DIFFERENT CONFIGURATIONS OF FUZZY COGNITIVE MAPS APPLIED IN INDUSTRIAL PROCESSES

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Abstract—In this work, we present different configurations of Fuzzy Cognitive Maps (FCMs) controllers of three industrial processes. A first-order heat exchanger (Heatex) with a classic FCM compared with a Fuzzy Logic Controller (FLC) and the original PI controller designed by MatWorks®, using the Integral Absolute Error (IAE), the Integral Squared Error (ISE), settling time, overshoot and control signal. The second process is a fourth order alcoholic fermenter, using FCM as an adjustment mechanism for a PID controller tuned heuristically, using the same comparison parameters than the Heatex. The last process is a mixer tank, with two methods for Dynamic Fuzzy Cognitive Maps' (DFCMs) weight adjustment: the Hebbian learning algorithm (DFCM-Heb) and a weight-scheduling (DFCM-WS) configuration. In this process, the most satisfactory method (DFCM-Heb) was embedded in a PIC18F4520 to verify the low computational complexity of the DFCM. For the Heatex, the PI controller still the best option, however, the three controllers presented similar results. In the alcoholic fermenter process, the FCM-PID mechanism obtained the most satisfactory responses.

Keywords— Heat exchanger, alcoholic fermenter, mixer tank, Fuzzy Cognitive Maps, adaptive control.

Resumo— Neste trabalho, foram apresentadas diferentes configurações de controladores Mapas Cognitivos Fuzzy (FCMs) de três processos industriais. Um trocador de calor de primeira ordem (Heatex) com um FCM clássico comparado com um Controlador Lógico *Fuzzy* (FLC) e o controlador PI original projetado pela MatWorks®, usando a Integral do Erro Absoluto (IAE), Integral do Erro Quadrático (ISE), tempo de acomodação, máximo sobressinal e sinal de controle. O segundo processo é um fermentador alcoólico de quarta ordem, usando FCM como um mecanismo de ajuste para um controlador PID sintonizado heuristicamente, usando os mesmos parâmetros de comparação do que o Heatex. O último processo é um tanque misturador, com dois métodos para ajuste dos pesos de um Mapa Cognitivo *Fuzzy* Dinâmico (DFCM): o algoritmo de aprendizado de Hebbian (DFCM-Heb) e uma configuração de escalonamento dos pesos (DFCM-WS). Neste processo, o método mais satisfatório (DFCM-Heb) foi embarcado em um PIC18F4520 para verificar a baixa complexidade computacional do DFCM. Para o Heatex, o controlador PI ainda é a melhor opção, no entanto, os três controladores apresentaram resultados semelhantes. No processo de fermentação alcoólica, o mecanismo FCM-PID obteve as respostas mais satisfatórias.

Palavras-chave— Trocador de calor, fermentador alcoólico, tanque misturador, Mapas Cognitivos *Fuzzy*, controle adaptativo.

1 Introduction

In modern control systems, it is noticed that linear control becomes insufficient when the operating conditions of a system are not fixed. Thus, adaptive control is used. One of its objectives is to compensate variations in the parameters of nonlinear control systems (Åström and Wittenmark, 2008) which, in general, are an interconnection of components forming a configuration that produces a desired response (Ogata, 2010). An alternative is to use heuristic models or semi-quantitative methods like Fuzzy Cognitive Maps (FCMs), which encode experts' knowledge about the connections among the different parameters of the studied industrial process control. These methods could be preferred to other alternatives as they allow modeling of complex system dynamics, without the need for capturing the functional relationships between concepts of the real system by means of complex mathematical equations. In control systems, the main comparison between classical and fuzzy logic control provokes a general discussion of these two paradigms. Both in fuzzy and in FCM control, Fig. 1 (a), linguistic terms represent the degree of knowledge of the operator on the analyzed real-world plant. This fact provides the possibility of controlling the process without having its mathematical model, unlike classical control, Fig. 1 (b), which requires the model and its simplifying assumptions to the controller design, adding one more step in the paradigm, to prove the theorem stability (Ross, 2010).

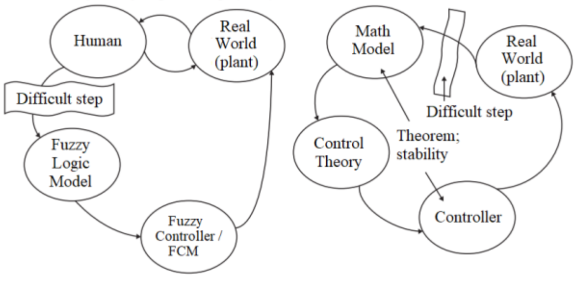

Figure 1. (a) Fuzzy/FCM and (b) classical paradigm. Adapted from (Ross, 2010)

In this way, FCMs can encode control tactics that are imprecise in nature, commonly expressed in linguistic terms, which is helpful when it is difficult to obtain a mathematical model of the process.

FCMs allow dealing with subjective and vague linguistic variables used by domain experts and handling uncertainties due to their approximate knowledge using Fuzzy Logic (Passino and Yurkovich, 1998), such as the heuristic process used in this work.

There are many applications of FCMs in process control. In the work of (Mendonça *et al.*, 2013), the authors used a Fuzzy-PID controller development of an alcoholic fermenter process proposed in (Maher, 1995). Also, (Lima and Serra, 2015) proposed a robust Fuzzy controller implemented for visualization and control of a thermal process.

In this work, the objective is to investigate the application of systems based on FCMs, designed using experts' knowledge and compare their results with the more classical methods. We present three examples of industrial processes in this work. Intelligent control methods were used to tune the gains of a classical PID controller of an alcoholic fermenter, were directly applied as controllers in a heat exchange process (Heatex), and a Dynamic Fuzzy Cognitive Map (DFCM) with two weight's adaptation methods: Hebbian learning algorithm (DFCM-Heb) and a weight-scheduling configuration (DFCM-WS).

The paper is organized as follows. Section 2 describes the processes and presents a brief background about Fuzzy Logic and FCM, presenting our contribution in the intelligent control area. In Section 3, we show the obtained results and compare the other techniques. Finally, in Section 4, we outline some conclusions and directions for future work.

2 Background and Processes' Description

In this section, we present a brief introduction of the industrial processes used in this work, namely the *Heatex*, the *Alcoholic Fermenter* and the *Mixing Tank*. In addition, we briefly describe Fuzzy Logic and the FCM technique applied in three different industrial processes.

2.1 Heatex process description

The original Heatex process used as a testbed in this work is found in the Matlab® documentation and in (Mollon *et al.*, 2017), among other works. It is described as a chemical reactor, called the stirring tank. In this process, the top piping provides liquid to be mixed in the tank. Then, this liquid must be maintained at a constant temperature from the variation of the amount of steam supplied to the heat exchanger (lower tube) by means of its control valve, which performs the control action through a PI controller.

The disturbance sources in this process are the variations in the temperature of the input flow, given by a disturbance plant. The Heatex process was designed using a Fuzzy Logic Controller (FLC) as well as a FCM controller, analyzed in the feedback form. The block diagram of the system is depicted by Fig. 2.

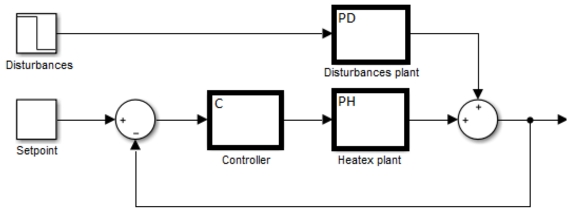

Figure 2. Heatex block diagram

The process is governed by two transfer functions: the mixer plant (Heatex) PH (1) and the disturbance plant PD (2), and the control is made through a setpoint, as shown in Fig. 2.

$$PH = {}^{1}\!/_{21.3s+1} \quad (1)$$

$$PD = {}^{1}\!/_{25s+1} \quad (2)$$

2.2 Alcoholic Fermenter Process Delimitation

Fermentation is a process of energy release in which there is no oxygen participation, and is used in industrial fermentation processes for manufacturing alcoholic beverages. Fig. 3 shows a real alcoholic fermenter (a) and the simulated one used in this work (b). In Fig. 3 (b), the F_{in} valve is responsible for the substrate flow in the tank, and F_{out} valve regulates the product's flow out of the tank. These two valves are controlled by two independent PID controllers, which are adapted by the proposed tuning mechanisms, FCM-PID and Fuzzy-PID.

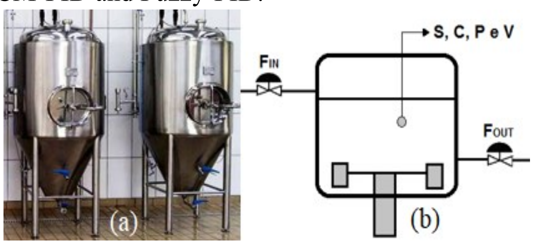

Figure 3. Real (a) and simulated (Mendonça *et al.*, 2013) (b) alcoholic fermenters

The fermentation process used in this work was inspired from the initial proposal of Maher (Maher, 1995), which has been a recurrent system for validation of different control architectures. More details can be found in (Mendonça *et al.*, 2013).

The process has four state variables: the concentrations (g/l) of substrate (*S*), the biomass (*C*), the product (*P*), and the volume (*V*) of the fermentation tank.

In this process, four differential equations govern the system's behavior, and are given by equations (3) to (7). The variables are the same as found in *(Mendonça et al.*, 2013).

$$\frac{dS}{dt} = -\frac{1}{Y_{C/S}}\mu_c + \frac{F_{in}}{V}Sa - \frac{F_{out}}{V}S \quad (3)$$

$$\frac{dC}{dt} = \mu_c - \frac{F_{out}}{V}S \quad (4)$$

$$\frac{dP}{dt} = \frac{Y_{P/S}}{Y_{C/S}}\mu_c - \frac{F_{out}}{V}P \quad (5)$$

$$\frac{dV}{dt} = F_{in} - F_{out} \quad (6)$$

$$\mu_c = \mu_0 \frac{S}{K_s + Sa}\left(1 - \frac{P}{P_m}\right) \quad (7)$$

Important system dynamics factors are the large accommodation time and high correlation between the state variables. It is also noticed that it is a non-minimal phase system, as seen in (Mendonça *et al.*, 2013), with stabilization depending strictly on the correct concentrations to occur, thus being a MIMO control.

Some restrictions must be respected to ensure a correct fermentation setpoint campaign. For example, the concentration of biomass (*C*) should not exceed 8 g/l, while the substrate (*S*) should remain above 0.5 g/l, otherwise the reaction would end, and hence the process should be restarted again. Another restriction is the setpoint range of 10 to 50 g/l for *P*, according to the assumptions made in (Mendonça *et al.*, 2013).

2.3 Fuzzy Logic

Fuzzy logic, created by Zadeh, is an extension of Boolean logic (Zadeh, 1965), based on the theory of fuzzy sets, which is a generalization of the classical set theory. A key concept in fuzzy logic is membership functions. A fuzzy set A in the universe of discourse X is characterized by a membership function $\mu_A: X \rightarrow [0, 1]$. A degree of zero means that the value is not in the set, a degree of one means that the value is totally representative of the set, and a degree confined between zero and one means the value is partially in the set.

The shape of the membership function is often chosen based on the advice of an expert or by statistical studies. A Sigmoid shape, Triangular, Trapezoidal, Gaussian or any other type can be used. The concept of membership functions discussed above allows the definition of fuzzy natural language systems that make use of linguistic variables, where the universe of discourse of a variable is divided into a number of fuzzy sets with a linguistic description attributed to each one. In this work, Fuzzy systems were used as a way of representing the expert's knowledge of the analyzed processes.

2.4 Fuzzy Cognitive Maps

A FCM is a soft computing technique that combines the advantages of Artificial Neural Networks (ANNs) and Fuzzy Logic, using existing knowledge and human experience to model complex systems (Papageorgiou, 2014). Due to their simplicity, support for ambiguous (Fuzzy) knowledge, they are applicable in many areas, such as medicine, engineering, software development, etc. FCMs emerged from Kosko's work (Kosko, 1986), which expanded the concepts of Axelrod's (Axelrod, 1976) and Tolman's (Tolman, 1948) previous Cognitive Maps works. FCMs introduced fuzziness to Cognitive Maps, by using numeric descriptions (fuzzy binaries) of causal influences instead of positive or negative symbols.

In a FCM, the value $A_i^{(k+1)}$ of each concept C_i at iteration $k+1$ is calculated as a function of the sum of $A_i(k)$ at iteration k, with the product of $A_j(k)$ of the concept C_j by w_{ij}, which is the value of the causal link between C_j and C_i, given in the range [-1 1]. The mathematical representation of FCM inference is given by (8).

$$A_i^{(k+1)} = f(A_i^{(k)} + \sum_{\substack{j=1 \\ j \neq i}}^{N} A_j^{(k)} * w_{ji}) \quad (8)$$

In (8), *f(.)* denotes a threshold function like sigmoid to squash the values within the range [0 1], as shown in (9), where λ is a real positive number, which determines the steepness of *f(.)*, and x is the value of A_i at the equilibrium point.

$$f(x) = 1/(1 + e^{-\lambda x}) \quad (9)$$

It is not scope of this work to analyze the stability of the FCM. However, these equations combined suggest stability similarly to the work (Boutalis *et al.*, 2009), which shows that threshold sigmoid functions have interval previous defined and are continuous differentiable. Also, the calculated values and causes their convergence to the same specific value (Eleni and Petros, 2017).

The stability initials analysis and results have been presented by the same authors in (Eleni and Petros, 2017). This study was done by using an appropriately defined contraction mapping theorem and the non-expansive mapping theorem. In other way, Kosko examined Associative Memories stability by identifying a Lyapunov or energy function with associative memory states (Boutalis and Kottas, 2008; Kosko, 1988; Martchenko *et al.*, 2003).

2.5 Design of Heatex Process Controller

For the Heatex control, a Fuzzy controller (FLC) and a FCM controller were developed, and were compared to the original PI controller in Matlab®, similarly as seen in work (Mollon *et al.*, 2017), which the FCM controller was compared with ANN-FCM and other techniques.

The FCM controller was created at first, considering errors in the same way that in the PID controller, which are namely the error (*Error*) and the differential error (*Errordiff*) for each iteration. Due to the low complexity of this system, it was unnecessary to use the error integral as expected.

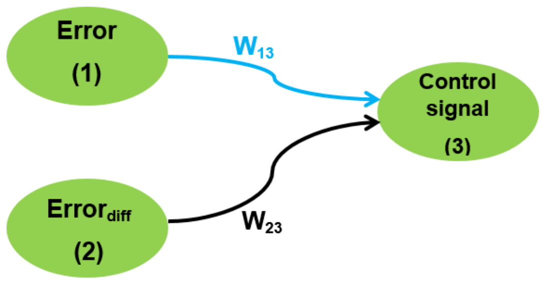

Figure 4. FCM used in the Heatex process

For the FCM controller, Simulink® was used to modify the structure of the controller used in (Puheim *et al.*, 2015). Figs. 4 and 5 show, respectively, the FCM created and its version in Simulink®.

The causal relationships of the FCM were defined heuristically. The causal weight values were chosen as W_{13}=0.75 and W_{23}=0.2.

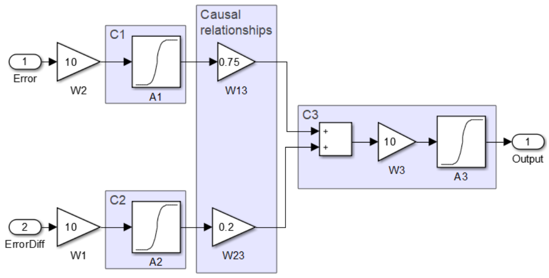

Figure 5. Heatex FCM controller – Simulink®

The second step was to create the FLC. In this process, the rule base used was the same as the one proposed by (Passino and Yurkovich, 1998) to control an inverted pendulum, with 25 rules, three triangular (center) and two trapezoidal (borders) pertinence functions. The inputs, like in the FCM controller, are *Error* and $Error_{diff}$ and the output is the control signal.

System simulations were run in Simulink® for the FCM and FLC controllers and data was collected for the Integral Absolute Error (IAE), Integral Squared Error (ISE), 2% settling time (*Ts*) and overshoot analysis in order to compare the different alternatives.

2.6 Design of Alcoholic Fermenter Process Controller

We designed an adaptive PID controller with FCM and Fuzzy adjustment mechanisms using Maher's approach (Maher, 1995). Subsequently, as in the Heatex process, the results were compared with the PID controller used as the basis for the tuning mechanisms.

In this work, we used a maximum tank volume (*V*) of 4.75 l and a minimum volume of 1 l. Accordingly, if the former case occurs, the F_{in} valve is completely closed, and if the latter case occurs, the valve F_{out} is closed (Mendonça *et al.*, 2013). As discussed in this work, equations (3) to (7) were used to simulate this process in Matlab®.

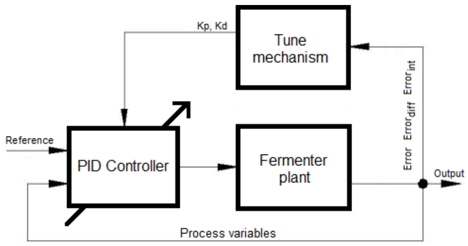

Figure 6. Auto tune architecture

The architecture shown in Fig. 6 was used as a tuning mechanism for the both FCM-PID and Fuzzy-PID controllers presented in this work. The variables *Error*, $Error_{int}$, and $Error_{diff}$ represent the errors related to the gain parameters of the PID, which are respectively *error*, *integral error* and *differential error*. The tuning mechanism interprets the errors coming from the parameters of the controller and, from the analysis proposed for each mechanism, applies multipliers to the proportional (K_p) and derivative (K_d) PID gains, adapting their values at each iteration.

For a better validation among the tuning mechanisms used, a fermentation campaign was developed (group of setpoint values to be followed) that can describe a real fermentation campaign according to the restrictions imposed in this work.

The initial step in the development was the tuning of the initial parameters of the PID controller: K_p, K_d and K_i, through the heuristic and process analysis. The values reached are K_p=2, K_d=4.95 and K_i=0.35.

The first tuning mechanism to be developed was the FCM-PID, using a domain expert's knowledge of the process. The developed FCM is shown in Fig. 7, where concepts 4 and 5 correspond to the K_p and K_d gain multipliers to be applied in the PID. In this work, the relation between computational cost and results' improvement did not justified the use of K_i gain multipliers.

From the expert's knowledge employed in the FCM, it was noticed that there is a weak negative influence in all relationships. The overall FCM weights are: W_{14}=-0.28, W_{15}=-0.30, W_{24}=W_{25}=-0.25, W_{34}=-0.15 and W_{35}=-0.17.

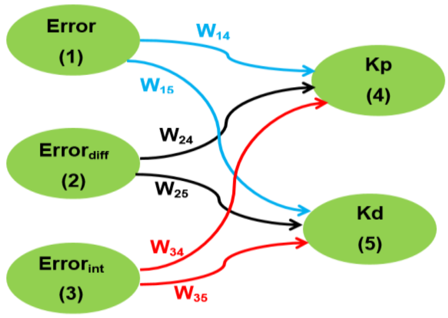

Figure 7. FCM used in the alcoholic fermenter process

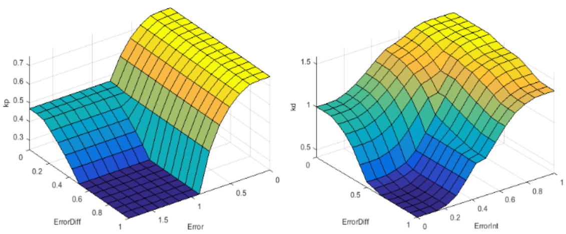

Figure 8. Fuzzy surfaces for the fermenter process

The Fuzzy-PID mechanism had its rules and membership functions also adjusted heuristically, based on the relationships of the FCM-PID, with the same concepts used in the FCM.

The FLC system used was a weighted Mamdani (Mamdani, 1974) with 3 inputs (*Error*, $Error_{diff}$ and $Error_{int}$), 2 outputs (K_p and K_d multipliers) and 18 rules. The pertinence functions were created to reach three ranges of values, namely "small", "medium" and "large" for inputs and outputs, using trapezoidal functions at the edges and a triangular one in the center.

The inputs (absolute errors) range from 0 to 1 (100% positive error). The K_p output range is [0 1.5] and K_d is [0 2], both adjusted heuristically, obtaining the Fuzzy surfaces, two of which are shown in Fig. 9.

As can be seen in Figs. 4 and 8, in this work the FCM corresponds to a simple acyclic graph, different from Kosko's original proposal (Kosko, 1986). In this way, according to (Yuan Miao *et al.*, 2001) and (Mendonça *et al.*, 2013) the construction of large cognitive maps by steps always generates smaller maps usually acyclic, which correspond to well defined cause-effect relations.

2.7 Simulated and Embedded Mixer Tank Control

For the last process analyzed in this work, we will use a recurrent case study used in works such as (Souza *et al.*, 2017). This case was selected due to their need for refinements in the FCM's causal relationships in way to do a satisfactory control of the mixer tank using exclusively experts' knowledge.

The process, shown in Fig. 9, consists of a tank with two input valves, V_1 and V_2 (each one for a different liquid), a mixer, an output valve for final product removal, and a specific gravity (G) meter (gauger) for the product measurement. In this case, for exemplification, we will use water (G=1) and soybean oil (G=0.9).

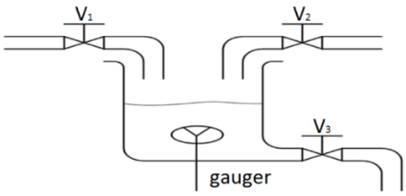

Figure 9. Mixer tank (Souza *et al.*, 2017).

During the process functioning, V_1 and V_2 insert the different liquids in the tank, generating a reaction and producing, consequently, a new liquid with a new specific gravity, respecting the specified *Volume* level and G. At this time, V_3 is opened in accordance with the selected output campaign. The gauger measures the control quality of the produced liquid. The tank has two startup states, as shown in Fig. 10.

The first state is an empty condition, causing the full opening of V_1 and V_2 and closing V_3 until the minimum Volume desired is reached, thereby initializing the controller. The second state, full tank condition, has the inverse functioning: fully open V_3 and close V_1 and V_2 until the maximum volume (V) desired is reached, starting the controller.

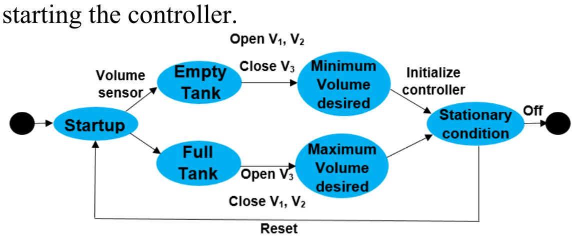

Figure 10. Mixer tank state machine diagram

Although being relatively simple, this process is a MIMO (Multiple Inputs and Multiple Outputs) type, with two inputs and two outputs and coupled variables. When the value of G reaches the desired range specified, the liquid mixed is ready. The liquid removal is only possible when V is also in its specified range. Thus, the control consists of keeping G and V in their desired ranges.

The concepts (C_i) and cognitive model are: C_1 - State of the V_1; C_2 - State of the V_2; C_3 - State of the V_3; C_4 - quantity of mixture (volume) in the tank, which depends on the operational state of the valves V_1, V_2 and V_3; C_5 - value measured by the gauger for the liquid's specific gravity. The valves have three states: closed, open or partially open.

The process design uses the mass conservation principle in incompressible fluids in order to generate a set of differential equations representing its behavior, and is used to test the DFCM controller. As a result, the volume of the tank is the sum of its initial volume and the input flow of V_1 and V_2 minus the output V_3 (10).

In this way, the weight in the tank follows the principle as shown in (11). The values used for m_{e1} and m_{e2} were 1.0 and 0.9, respectively.

$$V_{tank} = V_i + V_1 + V_2 - V_3 \qquad (10)$$

$$Weight_{tank} = M_i + (V_1.m_{e1}) + (V_2.m_{e2}) - M_{out} \qquad (11)$$

In this case, a Dynamic Fuzzy Cognitive Map (DFCM) is used to control the mixer, which should maintain levels of volume and mass within specified limits through the adaptation of the causal relationships (weights, given by W_{ij}).

We used two methods for the adaptation of the FCM weights: first by using the Hebbian learning algorithm, and second using weight-scheduling according to the V_3 campaign, through a Genetic Algorithm (GA) (Holland, 1992) with 30 individuals (real numbers), tournament, simple crossing and 1% mutation.

To the dynamical adaptation of the DFCM weights it was used the Hebbian learning algorithm for FCM (DFCM-Heb), an adaptation of the classic Hebbian method, as well as used in, for example, (Souza *et al.*, 2017). In this paper, this method is also used to update the intensity of causal relationships.

The Hebbian learning algorithm provides the following control actions: if G or V of the liquid mixture increases, the input valves have a weight negatively intensified and tend to a more quickly close. On the other hand, if G or V decreases, V_1 and V_2 have a causal relationship positively intensified. The mathematical equation is presented in (Souza *et al.*, 2017).

In the weight-scheduling approach (DFCM-WS), the weight vectors is obtained through a GA algorithm which selects the most adequate weight according to the setpoint. Otherwise, the Reinforcement Learning (Sutton and Barto, 2017) can be used as a tool for adjustment or online tune for FCMs, as seen in (Mendonça *et al.*, 2011).

In this process, firstly a GA is used to choose a set of weights accordingly to the V_3 campaign, generating weight-scheduling (DFCM-WS). Thus, the Hebbian method is used to adapt the weights of the DFCM (DFCM-Heb) in the same campaign. Finally, the best method is chosen to embed in a PIC18F4520 platform, which actuate as the controller while Matlab® assume the process.

3 Results and discussion

3.1 Heatex Process Control Results

In this process, a fixed setpoint was chosen as 0, in the three controllers, namely the non-adaptive PI, FCM controller and FLC. The results of analysis of the different control parameters (IAE, ISE, overshoot and *Ts*) are shown in Table 1.

Table 1. Results – Heatex process

	PI	FCM	FLC
Ts (10^5 s)	1.7683	1.1538	1.2462
Overshoot	0.5310	0.6762	0.5257
IAE	0.0991	0.1472	0.1171
ISE	0.0362	0.0746	0.0481

In Fig. 11, the values of the control signal, setpoint, disturbances inserted in the process, *Error* and $Error_{diff}$ used for the intelligent controllers' development are also shown, with the Output representing the temperature obtained in the Heatex.

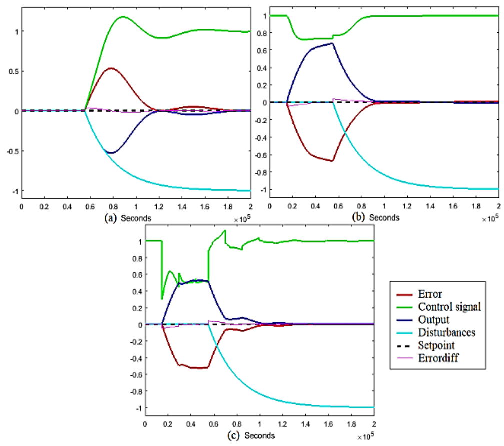

Figure 11. Heatex results – (a) PI, (b) FCM, (c) FLC

We can notice from the analysis of Fig. 11 that the output temperature changes from the setpoint before the beginning of the disturbances caused in the system, for both the FCM and FLC controllers, as opposed to the original PI controller of Matlab®, which is expected to be the best in this process.

The results of Table 1 confirm that the PI controller is still the best option for the Heatex process control. However, from the analysis of Fig. 11, it can be noticed that the main advantage of the two intelligent controllers was the lower *Ts* value especially for the FCM controller.

Moreover, the FLC's overshoot is lower than in the Matlab® PI controller. However, the analysis of the results shows that the control signal of the FLC controller is the most unstable compared to the other simulated controllers, which in a practical situation could result in damaging the system components. It is emphasized that other weights could be used in the FCM, and different rules and pertinence functions for the FLC.

3.2 Alcoholic Fermenter Process Control Results

The fermentation campaign simulations were performed for the PID, FCM-PID and Fuzzy-PID. The results for the parameters *P*, *S*, *V* and *C* for the last two cases are shown in Fig. 12. It can be observed that the different process variables are within the desired ranges for all tested approaches. However, the FCM-PID presented the lowest values for all analyzed aspects, indicating that this mechanism caused less-variant values for the analyzed parameters.

In relation to the gain variations, it was observed that K_p and K_d are strongly calibrated in the setpoint changes, and their values decreased for both FCM-PID and Fuzzy-PID. We also obtained the highest gain values in these tuning mechanisms, which suggests that these two tuning mechanisms use more relevant changes to achieve the desired results.

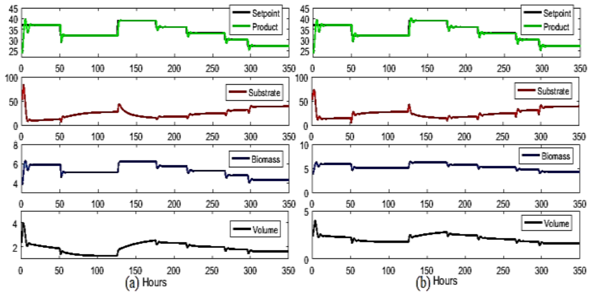

Figure 12. Results – (a) FCM-PID controller, (b) Fuzzy-PID controller

As in the previous analysis, the errors reached their highest values at the setpoint changes, where the controller gain adaptations achieved higher levels. It should be noticed that in this work, we only used the sum of the current error with the previous one for $Error_{int}$.

The analysis of the used control parameters is shown in Table 2, for the first simulation step. For the settling time (*Ts*), there is a slight advantage for PID and FCM-PID, since the difference found is small, due to the high number of hours (350) used. The higher Fuzzy-PID's *Ts* value also indicates a smoother setpoint stabilization curve compared to the FCM-PID tuning mechanism.

As for the overshoot, the FCM-PID presents an advantage, since it produces the lowest value. In the IAE and ISE analysis, the results of the PID were the worst due to its non-adaptation. However, for the ISE, the values obtained were similar among the three analyzed controllers. The results of the IAE were in agreement with the others, with the FCM-PID having lower values compared to the conventional PID and Fuzzy-PID. Moreover, a performance analysis was performed, obtaining the execution times of the Matlab® simulation scripts.

Table 2. Results – Alcoholic Fermenter process

	PID	FCM-PID	Fuzzy-PID
Ts	15.0000	15.0000	20.0000
Overshoot	1.8071	1.8100	2.5019
IAE	1.2827	0.9775	1.0755
ISE	0.0517	0.0487	0.0497

FCM-PID is slightly slower than PID, while the Fuzzy-PID is approximately 10s slower than the PID controller. Hence, it can be concluded that the FCM-PID is the best adjustment mechanism for the Alcoholic Fermenter Process.

3.3 Mixer Tank Control Results

In this case, the desired ranges for *G* and *V* are, respectively, [800 850] mg and [830 880] ml. The initial values are *G*=810 mg and *V*=830 ml. For the empty tank startup, the controller is initialized when *V* are reaches the lower desired range. In the full tank startup, the controller begins at the moment that *V* reaches the upper desired range.

Fig. 13 shows the weight evolution through the campaign and Fig. 14 shows the control results for *G* and *V*. Figs. 15 and 16 presents the weight evolution and the range control for the DFCM-WS, respectively. Finally, Fig. 17 show the results for the best method chosen, DFCM-Heb in the PIC18F4520. It is noteworthy that the weights for the embedded case have the same values of the simulated DFCM-Heb.

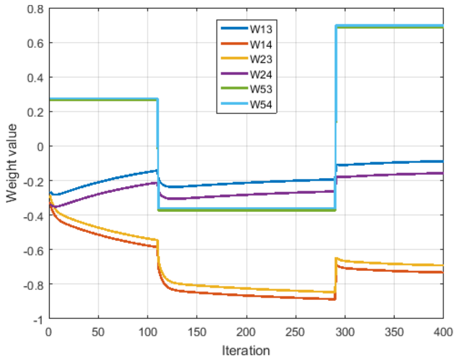

Figure 13. Evolution of the weights – DFCM-Heb

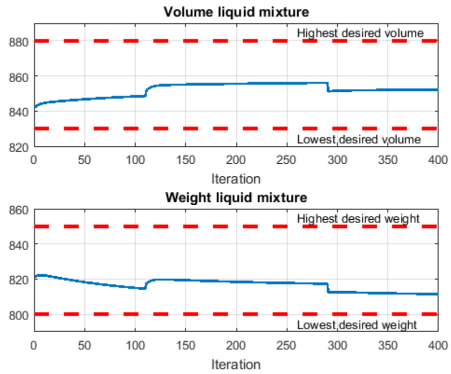

Figure 14. Mixer tank control – DFCM-Heb

The results from both DFCM-Heb and DFCM-WS were satisfactory, with the values G and V maintained in their desired ranges. In (Souza et al., 2017), a FLC and a Fuzzy-ANN (Artificial Neural Network) controller were also used to the mixing tank control.

The PIC embedded DFCM-Heb obtained corresponded to our expectations, presenting results without disturbances and slightly higher than its simulated form, unlike previously found in the Arduino platform (Souza *et al.*, 2017). Finally, the DFCM-Heb control showed more smooth weight changes than the weight-scheduling (DFCM-WS) variant.

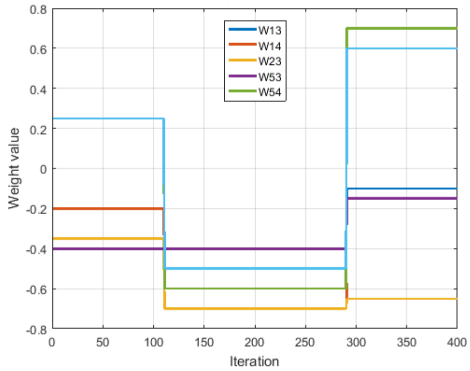

Figure 15. Evolution of the weights – DFCM-WS

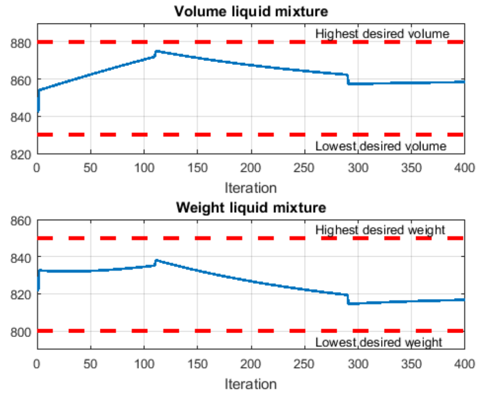

Figure 16. Mixer tank control – DFCM-WS

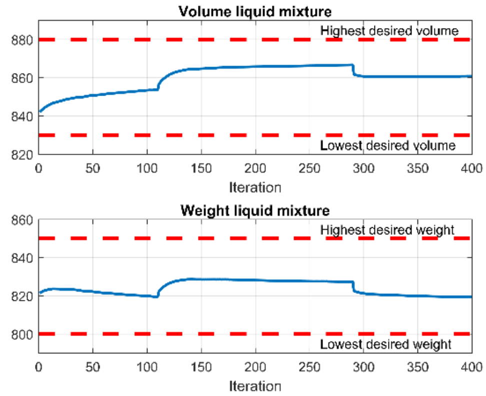

Figure 17. Mixer tank control – Embedded DFCM-Heb

4 Conclusions

For the Heatex, the results revealed that, even with the conventional PID being the best controller, the use of intelligent controllers should not be discarded, since the FLC controller presented similar results.

In the case of the alcoholic fermenter process, the FCM-PID mechanism obtained the best responses according to the analyzed parameters, obtaining the lowest values in all of them considering the analyzed campaign.

Finally, for the Mixer Tank, the results suggest that the Hebbian method presented more adequate weight values due to its online adaptation. Thus, the weight-scheduling need to be adjusted heuristically for every new V_3 campaign, going against the FCM principle of adaptability. In addition, the values of *G* and *V* obtained by the Hebbian have slightly modifications during the campaign, unlike the second approach, which presented more drastic changes.

Future research will focus on exploiting the potential of the soft computing techniques in industrial process control, including disturbances, new setpoint and others changes in the processes addressed. Three important research topics are considered. First, we would like to embed all the developed controllers in other platforms, like Raspberry PI, Toradex etc., in order to verify the low computational complexity, time response and software portability of the FCM-based controllers. Secondly, addressing a real-time MIMO controller for temperature and level in a real tank prototype, for example. The third topic is the stability analysis of the FCMs and the use of hardware-in-the-loop concept in the processes, important steps for further investigation.

References

Åström, K.J., Wittenmark, B., 2008. Adaptive Control, 2nd ed, Dover Books on Electrical Engineering. Dover Publications, USA.

Axelrod, R., 1976. Structure of decisions: the cognitive maps of political elites, 1st ed, The Structure of Decision The Cognitive Maps of Political Elite. Princeton University Press, Princeton, NJ, USA.

Boutalis, Y., Kottas, T., 2008. On the Existence and Uniqueness of Solutions for the Concept Values in Fuzzy Cognitive Maps, in: 47th IEEE Conference on Decision and Control. IEEE, Cancun, Mexico, pp. 98–104.

Boutalis, Y., Kottas, T.L., Christodoulou, M., 2009. Adaptive estimation of fuzzy cognitive maps with proven stability and parameter convergence. IEEE Trans. Fuzzy Syst. 17, 874–889.

Eleni, V., Petros, G., 2017. New Concerns on Fuzzy Cognitive Maps Equation and Sigmoid Function, in: 2017 25th Mediterranean Conference on Control and Automation (MED). Valletta, Malta, pp. 1113–1118.

Holland, J.H., 1992. Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control and Artificial Intelligence, 1st ed, The University of Michigan Press. MIT Press, Cambridge, USA.

Kosko, B., 1988. Bidirectional Associative Memories. IEEE Trans. Syst. Man Cybern. 18, 49–60.

Kosko, B., 1986. Fuzzy cognitive maps. Int. J. Man. Mach. Stud. 24, 65–75.

Lima, F., Serra, G., 2015. Fuzzy PID controller multiobjective genetic design. 2015 IEEE 10th Conf. Ind. Electron. Appl.

Maher, M., 1995. Modélisation et élaboration d'algorithmes d'estimation et de commande : application à un bioprocédé.

Mamdani, E.H., 1974. Application of fuzzy algorithms for control of simple dynamic plant. Proc. Inst. Electr. Eng. 121, 1585. https://doi.org/10.1049/piee.1974.0328

Martchenko, M.A.S., Ermolov, I.L., Groumpos, P.P.P., Poduraev, P.J. V, Stylios, C.D., 2003. Investigating Stability Analysis Issues for Fuzzy Cognitive Maps, in: 11th Mediterranean Conference on Control and Automation - MED'03. Rhodes, Greece, pp. 1–7.

Mendonça, M., Angelico, B., Arruda, L.V.R., Neves, F., 2013. A dynamic fuzzy cognitive map applied to chemical process supervision. Eng. Appl. Artif. Intell. 26, 1199–1210.

Mendonça, M., de Arruda, L.V.R., Neves Jr, F., 2011. Autonomous navigation system using Event Driven-Fuzzy Cognitive Maps. Appl. Intell. 37, 175–188.

Mollon, M.F., Kaneko, E.H., Chaves, W.D.S., Niro, L., Marcio, A., Montezuma, F., 2017. Control of Non-linear Equation of Submarine Using PI-like Fuzzy Controller. Int. J. Adv. Eng. Res. Sci. 6495, 85–91.

Ogata, K., 2010. Modern Control Engineering, Control Engineering.

Papageorgiou, E.I. (Ed.), 2014. Fuzzy Cognitive Maps for Applied Sciences and Engineering. Springer-Verlag Berlin Heidelberg, Heidelberg.

Passino, K.M., Yurkovich, S., 1998. Fuzzy Control, 1st ed. Addison Wesley, Menlo Park, CA, USA.

Puheim, M., Vaščák, J., Madarász, L., 2015. A proposal for Multi-Purpose Fuzzy Cognitive Maps library for complex system modeling, in: SAMI 2015 - IEEE 13th International Symposium on Applied Machine Intelligence and Informatics. Herl'any, Slovakia, pp. 175–180.

Ross, T.J., 2010. Fuzzy logic with engineering applications, 3rd ed. John Wiley & Sons, New Mexico, USA.

Souza, L.B. De, Soares, P.P., Barros, R.V.P.D., Mendonça, M., Papageorgiou, E., 2017. Dynamic Fuzzy Cognitive Maps and Fuzzy Logic Controllers Applied in Industrial Mixer.

Sutton, R.S., Barto, A.G., 2017. Reinforcement Learning: An Introduction, 2nd ed. MIT Press, Cambridge, USA.

Tolman, E.C., 1948. Cognitive maps in rats and men. Psychol. Rev. 55, 189–208.

Yuan Miao, Zhi-Qiang Liu, Chee Kheong Siew, Chun Yan Miao, 2001. Dynamical cognitive network - an extension of fuzzy cognitive map. IEEE Trans. Fuzzy Syst. 9, 760–770.

Zadeh, L.A., 1965. Fuzzy Sets. Inf. Control 353, 338–353.