Proceedings of the 5th WSEAS Int. Conf. on SIMULATION, MODELING AND OPTIMIZATION, Corfu, Greece, August 17-19, 2005 (pp295-300)

# Decision Making by Simulating Fuzzy Cognitive Map Models

ATHANASIOS K. TSADIRAS
Department of Informatics
Technological Educational Institute of Thessaloniki
P.O.BOX 14561, 54101 Thessaloniki
GREECE

*Abstract:* - In this paper we propose the use of Fuzzy Cognitive Map (FCM) models for decision making through simulations. FCMs create models as collections of concepts and the various causal relations that exist between these concepts. The concepts are represented by nodes and the causal relationships by directed arcs between the nodes. Each arc is accompanied by a weight that defines the type of causal relation between the two nodes. The sign of the weight determines the positive or negative causal relation between the two concepts-nodes.

In this paper the decision making capabilities of the FCM models are examined and presented using a model concerning a car industry. The model is examined dynamically through simulations, in order to simulate scenarios proposed by decision makers. Predictions are made by viewing dynamically the consequences of the scenario's actions. Conclusions are drawn for the use of FCM models for decision making and possible ways are identified, to increase the quality of the constructed FCM model.

*Key-Words:* - Fuzzy Cognitive Maps, Modeling, Simulation, Decision Making, Artificial Intelligence, Neural Networks

## 1 Introduction to Fuzzy Cognitive Maps

Fuzzy Cognitive Maps (FCMs) have been introduced by Kosko [1], [2] based on Axelord's work on Cognitive Maps [3]. An example of FCM model concerning a car industry is given in figure 1 (modified version from original found in [4]). FCMs are used to create models as collections of concepts and the various causal relations that exist between these concepts.

The nodes of the FCM represent the concepts of the model and the directed arcs between the nodes represent the causal relationships that exist among the concepts. Every arc is accompanied by a positive or a negative weight which define both the type and the strength of causal relation between the two nodes/concepts. Positive/negative causal relation between two concepts $C_i$ and $C_j$ means that an increase/decrease of the activation level of concept $C_i$ will increase/decrease $C_j$. Negative causal relation between $C_i$ and $C_j$ means that an increase/decrease of concept Ci will decrease/increase $C_j$.

Each concept $C_i$ is accompanied with a number $A_i$ which represents its level of activation. If *n* is the number of concepts of an FCM, the vector $A^t = [A_1^t, A_2^t, ..., A_n^t]$ gives the state of the FCM at time step *t*, where $A_i^t$ is the activation level of concept $C_i$ at time step *t*.

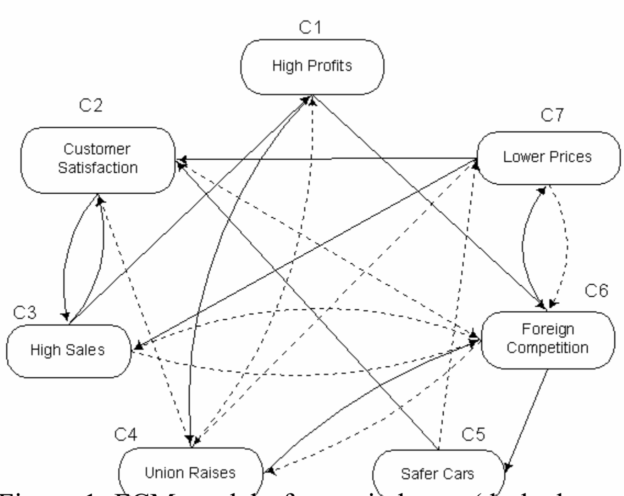


Figure 1. FCM model of a car industry (dashed arcs represent negative causal relationship, modified version of original taken from [4])

*W* is also defined as an n×n matrix where $w_{ij}$ is the weight of the arc that connects $C_i$ and $C_j$ (it is taken that $w_{ii}$ =0, i=1,...,n because no loop from a concept to itself is allowed). The activation level of all concepts is updated simultaneously. This means that $A^{t+1} = [A_1^{t+1}, A_2^{t+1}, ..., A_n^{t+1}]$ where $A_i^{t+1}$, i=1,...,n is given by the following formula:

$$A_i^{t+1} = f(\sum_{j=1}^{n} A_j^t w_{ji}) \quad (1)$$

Function *f()* allows the activation to take a value among the distinct values that are allowed (usually 0,1). Using matrix notation, eq. (1) can be written as $A^{t+1} = f(A^t W)$. The type of *f()* varies but the commonest choices are the step threshold function at 0, 1 and the sign function.

## 2 Certainty Neuron Fuzzy Cognitive Maps

In FCMs, in a strict binary manner, each concept can be either activated or not activated. Certainty Neuron Fuzzy Cognitive Maps (CNFCMs) were introduced [5] to provide additional fuzzification to FCMs by allowing each concept's activation to be activated just to a degree. In CNFCM the activation level of each concept can be any value of the interval [-1,1] and not only one of the two levels –1 and 1. The aggregation of the influences that each concept receives from other concepts is handled by function $f_M()$ that was used in MYCIN Expert System [6], [7] for the handling of certainty factors. A detailed analysis of the dynamical behaviour and the characteristics of function $f_M()$ can be found in [8].

Certainty Neurons are defined as artificial neurons that use this function as their threshold function [9]. Using such neurons, the updating function of CNFCMs is the following:

$$A_i^{t+1} = f_M(A_i^t, S_i^t) - d_i A_i^t \quad (2)$$

where $A_i^{t+1}$ is the activation level of concept $C_i$ at time step *t+1*, $S_i^t = \sum_j w_{ji} A_j^t$ is the sum of the weighted influences that concept $C_i$ receives at time step *t* from all other concepts, $d_i$ is a decay factor and

$$f_M(A_i^t, S_i^t) = \begin{cases} A_i^t + S_i^t(1 - A_i^t) = A_i^t + S_i^t - S_i^t A_i^t & \text{if } A_i^t \geq 0,\ S_i^t \geq 0 \\ A_i^t + S_i^t(1 + A_i^t) = A_i^t + S_i^t + S_i^t A_i^t & \text{if } A_i^t < 0,\ S_i^t < 0 \quad \left|A_i^t\right|,\left|S_i^t\right| \leq 1 \\ (A_i^t + S_i^t) \big/ \left(1 - \min\left(\left|A_i^t\right|,\left|S_i^t\right|\right)\right) & \text{otherwise} \end{cases} \quad (3)$$

is the function that was used for the aggregation of certainty factors to the MYCIN expert system.

## 3 Construction of FCM models based on the opinions of many experts

In FCM model construction, the reliability of the model increases, as the number of the domain experts that provide their opinion also increases. This means that asking for opinions of more experts will lead to the construction of a better FCM model. Especially now, with Internet technology making communication and interactions of experts/colleagues around the world very easy, the FCM model can be more reliable and much more easily developed.

Lets imagine that there are k experts that will participate into the construction of an FCM model. That means that if initially each expert was left alone to develop his FCM model, there will be initially k different FCM models. Each such model will have a weight matrix $W_i$ of dimension $n_i \times n_i$ where $n_i$ the number of concepts that expert *i* is using. These models will have some common concepts and some different concepts. Entering to an FCM model a concept that was not proposed by the expert that created it (but it was proposed by some other expert in his FCM model), will lead to the insertion of a new column and a new row to the weight matrix of the model, both to be full with zeros. In this way, we can increase the dimension of the $W_i$ matrices of the *i* FCM models, from dimension $n_i \times n_i$ to dimension $n \times n$, with *n* to be the number of different concepts that all experts are using. These new augmented matrices $F_i$ have the same dimensions $n \times n$ and can be added. Weight matrix *F* that is defined as

$$F = (F_1 + F_2 + ... + F_k) \times \left(1/k\right) \quad (4)$$

has dimension $n \times n$ and is created by adding the opinion of all company's experts. This new FCM model is called augmented FCM [2,10,11]. Positive and negative weights are neutralized meaning that contradicting opinions of experts are eliminated. Some experts would prefer to leave these contradictions in the model in order differences to be discussed. In this case Negative-Positive-Neutral logic should be followed [12,13,14].

Often experts that participate in the construction of the augmented FCM are not of the same reliability. To take more into account the opinions of the more reliable experts, a reliability weight *ai* is attached to each expert [2]. The more reliable an expert is, the bigger that reliability weight is. In this case, the matrix of the augmented FCM is estimated in the following way:

$$F = (a_1 F_1 + a_2 F_2 + \ldots + a_k F_k) \times \left(\frac{1}{a}\right) \qquad (5)$$

where $a = a_1 + a_2 + \ldots + a_k$ is the normalization factor.

Having developed such an augmented FCM model that integrates the opinions of all company's domain experts, the FCM decision making process can begin, with each expert being able to participate.

It can also be noticed that the above augmented FCM model construction technique can be used in the opposite way, that is for evaluation the reliability of each expert [15,16].

## 4 Simulations of a car industry FCM model

In our study we will use the FCM model of figure 1 to examine the group decision making capabilities of FCM structure. The FCM model of figure 1 is a modified version of the model presented in [4] and concerns an imaginary car industry. According to the car industry FCM model of Figure 1, the concepts that were identified as playing important role in the decision making process of the car industry, are the following:

| | |
|---|---|
| C1: High Profits<br>C2: Customer Satisfaction<br>C3: High Sales<br>C4: Union Raises | C5: Safer Cars<br>C6: Foreign Competition<br>C7: Lower Prices |

The weights of the causal relationships that according to the experts exist in the model and construct the weight matrix of the model, are presented in Appendix A.

In FCM technique, decision making conclusions are drawn by simulating the model in a computer system. Scenarios are introduced to the system and the consequences of the corresponding actions are predicted. The model of figure 1 was simulated using the CNFCM technique that was presented in section 3.

In the first scenario, all the concepts of the model were left free to interact with each other. The result of the simulation is shown in figure 2.

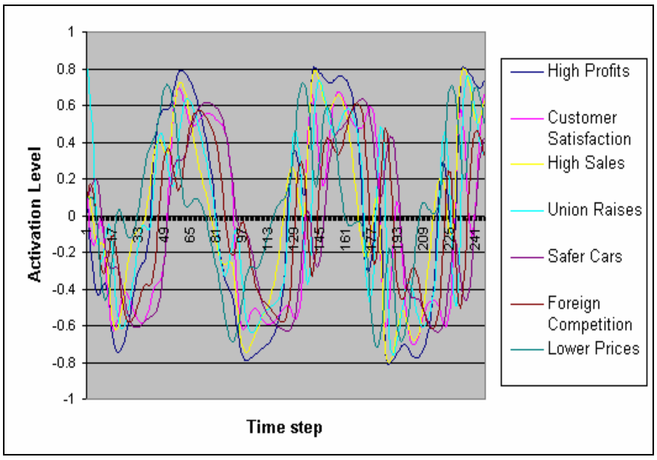


Figure 2: The limit cycle behaviour of the car industry model when all concepts are free to interact (scenario #1).

The system enters a complex limit cycle behaviour, returning periodically to the same state. It can be concluded that if the concepts of the car industry model are free to interact and there is no external influence to them from concepts not represented to the model, the concepts of the model strongly interact with each other, not letting some concepts be "winners" by having positive activation and some to be "losers" by having negative activation.

In the second scenario, we assume that a decision to produce safer cars was taken. The degree that cars' safety will be improved is "very" or equal to the degree 80% (or 0.8 in the interval [0,1]). The scenario is introduced to the model by assigning concept C5: "Safer car" with activation level equal to 0.8 during the whole simulation process. As it is shown in figure 3, the system after some interactions reaches an equilibrium point.

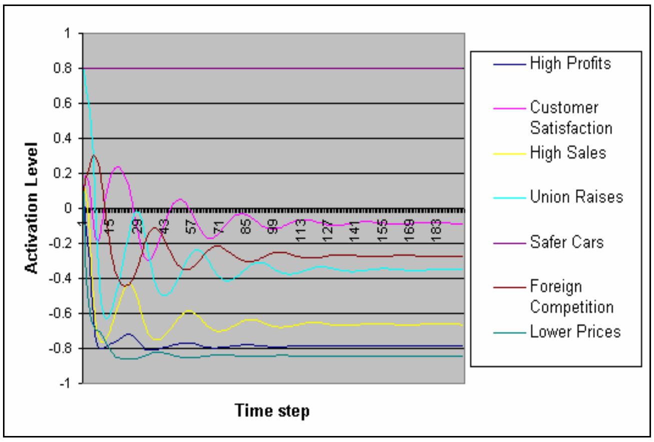


Figure 3: Transition phase of Car Industry FCM model towards an equilibrium point when concept "Safer car" is set to 0.8 (scenario #2)

Proceedings of the 5th WSEAS Int. Conf. on SIMULATION, MODELING AND OPTIMIZATION, Corfu, Greece, August 17-19, 2005 (pp295-300)

The concepts of the system have at equilibrium the following activation levels:

| High Profits | Customer Satisfaction | High Sales | Union Raises |
|---|---|---|---|
| -0.786 | -0.083 | -0.662 | -0.349 |
| Safer Cars | Foreign Competition | Lower Prices | |
| 0.8 | -0.271 | -0.842 | |

Conclusions that can be drawn from studying the activation levels of concepts at equilibrium are the following: The car industry in its attempt to create "very" safer cars increased the cost of car production. This also led to an increase of the cars prices (Lower Prices =-0.842). Although customers were satisfied by the production of safer cars, the increase of the price made them not to be satisfied (overall Customers Satisfaction =-0.083). Sales and profits were severely decreased (High Sales=-0.662, High Profits= -0.786 and a decrease is also shown to Foreign Competition but to a lower degree. Union Raises were decreased due to the decrease of profits.

In the third scenario we assume that the decision was to produce a "little" safer cars (instead of "very" safer cars). The degree that the car will be safer is estimated to be 20% (or 0.2 in the interval [0,1]). The scenario is introduced to the model once again by setting concept C5: "Safer car" with activation level equal to 0.2 during the whole simulation. As it is shown in figure 4, the system after some interactions reaches a different equilibrium point.

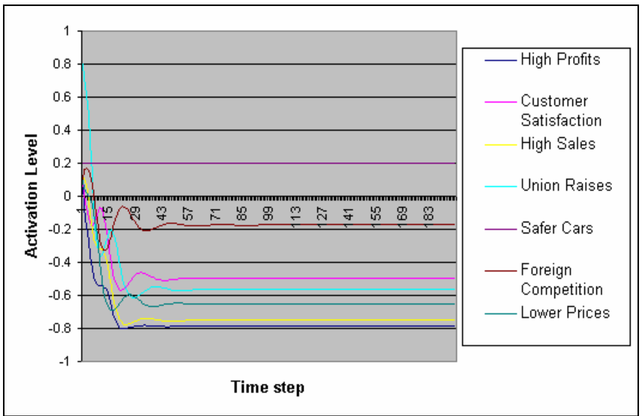


Figure 4: Transition phase of car industry FCM model towards an equilibrium point when concept "safer car" is set to 0.2 (scenario #3)

The concepts of the system have at equilibrium the following activation levels: (the signs after the activation levels represent the increase or decrease towards the equilibrium in the previous scenario):

| High Profits | Customer Satisfaction | High Sales | Union Raises |
|---|---|---|---|
| -0.787 (0) | -0.497(-) | -0.751(-) | -0.565(-) |
| Safer Cars | Foreign Competition | Lower Prices | |
| 0.2(-) | -0.174(+) | -0.651(+) | |

Conclusions that now can be drawn are the following: The car industry in its attempt to create even "little" safer cars increased once again the cost of car production. That led to an increase of the cars prices (Lower Prices =-0.651). Although customers were satisfied by the production of safer cars, the increase of the price made them overall to be unsatisfied (Customers Satisfaction =-0.497). Sales and profits were severely decreased (High Sales=-0.751, High Profits= -0.787) and a decrease is also present to Foreign Competition but to a much lower degree. Union Raises were decreased due to the decrease of profits.

Interesting conclusions can also be drawn by comparing the results of the last two scenarios. For example, that by making cars a "little" safer (scenario #2) and not "very" safer (scenario #3), the car industry managed both to increase prices and keep more unsatisfied the customers (scenario #3 is worse than scenario #2). Furthermore, the car industry is shown very sensitive to costs cause by improving the safety of the car.

The fourth scenario that was introduced to the system for simulation, assumes that the car industry decided to decrease a "little" the prices of its cars. Translating the linguistic value "little" to the value 0.2 of the interval [0,1], the new scenario was introduced to the model. The result of the simulation is shown figure 5.

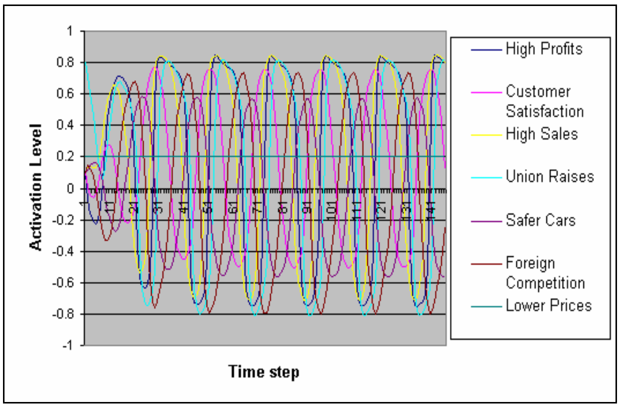


Figure 5: The limit cycle behaviour of the car industry model when concept "lower prices" is set to 0.2 (scenario #4)

The system reached a limit cycle behaviour, with no concept to be "winner" or "loser" but all of them to be periodically high and low. This means that from the action to decrease a little the price of the cars, no clear predictions of the consequences can be made.

The fifth scenario that was introduced to the system for simulation, assumes that the car industry decided to decrease "severely" the prices of its cars. Translating the linguistic value "severely" to the value 0.5 of the interval [0,1], the new scenario was introduced to the model. The results of the simulation are shown in figure 6.

The system reached equilibrium with concepts to have the following activation levels:

| High Profits | Customer Satisfaction | High Sales | Union Raises |
|---|---|---|---|
| 0.782 | 0.688 | 0.755 | 0.606 |
| Safer Cars | Foreign Competition | Lower Prices | |
| 0.363 | 0.191 | 0.5 | |

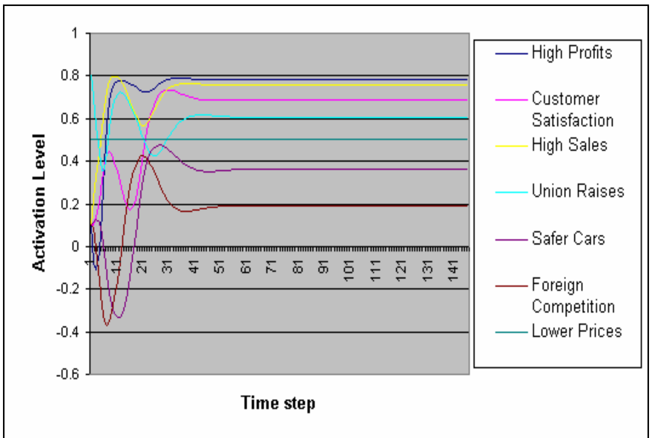


Figure 6: Transition phase of car industry FCM model towards an equilibrium point when concept "Lower Prices" is set to 0.5 (scenario #5)

Conclusions that can be drawn are the following: The car industry by severely decreasing the prices of the cars, created very satisfied customers (Customers Satisfaction =0.688), increased sales and profits (High Sales=0.755 High Profits= 0.782). The Union Raises in now increased because of the high profits of the car industry (Union Raises=0.606). Foreign Competition is increased (Foreign Competition= 0.191) which lead also to a pressure to the car industry to make safer cars (Safer cars=0.363).

## 5 Summary - Conclusions

In this paper the decision making capabilities of FCM models were examined, using an FCM model concerning a car industry. Various scenarios were introduced to the model and through computer simulations, predictions were made. The representing and decision making capabilities of the FCM structure were presented.

The FCM technique was identified as a useful Decision Support tool, since it is capable of providing support to decision makers, by making predictions on various scenarios that are imposed to the FCM model. The uncertainty handling capabilities of FCM models make also the technique suitable for decisions were uncertainty and fuzziness exist

*References:*


[1] Kosko B., *Fuzzy Cognitive Maps*, Inter. Jour. of Man-Machine Studies, vol. 24, 1986, pp.65-75.

[2] Kosko B., *Neural Networks and Fuzzy Systems*, Prentice-Hall, 1992.

[3] Axelrod R., *Structure of Decision,* Princeton: Princeton University Press, 1976.

[4] R. C. Eberhart and R. W. Dobbins, *Neural Network PC Tools*: Academic Press, 1990.

[5] A. K. Tsadiras and K. G. Margaritis, "Cognitive Mapping and the Certainty Neuron Fuzzy Cognitive Maps," *Information Sciences*, vol. 101, pp. 109-130, 1997.

[6] E. H. Shortliffe, *Computer-based Medical Consultations:MYCIN*. New York: Elsevier, 1976.

[7] B. G. Buchanan and E. H. Shortliffe, *Rule-Based Expert Systems. The MYCIN Experiments of the Stanford Heuristic Programming Project*. Reading, MA: Addison-Wesley, 1984.

[8] A. K. Tsadiras and K. G. Margaritis, "The MYCIN Certainty Factor Handling Function as Uninorm Operator and its Use as Threshold Function in Artificial Neurons," *Fussy Set and Systems*, vol. 93, pp. 263-274, 1998.

[9] A. K. Tsadiras and K. G. Margaritis, "Using Certainty Neurons in Fuzzy Cognitive Maps," *Neural Network World*, vol. 6, pp. 719-728, 1996.

[10] J. A. Dickerson, "Virtual Worlds as Fuzzy Dynamical Systems," in *Technology for Multimedia*, B. Shen, Ed.: IEEE Press, 1996.

[11] B. Kosko, "Hidden Patterns in Combined and Adaptive Knowledge Networks," *International Journal of Approximate Reasoning*, vol. 2, pp. 377-393, 1988.

[12] W.-R. Zhang, S.-S. Chen, and J. C. Bezdek, “Pool2: A Generic System for Cognitive Map Development and Decision Analysis,” *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 19, pp. 31-39, 1989.

[13] W.-R. Zhang, S.-S. Chen, W. Wang, and R. S. King, “A Cognitive-Map-Based Approach to the Coordination of Distributed Cooperative Agents,” *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 22, pp. 103-114, 1992.

[14] W.-R. Zhang, “NPN Fuzzy Sets and NPN Qualitative Algebra: A Computational Framework for Bipolar Cognitive Modeling and Multiagent Decision Analysis,” *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 26, pp. 561-574, 1996.

[15] W. R. Taber, “Estimation of Expert Weights Using Fuzzy Cognitive Maps,” presented at First International Conference of Neural Networks, San Diego, 1987.

[16] W. R. Taber and R. O. Deich, “Risk Weighting in Knowledge Bases Using Fuzzy Cognitive Maps,” presented at First International Conference of Neural Networks, 1988.

## Appendix A

Weight matrix of the car industry FCM model

| | High Profits | Customer Satisfaction | High Sales | Union Raises | Safer Cars | Foreign Competition | Lower Prices |
|---|---|---|---|---|---|---|---|
| High Profits | 0 | 0 | 0 | 0.8 | 0 | 0.9 | 0 |
| Customer Satisfaction | 0 | 0 | 0.7 | 0 | 0 | -0.4 | 0 |
| High Sales | 0.98 | 0.3 | 0 | 0 | 0 | -0.4 | 0 |
| Union Raises | -0.4 | -0.6 | 0 | 0 | 0 | 0.3 | 0 |
| Safer Cars | 0 | 0.8 | 0 | 0 | 0 | 0 | -0.5 |
| Foreign Competition | 0 | 0 | -0.8 | -0.7 | 0.3 | 0 | 0.5 |
| Lower Prices | 0 | 0.8 | 0.7 | -0.4 | 0 | -0.5 | 0 |