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Identification and Modeling of Air Pollutions using Adaptive Nero Fuzzy Systems (ANFIS)

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Abstract—**Usage of the new technology and new inventions are making the human life more and more convenient but alongside they are having several disadvantages as well. Air Pollution is a major drawback of a growth. Major sources of Air pollution are vehicle emitting lot of smoke, dust and other human generated garbage. Increasing So2 and No2 in air is the main cause of air pollution. In this paper, I am proposing a scheme to show the prediction of Air Pollution in urban areas using ANFIS controller applied to the historical data. I have also discussed the scheme for the prediction of O3 based on NO2 and SO2 measurements. Several researchers have proposed different techniques to predict the pollution including application of ANFIS. The techniques of artificial intelligence based in fuzzy logic and neural networks have been frequently applied together. The reasons to combine these two paradigms come out of the difficulties and inherent limitations of each isolated paradigm. Such an intelligent system based on hybrid 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. Where, ANN learns from scratch by adjusting the interconnections between layers, Fuzzy Inference System 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 and others. My Proposed Algorithm mainly oriented on the pollution occurring due to vehicle smoke in Egypt. This paper presents a current work for developing a short-term forecasting model for air pollution (nitrogen dioxide NO2, sulpher dioxide SO2 and ozone O3) in a selected spot of Cairo city. 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 based on the scaling and changing of the shapes, NN, scheme for the prediction of 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 based on the weights and bias. The first NN is composed of three layers. The first layer has four nodes which represent wind speed, wind direction, temperature, and (SO2 or NO2) level for industrial sources. The output layer predicts SO2 or NO2 levels for defined urban areas. The second NN is composed of three layers. The first layer has five nodes which represent wind speed, wind direction, temperature, SO2 level, and NO2 level for industrial sources. The output layer predicts the O3 level. The neural net modeling schemes have been trained using recorded data (1998 and 1999) from monitoring stations in Cairo City. System performance is evaluated and results of air pollution forecasting has indicated an average of 80% correct percentage based on 70% of the data have been used for training and 30 % for testing.**

Keywords—component; ANFIS, ANN, NN, FIS, Fuzzy controller

I. Introduction

Air pollution has become an exceedingly inescapable part of urban living. For nonlinear dynamic systems, the conventional techniques of modeling and identification are difficult to implement and sometimes impracticable. However, other techniques based on fuzzy logic are more and more used for modeling this kind of process [1]. Among the different fuzzy methods, the Takagi Sugeno model (TS) has attracted most attention [2]. 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. 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 [4, 5]. Modeling of urban air pollution is an important facet of pollution control and abatement [1, 2, 6]. 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, sulphur 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.

II. PROBLEM FORMULATION

A. Defeintion of problem

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, 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.

B. 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.1 and Fig.2. Thirty wind direction values have also been generated based on relative time duration ratio.

III. ANFIS 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.

IV. MODELS OF ANFIS 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. (2). Fig. (3) Shows the second model of fuzzy neural system. Fig (4) shows the Simulink Model of fuzzy Logic Controller. Fig (5) presents the structure of fuzzy model.

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.3. 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.

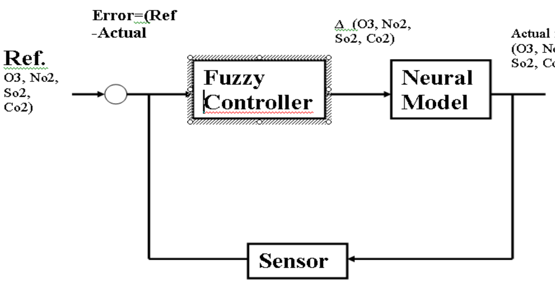


FIG. (1) PROPOSED MODEL

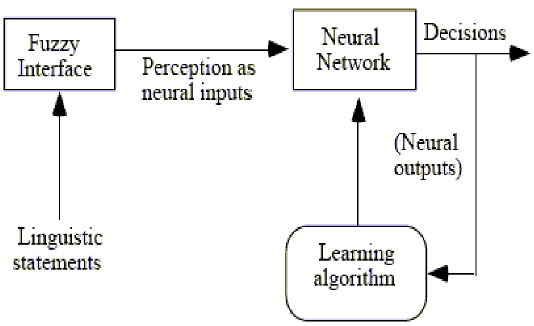


Fig. (2) First Model of ANFIS Systems

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

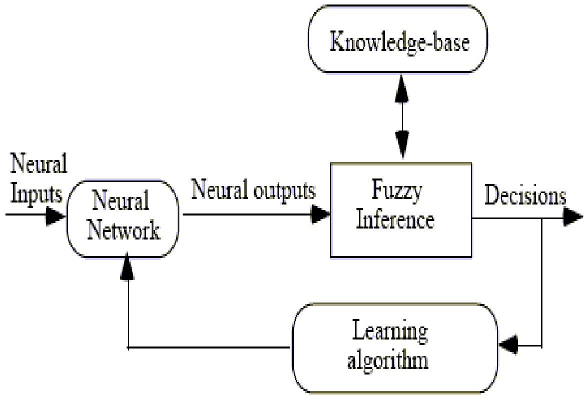


Fig. (3) Second model of ANFIS system

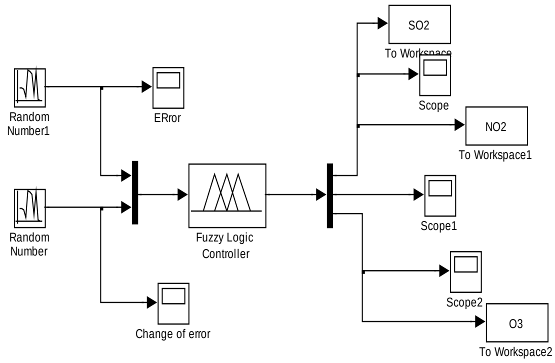


Fig (4) Simulink Model of fuzzy Logic Controller

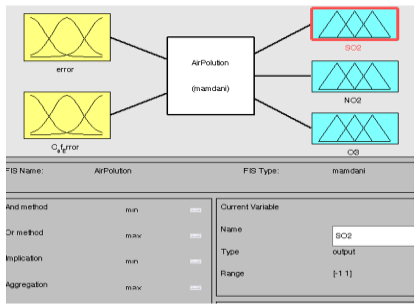


Fig (5) Fuzzy Model

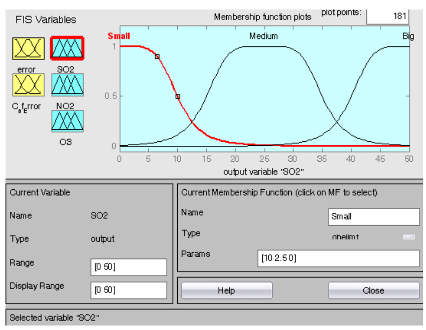


Fig (6) Membership Function for SO2

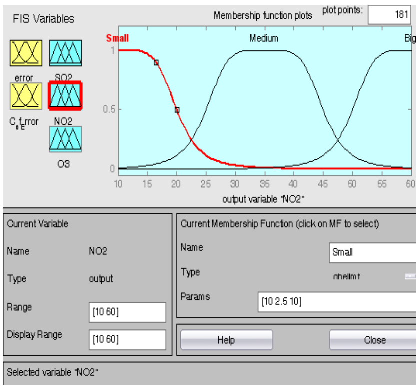


Fig (7) Membership Function for NO2

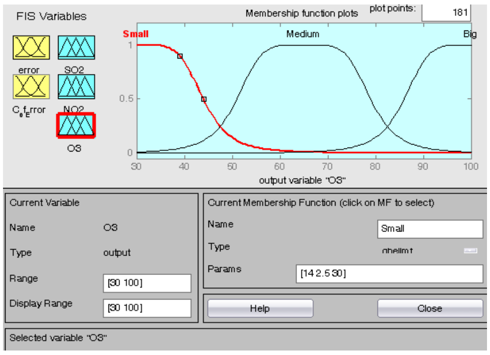


Fig (8) Membership Function for O3

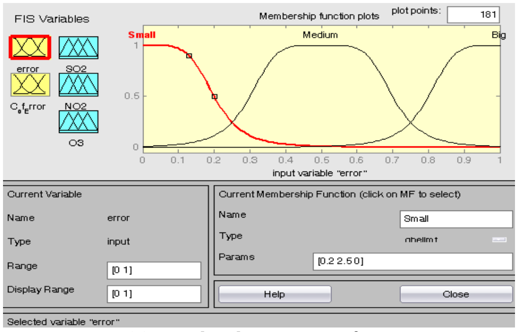


Fig (9) Membership Function for Error

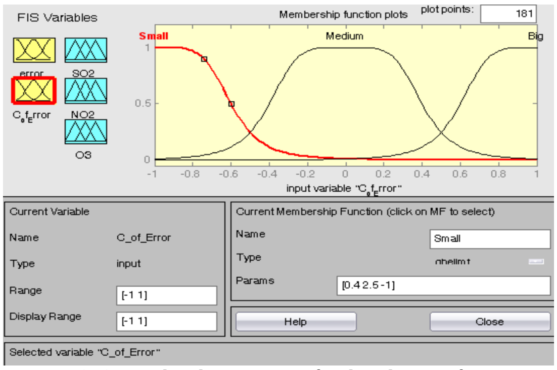


Fig (10) Membership Function for the Change of Error

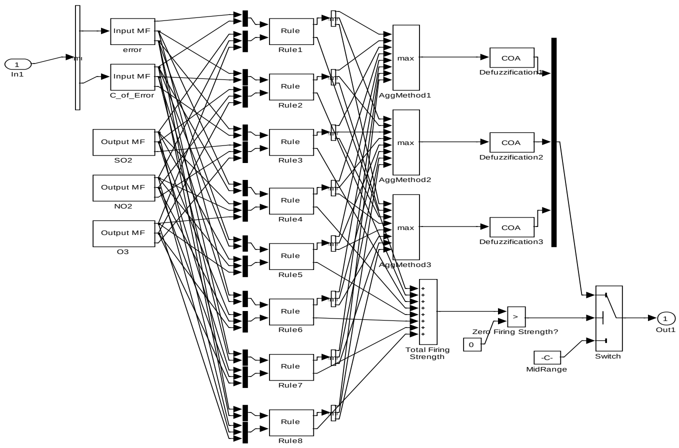


Fig (11) Membership from inputs to outputs flow of rule base

base

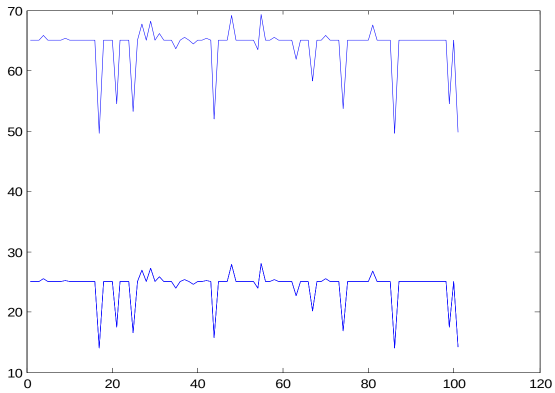


Fig (12) System Response of So2

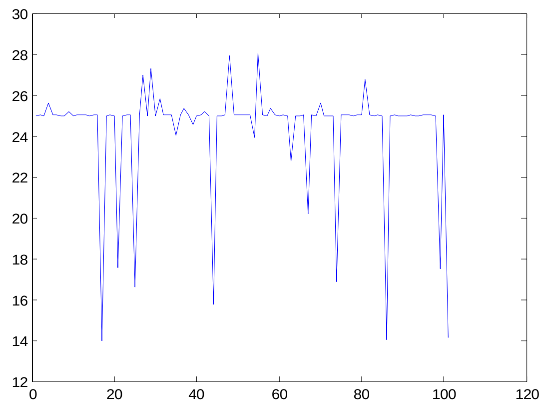


Fig (13) System Response of No2

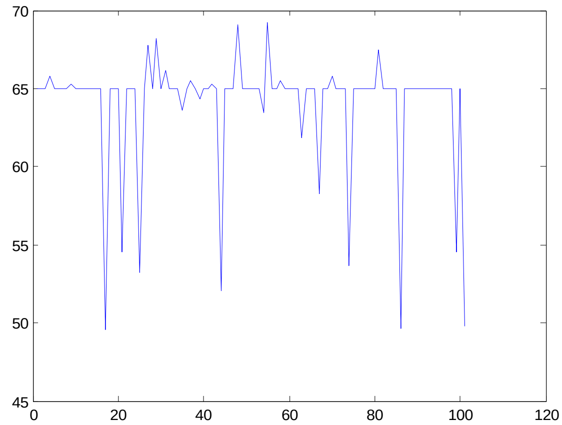


Fig (14) System Response of O3

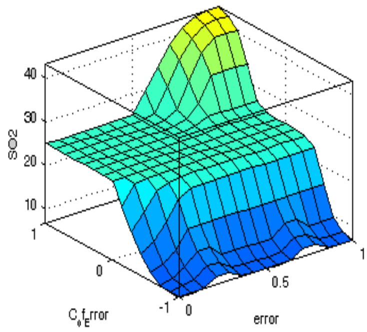


Fig (15) System Response of So2

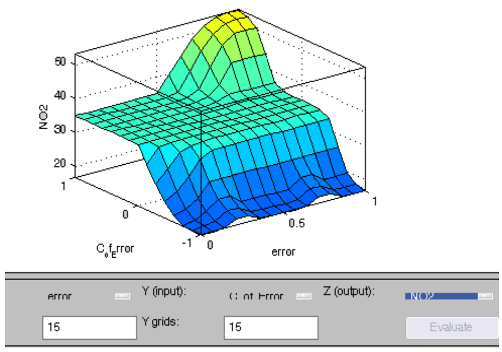


Fig (16) System Response of No2

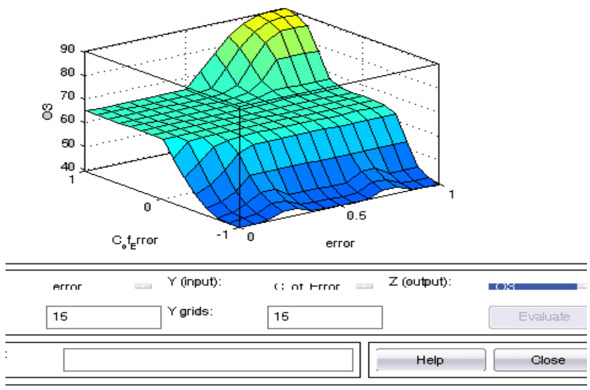


Fig (17) System Response of O3

Fig (6) displays the input membership function of So2 . Fig (7) display the input membership function of NO2, and Fig (8) display the input membership function of o3. Fig (8) and Fig (9) present the Membership Function of error and Change of Error. Fig (10) display the Membership from inputs to outputs flow of rule base. Fig (11)present the Membership from inputs to outputs flow of rule base. From Fig (12) to Fig (14) shows the system response of NO2, SO2 and O3 respectively. From Fig (15) to Fig(17) shows the surface system response of NO2, SO2 and O3 respectively.

In this paper we are using the First Model of Fuzzy Neural Systems. The rule bases used in the implementation as follow.

V. 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)
8-If (error is small) and (c_of_error is Big) then (So2 is Big) (No2 is Small)(O3 is Small)

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

VI. 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 5, 6, and 7. 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.

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%			

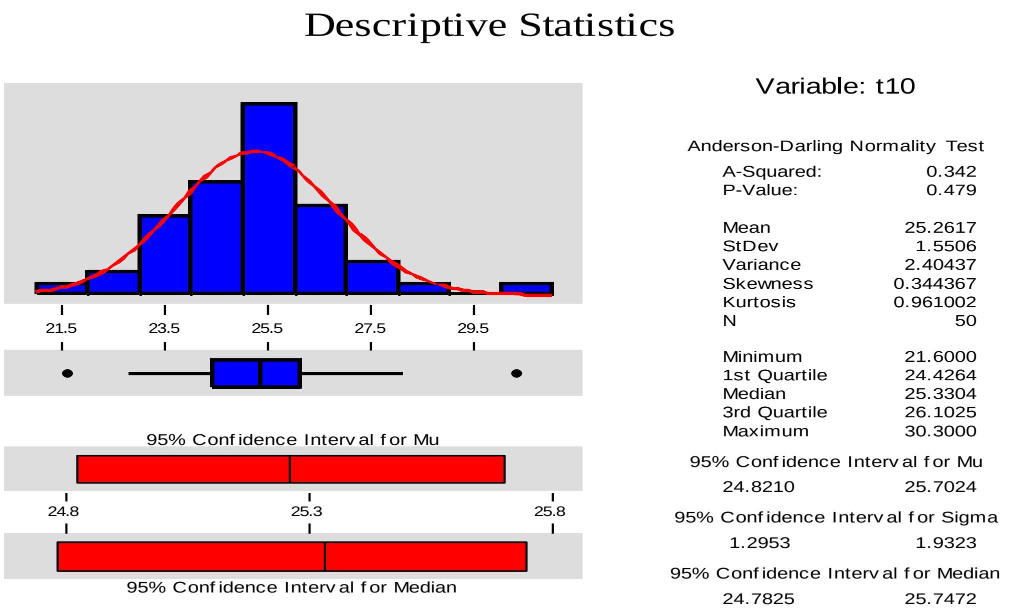
Table 4. O3 classifier performance table

	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	----	------



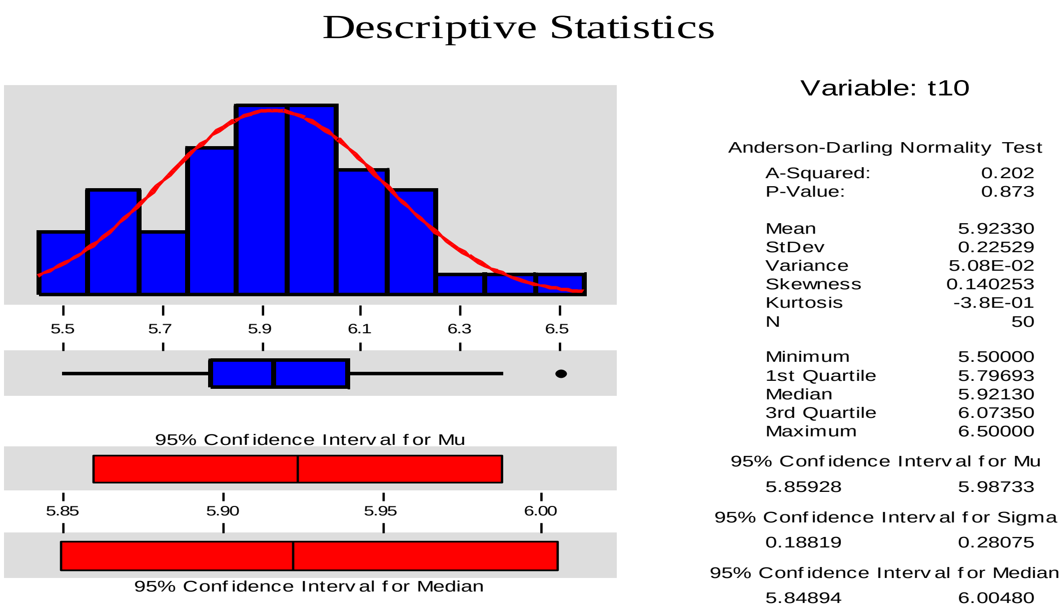


Fig.18.Descriptive statistic of generated data of Oct., wind speed

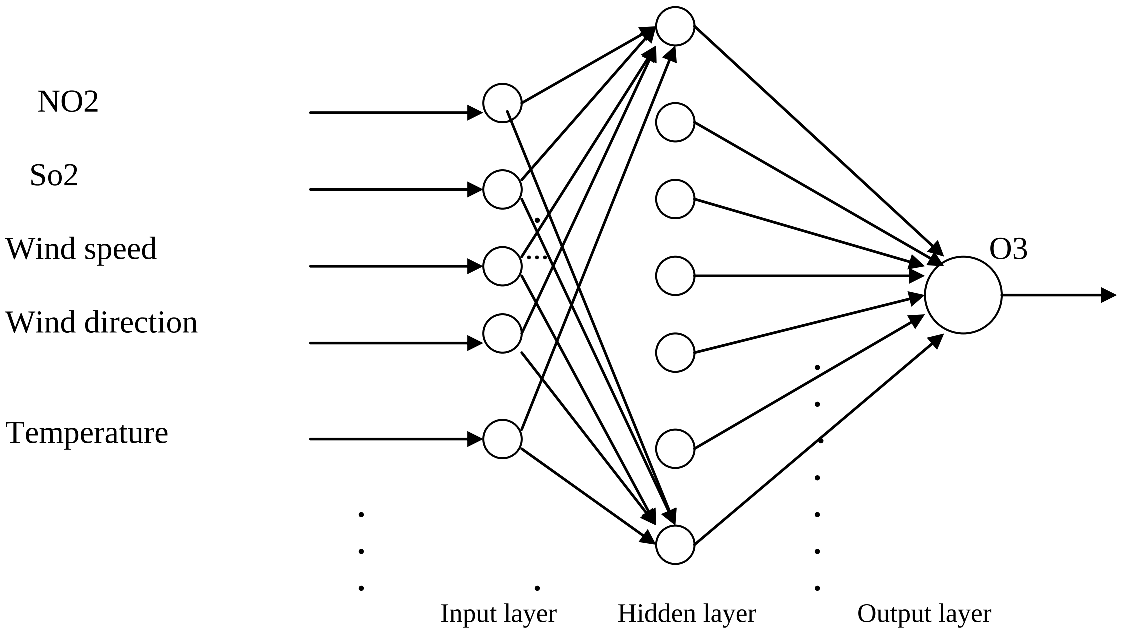


Fig.19 Neural net model for ozone prediction: output, based on measured (NO2, SO2, wind speed and direction, temperature): input

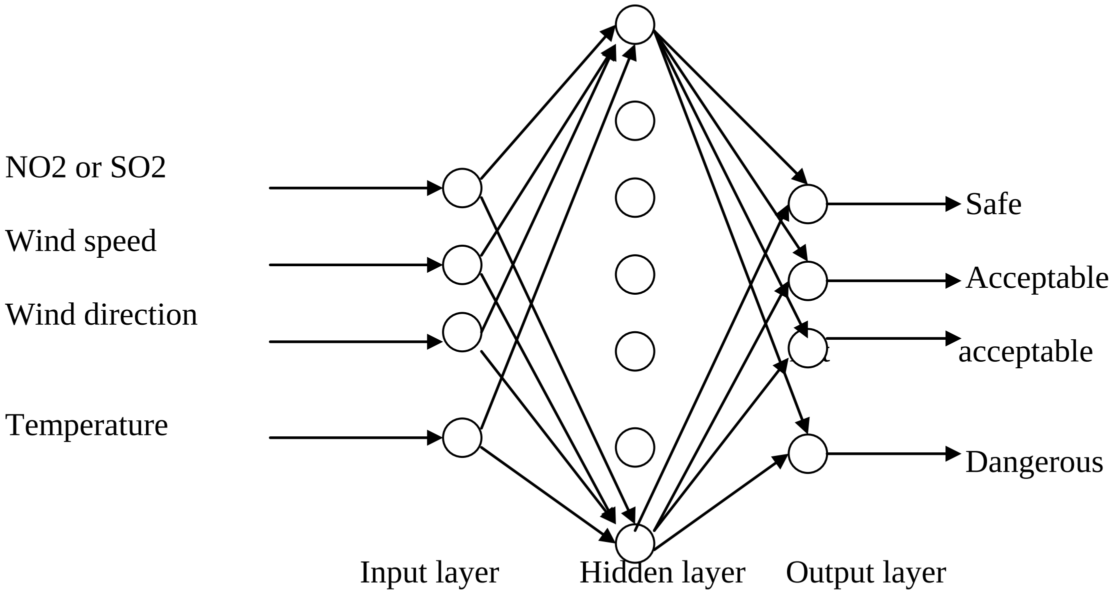


Fig.20. Neural net classification scheme for categorizing (on four classes) NO2 or SO2 levels on urban areas: output, based on measured level values of (NO2 or SO2, wind speed, wind direction, temperature) on industrial areas : input.

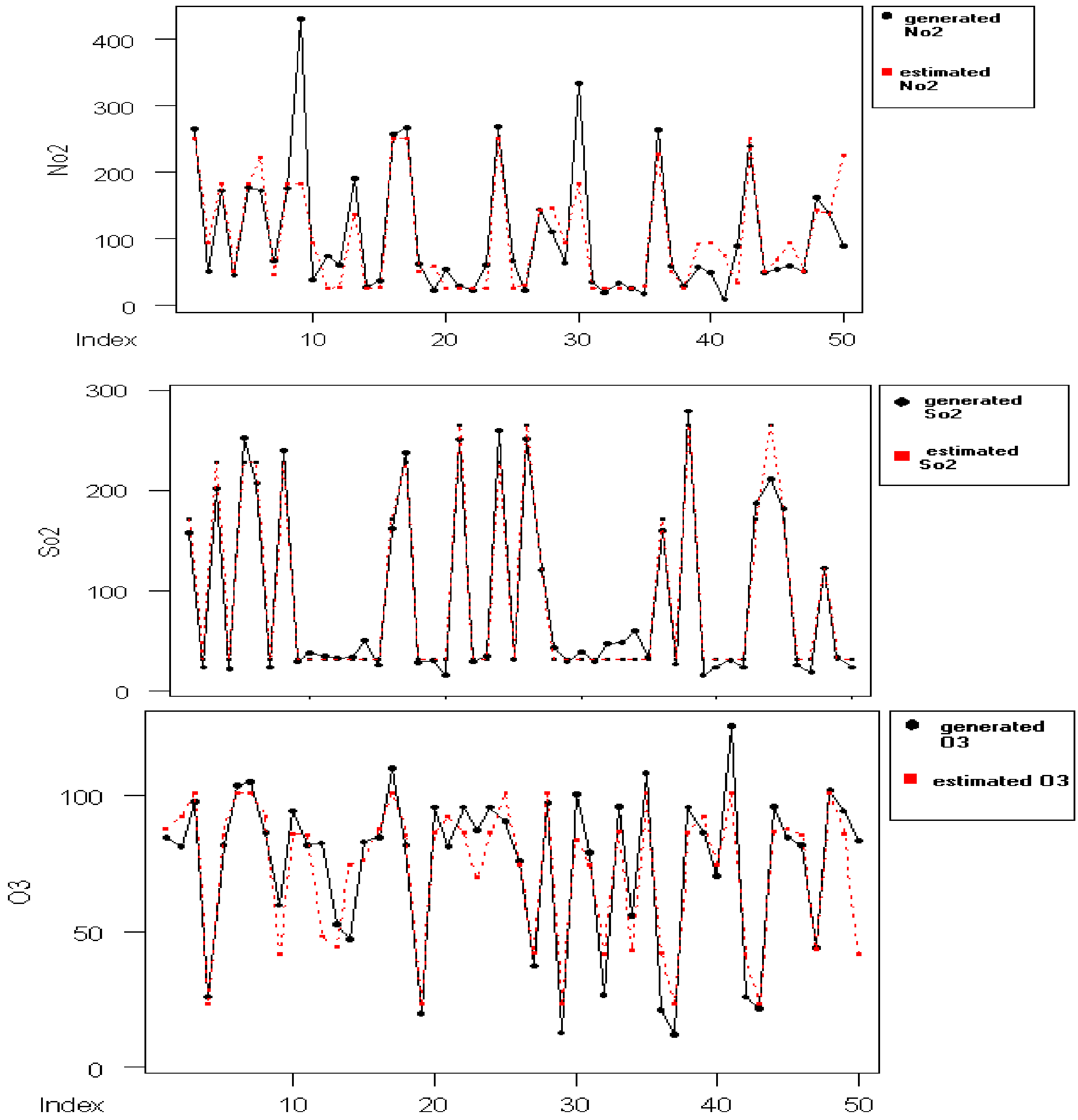


Fig.21 Graph of O3: measured (solid line), and predicted (dotted line)

VII. CONCLUSION

Fuzzy Inference Systems (FISs) and Artificial Neural Networks (ANNs), as two branches of Soft Computing Systems (SCSs) that pose a human-like inference and adaptation ability, have already proved their usefulness and have been found valuable for many applications [1],[2]. They share a common framework of trying to mimic the human way of thinking and provide an effective promising means of capturing the approximate, inexact nature of the real world process. In this paper we propose an Adaptive Neuro-Fuzzy Logic Control approach (ANFLC) based on the neural network learning capability and the fuzzy logic modeling ability. The approach combines the merits of the both systems, which can handle quantitative (numerical) and qualitative (linguistic) knowledge. The development of this system will be carried out in two phases: The first phase involves training a multi-layered Neuro-Emulator network (NE) for the forward dynamics of the plant to be controlled; the second phase involves on-line learning of the Neuro-Fuzzy Logic Controller (NFLC). Extensive simulation studies of nonlinear dynamic systems are carried out to illustrate the effectiveness and applicability of the proposed scheme. This paper presented a proposed ANFIS 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.

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