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Application of Neuro-Fuzzy in Prediction of Air Pollution in Urban Areas

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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 neuro fuzzy 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 Neuro-Fuzzy. 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 urban areas. I have applied various fuzzy rules to show the severity of the air pollution in occurring due to smoke generated from vehicles and dust in nearby areas of Jabalpur. Data has been collected from office of Survey of India in Jabalpur.

Keywords: Air pollution, Artificial Neural Networks (ANN), Neuro fuzzy system, neural networks

1. INTRODUCTION

Air pollution mainly results from anthropogenic (human) activities and has diverse causes and sources. “Stationary sources”, such as factories, power plants, and smelters; “areasources”, which are smaller sources such as dry cleaners and degreasing operations; “mobile sources”, such as cars, buses, planes, and “natural sources”, such as wind blown dust and wildfires, all contribute to air pollution. The two main sources of pollutants in urban areas are transportation (predominantly automobiles) and fuel combustion in stationary sources, including residential, commercial, and industrial heating and cooling.

Motor vehicles produce high levels of carbon monoxides (CO) and a major source of hydrocarbons (HC) and nitrogen oxides (NOx), whereas, fuel combustion in stationary sources is the dominant source of sulfur dioxide (SO2).

Human beings breathe in and out approximately once every 4sec, which equates to over 8million times a year. Urban air pollution is therefore one of the most important environmental issues that may be considered due to its direct effect on human health. It is known that exposure to high concentrations of air pollution over short periods of time (usually seconds) is far more harmful to human health than long term exposure to lower concentrations. So2 and No2 are the major sources of air pollution and their existence and harms are to discussed properly before estimating their existence in air.

Sulphur dioxide (SO2):

SO2 is prevalent in most industrial raw materials, including crude oil, coal, and common ores like aluminum, copper, zinc, lead, and iron. Sulphur gases are produced when fuel, such as oil and especially coal, is burnt, during mining and industrial processes, e.g. when petrol is extracted from crude oil and naturally from volcanic eruptions.

Health effects of SO2 gas are irritation to the eyes and respiratory system, reduced pulmonary functions and aggravation to respiratory diseases such as asthma, chronic bronchitis and emphysema. Exposure to extremely high concentrations will cause permanent damage to the respiratory system as well as extreme irritation to the eyes (due to production of dilute sulphuric acid around the eyes). When SO2 reacts with other chemicals in the air to form tiny sulphate particles, these may also be inhaled in which case they gather in the lungs and are associated with increased respiratory symptoms and disease, difficulty in breathing, and premature death.

Ozone (O3):

Ozone (O3) is a colourless gas formed at ground level by reactions involving VOCs and nitrogen oxides. Ground level ozone can be transported great distances by prevailing winds. Short-term exposure (1–3 h) to moderate ozone concentrations have been linked to increased hospital admissions for respiratory complaints. Repeated exposure is linked with increased susceptibility to respiratory infection, lung inflammation and aggravation of pre-existing respiratory diseases such as asthma. Other health effects of exposure to ozone are decreases in lung function and increased respiratory symptoms such as chest pains and coughing. Children active outdoors are the group at greatest risk of developing symptoms during levels of high ozone concentration.

Nitrogen oxides (NOx):

Nitrogen oxides or NOx (NO, NO2 andNO3) are a group of highly reactive gases containing nitrogen and oxygen.

Indoor air pollution and urban air quality are listed as two of the worlds worst pollution problems in the 2008 Blacksmith Institute World's Worst Polluted Places report. 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.

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.

2. DISCUSSIONS ON AIR POLLUTION

In this study, our design inputs will include the previous days' data records of SO2, O3,CO, PM10, NO2, as well as some meteorological parameters such as temperature, humidity, and wind speed, etc. Those daily records are provided by the Department of Meteorology in average values and for the periods from 1994.4 to 2003.9. Since our model have 10 inputs and according to the previous discussion, the subtractive clustering method will significantly minimize the number of fuzzy rules so that those rules could make a more accurate prediction.

Furthermore, the missing percentage for total observed data is about 10%. But from 2001.9 to 2002.12, there is not any missing data at all. Hence, we presented two simulations, one of which is to use the data records from 1994.4 to 2002.12 as the training data and for those inputs that are missing will be pre-processed before applying to ANFIS, and the other is based on the inputs from 2001.9 to 2002.12. Both of the simulation results will be tested by the API data records from 2003.1 to 2003.9. We set m=5 as the imputation steps size for all the imputation process.

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 these available statistically abstracted data, t(assuming one reading/day) normally distributed temperature values and thirty normally distributed wind speed values have been generate.

Air pollution index

As a result of the growth of economy, air quality is a major concern for us. The air pollution index (API) had been introduced in many areas for public to enhance awareness, and it is an index which represents the daily air quality in the urban cities. The first API system was presented by the US Environmental Protection Agency in 1970s as Pollution in a Standard Index, and now is widely used to highlight the severity of air pollution and the risk of health problems in worldwide.

The diffusion mechanism of air pollutants is very complicated and depends on several parameters, such as hydrocarbon (O3), nitrogen dioxide (NO2), suspended particulates and sulfur dioxides (SO2), and so on. It is also strongly affected by both weather conditions (e.g. temperature, humidity, wind speed and direction.) and the presence of primary pollutants that react with each other. It's hard to make a prediction for the API based on the traditional mathematical skills since its ill-defended and complicated structure. Thus many researchers introduced a number of approaches to forecasting the API, and the most commonly use is the Artificial Neural Network (ANN), which is a computational model based on biological neural network.

ANN is generally trained by means of training data, and due to its generalization properties, hence it had been widely used for modeling and forecasting. Especially, it had been successfully applied in the field of air quality prediction in the past decade. From a different viewpoint, Takagi and Sugeno explored a systematical method to

Fuzzy Inference. It can apply the human knowledge and reasoning processes without employing precise quantitative analyses; however, there is still no standard methods existing for transforming the human knowledge or experience into the rule base of a fuzzy inference system. In addition, an effective method should be defined for tuning the membership functions so that the output error measure is minimized or a performance index is maximized.

3. DISCUSSIONS ON NEURO FUZZY SYSTEM

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 , 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 de-fuzzyfication.

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.

Neuro fuzzy systems

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 leads 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. A neuro-fuzzy system is based on a fuzzy system which is trained by a learning algorithm derived from neural network theory. The (heuristically) learning procedure operates on local information, and causes only local modifications in the underlying fuzzy system.

A neuro-fuzzy system can be viewed as a 3-layer feed forward neural network. The first layer represents input variables, the middle (hidden) layer represents fuzzy rules and the third layer represents output variables. Fuzzy sets are encoded as (fuzzy) connection weights. It is not necessary to represent a fuzzy system like this to apply a learning algorithm to it. However, it can be convenient, because it represents the data flow of input processing and learning within the model. 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.

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.

Models of fuzzy neural systems

In response to linguistic statements, the fuzzy interface block provides an input vector to multi-layer neural networks. 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, shows the SimuLink Model of fuzzy Logic Controller.

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

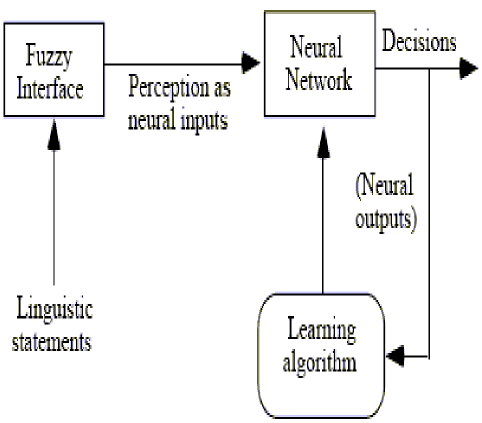


Figure1. Model of Fuzzy Neural Systems

Its disadvantages are: impossible interpretation of the functionality; difficulty in determining the number of layers and number of neurons.

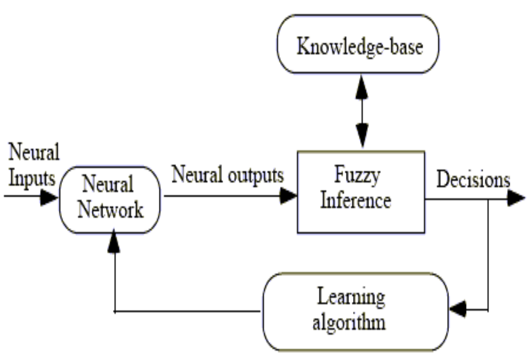


Figure2. Second Model of Fuzzy Neural System

We are using the First Model of Fuzzy Neural Systems. The structure of Fuzzy Model is presented in. The initial membership function is shown in for inputs Membership from inputs to outputs flow of rule base. The system response SO2, NO2,O3 are shown in show the three dimensional of SO2, NO2, O3.

The proposed prediction schemes use three-layered neural nets with supervised back propagation learning algorithm . The first neural net for the prediction of O3 level.The input layer has five nodes (NO2, SO2, WS, WD, T), the middle hidden layer has (on the average) 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 neural networks. Neural net for ozone prediction: output, based on measured (NO2, SO2, wind speed and direction, temperature) input. 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.

4 RESULTS

After running the simulation created in MATLAB, Emissions of NO2 or SO2 in urban area can be categorized as shown in table.

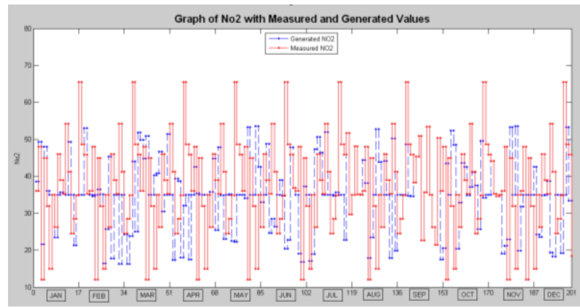
Results of NO2, SO2, and O3 classification nets are summarized in performance tables, where diagonal data represent correct class and off-diagonal represent misclassify data. Sample of the results of neural net prediction schemes for NO2, SO2, O3 are shown in figures. The performance of the prediction scheme is evaluated in terms of mean squared error MSE as recorded in table, where the first column provides the range of reading values for NO2, SO2 or O3. Data has been taken from Office of Survey of India, Jabalpur, Madhya Pradesh for working on the simulation.

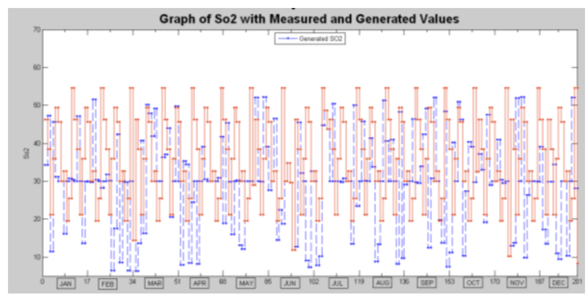
Category	Range	
	No_2/So_2	O_3
Safe (S)	0-15	0-30
Acceptable (A)	16-30	31-45
Not Acceptable (NA)	30-40	45-70
Dangerous (D)	>40	>70

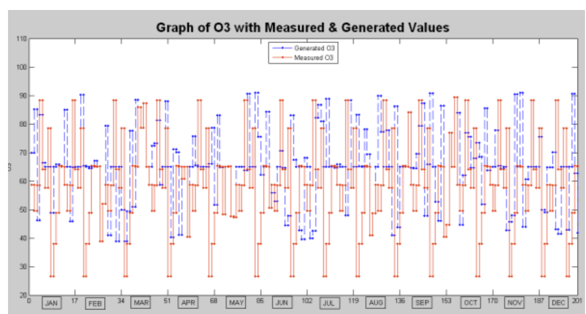
PREM NAGAR CHOWK (SO_2)				
Category	S	A	NA	D
Safe (S)	7			
Acceptable (A)		1		
Not Acceptable (NA)			1	
Dangerous (D)				1
PREM NAGAR CHOWK (NO_2)				

Category	S	A	NA	D
Safe (S)	7			
Acceptable (A)		5		
Not Acceptable (NA)			2	
Dangerous (D)				3
PREM NAGAR CHOWK (O_3)				
Category	S	A	NA	D
Safe (S)	1			
Acceptable (A)		4		
Not Acceptable (NA)			5	
Dangerous (D)				2
MALGODAM CHOWK (NO_2)				
Category	S	A	NA	D
Safe (S)	2			
Acceptable (A)		0		
Not Acceptable (NA)			4	
Dangerous (D)				2
MALGODAM CHOWK (SO_2)				
Category	S	A	NA	D
Safe (S)	10			
Acceptable (A)		0		
Not Acceptable (NA)			0	
Dangerous (D)				0
MALGODAM CHOWK (O_3)				
Category	S	A	NA	D
Safe (S)	0			
Acceptable (A)		5		
Not Acceptable (NA)			5	
Dangerous (D)				1
BLUME CHOWK (NO_2)				
Category	S	A	NA	D
Safe (S)	3			
Acceptable (A)		2		
Not Acceptable (NA)			1	
Dangerous (D)				2
BLUME CHOWK (SO_2)				
Category	S	A	NA	D
Safe (S)	7			
Acceptable (A)		0		
Not Acceptable (NA)			0	
Dangerous (D)				0
BLUME CHOWK (O_3)				
Category	S	A	NA	D
Safe (S)	1			
Acceptable (A)		4		
Not Acceptable (NA)			2	
Dangerous (D)				1
RADDI CHOWKI (NO_2)				
Category	S	A	NA	D
Safe (S)	4			
Acceptable (A)		1		
Not Acceptable (NA)			2	
Dangerous (D)				1
RADDI CHOWKI (SO_2)				

Category	S	A	NA	D
Safe (S)	7			
Acceptable (A)		0		
Not Acceptable (NA)			0	
Dangerous (D)				0
RADDICHOWKI (O_3)				
Category	S	A	NA	D
Safe (S)	1			
Acceptable (A)		4		
Not Acceptable (NA)			2	
Dangerous (D)				1







5 CONCLUSIONS

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. 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.

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