FACTS: Fuzzy Assessment and Control for Temperature Stabilization
Regulating Global Carbon Emissions with a Fuzzy Approach to Climate Projections

Bernardo A. Bastien Olvera[1] and Carlos Gay y Garcia[1,2]

[1] *Programa de Investigación en Cambio Climático, Universidad Nacional Autónoma de México, Ciudad de México, Mexico*

[2] *Centro de Ciencias de la Atmósfera, Universidad Nacional Autónoma de México, Ciudad de México, Mexico*

Keywords: Climate Change, Temperature Stabilization, Carbon Emissions, Fuzzy Logic, Fuzzy Inference System, Neural Network.

Abstract: This work presents a new approach for assessing the climate system and for stabilizing the temperature and other climate parameters. FACTS, as we call it, is a fuzzy inference system that overview certain climate state, and is able to generate the CO2 emissions reduction needed to implement in order to stabilize the temperature. FACTS was constructed using a neural network optimization process along with data generated by a classical emissions pathfinder. Then, it was embedded in MAGICC6, a simple climate model that was forced by the four Representative Concentration Pathways until and ultimately stabilized by the proposed methodology.

1 INTRODUCTION

In the process of understanding and modelling the climate system is involved a trade-off between resolution, computational efficiency and focus on individual parameters. Every level of complexity for climate models has its own benefits and the choice of using one or another depends on the purpose of the study.

Simple climate models such as MAGICC (Meinshausen et al., 2011) could emulate complex three-dimensional coupled atmosphere-ocean general circulation models (AOGCMs), and focus on just some specific parameters and on their effects on climate. This simple models alongside with clear climate goals, are very useful for policy-makers to easily asses the impacts of possible green-house gases emissions. The current climate target is to stabilize the surface temperature well bellow 2°C above preindustrial levels (UNFCC, 2015).

A methodology to reach a long-term temperature target is to discover, build up, or imagine the pathways that could lead to the stabilization (Garg et al., 2014; Belenky, 2015; Rogelj et al., 2013) and try to adjust the real emissions rate to one of the possible stabilization routes (UNEP, 2015) . Meinshausen et al. (2005) created SiMCaP, an algorithm that is able to find multi-gas emissions pathways that stabilize the temperature (using the MAGICC 4.1 model) through a trial and error selection process of existing economically-feasible scenarios in the literature and an extrapolation to other gases using an equal quantile way.

We used the ANFIS structure (Shing and Jang, 1993) to create and optimize our model. Particularly in this study, we used the CO_2 stabilization routes given by SiMCaP to relate each year emissions growth or decrease, to the climate variables of the previous year through a sugeno-type fuzzy inference system. The fuzzy inference system learnt rules based in a neural network optimization process, in order to create a mean global temperature control that is function of just climate variables.

The 'Fuzzy Assessment and Control for Temperature Stabilization' (FACTS) that we propose has great advantages in terms of its capability for creating pathways independently of preconceived scenarios in literature. Its fuzzy nature is able to absorb the uncertainty associated to the input climate variables, and the simplicity of its mathematical structure allows to insert FACTS into different simple climate models in order to reach the temperature stabilization in real-time mode while running the model.

Moreover, FACTS perform a fuzzy assessment of the climate state at every time-step, through the evaluation of the membership degree of certain climate parameters to fuzzy sets defined linguistically. This is

Olvera, B. and García, C.
FACTS: Fuzzy Assessment and Control for Temperature Stabilization - Regulating Global Carbon Emissions with a Fuzzy Approach to Climate Projections.
DOI: 10.5220/0006011603570362
In *Proceedings of the 6th International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH 2016)*, pages 357-362
ISBN: 978-989-758-199-1

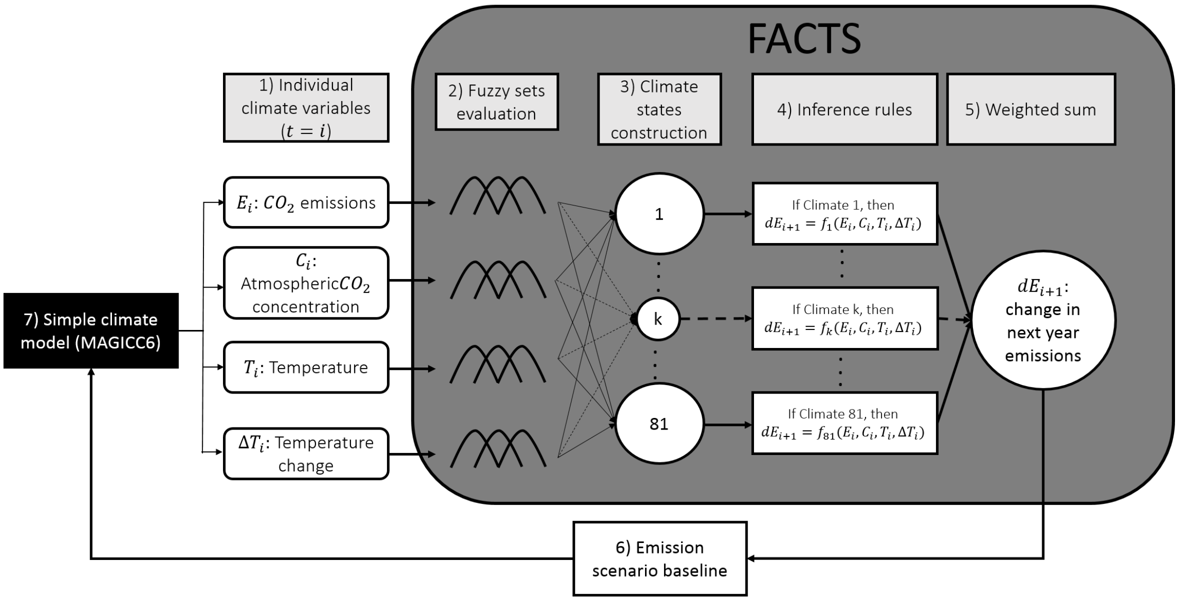

Figure 1: Structure of FACTS incrusted on a simple climate model.

presented as a new methodology for describing more realistically the climate system in simple and clear words in order to create a common language between decision-makers and the modelling community.

2 FACTS STRUCTURE

A concise overview of the 'Fuzzy Assessment and Control for Temperature Stabilization' is presented in Figure 1.

(1) First, FACTS receive climate parameters of year i: the CO_2 emissions; the atmospheric CO_2 concentration; the average global temperature; and the temperature change ($T_i - T_{i-1}$).

(2) Each variable's domain is divided in three fuzzy sets that represent the linguistic categories *low*, *medium* and *high*, or *null*, *low* and *medium*, depending on the variable, so that every value in the domain has its membership degree to the fuzzy sets, ranging from zero (no membership) to one (full membership) (Zadeh, 1965). In this stage the climate assessment takes place in order to provide a fuzzy description of the climate state.

In step (3) takes place a combination of fuzzy sets from the different climate variables, which creates all possible -81- climate states, such as: 1. *low emissions/concentration/temperature & null temperature increment*, 2. *medium emissions/concentration/temperature & low temperature increment*, 3. *high emissions/concentration/temperature & medium temperature increment*, 4. *high emissions/concentration, medium temperature & null temperature increment*, and so on. The eighty one climate states are represented by a combination of four climate fuzzy sets linked by an '&' operator, which assigns a weight to the combination: the minimum membership degree of the four climate parameters (given in step (1)) evaluated in the four fuzzy sets that build up the climate state.

(4) Each climate state lead to an IF-THEN rule (Zadeh, 1975; Takagi and Sugeno, 1985), which relates the membership degree of the parameters to the climate state k, to the function f_k that describes, for that particular climate state, the change in emissions that would need to be made in the year $i+1$ in order to stabilize the mean temperature.

Finally, a weighted sum of the eighty one inference rules is made in step (5) using the weight as described in step (3), so we obtain the ultimate value of the change in future CO_2 emissions and add it to the emission scenario baseline (6), which serves as an input for the climate model (7).

3 OPTIMIZATION PROCESS

A neural network was formed by operational nodes and links that receive an input matrix and create multiple signal flows through the system which ultimately give as a result a single output that is compared with an output target, then, its made a parameter adjustment in the operational nodes using an error-

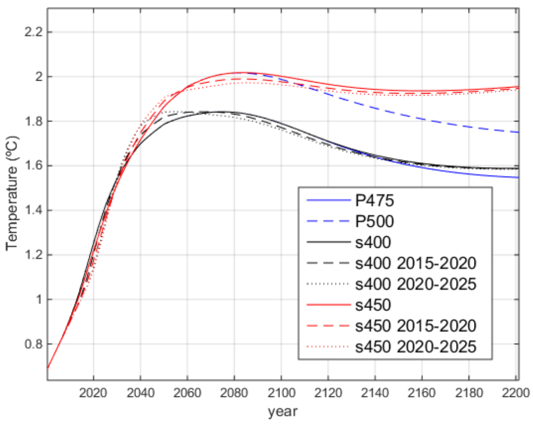

Figure 2: Temperature stabilization from SiMCaP data (Meinshausen et al., 2005).

decreasing function (Jang et al., 1997). In the optimization process of FACTS, a fuzzy inference system is encrusted in a neural network, and the parameter tuning is made in the eighty one functions of the step (4) in Figure 1, that way we created a neuro-adaptive fuzzy inference system (Shing and Jang, 1993).

The input matrices used for optimizing FACTS were 5 time-series (P475, S400 2015-2020, S400 2020-2025, S450 2015-2020, S450 2020-2025) of climate parameters (CO_2 emissions, atmospheric CO_2 concentration, average global temperature and temperature change) from 2005 to 2200, that reach temperature stabilization between 1.5°C and 2°C, within years 2100 and 2200, as shown in Figure 2. The climate parameters are the result of running MAGICC4 (Wigley, 2003) with 5 multi-gas pathways found by SiMCaP (Meinshausen et al., 2005), the CO_2 components of this pathways were the output target of FACTS, since the objective is to find fuzzy inference rules that stabilize temperature through CO_2 emissions control.

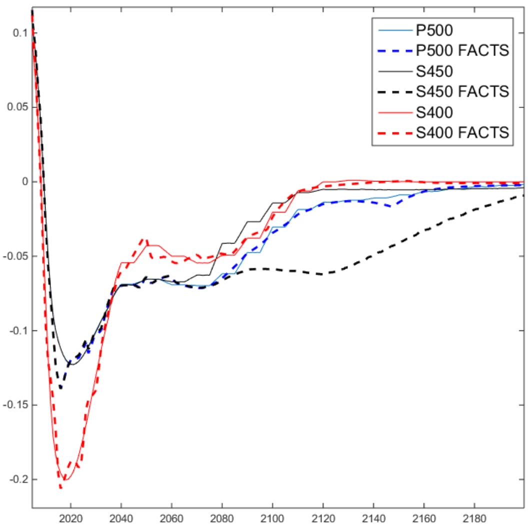

Figure 3: Original SiMCaP reduction pathways (Meinshausen et al., 2005) and FACTS generated pathways.

Each year i in the time-series contains the four input climate parameters and the output target, which is sufficient to evaluate the error-decreasing function and make a small adjustment to the FACTS parameters. Since the time-series have 195 years, there were made 975 parameters' adjustments each epoch, and we ran the optimization process from 1 to 30 epochs in order to find the point where the least error between the FACTS output and the output target was reached, which was localized in the epoch number 3. So we used the FACTS that was optimized 3 epochs, i.e. almost 3 000 small parameters' adjustments.

4 VALIDATION

The remaining time-series of Figure 2 that were not used in the optimization process: P500, S450 and S500 served for validating FACTS efficiency. As we can see in Figure 3, the result of using FACTS to calculate what should be the future emissions to fit the temperature stabilization pathways is very close to the real calculation by SiMCaP.

We can observe (Figure 3) that the FACTS generated emissions are closer to the SiMCaP original pathways in the case of P500 and S400, nevertheless, in the case of S450, FACTS created a more intense reduction pathway than the original. This is by virtue of the fuzzy nature of the system, which absorbed in the optimization process a greater amount of output targets that tend to 1.5°.

Fuzzy logic is not a precise method for measure variables or relating values, but is powerful by means of absorbing uncertainty and solving problems efficiently. In that context, it is recognizable the fuzzy behaviour in S450 FACTS pathway.

5 RESULTS

We implement FACTS control on emissions in different climate scenarios in order to stabilize the global average temperature. We used the four Representative Concentration Pathways (RCPs) (Moss et al., 2007) to run MAGICC6 and create different climate scenarios until 2025, when FACTS control begins and propose a 5-year-constant change in CO_2 emissions until 2100.

Despite FACTS was tuned with climate parameters coming from MAGICC4.1 (Wigley, 2003), in this experiment we used MAGICC6 (Meinshausen et al.,

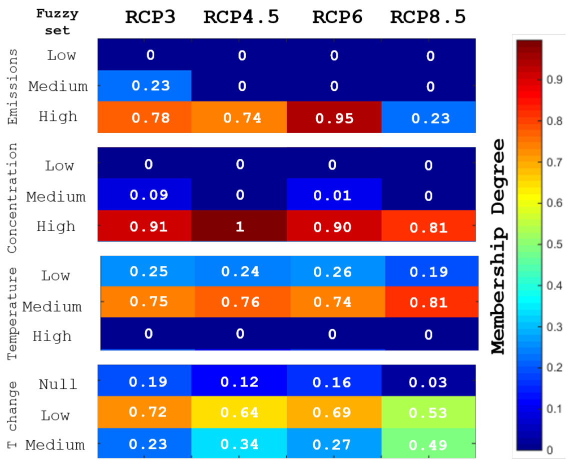

Figure 4: Fuzzy climate states at year 2025. This diagram represents four climate scenarios obtained by MAGICC6 and evaluated by FACTS fuzzy sets, each column represent an RCP scenario that contains the membership degree of the climate parameter (CO_2 emissions, CO_2 atmospheric concentration, Temperature and Temperature change) to climate fuzzy descriptors such as *low*, *medium* or *high*.

2011) in order to have better climate projections according to the adjustments in the carbon cycle and other important improvements in the new release.

FACTS was activated at year 2025 in order to simulate a real-life situation with 2 important characteristics. First, according to the Paris Agreement (UNFCC, 2015), the countries will release new CO_2 emission goals every five years starting in 2025. Second, the years gap that exist from now to 2025, is crucial in the formation of the climate states that will serve as the first input for FACTS in 2025, that is the reason why we let the climate states to build up before 2025 under the 4 RCPs, as we can see in Figure 4.

The FACTS output is the next-year change in emissions, but in this experiment we configured FACTS in order to give the average change in the next 5 years. This was made assuming that national governments are able to pursue more easily a constant emissions' reduction rather than a 5-year not-constant emissions pathway.

The Figure 5 shows the temperature projections under the four RCPs, with (solid lines) and without (dashed lines) control in emissions. As we can see, FACTS controls the temperature under 2°C when the climate state in 2025 was driven by RCP3 and RCP4.5; when the climate state was driven by RCP6, FACTS control the temperature around 2.1°C; finally, if we follow the business as usual pathway until 2025 (RCP 8.5), FACTS is not capable to stabilize the temperature at the levels agreed by the international community.

Figure 6 shows the emissions pathways that lead

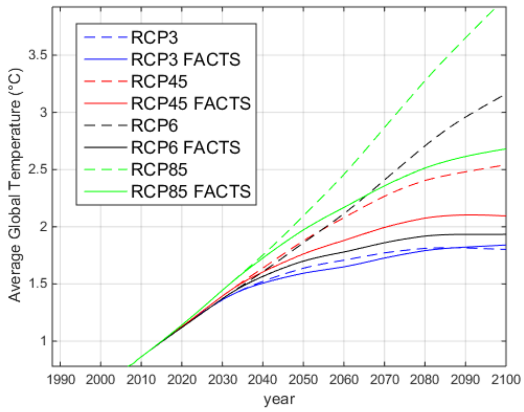

Figure 5: Temperature stabilization using FACTS.

to the temperatures observed in Figure 5. RCP3 and RCP6 are scenarios that start with not very high emissions, so the post-2025 stabilization route is somewhat smooth. On the other hand, RCP4.5 starts with higher emissions, which eventually lead the stabilization route to reach the maximum decreasing capacity, in 2050. Finally, RCP8.5 states a climate state in 2025 that immediately pushes FACTS to decrease the maximum possible emissions.

The final state of the climate is evaluated finally by FACTS at year 2100, as shown in Figure 7. It is clear the change in specific parameters that match with an stabilized climate, such as the low emissions, high concentration, high temperature and null or low temperature change.

6 DISCUSSION

FACTS is not just a simple control on emissions, Figure 4 shows that every time FACTS is used, there is an evaluation of the climate state that could be described in a linguistic way, for example, we can say that RCP3 generates an scenario in 2025 where CO_2 emissions are *fairly* high ("fairly" is a fuzzy concept that could be result of the combination of the membership degree 0.23 to medium and 0.78 to high), the atmospheric CO_2 concentration is *significantly* high, the temperature is *moderately* medium and the temperature change is *kind of* low.

The climate states trigger different amounts of reduction in order to reach an stable climate state as shown in Figure 7. Nevertheless, much more work need to be done, almost counter-intuitive, we can observe that the projected temperature under RCP 8.5 in 2100 does not belong to any fuzzy set, while it should completely belong to the *high* temperature fuzzy set. This is because fuzzy sets were made to fit the data used as training in the optimization process. So fuzzy

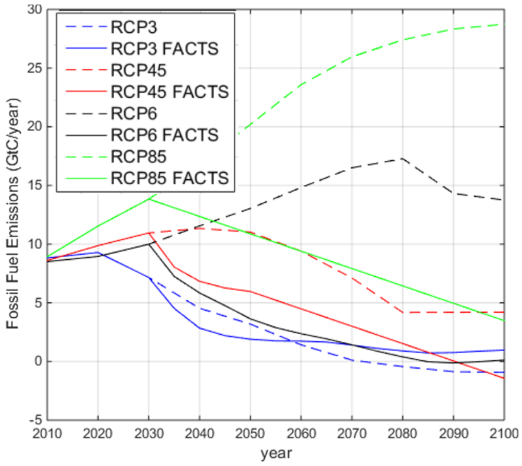

Figure 6: FACTS control in Emissions.

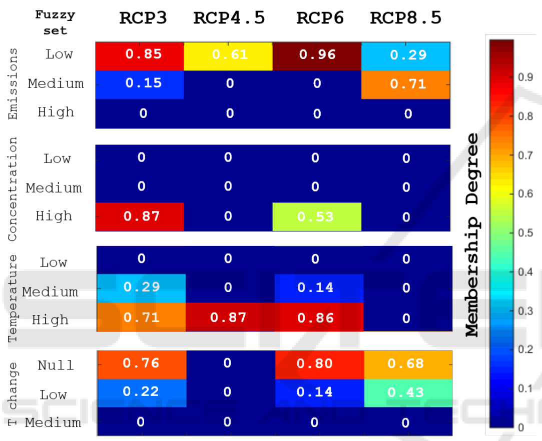

Figure 7: Fuzzy climate states after the control was implemented. Year 2100. This diagram represents four climate scenarios obtained by MAGICC6 and evaluated by FACTS fuzzy sets, each column represent an RCP scenario that contains the membership degree of the climate parameter (CO_2 emissions, CO_2 atmospheric concentration, Temperature and Temperature change) to climate fuzzy descriptors such as *low*, *medium* or *high*.

sets must be tuned manually in order to broaden their domain, for example, any temperature from 2.5C to infinity should belong to the *high* temperatures' fuzzy set.

The optimization data was taken from SiMCaP simulations, that were created based on literature scenarios, nevertheless, FACTS structure allows to merge the strategies used these different world-wide proposed scenarios. That is the reason why FACTS is able to create stabilization pathways that match with feasible reduction rates, and not always will be possible to stabilize temperature as observed in RCP85 FACTS (Figure 5).

Finally it is important to specify that FACTS never really uses the great number of inference rules (81) at the same time. Whenever it is used with certain climate parameters, there is an automatic elimination of inference rules, that provide a lot simpler fuzzy control. In Figure 4 if we eliminate the rules that are linked to the fuzzy sets which membership degree is zero (or very close to zero) for the climate parameters of RCP3 at year 2025, the number of inference rules reduces to 12. Since fuzzy inference systems are evaluated parallel and the functions of each rule are linear equations, is very efficient to embed FACTS in a climate model such as MAGGIC and run the stabilization process and the model projections within a few seconds ($\sim 5s$) in an ordinary personal computer.

7 CONCLUSIONS

Even for scientists is hard to understand the consequences of increasing the temperature certain degrees in certain period of time. In negotiations, there is a continuous translation between climate numerical parameters and human communication structure. FACTS presents an straightforward bridge between both languages, that allows stake-holders to negotiate in the same language that is used in a climate stabilizer and descriptor. In the context of the actual climate change challenge that is facing humanity, this singular type of climate approaches are very important.

REFERENCES

Belenky, M. (2015). Achieving the u.s. 2025 emissions mitigation target. *Available at: http://www.climateadvisers.com/wpcontent/uploads/ 2013/12/US-Achieving-2025-Target_May-20151.pdf* .

Garg, A., Shukla, P., and K., B. (2014). India report - alternate development pathways for india: Aligning copenhagen climate change commitments with national energy security and economic development. low climate impact scenarios and the implications of required tight emission control strategies [limits]. *Ahmedabad, India: Indian Institute of Management, Ahmedabad*.

Jang, J.-S. R., Sun, C.-T., and Mizutani, E. (1997). *Neuro-fuzzy and soft computing*. Prentice Hall, Englewood Cliffs, N.J.

Meinshausen, M., Bill, H., Wigley, T., Vuuren, D. V., Elzen, M. D., and Swart, R. (2005). Multi-gas emissions pathways to meet climate targets. *Climatic Change*, 17(27).

Meinshausen, M., Raper, S., and Wigley, T. (2011). Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, magicc6 - part 1: Model description and calibration. *Atmos. Chem. Phys.*, 11:1417–1456.

Moss, R., Babiker, M., Brinkman, S., Calvo, E., Carter, T., Edmonds, J., Elgizouli, I., Emori, S., Erda, L., Hibbard, K., Roger, J., Kainuma, M., Kelleher, J., Lamarque, J. F., Manning, M., Matthews, B., Meehl, J., Meyer, L., Mitchell, J., Nakicenovik, N., O'Neill, B., Pichs, R., Riahi, K., Rose, S., Runc, P., Stouffer, R., van Vuuren, D., Weyant, J., Wilbanks, T., van Ypersele, J. P., and Zurek, M. (2007). Towards new scenarios for analysis of emissions, climate change, impacts, and response strategies. *IPCC Expert meeting report*.

Rogelj, J., McCollum, D. L., ONeill, B. C., and Riahi, K. (2013). 2020 emissions levels required to limit warming to below 2c. *Nature Climate Change*, 3.

Shing, J. and Jang, R. (1993). Anfis: Adaptive network-based fuzzy inference system. *IEEE, Transactions on systems, man, and cybernetics*, 23.

Takagi, T. and Sugeno, M. (1985). Fuzzy identification of system and its application to modeling and control. *IEEE, SMC*, 15:199–249.

UNEP (2015). The emissions gap report. *United Nations*.

UNFCC (2015). Paris agreement. *Conference of the Parts*.

Wigley, T. (2003). *MAGICC/SCENGEN 4.1: Technical Manual*. UCAR-Climate and Global Dynamics Division, Boulder, Colorado.

Zadeh, L. A. (1965). Fuzzy sets. *Information and control*, 8:338–353.

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning. *Inf. Sci*, 8:199–249.