# Neuro Fuzzy Modeling Scheme for the Prediction of Air Pollution

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**Abstract:** The techniques of artificial intelligence based in fuzzy logic and neural networks are frequently applied together. The reasons to combine these two paradigms come out of the difficulties and inherent limitations of each isolated paradigm. Hybrid of Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS) have attracted the growing interest of researchers in various scientific and engineering areas due to the growing need of adaptive intelligent systems to solve the real world problems. ANN learns from scratch by adjusting the interconnections between layers. FIS is a popular computing framework based on the concept of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. The structure of the model is based on three-layered neural fuzzy architecture with back propagation learning algorithm. The main objective of this paper is two folds. The first objective is to develop Fuzzy controller, scheme for the prediction of the changing for the NO2 or SO2, over urban zones based on the measurement of NO2 or SO2 over defined industrial sources. The second objective is to develop a neural net, NN; scheme for the prediction of O3 based on NO2 and SO2 measurements.
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## 1. Introduction:

The modern techniques of artificial intelligence have found application in almost all the fields of the human knowledge. However, a great emphasis is given to the accurate sciences areas; perhaps the biggest expression of the success of these techniques is in engineering field. These two techniques neural Networks and fuzzy logic 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 was born by the fusing of these two techniques. As each researcher combines these two tools in different way, then, some confusion was created on the exact meaning of this term. Still there is no absolute consensus but in general, 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 a first phase, called learning phase, it behaves like neural networks that learns its internal parameters off-line. Later, in the execution phase, it behaves like a fuzzy logic system. Separately, each one of these techniques possesses advantages and disadvantages that, when mixed Together, theirs cooperage provides better results than the ones achieved with the use of each isolated technique.

The advantages of a combination of ANN and FIS are obvious. There are several approaches to integrate ANN and FIS and very often it depends on the application. We broadly classify the integration of ANN and FIS into three categories namely concurrent model, cooperative model and fully fused model. This paper starts with a discussion of the features of each model and generalizes the advantages and deficiencies of each model. We further focus the review on the different types of fused neuro-fuzzy systems and citing the advantages and disadvantages of each model.. In fact, this model consists of if then rules with fuzzy antecedents and mathematical functions in the consequent part. The task of system identification is to determine both the non-linear parameters of the antecedents and the linear parameters of the rules consequent.

Air pollution is the introduction of chemicals, particulate matter, or biological materials that cause harm or discomfort to humans or other living organisms, or ,damages the natural environment into the atmosphere.

The atmosphere is a complex dynamic natural gaseous system that is essential to support life on planet Earth. Stratospheric ozone depletion due to air pollution has long been recognized as a threat to human health as well as to the Earth's ecosystems.
Indoor air pollution and urban air quality are listed as two of the world's worst pollution problems in the 2008 Blacksmith Institute World's Worst Polluted Places report.[1]

An air pollutant is known as a substance in the air that can cause harm to humans and the environment. Pollutants can be in the form of solid particles, liquid droplets, or gases. In addition, they may be natural or man-made.[2]

Pollutants can be classified as either primary or secondary. Usually, primary pollutants are substances directly emitted from a process, such as ash from a volcanic eruption, the carbon monoxide gas from a motor vehicle exhaust or sulfur dioxide released from factories.

Secondary pollutants are not emitted directly. Rather, they form in the air when primary pollutants react or interact. An important example of a secondary pollutant is ground level ozone — one of the many secondary pollutants that make up photochemical smog.

Air pollution has become an exceedingly inescapable part of urban living. The presence of pollutants is reported to cause adverse effects on human health as well as damage to structures [1, 2, 3]. Air quality in Cairo City is an important public concern. Average daily emissions of primary pollutants, such as hydrocarbons, nitrogen oxides, carbon monoxide, and others are among the largest in the world. Private and public transportation as well as industrial activities contribute the most to these emissions. When primary pollutants are exposed to sunshine, they undergo chemical reactions and yield a wide variety of secondary pollutants, Ozone, O3, being the most important one. Besides the health problems this molecule may cause, ozone is considered as an indicator of air quality in urban atmospheres [1, 2]

Modeling of urban air pollution is an important facet of pollution control and abatement [1, 2, 3]. Models explain the occurrence, intensity, and movement of pollutants in order to predict pollutant levels at locations away from defined sources. Air pollution prediction is inherently a difficult problem for conventional and stochastic modeling methods due to its intrinsic dynamic, random, and nonlinear nature. In this paper, however; a sophisticated modeling scheme for the prediction of air pollution (nitrogen dioxide NO2, sulpher dioxide SO2 and ozone O3) using neural nets is proposed. Neural network modeling scheme provides an efficient computational tool for mapping input-output or cause-effect relationships and establish an intelligent what if scenarios based on robust learning mechanisms. The proposed prediction schemes have been applied to study the effect of industrial and traffic areas: Tabbin, Shoubra, Fum elkhalieg, Gomhorya and Kulaly on urban areas: Maadi and Giza.

**2. Problem Formulation**

The prediction problem has been formulated as follows:

(a) For given measured readings of NO2 and SO2 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 NO2 and SO2 at urban areas?

(b) For given measured readings of NO2 and SO2 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 O3 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 (NO2 or SO2 level, temperature T, winds speed WS and wind direction WD) as input values and computes NO2 or SO2 estimates for urban areas. The second prediction scheme computes estimates of O3 levels as output values based on NO2, SO2, 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 (NO2 or SO2 or O3) 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.

**3- 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 expert to determine the inference logical rules;

**4 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.

**5 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.

**5 Models of fuzzy neural systems**

*In* response to linguistic statements, the fuzzy interface block provides an input vector to a multi-layer neural network [15]. The neural network can be adapted (trained) to yield desired command outputs or decisions as shown in Fig. (1). Fig. (2) shows the second model of fuzzy neural system. Fig (3) shows the SimuLink Model of fuzzy Logic Controller

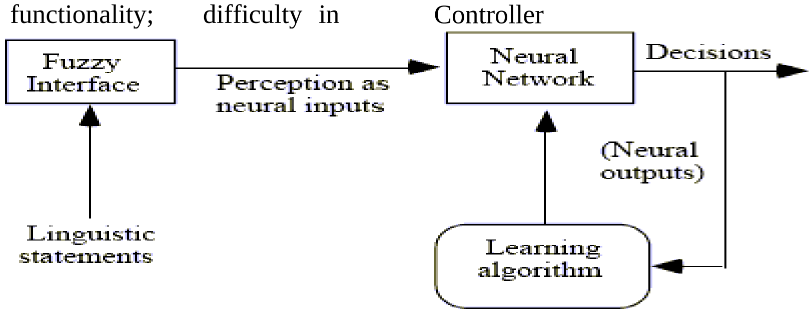


***Fig. (1) First Model of Fuzzy Neural Systems***

**• A multi-layered neural network drives the fuzzy inference mechanism.**

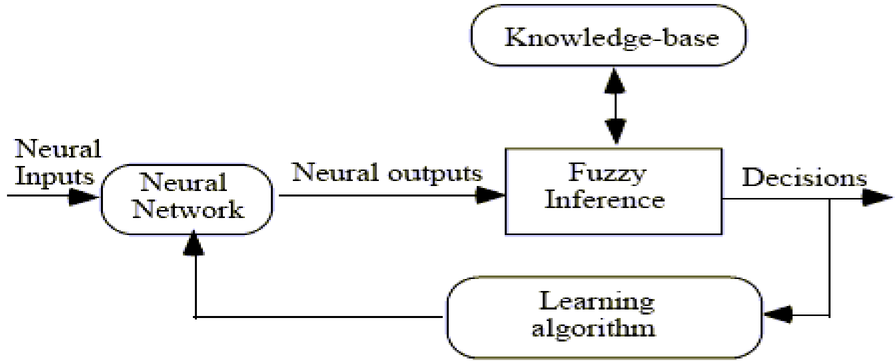


Fig. (2) Second model of fuzzy neural system

In this paper we are using the First Model of Fuzzy Neural Systems. The structure of Fuzzy Model is presented in Fig (11). The initial membership function is shown in Fig (12, 13, 14) for inputs. Fig (17) Membership from inputs to outputs flow of rule base. The system response SO2, NO2, O3 are shown in Fig(18, 19, 20). Fig(21, 22, 23) show the three dimensional of SO2, NO2, O3. The simplification rule base used in the implementation as follow.

**Rule Base**

1-If (error is small) and (c_of_error is Small) then (So2 is Small)(No2 is Small)(O3 is Small)

2-If (error is Medium) and (c_of_error is Medium) then (So2 is Medium )(No2 is Medium)(O3 is Medium)

3-If (error is small) and (c_of_error is big) then (So2 is Big)(No2 is Big)(O3 is Big)

4-If (error is Big) and (c_of_error is Big) then (So2 is Big)(No2 is Big)(O3 is Big)

5-If (error is small) and (c_of_error is Small) then (So2 is Small)(No2 is Small)(O3 is Small)

6-If (error is Big) and (c_of_error is Small) then (So2 is Small)(No2 is Small)(O3 is Small)

7-If (error is Big) and (c_of_error is Medium) then (So2 is Medium)(No2 is Medium)(O3 is Medium)

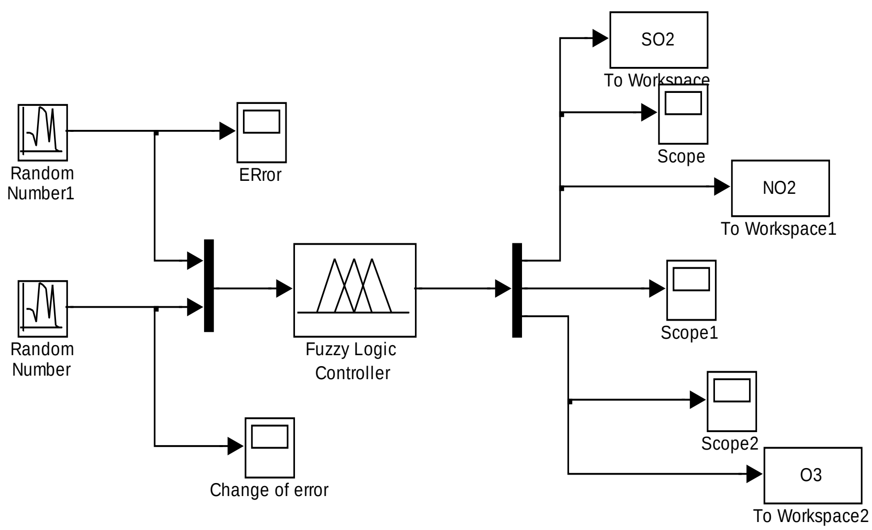


**Fig (3) SimuLink Model of fuzzy Logic Controller**

**6. Data preparation**

Recorded Data for the amount of NO2, SO2, and O3 in air have been obtained from Egyptian environmental affairs Authority (EEAA) in the form of average value per month for the years 1998, 1999 for the following areas:

(One) Industrial areas: Tabbin and Shoubra. (b) Traffic areas: Fum elkhalieg, Gomhorya, and Kulaly. © Urban areas: Maadi and Giza.

Normally distributed emission data have been generated using given mean values, and assuming variance values. Available data lie mainly only in the first two classes or categories. In order to completely perform the learning or training phase of the classifier, data samples for the second two classes have been generated within the limits of each class.

Data of temperature, wind speed, and wind direction have been obtained from weather Forecasting Authority for the years 1998, 1999. Data of temperature has been provided in the form of: (minimum, maximum, and average) temperature values (in degree centigrade) per month. Wind speed has been provided as average value in knots per month. Wind directions have been provided in the form of a table with rows representing twelve dominant wind direction sectors, columns representing range of dominant wind speed values, and cell value representing time duration of specific wind speed range within a specific wind direction sector. Based on theses available statistically abstracted data, thirty (assuming one reading/day) normally distributed temperature values and thirty normally distributed wind speed values have been generated, see Fig.4 and Fig.5. Thirty wind direction values have also been generated based on relative time duration ratio.

## 7. 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 [4, 5, 6, 7]. The first neural net for the prediction of O3 level is shown in Fig.6. The input layer has five nodes (NO2, SO2, WS, WD, T), the middle hidden layer has (on the average) 15 nodes, and the output layer has one complex node (O3). The second neural has the same architecture as the first neural net, but with four input nodes (NO2 or SO2, WS, WD, T). The output node provides either NO2 or SO2 level based on the input feature vector first element value (NO2 or SO2). Neural nets are also reconfigured to have four nodes in the output with only one node is firing at a time representing the category or class (safe S , acceptable A, not acceptable NA, dangerous D) of output O3 level in the first neural net, and NO2 or SO2 category in the second neural net, see Fig.7.

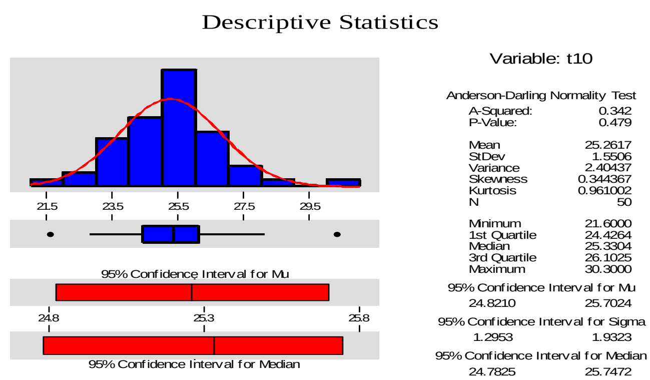


**Fig.4. Descriptive statistic of generated data of Oct., temperature**

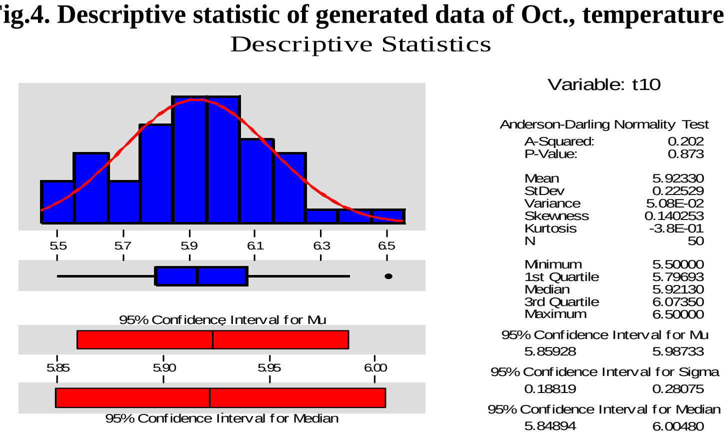


**Fig.5.Descriptive statistic of generated data of Oct., wind speed**

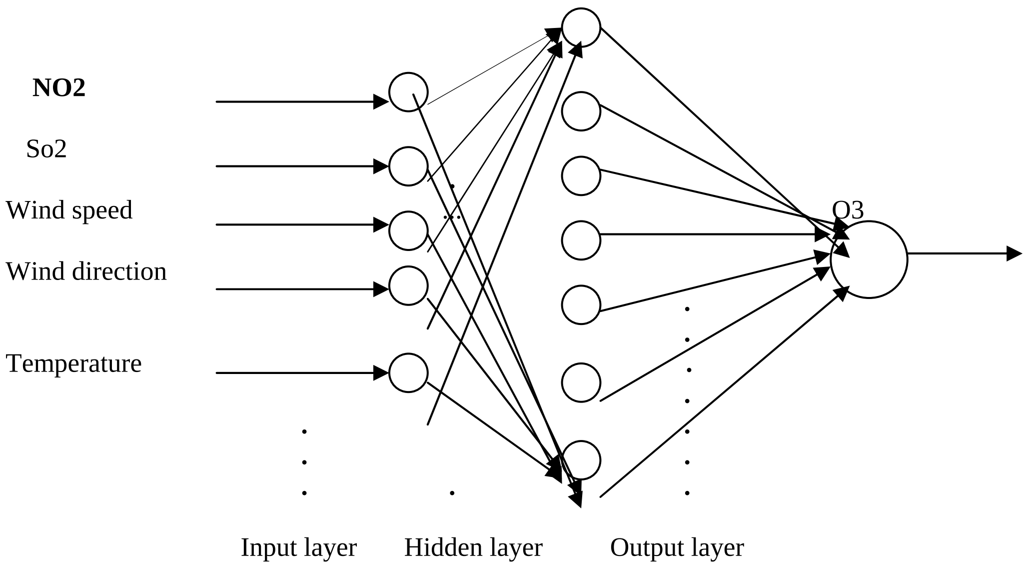


**Fig.6. Neural net model for ozone prediction: output, based on measured (NO2, SO2, wind speed and direction, temperature): input**

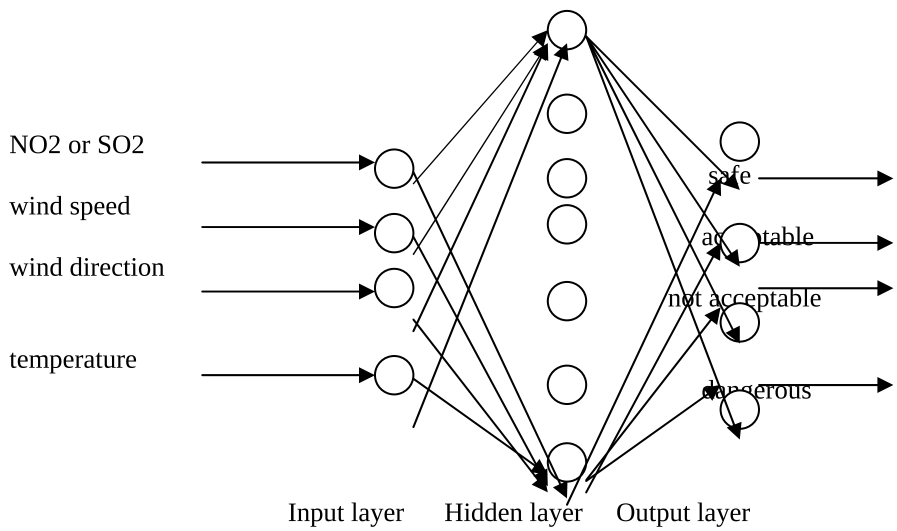


**Fig.7. Neural net classification scheme for catogorizing ( on four classes) NO2 or SO2 levels on urban areas: output, based on measured level values of (NO2 or SO2, wind speed, wind direction, temperature) on industrial areas : input.**

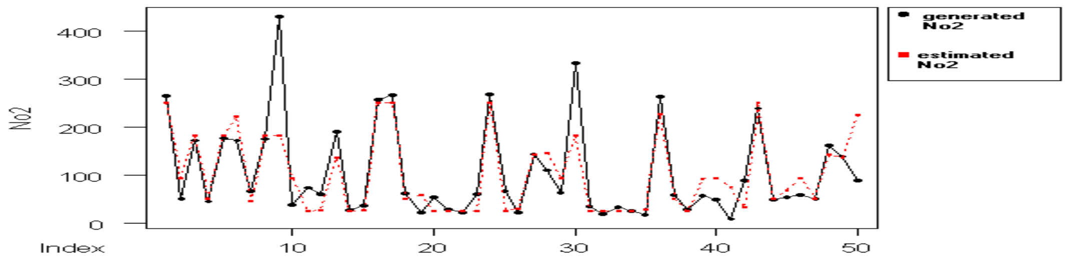


**Fig.8. Graph of No2: measured (solid line) and predicted (dotted line)**

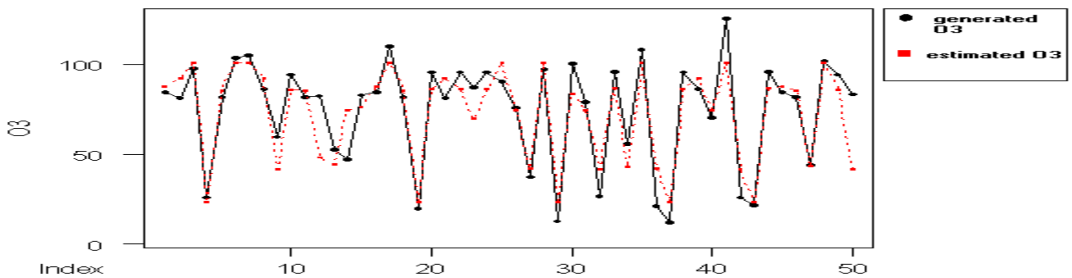


**Fig.9 Graph of So2: measured (solid line) and predicted (dotted line)**

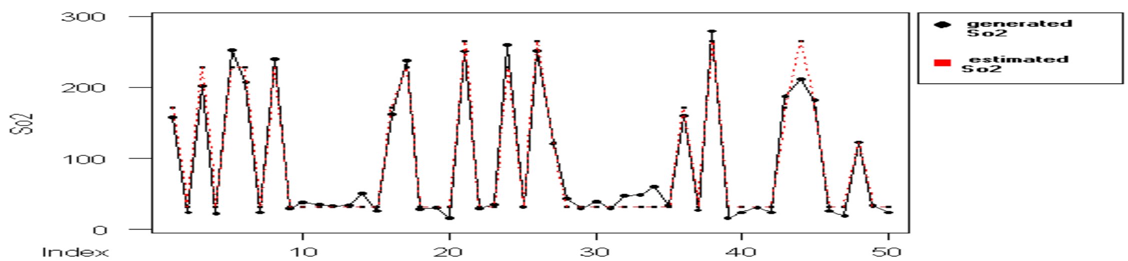


**Fig.10 Graph of O3: measured (solid line), and predicted (dotted line)**

**6. Results and Performance Evaluation**

Emissions of NO2 or SO2 on urban area can be categorized as shown in table1**.** The neural net schemes have been set as follows: train data set: 85 %, validation data set: 5%, and test data: 10% where data order is set to be random.

Results of NO2, SO2, and O3 classification nets are summarized in performance tables 2, 3, and 4, where diagonal data represent correct class and off-diagonal represent misclassify data. Sample of the results of neural net prediction schemes for NO2, SO2, O3 are shown in figures 8, 9, and 10. The performance of the prediction scheme is evaluated in terms of mean squared error MSE as recorded in table 5, where the first column provides the range of reading values for NO2, SO2 or O3.

**Table1.Range and categories of NO2 and SO2 emissions**

| Category | Range | |
|---|---|---|
| | NO2/SO2 | O3 |
| Safe (S) | 0-100 | 0-30 |
| Acceptable (A) | 101-150 | 31-50 |
| Not acceptable (NA) | 151-200 | 50-100 |
| Dangerous (D) | >200 | >100 |

**Table 2. NO2 classifier performance table**

| Year | 1998 | | | | 1998 and 1999 | | | | 1999 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Class / categ. | S | A | NA | D | S | A | NA | D | S | A | NA | D |
| S | 86 | 8 | 0 | 0 | 108 | 6 | 0 | 0 | 165 | 0 | 0 | 0 |
| A | 14 | 30 | 0 | 0 | 13 | 23 | 0 | 0 | 1 | 0 | 0 | 0 |
| NA | 1 | 8 | 0 | 0 | 0 | 13 | 0 | 0 | 0 | 0 | 0 | 0 |
| D | 0 | 8 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 | 0 |
| % correctrecog | 77.33336 % | | | | 78.915665 % | | | | 99.397591 % | | | |

**Table 3. SO2 classifier performance table**

| Year | 1998 | | | | 1998 and 1999 | | | | 1999 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Class / categ. | S | A | NA | D | S | A | NA | D | S | A | NA | D |
| S | 43 | 0 | 0 | 0 | 96 | 1 | 0 | 0 | 64 | 0 | 0 | 0 |
| A | 4 | 5 | 0 | 1 | 2 | 4 | 3 | 0 | 0 | 0 | 0 | 1 |
| NA | 0 | 3 | 0 | 1 | 0 | 3 | 18 | 2 | 0 | 0 | 4 | 6 |
| D | 0 | 1 | 0 | 2 | 0 | 2 | 1 | 33 | 0 | 0 | 0 | 30 |
| correc recog. | 83.3 % | | | | 91.5 % | | | | 93.3% | | | |

**Table 4. O3 classifier performance table**

| | Safe | Accept | Not Accept | Dangerous |
|---|---|---|---|---|
| Safe | 10 | 1 | 0 | 0 |
| Accept | 2 | 0 | 2 | 0 |
| Not Accept | 1 | 0 | 48 | 0 |
| Dangerous | 0 | 0 | 10 | 0 |

Average percentage of correct recognition for O3 classification scheme is 80 %

**Table 5. Performance table for prediction neural net schemes.**

| | Rang | 1998 | 1999 | 1998and 1999 |
|---|---|---|---|---|
| NO2 | 10-400 | 20.53 | 7.726 | 16.84 |
| SO2 | 10-290 | 15.45 | 6.89 | 13.486 |
| O3 | 20-170 | 8.505 | ---- | ------ |

## 7. Conclusion

This paper presented proposed fuzzy neural schemes for forecasting and classifying of NO2; SO2 emissions over urban areas based on measured emissions over industrial areas. The scheme also provides predictions of O3 emissions based on NO2 and SO2 measurements. The performance of the proposed scheme is evaluated in terms of average percentage of correct recognition and mean squared error value, however the accuracy of the performance is limited to the available data. In other words some of the data are provided in terms of mean value per month like NO2, SO2, O3 emissions, other data are either provided in terms of range of values like wind directions, or minimum and maximum values per month like temperature. Data have been generated from normal distributions with available provided mean, variance (or proposed), and range parameters. However, correlation of specific day data (temperature, wind speed, wind direction, NO2 or SO2 or O3 measurement) is not guaranteed since day data are statistically generated assuming one measurement per day. System performance could be more accurate and more reliable if detailed true daily-recorded data are used.

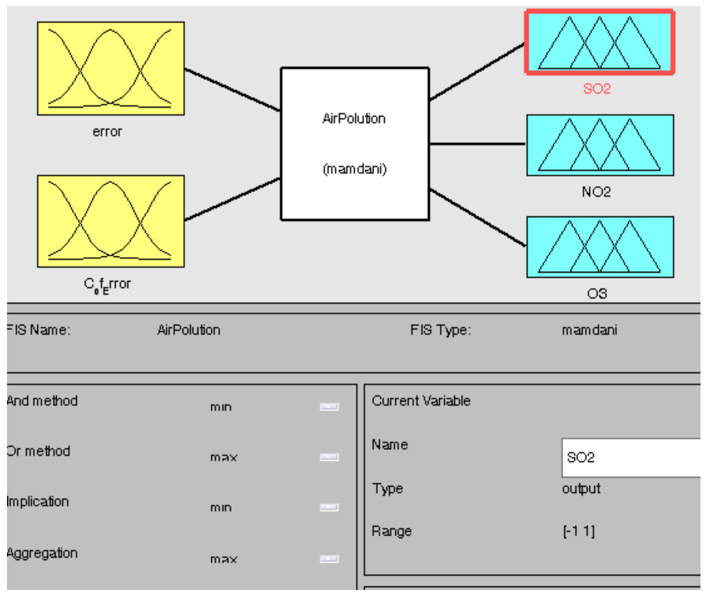


**Fig (11) Fuzzy Model**

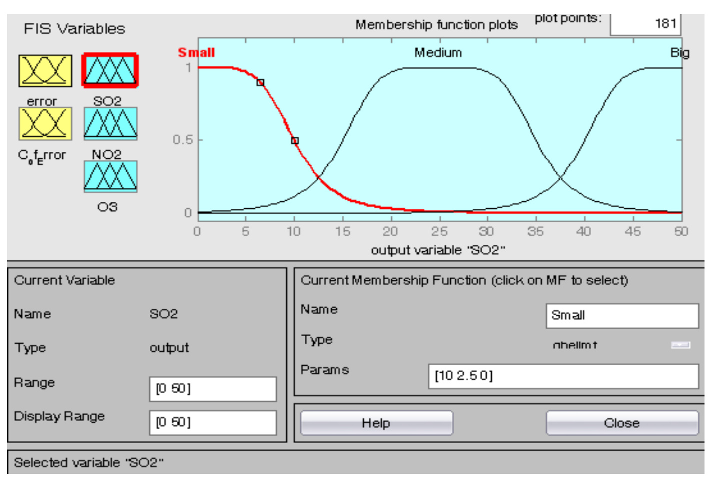


**Fig (12) Membership Function For SO2**

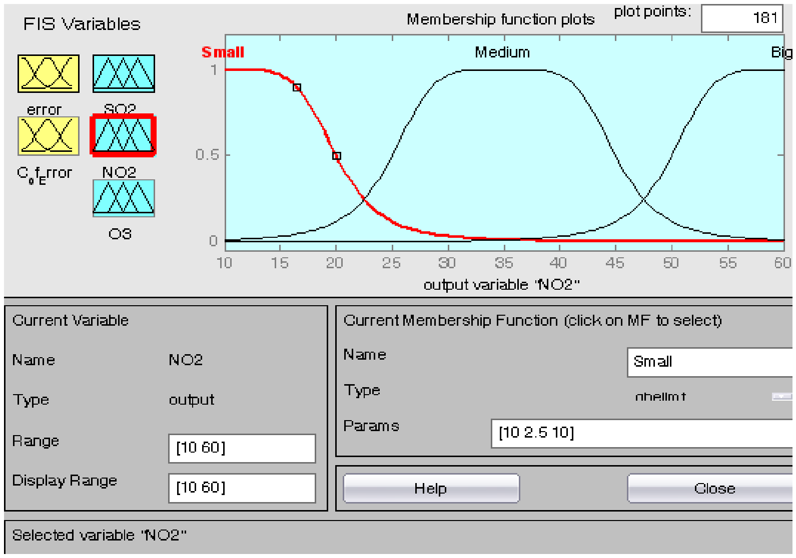


**Fig (13)Membership Function For NO2**

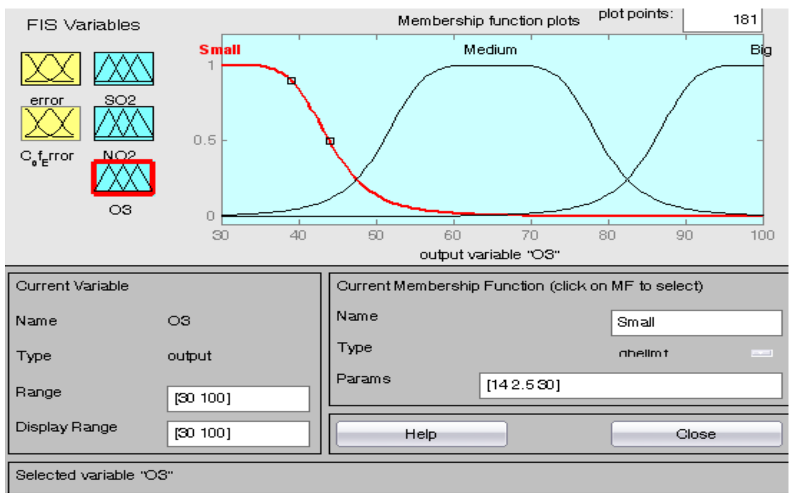


**Fig (14) Membership Function For O3**

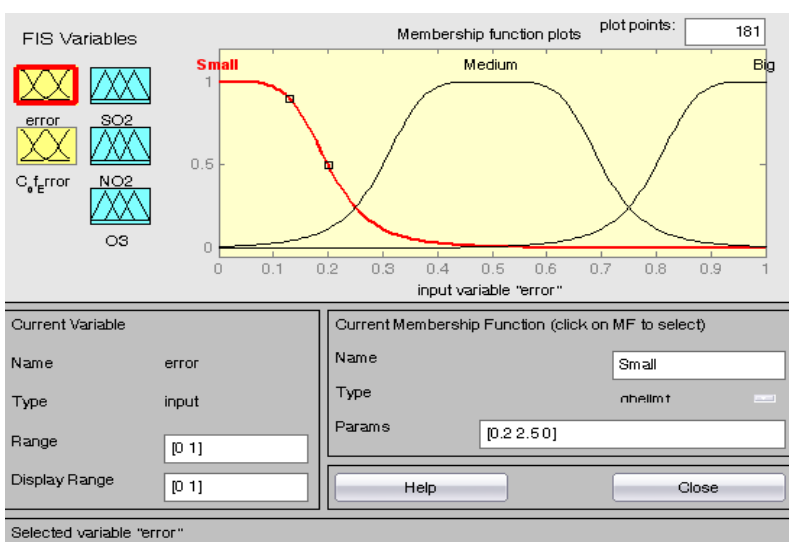


**Fig (15) Membership Function for Error**

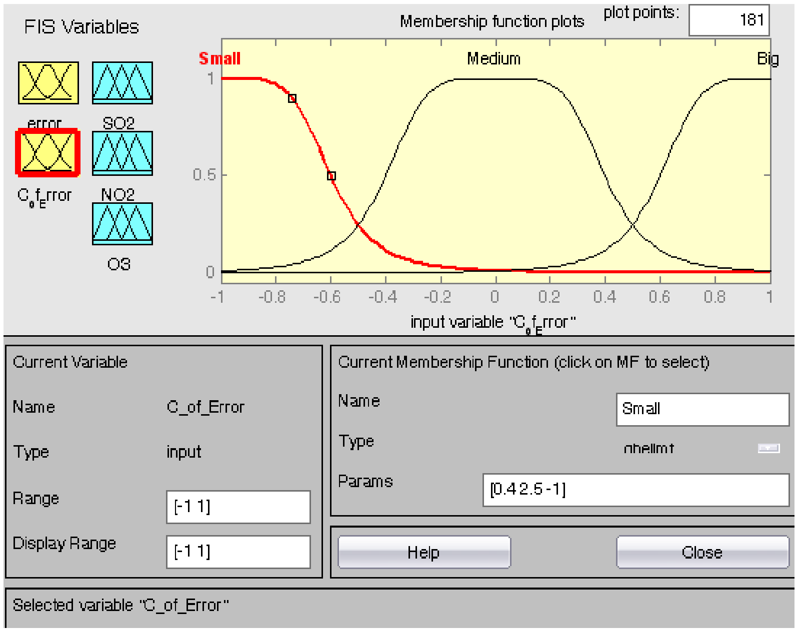


**Fig (16) Membership Function For Change of Error**

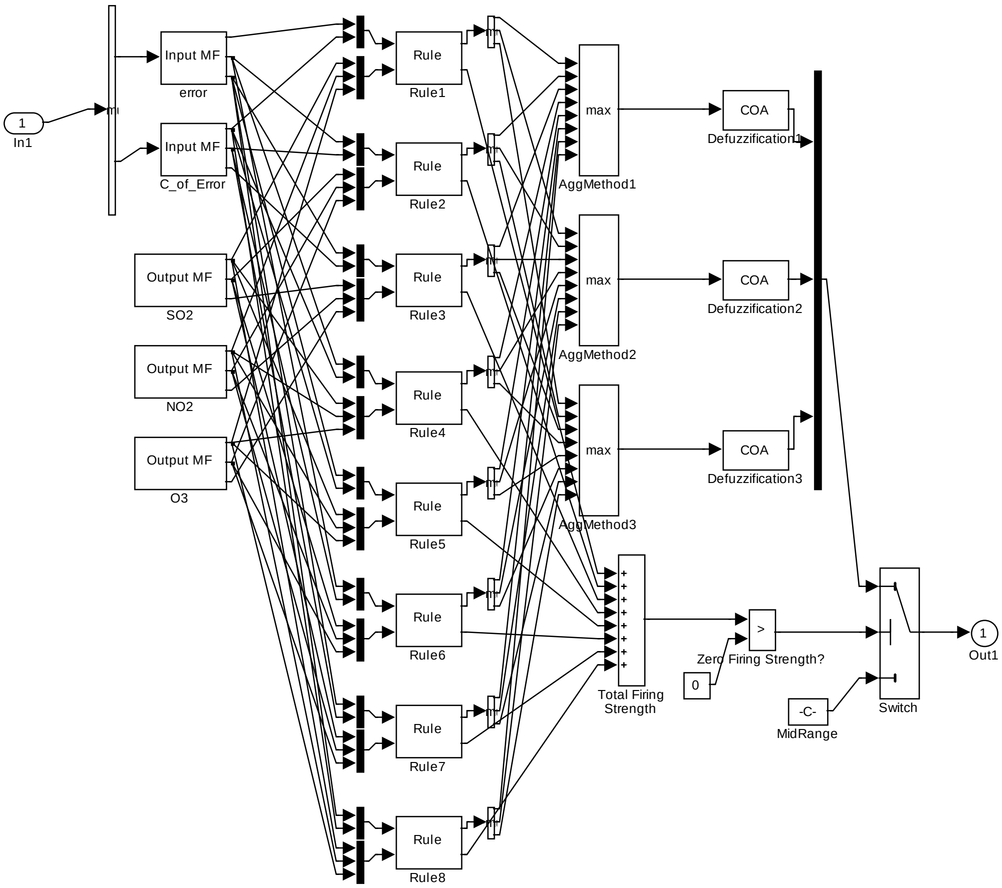


**Fig (17) Membership from inputs to outputs flow of rule base**

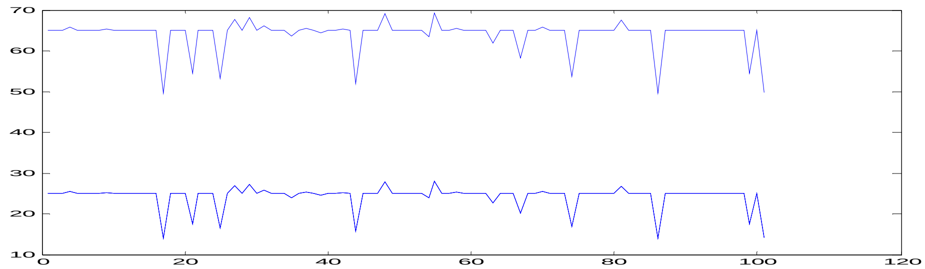

Fig (18) System Response of So2

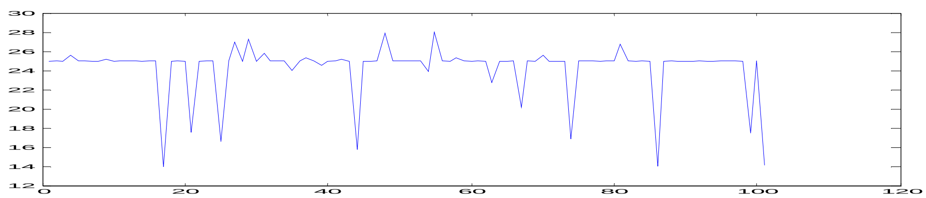

Fig (19) System Response of No2

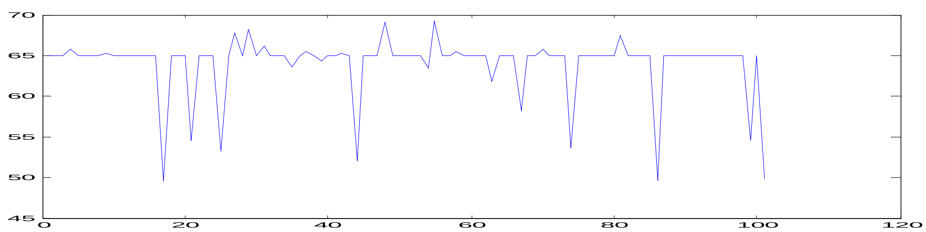

Fig (20) System Response of O3

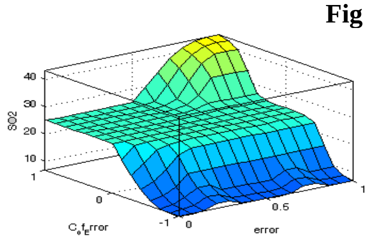


Fig (21) System Response of So2

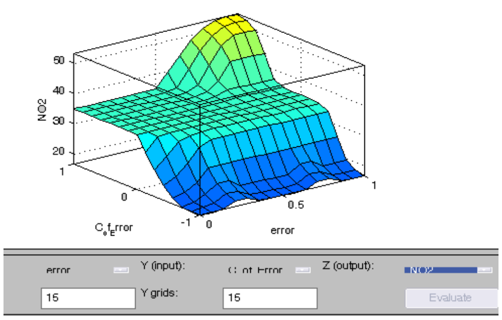


Fig (22) System Response of No2

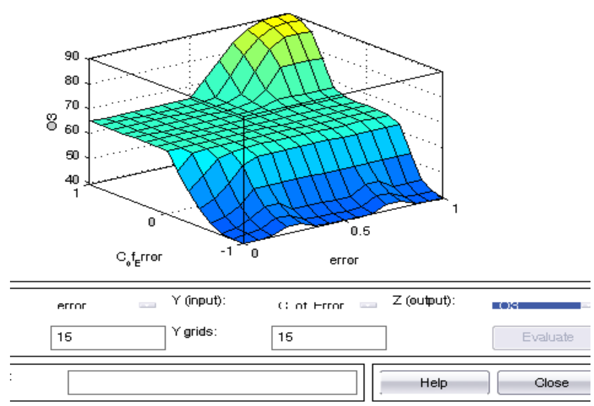


Fig (23) System Response of O3

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