Introduction to Modeling of Complex Systems Using Fuzzy Cognitive Maps

[1]*Michal PUHEIM (1st year)*
Supervisor: [2]Ladislav MADARÁSZ
Consultant: [3]Ján VAŠČÁK

[1,2,3]Dept. of Cybernetics and Artificial Intelligence, FEI TU of Košice, Slovak Republic

[1]michal.puheim@tuke.sk, [2]ladislav.madarasz@tuke.sk, [3]jan.vascak@tuke.sk

***Abstract*—Complex systems are known to be difficult to describe using conventional mathematical models because of high number of sub-elements which have complicated mutual relations and dependencies. In this paper we discuss the possibility of using the fuzzy cognitive maps as method to model such systems. Fuzzy cognitive maps are inference networks in form of directed graphs with possibility of nested cyclic loops which are currently widely used to analyze causal relations within complex systems. Fundamental principles and advantages of fuzzy cognitive maps for purpose of modeling are discussed within the paper. We also focus on revealing the shortcomings of this method along with possible enhancements which could improve the resulting models of the system.**

***Keywords*—modeling, complex system, fuzzy cognitive maps.**

I. Introduction

Continual advancement of human knowledge in all technical and non-technical areas results in creation of more and more complex systems. Complex system in general is multi-dimensional and multi-parametric system with complex dynamics and non-linear behavior. In order to ensure safe and stable operation of such system it is necessary to be able to describe and predict its behavior to detect possible malfunction. This is the task of diagnostics and it cannot be accomplished without adequate model of the given system. In case that it is necessary to control and direct the operation of the system it is also useful to have a model which can be used to try and test the control algorithms before their application on the real physical system. Therefore modeling and simulation of the system is very important task which should not be neglected.

However there are problems with formal modeling and simulation of complex systems. This is due to their high internal complexity because of which it is not feasible and often even not possible to construct exact mathematical models. Consequently it is necessary to look for other options to implement system models. The last decade has seen the growing popular trend to create system models using soft computing methods based on means of artificial intelligence such as neural networks or more recently the fuzzy cognitive maps. In contrast with exact mathematical methods these approaches enable us to describe complex systems at least to some extent, but the accuracy of created models varies from case to case and they often cannot describe the system in whole operational range. Because of this it is imperative to look for ways how to further develop the existing methods and in consequence improve the resulting models.

II. Review of the Research Area

Goal of our research is to explore the possibilities of fuzzy cognitive maps applied to model complex systems. In following subsections we briefly describe the nature of complex systems, present the foundation of fuzzy cognitive maps and their application to modeling of complex systems.

A. Complex Systems

Complex system (CS) is such a system that consists of finite number of elements or subsystems and is characterized by following properties [1]:

- large number of elements, which can change in position and size,
- hierarchical structure,
- set of relations between elements,
- self-controlling elements (active systems),
- dynamic change in shape and size,
- dynamic change in connections between elements.

Structure of CS is determined by set of all of the elements and relations between these elements. The elements of a complex system may themselves be complex systems. Classical approaches aiming to describe the structure of CS are typically graphs, oriented graphs or structural and interaction matrices [1]. Fuzzy cognitive maps can be used to represent CS in either of these ways.

B. Fuzzy Cognitive Maps

Cognitive map (CM) in general is oriented graph, where nodes represent concepts (elements of attributes of the modeled system) and edges determine mutual relations between these concepts. Values of either concepts or edges are often represented by three crisp values -1, 0 and 1. Advantage of cognitive map is clear and comprehensible knowledge representation, which can be easily visualized in graph form [2].

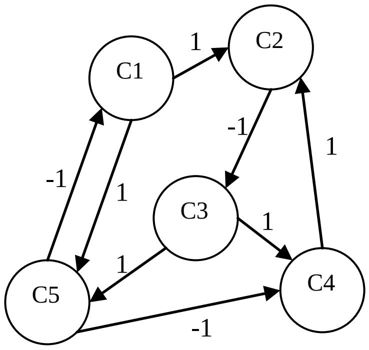

Fig. 1. Example of simple cognitive map with crisp edges.

Fuzzy cognitive maps (FCM) were proposed by Kosko [3] in 1986 as extension to the traditional cognitive maps. FCMs are similarly to traditional cognitive maps represented as oriented graphs (with possible feedback connections), emphasizing causal relations between concepts, which are either positive, negative or none [4][5]. But in addition to traditional CM it also takes into account the degree of influence of these relations expressed by according linguistic value. In principle it can be said, that FCM is fuzzy oriented graph which model the given system and its behavior using the concepts and its mutual relations.

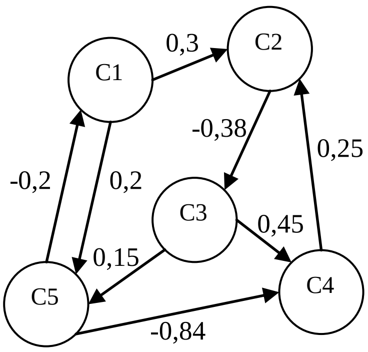

Fig. 2. Example of simple fuzzy cognitive map.

There are multiple formal definitions of FCM, but most common one is given by Chen [6], where FCM is defined as the quadruple:

$$\text{FCM} = (C, W, \alpha, \beta), \qquad (1)$$

where [2]:

- $C = \{C_1, C_2, ..., C_n\}$ is finite set of cognitive units (concepts),
- $W = \{w_{11}, w_{12}, ..., w_{nm}\}$ is finite set of oriented connections between concepts,
- $\alpha \rightarrow [-1, 1]$ is a membership function placed in a concept and the result is a grade of membership for values entering this concept,
- $\beta \rightarrow [-1, 1]$ has the same meaning as α but for edges.

Concept C_i ($i = 1, 2, ..., n$) indicates the state, procedure, event or variable of the modeled system [5] and its value A_i is from range [-1, 1] (or based on the implementation from range [0, 1]). Directed connection between concepts C_i and C_j determines the causality of influence between these concepts and is represented by weight w_{ij}, which is determined by fuzzy value from range [-1, 1]. Therefore there are three basic states of operation for the weight w_{ij} [5]:

a) weight has positive value ($w_{ij} > 0$), so the increase (decrease) in value of the concept C_i leads to increase (decrease) in value of the concept C_j.
b) weight has negative value ($w_{ij} < 0$), so the increase (decrease) in value of the concept C_i leads to decrease (increase) in value of the concept C_j.
c) weight has zero value ($w_{ij} = 0$), which means that there is no causal relation between concepts C_i and C_j.

General rule to compute the value of the concept C_i in every simulation step is to calculate the influence of other concepts connected to the concept C_j. Therefore if $A_j(t)$ is the value of the concept C_j in the time t, then the value $A_j(t+1)$ of the concept C_j in the time $t+1$ will be influenced by the values $A_i(t)$ of other concepts C_i in the time t as follows [5]:

$$A_j(t+1) = p\left(A_j(t) + \sum_{i=1; i \neq j}^{n} A_i(t).w_{ij} \right) \qquad (2)$$

where w_{ij} are weights on the connections between concepts C_i and the concept C_j. Squashing (threshold) function $p(x)$ limits the resulting value x into the range [0, 1] (or [-1,1]) [5]. Behavior of the resulting FCM depends greatly upon the type of the squashing function [4]. Among most used squashing functions $p(x)$ we can count the following [4]:

- bivalent,

$$p(x) = \begin{cases} 0, & x \leq 0 \\ 1, & x > 0 \end{cases} \qquad (3)$$

- trivalent,

$$p(x) = \begin{cases} -1, & x \leq -0.5 \\ 0, & -0.5 < x < 0.5 \\ 1, & x \geq 0.5 \end{cases} \qquad (4)$$

- logistic (sigmoid),

$$p(x) = \frac{1}{1 + e^{-mx}} \qquad (5)$$

C. *Modeling of complex systems using FCM*

The model of the system is typically constructed based on the data measured during the operation of the system and later used to solve tasks such as prediction, diagnostics, interpreting, monitoring, control, classification, etc. When the means of artificial intelligence such as FCM are used for *creation of the model* this process is often interchangeably called the *learning of the model*.

Disadvantage of FCM is that similarly as other types of fuzzy inference systems it does not incorporate built-in learning mechanism [2]. Design of learning methods is difficult because of complex structure and variability of FCM (especially when used to model complex system). For this reason the set of concepts is usual given *a priori* by expert (or according to given system parameters) and only the set of weights is subjected to the automatic learning process [2][4].

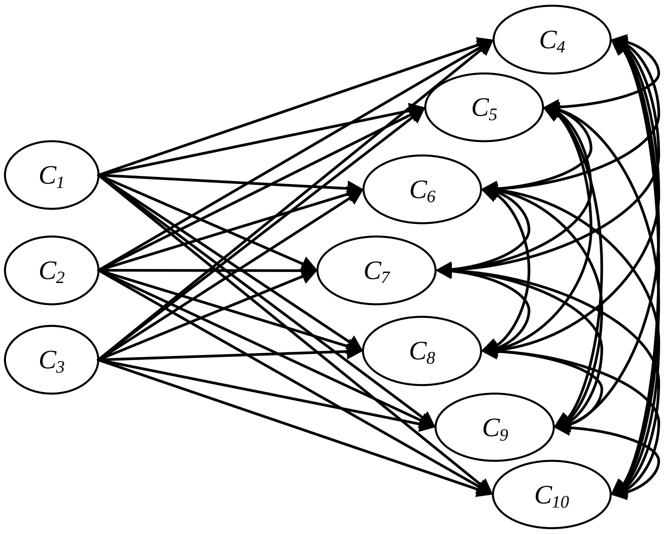

Fig. 3. FCM before learning process. Set of concepts is usualy given by expert a priori and only set of weights is subjected to the learning process.

Methods used to learn the FCM are usually based on approaches used in the area of artificial neural networks, mostly based on the least mean square or delta rule methods. It is also possible to use evolutionary or population based algorithms. Here is the list of the most common learning methods [2][4][7][8][9]:

- Hebbian Learning based methods:
  - Differential Hebbian Learning,
  - Active Hebbian Learning,
  - Nonlinear Hebbian Learning,
  - Data Driven Hebbian Learning.
- Least Mean Square based methods:
  - Delta Rule,
  - Backpropagation of Error,
  - Backpropagation through Time.
- Population algorithms:
  - Genetic algorithm,
  - Particle Swarm Optimization,
  - Simulated annealing,
  - Tabu search.

III. Problem Summary

Relations between system elements in the real world are neither symmetric nor monotonic as it is in case of models realized by basic FCMs. Furthermore each individual pair of system elements may not necessarily have only one mutual relation. It is possible that there there are multiple varying relations between elements [10]. Most of the real world systems have non-linear dynamics often higher than second order. In contrast to this, the dynamics of the basic FCM is only first order, where each actual state of concepts within the FCM depends only upon the last previous state. Therefore FCM cannot handle randomness associated to complex domains [10]. This may cause problems when FCM is used to create model of complex system.

A. Advantages of FCM

Main advantages of modeling approaches which utilize the fuzzy cognitive maps are [6]:

- simplicity of map design and parameter setting,
- flexibility of representation (it is easy to add or remove new concepts),
- simplicity of usage, comprehensibility and transparency for non-technical experts,
- low computational complexity,
- ability to describe dynamic systems thanks to feedback and recurrent structure of map design.

Advantage of FCMs over other modeling approaches such as Bayesian Networks (BS) or Petri Nets (PN) is that it is easy to create FCM model even by a non-expert because of its comprehensibility and modularity. In case of BS or PN it is not evident for non-experts in the field how to construct model of the system using these approaches [11][12]. It is also possible, that FCM is created by multiple experts using different approaches. This possibility is out of the question in case of PN, because it is not well established how to combine different PN which describe the same system [11][12].

B. Shortcomings of FCM Used for CS Modeling

There are several limitations of conventional FCMs when applied to modeling of complex systems. These can be summarized as follows [10][13]:

- Edges' weights are just linear.
- FCM models lack time delay in the interactions between nodes.
- FCMs cannot to represent logical operators (AND, OR, NOT, and XOR) between ingoing nodes.
- FCMs cannot model multi-meaning (grey) environments.
- It does not include a possible multi-state (quantum) of the concepts.
- It cannot to handle more than one relationship between nodes.
- Many real world causal relations are neither symmetric nor monotonic as FCM model.
- FCM dynamic is the first order, where the next state depends just of the previous one.

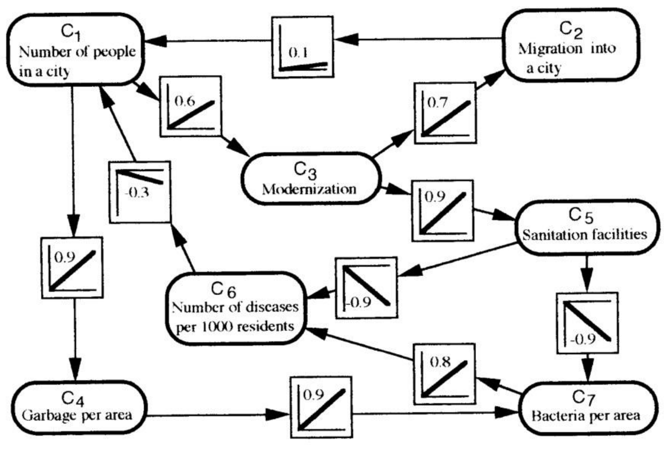

Fig. 4. One of the problems with FCMs is that relations between concepts are represented only as linear functions [14].

C. Solution Proposal to Problems of FCM

If we take into account the shortcomings of FCM from the previous section, it is clear that basic FCM may not be sufficient for modeling of complex systems. As a result, it is necessary to suggest some adjustments to the basic structure of FMC. In order to overcome the problems of basic FMC the following already established extensions can be taken into consideration [14]:

- weights extended to nonlinear membership functions,
- conditional weights,
- time-delayed weights.

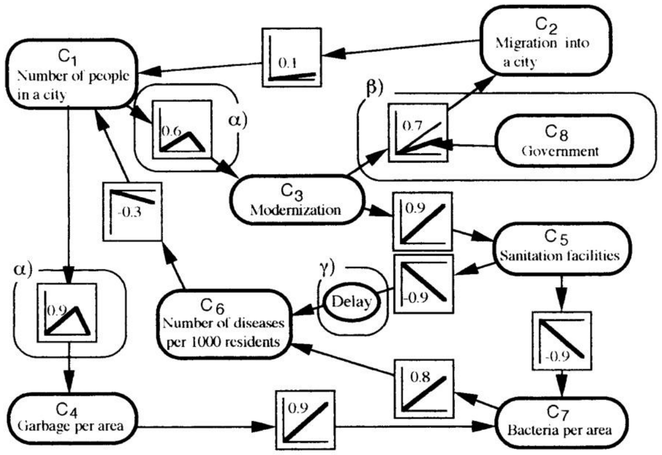

Fig. 5. FCM extended by nonlinear (α), conditional (β) and time-delayed (γ) weights [14].

However, there are other possible options to adjust the basic structure of FCM using ways and means from artificial intelligence and control theory, such as derivative and integral causal relations, multi-parametric polynomial weights between concepts, parameterized nonlinear function used to update the value of the concept or hybridization of FCM structure with use of artificial neural networks.

IV. Conclusion

Fuzzy cognitive maps can be considered as viable solution to modeling of complex systems [15][16]. However in order to be able to represent more complicated relations between system elements (or FCM concepts), it is necessary to replace simple linear weights by more general causal relations, possibly utilizing neural networks [17]-[20]. This should be the object of further research.

After the suitable solution is found, our next goal will be creation of FCM based model of complex thermodynamic system represented by small turbojet engine [21].

Acknowledgment

The work presented in this paper was supported by VEGA, Grant Agency of Ministry of Education and Academy Science of Slovak Republic under Grant No. 1/0298/12 – “Digital control of complex systems with two degrees of freedom.” The work presented in this paper was also supported by KEGA under Grant No. 018TUKE-4/2012 – “Progressive methods of education in the area of control and modeling of complex systems object oriented on aircraft turbo-compressor engines.”

References

[1] Madarász, L., Inteligentné technológie a ich aplikácie v zložitých systémoch (2. upravené vydanie). University Press Elfa, TU Košice, 2005. 348 pp. ISBN 80-89066-75-5.

[2] Vaščák, J., Madarász L., "Adaptation of Fuzzy Cognitive Maps – a Comparison Study," Acta Polytechnica Hungarica, Vol. 7, No. 3, pp.109,122, 2010. ISSN 1785-8860.

[3] Kosko B., "Fuzzy Cognitive Maps", International Journal of Man-Machine Studies, Elsevier, Vol. 24, No. 1, pp. 65-75, 1986

[4] Papageorgiou, E.I., "Learning Algorithms for Fuzzy Cognitive Maps – A Review Study," IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, vol.42, no.2, pp.150,163, March 2012. ISSN 1094-6977.

[5] Ketipi, M.K., Koulouriotis, D.E., Karakasis, E.G., Papakostas, G.A., Tourassis, V.D., "Nonlinear cause-effect relationships in Fuzzy Cognitive Maps," 2011 IEEE International Conference on Fuzzy Systems (FUZZ), pp.836,843, 27-30 June 2011. ISBN 978-1-4244-7315-1.

[6] Chen S. M., "Cognitive-Map-based Decision Analysis Based on NPN Logics", Fuzzy Sets and Systems, Elsevier, Vol. 71, No. 2, pp. 155-163, 1995

[7] Gregor, M., Groumpos, P. P., "Training Fuzzy Cognitive Maps Using Gradient-Based Supervised Learning", IFIP Advances in Information and Communication Technology, Volume 412, pp 547-556, Jan. 2013. ISBN 978-3-642-41141-0.

[8] Gregor, M., Groumpos, P. P., "Tuning the Position of a Fuzzy Cognitive Map Attractor Using Backpropagation through Time", 2013. Unpublished.

[9] Stach, W., Kurgan, L., Pedrycz, W., "Data-driven Nonlinear Hebbian Learning method for Fuzzy Cognitive Maps," IEEE International Conference on Fuzzy Systems (FUZZ), IEEE World Congress on Computational Intelligence. pp.1975,1981, 1-6 June 2008. ISBN 978-1-4244-1818-3

[10] Papageorgiou, E. I., Salmeron, J. L., "A Review of Fuzzy Cognitive Maps research during the last decade," IEEE Transactions on Fuzzy Systems, vol.21, no.1, pp.66,79, Feb. 2013. ISSN 1063-6706.

[11] León, M., Rodriguez, C., García, M.M., Bello, R., Vanhoof, K., “Fuzzy Cognitive Maps for Modeling Complex Systems”. Advances in Artificial Intelligence. 9th Mexican International Conference on Artificial Intelligence, MICAI 2010, Pachuca, Mexico, November 8-13, 2010, Proceedings, Part I, pp 166-174. Springer Berlin Heidelberg. ISBN 978-3-642-16760-7

[12] Li, X.: Dynamic Knowledge Inference and Learning under Adaptive Fuzzy Petri Net Framework. IEEE Transactions on Systems, Man, and Cybernetics – Part C: Applications and Reviews. vol.30, no.4, pp. 442-450, Nov 2000. ISSN 1094-6977

[13] Lazzerini, B., Mkrtchyan, L., "Risk Analysis Using Extended Fuzzy Cognitive Maps," 2010 International Conference on Intelligent Computing and Cognitive Informatics (ICICCI), pp.179,182, 22-23 June 2010. ISBN 978-1-4244-6640-5.

[14] Hagiwara, M., "Extended fuzzy cognitive maps," 1992 IEEE International Conference on Fuzzy Sysems, pp.795,801, 8-12 Mar 1992. ISBN 0-7803-0236-2.

[15] Stylios, C.D.; Groumpos, P.P., “Fuzzy Cognitive Maps in modeling supervisory control systems”.Journal of Intelligent & Fuzzy Systems: Applications in Engineering and Technology archive. Volume 8 Issue 2, pp. 83-98. March 2000. ISSN 1064-1246

[16] Stylios, C.D.; Groumpos, P.P., "Modeling complex systems using fuzzy cognitive maps," IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans, vol.34, no.1, pp.155,162, Jan. 2004 ISSN 1083-4427.

[17] Haykin, S., "Neural Network - A Comprehensive Foundation", Macmillian Publishing, 1994. ISBN 0-02-352781-7

[18] Funahashi, K., "On the Aproximate Realization of Continuous Mapping by Neural Networks,” Neural Networks, Volume 2 Issue 3, 1989, pp. 183-192, ISSN 0893-6080.

[19] Sinčák, P., Andrejková G., "Neurónové siete – Inžiniersky prístup" Dopredné neurónové siete, č. 1. Košice: Elfapress, ISBN 80-88786-38-X, 1996.

[20] Werbos, P.J., "Backpropagation through time: what it does and how to do it," Proceedings of the IEEE , vol.78, no.10, pp.1550,1560, Oct 1990. ISSN 0018-9219

[21] Lazar, T., Madarász L., et al., "Inovatívne výstupy z transformovaného experimentálneho pracoviska s malým prúdovým motorom," monografia, FEI, LF, TUKE, elfa, s.r.o., Košice 2011, ISBN 978-80-8086-170-4, EAN 978 8080 861704