Air quality index and public health: Modelling using fuzzy inference system

Bouharati Saddek^{1, 2, *}, Benzidane Chahra², Braham-Chaouch Wafa³, Boumaïza Souad²

¹Laboratory of Intelligent Systems, Faculty of Technology, UFAS Setifl University, Algeria
²Faculty of Natural Sciences and Life, UFAS Setifl University, Algeria
³Research Unit Renewable Saharan Environments (URER. MS), Adrar, Algeria

Email address

sbouharati@yahoo.fr (Bouharati S.), veogg1@yahoo.fr (Braham-Chaouch W.), chagrouz@live.fr (Benzidane C.), souadboumaiza86@yahoo.com (Boumaiza S.)

To cite this article

Bouharati Saddek, Benzidane Chahra, Braham-Chaouch Wafa, Boumaïza Souad. Air Quality Index and Public Health: Modelling Using Fuzzy Inference System. *American Journal of Environmental Engineering and Science*. Vol. 1, No. 4, 2014, pp. 85-89.

Abstract

The Air Quality Index (AQI) is divided into some categories indicating increasing levels of health concern. An AQI value over certain threshold represents hazardous air quality whereas, if it is below a certain value, the air quality is good. Each country or continent established its standards and limits as color code corresponding to a range of index values (very low, low, medium, high and very high). Each color matches the effect of air pollution on a category of sensitive population when this pollution is likely to be affected. The problem is that the limits on these index values are sharp and characterized by their uncertainty and imprecision. For the effect on a population group is very complex to predict accurately. It depends from one person to another even it belongs to the same category of classification. It is not that from a unit value index to switch from one color to another such category of people will be affected and the other is no longer relevant. In this study, we find that the transition between ranges colors normally is fuzzy due to their incertitude effect on levels of health population concern. We found it useful to have analytical techniques based on artificial intelligence, especially the principles of fuzzy logic tool. The use of the Fuzzy inference system, demonstrate his capability for addressing the complex problems of uncertainty data. The FIS model was structured to prevent the nature of risk disease according the AQI values in inputs of system.

Keywords

Air Pollution, Air Quality, Artificial Intelligence, Fuzzy Logic

1. Introduction

Numerous countries air quality agencies developed basic forecasting approaches in an attempt to reduce exposure, thereby reducing the impact of poor air quality on human health. These forecasts, which generally focused on urban scales, were often based on statistical models that forecast pollutant concentrations based on equations that had been trained or fitted to historical air quality [most often ozone (O_3)] and meteorological data [1]; [2]; [3]; [4] [5]. The prevalence of these air quality forecasts, as well as their level of sophistication, increased considerably during the 1990s as states and municipalities began establishing Ozone Action Day (OAD) programs [6]; [7]; [8]; [9]; [10]. The purpose of

the AQI is to help you understand what local air quality means to quality health. To make it easier to understand, the AQI is divided into six categories: Each category corresponds to a different level of health concern. The six levels of health concern and what they mean are:

Open Science

"Good" The AQI value for your community is between 0 and 50. Air quality is considered satisfactory, and air pollution poses little or no risk.

"Moderate" The AQI for your community is between 51 and 100. Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a very small number of people. For example, people who are unusually sensitive to ozone may experience respiratory symptoms.

"Unhealthy for Sensitive Groups" When AQI values are

between 101 and 150, members of sensitive groups may experience health effects. This means they are likely to be affected at lower levels than the general public. For example, people with lung disease are at greater risk from exposure to ozone, while people with either lung disease or heart disease are at greater risk from exposure to particle pollution. The general public is not likely to be affected when the AQI is in this range.

"Unhealthy" Everyone may begin to experience health effects when AQI values are between 151 and 200. Members of sensitive groups may experience more serious health effects.

"Very Unhealthy" AQI values between 201 and 300 trigger a health alert, meaning everyone may experience more serious health effects.

"Hazardous" AQI values over 300 trigger health warnings of emergency conditions. The entire population is more likely to be affected.

As human physiology and immune system differs from one person to another, it is impossible they suffer the same effects of atmospheric pollution. Also, the sensitivity to contaminants varies from one person to another. While setting boundaries or boundaries between different categories is uncertain, imprecise and inaccurate. The transition from one category to another is in a fuzzy environment. The analysis of these parameters by fuzzy logic is then perfectly adequate. For this, we give an overview on the basic principles of fuzzy logic.

2. Fuzzy Approach of Air Pollution

| Air Quality Index (AQI) Values | Levels of Health Concern | Colors |
|-----------------------------------|-----------------------------------|--------|
| 0 to 50 | Good | Green |
| 51 to 100 | Moderate | Yellow |
| 101 to 150 | Unhealthy for Sensitive Groups | Orange |
| 151 to 200 | Unhealthy | Red |
| 201 to 300 | Very Unhealthy | Purple |
| 301 to 500 | Hazardous | Maroon |

| Fig I. Discrete transition represen | tation |
|-------------------------------------|--------|
|-------------------------------------|--------|

| Air Quality Index (AQI) Values | Levels of Health Concern | Colors | |
|-----------------------------------|--|--------|--|
| 0 to 50 | Good | Green | |
| 51 to 100 | Moderate | Yellow | |
| 101 to 150 | 1 to 150 Unhealthy for Sensitive Groups | | |
| 151 to 200 | Unhealthy | Red | |
| 201 to 300 | Very Unhealthy | Purple | |
| 301 to 500 | Hazardous | Maroon | |

Fig 2. Fuzzy transition representation

The approach that the typical air pollution, consists of a number of air quality index erected to provide multiple levels of pollution. Accordingly, hazardous effect occurs in a context of the transition from the color band to another which is the threshold for pollution reaches a population category. The boundary between two colors codes representing two levels of air pollution (fig.1) [11] cannot be understated,

because the sensitivity of the people is not so precise and equivalent to each other. In our study, we found it useful that the boundaries must be fuzzy. By this mode of reasoning, we come much more to the accuracy of the result (Fig.2).

3. Fuzzy Logic Inference

The fuzzy logic approach, a sub-field of intelligent systems, is being widely used to solve a wide variety of problems in medical, biological and environmental applications. Fuzzy logic deals with the analysis on a higher level, using linguistic information acquired from domain experts. The fuzzy logic concept provides a natural way of dealing with problems, and the source of imprecision is an absence of sharply defined criteria rather than the presence of random variables. The fuzzy approach considers cases where linguistic uncertainties play some role in the control mechanism of the phenomena concerned [12]. Fuzzy inference systems (FIS) are powerful tools for the simulation of nonlinear behaviors with the help of fuzzy logic and linguistic fuzzy rules [13]. Especially for medical expert systems, the theoretical framework of fuzzy logic in a rich environment is very adequate. The adequacy of each approach is borne out by the success of the model in practice [14]. In this study, we propose a fuzzy algorithm in decision-making. For all the algorithms presented below, there is a common rule form for rules that associate an observation vector.

3.1. Fuzzy Logic Modeling Assemble Input-Output Data Rules Basis

As the effect of each parameter remains in the field of imprecise and fuzzy, each variable is represented by a membership function. The degree of influence on the risk factor is reflected by a degree in the fuzzy membership function. The first step is to collect all inputs Expression of problem. The rules determined by the choice of the fuzzy membership function are defined for each input variable. In general form, If X1 is X1(1), and X2 is X2(2), and \dots Xn is Xn(n), then Y1 is Y1(1). After system is done, we can choose randomly values for inputs and read instantly the result at output [15]. In our case, each color represents a degree of occurrence of each pollution level concerned. As the degree of risk cannot be measured with precision, saw its uncertain nature, this level is represented by a fuzzy contour. Each color band is assigned a membership function. All the risk factors are the inputs of the system. "If-then" rules lie in the basis of Fuzzy Expert System. Here, linguistic values such as small, medium, or big are used and these linguistic values have appropriate membership values. Fuzzy theory is used to apply a linguistic controlling strategy dependent on human knowledge in fuzzy engine system and especially in Automatic Control System. After deciding on designing a Fuzzy system the first step to follow is to collect the rules of "if-then" determined by the human expert or the medical observations.

The output of the fuzzy reasoning system is the degree of risk of occurrence of a hazardous effect. Once the program is

established, it allows direct reading of the result to the output instantly just by randomly assigning.

4. Fuzzyfication

In order to make fuzzyfication the linguistic expressions





below are used. The proposed fuzzy logic risk factors system

consists of four inputs variables. Fuzzy variable "AQI" has the linguistic values Green; Yellow; Orange; Red; Purple; Maroon.

Fig 3. Plot of inputs-output fuzzy system

Effect

4.1. Fuzzyfication of Inputs 4.2. Fuzzyfication of Output

Figure 3 shows the fuzzyfication of input 1 representing the degree of risk in factor1. In the same way, other inputs factors are fuzzyfied (Fig. 4). Figure 5 shows the fuzzyfication of the output representing the effect risk of occurrence of an air pollution degree.

Fig 4. Plot of input fuzzy variable "Air Quality Index (AQI) Values"



Fig 5. Plot of output fuzzy variable "Levels of Health Concern"

4.3. Inference Engine

4.4. Defuzzyfier

input variable "OA!

The inference engine consists of AND operator, in fact this operator select minimum input value for the output and also this is not the logical AND. This inference engine takes four inputs from the fuzzyfier to produce the output result value according to the min-max composition. This method uses min-max operation between the inputs and output. According measured values, fuzzy rules are established. The rules must include all possible combinations. This system has one output that describes the air velocity. We can say that it shows the probability of air pollution according input variables. The crisp value output is given by the defuzzyfication process after estimating its input values. In this system we have center of average (C.O.A) method which has the mathematical expression that is: (Σ Si.Ri / Σ Ri). In the defuzzyfication the exact expression is obtained with "centroïd" method according to validity degree. The output value according to the input values obtained from the designed fuzzy engine system [16].

87

5. Results and Discussion

The air pollution effect on levels of health concern is based on fuzzy logic model. It is designed for measurement of different values of quality air index. This system consists of one input variables. The rule base of this system is used to determine the output parameter values of level health according to the inputs values. MATLAB 10 simulation is used by applying rules. Figure 5 shows the MATLAB- rule viewer and simulation result. One plot at a time shows the relation between any inputs with output wherein the numerical values to the output values are assigned to the linguistic terms of the health effect of Figure 6. The values of the indexes of the air pollution and can be instantly set to randomly read the score at the output. The designed system can be extended for any number of inputs. We can define this system for any number of inputs. The design work is being carried out to design state of the art fuzzy logic level health concern prediction system in future using hybrid neuro-fuzzy system.



Fig 6. The result of the level health

6. Conclusion

The complexity of human physiology and its response to atmospheric pollutants makes it impossible to classify the index of air pollution depends on its effect in a precise manner. One of the problems in quality air pollution effect modeling is the vagueness in the values according the natural proprieties in the real environment. In this study, for having an idea about rate of risk effect, we used different probably impact factors. The data were analyzed by the fuzzy logic modeling technique in an attempt to predict the effect of each quality air index. With the fuzzy modeling, we can represent imprecise data and produce a precise output in the form of fuzzy members. From the results obtained by this study, appear to be a useful tool for health effect identification, quantification and development of early warning systems. The result of the fuzzy algorithm so far is a numeric and symbolic terms.

References

- McCollister, G., and Wilson, K. 1975. Linear stochastic models for forecasting daily maxima and hourly concentrations of air pollutants. *Atmos. Environ.*, 9, 417–423.
- [2] Aron, R., and Aron, I. 1978. Statistical forecasting models: Carbon monoxide concentrations in the Los Angeles basin. J. Air Pollut. Control Assoc., 28, 681–684.

- [3] Wolff, G, and Lioy, P. 1978. An empirical model for forecasting maximum daily ozone levels in the northeastern U.S. J. Air Pollut. Control Assoc., 28, 1035–1038.
- [4] Lin, Y., 1982. Oxidant prediction by discriminate analysis in the South coast air basin of California. *Atmos. Environ.*, 16, 135–143.
- [5] Robeson, S., and Steyn, D. 1990. Evaluation and comparison of statistical forecast models for daily maximum ozone concentrations. *Atmos. Environ.*, 24B, 303–312.
- [6] Brian, E. and al. 2010. Using National Air Quality Forecast Guidance to Develop Local Air Quality Index Forecasts American Meteorological Society. 313-326
- [7] Hubbard, M., and Cobourn, W.1998. Development of a regression model to forecast ground-level ozone concentrations in Jefferson County, Kentucky. *Atmos. Environ.*, 32, 2637–2647.
- [8] Gaza, R. 1998. Mesoscale meteorology and high ozone in the northeast United States. J. Appl. Meteor., 37, 961–967.
- [9] Davis, J., and Speckman, P. 1999. A model for predicting maximum and 8 h average ozone in Houston. *Atmos. Environ.*, 33, 2487–2500.
- [10] Ryan, W. 1995. Forecasting severe ozone episodes in the Baltimore metropolitan area. *Atmos. Environ.*, 29, 2387–2398.
- [11] Ryan, W., Piety, R. and Luebehusen, E. 2000. Air quality forecasts in the Mid-Atlantic region: Current practice and benchmark skill. *Wea. Forecasting*, 15, 46–60.

- [12] US EPA. 9 December 2011. Retrieved 8 August 2012.
- [13] Demir, F. Korkmaz, K. 2008. Prediction of lower and upper bounds of elastic modulus of high strength concrete, *Constr. Build Mater* 22 1385-1393.
- [14] Inan, G., Göktepe, A.B., Ramyar, K., Sezer, A. 2007. Prediction of sulfate expansion of PC mortar using adaptive neurofuzzy methodology, *Build Environ*. 1264-1269. 42.
- [15] Abed-Cheniti, K., Dekhili, M., Bouharati, S. 2013. Morphological Characterization of Three Legumes (Vicia spp.) in the Semi-Arid Region of Setif-Algeria using Fuzzy Logic Inference System. *International Journal of Science and Engineering Investigations* Vol. 2, issue 12, 95-99.
- [16] Allag, F. Zegadi, R. Bouharati, S. Tedjar, L. Bouharati, I. 2013. Dynamic of air pollution and its effect on newborns: Analysis using fuzzy logic inference system. *Wulfenia Journal*, part no. 2. Pp. 18-25.