FUZZY APPROACHES FOR MODELING DYNAMICAL ECOLOGICAL SYSTEMS

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Abstract: This research shows the usefulness of fuzzy logic approaches for modelling and simulation of complex dynamical systems. Several hybrid soft computing methodologies based on fuzzy logic, such are neuro-fuzzy systems, genetic-fuzzy systems and the Fuzzy Inductive Reasoning are applied to a real dynamical system in the ecological domain, i.e. the global temperature change. The ocean-atmosphere system is represented in this work by using an energy balance model that reproduces a range of temperatures increase that agrees with that reported by the IPCC. The results obtained by all the fuzzy approaches studied are good, although the Fuzzy Inductive Reasoning methodology performs clearly much better that the other approaches for the application studied from the prediction accuracy point of view.

1 INTRODUCTION

The global climate is a highly complex system in which take place many physical, chemical, and biological processes, in a wide range of space and time scales. These processes are simulated by global circulation models, which are computer models based on the fundamental laws of physics and they are the principal tool for predicting the response of the climate to increases in greenhouse gases. With the increase of computational resources, complex global models are frequently being used to assess the response of the climate system to the projected increase in the amount of greenhouse gases. All model experiments point to global warming through the coming centuries. These models, however, are not perfect representations of reality because, among other reasons, they do not include important physical processes (e.g. ocean eddies, gravity waves, atmospheric convection, clouds and small-scale turbulence) that are known to be key aspects of the climate system but that are too small or fast to be explicitly modelled (Williams, 2005). In addition, the high complexity of the climate system represents, by itself, a crucial constraint in the prediction of future climate change. Therefore, even the most complex climate models are unable to project how climate will change with certainty, as it is reflected in the wide range of temperature increase reported by the IPCC 4AR (IPCC, 2007).

Simple models of the climate system have been developed and used to gain physical insight into major features of the behaviour of the climate system. These simple models have also been frequently used to conduct sensitivity studies and to produce climate projections for a range of assumptions about emissions of carbon dioxide and other greenhouse gases.

Fuzzy logic is a very powerful approach for managing uncertainties inherent to complex systems. Fuzzy systems have demonstrated their ability to solve different kind of problems like control (e.g. Watanabe et al., 2005) and have been successfully applied to a wide range of applications, i.e. signal and image processing (Bloch, 2005) and medical applications (Nebot et al., 2003), etc. To the authors' knowledge, there are very few studies that apply fuzzy logic approaches to study the global temperature change problem.

In the next section, we use a simple box model of the ocean-atmosphere to assess the response of the global mean temperature to changes in the thermal forcing and to model parameters. This model depends on a small number of parameters which are

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treated directly as fuzzy logic sets. Section 3 describes shortly the hybrid fuzzy methods studied and presents the results. Section 4 presents a comparison table of the different methodologies performances and discusses the results. Finally the conclusions of this work are given.

2 GLOBAL TEMPERATURE CHANGE EXPERIMENT

In this section, we use a box model of the ocean-atmosphere to determine whether this simple model is able to reproduce the wide range of temperature increase reported by the IPCC, when plausible model parameters and surface forcing are used.

The ocean-atmosphere system is represented by using a simple energy balance model consisting of two boxes that represent the atmosphere (one over the land and the other over the ocean) and two boxes that represent the oceanic mixed layer coupled to a diffusive ocean (Fig. 1).

The analytical solution of this kind of model can be found in Wigley and Schlesinger (1985). The brief description given here follows closely that of McGuffie and Henderson-Sellers (2005). The heating rate of the mixed layer is calculated by assuming a constant depth in which the temperature difference (ΔT), associated with some perturbation, changes in response to: changes in the surface thermal forcing (ΔQ); the atmospheric feedback, which is expressed in terms of a climate feedback parameter (λ); leakage of energy from the mixed layer to the deeper ocean (ΔM). This energy flux is used as an upper boundary condition for the diffusive deep ocean in which the thermal diffusion coefficient (K) is assumed to be a constant.

The equations describing the rates of heating in the two layers are: for the mixed layer, with total heat capacity Cm,

$$C_m \frac{d\Delta T}{dt} = \Delta Q - \lambda \Delta T - \Delta M \quad (1)$$

for the deeper ocean layer,

$$\frac{\partial \Delta T_0}{\partial t} = K \frac{\partial^2 \Delta T_0}{\partial^2 z} \quad (2)$$

At the interface between the surface and the deeper layers, there is an energy source which acts as a surface boundary condition (2). A simple parameterization is used by imposing continuity between the mixed-layer temperature change (ΔT) and the deeper-layer temperature change evaluated at the interface, $\Delta T_0(z=0,t)$, i.e. $\Delta T_0(0,t) = \Delta T(t)$.

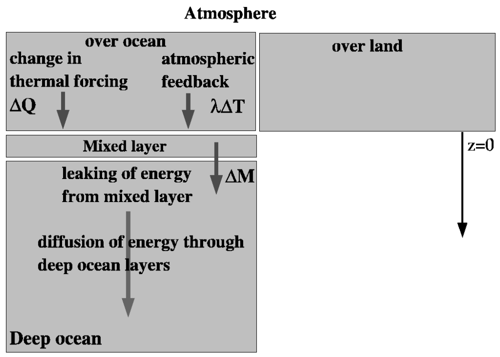

Figure 1: Ocean-atmosphere system using a simple energy balance model.

With this formulation, ΔM can be calculated from

$$\Delta M = -\gamma \rho_w c_w K \left\{ \frac{\partial \Delta T_0}{\partial z} \right\} \Bigg|_{z=0} \quad (3)$$

and used in (1). In the last equation, γ is the parameter utilized to average over land and ocean (values between 0.72 and 0.75), ρ_w is the water density and c_w is its specific heat capacity.

Equations (1) and (2) are integrated numerically for a period of 100 years using a forward Euler scheme and a vertical grid for the deep ocean. All model experiments are performed using a time step of one day and a vertical grid with 100 points and a spacing of 5 m, which represents a deep ocean layer of 500 m. The internal model parameters and the change in thermal forcing vary as follows: λ varies from 0 to 4 $Wm^{-2}K^{-1}$, with increments of 0.25; K varies from 10^{-4} to $10^{-5} m^2 s^{-1}$, with increments of 0.5×10^{-5}; ΔQ varies from 0 to 8 Wm^{-2}, with increments of 0.5. A total of 6069 integrations (each one corresponding to a combination of the varying internal model parameters and the thermal forcing) are carried out over the 100-year period. This range of temperatures increase agrees with that reported by the IPCC (IPCC, 2007).

3 FUZZY MODELING APPROACHES

As Klir stated in his book (Klir and Elias, 2002), the view of the concept of *uncertainty* has been changed in science over the years. The traditional view looks to uncertainty as undesirable in science and should be avoided by all possible means. The modern view is tolerant of uncertainty and considers that science should deal with it because it is part of the real world. This is especially relevant when the goal is to construct models. The fuzzy set theory, introduced in (Zadeh, 1965), allow dealing with uncertainty in a natural way, by means of the concept of objects that have not precise boundaries (fuzzy sets). In this paper three hybrid approaches of fuzzy systems are used to model the global temperature change in the earth, i.e. neuro-fuzzy systems, genetic-fuzzy systems and the Fuzzy Inductive Reasoning methodology.

3.1 Neuro-fuzzy Systems

A neuro-fuzzy system is a fuzzy system that uses learning methods derived from neural networks to find its own parameters, as the membership functions of the input variables. In this work the Adaptive Network based Fuzzy Inference System (ANFIS) is used since is one of the more popular neuro-fuzzy system reported in the literature (Jang, 1993). ANFIS is a function of the Fuzzy toolbox of Matlab

ANFIS represents a Sugeno-type neuro-fuzzy system in a five-layer feedforward network architecture (see Fig. 2). The rule base must be known in advance and ANFIS adjusts the membership functions of the antecedents and the consequence parameters applying a mixture of backpropagation and least mean squares procedure. The main characteristic of the Sugeno inference system is that the consequent or output of the fuzzy rules is not a fuzzy variable but a function, as shown in equation (4).

$$\begin{aligned} &\text{Rule}_1\text{:}\quad \text{If X is } A_1 \text{ and Y is } B_1 \text{ then } f_1 = p_1{*}x + q_1{*}y + r_1 \\ &\text{Rule}_2\text{:}\quad \text{If X is } A_2 \text{ and Y is } B_2 \text{ then } f_2 = p_2{*}x + q_2{*}y + r_2 \end{aligned} \qquad (4)$$

This has the advantage that the fuzzy system functions are differentiable and learning algorithms based on gradient descendent methods are applicable. Fig. 2 shows the Sugeno type fuzzy reasoning model (plot (a)) and its equivalent ANFIS network structure (plot (b)).

In the application at hand the ANFIS model is composed of 27 Sugeno rules, as the ones described in equation (4), due to the fact that 3 membership functions were used to represent the three input variables. The ANFIS parameters are optimized by using a set of 5395 data points obtained from the experiment explained in section 2.

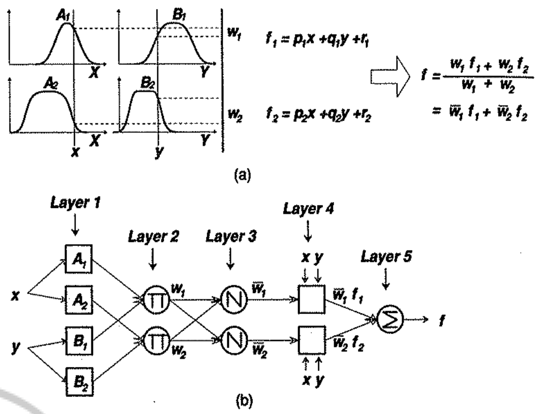

Figure 2: (a) Sugeno type fuzzy reasoning model. (b) Equivalent ANFIS model. Figure extracted from (Jang, 1993).

The ANFIS model is validated by predicting the temperature change of 674 data points not used for training the model (also obtained from section 2.2). ANFIS is able to predict very accurately the temperature change test values, with a very low normalized mean square error in percentage (MSE) of 2.38%. The MSE is computed by means of equation (5).

$$MSE = \frac{E\left[\left(y(t) - \hat{y}(t)\right)^2\right]}{VAR\left[y(t)\right]} .100\% \qquad (5)$$

where $\hat{y}$ *(t)* is the predicted output, *y(t)* the system output and VAR denotes variance. The real vs. the predicted test data is shown in Fig. 3.

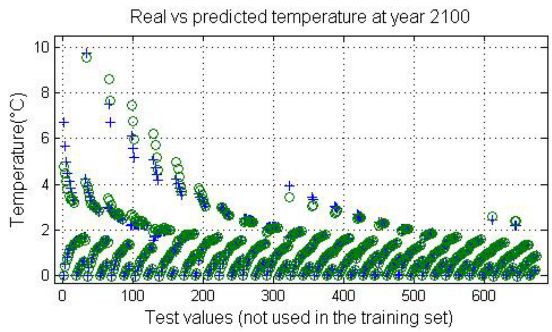

Figure 3: Real ('+') vs. Predicted ('o') test values when using the ANFIS model to predict the temperature increase at year 2100.

3.2 Genetic-fuzzy Systems

A Genetic Fuzzy System (GFS) is basically a fuzzy system augmented by a learning process based on evolutionary computation, which includes genetic algorithms, genetic programming, and evolutionary strategies, among other evolutionary algorithms (Cordon et al., 2001). In this study three different GFS based on iterative rule learning are analyzed, i.e. TSK-IRL-R, MOGUL-TSK-R and MOGUL-IRLHC-R. All of them are functions of the Keel software (Keel, 2004).

In the iterative rule learning approach each chromosome in the population represents a single fuzzy rule, but only the best individual is considered to form part of the final rule base. Therefore, it is runed several times to obtain the complete knowledge base. The advantage is that it reduces substantially the search space, because in each iteration only a fuzzy rule is searched. A postprocessing stage is needed to force the cooperation among the fuzzy rules generated in the first stage.

3.2.1 TSK-IRL-R

The Iterative Rule Learning of Takagi–Sugeno-Kang Rules (TSK-IRL-R) approach is a two-stage evolutionary process to automatically learn knowledge bases from examples (Cordon and Herrera, 1999). The learning process is divided into the generation and the refinement stages. The generation stage allows to automatically deriving a preliminary Sugeno knowledge base from the training data set. It decides the number of rules and determines their consequent parameters, generating a locally optimal knowledge base. The refinement stage takes the preliminary knowledge base obtained in the previous stage and globally refines it by tuning the antecedent membership function and consequent parameter definition.

The generation process is based on a (μ, λ)-evolution strategy, in which the fuzzy rules with different consequents compete among themselves to form part of the preliminary knowledge base. The refinement process adapts the antecedents and consequents of the fuzzy rules by means of a hybrid evolutionary approach composed of a genetic algorithm and an evolution strategy to obtain a set of rules that cooperate in the best possible way.

The same training and data sets described before are used for the TSK-IRL-R algorithm to obtain a fuzzy model of the system under study. The mean square error in percentage (MSE, described in equation (5)), obtained when this model is used to predict the test data set is 3.03%. This error, although is slightly higher than the one obtained by ANFIS, is quite low and the plot of the real vs. the predicted test data looks really similar to the one of ANFIS, presented in Fig. 3.

3.2.2 MOGUL-TSK-R

MOGUL is a Methodology to Obtain Genetic fuzzy rule-based systems Under the iterative rule Learning approach. This methodology is composed of some design guidelines that will allow us to obtain genetic fuzzy rule base systems (GFRBS) to design different types of fuzzy rule bases, i.e. descriptive and approximate Mamdani-type and Sugeno-type.

The MOGUL-IRLHC-R is a MOGUL approach base in the Sugeno type of rules (Alcalá et al., 2007). The main differences respect the TSK-IRL-R is that in the first stage it performs a local identification of prototypes to obtain a set of initial local semantics-based Sugeno rules. On the other hand the cooperation between rules is accomplished in the second stage by means of a genetic niching-based selection process to remove redundant rules and a genetic tuning process to refine the fuzzy parameters. The MOGUL-TSK-R approach proposes to use Mamdani fuzzy rules as fuzzy prototypes to identify a set of fuzzy subspaces grouping data with similar behaviour. The prototypes are then use to identify Sugeno fuzzy consequences.

The same data sets used before are used to obtain a MOGUL-TSK-R model of the global warming problem. In this case the MSE (see equation (5)) obtained is 3.09%, equivalent that the one reached with the TSK-IRL-R model.

3.2.3 MOGUL- IRLHC-R

The MOGUL-IRLHC-R algorithm is also an iterative rule learning approach that uses the MOGUL paradigm, but in this case the goal is to learn constrained approximate Mamdani-type knowledge bases from examples (Cordón and Herrera, 2001). It consists of three stages: an evolutionary generation process, a genetic multisimplification process and a genetic tuning process. The first stage generates a set of fuzzy rules with constrained free semantics covering the training set in an adequate form. The second stage performs a selection of rules using a binary coded genetic algorithm with a genotypic sharing function and a measure of the fuzzy rule base system performance. The idea is to remove redundant rules while maximizing the cooperation among the staying rules. The third stage performs a tuning based on a real coded genetic algorithm and the previous performance measure. It adjusts the membership functions of each rule in each possible fuzzy rule base derived from the multisimplification process.

Then, the more accurate fuzzy rule based obtained is the final output of the MOGUL-IRLHC-R algorithm.

When applied to the problem at hand we obtain a MSE of 10.08%. It is clear that the performance decreases with respect the results obtained by the approaches presented so far, i.e the genetic-fuzzy systems and ANFIS.

3.3 Fuzzy Inductive Reasoning (FIR)

FIR methodology emerged from the general systems problem solving (GSPS) architecture developed by Klir (Klir and Elias, 2002). It is able to perform a selection of the system relevant variables and to obtain the causal and temporal relations between them in order to infer the future behavior of that system. It offers a model-based approach to predicting either univariate or multi-variate time series. A FIR model is a qualitative, non-parametric, shallow model based on fuzzy logic. FIR is executed under the Visual-FIR platform that runs under the Matlab environment (Escobet et al., 2007).

The model identification function is responsible for finding causal spatial and temporal relations between variables that offer the best likelihood for being able to predict the future system behavior from its own past, thereby obtaining the best model. The FIR model is composed by its structure or set of relevant variables (called mask) and a set of input/output rules that represent the systems' history behavior (called pattern rule base). A mask denotes a dynamic relationship among qualitative variables. The optimality of the mask is evaluated with respect to the maximization of its forecasting power that is quantified by means of a quality measure, based mainly on the Shannon entropy. Once the best mask has been identified, it can be applied to the qualitative data matrices that were previously obtained in the discretization process, resulting in a pattern rule base.

Once the FIR model is available, a prediction of future output states of the system can take place using the FIR inference engine that is based on a variant of the k-nearest neighbor rule, i.e., the 5-NN pattern matching algorithm. The forecast of the output variable is obtained by means of the composition of the potential conclusion that results from firing the five rules, whose antecedents best match the actual state. The contribution of each neighbor to the estimation of the prediction of the new output state is a function of its proximity. A detailed description of FIR methodology and Visual-FIR platform can be found in (Nebot et al., 2003; Escobet et al., 2007).

The same training and test data sets described in the ANFIS section have been used for training and test the FIR model. As explained before, in order to obtain a FIR model it is first necessary to convert the quantitative data into qualitative data by means of the discretization function. In this case, all the 3 input variables are discretized into 3 classes, i.e. low, medium and high, whereas the output variable, is discretized into 5 classes, i.e. very low, low, medium, high and very high, following the experts knowledge. The optimal mask obtained is composed of all the system input variables. Therefore, FIR finds that all three input variables are important and that there is not redundancy in them.

The FIR model obtained is very precise when it is used to predict a test data set of 674 values, not used in the training set. As can be seen in Fig. 4, the real and the predicted values are almost undistinguishable one from each other, being the MSE extremely low, i.e. of 0.25%.

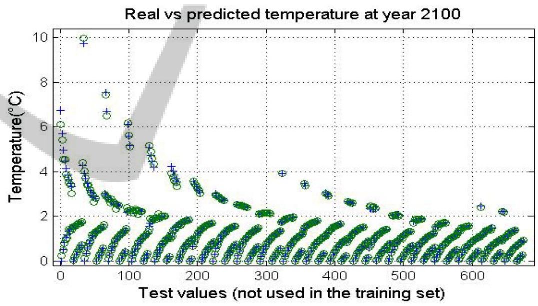

Figure 4: Real ('+') vs. Predicted ('o') test values when using the FIR model to predict the temperature increase at year 2100.

4 RESULTS AND DISCUSION

Table 1 summarizes the results obtained for each of the fuzzy approaches presented in this paper when applied to the global temperature change problem.

If we focus in the prediction performance it is clear that the FIR methodology is the best one, much better than the neuro-fuzzy and genetic-fuzzy systems approaches. However, if we center in the number of rules, ANFIS is the best choice because is the one that captures the behavior of the system with the lower number of rules.

It is also interesting to confirm that genetic approaches need considerably much time than ANFIS and FIR to learn de fuzzy rule bases.

Table 1: Results of all fuzzy approaches to the global temperature change problem.

Method	MSE	#Rules	Time
ANFIS	2.38%	27	15sec.
TSK-IRL-R	3.03%	50	50min.
MOGUL-TSK-R	3.09%	121	>60min.
MOGUL-IRLHC-R	10.08%	34	28min.
FIR	0.25%	56	5sec.

Therefore, it can be concluded that the different fuzzy approaches used to model the global temperature change problem are useful for the task at hand, because all of them have a high level of prediction accuracy. Depending on the users interests it can be more desirable to choose a methodology with high precision in the prediction, like FIR, or a less precise model but with a small number of rules in it, like ANFIS, MOGUL-IRLHC-R or TSK-IRL-R.

This work is an initial attempt to compare different types of fuzzy modeling approaches when dealing with ecological systems. It does not pretend, at this point, to be an exhaustive and rigorous comparison, but to give a first inside into hybrid fuzzy modeling of ecological problems. The next step is to incorporate other fuzzy-based methodologies, such is the LR-FIR, which is an attempt to reduce the number of FIR rules obtained while minimizing the loss of precision in the prediction. Finally, we plan to study other ecological problems mainly focused in climate systems.

5 CONCLUSIONS

This paper studies the usefulness of hybrid fuzzy modelling approaches when dealing with a real ecological system, i.e. the global temperature change. A box model of the ocean-atmosphere, that reproduces satisfactorily the wide range of temperature increase reported by the IPCC, is used.

From the temperature increase calculated with the box model, different hybrid fuzzy models are built. Concretely, the ANFIS that is a neuro-fuzzy system, the TSK-IRL-R, MOGUL-TSK-R and MOGUL-IRLHC-R that are genetic-fuzzy systems based on the iterative rule learning approach, and the FIR methodology. All the models are able to predict accurately the global temperature increase in the year 2100. The fuzzy models presented in this paper are simpler than the box model and are much more understandable from a policy maker point of view.

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