

# Rule Based Fuzzy Cognitive Maps in Socio-Economic Systems

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**Abstract** — *This paper shows how Rule Based Fuzzy Cognitive Maps can be useful to model qualitative socio-economic systems, by discussing and presenting a macroeconomic model that, although developed eight years ago and based on simple qualitative rules, described and predicted the current economic crisis when the policy behavior of the banking system regarding tax-rates was assumed similar to the one that ended up occurring.*

**Keywords** — Qualitative Modelling of Dynamic Systems, Rule Based Fuzzy Cognitive Maps, Socio-Economic Systems.

## 1 Introduction<sup>♦</sup>

Economic models have traditionally been based on mathematics. Econometry, the quantitative science of modelling the economy, focus on creating models to help explain and predict variables of interest in economics. However the most common econometric models are usually very imprecise and are not usually valid but on a very short term. This can easily be seen on the regular predictions made to most macroeconomic indicators: most yearly predictions made by governments, economic entities or independent experts, must usually get corrected every trimester due to inaccuracies in the models used to predict their values. This is essentially due to the fact that most econometric models tend to ignore the existence of the feedback loops that make any alteration in any component of the model to potentially be propagated until that component is affected by its own previous change on a relatively short term.

The more precise models that try to address this issue are usually based on differential equations [13, 20]. However, due to the dimension of these systems (very high number of variables involved), these models demand a strong knowledge in mathematics, and a huge amount of time to be developed. However, even when these kinds of models are possible, they usually tend to ignore that economy is a social science, and therefore is subject to qualitative uncertainties due to human and social factors that are not easily captured using strict quantitative mathematic models.

<sup>♦</sup> This work was supported in part by the FCT - Portuguese Foundation for Science and Technology under project PTDC/MAR/66231/2006

The use of approaches that include both the existence of feedback cycles and the intrinsic qualitative social nature associated with economy, should lead to the implementation of more accurate models.

Dynamic Cognitive Maps (DCM), where Rule Based Fuzzy Cognitive Maps (RB-FCM) are included, are a qualitative approach to modeling and simulating the Dynamics of Qualitative Systems (like, for instance, Social, Economical or Political Systems) [2,3,4,5,6,7,8,9,10,11]. RB-FCM were developed as a tool that can be used by non-engineers and/or non-mathematicians and eliminates the need for complex mathematical knowledge when modeling qualitative dynamic systems. In this paper one shows that RB-FCM can be used to model socio-economical systems using as an example a model that was originally designed eight years ago, but that can explain and simulate the current world economic situation.

## 2 Dynamic Cognitive Maps

The term Dynamic Cognitive Maps has been recently used to describe techniques that allow simulating the evolution of cognitive maps through time. Axelrod [1] work on cognitive maps (CM) introduced a way to represent real-world qualitative systems that could be analyzed using several methods and tools. However, those tools only provided a way to identify the most important structural elements of the CM. Complete, efficient and practical mechanisms to analyze and predict the evolution of data in CM were not available for years due to several reasons. System Dynamics tools like those developed by J.W.Forrester [12] could have provided the solution, but since in CM numerical data may be uncertain or hard to come by, and the formulation of a mathematical model may be difficult, costly or even impossible, then efforts to introduce knowledge on these systems should rely on natural language arguments in the absence of formal models. Fuzzy Cognitive Maps (FCM), as introduced by Kosko [15, 16, 17], were developed as a qualitative alternative approach to system dynamics. However, although very efficient and simple to use, FCM are causal maps (a subset of cognitive maps that only allow basic symmetric and monotonic causal relations between concepts)[9], and, in most applications, a

FCM is indeed a man-trained Neural Network that is not fuzzy in a traditional sense and does not exploit usual fuzzy capabilities. They do not share the properties of other fuzzy systems and the causal maps end up being quantitative matrixes without any qualitative knowledge.

Several evolutions and extensions have been added to the original FCM model, but none addresses so many FCM issues as RB-FCM. RB-FCM were developed as a tool that models and simulates real world qualitative system dynamics while trying to avoid the limitations of those approaches. The following sub sections resume some features of RB-FCM that are useful to the comprehension of this paper.

### 2.1 Rule Based Fuzzy Cognitive Maps

RB-FCM allow a representation of the dynamics of complex real-world qualitative systems with feedback, and the simulation of events and their influence in the system. They can be represented as fuzzy directed graphs with feedback, and are composed of fuzzy nodes (Concepts), and fuzzy links (Relations). RB-FCM are true cognitive maps since are not limited to the representation of causal relations. Concepts are fuzzy variables described by linguistic terms, and Relations are defined with fuzzy rule bases.

RB-FCM are essentially iterative fuzzy rule based systems where we added fuzzy mechanisms to deal with feedback, introduced timing mechanisms [8] and new ways to deal with uncertainty propagation, and were we defined several kinds of Concept relations (Causal, Inference, Alternatives, Probabilistic, Opposition, Conjunction, etc. [2,5]) to cope with the complexity and diversity of the dynamic qualitative systems we are trying to model. Among new contributions brought by RB-FCM, there is a new fuzzy operation – the Fuzzy Carry Accumulation - [4,7], which is essential to model the mechanisms of qualitative causal relations (FCR – Fuzzy Causal Relations) while maintaining the simplicity and versatility of FCM.

There are 2 main classes of Concepts: **Levels**, that represent the absolute values of system entities (e.g., LInflation is Good); and **Variations**, that represent the change in value of a system entity in a given amount of time (e.g., VInflation increased very much). By allowing the definition of both the absolute value of a concept and its change through time, RB-FCM have the means to properly model the dynamics of a system.

#### 2.1.1 Expressing Time in Dynamic Cognitive Maps

Time is probably the most essential factor when modeling a dynamic system. However, most DCM approaches seem to ignore this fact. In order to maintain consistency in the process of modeling the dynamics of a qualitative system, it is necessary to develop and introduce timing control mechanisms. To allow the representation of time flow, delays, and the inhibition of certain relations when they have no influence on a given instant, changes were made to the engine of RB-FCM. More details regarding RB-FCM time

mechanisms can be found in [8,11]

## 3 A Qualitative Macro Economic Model as an Example of DCM Modeling in Socio-Economic Systems

In this section one presents a model that was developed eight years ago. The primary goal when this problem was approached was to show the capabilities and ease of use of RB-FCM to model the dynamics of qualitative real world systems. Even if the final model is rather complex and does not contain apparent flaws, it is not, and was never intended to be, a complete model, since it wasn't developed by economic experts (even though some were consulted). However, as it can be seen in the obtained results, the model exhibits a behaviour that is able to describe the current economic crisis and the reasons that lead to it.

Classic cognitive mapping techniques [1] were used as the first step to obtain the model: the concepts and relations were extracted from a short column published in Portuguese newspaper Público in the year 2001 consisting on an economic expert analysis regarding “Short-term Tax Rate evolution in Europe” [18]. Throughout the text, the author introduced several concepts, supporting its theories while explaining the relations between concepts using qualitative knowledge. The “classic” CM obtained was much simpler than the one presented here, which was expected, since the analysis of the dynamics of a much more complex model – like the one we ended up obtaining – would require several months of work using traditional quantitative econometric approaches. The first model used only the most important concepts (the ones really necessary to a short term analysis): Tax Rates, Inflation, Consumption, Oil Price, and Food Cost. Even with such a few concepts, a realistic model becomes rather difficult to analyse due to the complexity of the relations that affect the involved concepts. However, since the goal was to show RB-FCM potential to deal with larger systems and long-term simulations, the model was evolved to be more realistic therefore including more concepts and much more relations. On this step, 13 concepts were added to the original 5 (Figure 7).

At the end of this phase of the modelling process one obtained a classic Cognitive Map – basically a graph where the nodes were the Concepts and each edge represented an existing unknown relation between a pair of Concepts.

### 3.1 Concept Modelling

The next step was refining the concepts to obtain a linguistic fuzzy representation for each one. This step consisted in defining the class(es) (Variation, Level) and the linguistic terms and membership functions for each concept. In dynamic systems, variations are much more important than absolute values, therefore, most concepts are Variations, some are Levels, and a few key concepts like Inflation, Tax Rate, etc., are both Variations and Levels (the Level value of these concepts is actualized according to its Variation using a special LV relation [5]).

The linguistic terms of Levels must have a direct correspondence with the real world values. Therefore we allied common sense and expert consulting (using straight questions like “what do you consider a high value for Inflation?”, and receiving answers like “around 4%”) to define their membership functions. In the particular case of Levels that depend on LV relations, it was also necessary to define the real-world meaning of a certain amount of variation (e.g., a “Small” increase on inflation is around 0.3%). Figure 5 shows the linguistic terms of the Level concept LInflation.

Variation linguistic terms usually represent qualitative terms without a direct correspondence to absolute values. E.g., VInflation has 11 linguistic values ranging from “Huge Decrease” to “Huge Increase” (Figure 6). Linguistic terms of Variations can usually be represented by standard sets, which simplify and accelerate the modelling process [10].

3.2 Qualitative Modelling of a Qualitative Dynamic System

The huge advantages of using Fuzzy Rule Bases (FRB) to define qualitative relations between Concepts has been largely discussed and proved [2,3,5,9,11]. The major drawback of rule-based fuzzy inference, the combinatorial explosion of the number of rules, is avoided in RB-FCM by the use of Fuzzy Causal Relations and the Fuzzy Carry Operation [4]. Another important feature of RB-FCM is the simplicity of the process of insertion and removal of Concepts and/or Relations, which also reduces the modelling complexity of FRB [4]. Therefore one has in RB-FCM an adequate tool to model qualitative relations. However, the single fact of using linguistic rule bases to model relations does not guarantee the qualitative nature of the model. Let us see the example of Inflation modelling:

A pseudo-qualitative approach using FRB would try to closely map the widespread quantitative approaches: Inflation value is predicted by a weight averaged sum of several factors (Estimated Oil inflation, estimated Food price inflation, etc.). This method is highly dependent on the precision and validity of each factor real-world absolute value. In the proposed model, a novel approach where rules are independent from the real world absolute values was used. The model is based on a qualitative definition of inflation: Economics theory states that economic growth depends on inflation – without inflation there is no growth; In fact, the worst economic crisis (30’s for instance) are associated with deflation; Therefore, it is desirable and expected that all factors that affect inflation have a certain cost increase – If all factors suffer a normal increase, then the inflation will maintain its normal and desired value. Therefore, one can state the following qualitative relation for each of those *n* factors:

“If factor<sub>*n*</sub> has a normal increase, then Inflation will maintain”

This statement is part of the fuzzy rule base of a causal relation. Since fuzzy causal effects are accumulative and their effect is a variation in the value of the consequent, then if all factors that cause inflation have the normally expected increase, Inflation will not vary. If some factors increase more than expected and the others maintain their value then inflation will somehow increase. If a factor increase less than normal, or even decreases, then its effect is a decrease in inflation (note that the final variation of Inflation is given by the accumulation of all causal variation effects – e.g., if some pull it down a bit, and one pulls it up a lot, in the end inflation still can maintain its normal value).

It is possible to build a completely qualitative and sound causal FRB to model each factor influence of Inflation, without ever referring to absolute values. If one intends to model inflation in South America, one can maintain the rule base. All that needs to be changed are the linguistic terms of the Level Concept associated to Inflation (for instance, normal inflation would become around 8 %, and so on...). Obviously some factors are more important than others (a large increase in food might cause a large increase in Inflation, but what is considered a large increase in Oil might only cause a small increase in Inflation – average Oil price varied over 100% in the last 2 years, but other factors had a slightly above average increase, and therefore inflation had mild increase instead of a sever one...). This “relative” importance is easily modelled as a causal effect in a FRB. Table I represents an example of a causal FRB. One can also mention the fact that oil price variation has a delayed effect in inflation. RB-FCM provide mechanisms to model these kinds of timing issues [8,11]

TABLE I: FCR7 +sl Food Cost, Inflation

If Food Cost Decreases VeryMuch,	Inflation has a Large Decrease
If Food Cost Decreases Much,	Inflation has a Large Decrease
If Food Cost Decreases,	Inflation has a Large Decrease
If Food Cost Decreases Few,	Inflation Decreases
If Food Cost Decreases VFew,	Inflation Decreases
If Food Cost Maintains,	Inflation Decreases
If Food Cost Increases VFew,	Inflation has a Small Decrease
If Food Cost Increases Few,	Inflation has a Very Small Decrease
If Food Cost Increases Normally,	Inflation Maintains
If Food Cost Increases M,	Inflation has a Small Increase
If Food Cost Increases VM,	Inflation Increases

This kind of qualitative approach was used throughout the model when causal relations were involved.

As it was mentioned above, Variations usually have a standard set of linguistic terms. These allow the predefinition of certain common fuzzy causal relations (FCR). These FCR are called macros and were used to reduce the modelling effort.

The model includes other than causal relations. For instance: Oil price variation was modelled using a classic fuzzy inference rule base (FIRB) based on oil Offer/Demand (where Oil offer was decided in simulated periodic OPEP meetings); the Tax Rates were modelled considering that Banks were managed as a common business with profit in

mind – for example, an increase in money demand would increase Tax Rates (this would be changed later (see 3.4)).

Regarding timing considerations, the system was modelled considering a one month period between iterations.

It is obviously impossible to detail every aspect of the system modelling in this paper. provides a graphic representation of the final RB-FCM model. The system consists of 18 concepts and around 400 fuzzy rules to express relations (most were automatically generated using macros). The system was described using RB-FCMsyntax (a dedicated language) – a complete description is available in [2]. Here are some guidelines regarding the description of relations in Figure 7: “FCR+” stands for a standard positive causal relation (an increase in the antecedent will cause an increase in consequent), and “FCR-“ a standard negative relation (increase causes a decrease). Several “+” or “-“ represent stronger effects. A “/” represents an attenuated effect. “sl” and “sr” represent biased effects (non symmetric causal relations. A “?” represents a relation which cannot be symbolically described (one must consult the FCR). A “d” represents a delay in the effect. FIR stands for Fuzzy Inference Relation. The number after FCR or FIR is the label for the complete description of the rule base.

### 3.3 Simulation results<sup>1,2</sup>

The simulation of the original system provided rather interesting results. The evolution of the system through time was rather independent from the initial values and the external effects. After a certain period of time, that could vary from a few months to several years (depending on a conjugation of external factors like a war, or a severe cut in oil production), economy would end up collapsing: deflation, negative growth, 0% tax-rates. Figure 1 represents one of those cases.

Initially one could think that there was a major flaw in the model (or in the RB-FCM mechanisms), but after a discussion and analysis of the results with an economics expert, the culprit was found: the model approached the economic situation before the creation of entities that control Interest Rates (like the U.S. Federal Reserve, the European Central Bank). The lack of these entities was the main cause to economic instability until 1930’s. In fact, Economics was known in the 18<sup>th</sup> and 19<sup>th</sup> century as the “Dark Science”, because all theories indicated that economy was not sustainable. According to the simulation results, depression always comes after a growth period and due to an exaggerate increase in tax rates (the banks try to maximize their profit in a short period, and their greed cause an apparently avoidable crisis). Notice the similarity with the present economic crisis - one will return to this point later on. Therefore, to support the referred theory, a simple model of the European Central

Bank behaviour regarding interest rates was added to the model.

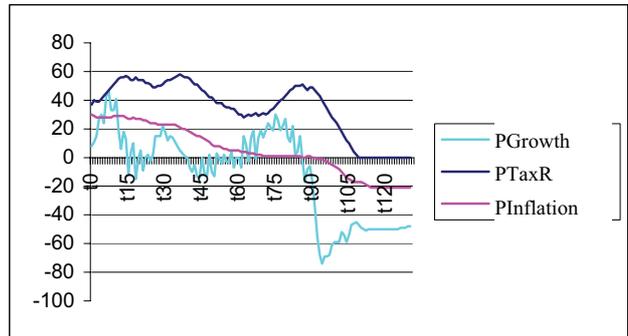


Figure 1 – Serious economic crisis: Negative growth and deflation (Predicted Growth, Predicted TaxRate, Predicted Inflation,)

### 3.4 Modelling European Central Bank Influence

To simulate ECB influence, a Fuzzy Inference Subsystem (FISS) – a RB-FCM block used to model the process of decision making of system entities (FISS timing mechanisms are independent of the RB-FCM) – was added to the model (Figure 2). This FISS ended up as a simple FRB with 48 rules (each with 2 antecedents)[2]. These rules were designed to inhibit the greedy bank behaviour that was identified as the cause to the unavoidable crisis.

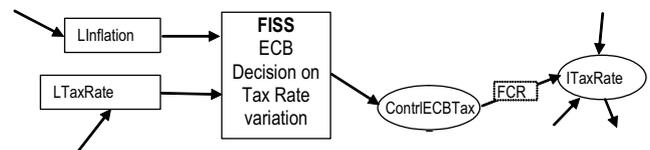


Figure 2 – FISS: ECB decision on Interest Rate variation

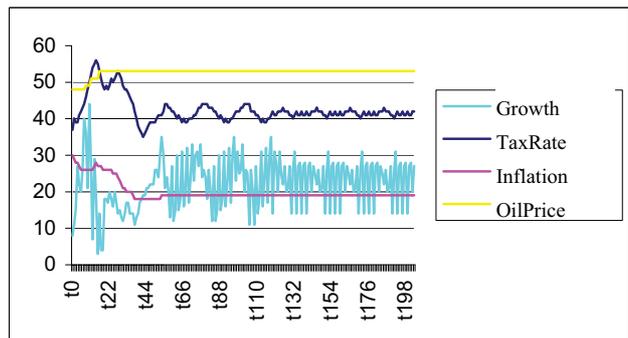


Figure 3 – Avoiding economic crisis trough ECB Interest Rate control

### 3.5 Complete Model Simulation

With the introduction of the ECB-FISS, system behaviour changed completely and serious crisis were avoided under normal circumstances (Figure 3). One of the most interesting results was the fact that, under normal circumstances, the economic model stabilizes around the real-world BCE predicted ideal target value for inflation (slightly below 2%)

<sup>1</sup> Note: This section refers to an initial version of the system that did not include concept 17

<sup>2</sup> All variables are in % and must be divided by 10 (e.g., 15 represents 1.5%)

and growth (averaging slightly above 2%). Note that these values are not imposed anywhere in the model, they result from the system itself.

However, the ECB and private bank behaviour in the last two years was incredibly similar to the greedy behaviour exhibited by the model without ECB. Tax rates – see Euribor historical data [14], Figure 4 – were severely increased between 2006-08 under the pretext of controlling inflation, but, as it was found later, mostly because private banks were needing to increase their tax rates to protect themselves against prior mistakes. The variation of the Euribor tax rate + 0.8% spread rate in the last 10 years (120 month), is very much similar to what was predicted in the “greedy” model that was presented 8 years ago. As a result of that, and, as the original model predicted, we are entering a severe economic crisis as a result of that policy. Given that this is a very long term 10 year simulation (done 8 years ago), the results are incredibly more accurate than current models, that don’t usually attempt to predict for longer than 2 years and usually with very inaccurate results. As a proof of this, less than 1 year ago all major economic actors were still insisting on increasing tax rates having inflation control in mind, and no major economic actor was even suspecting that deflation would be the real concern in less than 8 months.

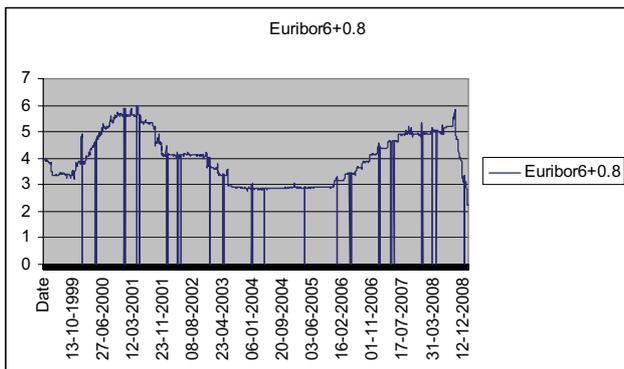


Figure 4 – Euribor6+0.8 for the last 120 months

#### 4 Conclusions, Applications, and Future Developments

In this paper we exemplified how one can use DCM to model complex qualitative socio-economic systems, avoiding the need to use extensive and time consuming differential equation models, while obtaining very interesting and encouraging results.

By using true qualitative modelling techniques, one obtained results that look more realistic (plausible) than those obtained using quantitative approaches – where results almost never show the short term uncertainties that are so characteristic of qualitative real-world dynamic systems. In the end, the results of the presented model, that was developed eight years ago, are surprisingly realistic and could have been used to predict and avoid the current world

economic crisis, even if one considers its necessary incompleteness.

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