**Atmospheric
Chemistry
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Discussions**

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Interactive comment on "Ozone prediction based on meteorological variables: a fuzzy inductive reasoning approach" *by* A. Nebot et al.
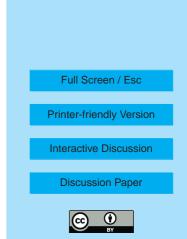
A. Nebot et al.

Received and published: 20 August 2008

Response to the comments received in August 6th by the anonymous refree #2

We are afraid that reviewer #2 does not understand the modeling approach that we propose in our work to deal with ozone predictions and, therefore, the novelty of this research. In his/her review he/she refers to 'the statistical model' that we have introduced. However, in this work we are not dealing with statistical methods but with a fuzzy logic methodology that belongs to the artificial intelligence area and that has a totally different focus.

Maybe it would help if we include in the paper some basic concepts of fuzzy logic. However, the editor asks for the minimum amount of technical 'details', therefore we have reduced the technical aspects of the methodology as much as possible.

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It is important to know, in order to understand the research done in our paper, that fuzzy logic, based on fuzzy sets, is a superset of conventional two-valued logic that has been extended to handle the concept of partial truth, i.e. truth values between completely true and completely false.

In classical set theory, when A is a set and x is an object, the proposition 'x is a member of A' is necessarily true or false, whereas, in fuzzy set theory, the same proposition is not necessarily either true or false, it may be true only to some degree. In this case, the restriction of classical set theory is relaxed allowing different degrees of membership for the above proposition, represented by real numbers in the closed interval [0,1], i.e.

For example, if we use 5 membership functions to define the variable ambient temperature, i.e. cold, fresh, normal, warm and hot, then, a temperature of $23°C$ can be a member of the class normal with a grade of 0.89 and a member of the class warm with a grade of 0.05. The definition of the membership functions may change with regard to who define them. For example, the class normal for ambient temperature variable in Mexico City can be defined as described before. However, the same class in Anchorage will be defined, more likely, in the range from $-8°C$ to $-2°C$. It is important to understand that the membership functions are not probability functions but subjective measures. The opportunity that brings fuzzy logic to represent sets as degrees of membership has a broad utility. On the one hand it provides a meaningful and powerful representation of measurement uncertainties, and, on the other hand it is able to represent efficiently the vague concepts of natural language. Going back to the example of ambient temperature, it is more common and useful for people to know that tomorrow will be very hot than to know the exact temperature grade.

At this point, the question is, once we have the variables of the system that we want to study described in terms of fuzzy sets, what can we do with them? The membership functions are the basis of the fuzzy inference concept. The compositional rule of inference is the tool used in fuzzy logic to perform approximate reasoning. Approximate reasoning is a process by which an imprecise conclusion is deduced from a collection

of imprecise premises using fuzzy sets theory as the main tool.

The Fuzzy Inductive Reasoning methodology used in the paper is based on fuzzy logic and has its own inference rule that is an hybrid between approximate reasoning and pattern recognition, but that has nothing to do with statistical approaches, i.e. we are not dealing with probability functions but with membership functions.

In the paper it is shown that the results obtained using this approach compare favourably with those reported in Lin and Cobourn, 2007 and Chaloulakou et al., 1999.

With respect the specific comments of the referee #2:

1.The 'time of day' variable is included in this study as a way to represent or capture the precursors of ozone. Clearly it helps a lot to predict diurnal/nocturnal variations whereas the other variables that FIR model finds relevant for ozone prediction (i.e. previous values of ozone, wind direction and wind speed) are the ones that help to predict the daily ozone peak.

As reviewer #2 propose in his/her comment number 1, it is possible to work only with the deviation from the average daily cycle signal. It is a valid approach as it is the one presented in our paper. We do not think that there is any gain or advantage of using the approach proposed by referee #2. In both cases the main goal (predicting maximum ozone values) is addressed, and therefore, the same practical results would be obtained.

2.As mentioned before, the FIR methodology has been reduced as much as possible in the paper trying to follow the recommendation of the Editor. However, the overall methodology can be explained in more detail if it is considered necessary in order that the readers can understand in a better way the research done in this paper.

We do not agree with the comments of the referee when he/she says that: 'the system would lose any practical skill very quickly' or 'I would be surprise if there is any skill for a forecast of one week'. First of all, the prediction performance of the model is, obviously,

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directly related to the prediction accuracy of the meteorological variables. In the paper it is shown that if accurate values of the meteorological variables are provided the FIR model is able to give good predictions of ozone several days in advance. We think that the 'practical skill' of the FIR model is clearly demonstrated in the paper. The usefulness of the model in real life depends on having available accurate forecast values of wind direction and wind speed variables. Obviously, forecasts of these variables for one day are much more reliable and precise than forecasts for an entire week or two weeks. This is clearly explained in the paper, and, ozone predictions for one or more days in advance are very useful to prevent possible contingencies. There is not much research in the literature that deal with ozone predictions some days in advance with the goal to predict possible contingencies before they occur. Therefore, we think that the approach used in this work is of interest for ACP readers.

3.We think that section 4.3 of the paper gives a good idea of the prediction skill of FIR models. As referee #2 says, 'one day forecasts are much improved over the monthly forecast'. However, this is not because the initial conditions are improved as he/she pointed out, but because, as explained in the paper, we perform long term predictions. Long term predictions means that the model forecasts a set of values (hourly in our case) in a unique run. When long term prediction is performed, previously predicted values of ozone are used to forecast the next value of this contaminant. Therefore, predictions of one day (24 values) should be necessarily more accurate than predictions of one month (700 values), due to the fact that the prediction error is propagated to the next predicted values.

Interactive comment on Atmos. Chem. Phys. Discuss., 8, 12343, 2008.

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