# Dynamic Fuzzy Cognitive Maps Embedded and Classical Fuzzy Controllers Applied in Industrial Process

Lucas Botoni de Souza
Ruan Victor Pelloso Duarte Barros
Márcio Mendonça
DAELE (Electric Department)
UTFPR-CP - Cornélio Procópio, Brazil
lucasbotoni@hotmail.com
ruan_pelloso@yahoo.com.br
mendonca@utfpr.edu.br

Elpiniki I. Papageorgiou
Department of Computer Engineering
Technological Education Institute/ University of Applied Sciences of Central Greece
Lamia, Greece
epapageorgiou@teiste.gr

*Abstract*— **This research presents the application of intelligent techniques to control an industrial mixer. The controller design is based on Hebbian learning for evolution of Fuzzy Cognitive Maps. A Fuzzy Classic Controller and Artificial Neural Network was used to validate the simulation results. Experimental simulations and analysis in this control problem was made. In addition, the results were embedded using algorithms into the Arduino platform.**

***Keywords-Dynamic Fuzzy Cognitive Maps; Hebbian Learning; Arduino Microcontroller; Process Control; Fuzzy Logic; Artificial Neural Network.***

## I. INTRODUCTION

In general, some of the difficulties found in acquiring knowledge in different areas of engineering (such as robotics, control or process control) are how to recognize the processes /systems; how to identify important variables and parameters. In addition, some questions are important: how to classify the type of physical problem; how to identify the family of mathematical models that can be associated; how to select the method and / or tool for the search and analysis of the model.

The final output of modern processes is significantly influenced by the selection of the set points of the process variables, as they fundamentally impact the product quality characteristics and the process performance metrics [1]. In this context, it is possible to define the main goal of this research: the development of techniques based on knowledge for the industrial mixer process control, a classic problem of Fuzzy Cognitive Maps area. It is worth mentioning this work is inspired by a previous work [2].

The article proposal is a different setup, especially the initial situation and a comparison with a new controller using Fuzzy-Logic with ANN (artificial neural network). The motivation of this research is developments in intelligent control area, expanding the adaptive concept and studying the feasibility of an autonomous control in practice.

Intelligent control techniques take control actions without depending on a complete or partial mathematical model. In these cases, human beings can deal with complicated processes based on inaccurate and/or approximate information. The strategy adopted by them is also of imprecise nature and usually capable of being expressed in linguistic terms. Thus, by means of Fuzzy Logic concepts, it is possible to model this type of information [3].

In general, 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 like the Artificial Neural Networks (ANN), 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 Neural Networks [4]-[6], with applications in different areas of knowledge [7]-[14]. Besides the advantages and characteristics 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. Dynamic Fuzzy Cognitive Maps (DFCM) should be developed to a model that can manage behaviors of non-linear time-dependent system and sometimes in real time. Classic FCM has drawback for time modeling [12]. In this way, examples of different variation of the classic or standard FCMs [4] can be found in the recent literature, e.g., [12]-[18].

This paper has two objectives. First objective is the development of two controllers using an acyclic DFCM with same knowledge as this of Fuzzy and Fuzzy Neural Controller, and with similar heuristic, thus producing comparable simulated results. Second goal is to show an embedded DFCM in the low-cost processing microcontroller Arduino with more noise and disturbances (valve locking) to test the adaptability of the DFCM. To reach the goals, we initially use the similar DFCM proposed initially in [13] to control an industrial mixing tank. As opposed to [13], we use the Hebbian algorithm to dynamically adapt the DFCM weights. In order to validate our DFCM controller, we compared its performance with a Fuzzy Logic Controller. This comparison is carried out with simulated data.

This work is developed as follows: Section 2 discusses the process development; Section 3 presents controllers development; Section 4 presents the DFCM development; Section 5 discusses results; Section 6 concludes and addresses future works.

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## II. Development

To demonstrate the evolution of the proposed technique (DFCM) we will use a case study well known in the literature as seen in [2][5] and others. This case was selected to illustrate the need for refinement of a model based on FCM built exclusively with knowledge. The process shown in Fig. 1 consists of a tank with two inlet valves for different liquids, a mixer, an outlet valve for removal of the final product and a specific gravity meter that measures the specific gravity of the produced liquid. In this research, to illustrate and exemplify the operation of the industrial mixer, the liquids are water with specific gravity 1 and soybean oil with a specific gravity of about 0.9.

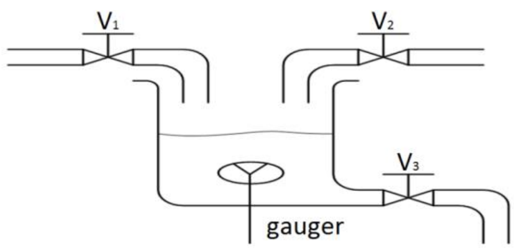


Figure 1. Mixer tank (Source: adapted from [20]).

Valves (V1) and (V2) insert two different liquids (specific gravities) in the tank. During the reaction of the two liquids, a new liquid characterized by its new specific gravity value is produced. At this time, the valve (V3) empties the tank in accordance with a campaign output flow, but the liquid mixture should match the specified levels of the volume and specific gravity.

Although relatively simple, this process is a Two Inputs Two Outputs (TITO) 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. 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:

$$V_{min} < V < V_{max} \tag{1}$$

$$G_{min} < G < G_{max} \tag{2}$$

In this study, it was tried to limit these values from approximately the range of 810 to 850 [mg] for the mass and approximately the range of 840 to 880 [ml] for the volume. The initial values for mass and volume are 800mg and 850ml respectively. According to Papageorgiou and collaborators [21], through the observation and analysis of the process, it is possible for experts to define a list of key concepts related to physical quantities involved. The concepts and cognitive model are:

- 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 mixture (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 specific gravity of the liquid.

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

The process model uses the mass conservation principle in incompressible fluid to derive a set of differential equations representing the process used to test the DFCM controller. As a result, the tank volume is the volume over the initial input flow of the inlet valves V1 and V2 minus the outflow valve V3, this valve V3 and the output campaign was introduced in this work to increase the complexity original process [20]. Similarly, the mass of the tank follows the same principle as shown below. The values used for $m_{e1}$ and $m_{e2}$ were 1.0 and 0.9, respectively.

$$\mathrm{V_{tank}} = \mathrm{V_i} + \mathrm{V_1} + \mathrm{V_2} - \mathrm{V_3} \tag{3}$$

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

## III. Fuzzy Controller Development

To establish a correlation and a future comparison between techniques, a Fuzzy Controller was also developed. The Fuzzy rules base uses the same heuristic control strategy and conditions.

Fuzzy logic has proved to can provide satisfactory non-linear controllers even when only the nominal plant model is available, or when plant parameters are not known with precision [22]-[24]. Fuzzy Control is a technique used for decades, especially in process controlling [5].

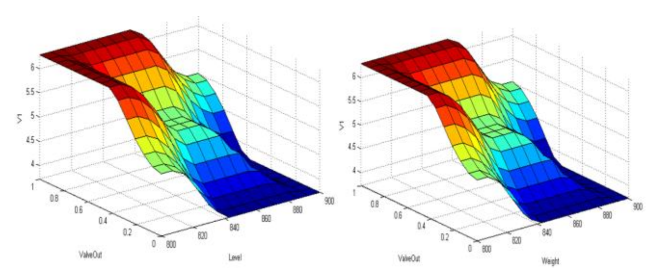

Figure 2. Fuzzy Controller Surfaces, V1 and V2.

It is a motivation to validate DFCM, so in this study it was used the same approach for two controllers, with two different formalisms. It is not in the scope to discuss the development of the Fuzzy Controller, but, some details of the structure are pertinent: functions are triangles and trapezoidal and 6 rules are considered in its base. The surface of this controller is showed in Fig. 2. Moreover, the rules are

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symmetric and similar by two output valves; in this specific case the surface of valve 2 is the same as in valve 1. The examples of base rules are:

1. If (Level is medium) or (Valve Out is medium) then (V1 is medium) and (V2 is medium).
2. If (Level is high) or (Valve Out is low) then (V1 is low) and (V2 is low).
3. If (Weight is medium) or (Valve Out is medium) then (V1 is medium) and (V2 is medium).

The rules and structure of the Fuzzy Controller used on its development was based on the DFCM heuristic.

Figure 3 show structure with same variables input and output like DFCM.

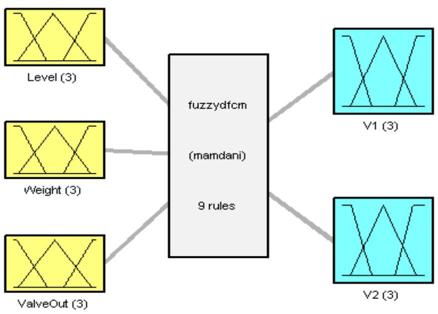


Figure 3. Fuzzy Structure.

A Fuzzy-ANN cascade controller had its ANN (multilayer perceptron) trained with the output data of the Fuzzy controller. The topology was empirically chosen by observing the learning time and output error. Therefore, 200 neurons were used on its hidden layer. Moreover, there were used 6000 points from inside the control region.

## IV. DFCM DEVELOPMENT

The structure of the DFCM controller is similar to the developed Fuzzy controller, using same heuristics, e.g., if the output valve (V3, in accordance to Fig. 1) increases its flow, the inlet valves (V1 and V2) increase too. In other hand, in case volume and weight of the mixture increase, the inlet valves decrease. For example, the relationships W54 and W53, in the DFCM, are similar in effects or control actions of the Fuzzy controller's base rules.

The development of the DFCM is made through three distinct stages. First, the DFCM is developed as structure, concepts and causal relationships, similar to a classic FCM, where concepts and causal relationships are identified through sensors and actuators of the process. The concepts can be variables and/or control actions, as already mentioned.

The output valve is defined by a positive relationship, i.e., when the campaign increases, the output flow (V3) also increases, similarly, the input valves increase too; moreover, when the mixture volume and weight increase, V1 and V2 decrease. In both cases, the flow of the valves increases or decreases proportionally. The second development stage is the well-known Genetic Algorithm [25]. The Fig. 4 shows the schematic graph of a DFCM controller.

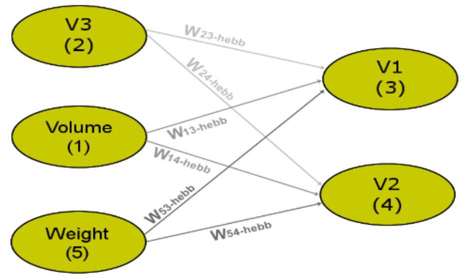


Figure 4. DFCM Controller

In this research, the initial values of causal relationships are determined through genetic algorithms. The genetic algorithm used is a conventional one, with a population of 20 individuals, simple crossing and approximately 1% of mutation. The chromosomes were generated by real numbers with all the DFCM weights, individuals were random and the initial method of classification was the tournament method with 3 individuals.

Finally, the fitness function for simplicity considers the overall error of the two desired outputs with 60 generations of the Genetic Algorithm proposed; it stabilizes and reaches the initial solution for the opening of the valves, approximately 42%.

Table 1 shows initial values of the DFCM weighs. Different proposals and variations of this method applied in tuning FCM can be found [16].

TABLE I. INITIALS CASUAL RELATIONSHIP WEIGHTS

| *W23* | *W24* | *W13* | *W14* | *W53* | *W54* |
|---|---|---|---|---|---|
| -0.23 | -0.26 | -0.26 | -0.26 | 0.23 | 0.15 |

The third stage of the DFCM development concerns the 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 dynamically tuned. To perform this, function a new kind of concept and relation was included in the cognitive model.

To dynamically adapt the DFCM weights we used the Hebbian learning algorithm for FCM that is an adaptation of the classic Hebbian method [4]. Different proposals and variations of this method applied in tuning or in learning for FCM are known in the literature, for example [15]. 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 process variable, equations 5 and 6 show this. Specifically, the application of Hebbian learning algorithm provides control actions as follows: if the weight or volume of the liquid mixture increases, the inlet valves have a causal relationship negatively intensified and tend to close more quickly. In addition, if the volume or weight mixture decreases, the inlet valves have a causal relationship positively intensified. The mathematical equation is presented in (5).

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

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Where: ΔAi is the concept variation resulting from causal relationship, and it is given by ΔAi = Ai (k)-Ai (k-1), γ is the learning rate at iteration k.

This version of the Hebbian algorithm is an evolution of the two proposals of Matsumoto and collaborators [26].

Causal relationships that have negative causality has negative sign and similarly to positive causal relationships. The equations applied in this work are adapted of the Hebb original version.

$$W_i(k) = k_p * (W_{ij}(k-1) - \gamma * \Delta A_i) \tag{6}$$

Where: γ=1, and **kp** is different for every weight pairs. It has their assigned values empirically by observing the dynamics of process performance, recursive method, **kp** =40 for (W14; W23), **kp** =18 for (W13; W24) and kp =2.35 for (W53; W54), with normalized values.
The DFCM inference is like Classic FCM [4], and the inference equations are shown below (equation 7 and 8).

$$\mathrm{A_i} = \int \left( \sum_{\substack{j=1 \\ j\neq i}}^{n} (\mathrm{A_j} \cdot \mathrm{W_{ji}}) \right) + \mathrm{A_i^{previous}} \tag{7}$$

$$\mathrm{f(x)} = \frac{1}{1+e^{-\lambda x}} \tag{8}$$

Fig. 5 shows the results of Hebbian Learning Algorithm for FCM considering the variations ΔAi of the concepts concerning volume, weight, outlet valve state, and the weights of the causal relationship in the process. This figure also shows the evolution of the weights of the causal relationships during the process into a range of [-1, 1].

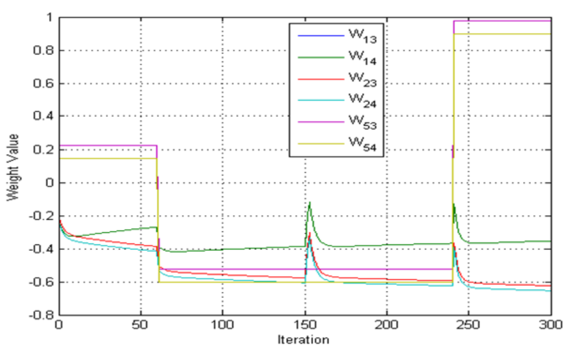


Figure 5. Evolution of the weights in the Hebbian Learning

## V. SIMULATED EXPERIMENTAL RESULTS

The results of DFCM are shown in Fig. 6, which shows the behavior of the controlled variables within the predetermined range of the volume and 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 the output flow is also predetermined. In this initial experiment, a campaign with a sequence of values ranging from 7, 5 and 11 ml/min can be a set-point output flow (outlet valve). Similarly, the results of the Fuzzy Controller are shown in Fig. 7. It is observed that the behavior of DFCM and Fuzzy controllers were similar when the tank is empty, with a slightly advantage for the Fuzzy controller that reached the desired result after 230 steps, while the DFCM needed 250 steps with the adaptation off.

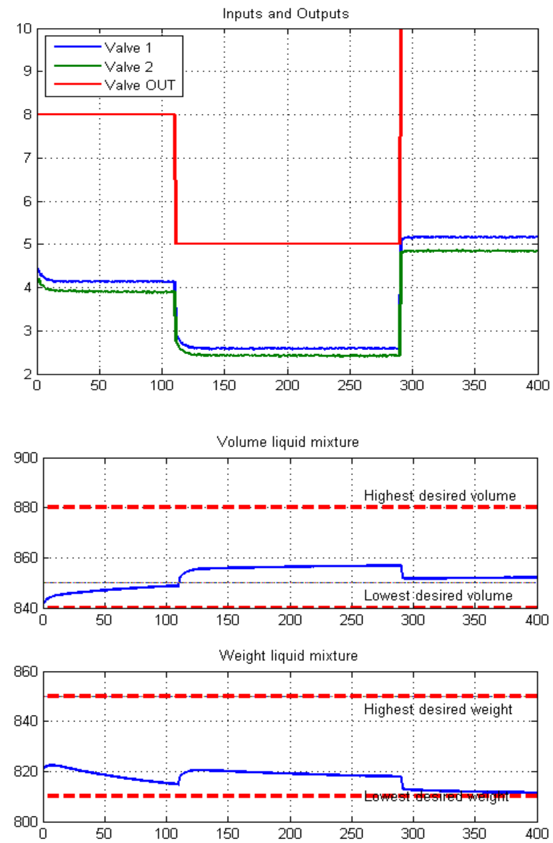


Figure 6. Valver and Results of the DFCM Controller

Table 2 shows that the simulated numeric results of the DFCM controller had a similar performance compared to the conventional Fuzzy Logic Controller, and DFCM embedded in Arduino with small difference in same conditions, with simulated small noise.

TABLE II. QUANTITATIVE RESULTS

| | *DFCM* | *DFCM-Arduino* | *Fuzzy Logic* | *Fuzzy-ANN* |
|---|---|---|---|---|
| | **Max-Min** | **Max-Min** | **Max-Min** | **Max-Min** |
| **Volume Mix (ml)** | 13.6 | 16.9 | 31.2 | 51.9 |
| **Weight Mix (mg)** | 17.1 | 14.1 | 27.5 | 31.2 |

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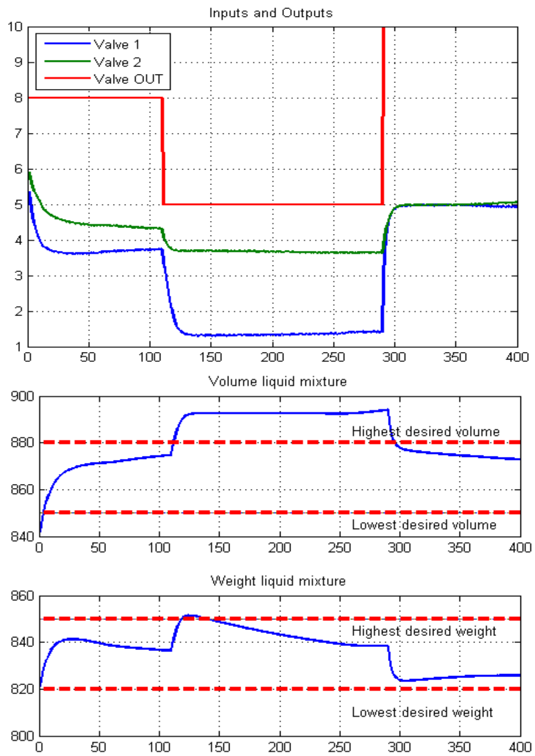


Figure 7. Valves and Results of the Fuzzy Controller

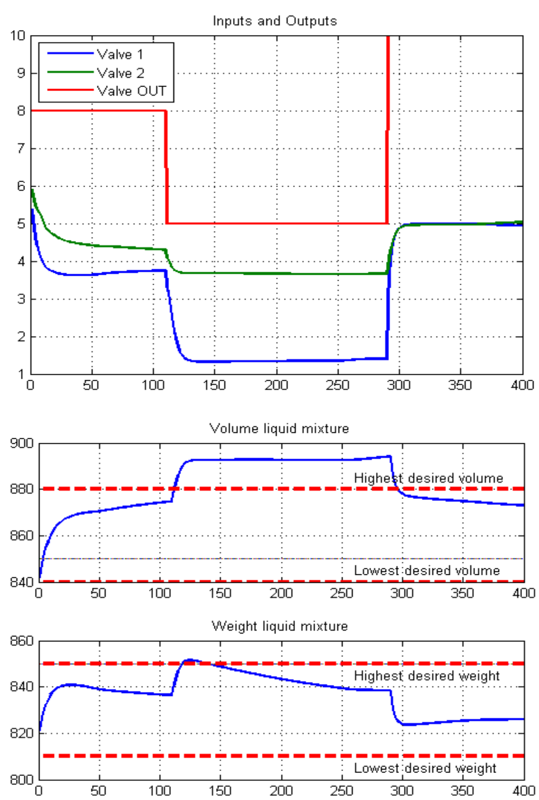


Figure 8. Valves and Results of the Fuzzy-ANN Controller

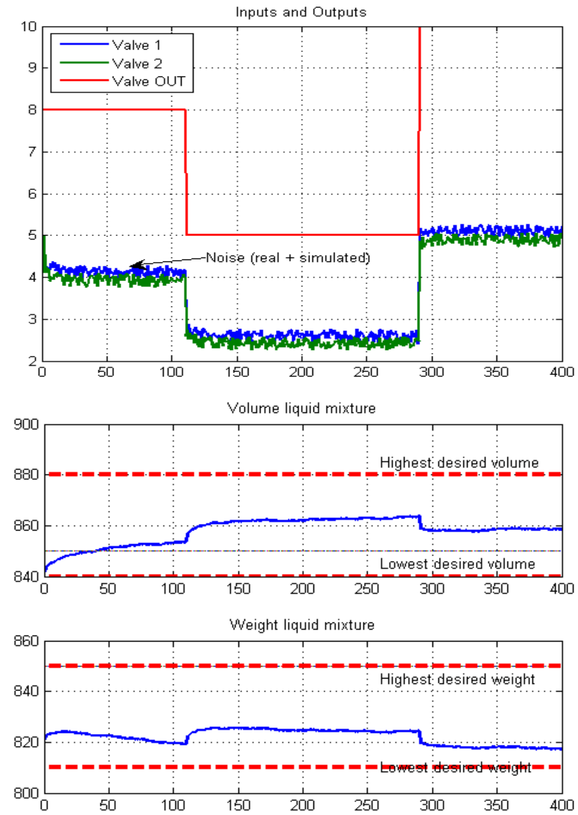


Figure 9. Valves and Results of the Arduino embedded DFCM

In order to extend the applicability of this work, the developed DFCM controller is embedded into an Arduino platform which ensures the portability of the FCM generated code. Arduino is an open-source electronic prototyping platform. Arduino was chosen because it is a cheap controller, and mainly because of its low processing capacity, to emphasize the low computational complexity of FCM [16].

The equations for volume and weight are calculated by Matlab, 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. Details on how this technique can be used are presented in Matlab Tutorial, Matlab and Arduino codes, by accessing the link [27]. The cycle of communication between Arduino to Matlab can be checked in [26].

Fig. 9 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 DFCM simulated with noise and disturb in the valve 1. The noise in Fig. 9 is the sum of the real noise, observed in data transference between Arduino and Matlab, and a simulated white noise. Equation (9) shows the composition of the experiment noise.

$$Noise_{Experiment} = Noise_{Simulated} + Noise_{Arduino-Matlab} \quad (9)$$

## VI. CONCLUSION

The contribution of this study focuses on the introduction of Fuzzy Cognitive Maps in the embedded control area. In simulated data, the results are similar for the three controllers, with a small advantage for DFCM with or without Arduino, observed that DFCM controller is adaptive. The results obtained from both controllers were quite the same. However, the Fuzzy-ANN did not have any significant improvement, there was a slightly reduction of the noise which can be a major factor on industrial plants.

From the data obtained from Arduino microcontroller, based on the variations of the DFCM embedded in the platform, it is observed that the controlled variables were in well-behaved ranges, which suggests that the DFCM codes have low computational complexity due to the simplicity of its inference mathematical processing.

Thus, we can emphasize the portability and the possibility of developing DFCM controllers on low cost platforms. In short, this work showed that DFCM can be embedded in low cost microcontrollers.

Future studies will quantify the computational complexity of the DFCM, for a more general conclusion, results with real prototype. Finally, other controllers with dynamic adaptation, like adaptively fuzzy controllers, ANFIS can be used for the comparison.

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