The Fuzzy Cognitive Maps: History, Applications and Challengers

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Outline

- Introduction
- Theoretical Bases
- Extensions
    - Learning procedures,
    - FCM hierarchical model,
    - Dynamical FCM, etc.)
- Some Applications in different domains
    - Social systems,
    - Control systems,
    - Multiagent systems, etc.).
- Some FCM Tools
- Challengers

Introduction

- Decision makers and policy proponents face serious difficulties when approaching significant dynamic systems.

- Formulating a mathematical model may be difficult, costly, even impossible.
  - Developing the model typically requires a great deal of effort and specialized knowledge.
  - Systems involving significant feedback propagates casual influences and complicated chains may be nonlinear, in which case a quantitative model may not be possible.
  - Numerical data may be hard to come by or uncertain.

- A qualitative approach can be sufficient. If the results of this preliminary model are promising, the time and effort to pursue a quantitative model can be justified.

Introduction

•What is a "cognitive map" (CM)?

• A CM is an effort to simulate the behavior of a black box system through cause and effect relationships.

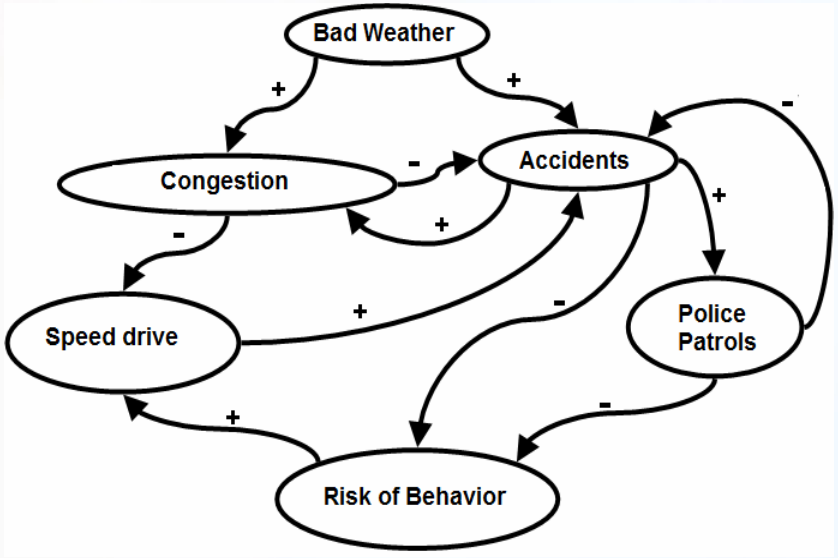
•At first, Axelord used cognitive maps as a formal way of representing social scientific knowledge and modeling decision making in social and political system.

•A CM can avoid many of the knowledge-extraction problems which are usually posed by rule based systems. This form of knowledge presentation presents problems such as:

- •Impossibility of have dynamic behavior;
- •Impossibility of have performance in real time, and so for

Introduction

- Relevant concepts in a domain are chosen. These concepts represent observable state within the domain. Variable concepts are represented by nodes in a directed graph. The value of a node reflects the degree to which the concept is active in the system at a particular time. This value is a function of the sum of all incoming edges multiplied and the value of the originating concept at the immediately preceding state.
- Relationships: They indicate as the concepts are affected with other concepts. The graph's edges are the casual influences between the concepts.



	Bad Weather	Conges -tion	Acci- dents	Speed	Police	Behavior
Bad Weather	0	+1	+1	0	0	0
Congestion	0	0	-1	-1	0	0
Accidents	0	+1	0	0	+1	-1
Speed	0	0	+1	0	0	0
Police	0	0	-1	0	0	-1
Behavior	0	0	0	+1	0	0

Different representations of a Cognitive Map:

a Graph Representation and the Connection Matrix.

Introduction

- The state of a given node is obtained from the prior states of all causal nodes. These states are multiplied by the edge weight between the two nodes. The sum of these products is taken as the input to a threshold function.

- In this way, we define the activation level of a concept:

A_i^{new} = S(∑nj=1 A_j^{new} E_{ji})+ A_i^{old}

- There are different threshold functions: bivalent, trivalent, and logistic signal.

$$S_i(x_i) = 0, x_i \le 0$$
$$S_i(x_i) = 1, x_i > 0$$

Bivalent

$$S_i(x_i) = -1, x_i \le -0.5$$
$$S_i(x_i) = 0, -0.5 < x_i < 0.5$$
$$S_i(x_i) = 1, x_i \ge 0.5$$

Trivalent

$$S_i(x_i) = \frac{1}{1 + e^{-cx_i}}$$

Logistic signal

Introduction

•A discrete time simulation is performed by iteratively applying the summation and threshold process to the state vector of the graph.

•The simulation halts if an equilibrium state is reached.

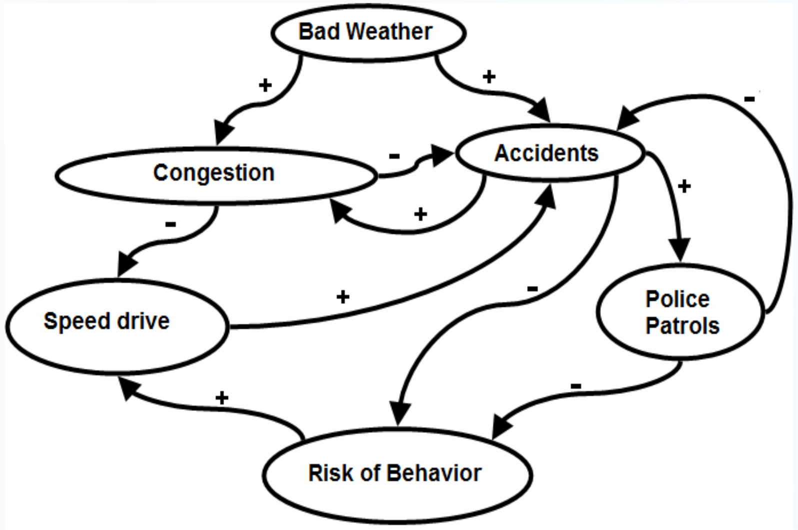
•The execution of a CM follows the following algorithm:

1 - To obtain an initial state C (0)

2- While the system does not converge

a- To calculate the present state by means of $C_m(i+1) = S\left[\sum_{k=1}^{N} w_{m,k} \cdot C_k(i)\right]$

b- to go to step 2



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Speed	0	0	+1	0	0	0
Police	0	0	-1	0	0	-1
Behavior	0	0	0	+1	0	0

Accidents(i+1)= S[1 * BadWeather(i) -1 * Congestion(i)
+1 * Speed drive (i) -1 * Police Patrols(i)]

Theoretical Bases

Theoretical Bases

Fuzzy Cognitive Maps (FCM)

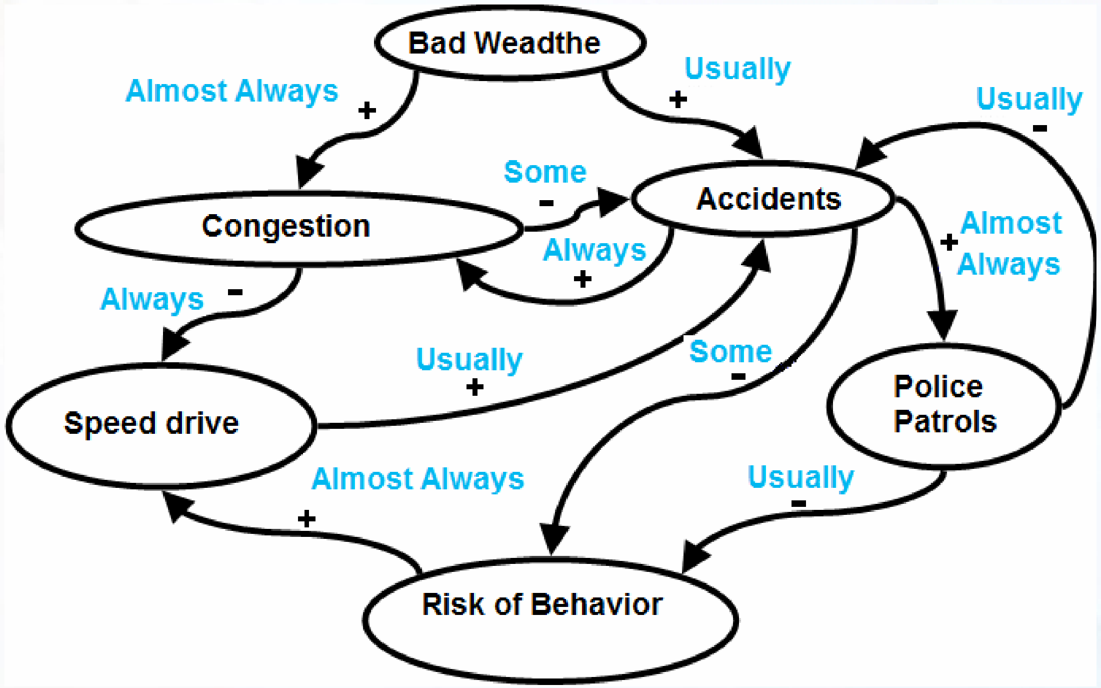
•They are proposed by Kosko to represent the causal relationship between concepts and analyze inference patterns.

•They are the fusion of the advances of the Fuzzy Logic, Artificial Neural Networks and Cognitive Maps theories. FCMs combine the robust properties of fuzzy logic and neural networks.

•FCMs represent knowledge in a symbolic manner and relate states, processes, policies, events, values and inputs in an analogous manner.

•The fuzzy indicates that FCMs are often comprised of concepts that can be represented as fuzzy sets, the causal relationships between the concepts can be fuzzy implications, or the threshold function applied to the weighted sums can be fuzzy in nature.

Theoretical Bases



Efect over the i concept vía causal relationship

$$I_l\left(C_i, C_j\right) = \min\left\{w_{p,p+1} : \left(p, p+1\right) \in \left(i, k_1^l, k_2^l, \ldots, k_n^l, j\right)\right\}$$

Total Efect

$$\mathrm{T}\left(\mathrm{C}_{\mathrm{i}}, \mathrm{C}_{\mathrm{j}}\right) = \max \mathrm{I}_{\mathrm{l}}\left(\mathrm{C}_{\mathrm{i}}, \mathrm{C}_{\mathrm{j}}\right)$$

Theoretical Bases

$$P = \{\text{some} \le \text{usually} \le \text{always}\}$$

$$I_1(C_1, C_5) = \min\{\text{always, usually}\} = \text{usually}$$

$$I_2(C_1, C_5) = \min\{\text{usually, some, some}\} = \text{some}$$

$$T(C_1, C_5) = \max\{I_1, I_2, I_3\} = \max\{\text{usually, some}\} = \text{usually}$$

Some Extensions

Some Extensions

1. Parallel FCMs
2. The second one focuses on the design of learning algorithms
3. FCM based on random neural networks.
4. FCM Hierarchical System
5. Rule Based Fuzzy Cognitive Map

Extensions

- There are two main approaches to develop Fuzzy Cognitive Maps
  - Deductive modeling (i.e., they use an expert knowledge from the domain of application)
  - Inductive modeling (i.e., they use learning algorithms to establish FCMs from historical data) .

- *Deductive modeling* is based on expert knowledge from the area of application.
  - Models are developed manually based on best knowledge with a group of experts.
  - This approach usually consists of the following three steps:

  1. Identification of key domain issues or concepts.
  2. Identification of causal relations among these concepts.
  3. Estimation of causal relations strengths.

- *Inductive modeling.* Automated and semi-automated approaches designed for learning FCM connection matrix, and their strength (weights) based on historical data.
  - In this case, the expert knowledge is substituted by a set of historical data and a computational procedure

Deductive modeling

- The development of a FCM often occurs within a group context. An expert draws a FCM according to his experience. The assumption is that combining incomplete, conflict opinions of different experts may cancel out the effect of oversight, ignorance and prejudice.

- The group matrix (E^G) could be computed as:

$$E_{ji}^{G} = \max_{t}\{E_{ji}^{t}\} \quad \text{or} \quad E_{ji}^{G} = \sum_{t=1}^{NE} b_t E_{ji}^{t} \quad \forall \text{ t=1 to number of experts (NE).}$$

Where E_{ji}^{t} is the opinion of the expert *t* about the causal relationship among C_j and C_i, and b_i is the expert's opinion credibility weight.

- In a distributed system, a FCM is constructed for each subsystem. Then all FCM are combined in one augmented matrix E for the whole system.

$$E = \begin{bmatrix} E_1 & 0 & 0 & 0 \\ 0 & E_2 & 0 & 0 \\ 0 & 0 & E_3 & 0 \\ 0 & 0 & 0 & E_4 \end{bmatrix}$$

- Using Historical Data

$$M = \{D_1, D_2, \ldots, D_m\} = \{[d_1^{\,1}, d_1^{\,2}, \ldots, d_1^{\,n}], [d_2^{\,1}, d_2^{\,2}, \ldots, d_2^{\,n}], \ldots, [d_m^{\,1}, d_m^{\,2}, \ldots, d_m^{\,n}]\}$$

$$W_{ji}^{t} = W_{ji}^{t-1} + \eta \cdot \left(\frac{\Delta d_j^{t} \cdot \Delta d_i^{t}}{\Delta^{+} d_j^{t} \cdot \Delta^{+} d_i^{t}} \right)$$

where

$$\Delta d_j^t = d_j^t - d_j^{t-1}$$

$$\Delta d_i^t = d_i^t - d_i^{t-1}$$

$$\Delta^+ d_j^t = d_j^t + d_j^{t-1}$$

$$\Delta^+ d_i^t = d_i^t + d_i^{t-1}$$

Learning Algorithms

- The main goal of learning in FCMs is to determine the values of the weights of the FCM that produce a desired behavior of the system.
- In general, two main learning paradigms are used: adaptive, and evolutionary algorithms
- The adaptive algorithms are often based on the idea borrowed from the theory of artificial neural networks that is called the differential Hebbian learning law.
  - The general idea is: if two neurons on the opposite side of a connection are activated simultaneously, then the weight of that connection is increased; else they are activated asynchronously, then the weight is decreased.
  - The idea of Hebbian learning has been adapted by Kosko to FCMs.

$$w_{ij}(t+1) = w_{ij}(t) + \gamma(t)\left[\Delta a_i \Delta a_j - w_{ij}(t)\right]$$

- The coefficient: $\gamma(t) = 0.1[1 - t/1]q$ changes over time. The constant parameter q should ensure that the value of the weight does not fall beyond [-1, 1]
- Let us notice that important features of equation:
  - The learned weights depend on the temporal order of raw data,
  - the change in activation of cause concept (with subscript i) is assumed as a necessary requirement of the change of the respective weight

Learning Algorithms

- The evolutionary learning approach: the initially random weights of FCM stored in W are optimized by the iterative evolutionary process.
- In this case, the relationships between concepts learned during the evolution depend on the applied fitness function designed by an expert for the considered task.

	Bad Weather	Conges-tion	Acci-dents	Speed	Police	Behavior
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Congestion	0	0	-1	-1	0	0
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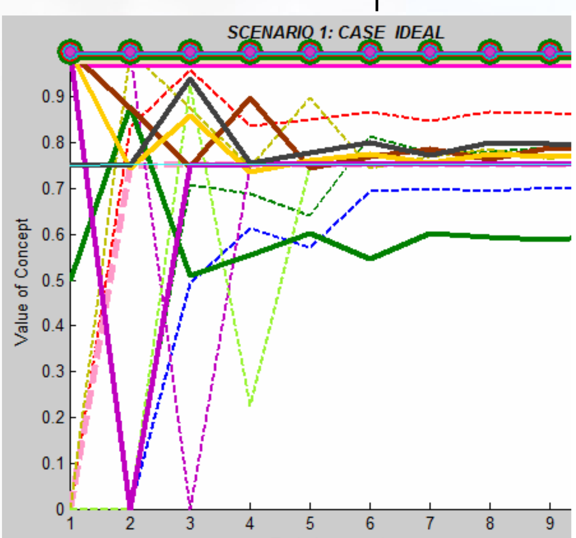
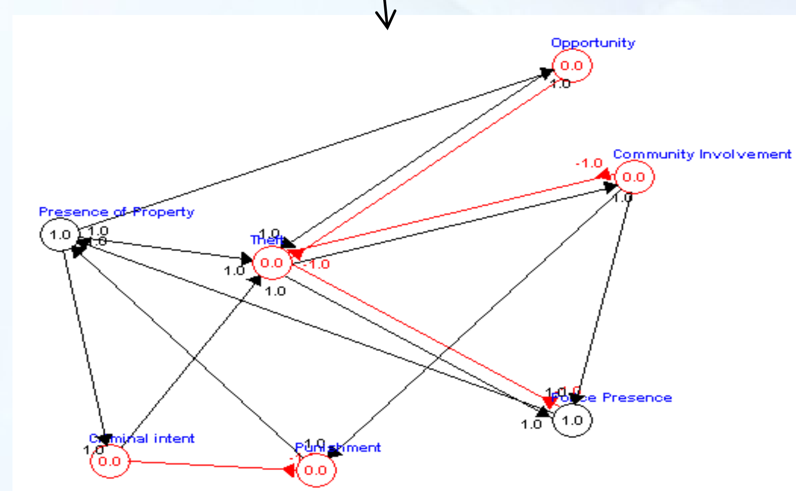
Speed	0	0	+1	0	0	0
Police	0	0	-1	0	0	-1
Behavior	0	0	0	+1	0	0

Learning Module (GA)

Connection Matrix



Input Data



Candidate FCM

Learning Algorithms

Some other approaches:

1. **The Balanced Differential Algorithm to learn FCMs from data.**
2. **Backpropagation learning procedure to enable the gradual learning of symbolic representations**
3. **Parallel Genetic Learning of Fuzzy Cognitive Maps**
4. **Multi-Objective Evolutionary Fuzzy Cognitive Maps for Decision Support**
5. **Fuzzy Cognitive Maps Learning through Swarm Intelligence (The Particle Swarm Optimization Algorithm)**

The desired behavior of the system is characterized by values of the output concepts that lie within prespecified bounds, determined by the experts.

The user is interested in restricting the values of these output concepts in strict bounds, which are crucial for the proper operation of the modeled system.

Thus, the main goal is to detect a weight matrix W that leads the FCM to a steady state at which, the output concepts lie in their corresponding bounds.

The latter is attained by imposing constraints on the potential values assumed by weights.

Learning Algorithms

To do this, the following objective function is considered :

$$F(W) = \sum_{t=1}^{m} H(Q_{out_t}^{min}) \left| Q_{out_t}^{min} \right| + \sum_{t=1}^{m} H(Q_{out_t}^{max}) \left| Q_{out_t}^{max} \right|$$

Where H is the well–known Heaviside function, i.e. H(x) = 0, if x < 0, and H(x) = 1 otherwise; $Q_{out_t}^{min} = A_{out_t}^{min} - A_{out_t}$ and A_{out_t} are the steady state values of the output concepts that are obtained using the weight matrix W.

•Obviously, the global minimizers of the objective function F are weight matrices that lead the FCM to a desired steady state.

•The application of PSO for the minimization of the objective function F, starts with an initialization phase, where a swarm of weight matrices is generated randomly, and it is evaluated using F.

•Then, Vi(t + 1) = Xi(t) + Vi(t) + c(Pg(t) − Xi(t)) and Xi(t + 1) = Xi(t) + Vi(t + 1) are used to evolve the swarm.

Assume g to be the index of the particle that attained either the best position of the whole swarm.

•When a weight configuration that globally minimizes F is reached, the algorithm stops.

Rule Based Fuzzy Cognitive Map

•It is proposed as an evolution of Fuzzy Causal Maps (FCM) that allow a more complete representation of cognition, since relations other than monotonic causality are made possible.

•It presents a method to implement Fuzzy Causal Relationship.

•It consists of nodes (representing concepts), and fuzzy rule bases (which relate and link concepts). Each concept contains several membership functions.

"If the *variable 1 (input* variable) has *feature A Then the variable 2 (output variable)* has *feature B.*

•Any kind of relation that can be represented by fuzzy rules is allowed: opposition, similarity, implication, traditional fuzzy reasoning, etc.

•The concept can be represented either by a crisp or fuzzy value.

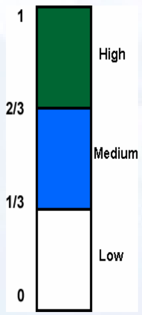
•The set of rules obviously depend on the amount of membership functions and intended meaning.

Rule Based Fuzzy Cognitive Map

•Other FCM have been recently proposed based on adjusting functions . The relationships are established using an adjustment function based on rules

•For instance, it is assumed that the state of the concepts in a modeled system can be located in three zones :

- ✓A concept has a *high state* (between 2/3 and 1) when it works correctly and contributes substantially with the functioning of the modeled system.
- ✓A concept has a *medium state* (between 1/3 and 2/3) when its functioning must be validated and its contributions to the systems' functioning is not so substantial, and so on.



•The relationship values are taken from the following table:
The following rules could be built under these three states

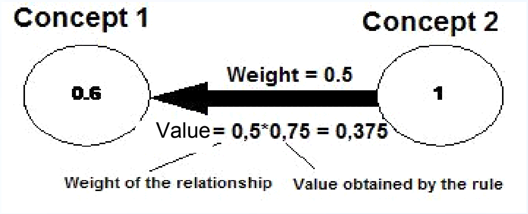
- ✓If the preceding concept is **High** and the consequent one is also **High** then the relationship is **Complete$^+$**(1.0).
- ✓If the preceding concept is **High** and the consequent one is **Medium** then the relationship is **High$^+$** (0.75).

Value	Linguistic Variable
1.00	Complete$^+$
0.75	High$^+$
0.50	Medium$^+$
0.25	Low$^+$
0.00	Null
-0.25	Low$^-$
-0.50	Medium$^-$
-0.75	High$^-$
-1.00	Complete$^-$

Rule Based Fuzzy Cognitive Map

•These rules would be used to determine all the relationships between the different concepts, but each one would have a weight defined by the experts that could vary from relationship to relationship.

•For example, if we take the relationship between Concept 1 and Concept 2, and it is assumed that Concept 2 has a High state and that Concept 1 has a Medium state, then the relationship resulting from the rules would yield a high^{+} value (that is, 0.75). This value is multiplied by the weight of the relationship and if we assume that the weight of this relationship is 0.5, then the final result of the relationship would be 0.375.



•The fuzzy rule for each interconnection is evaluated using fuzzy reasoning and the inferred fuzzy weight is defuzzified using the Center of Gravity defuzzification method

FCM based on random neural networks

- FCM based on the random neural network model called the Random Fuzzy Cognitive Map (RFCM).

- This model is based on the probability of activation of the neurons/concepts in the network.

- To calculate the state of a neuron on the RFCM (the probability of activation of a given concept C_j), the following expression is used:

$$q(j) = \min\{\lambda^+(j), \max\{r(j), \lambda^-(j)\}\}$$

where $\lambda^+(j) = \max_{i=1,n}\{\min\{q(i), W^+(i,j)\}\}$ $\lambda^-(j) = \max_{i=1,n}\{\min\{q(i), W^-(i,j)\}\}$

In addition, the fire rate is $r(j) = \max_{i=1,n}\{W^+(i,j), W^-(i,j)\}$

- The general procedure of the RFCM is the following:

1. Design the configuration of the FCM.
2. Call the Initialization phase
3. Call the Simulation phase

FCM based on random neural networks

•The RFCM can be used like an associative memory. In this way, when we present a pattern to the network, the network will iterate until generate an output close to the information keeps.

•The input is an initial state S_0= {$s_{1, \dots}$, s_n}, such as $q^0(1)=s_1$, …, $q^0(n)=s_1$ and $s_i \in [0, 1]$ (set of initial values of the concepts ($S_0=Q^0$)).

•The output $Q^m=\{q^m(1), \dots, q^m(n)\}$is the prediction of the RFCM such as *m* is the number of the iteration when the system converge.

•During this phase, the RFCM is trained with a reinforced learning procedure.

$$W_{ij}^{t} = W_{ij}^{t-1} + \eta\left(\Delta q_i^t \Delta q_j^t\right)$$

where Δq_i^t is the change in the i^{th} concept's activation value among iterations *t* and *t-1*.

•The algorithm of this phase is:

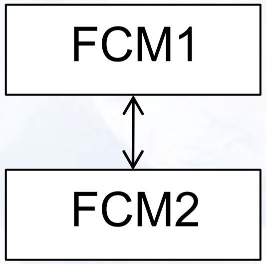
1. Read input state Q^0
2. Until system convergence

    Calculate q(i)

    Update W^t

FCM Hierarchical System

•For the case of two levels, the macroalgorithm is:



1. Values of the concepts on lower level
2. Interface (fuzzy rules)
3. New values of upper concepts
4. If accept values of upper concepts then final decision
5. Else update concepts on lower level (Interface (fuzzy rules))

•The interface is a set of fuzzy rules. An example of the fuzzy rules:

- If value of OUT-LC1 is very high values then value of UC2 is very high.

•In the same way, we can define a set of fuzzy rules for the interface from the upper-level toward the lower-level

Some Applications in different domains

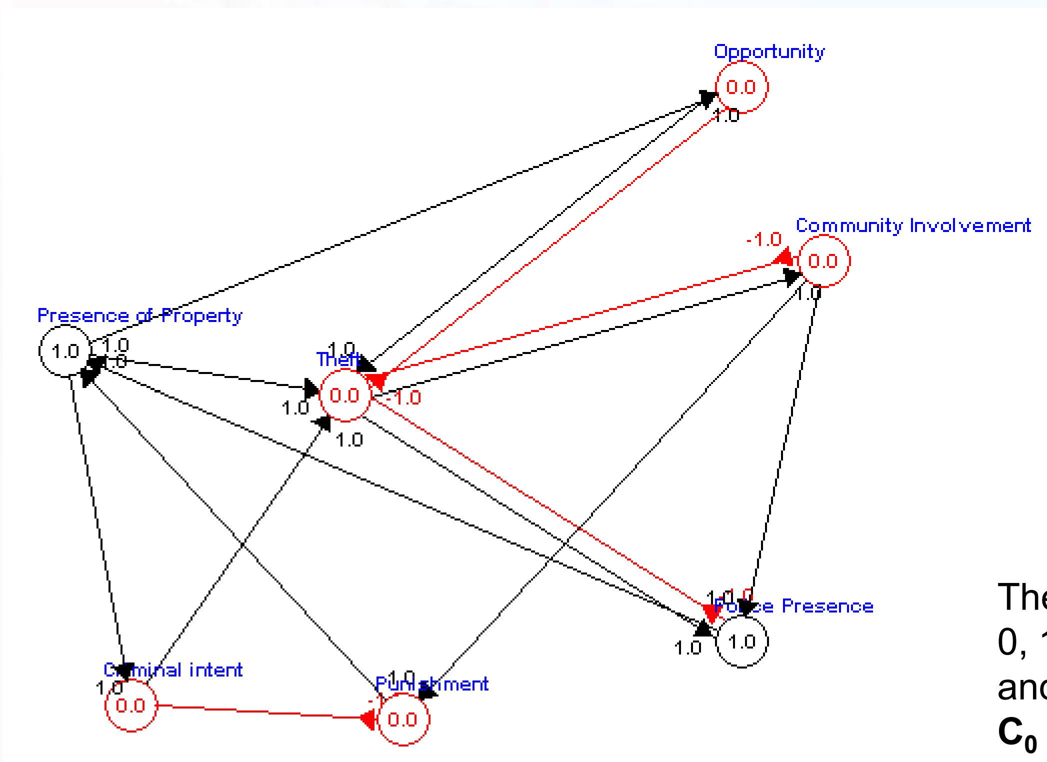
Some Applications in different domains

•FCMs have gradually emerged as a powerful modelling and simulation technique applicable to numerous research and application fields: administrative sciences, game theory, information analysis, popular political developments, electrical circuits analysis, cooperative man–machines, distributed group-decision support, etc.

1. FCMs have been used to model and support a plant control system, to model the supervisor of a control system or of manufacturing systems, etc.
2. FCMs have been used in multiagents system to represent different types of knowledge in a group of agents, to support the building of group consensus,
3. FCM has been used to structure virtual worlds that change with time .
4. In business FCMs can be used for product planning
5. In computer assisted learning FCMs enable computers to check, whether students understand their lessons

Social Systems

This map attempts to model property theft in a community.



C_0 = (0, 0, 1, 0, 0, 1, 0)

We then obtain the discrete time series

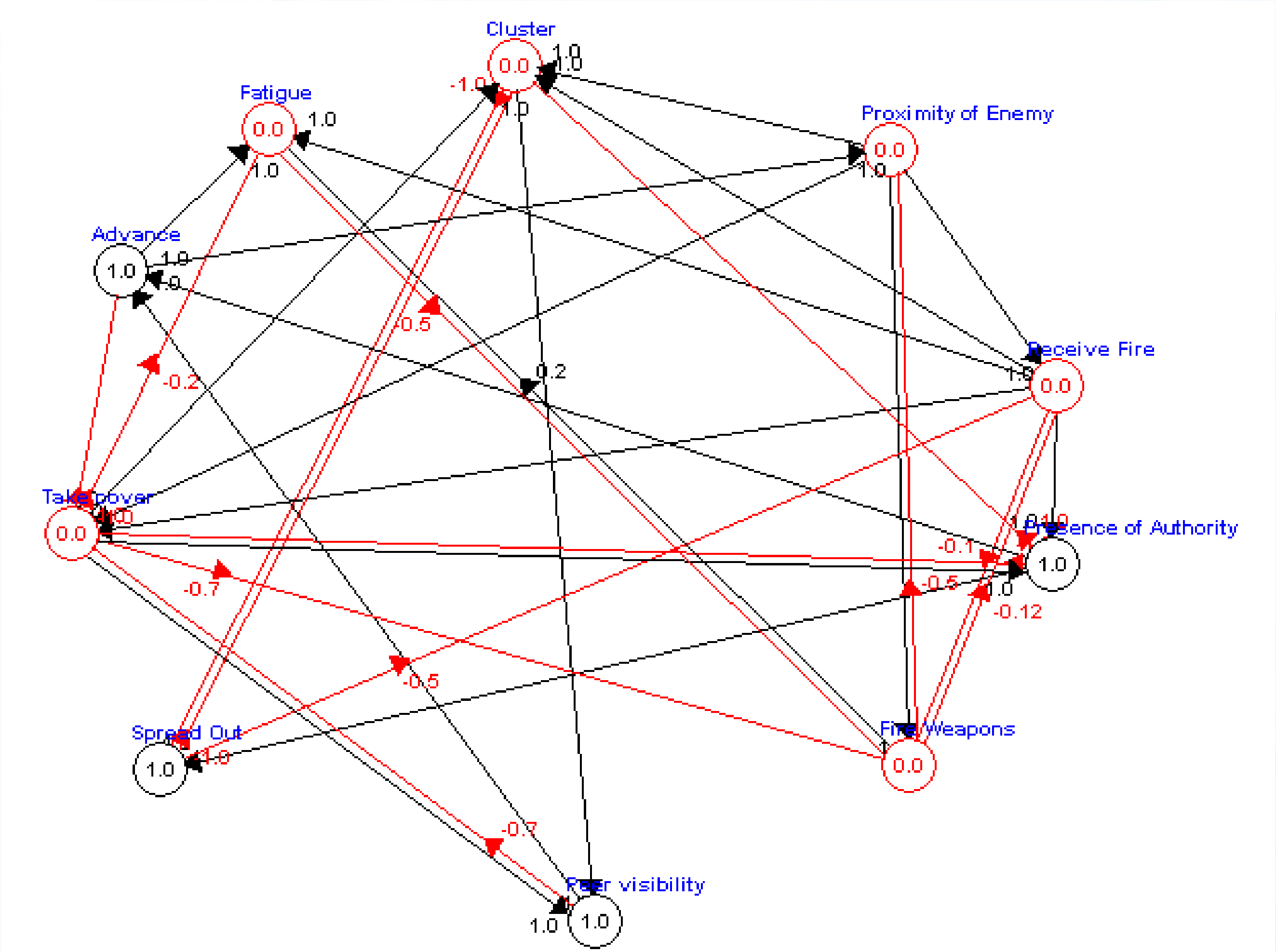
C_0 = (0, 0, 1, 0, 0, 1, 0)
C_1 = (1, 0, 0, 0, 1, 1, 0)
C_2 = (1, 0, 0, 0, 1, 0, 1)
C_3 = (0, 1, 1, 0, 0, 0, 1)
C_4 = (0, 1, 1, 1, 0, 1, 0)
C_5 = (1, 0, 1, 1, 0, 1, 0)
C_6 = (1, 0, 0, 0, 0, 1, 1)
C_7 = (0, 1, 1, 0, 1, 0, 1)

The range of allowable state values is now [-1, 0, 1], i.e., we can have negative, indifferent, and positive concept activation.

C_0 = (-1, -1, 1, -1, -1, 1, -1)
…
C_6 = (1, -1, -1, -1, 0, 1, 1)
C_7 = (0, 1, 0, -1, 1, -1, 1)
C_8 = (-1, 1, 1, 1, 0, -1, -1)
C_9 = (0, -1, 0, 1, -1, 1, -1)

Virtual Worlds

An FCM modeling a squad of soldiers in combat.



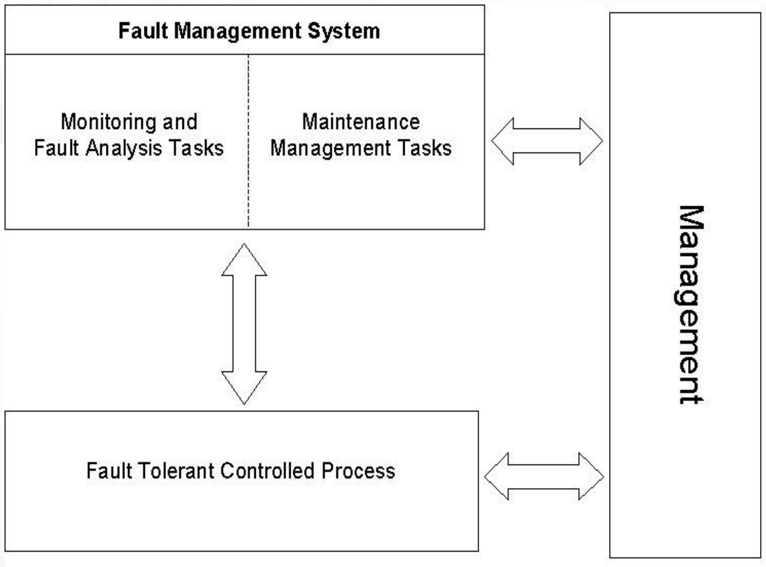
Jose Aguilar

From the initial state vector
C0 = (0, 0, 0, 1, 0, 1, 1, 0, 1, 0)

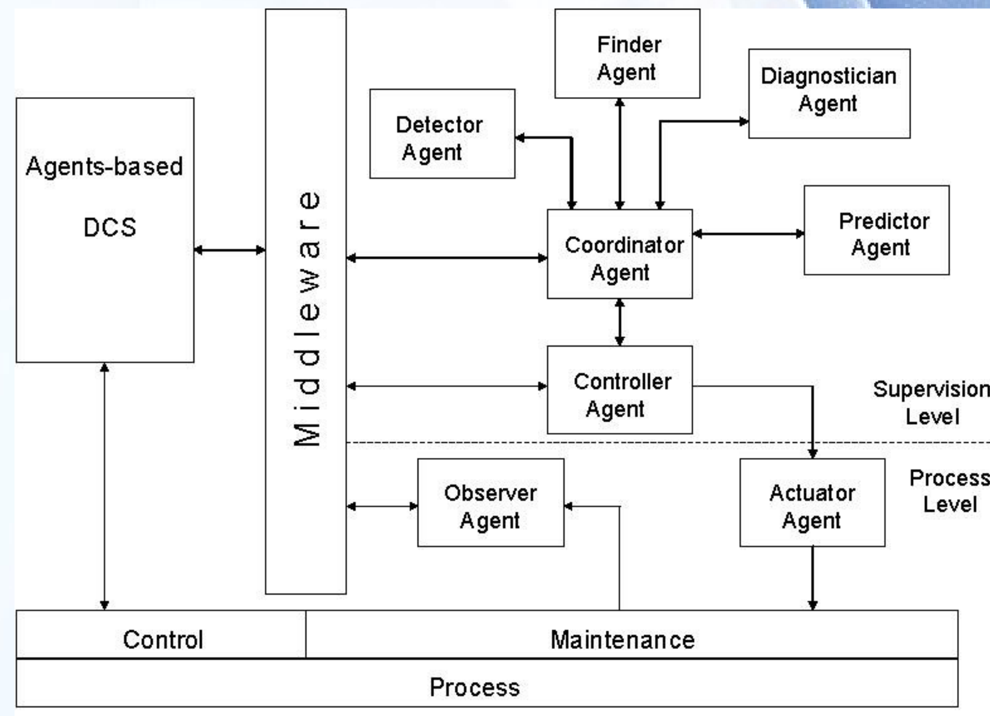
That is, the squad advancing in good order under the control of the squad leader, and no external influences, we reach the five step limit cycle

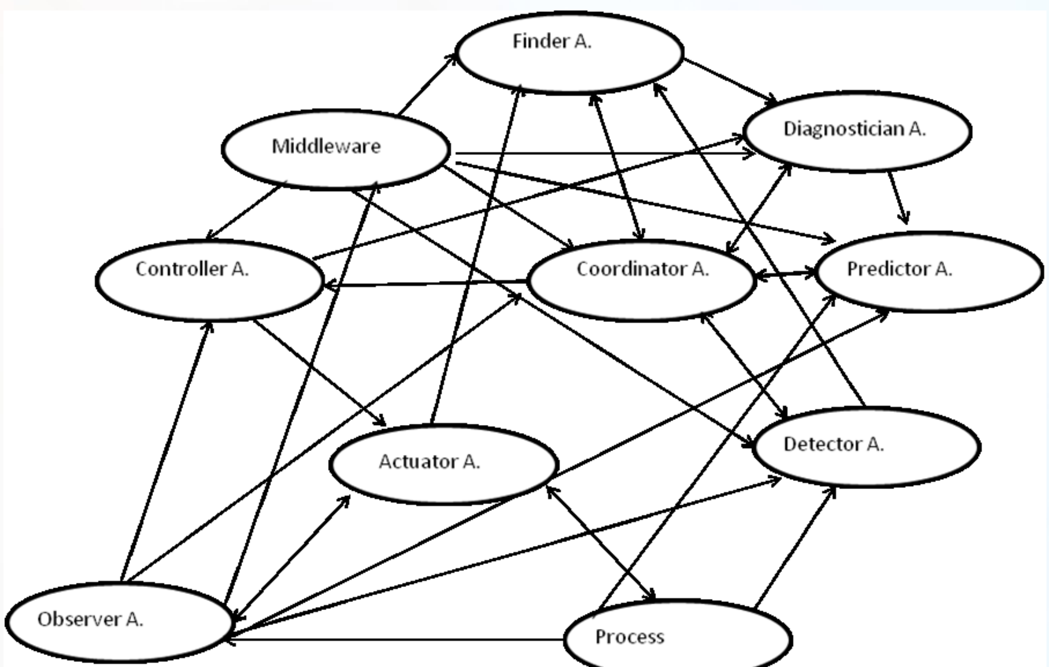
C7 = (1, 1, 1, 1, 0, 1, 0, 1, 0, 1)
C8 = (1, 0, 1, 1, 0, 1, 0, 1, 1, 0)
C9 = (1, 1, 0, 1, 0, 1, 0, 0, 1, 1)
C10 = (0, 1, 1, 0, 1, 1, 0, 0, 1, 1)
C11 = (1, 1, 1, 1, 1, 0, 0, 1, 1, 1)

Fault management system



MAS





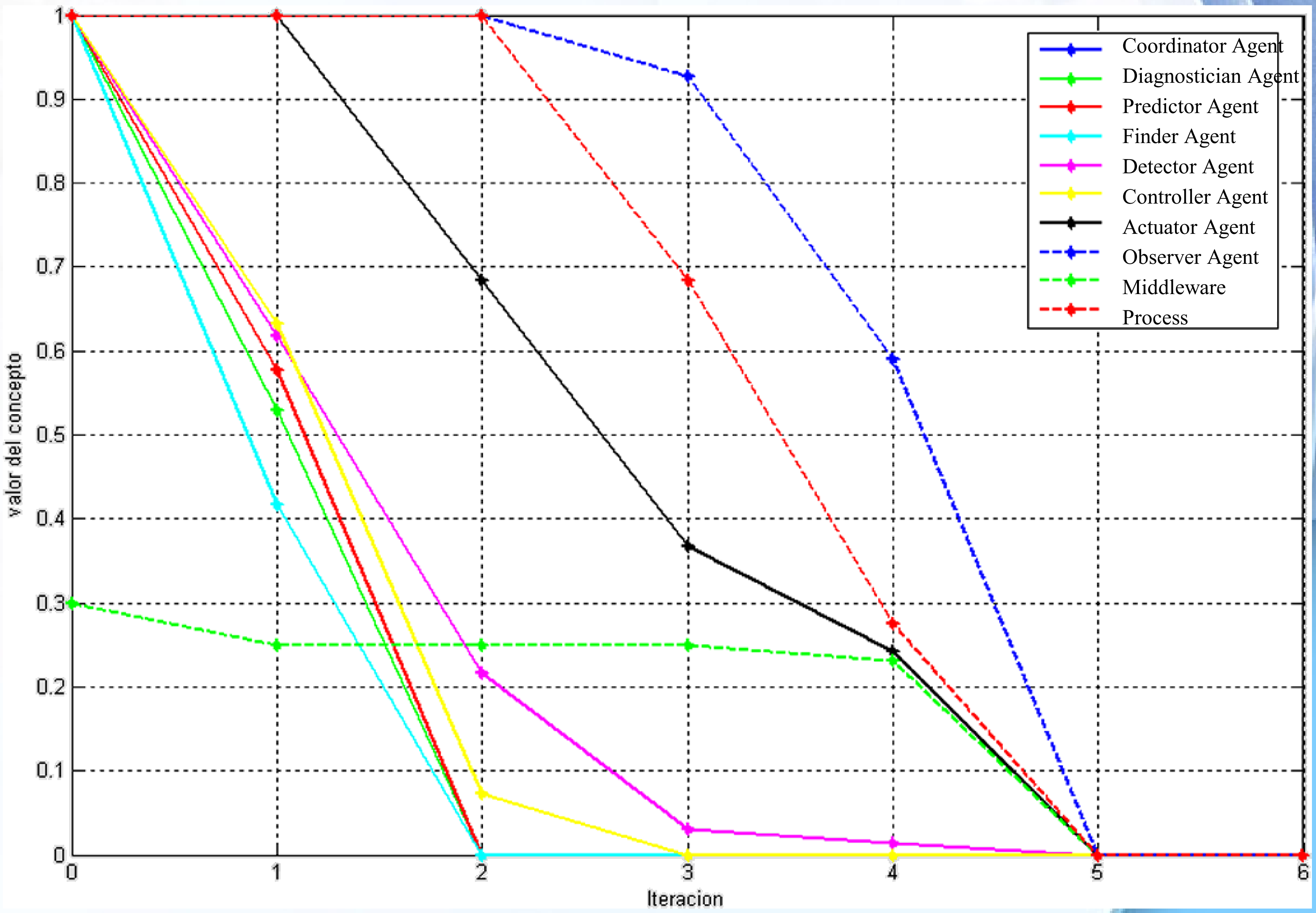
FCM

Fault management system

- If the antecedent concept is High and the consequent one is High then the relationship is complete+ (1.0)
- If the antecedent concept is High and the consequent one is Medium then the relationship is high+ (0.75)
- If the antecedent concept is High and the consequent one is low then the relationship is low+ (0.25)
- If the antecedent concept is Medium and the consequent one is High then the relationship is high+ (0.75)
- If the antecedent concept is Medium and the consequent one is Medium then the relationship is average (- 0.5)
- If the antecedent concept is Medium and the consequent one is Low then the relationship is high (- 0.75)
- If the antecedent concept is Low and the consequent one is High then the relationship is high (- 0.75)
- If the antecedent concept is Low and the consequent one is Medium then the relationship is average (- 0.5)
- If the antecedent concept is Low and the consequent one is Low then the relationship is complete (- 1.0)

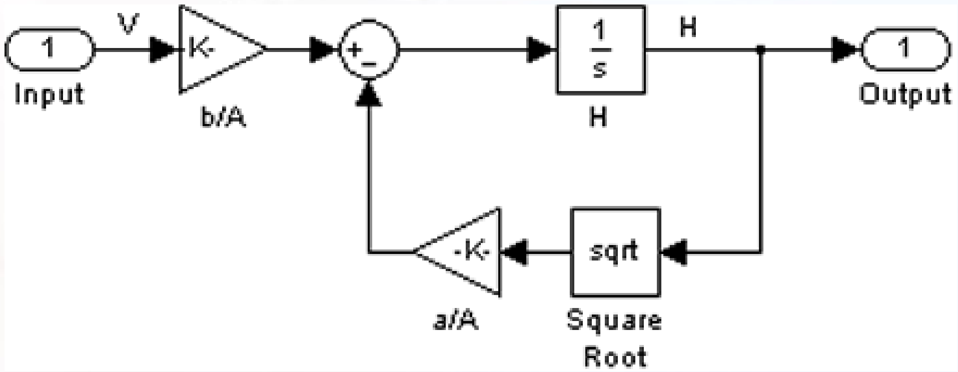
Fault management system

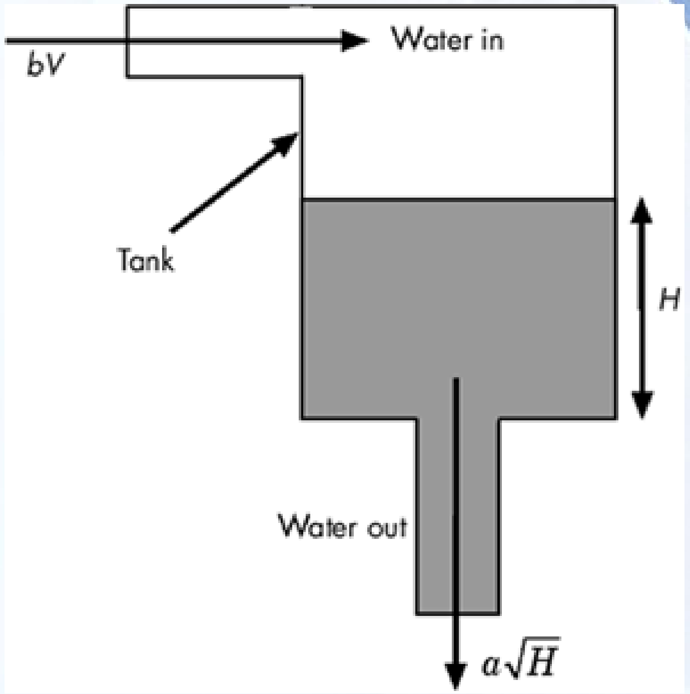
Evolution of the agents with a Middleware with value of 0.3



Dynamic Equations

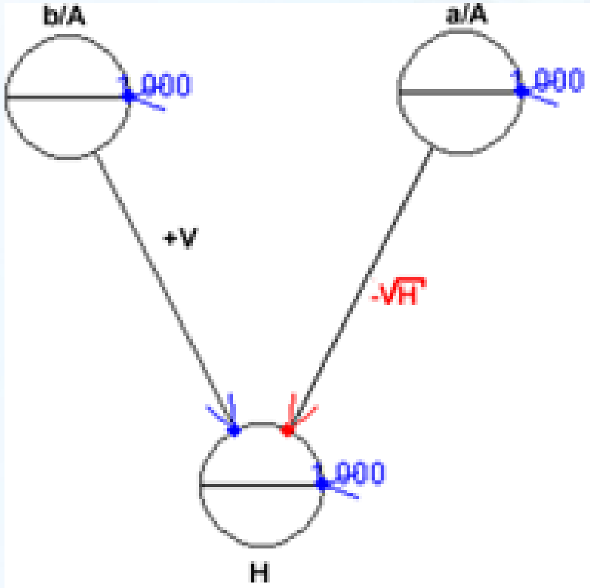
$$\frac{dVol}{dt} = A\frac{dH}{dt} = b \cdot V - a \cdot \sqrt{H}$$





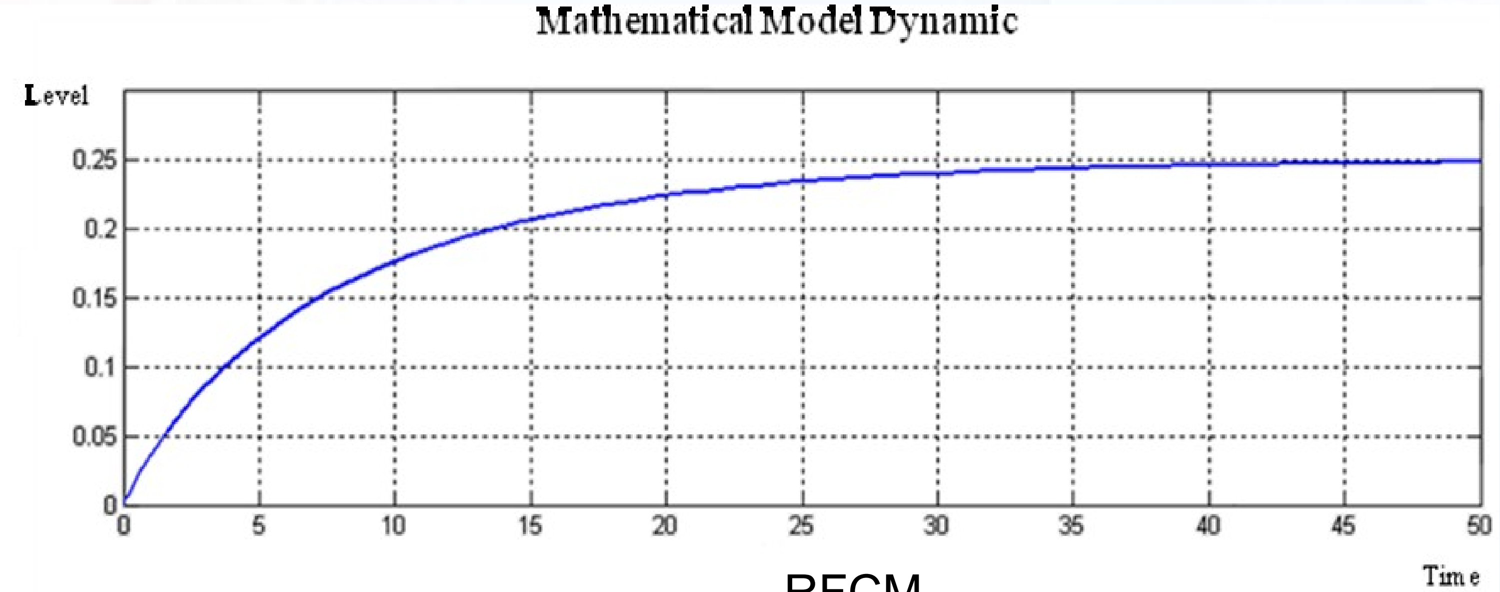
The dynamic relationships are defined of the following form:

•The relationship between the constant of input stream and the Level is given by the value of the applied voltage to pump V.
•The relationship between the constant of the exit flow and the level is given by the squared root of the value of the concept that represents the level.

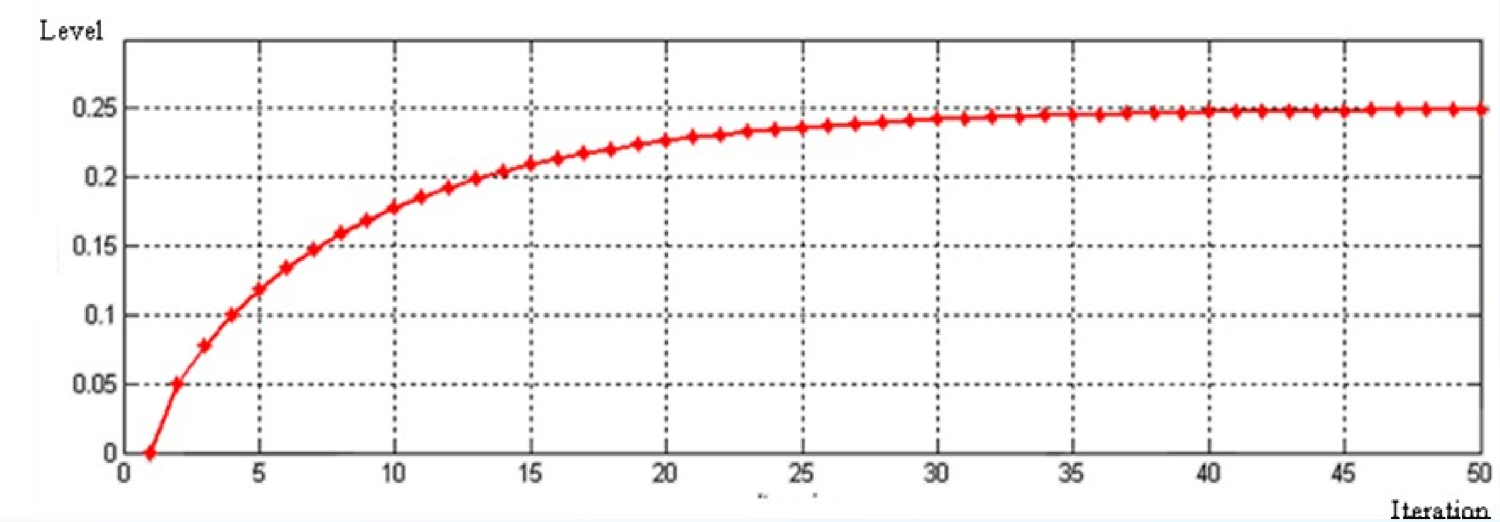


Dynamic Equations

The dynamic for V= 0,2

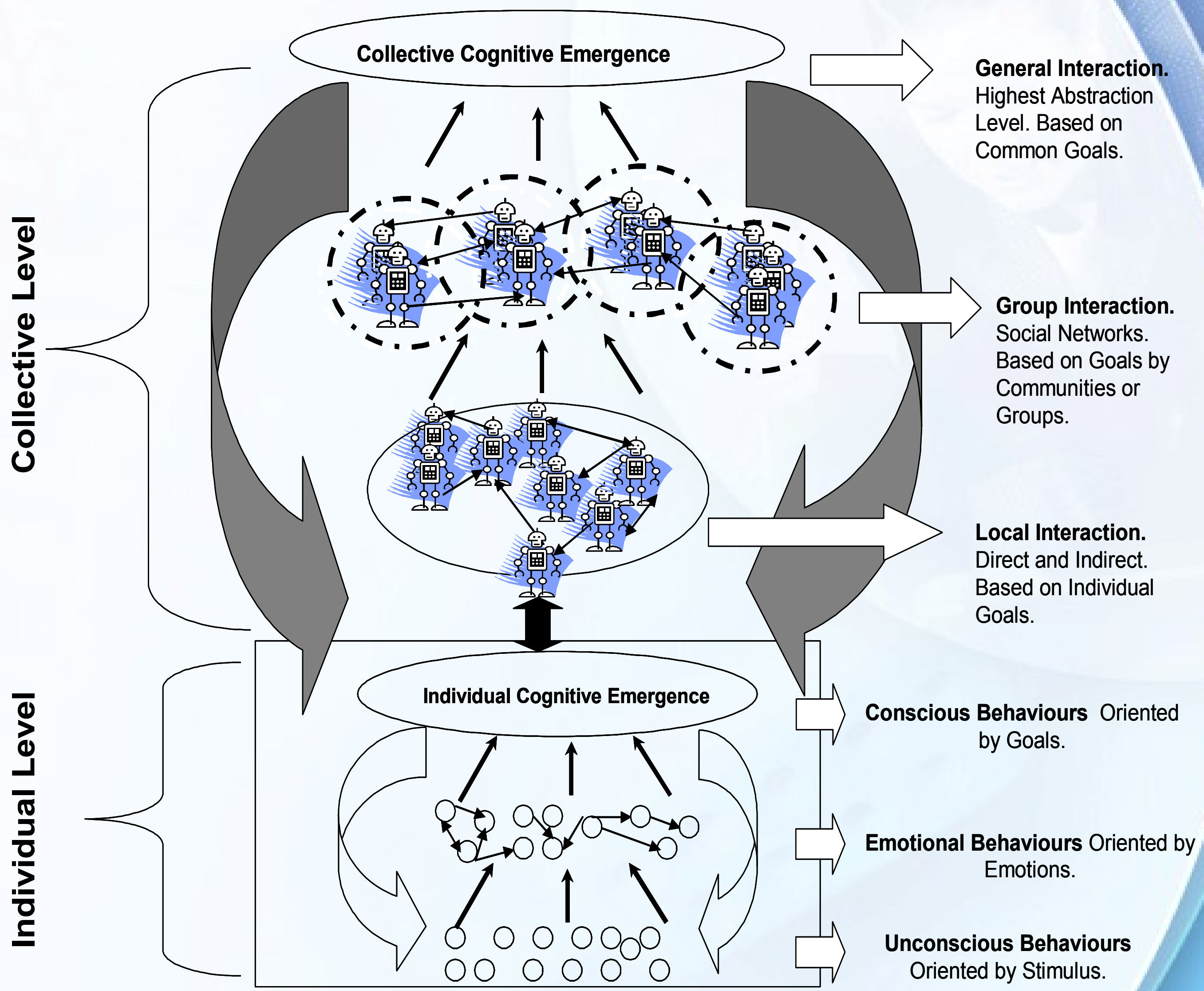


RFCM



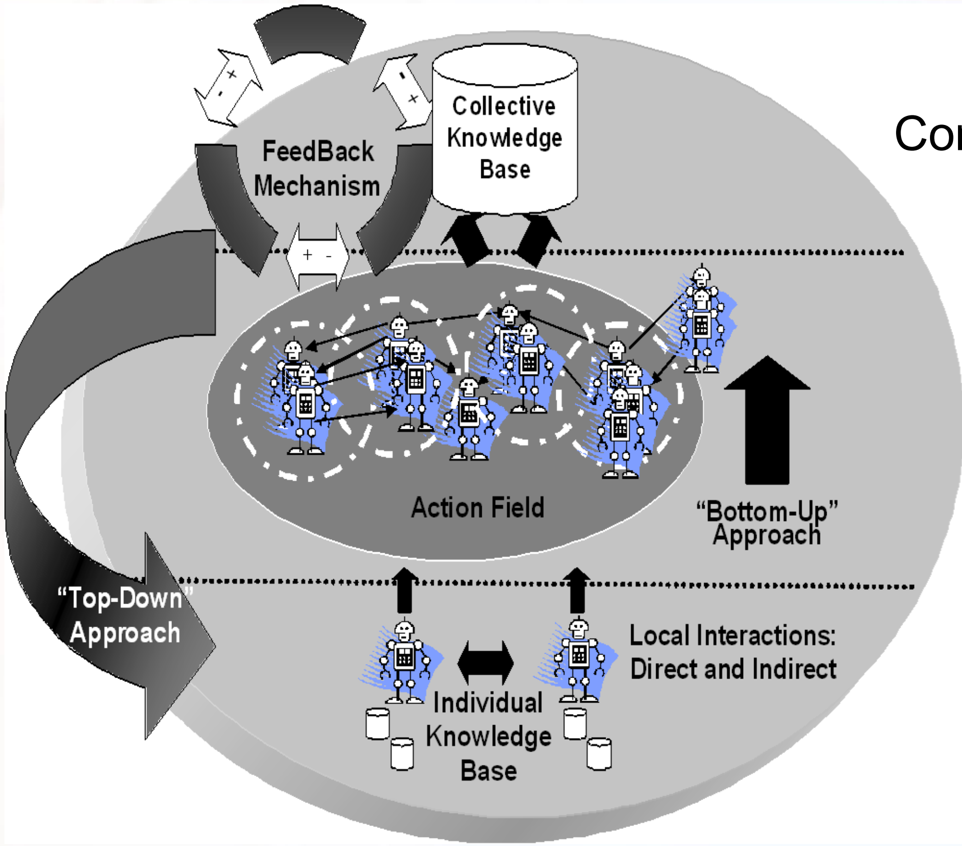
MA-SOS

To design a Multiagent Architecture for <u>Self-Organizing systems</u> i.e *systems which produces a state of a community of agents where agents' actions mutually adapt in a coherent way through behaviors that emerge from local interactions among them and from the changes that take place in the environment*

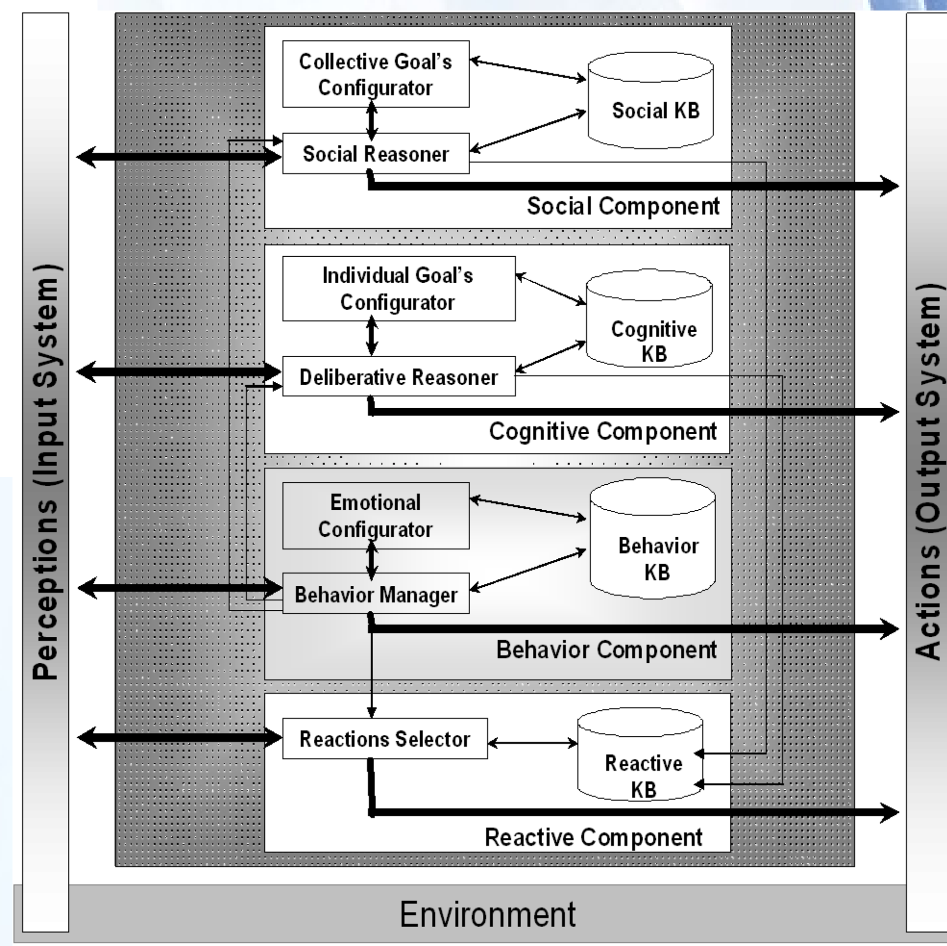


MA-SOS

Components at Collective Level

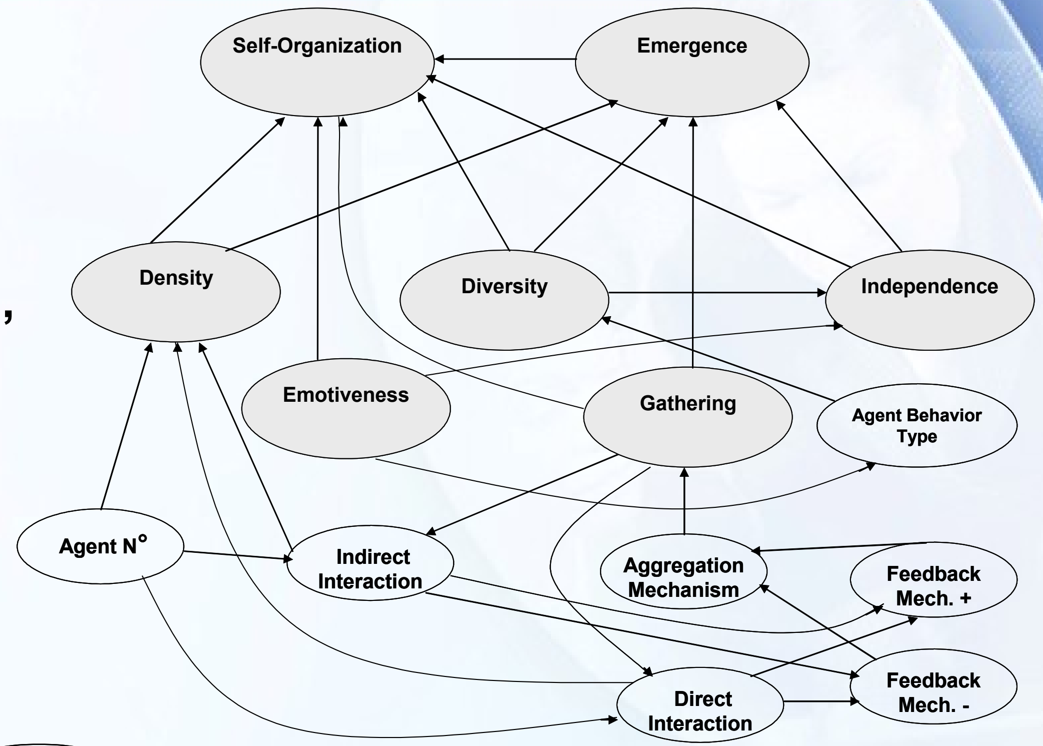


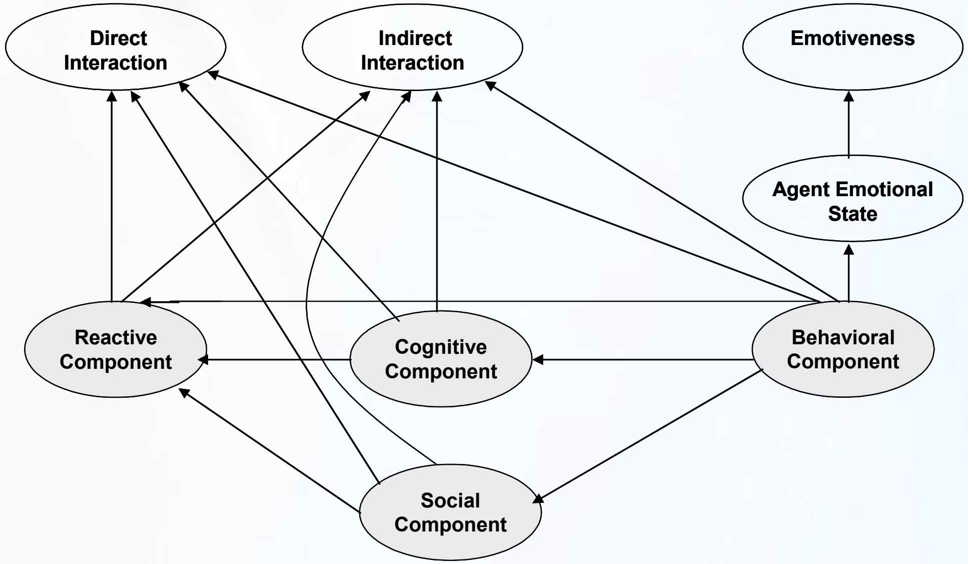
Components at Individual Level



FCM for MASOS

FCM for Concepts linked to self-organized, emerging properties

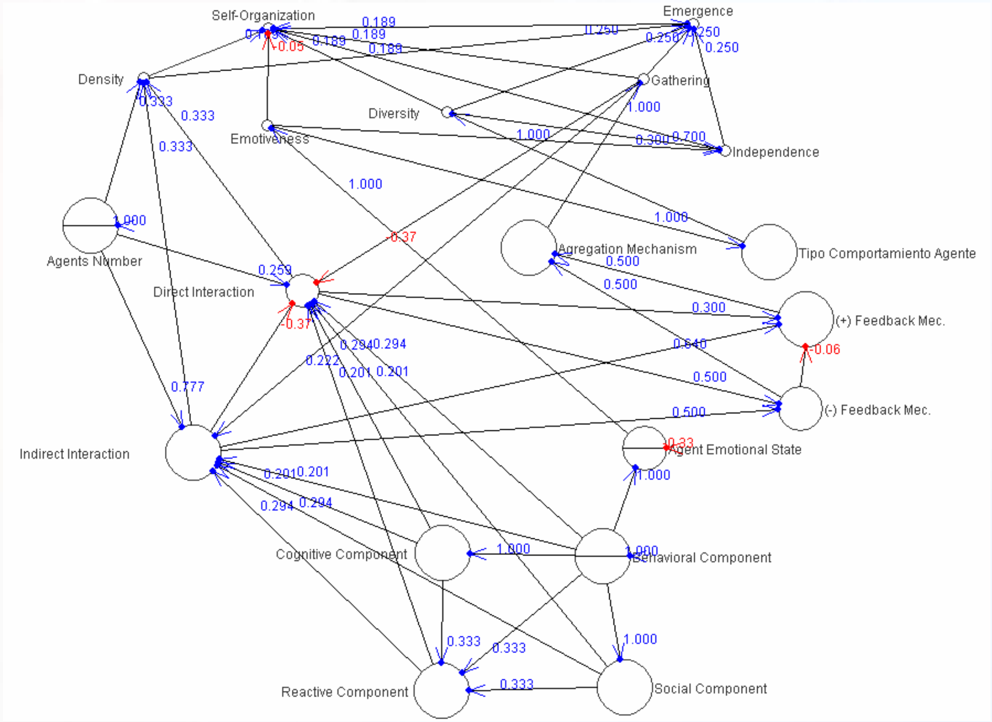




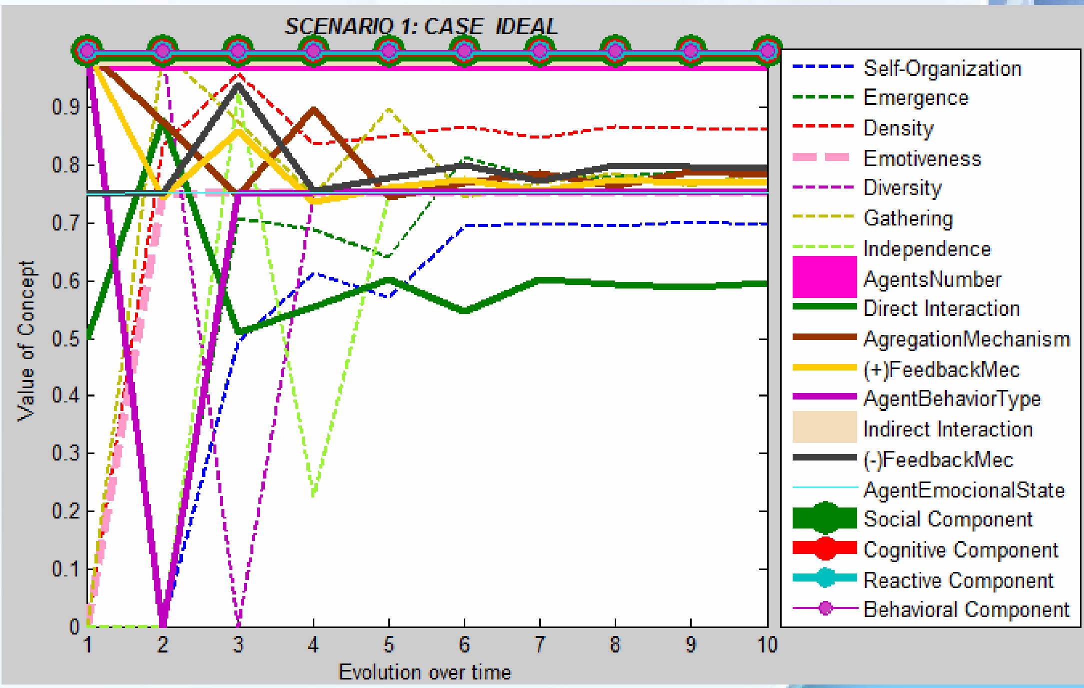
FCM for Architectonic Concepts

FCM for MASOS

- **Study Case: Free Software Development based on communities using the Bazaar Paradigm**



Scenario 1: Ideal Case for the LKDC

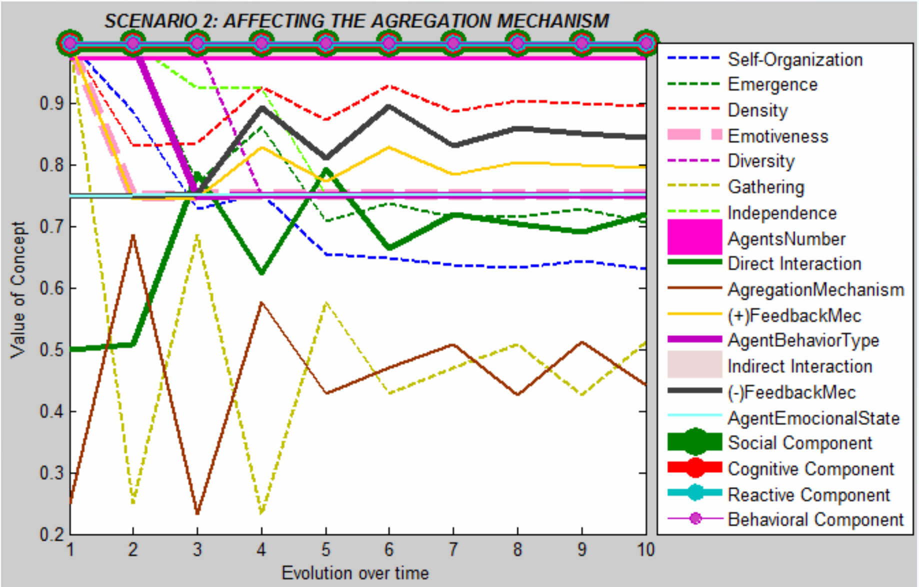


FCM for MASOS

- **Study Case: Free Software Development based on communities using the Bazaar Paradigm**

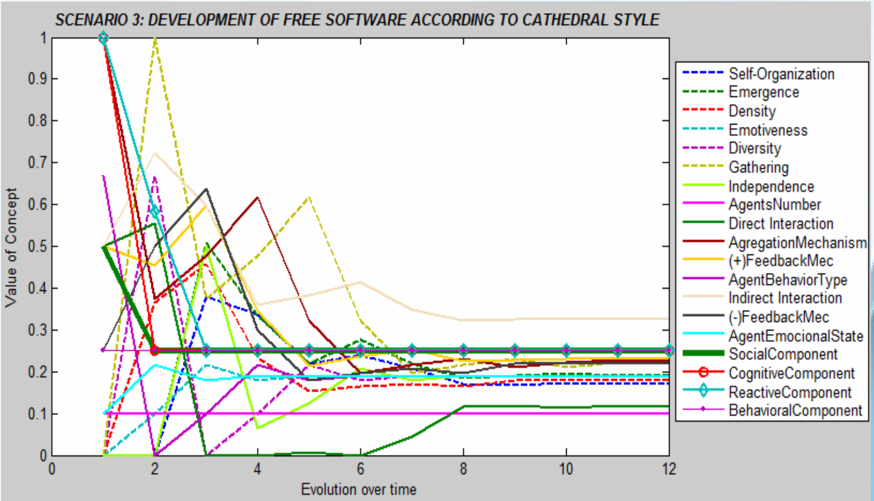
Scenario 2: Affecting the Aggregation Mechanism.

In this case, the initial value of the aggregation concept will begin in 0.25, which represents a decrease in its performance of approximately 68 % with respect to its ideal value for the LKDC.



Scenario 3: Free Software Development through Cathedral Style

Number of agents 0.1 the direct interactions 0.5, and indirect 0.5. (reduced group of participants)and quality of the social component is diminished (0.5) and the emotional state (0.1) (establishment of a style of leadership and coordination)



Some FCM Tools

Several tools based on FCMs have been developed for different problems.

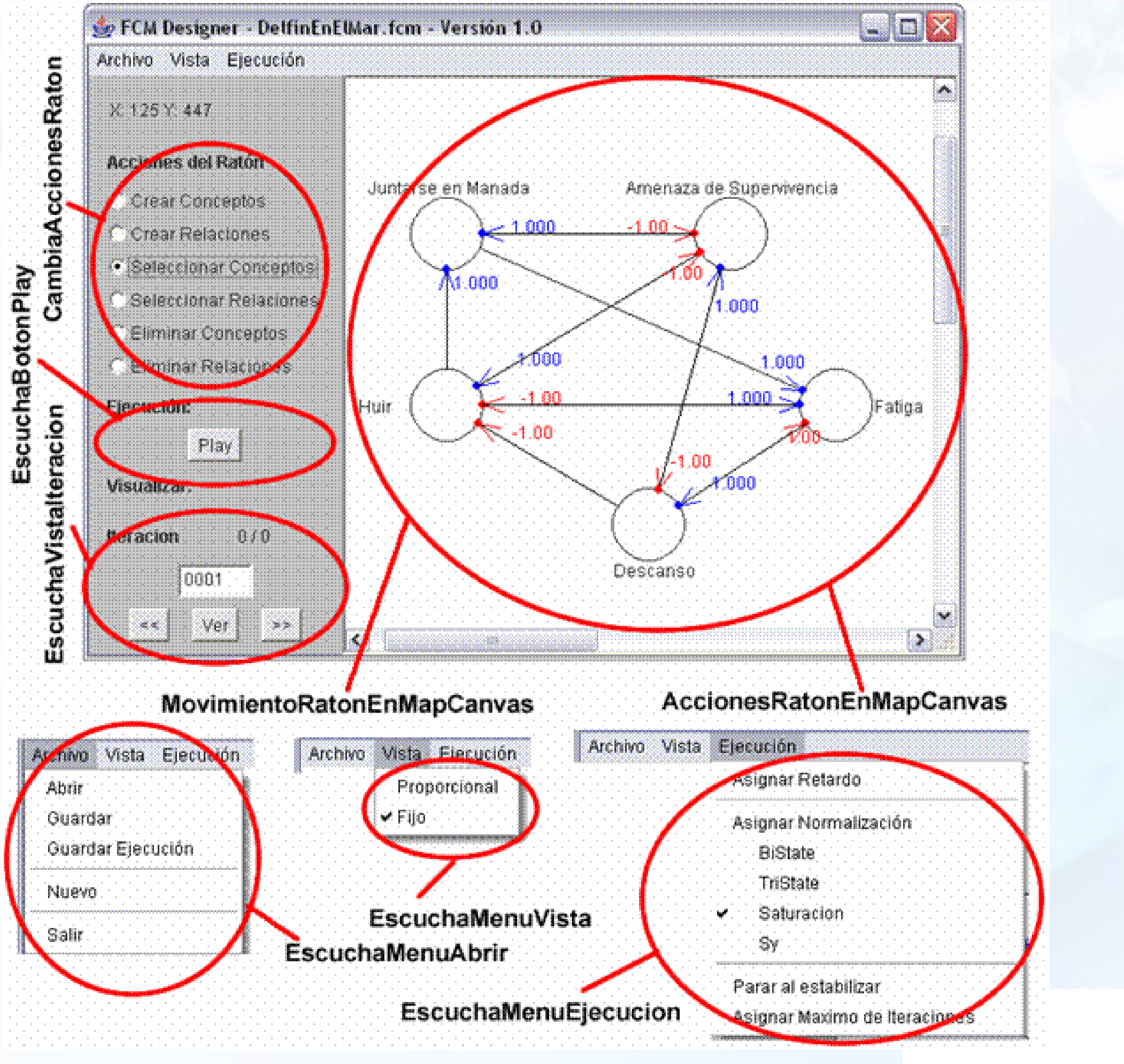
- The FCModeler tool displays the known using interactive graph visualization. The system also models pathway interactions and the effects of assumptions using a FCM-based modelling tool.
  http://orion.math.iastate.edu/danwell/GET/GETFC.html

- CARTES CAUSALES DANS LES SYSTÈMES MULTIAGENTS (Multiagent-Causal Maps.1.0
  Directeur : Brahim Chaib-draa ,
  http://www.damas.ift.ulaval.ca/~fabiola/recherche/

- Amit Roy has written an FCM tool as Python CGI.
  http://www.artecs.net/cgi-bin/FCM.cgi

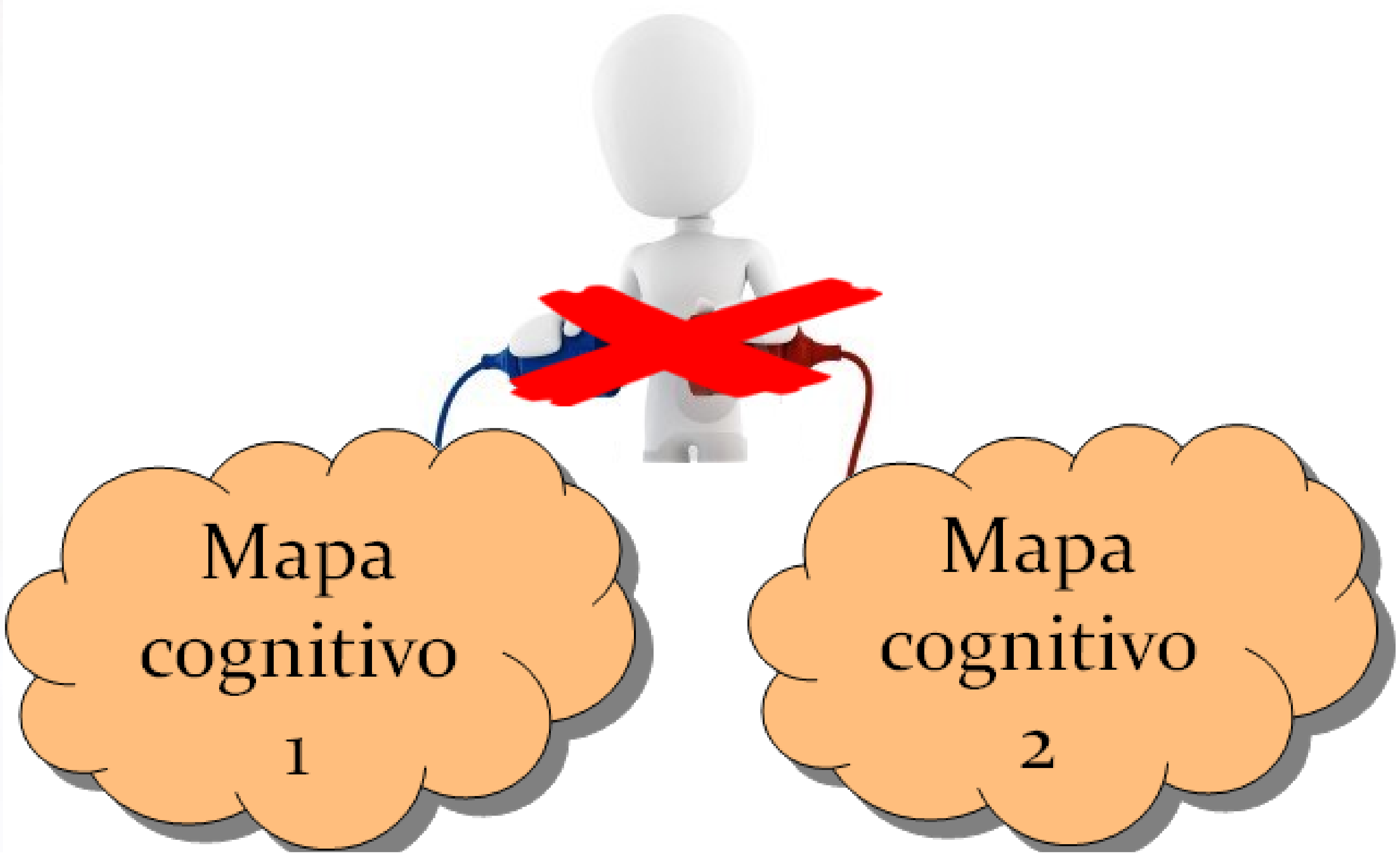
- The fuzzy cognitive map applet.
  http://www.ochoadeaspuru.com/fuzcogmap/software.php

FCM Designer

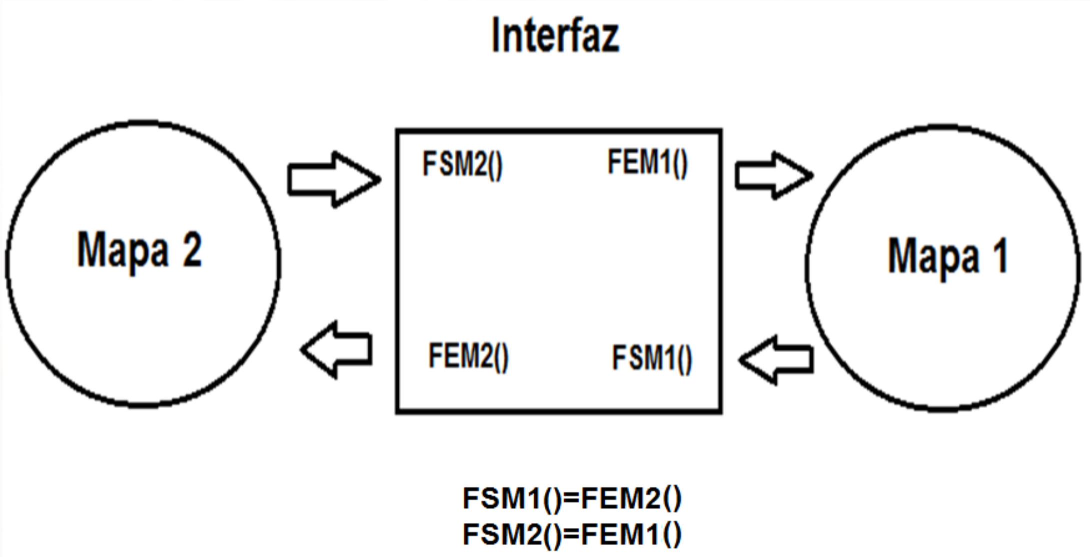


Extensión a FCM Designer: Mapas Cognitivos
Para el Caso Multicapa

Problemática



Diseño y Funcionamiento



- **Tipos de Reglas**
- **Conexión**
- **Ecuaciones**
- **Difusas**

Nueva Ecuación

Función anterior $$C_m(i+1) = S\left[\sum_{k-1}^{N} w_{m,k} \cdot C_k(i)\right]$$

Función Nueva $$C_m(i+1) = S\left[\sum_{k-1}^{N} w_{m,k} \cdot C_k(i)\right] + F(mp);$$

Donde:

$\boldsymbol{C_m}$ ***(i+1)*** = Indica el valor del concepto en la siguiente iteración.

N = Indica el numero de conceptos.

$\mathbf{w_{n,k}}$ = Indica el valor de la relación causal que imparte el concepto $\mathbf{C_k}$ sobre el concepto $\mathbf{C_m}$.

S(y) = Función utilizada para normalizar el valor del concepto.

F(mp) = función de entrada del mapa generada por la interfaz.

Algoritmo de la Extensión

Repita mientras el MCD1 y MCD2 no converjan globalmente o alcance el máximo de iteraciones.

Repita mientras MCD1 no converja o alcance el máximo de iteraciones.

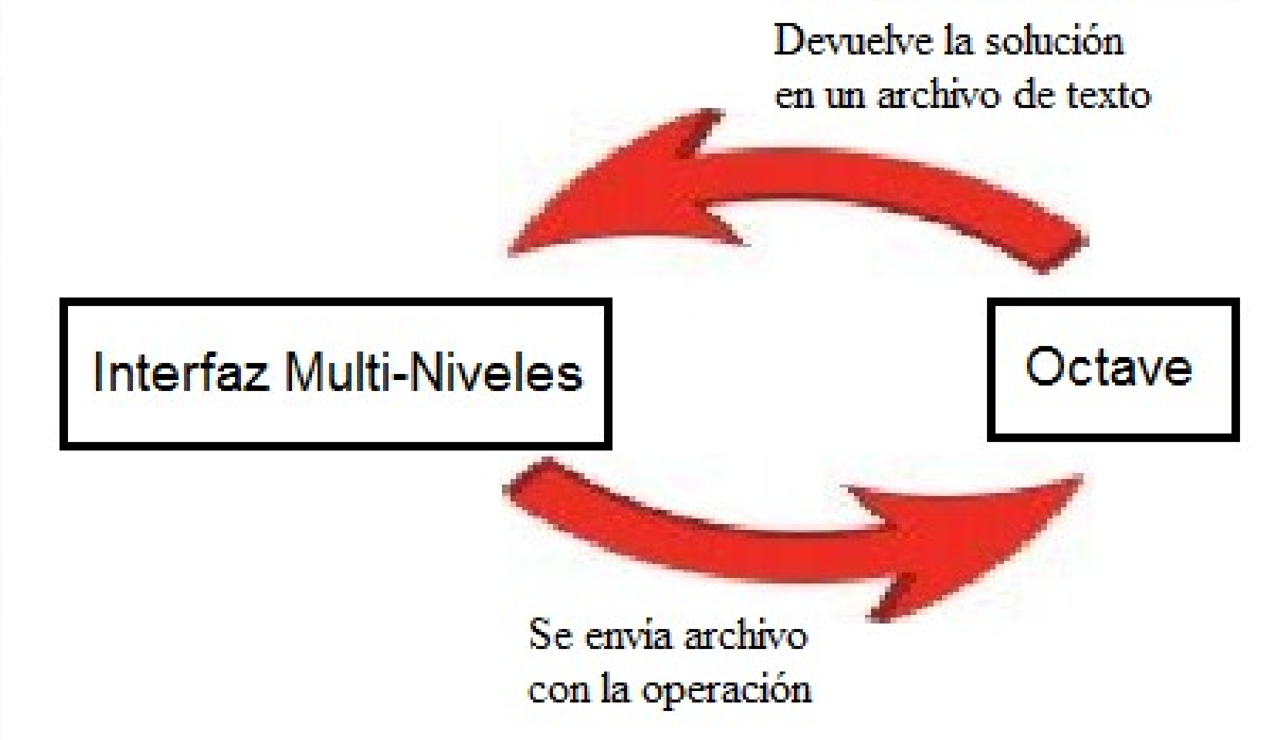
Repita mientras MCD2 no converja o alcance el máximo de iteraciones.

Invocar Interfaz.

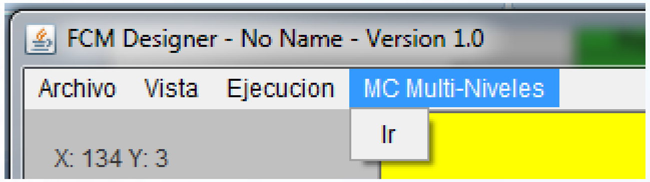
MCD1= Mapa cognitivo difuso 1

MCD2= Mapa cognitivo difuso 2

Comunicación con Octave

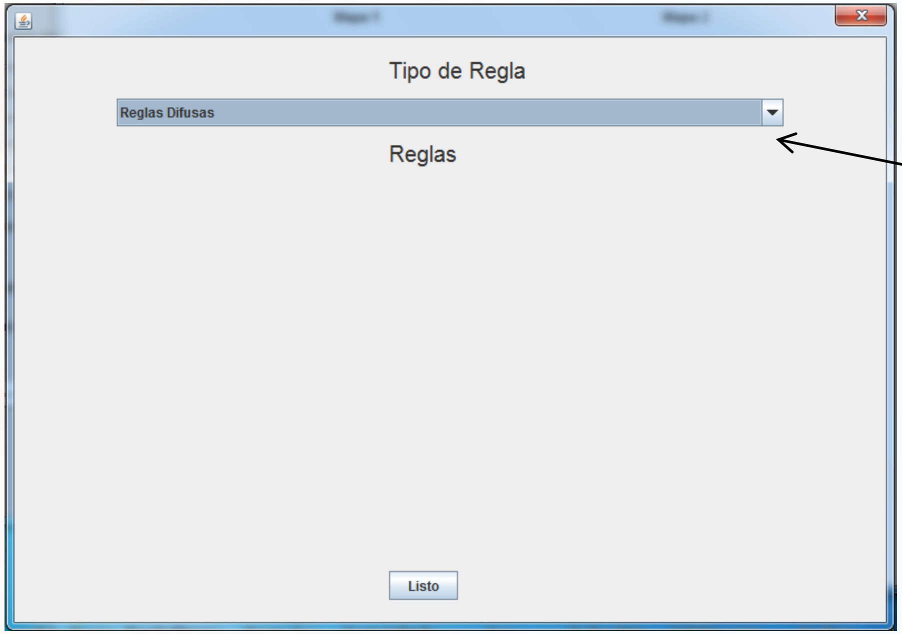


FCM Designer Tool Multicapa



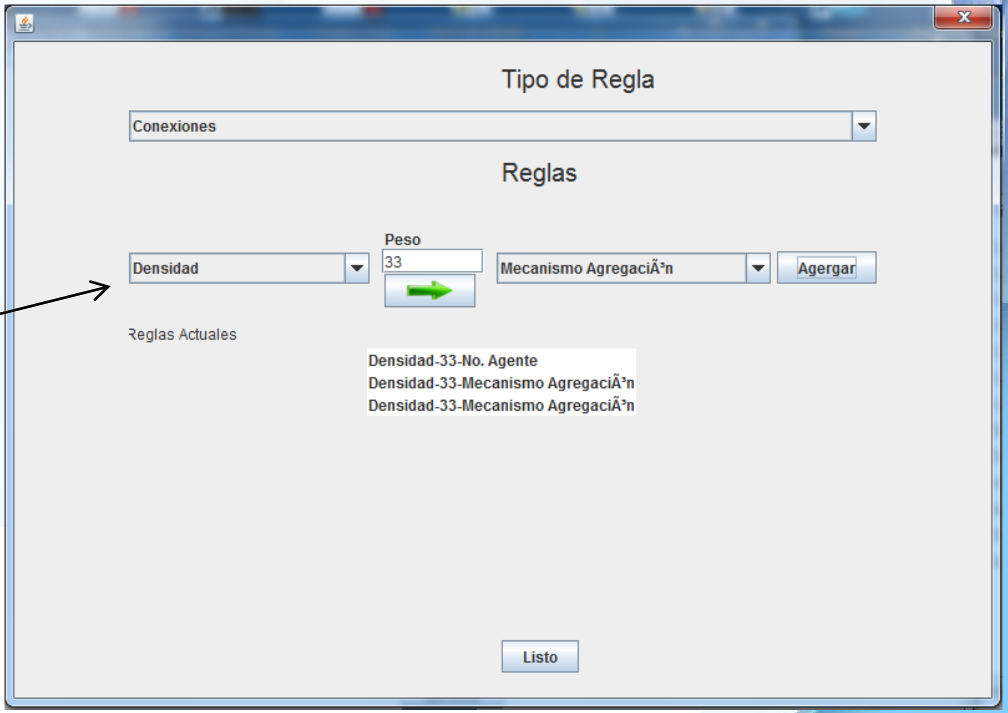
Interfaz para el caso multicapa

FCM Designer Tool Multicapa



Interfaz con reglas difusa (se invoca a octave))

Interfaz con conexiones



Caso de Estudio: Wikipedia Ingles

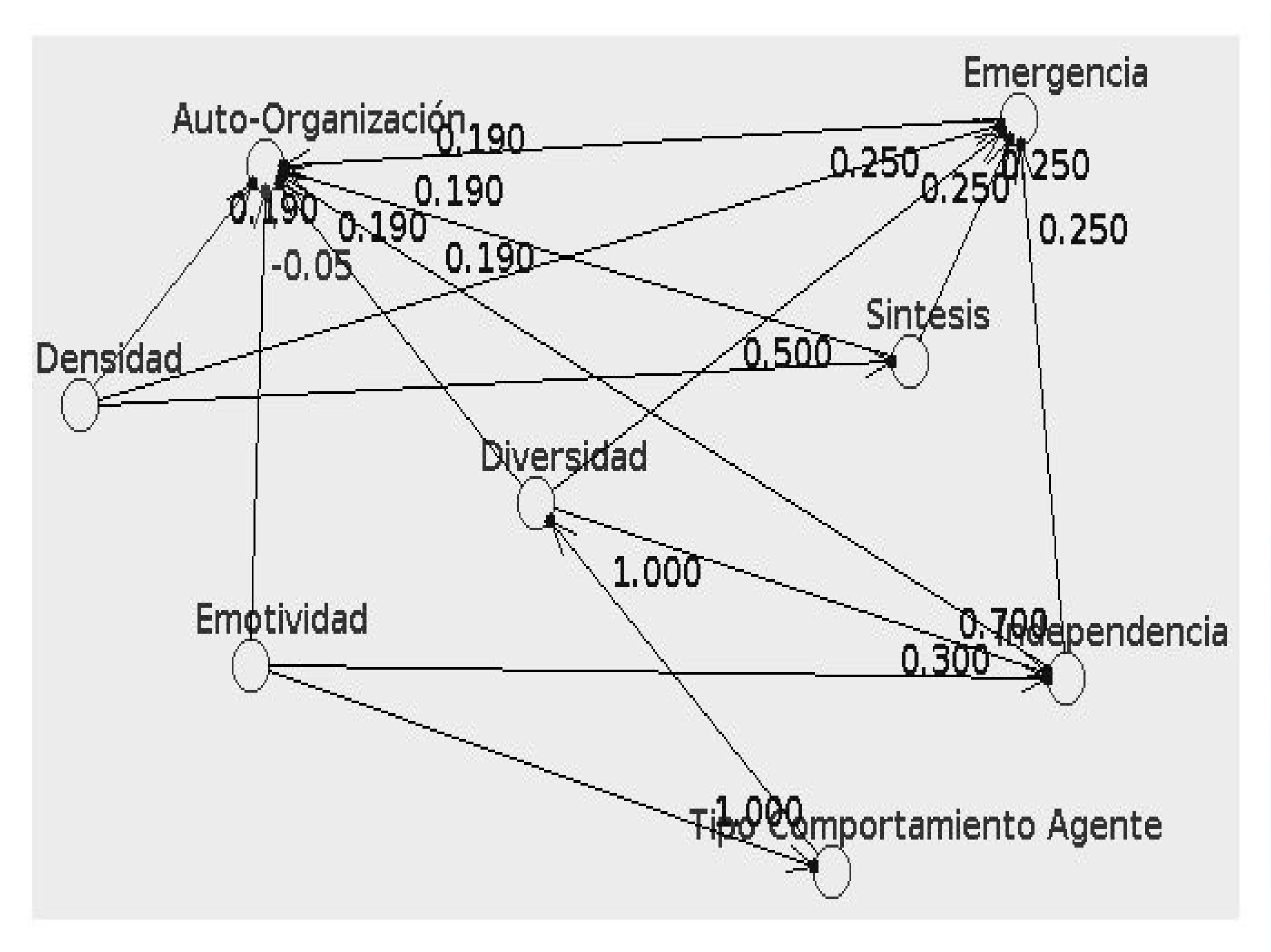
- Tipo de Reglas: Conexión.

Concepto Origen	Peso	Concepto Destino
Síntesis	0,110	Interacción Direc.
Síntesis	-0,160	Interacción Ind.
Mec. Agregación	0,500	Síntesis
Tipo de Emoción	1,000	Emotividad
Interacción Direc.	0,100	Densidad
Interacción Ind.	0,566	Densidad
Nro. Agentes	0,333	Densidad

Tabla 1: Reglas de conexión.

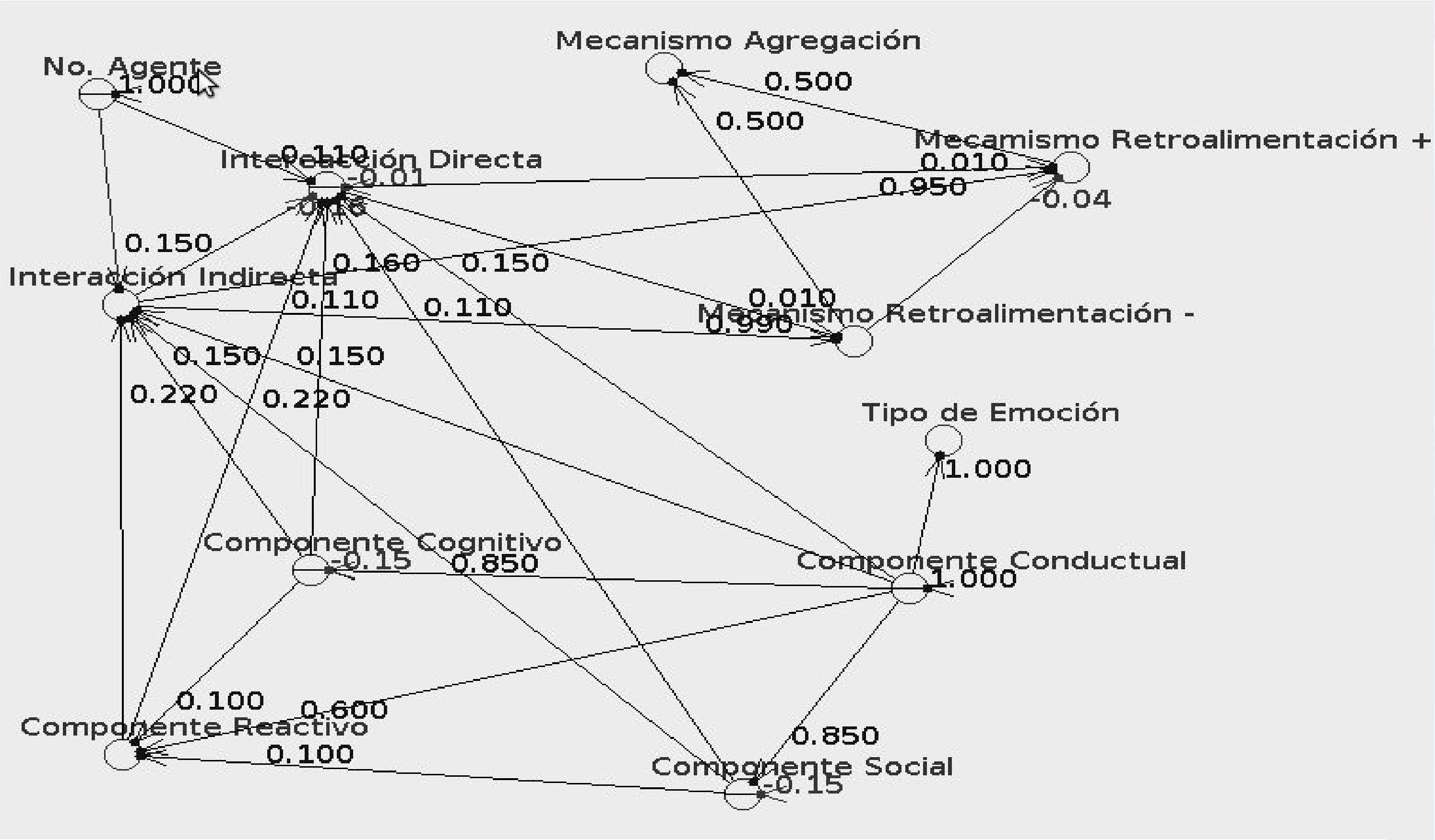
Mapa Nivel 1

- Cantidad Conceptos: 8



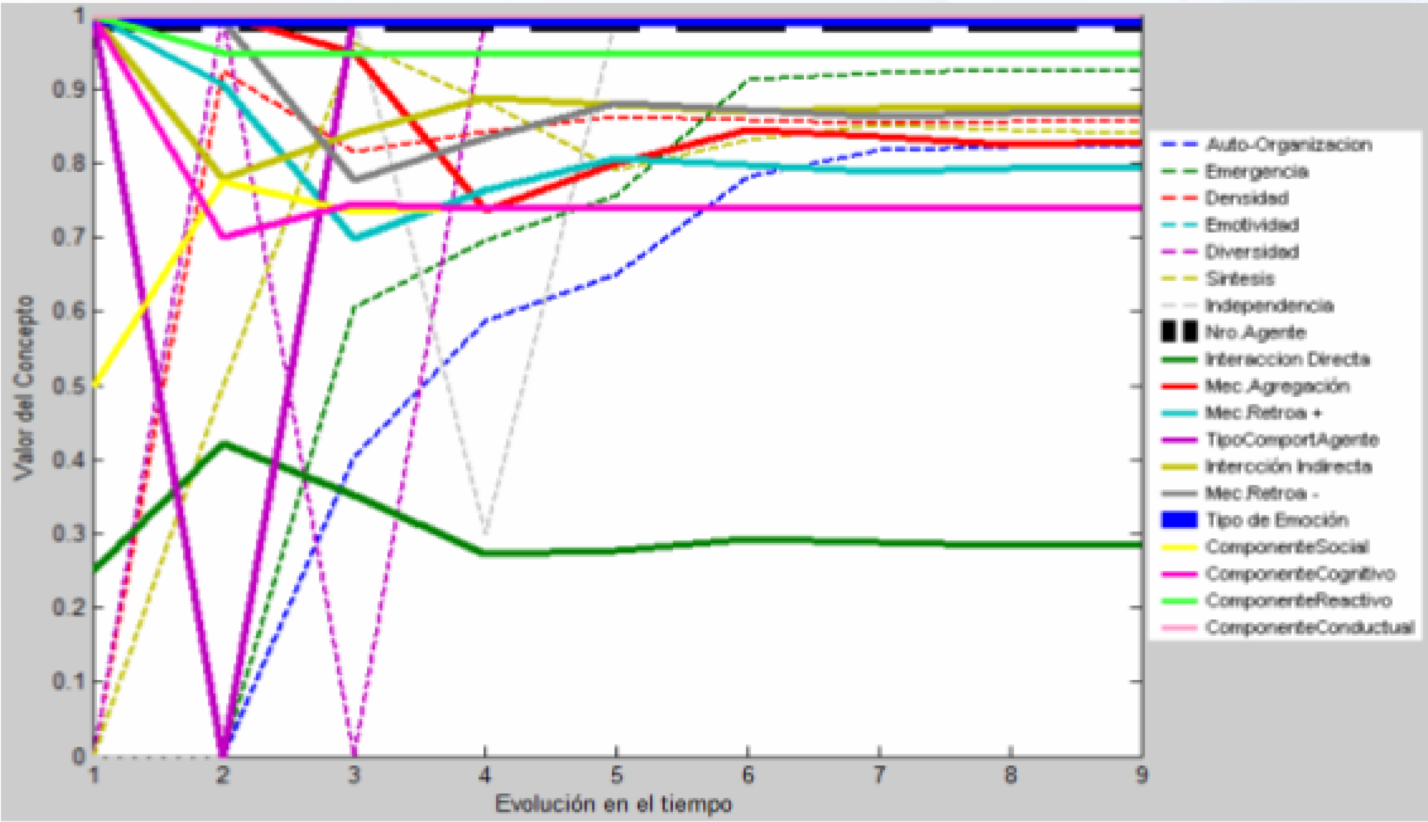
Mapa Nivel 2

- Cantidad de Conceptos: 11



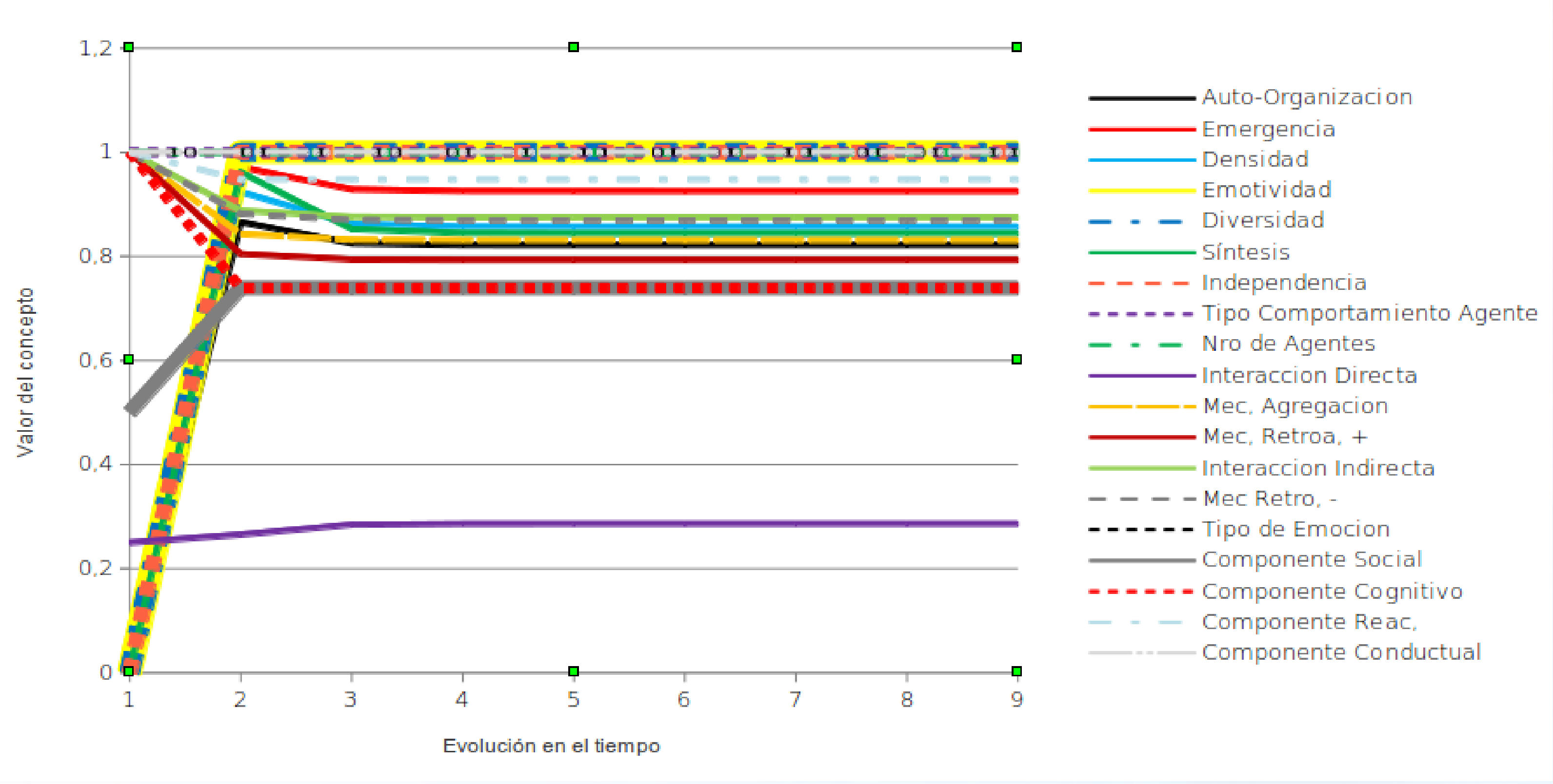
Análisis de Resultados

El gráfico muestra los resultados para el mapa cognitivo de una sola capa de la Wikipedia en Ingles.

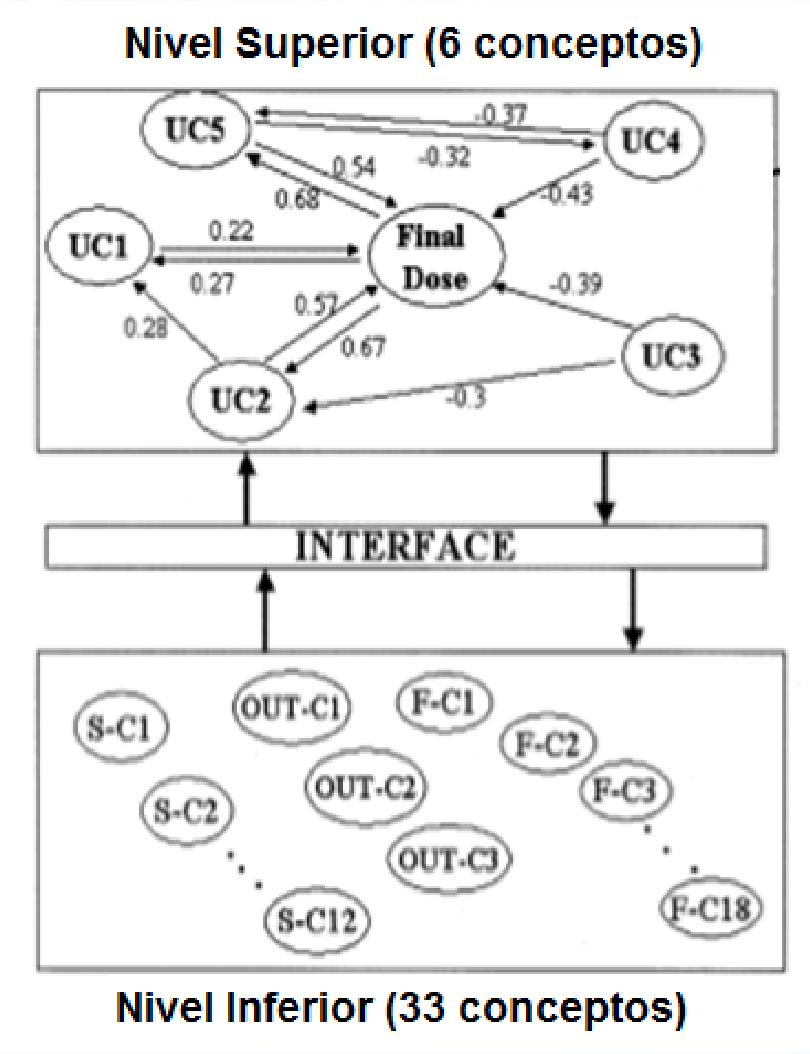


Análisis de Resultados

El gráfico muestra los resultados para el mapa cognitivo de dos capas de la Wikipedia en Ingles



Caso de Estudio: Radioterapia



Tipo de Regla: Difusa

Reglas de la interfaz

IF value of OUT-C1 is very high AND values of (OUT-C2 AND OUT-C3) are very low, THEN value of UC2 is very high.

IF value of OUT-C1 is the highest AND values of (OUT-C2 AND OUT-C3) are the lowest, THEN value of UC2 is highest.

IF value of OUT-C1 is high AND values of (OUTC2 OR OUT-C3) are low, THEN value of UC2 is high.

IF value of OUT-C1 is very high AND values of (OUT-C2 OR OUT-C3) are low, THEN value of UC2 is high.

IF value of S-C3 is very low AND values of (S-C7 AND S-C9 AND S-C10) are very high, THEN value of UC3 is high.

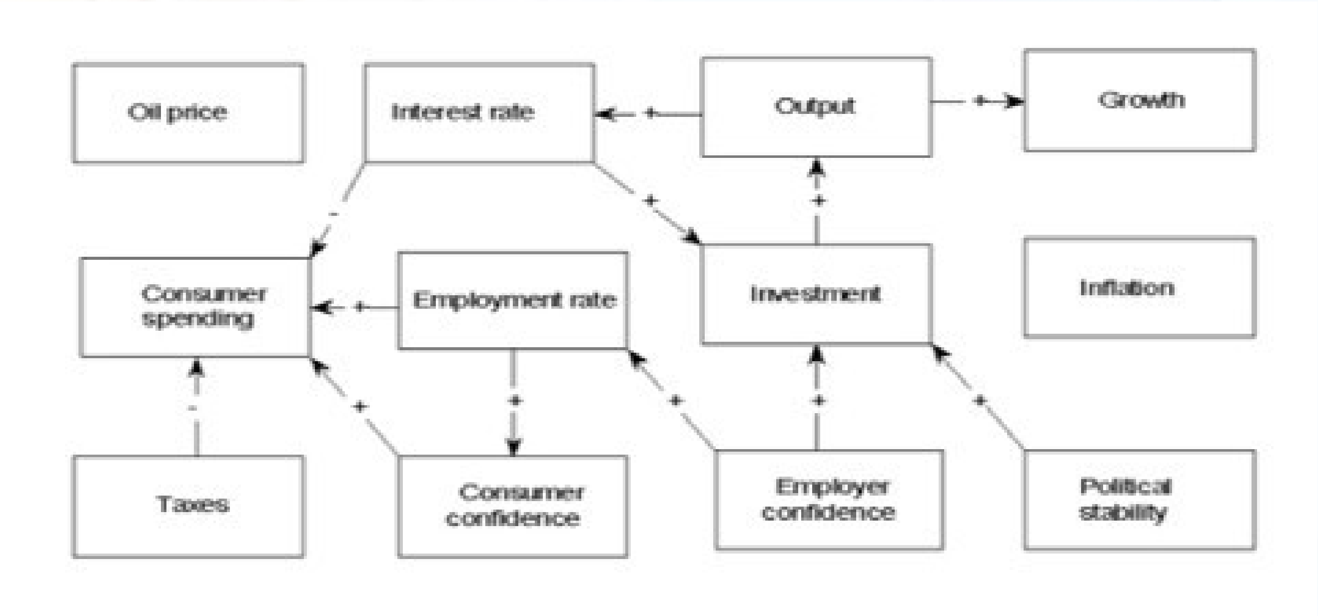
Conclusions

•Obviously, the success of a particular FCM model depends greatly on the selection of concept nodes and the interpretation of state vectors.

•Generally, a FCM exhibits a number of desirable properties that make it attractive:

- •Provide qualitative information about the inferences in complex dynamic models.
- •Can represent an unlimited number of reciprocal relationships.
- •Facility the modeling of dynamic, time evolving phenomena and process (it has defined learning procedure).
- •Has a high adaptability to any inference with feedback.
- • Another important characteristic is its simplicity, the result of each cycle is computed from an specific equation.
- •Most of the computations are intrinsically parallel and can be implemented on SIMD or MIMD architectures.
- •The ability to easily model uncertain systems at low cost and with adaptive behavior

Challengers



The figure is incomplete, and the relationships between the factors may be wrong

The fuzzy map will grow better and better as people contribute to it!!

An example of fuzzy maps library http://www.ochoadeaspuru.com/fuzcogmap/software.php:

1 .Donnelly's investment rules
2. Tax cuts
3. Correction fears grip US market
4. Money - This is a map derived from alternative currency/economic proponents