Rule Based Fuzzy Cognitive Maps - Qualitative Systems Dynamics

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Abstract

This paper focuses on the Rule Based Fuzzy Cognitive Maps (RB-FCM) potential to model the dynamics of qualitative real-world systems that include feedback links. It presents a general overview of RB-FCM and proposes a set of possible concepts and relations. It also provides guidelines to introduce time as an important qualitative entity in cognitive maps.

1. Introduction

Decision makers usually face serious difficulties when approaching significant, real-world dynamic systems. Such systems are composed of a number of dynamic entities which are interrelated in complex ways, usually including feedback links which propagate influences in complicated chains. Axelrod work on Cognitive Maps (CMs) [1] introduced a way to represent these systems, and several methods and tools like [2] or [3] allow the analysis of causal maps structure. However, complete, efficient and practical mechanisms to analyse and predict the evolution of data in CMs are necessary [4] but not yet available for several reasons. System Dynamics tools like [5] could be a solution, but since 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] and Influence diagrams [7] are a qualitative alternative approach to dynamic systems, but their characteristics [8] limits them to the analysis of systems composed of simple symmetric causal relations.

2. Rule Based Fuzzy Cognitive Maps [8] [9] [10]

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 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 [11]. Several simulations are necessary when possibilistic and/or probabilistic relations are involved.

What happens to a system when some event occurs? Introduction or removal of concepts and/or relations, or the change of state in one or more concepts affect the system in ways that are usually difficult or impossible to predict due to the complex feedback links. RB-FCM are a tool to predict the evolution through time caused by those changes. With the introduction of mechanisms that allow the inhibition of certain relations and/or concepts when they have no influence on a given instant [12](section5.), RB-FCM can deal with timing issues and become a tool to represent and analyse the dynamics of qualitative systems.

3. 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 Changes. Levels represent the absolute value of a concept in a given instant. Changes represent the variation of the concept since the last iteration. Some entities are represented by Levels, others by Changes, and some few need the use of both. Usually only the Change is important in causal relations (see 4.1), and since this are most used relations in CM [13], 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 Changes represent the variation of the concept, usually from Decrease Very Much to Increase Very Much, and usually have several restrictions [9]. The mbf of Levels represent their various possible values and are not restricted: they can range from the representation of a quantity, to its several possible states. When both Change and Level of a concept are present it is necessary to guarantee certain conditions whom are presented in 4.9.

4. Relations

As we said above, relations represent the interactions between the concepts involved in our system. In RB-FCM, relations are defined by the use of different kinds of fuzzy "If…Then" rule bases. In this section we describe the relations already implemented in RB-FCM. As long as new relations appear to be necessary, fuzzy mechanisms to support them should be developed.

4.1 Influence and Causality

One of the greatest problems one can find when working in the area of cognitive or causal maps, is the interpretation of what is a causal relation between two concepts. Some authors consider that any relation that involves some kind of "if…then" cause-effect is a causal relation (some might call it an influence relation). Although this assumption can be true under certain circumstances, there are enough different cases of "causation" to justify the definition of at least two different kinds of "causal" relations. That said, it is not our intention to impose a universal standard for the terms of causality and influence in causal maps, but rather define to what kind of relations we apply each term in the implementation of RB-FCM relations. In this section we describe how Influence and Causality relations are applied in RB-FCM.

Many authors [6][13] tend to consider that a **causal relation** between two concepts always involve change. It is the change in one concept that causes the effect, which in turn is a change in the other concept. Under these assumptions, <u>the effect of a causal relation is a relative variation that never imposes an absolute value</u>. Besides causal effects also are <u>accumulative</u>. For example, we can not say that an increase of 0.75% in the Interest Rate, will cause Inflation to rise up to the value of 2.3% because there might be other factors affecting inflation (Figure 1).

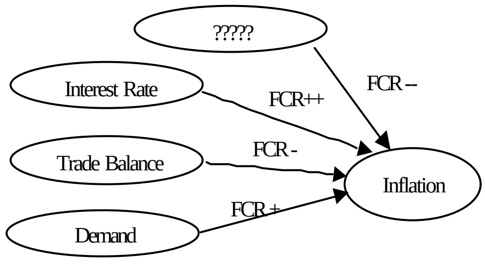

Figure 1 - Causal relations

We can only say that the increase in the Interest Rate will cause Inflation to raise a certain amount. Other causes (like Demand, Productivity or Trade Balance, among others…) also affect Inflation, and it is the accumulated result of all these causes that will provide the variation in inflation.

In RB-FCM we also admit that a Level may "cause" a causal relation, as long as only change is involved in the "target" concept.

Concluding, in RB-FCM we have a <u>Causal relation</u> when we are dealing with the <u>relative</u> variation of target concept and not with its absolute value.

Whenever we are dealing with absolute values, or when the relation tries to impose, or influence a certain value, we use the term **Influence relation** (although we are still dealing with a cause and an effect). One of the rules of a rule base representing an influence relation could be, for instance: "If Inflation is high and Employment is High, then government tries to lower the Deficit to 3%". Figure 2 represents part of a model where in certain conditions the government would try to force the Deficit to certain values. Of course these government measures could cause Inflation and Employment to change due to feedback loops. Influence relations are not accumulative: If two different "entities" try to impose (cause) the same value (effect), that result is achieved more easily. We can say that influence relations tend to reinforce themselves, instead of accumulating their values (like causal relations).

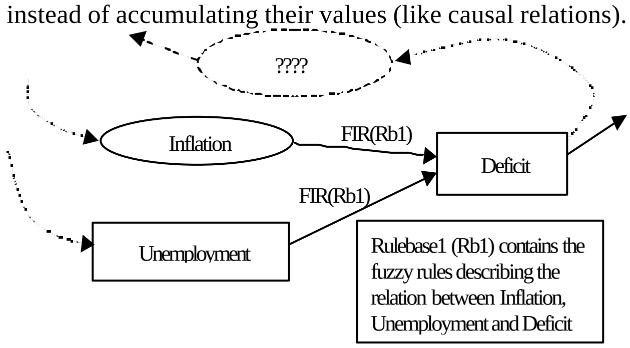

Figure 2 - Influence Relations

When we try to apply Fuzzy Sets and Logic to define causal and influence relations, one major problem arises:

As we defined it, causality is "**accumulative**". For example, we can say that (using "natural language"):

- If concept A and concept B each cause concept C to increase "little", then C will increase "more than a little"
- If two concepts A and B have the exact opposite effect on C, then C will not change
- If A affects C "a little" and B affects C "much", then C will increase "more than much"
- The effect when both decrease is similar.

However, a traditional fuzzy relation tends to **reinforce itself** like:

- If A and B cause C to increase "little" with a belief of 0.3 and 0.6, then concept C will increase "little" with a stronger belief (0.9)
- If A causes C to increase "little" and B causes C to increase "much", then C would increase somewhere between "little" and "much"
- Opposed effects tend to nullify each other (as in a causal relation).

So, "classic" FL "if…then" rule bases can be used to implement Influence relations, but a different mechanism must be used to implement Causal relations – and Causal associations are arguably the most used to describe our understanding of the world.

In [9] we presented the Fuzzy Causal Accumulation (FCA) and Fuzzy Causal Relations (FCR), which are fuzzy mechanisms that allow the implementation of the intended accumulative effect using classic fuzzy rule bases.

4.2 Influence Relations

As we mentioned above, Influence relations (FIR), are implemented and described using classic "If…Then" rule bases involving one or more concepts. FIR rules may combine several concepts using fuzzy operators like And, Or, etc. Any influence relation that can be expressed using natural language can usually be implemented using the adequate fuzzy sets and rules.

4.3 Fuzzy Causal Relations

Fuzzy Causal Relations (FCR), as they were introduced in [9], are similar in form to FIR, but their effects are, as we have seen above, rather different. The major formal difference is that since FCR are accumulative, a FCR rule involves at most two concepts. Several concepts may affect the same one, but the rule bases that express each relation are independent. For example, in Figure 1, the rule base defining the relation between Demand and Inflation can not contain rules involving any other concept.

FCR, in their most simple form, behave like the usual causal relations used in the classic causal maps (like FCM for instance), expressing positive or negative symmetric causality with different levels of strength. However, FCR can be used to represent non-symmetric/non-monotonic causal reasoning, like the one involved when we want to model biased opinions [10].

FCR are commutative and associative, and their properties allow concepts and/or relations to be added or removed from the system without increasing the system complexity more than necessary, since there is no combinatorial explosion of rules [9].

FCR main trade off for versatility and modelling potential is complexity and time consumption. While to define a causal relation in a FCM all we have to do is select positive or negative causality and a weight, in RBFCM we have to define one fuzzy *If..Then* rule for each mbf in the input concept. We can reduce this complexity with the implementation of **macros** to define simple monotonic symmetric causal reasoning. For example, the macro *A Affects_Much_Negatively B* (which in Figure 1 is expressed as FCR--), could be associated to a set of *n* fuzzy rules (*n* = number of mbf of *A*) that express that a small positive change in A causes a large negative change in B. For example:

"**If** A Decreases_Very_Few **then** B Increases_Few"
:::
"**If** A Increases **then** B Decreases_Much"
:::
"**If** A Increases_Much **then** B Decreases_Very Much"

On a FCM this macro would be the equivalent of a weight *-0.7* (for instance). These macros can also be used to define other types of more or less common causal relations like, for example, exponential causality. Common Macros include +,++,+++,-,--,---,exp+, exp-…

It should be noted though, that if we want to use all RBFCM modelling capabilities, then we have to define the relation rule by rule.

4.4 Probabilistic Relations

In a causal relation we are certain that in our model the effect always happens. Probability should be used in CM when we are not 100% sure that a cause causes a certain effect. Fuzzy Probabilistic Causal Relations are used in RB-FCM when the effect has a certain probability of happening. For example, Figure 3 models what happens to traffic accidents when there is ice in the road. It is not guaranteed that the number of accidents will increase or decrease with the alterations in ice conditions - since people might drive carefully if they are prepared for the conditions - although it is most certain that more ice causes more accidents. To model this situation, the example shows a probability of 85% that the change in road condition causes a change in the number of accidents[1].

[1] The model does not intend to be realistic, it is just an example…

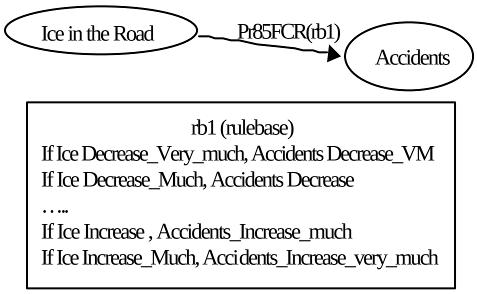

Figure 3 - Probabilistic Causal Relation

These kinds of situations can be easily modeled by several existing pure fuzzy probabilistic systems. However, in RB-FCM, probability relations are only one of several kinds of relations, and it is necessary to find a way to link the probabilistic events and the other fuzzy rule bases. Since we are dealing with the simulation of a system and we are trying to predict its evolution, one simple way to include the probabilistic relation is to generate a random number for each probabilistic relation in each iteration. If that number is lower than the probability given to the occurrence of the relation, then the value of the concept is actualized. Otherwise, no effect resulted from the cause. In order to analyze the effect of the probabilistic relation in the system, it is necessary to perform a set of simulations. A statistic analysis of the comparison of the final state or cycle of states of the system in each simulation, allow us to verify the importance of the probabilistic relation in the system.

Note that sometimes probability is confused as causality, as in the sentence “If the road is icy, the probability of accidents increases”. Here we are dealing with a causal relation in which the concepts are Ice_in_the_Road and Probability_of_Accidents (instead of Accidents).

4.5 Time dependent probabilistic

Time dependent probabilistic relations (TPrxFCR), are probabilistic relations in whom the probability of the occurrence of the effect is not a constant, but a function of time (see 5.). These relations allow the modeling of certain events that are more or less probable as time goes by - for example, the resistance of a city in siege.

4.6 Possibilistic

Possibilistic relations (PsR), are used when we want to simulate alternative complementary scenarios. Figure 4 shows an example with 2 different possibilities.

When the system includes different possibilities, and the event that trigger those possibilities occur, one separate simulation is launched for each possibility. The influence of each possibility in our system can then be studied by the comparison of each simulation. Note that due to feedback loops, the triggering event can occur again in each simulation, causing new simulations to be launched. This can lead to a dangerous combinatorial explosion in the number of simulations preventing any conclusions regarding the system, unless the system converges to a cycle of states that includes the triggering event – in this case we can have mechanisms that identify the loop and stop the launch of new scenarios.

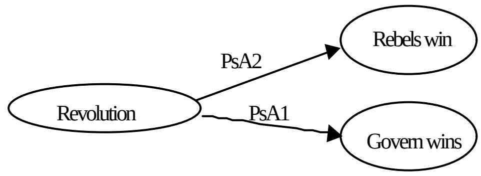

Figure 4 - Possibilistic Relations

Possibilistic relations can also be used to study alternatives when one has to make a decision.

4.7 Possibilistic/Probabilistic

Possibilistic/Probabilistic relations (PsPrR) define different alternatives (possibilities) with complementary probabilities, and are implemented in way similar to PrR.

4.8 Similarity

While trying to model a cognitive map of the negotiation process, we found the need to create a relation that could model the process of agreement. We found that if the concepts representing the proposal of both involved parts were enough similar, then an agreement could be reached. Several similarity fuzzy measures have been proposed, like [15][16], which can be easily applied in this context. A simpler approach could be the use of the alpha-cut of the intersection of the fuzzy representation of both concepts. In the negotiation process, each part could define an alpha-cut level over which he would agree on the proposal.

4.9 Level<>Change

As we saw in 3., the same entity can be represented in the system by either its absolute value (Level) or its change (Change) in the previous iteration. In order to maintain coherence it is necessary to define a direct relation between Levels and corresponding Changes. Depending on the system, these relations might be unidirectional or bi-directional (L->C, C->L, L<>C). If the Level is only used as a “source”, i.e., no relations lead to the Level (there are no FIR trying to impose a value to the concept), only C->L are necessary. If on the contrary, the Level is only used as a “target”, only L->C are necessary.

Whenever the Level or the Change assume new values, the LC relations update the value of the corresponding Change or Level. The CL relations might be of several kinds:

Whenever the involved concept is hard or impossible to quantify (like an abstract concept), the CL relation might be done recurring to classic fuzzy rule base inference by the use of rules like “If Change is Increase_Much and Level is Med, Then Level is Very_High”. The main obstacle to this kind of CL relation is the necessarily high number of rules, since Changes can usually have 10 mbf and Levels 5 or 7.

If possible, it is preferable to implement a FuzzyMath CL relation, in which the same variation in a Change concept has the same effect on the corresponding Level no matter its current value. The FuzzyMath CL relation rule base would contain rules like: "If Change is Increase_Very_Few then Level is (Level + IVF)", in which IVF would be a constant fuzzy number.

Finally it is possible that we can define a pure crisp CL relation in certain concepts, using the deffuzified values of the Change and Level.

It is necessary to guarantee or prevent by adequate measures, the cases where both Level and Change are the target of influence and causal relations simultaneously. This could result in inconsistencies in the system. It is preferable to avoid these situations, but it is possible to include rules in the CL rule base to deal with them.

5. RB-FCM and Time in Systems Dynamics

Time is essential in the study of systems dynamics (SD). When we are dealing with quantitative SD like [5], time is explicitly expressed in the mathematical equations used to describe the relations between concepts. However, in qualitative SD, time must be implicitly expressed when we are building the rule bases. Without imposing this implicit timing knowledge it is impossible to guarantee a minimally acceptable simulation. The following guidelines should be followed when building the model of a system.

It is important to choose a base time interval (btime) to represent each iteration (1 day, 2 days, 1 week, 1 month, etc.). When defining the relations, btime must always be implicitly present. The rules that represent causal effects are tightly dependent on btime: If btime is 1 day, then rules expressing the effect of a Level in Inflation would most certainly indicate a very small change. If however btime is 1 year then the rules would have to indicate a larger variation. Btime is obviously dependent on the system we are representing and on the time gap we are hoping to analyze. However smaller btimes usually need more detailed and complex rule bases.

In RB-FCM it is possible to include time intervals other than btime. Some concepts or relations only make sense at larger intervals. For example, some economic indicators only are published every 3 month or every year. Therefore, each concept and relation in RB-FCM can be associated with a time interval that indicates at which iterations should those concepts and/or relations be used. More details can be found in [12]

6. Conclusions and Future Developments

RB-FCM are proposed as a tool to design, implement and simulate the dynamics of qualitative systems. Mechanisms to implement several kinds of relations and concepts, and guidelines to include time in qualitative systems descriptions are presented in this work. Future developments in this work include the development of user-friendly software, a syntax to define relations and a compiler that translates them into a map. We are also trying to apply RB-FCM to different and diverse fields which in order to try to find new kinds of necessary relations.

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