Neural Approach Modeling Scheme for the Prediction of Air Pollution (No2, So2) Resulting from Traffic Exhaust in Cairo City Down Town

Abdalla M. Elramsisi[*1], Fareed Zaghlool [2], Tharwat O. S. ahanafy [2] and Abdou Saad El Din Moustafa [3]

[1]Egyptian air Force, R&D Center, Cairo, Egypt.
[2] Systems & Computer Dept. Director, Faculty of Engineering, Alazhar University, Cairo, Egypt.
[3]Arab Co. for Engineering & Systems Consultations (AEC) Certified Lead Auditor, Cairo, Egypt.
[*]s_ewiss@yahoo.com

Abstract: This paper presents a current work for developing a short-term forecasting model for air pollution (nitrogen dioxide NO2, sulpher dioxide SO2) in a down town of Cairo city. The structure of the model is based on three-layered neural network architecture with back propagation learning algorithm. The main objective of this paper is to develop a neural net,as a tool of modeling and artificial techniques (NN) , scheme for the prediction of NO2 or SO2, over urban zones of Cairo down time based on the measurement of NO2 or SO2 over defined traffic sources. 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 neural net modeling schemes have been trained using recorded data (2008 and 2009) 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 85% of the data have been used for training and 15 % for testing.

[Abdalla M. Elramsisi, Fareed Zaghlool, Tharwat O. S. ahanafy and Abdou Saad El Din Moustafa. **Neural Approach Modeling Scheme for the Prediction of Air Pollution (No2, So2) Resulting from Traffic Exhaust in Cairo City Down Town.** New York Science Journal 2010;3(12):142-149]. (ISSN: 1554-0200). http://www.sciencepub.net/newyork.

Keywords: Neural Approach Modeling Scheme; Prediction; Air Pollution; Traffic Exhaust'

1. Introduction

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

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.

The analysis of cost effective ways to reduce emissions played a major role since the 1970's. Binding emissions control targets for Sulphur Dioxides (SO2) and Nitrogen Oxide (NO2) were agreed upon with the backing of model calculations of the related costs of control strategies and even the most recent protocol to (Long –Range Transboundary Air Pollution (CLRTAP)).

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 and SO2) 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: Cairo Down town.

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).

Nature provides inherent methods for solving optimization problems, called genetic algorithms .Live organisms evolve ,adaption to changing environments ,mate and produce individuals even more fitter than its predecessors. The fitness of the individual denotes its ability to survive or to be fitter for a particular purpose. A genetic algorithm (GA) is a method for solving optimization problems that is based on natural selection, the process that drives biological evolution; A genetic algorithm repeatedly modifies a population of individual solutions. At each step , a genetic algorithm selects individuals at random from the current population to be parents, and uses them to produce them to produce the children for the next generation . Over successive generations, the population "evolves" towards an optimal solution. We can apply a genetic algorithm to solve a variety of optimization problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, non-differential, stochastic, or highly nonlinear. In this article, I will demonstrate how GAS can be applied to train artificial neural networks for classification purposes to serve the problem of reduce air pollution at urban city.

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?

Due to the complex relation between inputs and outputs, neural net stands as a reliable mapping tool for this application. The proposed neural net 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 neural net schemes are reconfigured to provide category or class (safe, acceptable, not acceptable, dangerous) for output (NO2 or SO2) 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) GAS will be applied to train artificial neural networks for classification purposes to serve the problem of reduce air pollution at urban city.

Inegrated Assessment Models (IAMs) applied in this context mostly use (d) single abatment cost curves as input to their optimization tools ,in order to identify the least –cost ways to achieve given reduction targets , and to assess the overall costs of strategies .Typically, the analysis focused on a single pollutant (e.g. SO2,NO2) with a usually linear relationship between emissions and concentrations ,respctively emissions and effects.

The case of acid rain and acidification in general (Gough et,al.1995) is one of the most prominent examples, where reductions of emissions of SO2 and /or NO2 would usually lead to reduced deposition in the same order of magnitude. The assessment models had to take into account transport of pollution through the air to some extent, in order to map the regional distribution of deposition changes, while chemicals transformation of pollutants did not play a major role yet.

When air pollution by troposphric ozone became the focus, the modeling task turned more difficult , as the relationship between the emissions of ozone precursor substances NOx and Non-Methane Volatile Organic Compounds , and to some extent Carbon Monoxide (CD) as well as the formation of ground level ozone is not linear. Thus ,the assessment models need to include more complex mechansms to account for these non-linearities. The situation becomes more difficult as soon as two pollutants were to be controlled , and measures existed, which would reduce the emissions of both pollutants when installed, usually with differing efficiency, thus creating the need for allocating cost proportions and allocate these to different single abatement cost curves, most of them are more or less arbitrary and reflect more the preference of the model developer than anything. In this paper ,these particular problems shall be discussed, with a focus on the current development towards multi- pollutant multi-effect assessment models where a robust and transparent methodlogy to solve this problem could prove to be vital.

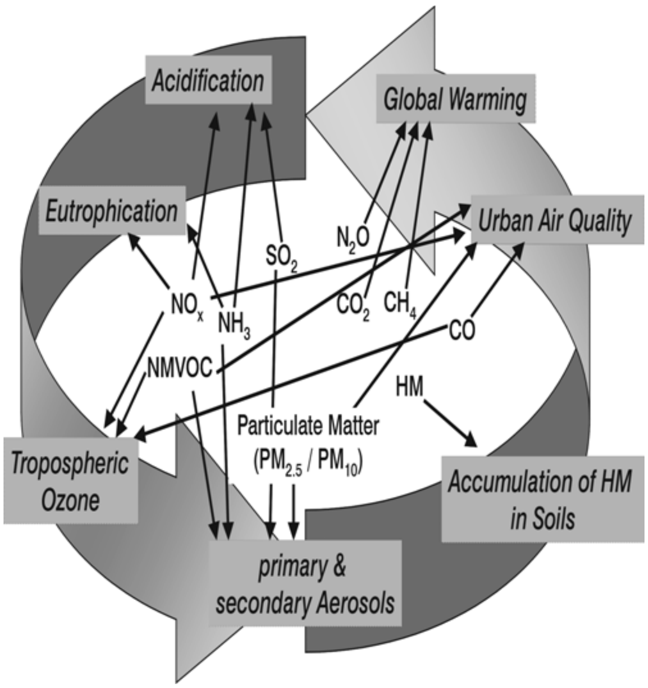


Figure 1. Illustrating the Multi-Pollutant Multi-Effect Environment for IAMs

3. Data preparation

Recorded Data for the amount of NO2, and SO2 in air have been obtained from Egyptian environmental affairs Authority (EEAA) in the form of average value per month for the years 2008, 2009 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 2008, 2009. 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.

4. 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 neural net for the prediction of NO2 or SO2 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 (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) NO2 or SO2 of output level in the neural net category, see Fig.3.

4.1 Back propagation learning algorithm

The back propagation learning algorithm can be divided into two phases: propagation and weight update.

Phase 1: Propagation

Each propagation involves the following steps:

1. Forward propagation of a training pattern's input through the neural network in order to generate the propagation's output activations.
2. Back propagation of the propagation's output activations through the neural network using the training pattern's target in order to generate the deltas of all output and hidden neurons.

Phase 2: Weight update

For each weight-synapse:

1. Multiply its output delta and input activation to get the gradient of the weight.
2. Bring the weight in the opposite direction of the gradient by subtracting a ratio of it from the weight.

This ratio influences the speed and quality of learning; it is called the *learning rate*. The sign of the gradient of a weight indicates where the error is increasing; this is why the weight must be updated in the opposite direction.

Repeat the phase 1 and 2 until the performance of the network is good enough.

Modes of learning

There are basically two modes of learning to choose from, one is on-line learning and the other is batch learning. In on-line learning, each propagation is followed immediately by a weight update. In batch learning, many propagations occur before weight updating occurs. Batch learning requires more memory capacity, but on-line learning requires more updates.

Algorithm

Actual algorithm for a 3-layer network (only one hidden layer):

Initialize the weights in the network (often randomly)

Do

For each example e in the training set

O = neural-net-output(network, e) ; forward pass

T = teacher output for e

Calculate error (T - O) at the output units

Compute delta_wh for all weights from hidden layer to output layer ; backward pass

Compute delta_wi for all weights from input layer to hidden layer; backward pass continued

Update the weights in the network

Until all examples classified correctly or stopping criterion satisfied

Return the network

As the algorithm's name implies, the errors (and therefore the learning) propagate backwards from the output nodes to the inner nodes. So technically speaking, backpropagation is used to calculate the gradient of the error of the network with respect to the network's modifiable weights. This gradient is almost always then used in a simple stochastic gradient descent algorithm to find weights that minimize the error. Often the term "backpropagation" is used in a more general sense, to refer to the entire procedure encompassing both the calculation of the gradient and its use in stochastic gradient descent. Backpropagation usually allows quick convergence on satisfactory local minima for error in the kind of networks to which it is suited.

Backpropagation networks are necessarily multilayer perceptrons (usually with one input, one hidden, and one output layer). In order for the hidden layer to serve any useful function, multilayer networks must have non-linear activation functions for the multiple layers: a multilayer network using only linear activation functions is equivalent to some single layer, linear network. Non-linear activation functions that are commonly used include the logistic function, the softmax function, and the gaussian function.

The backpropagation algorithm for calculating a gradient has been rediscovered a number of times, and is a special case of a more general technique called automatic differentiation in the reverse accumulation mode.

It is also closely related to the Gauss–Newton algorithm, and is also part of continuing research in neural backpropagation.

Multithreaded Backpropagation

Backpropagation is an iterative process that can often take a great deal of time to complete. When multicore computers are used multithreaded techniques can greatly decrease the amount of time that backpropagation takes to converge. If batching is being used, it is relatively simple to adapt the backpropagation algorithm to operate in a multithreaded manner.

The training data is broken up into equally large batches for each of the threads. Each thread executes the forward and backward propagations. The weight and threshold deltas are summed for each of the threads. At the end of each iteration all threads must pause briefly for the weight and threshold deltas to be summed and applied to the neural network. This process continues for each iteration. This multithreaded approach to backpropagation is used by the Encog Neural Network Framework.[10, 11,12]

Limitations

- The convergence obtained from backpropagation learning is very slow.
- The convergence in backpropagation learning is not guaranteed.
- The result may generally converge to any local minimum on the error surface, since stochastic gradient descent exists on a non-linear surface.
- The backpropagation learning is associated with the problem of scaling.

5. 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, and SO2, 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, 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, or SO2.

6. Conclusion

This paper presented proposed neural net schemes for forecasting and classifying of NO2; SO2 emissions over urban areas based on measured emissions over industrial areas. 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, 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 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.

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

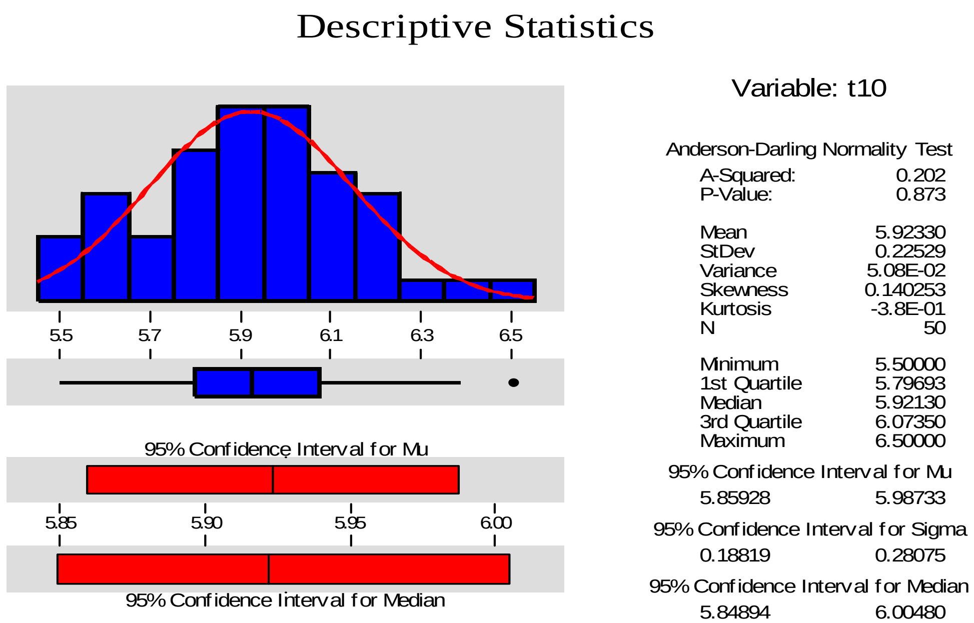
Year	2008				2008 and 2009				2009			
Class / categ.	S	A	NA	D	S	A	NA	D	S	A	NA	D
S	86	8	0	0	108	6	0	0	165	0	0	0
A	14	30	0	0	13	23	0	0	1	0	0	0
NA	1	8	0	0	0	13	0	0	0	0	0	0
D	0	8	0	0	0	3	0	0	0	0	0	0
% correctrecog	77.33336 %				78.915665 %				99.397591 %			

Table 3. SO2 classifier performance table

Year	2008				2008 and 2008				2009			
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 5. Performance table for prediction neural net schemes.

	Rang	2008	2009	2008 and 2009
NO2	**10-400**	**20.53**	**7.726**	**16.84**
SO2	**10-290**	**15.45**	**6.89**	**13.486**



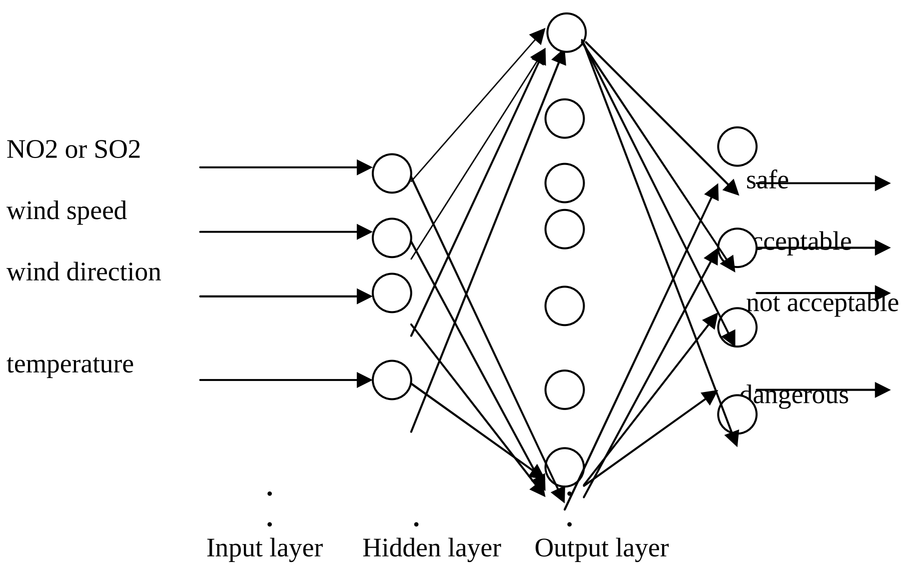


Fig.3. Neural net classification scheme for catogorizing (on four classes) NO2 or SO2 levels on urban areas: output, based on measured level values of (NO2 or SO2, wind speed, wind direction, temperature) on industrial areas : input.

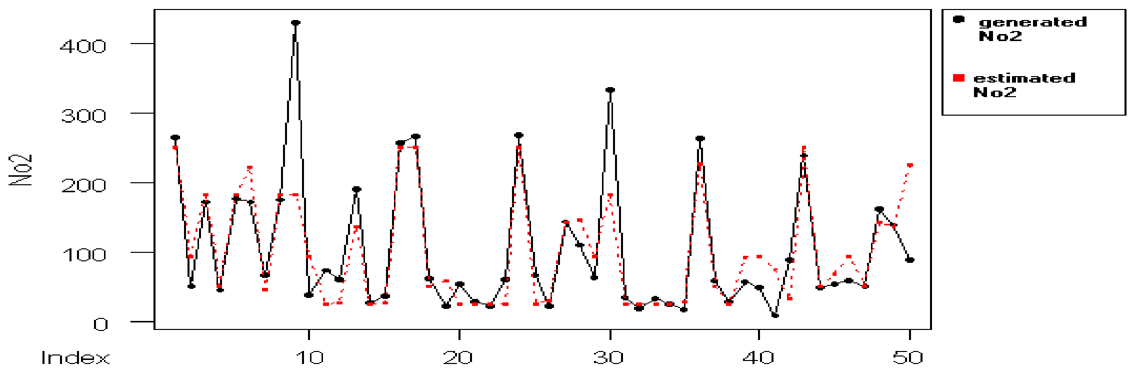


Fig.4. Graph of No2: measured (solid line) and predicted (dotted line)

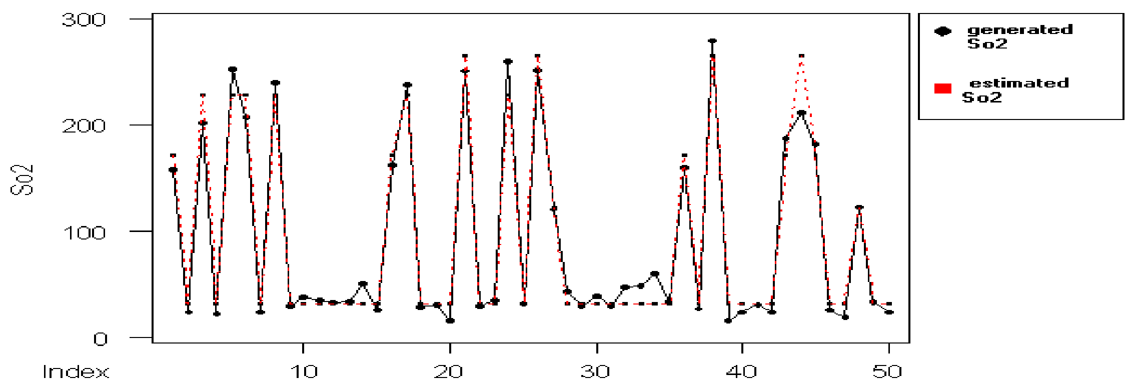


Fig. 5 Graph of So2: measured (solid line) and predicted (dotted line)

Corresponding author:
Abdalla M. Elramsisi
Egyptian air Force**,** R&D Center, Cairo, Egypt.

References:

1. J.C. Ruiz-Suarez, O.A. Mayora, R. Smith-perez, L.G. Ruiz-Suarez, *"A Neural Network-based Prediction Model of Ozone For Mexico City"*, Proceeding of air Pollution Theory and Simulation Conference 2000, pp.393-400.
2. Faizal A. Hasham, Stephen J. Stanley, Warren B. Kindzierski, *"Modelling Of Urban Air Pollution In The Edmonton Strathcona industrial Area Using Artificial Neural Networks"*, Proceeding of air Pollution Theory and Simulation Conference 2000, pp.246-255.
3. M. Boznar, P. Mlakar, *"Neural Networks- A New Mathematical Tool For Air Pollution Modelling"*, Proceeding of air Pollution Theory and Simulation Conference 2000, pp.259-266.
4. A.M. ELramsisi, Osama S. Elshehry, "A Fractal-Based Approach For Radar Target Recognition Using Neural Networks," *Proceedings of the first International Conference on Electrical Engineering, ICEENG, Military Technical College, Cairo,Egypt, 24-26 March, 1998, pp. 383-390.*
5. Mohamed Zaki, Abdallah EL-Ramsisi, Rostom Omran, " A Soft Computing Approach For Accurate Recognition of Occluded Shapes," *journal of intelligent and fuzzy systems, 9(2000) 85-99 ISSN 1064-1246, IOS press*
6. A.M. ELramsisi, W.I. Khedr, "A Computer Security Scheme for Dynamic User Identification, and Intruder Detection Using Neural Network Behavior-based Classifier," *Proceedings of the nineth International*

Conference on Computer Theory and Applications ICCTA'99, Alexandaria, Egypt, August 28-30, 1999, pp. 13-22.

7. A.M.ELramsisi, Osama S. Elshehry, "Three-View Target Recognition Using Neural Nets With Fractal Features and Moments Invariants In The Presence Of Noise," *Proceedings of the sixth International Conference on Artificial Intelligence Applications, ICAIA' 98 Cairo, Egypt, Feb. 18-23, 1998, pp. 183-195.*
8. Packing space inventory control: an artificial intelligence approach, *Dusan Teodorovic, panta Luce ,Dept of civial Engineering – Virginia Tech*
9. An Environmental Diagnosis Expert System *, Mihaela Opera , Dunea , University Petroleum – Gas of Ploiesti ,Department of Informatics, Bd.Bucuresti nr.3, Ploiesti, 100680, Romania*
10. Stuart Russell and Peter Norvig. *Artificial Intelligence A Modern Approach*. p. 578. "The most popular method for learning in multilayer networks is called Back-propagation. It was first invented in 1969 by Bryson and Ho, but was more or less ignored until the mid-1980s."
11. Arthur Earl Bryson, Yu-Chi Ho (1999). *Applied optimal control: optimization, estimation, and control*. Blaisdell Publishing Company or Xerox College Publishing. pp. 481.
12. J. Heaton http://www.heatonresearch.com/encog/mprop/compare.html Applying Multithreading to Resilient Propagation and Backpropagation.

11/2/2010