Automatic Implementation and Simulation of Dynamic Qualitative Systems using Fuzzy Boolean Networks and Fuzzy Rule-Based Cognitive Maps

João Paulo Carvalho **José A. B. Tomé**

INESC - Instituto de Engenharia de Sistemas e Computadores

IST – Instituto Superior Técnico

R. Alves Redol, 9, 1000 LISBOA

PORTUGAL

Phone: +351.21.3100262 Fax: +351.21.3145843

E-mail: joao.carvalho@inesc.pt jose.tome@inesc.pt

Abstract

This paper presents the overview of an ongoing project which goal is to obtain and simulate the dynamics of qualitative systems through the combination of the properties of Fuzzy Boolean Networks and Fuzzy Rule Based Cognitive Maps.

1. Introduction

Decision makers, whether they are social scientists, politicians or economists, usually face serious difficulties when approaching significant, real-world dynamic systems. Such systems are composed of a number of dynamic concepts interrelated in complex ways, usually including feedback links that propagate influences in complicated chains. Axelrod work on Cognitive Maps (CMs) [1] introduced a way to represent real-world qualitative dynamic systems, and several methods and tools [2][3] have been developed to analyze the structure of CMs. However, complete, efficient and practical mechanisms to analyze and predict the evolution of data in CMs are necessary but not yet available for several reasons [4]. System Dynamics tools like those developed by J.W.Forrester [5] could be a solution, but since in CMs 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 [6], are an alternative approach to system dynamics. However, in most applications, a FCM is indeed a man-trained Neural Network that doesn't share the qualitative properties of other fuzzy systems [7], and the modeled system ends up being represented by a quantitative matrix without any qualitative knowledge. Therefore, we can say that there are currently no tools available to adequately represent the dynamics of qualitative systems.

Even if we had the tools to represent and analyze those systems, a different issue would be the building of a qualitative CM. The standard methodology for acquisition of the necessary data relies usually on lengthy processes of individual and simplistic information collection: the result ends up being a list of quantitative relevant world concepts displayed as a matrix where weights represent the relations between those concepts [2][3][4][6]. Therefore we end up with quantitative CMs where any vestiges of a system with real-world rich qualitative entities and rich qualitative relations were simply ignored. Besides, there is the additional problem of combining the views of different analysts into one single map, which is usually done by simple math operations between the resulting matrixes.

This paper presents a general overview of an ongoing work that pretends to potentiate two original research lines to solve the problems presented above.

The first research line is in the potential use of really Qualitative Cognitive Maps as a tool not only to describe but also to simulate scenarios in qualitative real world systems like Social Conflicts, Political Science cases or Economic real-world problems. Fuzzy Rulebased Cognitive Maps (RB-FCM) [7][8][9][10] were introduced in previous works and are still being developed. They provide new Fuzzy Operators and a complete methodology for analysis and design of the dynamics of qualitative systems.

The second research line develops a new class of Boolean Neural Nets - Fuzzy Boolean Networks (FBN) [11][12][13]- which behave like fuzzy systems and are capable of non supervised learning of rules and of using the learned rules in qualitative reasoning.

2. Automatic Implementation and Simulation of Dynamic Qualitative Systems

This paper purposes and introduces the overall architecture of AISCMap (Automatic Implementation and Simulation of Cognitive Maps). AISCMap should automatically generate a RB-FCM using FBN for the acquisition of the rules, concepts and relations that compose the map, allowing the simulation of "What-if" scenarios in the qualitative system that it models.

AISCMAP can be described in the following steps:

a) Experts analyze the system and provide their inputs under several formats.

b) The FBN module learns and combines the expert knowledge and translates it into a cognitive map.

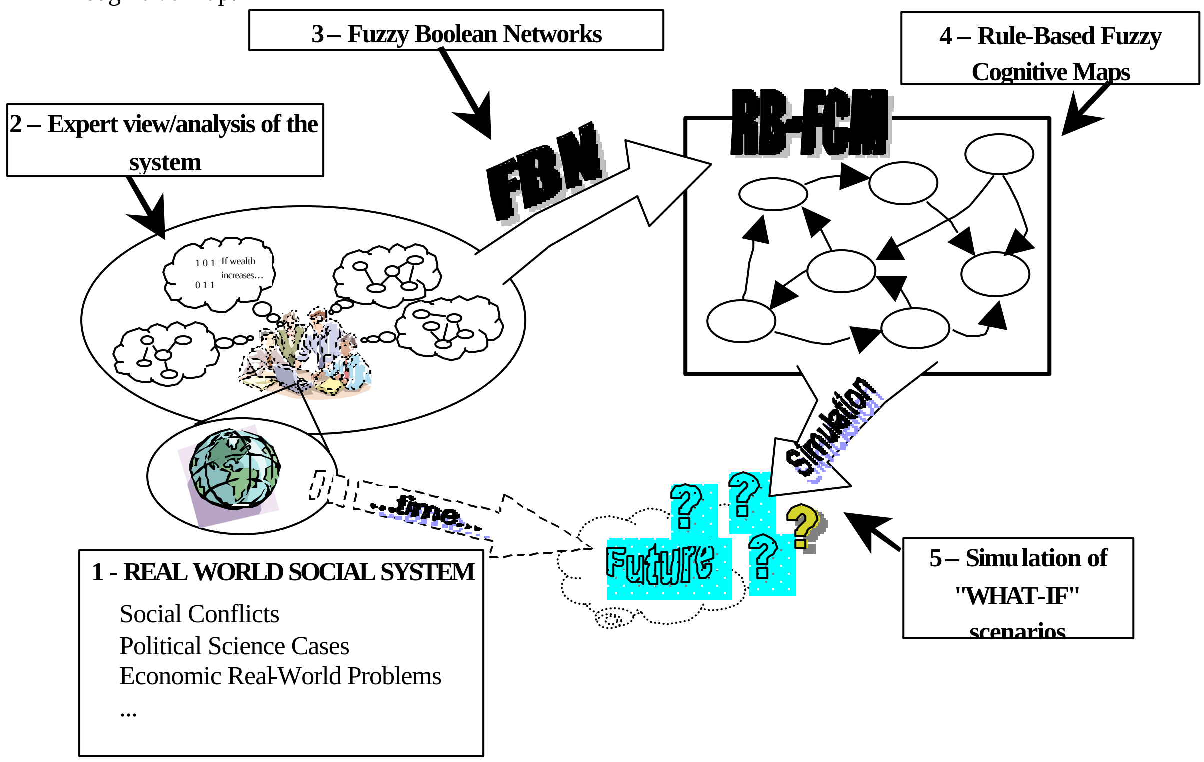
c) RB-FCM are used to represent and simulate the resulting system.

d) "What-if" scenarios can be simulated to predict the evolution of the modeled system.

The following sections provide a simplified description of AISCMap, including somewhat more detailed presentations of RB-FCM and FBN since they are essential to the understanding of the problem.

2.1. Fuzzy Boolean Networks

Neural Networks are known for their capability in apprehending relationships among variables, but is also well known their difficulty in expliciting these relations into human comprehensive rules [15]. Fuzzy logic based systems are very useful in explaining behaviors by a set of qualitative rules [14], but are not so good in which concerns learning of those rules. A synergetic cooperation between these two paradigms leads usually to hybrid systems that can learn and also explain the relationships by rules. However, these hybrid systems are usually an artificial engineered human work, where algorithms as well as fuzzy and neural components are "inserted" into the system. Although being based on common grounds, FBN are a new class of neural fuzzy systems that don't have



many things in common with other neuro-fuzzy systems. Fuzzy qualitative reasoning is a natural and emergent property of Boolean networks [11][12]. These nets present many similarities with natural systems. They are capable of learning rules from non-supervised experiments in a Hebbian-like manner and they can automatically adapt to the granularity [13] of the antecedent variables and select the relevant ones. FBN are Boolean Nets with Macroscopic Emergent Fuzzy Reasoning, which allows them to extract qualitative rules from experimental data [11][12]. Here are some of the main FBN features:

- Variables/Concepts are associated with neural areas
- Values are given by neural activation
- Local Random Neural Connections
- Macro Structured (Links connecting Areas)
- Hebbian like Non-supervised Learning by experiments
- Embedded Variable Selection and Granular adaptation

2.2. RB-FCM: Representing and Modeling Real World Qualitative Dynamic Systems

RB-FCM provide a representation of the dynamics of complex real-world qualitative systems with feedback and allow the simulation of the occurrence of events and their influence in the system. They are fuzzy directed graphs with feedback, which are composed of fuzzy nodes (**Concepts**), and fuzzy links (**Relations**). RB-FCM are true cognitive maps (CM) since are not limited to the representation of causal relations. Unlike FCM, concepts are fuzzy variables defined by fuzzy membership functions (mbf), and relations are defined with fuzzy rule bases. RB-FCM are essentially fuzzy rule based systems where we added fuzzy mechanisms to deal with feedback, and different kinds of relations in order to cope with the complexity and diversity of the qualitative systems we are trying to model.

RB-FCM are iterative: the current value of each concept is computed with its inputs previous values. The evolution of the system through time might reach equilibrium and converge to a single state or a cycle of states under certain conditions [10]. Several simulations are necessary when possibilistic and/or probabilistic relations are involved.

One of the main important uses for a dynamic model of a system is the analysis of "WHAT-IF" scenarios ("What happens to the system when some event occurs?"), since the change of state in one or more concepts or relations affect the system in ways that are usually difficult or impossible to predict due to complex feedback links. RB-FCM are well adapted to these analysis, since they can deal with the timing issues involved in the study of these scenarios (RB-FCM include mechanisms that allow the inhibition of certain relations and/or concepts when they have no influence on a given instant) and also because introduction or removal of concepts and/or relations are possible and easily done without the hassle of the exponential increase of rules usually associated with fuzzy rule-based systems [7][9].

2.2.1. Concepts

Concepts represent the actors, entities and social, political, economic or abstract concepts that compose our system. Examples of concepts might be Inflation, the actions of an influent Politic, a Revolution, the Wealth of an individual or a nation, the Welfare of population, Road conditions, etc.

In RB-FCM we can have 2 kinds of concepts: **Levels** and **Rates**[1]. Levels represent the absolute value of a concept in a given instant. Rates represent the variation of the concept since the last iteration. Some entities are represented by Levels, others by Rates, and some few need the use of both. Usually only the Rate is important in causal relations [9][10][16][17], and since these are the most used relations in CM [18], many systems do not need the absolute value of a concept.

Concepts are fuzzy variables. Each has a set of mbf that defines it. The mbf of a Rate represent the variation of the concept, usually from Decrease_Very_Much to Increase_Very_Much, or from Very_Much_Worse to Very_Much_Better, and usually have several restrictions [9]. The mbf of a Level represent its various possible values and are not restricted: they can range from the representation of a quantity, to its several possible states. When both Rate and Level of a concept are present it is necessary to guarantee certain conditions to maintain coherence between the absolute value of a concept and its variation. These conditions are presented in [10].

[1] In previous papers, Rates are referred as Changes. This alteration was made to maintain a certain coherence with Quantitative System Dynamics [5][19]

2.2.2. Relations

Relations represent the interactions between the concepts present in the system. In RB-FCM, relations are defined by the use of different kinds of fuzzy "If…Then" rule bases. Mechanisms to support the several types of relations have been developed [10]. Presently RB-FCM allow the following relations:

- **Fuzzy Causal Relations (FCR)** [9]- FCR use a new fuzzy operation (Fuzzy Carry Accumulation [9]) to provide a causal accumulative effect (not possible with usual fuzzy rule based inference) that allows the modeling of non symmetric/non monotonic accumulative causal reasoning.
- **Influence Relations (FIR)** - model influence relations using classic fuzzy "If…Then" rule bases.
- **Possibilistic Relations (Ps)**- allow the simulation of alternative complementary scenarios.
- **Invariant and Time Variant Probabilistic (Pr)** - introduce probability of occurrence to uncertain causal relations.
- **Possibilistic and Probabilistic (PrPs)**

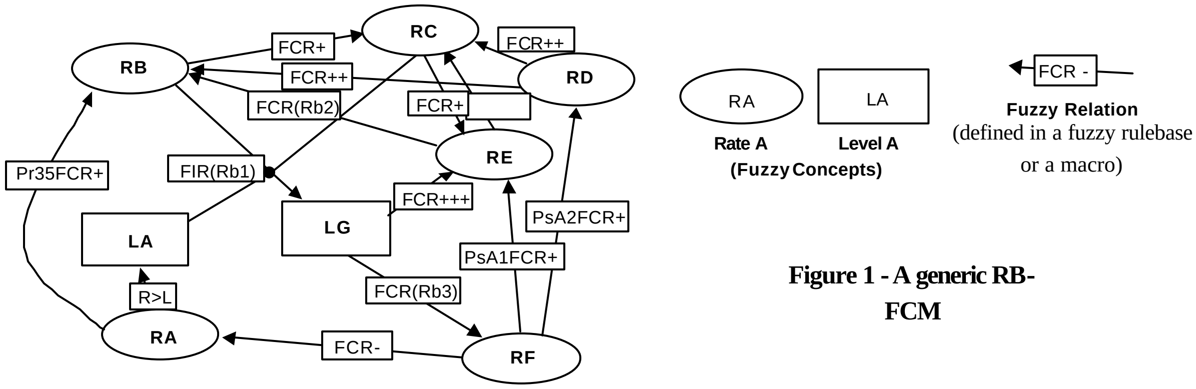


Figure 1 - A generic RB-FCM

- **Fuzzy Similarity (FS)** - measure the similarity of different concepts.
- **Level/Rate (L>R, R>L, R<>L)** - maintain coherence between a Level concept and its correspondent Rate.

2.2.3. RB-FCM Syntax

RB-FCMSyntax is a language that was developed to describe real-world qualitative systems in RB-FCM. It allows the definition of the concepts, relations, fuzzy mbf, etc. that compose the system. In order to simplify the description of the systems, macro mechanisms allow the definition of simple monotonic and symmetric causal relations (which are the only relations present in Fuzzy Causal Maps) with a single instruction.

A few examples:

- **CRate** Inflation → Defines a Rate concept named Inflation in the system
- **MBF** Good 60,80,90 → Defines the triangular mbf Good
- Inflation Decrease,Maintain,Increase → Defines the mbf of concept Inflation
- **FCR** CCorp_Results Good, CCorpValue IM → Defines the following Fuzzy Causal Relation: If Results of CorporationC are Good Then Stock Market Value Increases Much
- **FCR+** Interest_rate, Inflation → A macro (set of rules) that defines a positive causal relation between the Interest Rate and Inflation (If the Interest Rate increases then Inflation will increase, If the Interest Rate increases much then Inflation will increase much, If the Interest Rate decrease then Inflation will decrease, etc.)

2.3. Inputs for AISCMAP

The inputs for AISCMap consist of the output provided by expert's analysis of the system to be modeled. Even after debate, each expert usually has its own view of the problem and a preferred way of representing the system. There are several methods to represent a cognitive map, from a simple drawing expressing concepts and the connections between those concepts, to a complete and detailed description of the concepts and the nature and characteristics of the relations relating them (RB-FCM Syntax).

The simplest map consists of a list of relevant concepts and the indication of the existence or non-existence of a relation between each pair of concepts. These maps can be represented by a square matrix with "0" and "1". These are unfortunately the most commonly analyzed causal maps, and provide no qualitative description at all. These maps can be improved if one uses more detail to describe the relation, like a discrete or continuous value instead of a binary one. This value might represent the intensity or the importance of the relation in the expert view (still no qualitative knowledge, though, and limited to a single kind of relation, usually monotonic and symmetric causal relations).

The next step in detail includes a description of each concept (its possible values or states), and an identification of the kind of relation involved.

The ideal map description for a qualitative system should include the description of the concepts and relations using natural language (which would allow the representation of the nuances characteristic to these systems).

The problem with detailed descriptions relies on the fact that often experts are not able or do not have the time or data to provide the necessary detail. This problem can be solved if the experts provide examples instead of a complete description. Given enough examples for each relation, the FBN can extract fuzzy qualitative rules to completely describe the system.

These different types of descriptions not only must be somehow translated/introduced in AISCMAP, but they must also be somehow combined into a single map.

2.4. From FBN to RB-FCM: Structuring the maps

The FBN module of AISCMAP should extract RB-FCM concepts, rules and relations from the expert raw data combining them into a single qualitative cognitive map, being the map described using RB-FCMSyntax.

Therefore it is necessary to extend the working principles of the FBN to the problem of RB-FCM. This involves the adequate definition of the relationship between concepts and structure of the Maps and the neural areas and sub-areas as defined on the FBN.

In which concerns the relationship between the structure of the Maps and the neural areas of the FBN's, the following principles were taken:

- Each concept mentioned by experts is translated into a corresponding neural area.
- For each causal relation between two concepts results that each neuron on the consequent area receives m inputs coming from the outputs of randomly chosen antecedent neurons.
- For non-causal relations (which can have more than one antecedent), each consequent neuron receives a set of m inputs from each antecedent area (again, randomly chosen among the antecedent neurons on each area).

This means that there is a natural and automatic mapping from expert descriptions to the topology of the FBN. If there are different descriptions from different experts, a global topology is made including every concept and connection described. At this stage this can be done, since only the topology is established, without any quantitative or qualitative relationship among variables and, thus, without contradictions.

Once the network topology is established, the learning process [12] for such Boolean networks can be used to establish internal rules and relations:

a) If experimental raw data is used (examples), areas associated to the relevant concepts are intensified accordingly (in order learning can be performed), as follows:

- If there is a large number of Yes/No input data, either for antecedents or consequents or both, (e.g., a large number of experiments where the relevance is associated with the presence/absence of the concepts), input data can be directly mapped on neuron values. Actually, this implies a slightly modified version of the network topology since there is a need to "synchronize" the several Yes/No and the neural connections will not be completely random.
- If concepts have a continuous or multi-valued "universe of discourse" the intensification of the neurons on the corresponding area can be made proportionally, that is, the fraction of neurons set to "one" equals the value of the concept (this set of neurons is chosen randomly, though).

b) If experts expose their opinions using a qualitative language (e.g., if concept A increases concept C will decrease much, or, if concept A and concept B are medium concept C is low), each area is intensified accordingly, as above, in order to learn those assertions. It should be noticed that, as the topology of the network can accommodate feedback pathes, relative concept modifications, such as "increases a little", pose no major problem on the implementation. One may associate neural areas to those modifications (for antecedent concepts or consequent as well).

At this stage contradictions may exist, for example, two experts present different consequent results. If the number of learning experiments is large enough this pose no problem, since the learning process itself solves statistically these problems. If not, care must be taken and one may use, for each expert assertion, a number of experiments proportional to the importance given to the expert. These experiments are not repeated but, rather, they are generated randomly (in fact, the activated neurons are chosen randomly), but always in accordance with the assertion.

3. Conclusions

AISCMAP is an ongoing work that is the result of a synergic approach of two different areas. Most of its modules are on an advanced stage of evolution, and the obtained results are promising, but there is still a lot of work to be done especially on the interaction between the expert results and the inputs to the system; and on the interaction FBN/RB-FCM.

4. References

[1] Axelrod,R., The Structure of Decision: Cognitive Maps of Political Elites, Princeton University Press, 1976

[2] Laukkanen,M., Comparative Cause Mapping of Management Cognition:A computer Database For Natural Data,Helsinki School of Economics and Business Publications,1992

[3] Decision Explorer, Banxia Software

[4] Laukkanen,M. Conducting Causal Mapping Research:Opportunities and Challenges, in Managerial and Organizational Cognition, edited by Eden, C.and Spender, Sage,1998

[5] Forrester, J.W., several papers available in http://sysdyn.mit.edu/sd-intro/home.html

[6] Kosko,B., "Fuzzy Cognitive Maps", Int. Journal of Man-Machine Studies, 1986

[7] Carvalho,J.P.,Tomé, J.A., "Rule Based Fuzzy Cognitive Maps and Fuzzy Cognitive Maps - A Comparative Study", Proceedings of the 18th International Conference of the North American Fuzzy Information Processing Society, NAFIPS99, New York

[8] Carvalho, J.P., Tomé, J.A., "Rule Based Fuzzy Cognitive Maps- Fuzzy Causal Relations", Computational Intelligence for Modeling, Control and Automation, Edited by M. Mohammadian, 1999

[9] Carvalho,J.P.,Tomé,J.A., "Fuzzy Mechanisms For Causal Relations", Proceedings of the Eighth International Fuzzy Systems Association World Congress, IFSA'99, Taiwan

[10] Carvalho,J.P.,Tomé, J.A., "Rule Based Fuzzy Cognitive Maps – Qualitative Systems Dynamics", Proceedings of the 19th International Conference of the North American Fuzzy Information Processing Society, NAFIPS2000, Atlanta

[11] Tomé, J.A., "Counting Boolean Networks are Universal Approximators", Proceedings of the 1998 Conference of the North American Fuzzy Information Processing Society, Florida

[12] Tomé,J.A., "Neural Activation ratio based Fuzzy Reasoning", Proceedings of the 1998 IEEE World Congress on Computational Inteligence, Anchorage, Alaska

[13] Tomé, J.A., "Automatic Variable Selection and Granular Adaptation in Fuzzy Boolean Nets", Proceedings of the 18th International Conference of the North American Fuzzy Information Processing Society, NAFIPS99, New York

[14] Mamdani,E.and Gaines,B., "Fuzzy Reasoning and its Applications".London: Academic Press, 1981.

[15] Rumelhart,D.,G.Hinton, R.Williams "Learning Internal Representations by Error Propagation" Parallel Distributed Processing, vol I, chap.8. Cambridge,MA,MIT Press, 1986

[16] Kosko,B., "Fuzzy Thinking", Hyperion, 1993

[17] Kipersztok,O., "Uncertainty Propagation in Fuzzy Cognitive Maps for Ranking Decision Alternatives", Proceedings of the EUFIT97, Aachen, 1997

[18] Huff,A., "Mapping Strategic Thought", John Wiley and Sons, 1990

[19] Vensim, "The Complete Toolkit for Building and Using High Quality Dynamic Feedback Models", Vensim, http://www.vensim.com