Global Temperature Fuzzy Model as a Function of Carbon Emissions
A Fuzzy 'Regression' from Historical Data

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Abstract: There are several models that correlate global mean temperature with Carbon emissions using statistical analysis; in this study we approach the problem using fuzzy logic analysis and inference systems, which is a pioneer method in climate modelling. The process in which anthropogenic activity affects the atmospheric Carbon and therefore the global mean temperature, has been well studied but there are still a lot of unknown factors that play an important role in the process, e.g. punctual Carbon sequestration processes, economy-led emissions' fluctuations, etcetera. That way the process take no clear path and is when fuzzy logic is ideal to approach the system understanding. In this study a Fuzzy Inference System is developed, which model the problem using historical data from 1959 to present. Our model has good results quite comparable with statistical models and it can be used to project the future global mean temperature. The model was developed using SIMULINK extension from matlab.

1 INTRODUCTION

GHG emissions had been accelerating the actual climate change reflected in the increasing global mean temperature. So far, it has been a challenge to model the temperature change as a function of GHG emissions.

It had been developed diverse statistical techniques applied to historical data, which are used to find equations that relate temperature and CO_2 emissions, the different techniques involve intermediate variables between emissions and temperature, the most direct of those intermediate variables is the atmospheric Carbon concentration (Shefter et al., 2006), likewise, there are equations that have a big number of intermediate variables like Solar radiation, oceanic oscillations, other GHG and their respective radiative forcings (Kauffman et al., 2006). Equations (1) and (2) show the classical (statistical) way to address the problem.

$$\varepsilon E_i + \gamma Q_i = \Delta Q_{i+1} \quad (1)$$

$$\kappa Q_{i+1} + \tau T_{i+1} = \Delta T_{i+2} \quad (2)$$

The first equation relates Carbon emissions at time i with the increment of atmospheric CO_2 a time i+1, using as a secondary variable the Atmospheric CO_2 at time i. The second equation relates atmospheric CO_2 at time i+1 with the increment of temperature at time i+2, having as a secondary variable the temperature at time i+1. As we can see, the discretization nature of the equations and the fact that both equations are coupled, give us a predictability of two time steps ahead.

This work addresses the same problem with a fuzzy logic perspective, which creates the link between the variables using fuzzy sets and causality rules. So we can obtain dynamic coefficients in function of how much the input variables belongs to each fuzzy set. This structure that calculates the dynamic coefficients is better known as *Fuzzy Inference System (FIS)*. Such system is created using historical data from 1959 until now (Tans, 2014; Le Quéré et al., 2013).

Since the majority of the international emissions reports are released annually, the time step is one year. Finally we obtained a fuzzy model of mean global temperature as a function of Carbon emissions, which compared with 50 years of historical data we can observe a very similar behavior.

2 METHODOLOGY

We created two fuzzy inference systems based on

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the equations (1) and (2). The environment in which was developed was matlab, using the fuzzy logic toolbox.

Based on the historical data we generated the systems, which components are: input domains divided in fuzzy sets, output domain divided in fuzzy sets and causality rules that govern the system.

Details about the systems can be found in the appendix.

3 RESULTS

Figure 1 shows CO_2 increment at time i+1 as a function of Carbon emissions and atmospheric CO_2 at time i, analogously Figure 2 shows the temperature increment at time i+2. The relation between inputs and outputs of the FIS is given by the dynamic coefficients.

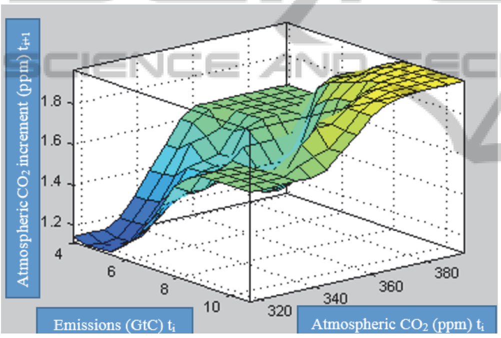

Figure 1: Increment of Atmospheric CO_2.

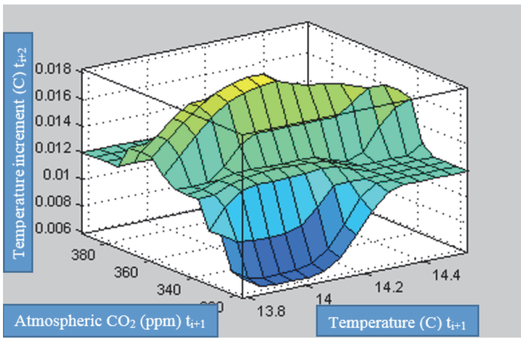

Figure 2: Temperature increment.

The fuzzy model was ran during 50 years starting in 1959 and the results were compared with the historical data. Such comparison is shown in Figure 3 and Figure 4.

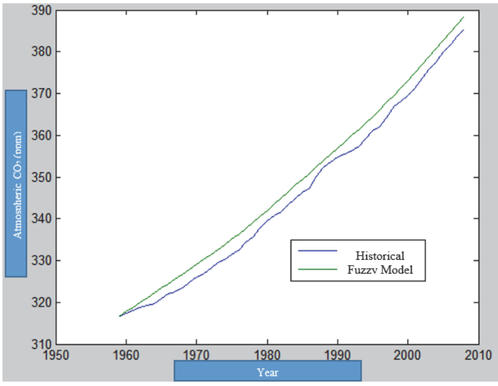

Figure 3: Comparison between historical Atmospheric CO_2 and the generated from the fuzzy inference system.

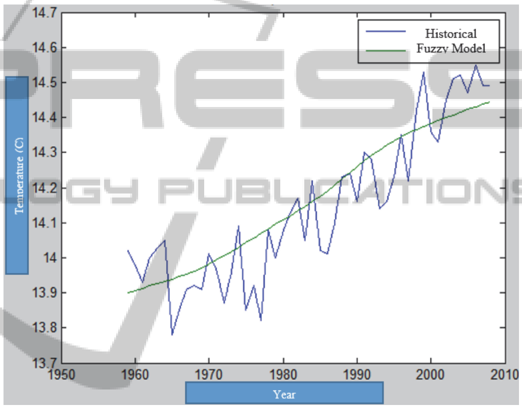

Figure 4: Comparison between historical Temperature and the generated from the fuzzy inference system.

4 DISCUSSION

As we can see in Figure 1 the model creates a positive causality between the increment of temperature and Carbon emissions, also the causality is positive between Atmospheric CO_2 and Atmospheric CO_2 increment. Broadly it can be said that most of statistical methods give the same results, but if we go further, it can be seen that the fuzzy model has non-linear behavior and its dynamic over time, i.e. the slope may vary depending of the combinations of Atmospheric CO_2 and Carbon emissions, this is an attribute that a fuzzy inference system has over a classic statistical method. These small slope changes represent unknown or not very well studied Carbon sinks or sources. Finally, is important to remark that the final desired result, shown in Figure 4, is the temperature which follows a path very proximate to the mean historical temperature.

5 CONCLUSSIONS

The fuzzy model crated can relate the change in mean global temperature with the carbon emissions. Thanks to it fuzziness allow us to involve variables with high uncertainty, such as measurements of annually emitted Carbon or Atmospheric CO_2 concentration.

This fuzzy model will be very useful to project future temperatures based on possible values of emissions, due to the uncertainty nature of the problem.

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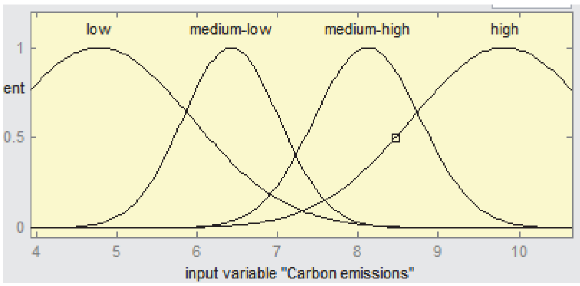
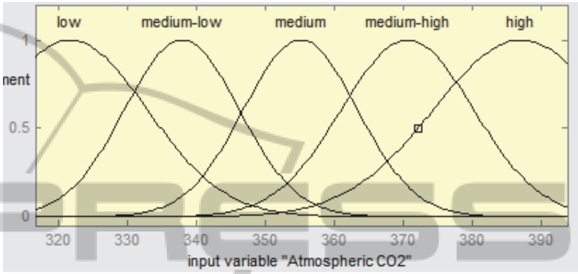
APPENDIX

It is shown here the fuzzy inference systems developed with matlab fuzzy logic toolbox.

The components of the first fuzzy inference system are:

INPUTS

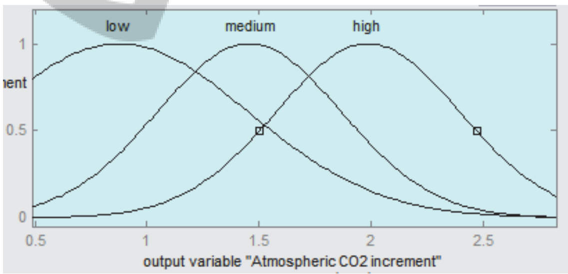




RULES

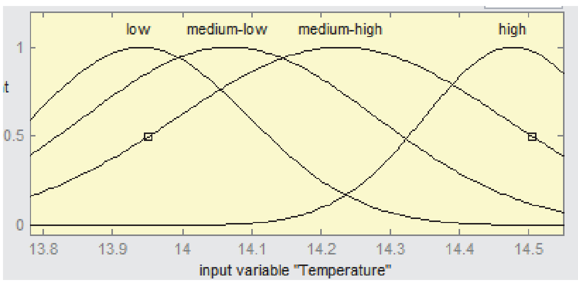
1. If (Carbon_.emissions is high) and (Atmospheric_.CO2 is high) then (Atmospheric_.CO2_.increment is high) (1)
2. If (Carbon_.emissions is medium-low) and (Atmospheric_.CO2 is medium-low) then (Atmospheric_.CO2_.increment is medium) (1)
3. If (Carbon_.emissions is low) and (Atmospheric_.CO2 is low) then (Atmospheric_.CO2_.increment is low) (1)

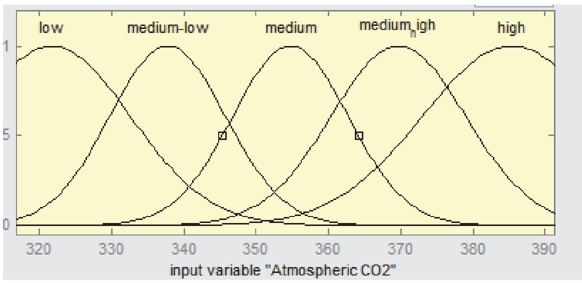
OUTPUT



The components of the second fuzzy inference system are:

INPUTS





RULES

1. If (Temperature is medium-high) and (Atmospheric_CO2 is medium) then (Temperature_increment is high) (1)
2. If (Atmospheric_CO2 is medium_high) then (Temperature_increment is medium) (1)
3. If (Temperature is high) and (Atmospheric_CO2 is high) then (Temperature_increment is low) (1)

OUTPUT