EMBEBED DYNAMIC FUZZY COGNITIVE MAPS APPLIED TO THE CONTROL OF AN INDUSTRIAL MIXER.

Douglas E. Matsumoto[1], Márcio Mendonça[1], Lúcia Valéria R. Arruda[2], Elpiniki Papageorgiou[3]

1. *Departamento de Engenharia Elétrica, Universidade Tecnológica Federal do Paraná*
    Av. Alberto Carrazai 1640, Cornélio Procópio, PR - 86300-000
    E-mails: `douglas.matsmoto@gmail.com,mendonca@utfpr.edu.br`

2. *Laboratório de Automação e Sistemas de Controle Avançado (LASCA).Universidade Tecnológica Federal do Paraná.*
    Av. Sete de Setembro 3165, Curitiba, PR - 80230-901
    E-mail: `lvrarruda@utfpr.edu.br`

3. *Technological Education Institute of Lamia, Department of Informatics and Computer Technology,*
    Greece   E-mail: `epapageorgiou@teilam.gr`

Abstract: This paper presents the application of intelligent techniques to control an industrial mixer. Control design is based on Hebb learning for dynamic tuning of fuzzy cognitive maps. In this context, this paper develops a dynamical fuzzy cognitive map (D-FCM) based on Hebbian Learning algorithms. Two strategies to update FCM weights are derived. The D-FCM is used to control an industrial mixer. Simulation results of this control are presented. Finally, results are provided extending some of the algorithms into the Arduino platform in order to acknowledge the performance of the techniques reported in this paper.

Keywords: Fuzzy Cognitive Maps, Hebb Learning, Arduino Platform, Process Control, Fuzzy Logic.

Resumo: Este artigo apresenta a aplicação de técnicas inteligentes para controlar um misturador industrial. Controle é baseado no aprendizado de Hebb para sintonia dinâmica de mapas cognitivos *fuzzy*, do inglês *Fuzzy Cognitive Maps* (FCM). Nesse contexto, este artigo desenvolve um mapa cognitivo *fuzzy* dinâmico (D-FCM) baseado no algoritmo de aprendizado Hebb. Duas estratégias para atualizar os pesos do FCM são derivadas. O D-FCM é usado para controlar um misturador industrial. Resultados de simulação são apresentados. Por fim, são fornecidos resultados estendendo alguns dos algoritmos para uma plataforma Arduino a fim de reconhecer o desempenho das técnicas apresentadas nesse artigo.

Palavras-chave: Mapa Cognitivo *Fuzzy*, Aprendizado De Hebb, Plataforma Arduino, Controle De Processo, Lógica *Fuzzy*.

1   Introduction

Artificial Intelligence (AI) has applications and development in various areas of knowledge, such as mathematical biology neuroscience, computer science and others. The research area of intelligent computational systems aims to develop methods that try to mimic or approach the capabilities of humans to solve problems. These news methods are looking for emulate human's abilities to cope with very complex processes, based on inaccurate and/or approximated information. However, this information can be obtained from the expert's knowledge and/or operational data or behavior of an industrial system (Passino and Yourkovich, 1997).

In this context, Fuzzy Cognitive Map (FCM) is a tool for modeling the human knowledge. It can be obtained through linguistic terms, inherent to fuzzy systems, but with a structure similar to the Neural Networks (NN), which facilitates data processing, and has capabilities for training and adaptation. FCM is a technique based on the knowledge that inherits characteristics of Cognitive Maps and Artificial Neu-

ral Networks (Kosko, 1986) (Glykas, 2010) (Kosko, 1992) with applications in different areas of knowledge (Dickerson, 1994) (Lee and Lee, 2003) (Papageorgiou, 2007) (Papageorgiou, 2006) (Huang and Wang, 1999) (Koulouriotis et al., 2001). Besides the advantages and characteristics of inherited from these primary techniques, FCM was originally proposed as a tool to build models or cognitive maps in various fields of knowledge. It makes the tool easier to abstract the information necessary for modeling complex systems, which are similar in the construction to the human reasoning. Thus, the Fuzzy Cognitive Maps aggregate benefits of the acquisition, processing and adaptability from data and information system to be modeled, with a capacity for intelligent decision making due to its heuristic nature. However, the FCM has troubles in time modeling, restricting for applications where the causes and effects occur simultaneously.

In order to circumvent these drawbacks, dynamical fuzzy cognitive maps, D-FCM, can be developed which have the capability to model and manage behaviors of non-linear time-dependent system and often in real time. Examples of different D-FCMs

can be found in the recent literature, as examples, we can cite Mendonça et al. (2013), Miao et al. (2010), Koulouriotis, Diakoulakis and Emiris (2001), Miao et al. (2001).

Specifically, the work of Mendonça et al. (2013) presents a type of D-FCM, which aggregates the occurrence of events and other facilities that makes appropriate this type of cognitive map, for the development of intelligent control and automation in an industrial environment. In this paper, we use the same D-FCM proposed to control an industrial mixing tank.

In this work, different from Mendonça et al. (2013), we use a hebbian algorithm to dynamically adapt the D-FCM weights. In order to validate our D-FCM controller, we compared its performance with a classic fuzzy logic controller. This comparison is carried out with simulated data. Moreover, to show the control portability, we embedded the D-FCM controller into a low cost platform based on Arduino.

2 Development

To demonstrate the evolution of the proposal technique (D-FCM) we will use a case study well known in the literature as seen in Passino and Yourkovich (1997), Axelrod (1976) and Stylios, Groumpos and Georgopoulos (1999) to test level controllers. This case was selected to illustrate the need for refinement of a model based on FCM built exclusively with knowledge. The process shown in Figure 1 consists of a tank with two inlet valves for different liquids, a mixer, an outlet valve for removal of liquid produced by mixing and density meter that measures the quality' of the produced liquid.
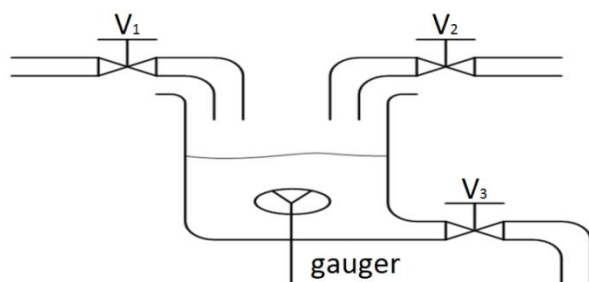

Fig. 1. Mixer Tank (Source: adapted from Stylios, Groumpos, Georgopoulos, 1999)

To model the process, it will be considered the equations that govern the balance sheet mass in the tank, which states that the flow rate (mass) of water entering and leaving the less equal and variation of mass in the tank and details of valves and sensors not were addressed.

Valves (V_1) and (V_2) insert two different liquids in the tank. During the reaction of the two liquids, a new liquid characterized by its density value is produced. At this time the valve (V_3) empties the tank in accordance with a campaign output flow, but the

liquid mixture should be in the specified levels. Although relatively simple, this process is a TITO (two inputs two outputs) type with coupled variables. To establish the quality of the control system of the produced fluid, a weighting machine placed in the tank measures the (specific gravity) produced liquid.

In this type of process, where the levels should be maintained at predetermined values to ensure its efficient functioning, we have two problems: the regulation, ie, fixed references and rejection of disturbance, where often the process and taken manually until the point of operation, and the tracking trajectory, which occur constant changes of reference. In this paper are addressed both problems.

When the value of the measured variable G (liquid mass) reaches the range of values between the maximum and minimum [Gmin, Gmax] specified, the desired mixed liquid is ready. The removal of liquid is only possible when the volume (V) is in a specified range between the values [Vmin and Vmax]. The control consists to keep these two variables in their operating ranges, as,

$$V_{min} < V < V_{max} \qquad (1)$$

and

$$G_{min} < G < G_{max} \qquad (2)$$

According to Papageorgiou et al. (2005), through the observation and analysis of operation of the process is possible for experts to define a list of key concepts related to physical quantities involved. The concepts and cognitive model is based on Papageorgiou's original FCM model, having the following concepts and structure:

Concept 1 - State of the valve 1 (closed, open or partially open).
Concept 2 - State of the valve 2 (closed, open or partially open).
Concept 3 - State of the valve 3 (closed, open or partially open).
Concept 4 - quantity of fluid (volume) in the tank, which depends on the operational state of the valves V1, V2 and V3.
Concept 5 - value measured by the G sensor for the density of the liquid.

Considering the initial proposed evolution for FCM we will use a D-FCM to control the mixer which should maintain levels of volume and mass within specified limits.

The process model uses the mass conservation principle to derive a set differential equations representing the process used to test the D-FCm controller. As a result the tank volume is the volume over the initial input flow of the intake valves V1 and V2 minus the outflow valve V3. Similarly, the mass of the tank follows the same principle as shown below.

$$V_{tank} = V_i + V_1 + V_2 - V_3 \qquad (3)$$

$$Weight_{tank} = M_i + (V_1 m_{e1}) + (V_2 m_{e2}) - M_{out} \quad (4)$$

Where V_i is the tank initial volume, V_3 the outlet valve, V_1 and V_2 are valves 1 and 2 respectively, M_i initial mixture mass, m_{e1} and m_{e2} is the specific gravity of the liquid 1 and 2 respectively and M_{out} is the mass removed by the outlet valve.

The development of the D-FCM is accomplished through two distinct stages. First the D-FCM is developed as a classic FCM where concepts and causal relationships are identified. The concepts can be variables and/or control actions, as already mentioned. However, the heuristic is related to the control condition of volume or weight of the mixture as it increases, where the inlet valves are closed, thus making it possible to assign inverse causal relationship between the concepts of levels and outlet valves. The output valve defines a positive relationship, when the output flow increases, according to a desired campaign. The intake valves also increases proportionally. The initial setting is done by using an algorithm based on heuristic optimization method of Simulated Annealing (Ghazanfari et al., 2007), in which an initial solution is cast as an initial guess and then solutions with a certain degree of randomness is tested systematically, until the system get the desired response. The figure 2 shows the schematic graph of a D-FCM controller.
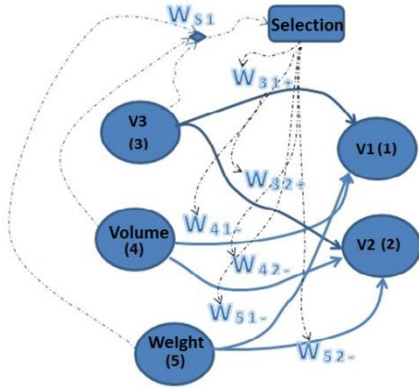

Fig. 2. D-FCM Controller

The second stage of development of the D-FCM is responsible for tuning or refinement of the model for dynamic response of the controller. In this case, when a change of output set-point in the campaign occurs, the weights of the causal relationships are tuned. To perform this function a new kind of concept and relation was included in the cognitive model. The relation selection assigns rules event-driven, which in this case was the change of set-point, levels of volume and weight of the liquid mixture.

Table 1. Casual relationship weights

State/Rules (D-FCM)	W31	W41	W32	W42	W51	W52
Initial value	-0.35	-0.40	-0.35	-0,40;	0,00	0,00
Rule 2 (Weight<840 mg)	-0,35	-0,40	-0,35	-0,40	0,20	0,20
Rule 3 (Weight<820 mg)	-0,35	-0,45	-0,35	-0,45	0,68	0,68

The D-FCM uses the concept of selection for switching the set of causal relations according to the basic rules of relation selection. D-FCM works similarly to a DT-FCM (Decision Tree - FCM) (Glykas, 2010) in another way, the D-FCM resembles a hybrid tool between a FCM and a temporal cyclic state machine, switched by triggering events similar to the work of Acampora and Loia (2007). The results of the weights of the causal relations found are shown in Table 1.

In order to establish a correlation and a future comparison between techniques of intelligent systems, a fuzzy controller was also developed. The fuzzy rule base implements weights assignment using the same heuristic control strategy.

As a result, both controllers fuzzy and D-FCM can be run under equal conditions supporting performance comparisons. As an example, we can mention some rules extracted from rule base established by experts:

If VOLUME is HIGH, then V1 is LOW, V2 is LOW;

If VOLUME is MEDIAN, then V1 is MEDIAN, V2 is MEDIAN;

If WEIGHT is LOW, then V1 is HIGH, V2 is HIGH;

In order to dynamic adapt the D-FCM weights we use the hebbian learning algorithm for FCM that is an adaptation of the classic hebbian method [2]. The initial values of causal relationships were developed in two ways: genetic algorithms and a method based on the heuristic method of simulated annealing used in the previous experiment.

The genetic algorithm used was classic, with a population of 20 individuals, simple crossing and approximately 1% of mutation. The chromosomes were generated by real numbers with all weights of the D-FCM, individuals were random and the initial method of classification was the method of the tournament with 3 individuals. And finally, the fitness function for simplicity considers the overall error of the two desired outputs. Figure 3 shows an evolution with 70 generations of the genetic algorithm proposed.

Table 2. Final values generated by the genetic algorithm

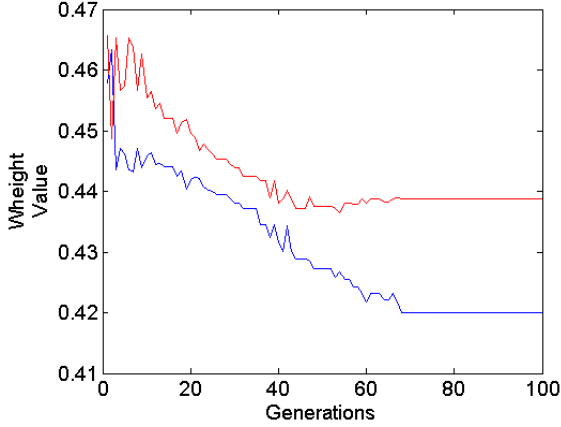| W. Values(D-FCM)	W13	W14	W23	W24	W53	W54
Final Value A.G.	-0.2659	-0.2314	-0.2549	-0.2498	0.1530	0.2146

Fig. 3 – Evolution of the weights in the genetic algorithm

Different proposals and variations of this method applied in tuning or in learning for FCM, are known in the literature (Papagergiou, 2012). In this paper, the method is used to update the intensity of causal relationships in a deterministic way according to the variation or error in the intensity of the concept or input variable. Specifically, the application of Hebb learning provides control actions as follows: if the weight or volume of the liquid mix increases, the intake valves have a causal relationship negatively intensified and tend to close more quickly. Conversely, if the volume or weight mixture decreases, the valves have increased its causality pursuing a control region. The mathematical equation is presented in Dickerson and Kosko (1994).

Two variations of the Hebbian learning will be presented. In the first case, a global error is assumed as the sum of the variation of only the volume concept. In the second case , the variation of volume, weight and output valve affects the causal relationships (fig. 2), for example, W51 and W52 are tuned according to the weight variation $\Delta A_i = V3(k) - V3(k-1)$. All values of γ forgetting factor were empirical. Finally, so that variations of the weights had the dynamics needed, any errors or variations of A were multiplied by a factor 20 gain value.

$$W_i(k) = W_{ij}(k-1) \pm \gamma \Delta A_i \qquad (5)$$

ΔA_i is the concept variation resulting from causal relationship, and it is given by $\Delta A_i = A_i(k) - A_i(k-1)$, γ is the learning rate at iteration k.

Causal relationships that have negative causality has negative sign and similarly to positive causal relationships. Equations 6-11 show the implementation of the proposal.

$$W_{51} = W_{51}(k-1) - 0.7\Delta A_i \times k_p \qquad (6)$$

$$W_{52} = W_{52}(k-1) - 0.7\Delta A_i \times k_p \qquad (7)$$

$$W_{41} = W_{41}(k-1) - 0.7\Delta A_i \times k_p \qquad (8)$$

$$W_{42} = W_{42}(k-1) - 0.7\Delta A_i \times k_p \qquad (9)$$

$$W_{31} = W_{31}(k-1) + 0.1\Delta A_i \times k_p \qquad (10)$$

$$W_{32} = W_{32}(k-1) + 0.1\Delta A_i \times k_p \qquad (11)$$

The results of D-FCM by Hebbian learning with only the volume parameter variation are shown in Fig. 5, which shows the behavior of the controlled variables within the predetermined range for the volume and the weight of the mixture. It is noteworthy that the controller keeps the variables in the control range and pursues a trajectory according to a campaign where output flow is also predetermined. In this initial experiment, a campaign with a sequence of values ranging from 7, 5 and 10 ml/min can be seen as set-point output flow (outlet valve). Fig. 6 shows the evolution of the weights of the causal relationships during the process.

The fig. 7 shows the results of Hebbian learning algorithm for FCM considering the variations ΔAi of the concepts concerning volume, weight and outlet valve, while in the fig. 8 is displayed the weights of the causal relationship in the process.

3 Experimental Results

In order to extend the applicability of this work, the developed D-FCM controller is embedded into an Arduino platform which ensures the portability of the FCM generated code. Arduino is an open-source electronics prototyping platform which uses ATMega series microcontrollers.
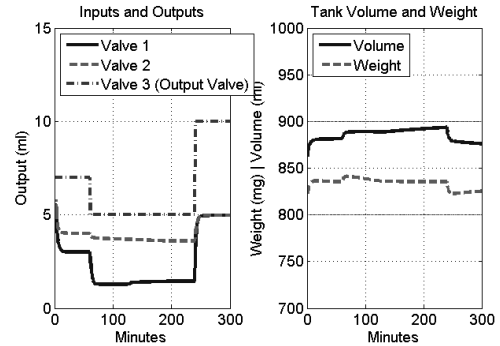

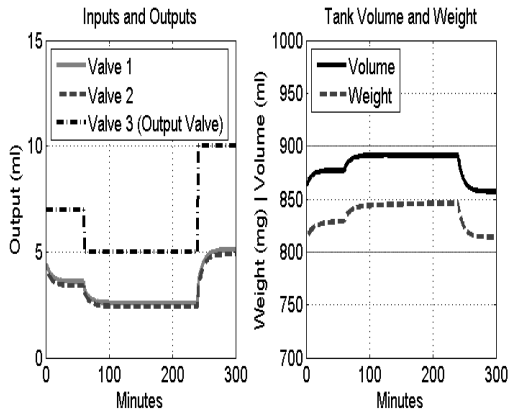Fig 4. . Inputs and outputs valves, Volume and weight (Fuzzy)

Fig. 5. Inputs and outputs valves, Volume and weight (HL global variation).
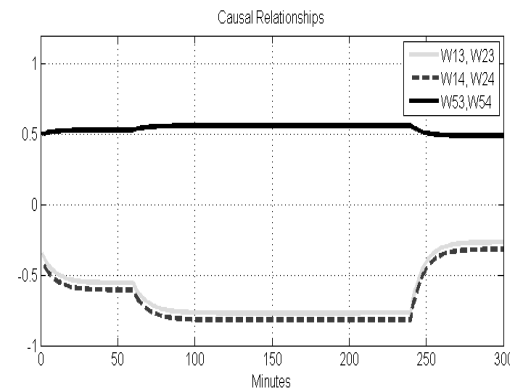

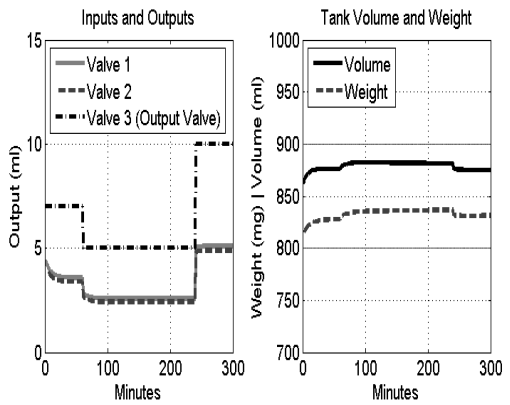Fig. 6. Causal Relationships in the process (HL global variation).

Fig. 7. - Inputs and outputs valves, Volume and weight (HL punctual variation)
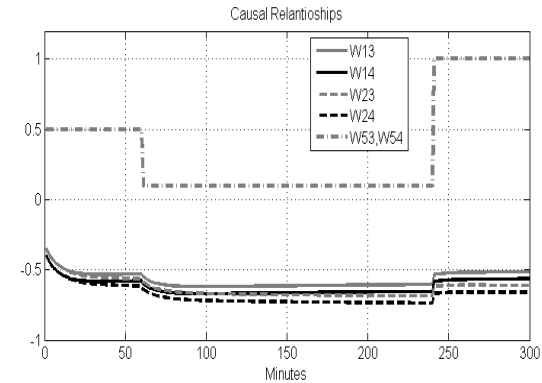

Fig. 8. Causal Relationships in the process (HL punctual variation).

The equations for level and weight are calculated by Matlab for simulating the process. Through a Serial communication established with Arduino, Matlab sends the current values of Volume, Weight and output valve to Arduino that receives these data, calculates the values of the concept 1 (valve 1) and concept 2 (valve 2) and then returns these data to Matlab. After this, new values of Volume and Weight are recalculated.
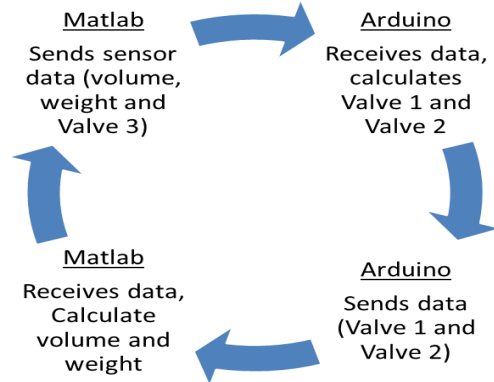

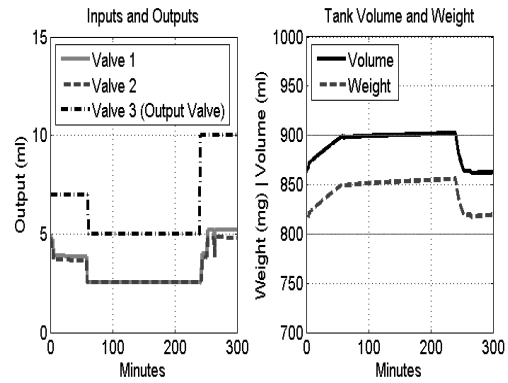Fig. 9. Cycle and image of the communication Matlab - Arduino

Fig. 10. - Inputs and outputs valves, Volume and weight (DT, Arduino)

Similarly, fig. 11 shows the results obtained with the Hebbian learning algorithm for FCM with the three parameters of ΔA_i.
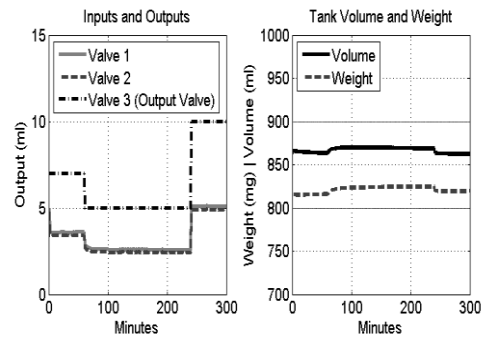

Fig. 11. - Inputs and outputs valves, Volume and weight (HL, Arduino)

Fig. 10 shows the results obtained with the Arduino platform providing data of the actuators Valve 1 and Valve 2 with Matlab performing data acquisition. The algorithm switches the sets of causal relations that operate similarly to a DT-FCM (decision tree - FCM), where the activation rules and weights are shown in Table 1.

4 Conclusions

Performing a comparison of the results, we see a decrease in the control range in the cases where there is variation in causal relationships by Hebbian learning algorithms. Figures 9 and 10 show the results.

From the data obtained from Arduino by the variations of the D-FCM embedded in the platform, it is observed that the controlled variables are in well behaved ranges, which suggests that the D-FCM codes have low computational complexity due to the simplicity mathematical processing compared with the classical fuzzy logic, for example. Thus, we can emphasize the portability and the possibility of developing D-FCM controllers on low cost platforms.

Future studies address a comparison with classical PID controllers, weighted Fuzzy controller or other intelligent controller. Finally, the application of the controller in a real mixer into a real data environment will be investigated.

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