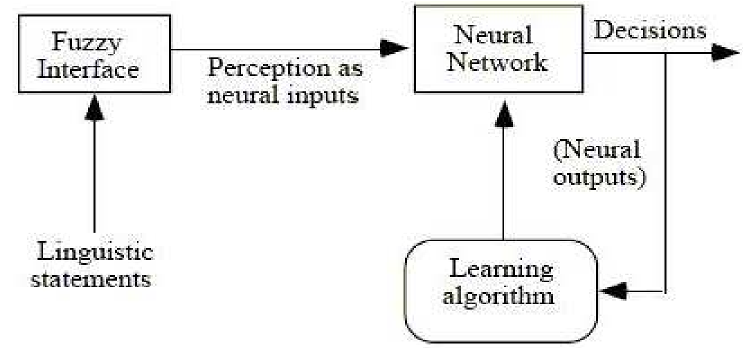

Figure 2: First Model of Fuzzy Neural Systems

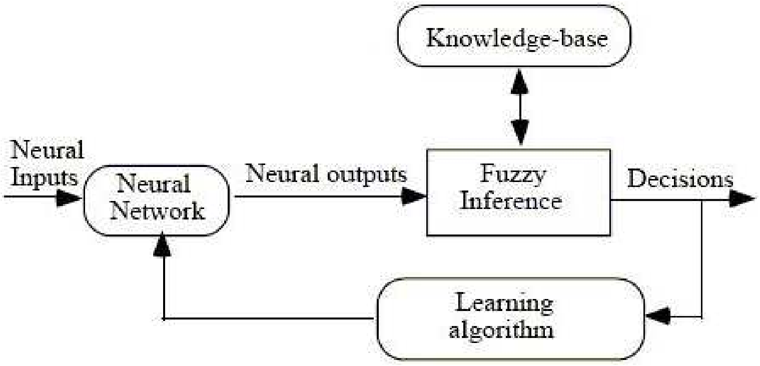

Figure 3: **Second Model of Fuzzy Neural Systems**

In the present paper the First Model of Fuzzy Neural Systems is used. The structure of Fuzzy Model is as presented in Figure 2.

NEURAL NETWORKS MODELING SCHEMES

Neural network is based on computer simulation of activities of human brain; neural network performs modeling without defined mathematical relation between variables. Neural network has two distinct learning techniques unsupervised Learning and supervised Learning.

The proposed prediction schemes use three-layered neural nets with supervised back propagation learning algorithm. The first neural net for the prediction of O_3 level is shown in Figure 4. The input layer has five nodes (NO_2, WS, WD, T), the middle hidden layer has (on the average) 15 nodes, and the output layer has one complex node (O_3). The second neural has the same architecture as the first neural net, but with four input nodes (NO_2, WS, WD, T). The output node provides either NO_2 or SO_2 level based on the input feature vector first element value (NO_2).

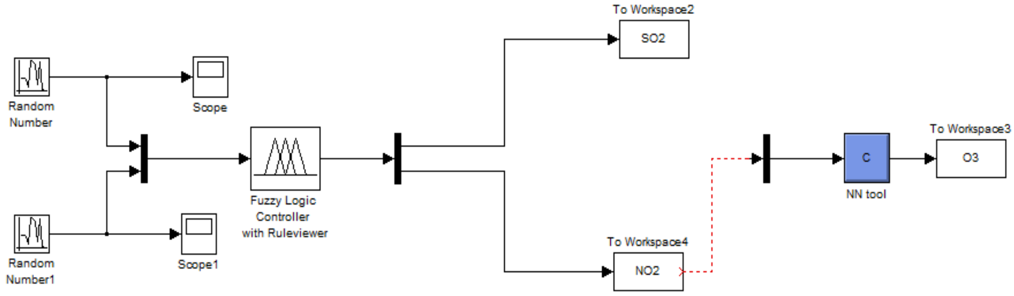

Figure 4: Simulink Model of Fuzzy Logic Controller

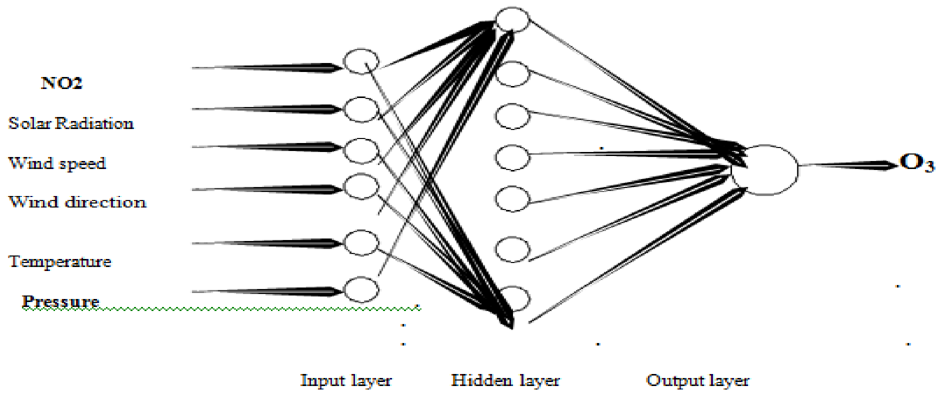

Figure 5: Neural Net Models for Ozone Prediction

ALGORITHM FOR NEURO-FUZZY MODELLING FOR AIR QUALITY PREDICTION

For designing the model for air quality prediction, certain step by step procedure i.e. an algorithm is designed for obtaining the best and the optimized model for air quality prediction.

The algorithm for Neuro-Fuzzy model is stated below:

Step 1: Selection of the input parameters i.e. meteorological parameters (Temperature, Average, Wind Speed, Relative Humidity, Mean Visibility) and the Output Parameters.

Step 2: Preprocessing of the data using the following formula:

$Y=(X-X_{max})/(X_{max}-X_{min})$

Step 3: Removal of the redundant data if any present.

Step 4: The data is divided into training, testing and validation set in different ratio.

Step 5: Initially perform the training of the network.

Step 7: Select the best and the optimized model with minimum error.

Step 7: Perform testing and validation of the model.

Step 8: Decide the linguistic variables for the model i.e. LOW, MEDIUM & HIGH.

Step 9: Prepare the If-Then rules.

Step 10: Selection of the membership functions and their values for all the parameters.

Step 11: Selection of the type of the model to be used i.e. Mamdani or Sugeno.

Step 12: Creating the Fuzzy Inference Engine (FIS).

RESULTS AND DISCUSSIONS

Results of Artificial Neural Networks

Artificial Neural Networks models are developed to predict NO_2 and SO_2 by taking the meteorological parameters such as atmospheric temperature, wind speed, wind direction, relative humidity, pressure and solar radiation as inputs. Ozone is predicted by taking meteorological parameters and predicted NO_2 as input variables.

Table 1: Performance Statistics of a Neural Network Model for NO_2 Concentration for Hyderabad Station

S. No	Statistical Parameter	Models	No. of Neurons	No. of Hidden Layers	R^2 (Correlation)		
					Training	Testing	Overall
1	CORRELATION	6-5-5-1	5	5	0.774	0.765	0.765
2		6-5-4-1	5	4	0.769	0.769	0.789
3		6-5-20-1	5	20	0.680	0.802	0.679
4		6-5-40-1	5	40	0.787	0.811	0.793
5		6-5-65-1	5	65	0.750	0.751	0.763
6		6-5-75-1	5	75	0.795	0.780	0.793
7		6-5-80-1	5	80	0.802	0.786	0.795
8		6-6-5-1	6	5	0.807	0.816	0.812
9		6-6-4-1	6	4	0.811	0.830	0.818
10		6-6-20-1	6	20	0.786	0.744	0.799
11		6-6-40-1	6	40	0.811	0.791	0.800
12		6-6-65-1	6	65	0.813	0.808	0.818
13		6-6-75-1	6	75	0.804	0.814	0.801
14		6-6-80-1	6	80	0.829	0.833	0.832
15		6-7-5-1	7	5	0.777	0.775	0.791
16		6-7-10-1	7	10	0.804	0.809	0.797
17		6-7-15-1	7	15	0.869	0.899	0.894
18		6-7-30-1	7	30	0.903	0.915	0.926
19		6-7-55-1	7	55	0.921	0.940	0.938
20		6-7-75-1	7	75	0.945	0.947	0.955
21		6-7-80-1	7	80	0.939	0.941	0.948

Table 2: Performance Statistics of a Neural Network Model for O_3 Concentration for Hyderabad Station

S. No	Statistical Parameter	Models	No. of Neurons	No. of Hidden Layers	R^2 (Correlation)		
					Training	Testing	Overall
1	CORRELATION	7-5-5-1	5	5	0.724	0.789	0.704
2		7-5-4-1	5	4	0.788	0.777	0.798
3		7-5-15-1	5	15	0.832	0.787	0.821
8		7-7-5-1	7	5	0.823	0.835	0.822
9		7-7-15-1	7	15	0.832	0.787	0.821
10		7-7-30-1	7	30	0.783	0.848	0.801
11		7-7-40-1	7	40	0.809	0.814	0.804
12		7-7-55-1	7	55	0.724	0.789	0.704
13		7-7-60-1	7	60	0.788	0.777	0.798
14		7-7-70-1	7	70	0.797	0.797	0.779
15		7-7-5-1	7	5	0.795	0.780	0.793
16		7-7-15-1	7	15	0.802	0.787	0.795
17		7-7-30-1	7	30	0.804	0.809	0.797
18		7-7-40-1	7	40	0.823	0.849	0.834
19		7-7-55-1	7	55	0.875	0.821	0.874
20		7-7-60-1	7	60	0.832	0.887	0.822
21		7-7-70-1	7	70	0.789	0.847	0.811
22		7-8-5-1	8	5	0.881	0.871	0.879
23		7-8-4-1	8	4	0.890	0.892	0.885
24		7-8-15-1	8	15	0.822	0.884	0.889
25		7-8-20-1	8	20	0.928	0.919	0.944
27		7-8-35-1	8	35	0.959	0.929	0.941
27		7-8-45-1	8	45	0.935	0.945	0.948
28		7-8-50-1	8	50	0.979	0.953	0.972
29		7-8-70-1	8	70	0.952	0.950	0.971

Table 3: Proposed Model for Prediction of NO_2 and O_3

S. No	Station Name		Concentrations				
			Network	Training	Validation	Testing	Overall
1	Hyderabad	NO_2	6-7-75-1	0.945	0.924	0.947	0.955
2	Hyderabad	O_3	7-8-50-1	0.979	0.964	0.953	0.972

RESULTS OF NEURO FUZZY

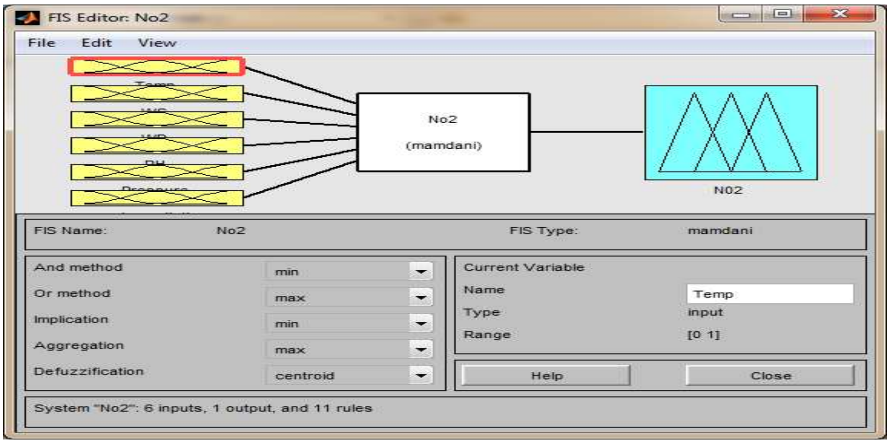

Figure 6: Fuzzy Logic Tool Box in Matlab for Prediction of NO_2

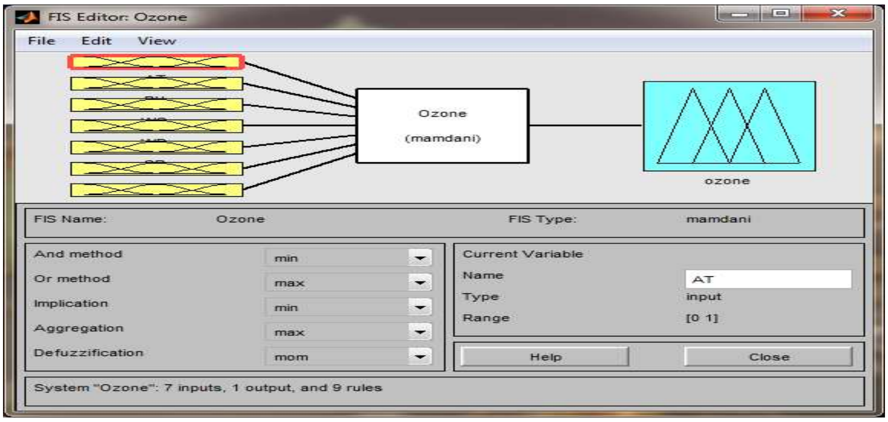

Figure 7: Fuzzy Logic Tool Box in Matlab for Prediction of O_3

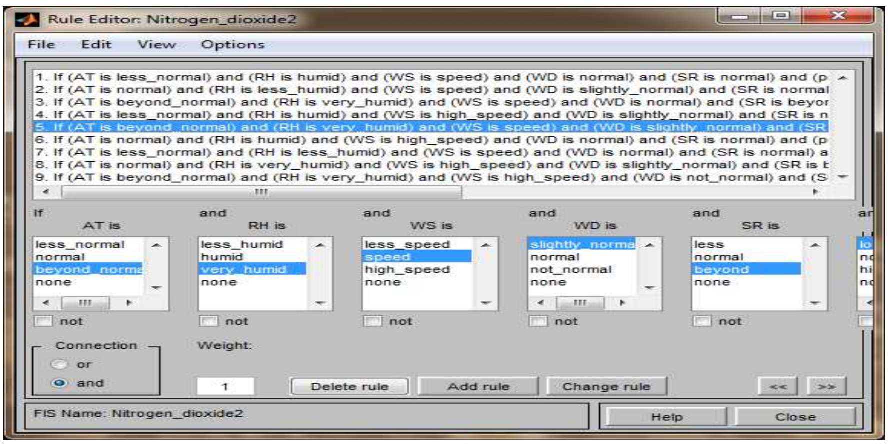

Figure 8: Rule Editor

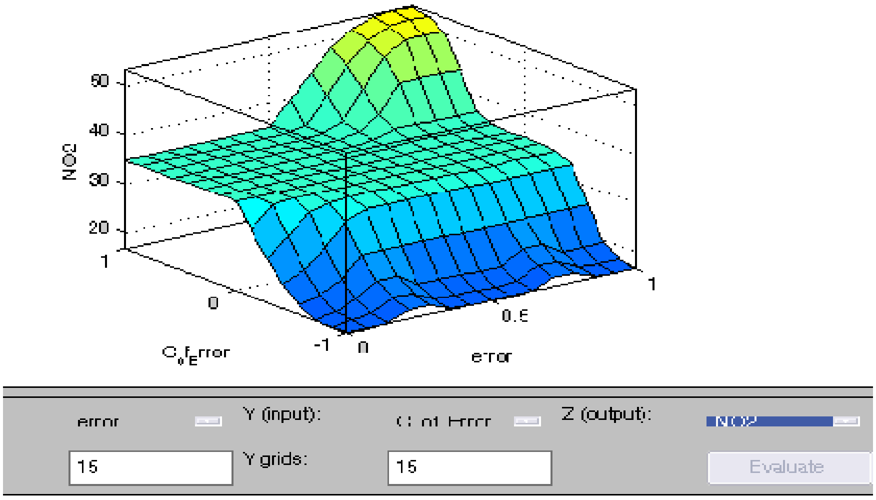

Figure 9: Surface Viewer

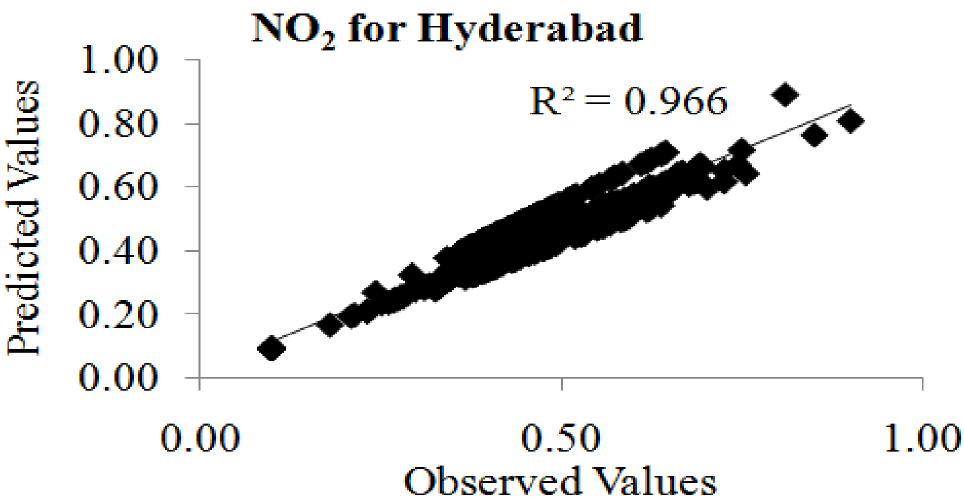

Figure 10: Regression Analysis of Observed Values Vs Predicted Values of NO_2 Concentrations for Hyderabad Region

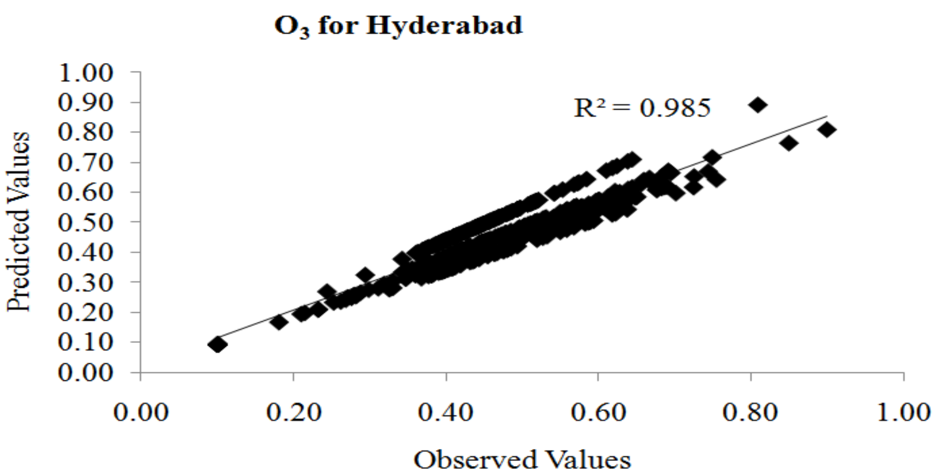

Figure 11: Regression Analysis of Observed Values Vs Predicted Values of O_3 Concentrations for Hyderabad Region

CONCLUSIONS

This paper presented a proposed fuzzy neural schemes for forecasting and classifying of NO_2 emissions over urban areas based on measured emissions over industrial areas. The scheme also provides predictions of O_3 emissions based on NO_2 measurements. The performance of the proposed scheme is evaluated in terms of regression value and mean squared error the present study has indicated that Neuro-Fuzzy model provided a well suited method and gave promising results for modeling of highly non-linear air pollution problem in urban and industrialized areas such as Hyderabad. The regression value for NO_2 for Hyderabad region with a proposed model of 6-7-75-1 gave promising results of 0.955 the prediction of NO_2 for Hyderabad using Neuro Fuzzy is 0.966. For the prediction of O_3 for Hyderabad 7-8-50-1 was the proposed model with regression value of 0.972 and regression value for the prediction of O_3 for Hyderabad region using Neuro Fuzzy is 0.985. Hence we can conclude that the present study has indicated that Neuro-Fuzzy model provided a well suited method and gave promising results for modeling of highly non-linear air pollution problem in urban and industrialized areas such as Hyderabad. Computational efforts can be reduced in Neuro-Fuzzy where as compared to ANN Model since Neuro-Fuzzy is a logic based model.

REFERENCES

1. *Abou – Bakr Ramadan (2012)* proposed an environmental prediction Model Using Fuzzy logic and neural networks- IJCSI International Journal of Computer Science Issues, Vol. 9, Issue 2, No 3, March 2012.
2. *Aparna soni. and Shailja Shukla(2014)* Application of Neuro-Fuzzy in Prediction of Air Pollution in Urban Areas.
3. *Chelani, A.B., & Hasan, M.Z (2001),* “Forecasting nitrogen dioxide concentration in ambient air using artificial Neural networks”. International Journal of Environmental Studies, 58:4, 487-499.
4. *Ersoy , K., Cho, S., 1992*. An algorithm to compute the degree of match in fuzzy systems. Journal of Fuzzy Sets and Systems. Vol. 49(1992), 285- 299.
5. *Figueiredo and Gomide***;** "Design of Fuzzy Systems Using Neuro-Fuzzy Networks", IEEE Transactions on Neural Networks, 1999, Vol. 10, no. 4, pp.815-827.
6. *Gopal Upadhyaya and Nilesh Dashore* - Fuzzy logic based model for monitoring air quality index- Indian Journal of Science and Technology- Vol. 4 issue 3 (March 2011) ISSN: 0974- 6846.
7. *H. R. Berenji and P. Khedkar***,** Learning and tuning fuzzy logic controllers through reinforcements. IEEE Trans. Neural Networks 3 (1992) 724740.