CAPÍTULO 1

INTEGRATION OF DYNAMIC FUZZY COGNITIVE MAPS IN CONTROLLERS FOR ENHANCED SECURITY IN INDUSTRIAL PROCESSES AND ENVIRONMENTAL IMPACT MITIGATION

Data de aceite: 07/07/2023

Márcio Mendonça
Universidade Tecnológica Federal do Paraná
PPGEM-CP - Programa de Pós-Graduação em Engenharia Mecânica PP/CP
Cornélio Procópio – PR
http://lattes.cnpq.br/5415046018018708

Andressa Haiduk
Dimension Engenharia
Ponta Grossa – PR
http://lattes.cnpq.br/2786786167224165

Fabio Rodrigo Milanez
Faculdade da Industria Senai
Londrina-PR
http://lattes.cnpq.br/3808981195212391

Vicente de Lima Gongora
Faculdade da Industria Senai
Londrina-PR
http://lattes.cnpq.br/6784595388183195

Emerson Ravazzi Pires da Silva
Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio – PR
http://lattes.cnpq.br/3845751794448092

Murilo da Silva
Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio – PR
http://lattes.cnpq.br/2992895439496724

Matheus Gil Bovolenta
Acadêmico - Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio – PR
http://lattes.cnpq.br/1518815195539638

Janaína Fracaro de Souza Gonçalves
Universidade Tecnológica Federal do Paraná
PPGEM-CP - Programa de Pós-Graduação em Engenharia Mecânica PP/CP
Cornélio Procópio – PR
http://lattes.cnpq.br/1857241899832038

Ângelo Feracin Neto
Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio – PR
http://lattes.cnpq.br/0580089660443472

Edinei Aparecido Furquim dos Santos
Centro universitário Uningá
Maringá - PR
http://lattes.cnpq.br/8706436030621473

Renato Augusto Pereira Lima
Inspetor Chefe da regional CREA Londrina.
Cornélio Procópio - PR
http://lattes.cnpq.br/3518337122740114

Wagner Fontes Godoy
Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Engenharia Elétrica (DAELE),
Cornélio Procópio - PR
http://lattes.cnpq.br/7337482631688459

Rodrigo Rodrigues Sumar
Universidade Tecnológica Federal do Paraná,
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio - PR
http://lattes.cnpq.br/1461760661483683

Edson Luis Bassetto
Universidade Tecnológica Federal do Paraná,
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio - PR
http://lattes.cnpq.br/5806912707344633

Francisco de Assis Scannavino Junior
Universidade Tecnológica Federal do Paraná Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio – PR
http://lattes.cnpq.br/4513330681918118

Gabriela Helena Bauab Shiguemoto
Universidade Tecnológica Federal do Paraná,
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio - PR
http://lattes.cnpq.br/3301713295448316

ABSTRACT— This paper presents the application of certain intelligent techniques to control an industrial mixer The controller design is based on Hebbian modification of Fuzzy Cognitive Maps learning mechanism. This research develops a Dynamic Fuzzy Cognitive Map (DFCM) based on Hebbian Learning algorithms. Fuzzy Classic Controller was used to help validate simulation results of an industrial mixer controlled by DFCM. Experimental analysis of simulations in this control problem was conducted. The environmental impacts, and process security for industrial mixers are also addressed. Additionally, the results were embedded

using efficient algorithms into the Arduino platform to acknowledge the performance of the codes reported in this research.
KEYWORDS-Fuzzy Cognitive Maps; Hebbian Learning; Arduino Microcontroller; Process Control; Fuzzy Logic, Artificial Neural Networks

RESUMO - Este artigo apresenta a aplicação de certas técnicas inteligentes para controlar um misturador industrial. O design do controlador é baseado no mecanismo de aprendizagem de Modificações Hebbianas de Mapas Cognitivos Fuzzy. Esta pesquisa desenvolve um Mapa Cognitivo Fuzzy Dinâmico (DFCM) baseado em algoritmos de aprendizagem de Hebb. Foi usado um Controlador Clássico Fuzzy para ajudar a validar os resultados de simulação de um misturador industrial controlado por DFCM. Foi realizada uma análise experimental das simulações neste problema de controle. Os impactos ambientais e a segurança do processo para misturadores industriais também são abordados. Além disso, os resultados foram incorporados usando algoritmos eficientes na plataforma Arduino para reconhecer o desempenho dos códigos relatados nesta pesquisa.
PALAVRAS-CHAVE: Mapas Cognitivos Fuzzy, Aprendizado Hebbiano, Microcontrolador Arduino, Controle de Processos, Redes Neurais Artificiais

1 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; To classify the type of physical problem; To identify the family of mathematical models that can be associated; To select the method and / or tool for the search and analysis of the model.

Indeed, the final output of modern processes is greatly influenced by the selection of optimal set points for process variables. These set points have a profound impact on both the product quality characteristics and the overall performance metrics of the process (MARCHAL; GARCÍA; ORTEGA, 2017). Hence, the primary objective of this research is to develop knowledge-based techniques for process control in the domain of industrial mixers, which represents a classic problem in the field of Fuzzy Cognitive Maps. It is important to note that this work builds upon and expands the findings of a previous study (MENDONÇA et al., 2016).

The article proposal is a different setup, in special 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 optimal control theory, robust control, and adaptive control, significantly expanding the automation concept and also studying the feasibility of an autonomous control in practice.

On the other hand, intelligent control techniques take control actions without depending on a complete or partial mathematical model. Otherwise, the ability of a human to find solutions to a particular problem is known as human intelligence. In short, 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 (ZADEH, 1992).

In general, Fuzzy Cognitive Map (FCM) is a tool for modelling 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 modelling complex systems, which are similar in the construction to the human reasoning. Dynamic Fuzzy Cognitive Maps (DFCM) needs to be developed to a model that can manage behaviours of non-linear time-dependent system and sometimes in real time. Examples of different variation of the classic FCMs can be found in the recent literature, e.g., (PAPAGEORGIOU, 2014)

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 succeed the goals, we initially use the similar DFCM proposed initially in [13] to control an industrial mixing tank. In contrary to (MENDONÇA et al., 2013), we use the Hebbian algorithm to dynamically adapt the DFCM weights. To validate our DFCM controller, we compared its performance with a Fuzzy Logic Controller. This comparison is carried out with simulated data.

2 | ENVIRONMENTAL IMPACTS

Industrial processes have significant impacts on the environment, particularly in relation to pollution, the use of natural resources, and the generation of waste. Industrial mixers, essential equipment in various industries such as chemical, food, pharmaceutical, and construction, also have environmental impacts that must be considered.

Firstly, industrial mixers consume energy to operate. Depending on the source of this energy, they can contribute to the emission of greenhouse gases. For example, if the energy comes from fossil sources such as coal or natural gas, the process of energy generation will result in the release of carbon dioxide, a potent greenhouse gas. Thus, one way to minimize this impact is to invest in energy efficiency and in renewable energy sources to power these mixers.

In addition, industrial mixers can also contribute to air, water, and soil pollution, depending on the substances being mixed. Toxic or dangerous chemical substances may release fumes or waste that are harmful to the environment. To mitigate this impact, it is essential to ensure proper handling of materials and waste, and to seek less toxic alternatives whenever possible.

Industrial mixers, like other equipment, also have an environmental impact associated with their manufacturing and end of life. The production of these devices involves resource extraction, energy use, and waste generation, while improper disposal can result in soil and water contamination. A strategy to reduce these impacts is to adopt circular economy principles, aiming to maximize the equipment's lifespan through maintenance and repair, reusing or recycling components at the end of their life, and choosing materials and manufacturing processes with low environmental impact.

In summary, although industrial mixers and other industrial processes have significant environmental impacts, there are several strategies that can be adopted to minimize these impacts. This includes improving energy efficiency, using clean energy sources, proper handling of materials and waste, seeking fewer toxic alternatives, and adopting circular economy practices (BRINKLEY et al., 1997).

3 | SECURITY ASPECTS

A segurança na indústria é uma questão de extrema importância, especialmente quando se trata de operação de equipamentos como misturadores, que podem apresentar riscos significativos se não manuseados adequadamente. Alguns aspectos cruciais a serem considerados incluem:

1. **Treinamento e Conhecimento dos Operadores**: É essencial que os operadores dos misturadores estejam completamente familiarizados com o equipamento, incluindo a sua operação adequada, manutenção, limpeza e ação apropriada em caso de emergências. Isso geralmente requer treinamento regular e atualizações sobre os protocolos de segurança.

2. **Equipamentos de Proteção Individual (EPIs)**: Os operadores devem sempre usar equipamentos de proteção individual adequados. Isso pode incluir óculos de segurança, luvas, protetores auriculares e vestuário de proteção, dependendo da natureza do trabalho.

3. **Manutenção e Inspeção Regular**: Os misturadores devem ser submetidos a inspeções regulares para garantir que estão em condições de trabalho seguras. Qualquer equipamento desgastado ou danificado deve ser reparado ou substituído imediatamente.

4. **Procedimentos de Emergência**: Deve haver procedimentos claros sobre o que fazer em caso de emergência, incluindo como desligar rapidamente o equipamento

e como acessar equipamentos de primeiros socorros e saídas de emergência.

5. **Sistemas de Bloqueio/Etiquetagem (Lockout/Tagout)**: Esses sistemas são projetados para garantir que o equipamento não possa ser operado enquanto estiver em manutenção ou inspeção.

6. **Avaliação de Riscos**: Deve-se realizar regularmente uma avaliação de riscos para identificar possíveis perigos e implementar medidas para mitigar esses riscos. Isso pode incluir a consideração de questões como a probabilidade de respingos de produtos químicos, a geração de poeira ou gases perigosos, a operação em ambientes potencialmente explosivos e outros riscos associados à operação do misturador.

7. **Conformidade com as Normas de Segurança**: As operações devem estar sempre em conformidade com as normas de segurança locais e nacionais, bem como qualquer outra legislação aplicável.

No geral, a segurança na operação de misturadores na indústria requer um compromisso constante com o treinamento, a manutenção, a avaliação de riscos e a conformidade com as normas de segurança (TENEVA et al., 2018).

4 | 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.

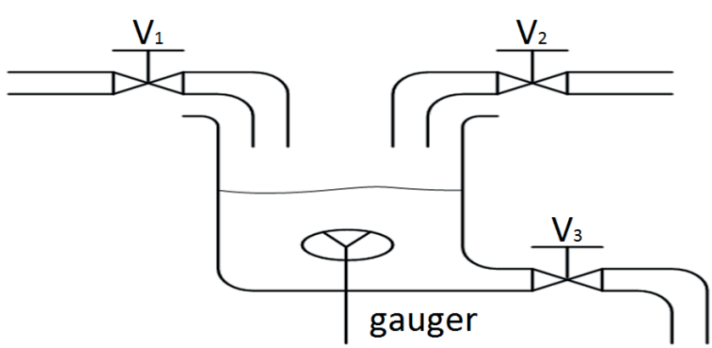

Figure 1 - Mixer tank (Source: adapted from [20]).

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 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.

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 of to keep these two variables in their operating ranges, as:

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

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

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 (PAPAGEORGIOU; STYLIOS; GROUMPOS, 2007), 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 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.

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

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

5 I 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 (ZADEH, 1992).

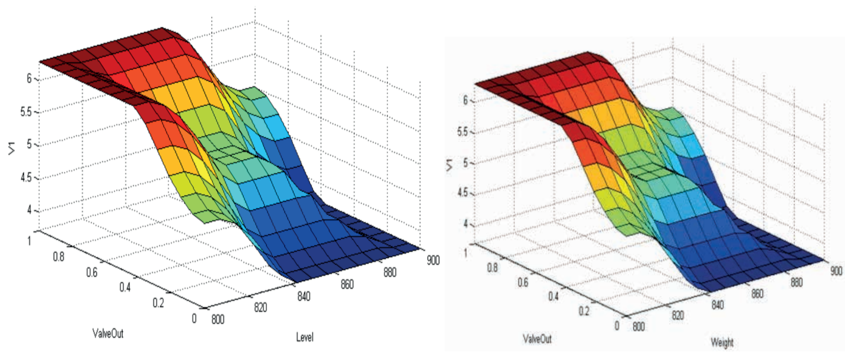

Figure 2 - Fuzzy Controller Surfaces, V1 and V2.

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 isn't 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 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.

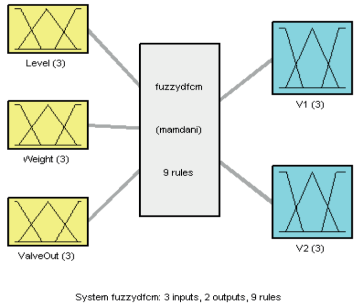

Figure 3 - Fuzzy Structure.

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.

5.1 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, like 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.

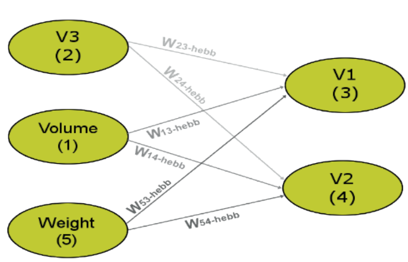

Figure 4 - DFCM Controller

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 (GOLDBERG; DEB, 1991) The Fig. 4 shows the schematic graph of a 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].

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

TABLE I. Initials Casual Relationship Weights

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 (KOSKO, 1986). Different proposals and variations of this method applied in tuning or in learning for FCM are known in the literature, for example (MENDONÇA et al., 2013). 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. On the other hand, if the volume or weight mixture decreases, the inlet valves have a causal relationship positively intensified. The mathematical equation is presented in (GLYKAS, 2010).

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

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 in (PAPAGEORGIOU, 2014).

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 original version.

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

Where: γ=1 for all, 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).

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

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

Figure. 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].

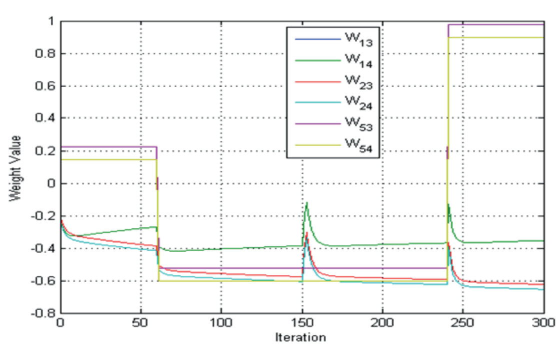

Figure 5 - Evolution of the weights in the Hebbian Learning

6 I SIMULATED EXPERIMENTAL RESULTS

The results of DFCM are shown in Fig. 6, which show 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.

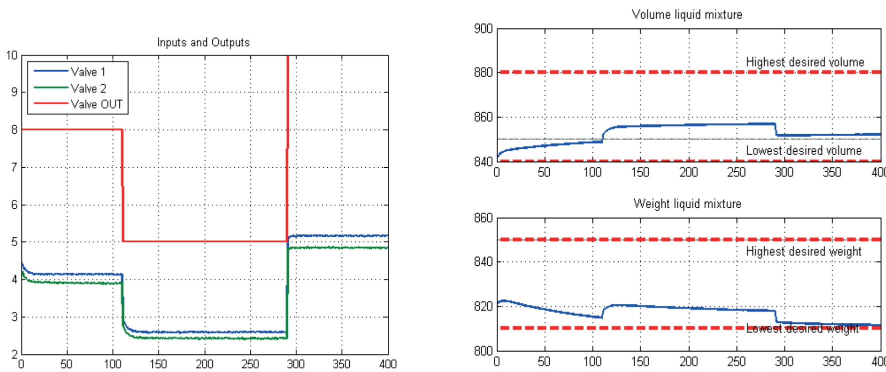

Figure 6 - Valve and Results of the DFCM Controller

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.

	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

TABLE II. Quantitative results

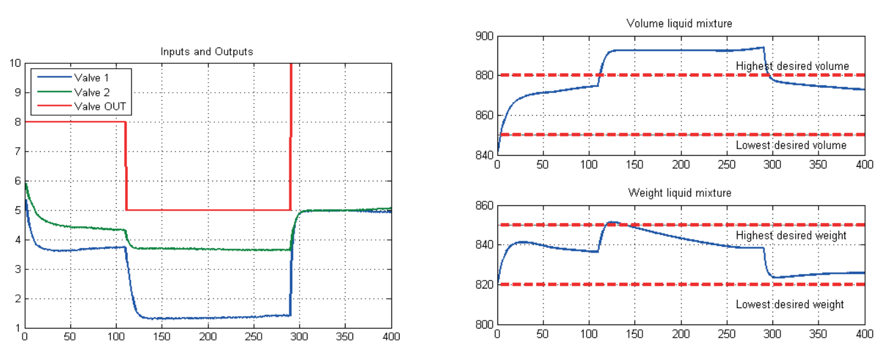

Figure 7 - Results of the Fuzzy Controller

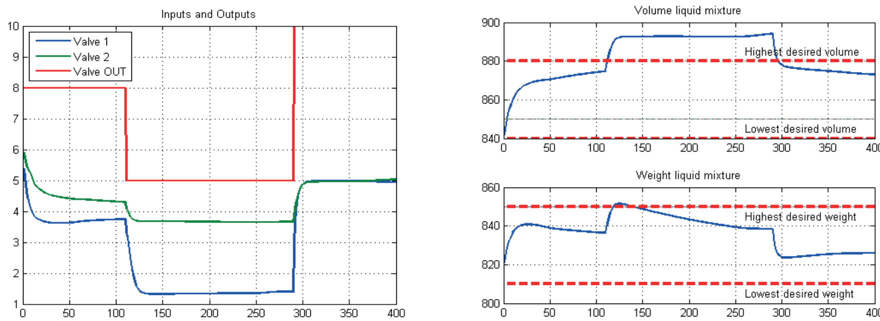

Figure 8 - Valves and Results of the Fuzzy-ANN Controller

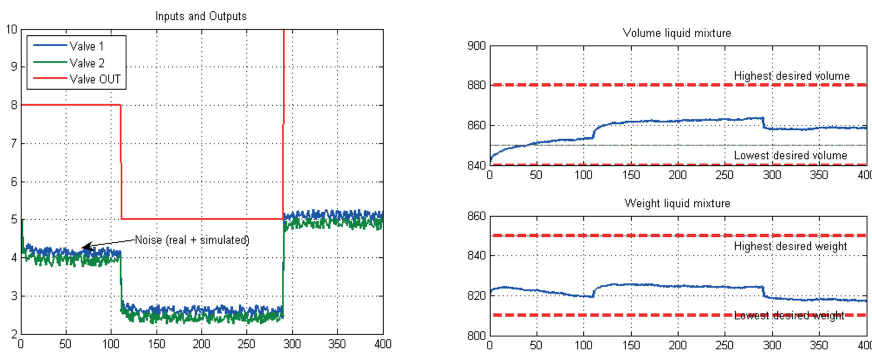

Figure 9 - Valves and Results of the Arduino embedded DFCM

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.

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.

Figure. 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.

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

7 I CONCLUSION

In conclusion, this study has highlighted the significance of incorporating Fuzzy Cognitive Maps (FCM) in the field of embedded control, while also considering the environmental impacts and security aspects. The simulation results demonstrated comparable performance among the three controllers, with a slight advantage observed for the DFCM controller, regardless of whether an Arduino microcontroller was utilized. This adaptive nature of the DFCM controller was a noteworthy feature. Although both controllers produced similar outcomes, the implementation of Fuzzy-Artificial Neural Network (Fuzzy-ANN) did not exhibit any significant improvements, except for a minor reduction in noise, which holds particular importance in industrial plants.

Furthermore, the data obtained from the Arduino microcontroller revealed that the controlled variables remained within desirable ranges when employing the DFCM embedded in the platform. This observation suggests that the DFCM codes possess low computational complexity, thanks to the simplicity of its inference mathematical processing. Consequently, this study highlights the portability and feasibility of developing DFCM controllers on low-cost platforms, emphasizing their potential for widespread adoption.

However, to provide a more comprehensive conclusion, future studies should explore real prototypes, which would offer a more realistic assessment of the DFCM controller's performance. Additionally, it would be valuable to compare other controllers with dynamic adaptation capabilities, such as adaptively fuzzy controllers and ANFIS, to further enhance the understanding of their effectiveness in embedded control systems. Considering the potential environmental impacts and security aspects in such comparative studies would provide a more holistic evaluation of the controllers' applicability and overall performance.

REFERENCES

MARCHAL, P. C.; GARCÍA, J. G.; ORTEGA, J. G. Application of Fuzzy Cognitive Maps and Run-to-Run Control to a Decision Support System for Global Set-Point Determination. IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. PP, no. 99, pp. 1-12, 2017.

MENDONÇA, M.; NEVES JR, F.; ARRUDA, L. V. R.; PAPAGEORGIOU, E.; CHRUN, I. Embedded Dynamic Fuzzy Cognitive Maps for Controller in Industrial Mixer. In: 8th International KES Conference on Intelligent Decision Technologies KES-IDT-16, 2016, Tenerife. KES-IDT-16, 2016. P. 1-10.

ZADEH, L. A. An introduction to Fuzzy logic applications in intelligent systems. Boston: Kluwer Academic Publisher, 1992.

KOSKO, B. Fuzzy cognitive maps. International Journal Man-Machine Studies, v. 24, n. 1, p. 65-75, 1986.

PAPAGEORGIOU, E.; STYLIOS, C.; GROUMPOS, P. A. Combined Fuzzy cognitive map and decision trees model for medical decision making. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society, v. 1, p. 6117-6120, 2006.

PAPAGEORGIOU, E. I. Fuzzy Cognitive Maps for Applied Sciences and Engineering from Fundamentals to Extensions and Learning Algorithms. Springer, 2014.

MENDONÇA, M.; ANGÉLICO, B.; ARRUDA, L. V. R.; NEVES, F. A dynamic fuzzy cognitive map applied to chemical process supervision. Engineering Applications of Artificial Intelligence, v. 26.

GOLDBERG, D. E.; DEB, K. A comparative analysis of selection schemes used in genetic algorithms. In: Foundations of Genetic Algorithms (FOGA). ISBN 1558601708. pp. 69-93. Morgan Kaufmann, 1991.

A.; NIKOLOVA-ALEXIEVA, V.; YANEVA, A. Concept Model for Assessment of the Economic Security Level in Food Industry Enterprises. In: International Conference on High Technology for Sustainable Development (HiTech), 2018, Sofia, Bulgaria. Proceedings... Sofia: Publisher, 2018. p. 1-3.

BRINKLEY, A.; KIRBY, J. R.; CHARRON, F. A joint industry approach to environmental impact evaluation of electrical and electronic products. In: Proceedings of the 1997 IEEE International Symposium on Electronics and the Environment. ISEE-1997, San Francisco, CA, USA, 1997.