Global Surface Temperature Model using Coupled Sugeno Type Fuzzy Inference Systems and Neural Network Optimization

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Abstract: In this research, a model that projects the mean global temperature as a function of anthropogenic carbon emissions was generated with two fuzzy inference systems, sugeno type. We propose that the climatic system is energetically balanced, and the albedo, solar constant and atmospheric transparency are all constants. Nevertheless, we assume that the surface temperature varies when the CO_2 concentration changes and depends on the system temperature itself. The second assertion states that any change in atmospheric CO_2 concentration depends on anthropogenic carbon emissions and the system actual concentration. The fuzzy inference systems were optimized using artificial neural networks that adjust the parameters according to a different data base that the one that was used to create the initial system. So that, we assure to find the hidden patterns and avoid overfitting. The principal results of this work are the temperature projections under IPCC scenarios and the discovering of the historical data hidden patterns.

1 INTRODUCTION

Climatic system is primarily driven by solar radiation and its interaction with the atmospheric greenhouse gases. In the most recent IPCC assessment report is stated that is very likely that anthropogenic activity increases global warming, so that, it is important to generate efficient models that project future climate, based in possible emissions scenarios that will allow the experts to plan mitigation and adaptation strategies. A better description of a single component of the system is given by simple models like an energy balance model (Budyko, 1969), in that sense we propose in this work a model that projects the mean surface global temperature, that assume that climatic system is in a balance that would possibly be altered just by the change in atmospheric CO_2 concentration. This model had been constructed using fuzzy logic (Zadeh, 1965), which mathematical structure allows to represent in a very accurate way the fuzzy nature of the problem in terms of the uncertainty of the involved processes. We have created two coupled fuzzy inference systems (Zadeh, 1975), sugeno type (Takagi and Sugeno, 1985), which causally relate input fuzzy sets to linear regression equations in certain degree that depends on the membership degree of the input variable to the different fuzzy sets of the input universe.

The fuzzy inference systems of the model were automatically constructed by MATLAB's fuzzy logic toolbox using a certain set of historical data, and then we optimized the parameters using neural networks (Jang et al., 1997) that worked with other data sets. Finally, we obtained a model that fits very well the historical data and the temperature behaviour from the past 50 years using historical emissions with a generated noise. The model is also used to project future temperature based on the IPCC emissions scenarios.

This kind of models had been recently explored in order to deal better with the complex interaction between physics of climate change and policy-makers (Gay-Garcia and Sanchez-Meneses, 2015). While models can be improved by the better understanding of the climatic system, the emissions scenarios will be always uncertain because they depend of the society's development and political decisions, that is the reason why experts promote the implementation of models that are more tolerant to uncertainty (Gay-Garcia et al., 2014).

2 MODEL PROPOSED

We have two basic statements in which this model relies on. First, the planet is in energetic equilib-

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rium, where the effective temperature, solar constant, albedo and atmospheric transparency are all constants, and, surface temperature (T) only varies with the change of atmospheric CO_2 concentration (Q) and temperature rate of change is function of the temperature itself (equation (2)). Secondly, we state that any change in atmospheric CO_2 concentration is function of CO_2 emissions (E) and the concentration itself (equation (1)).

$$\frac{dQ}{dt} = f(Q,E) \tag{1}$$

$$\frac{dT}{dt} = g\left(T, \frac{dQ}{dT}\right) \tag{2}$$

As we can see, equation (2) depends on the result of equation (1). Since we will work with historical data to obtain the behaviour of these equations, they will transform into discrete equations:

$$\Delta Q_{i+1} = g\left(Q_i, E_i\right) \tag{3}$$

$$\Delta T_{i+2} = f\left(\Delta Q_{i+1}, T_{i+1}\right) \tag{4}$$

2.1 Fuzzification

We can fuzzify the equations (3) and (4) by giving them a structure as follows:

$$\Delta Q_{i+1} = p_n Q_i + q_n E_i \quad Q_i, E_i \in A_n \tag{5}$$

$$\Delta T_{i+2} = r_n \Delta Q_{i+1} + s_n T_{i+1} \quad \Delta Q_{i+n}, T_{i+1} \in A_n \tag{6}$$

Where A_n is the $n-th$ fuzzy set of each universe of variables (Temperature, Concentration and Emissions). We defined linguistically A_1 as the set of low Temperature/Concentration/Emissions, A_2: medium and A_3: high. When we give a pair of input variables into equation (5), the system evaluates the membership degree of the elements to the fuzzy set A_1 and evaluates the equation using the parameters p_1, q_1, then it does the same for the fuzzy sets A_2 and A_3, and the final result will be the weighted sum of the three last results. Then, the output of equation (5) will be the input for equation (6) and the process described above will be repeated in order to obtain the final output, the temperature.

3 METHODOLOGY

The membership functions of the fuzzy sets and the parameters p, q, r, s were obtained analysing time-series of historical data (described in the Appendix) with MATLAB's fuzzy logic tool 'genfis3'. Then we optimized them using 'anfis' the adaptive neuro-fuzzy inference system tool that uses neural network theory and works with the same data from which the model was constructed, finally, we used a different data set that control the optimization and prevents over-fitting. Guided by the training error we decided to stop the optimization process whenever the error stops decreasing (either the training error or the control error), we reach that point after 10 epochs for the first Fuzzy Inference System (FIS-1), while the second Fuzzy Inference System (FIS-2) was trained 50 epochs. The results of the optimization can be seen in the Figure 1 and 2, as it can be observed, the optimized FIS describe better the path from the original data.

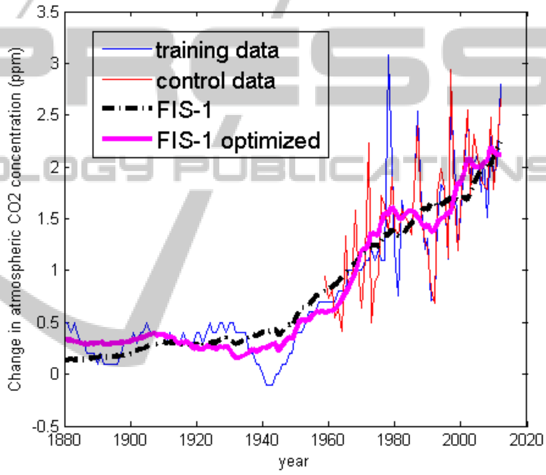

Figure 1: FIS-1 performance.

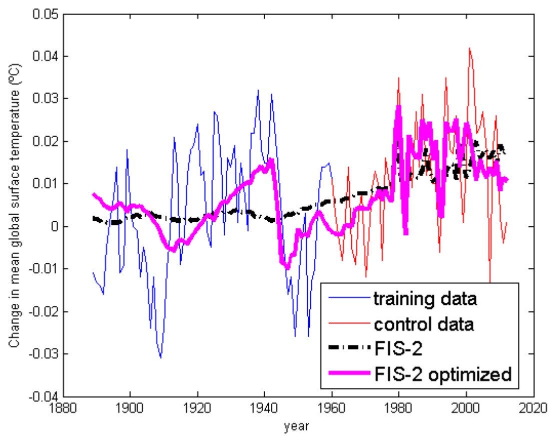

Figure 2: FIS-2 performance.

The final part of the process was to generate a simple script that unifies both FIS as we can see in the diagram of Figure 3. The first two inputs are the CO_2 emissions and atmospheric concentration at year

i which through the FIS-1, project the change in atmospheric CO_2 concentration at year $i+1$. This last variable works as input with the temperature at year $i+1$ in the FIS-2 that give us the change in temperature at year $i+2$. The next step is to add the change in concentration of year $i+1$ to the concentration at year i, and the temperature at year $i+2$ is obtained adding the change in temperature at year $i+2$ to the temperature at year $i+1$; these steps are shown in red lines. Finally, it only remains to give a value of the emissions at year $i+2$ so the second step of the model can be complete and we can obtain the change in temperature at year $i+3$ and so on. This means that when the model completes one cycle, the only necessary input is the emissions.

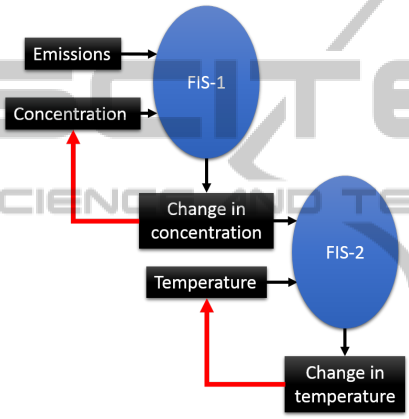

Figure 3: Model diagram.

3.1 Validation

We set the initial temperature and concentration values from 1959 and 1960 and we ran the model 50 times using the emissions from 1959 to 2010 adding a noise which amplitude was equal to the uncertainty of the data, every projection was different since the added noise was randomly obtained every time. In Figure 4 we note that 15 years after the first step, some projections start to be outside the error boundaries, so we chose other 15 years to project the temperature, and as we can see in Figure 5 those 15 years of projected temperature are inside of the error boundaries. So we validated our model for the first 15 years of projection.

Furthermore, we created another model using only historical data obtained before the year 2000. With that second model we projected the temperature from 2000 to 2015 and compare it to the actual historical data, that comparison serve as another method of validation for our main model, it means that the method actually works, since, as we can observe in Figure 6 almost every projected temperature is inside the uncertainty band of the historical data.

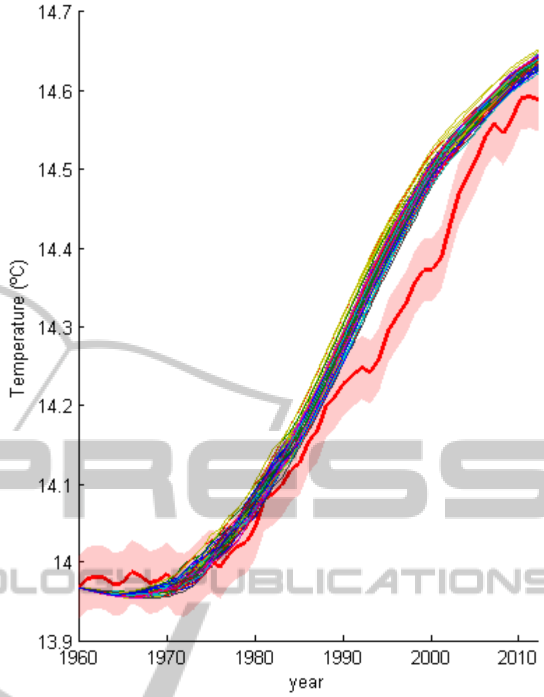

Figure 4: 50 Projections of generated emissions with noise. The red line is the historical data with its correspondient uncertainty band (also in red), the other colored and thinner lines are 50 projections made with historical emissions adding random noise each time a projection is made.

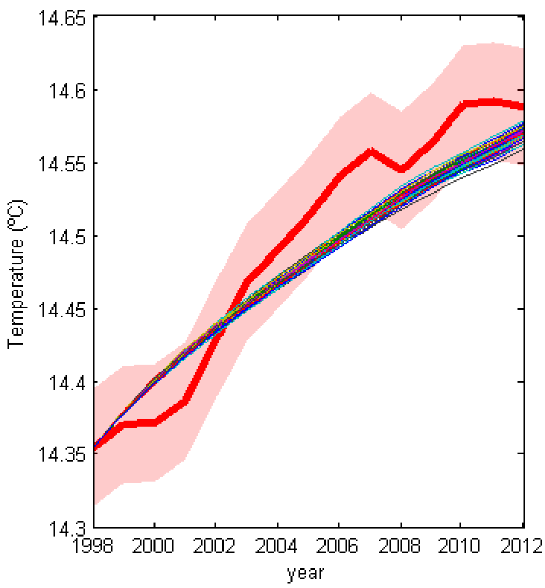

Figure 5: 15 years of projections from 1998 to 2012. The red line is the historical data with its correspondient uncertainty band (also in red), the other colored and thinner lines are 50 projections made with historical emissions adding random noise each time a projection is made.

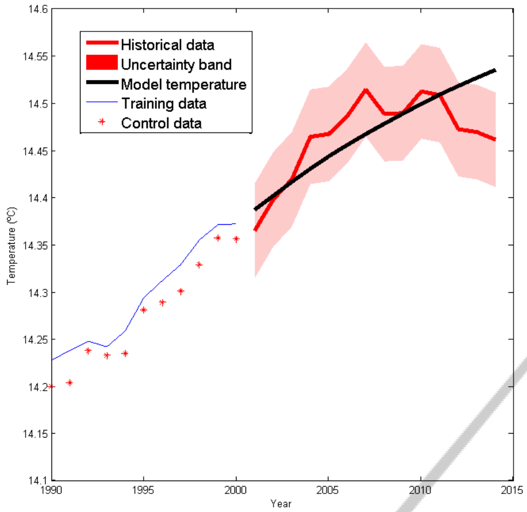

Figure 6: 15 years of projections from 2000 to 2015, using a model created only with data collected befor the year 2000. The red line is the historical data with its correspondient uncertainty band (also in red), the black line is a projection from 2000 to 2015 using the actual emissions. We also show the training and control temperature data, the training data goes back to 1880, the control data goes back to 1959.

4 PROJECTIONS

The principal and most controversial variable to project in climate change is the greenhouse gases emissions, so that it had been created some different scenarios based on socio-economic assumptions (Moss et al., 2007), these scenarios are standardized so climate models can be compared between them. IPCC's AR5 proposed the representative concentration pathways (Figure 7) which we will use to project future temperature with our model.

It is important to note the boundaries of the model. The first limitation is the 15 years that we defined as validated projections. Secondly, since the model was made with historical data, the membership functions of the fuzzy sets are just defined for certain elements of the variables universe. For the FIS-1, the upper limit of the atmospheric CO_2 concentration in which it works properly is around 440ppm and the upper limit of the emissions is 15GtC. The FIS-2 upper limit for temperature is around 15 C. We made a projection setting up the values at year 2010, according to the validation, this projection will make sense until 2025 (15 years of projection), which is the same year when the RCP 8.5 reaches the upper limit of the emissions in FIS-2. Figure 8 shows the 4 projections, RCP8.5 is the only scenario where the temperature is constantly increasing. We can note that, nevertheless the RCP2.6 temperature line is always above the

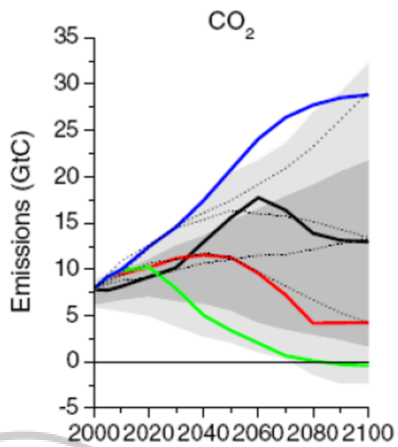

Figure 7: Emissions from the Representative Concentration Pathways. (Van Vuuren et al., 2011).

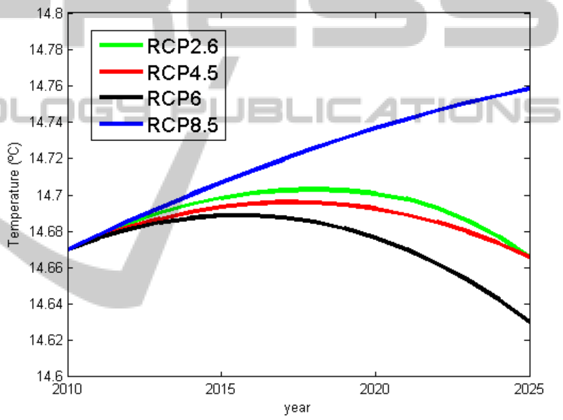

Figure 8: Fuzzy model projections based on RCPs scenarios.

temperature projected under RCP4.5, at the end of the projections the rate of decrease is greater in the more optimistic scenario, RCP2.6. It is also remarkable that the lowest temperature projection is the one made under the RCP6 scenario, which is not very straightforward to think intuitively, the hidden patterns, in the next section, could help to discover why this happens.

5 DISCUSSION

The parameters of the model were obtained analysing historical data and optimizing them using neural network theory, which allow us to find the hidden patterns that relied on the data. The membership functions were adjusted as well as the linear equation that implies every fuzzy set.

The final optimized parameters for the FIS-1 inference rules are:

- If Emissions and Concentration are *low*:
  $\Delta C = 0.333 Emissions - 0.025 Concentration + 7.225$
- If Emissions and Concentration are *medium*:
  $\Delta C = 0.563 Emissions - 0.004 Concentration - 0.513$
- If Emissions and Concentration are *high*:
  $\Delta C = -0.417 Emissions + 0.055 Concentration - 14.972$

As we can see in the equations above, when the emissions and concentration parameters go from low to high, the concentration becomes a factor of increment of itself, this talks about a positive feedback, and it could be related to some biotic cycles such as ocean acidification and its interaction with corals. Another way to view the rules and parameters is with the rules surface, as shown in Figure 9 where we can observe that the change in atmospheric CO_2 increases with the increment of emissions as long as atmospheric CO_2 concentration is low. The increment decays with the emissions when the atmospheric concentration is high.

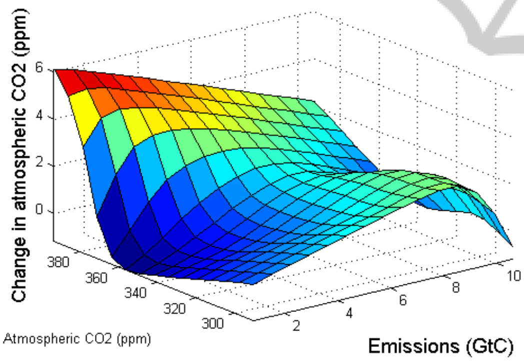

Figure 9: Rules surface of FIS-1.

The inference rules of the FIS-2 are:

- If Temperature and ΔC are *low*:
  $\Delta T = 0.066T - 0.005\Delta C - 0.9$
- If Temperature and ΔC are *medium*:
  $\Delta T = -0.006T + 0.022\Delta C + 0.072$
- If Temperature and ΔC are *high*:
  $\Delta T = -0.035T - 0.008\Delta C + 0.542$

By studying the rules, we can say that the temperature have a negative feedback, which can represent that some processes, that are cooling down the system, are triggered by high temperatures. The third rule by itself is counter-intuitive, so we should see the big picture: graphically displayed in Figure 10, it is shown that the surface describing the change in temperature is complex. If we do a transect with constant change in atmospheric CO_2 concentration it can

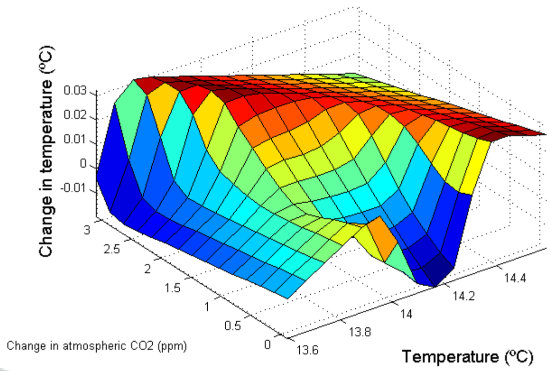

Figure 10: Rules surface of FIS-2.

easily be observed that the change in temperature describes a cyclic variation, which amplitude increase with greater temperatures and greater changes in atmospheric CO_2. This pattern could describe that the resilience of the system decays when the forcing increases.

6 CONCLUSIONS

In order to face climate change, we should have in mind the complexity of the system and have a clear idea of the factors that play a role in this unprecedented challenge. There had been developed a great variety of climatic models and from them socio-economic scenarios are generated and global political decisions are taken. The greatest contribution of this work, relies on the methodology of a fuzzy climate modelling that will allow to unify the different faces of climate change, in which questions as: 'How does *medium* changes in temperature would affect economic development in certain region?' or 'What actions need to be taken in order to reduce emissions into a *low* level?', will be answered in single-simulation processes;that way, policy-makers will have a real efficient tool to make the best possible decision. The presented model is the initial phase of a ground-breaking climate change modelling.

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APPENDIX

Here we present the data used in the construction and optimization of the model, also it is shown the data that served as control. See Table 1

Table 1: Historical Data.

	Variable	**Description**	**Source**
Data for model construction and optimization	Carbon emissions	Carbon emissions *estimation* by fossil fuels (1880 - 2012).	(Boden et al., 2013)
		Carbon emissions *estimation* by land-use change (1880 - 2012).	(Houghton et al., 2012)
	Atmospheric CO_2	Atmospheric carbon *estimation* through ice nuclei (1880 - 1978).	(Etheridge et al., 1998)
		Atmospheric carbon grow *estimation* (1980 - 2013).	(Dlugokencky and Tans, 2014)
	Global temperature	Mean global surface temperature *estimation* (1980 - 2013).	(NASA, 2014)
Data for controlling the optimization	Carbon emissions	Carbon emissions*observations* by fossil fuels (1959 - 2013).	(Boden et al., 2013)
		Carbon emissions *observations* by land-use change (1959 - 2012).	(Houghton et al., 2012)
	Atmospheric CO_2	CO_2 atmospheric concentration *observations* (1959 - 2013)	(Tans and Keeling, 2014)
	Global temperature	Mean global surface temperature *estimation* (1959 - 2013)	(NASA, 2014)