Journal of Engineering Research

ISSN 2764-1317 vol. 5, n. 8, 2025

ARTICLE 14
Acceptance date: 10/12/2025

CLASSIC AND GENERATIVE INTELLIGENT CONTROL APPLIED TO INDUSTRIAL MIXERS, WITH IMPROVEMENTS IN QUALITY, MANAGEMENT, SAFETY, AMONG OTHERS

Márcio Mendonça
Universidade Tecnológica Federal do Paraná (UTFPR) – Campus Cornélio Procópio/Londrina, Paraná – Brasil
Programa de Pós-Graduação em Ensino de Ciências Humanas, Sociais e da Natureza – PPGEN
Cornélio Procópio - PR
http://lattes.cnpq.br/5415046018018708

Vitor Blanc Milani
Universidade Tecnológica Federal do Paraná
Mestrando - PPGEM-CP - Programa de Pós-Graduação em Engenharia Mecânica CP/PG
Cornélio Procópio – PR
http://lattes.cnpq.br/4504374098250296

Cintya Wedderhoff Machado
Universidade Tecnológica Federal do Paraná (UTFPR) – Campus Cornélio Procópio/Londrina, Paraná – Brasil
Mestranda no Programa de Pós-Graduação em Ensino de Ciências Humanas, Sociais e da Natureza – PPGEN
Londrina - PR
http://lattes.cnpq.br/4604594140489347

Juliana Maria de Jesus Ribeiro
Universidade Tecnológica Federal do Paraná (UTFPR) – Campus Cornélio Procópio/Londrina, Paraná – Brasil
Mestranda no Programa de Pós-Graduação em Ensino de Ciências Humanas, Sociais e da Natureza – PPGEN
Londrina - PR
http://lattes.cnpq.br/6279504657014354

Fabio Rodrigo Milanez
UniSENAIPR-Campus Londrina
Londrina-PR
http://lattes.cnpq.br/3808981195212391

Iago Maran Machado
Universidade Tecnológica Federal do Paraná
Mestrando (aluno externo) - PPGEM-CP - Programa de Pós-Graduação em Engenharia Mecânica CP/PG
Cornélio Procópio – PR
http://lattes.cnpq.br/3808981195212391

Andressa Haiduk
Dimension Engenharia
Rio Negro - PR
http://lattes.cnpq.br/2786786167224165

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

Carlos Alberto Paschoalino
Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio - PR
http://lattes.cnpq.br/0419549172660666

Norwin Porfirio Carrasquel Poturo
Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de
UTFPR - PPGIT - Programa de Pós-graduação em Inovações tecnológicas
Campo Mourão -PR
http://lattes.cnpq.br/0512294788133450

Henrique Cavalieri Agonilha
Universidade Filadélfia (Unifil)
Londrina - PR
http://lattes.cnpq.br/9845468923141329

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

Roberto Bondarik
Universidade Tecnológica Federal do Paraná
Programa de Pós-Graduação em Ensino de Ciências Humanas, Sociais e da Natureza (PPGEN-CP/LD)
http://lattes.cnpq.br/6263028023417758

Eduardo Pegoraro Heinemann
Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio – PR
http://lattes.cnpq.br/0964474292409084

Armando Paulo da Silva
Universidade Tecnológica Federal do Paraná
Programa de Pós-Graduação em Ensino de Ciências Humanas, Sociais e da Natureza (PPGEN-CP/LD)
Cornélio Procópio–PR
http://lattes.cnpq.br/6724994186659242

Edinei Aparecido Furquim dos Santos
Governo do Paraná Secretaria de estado da Fazenda
Maringá-Pr
http://lattes.cnpq.br/8706436030621473

Marta Rúbia Pereira dos Santos
Centro Estadual de Educação Tecnológica Paula Souza
Etec Jacinto Ferreira de Sá – Ourinhos
Ourinhos - SP
http://lattes.cnpq.br/3003910168580444

Marco Antônio Ferreira Finocchio
Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio – PR
http://lattes.cnpq.br/8619727190271505

Abstract: This study presents the application of intelligent control techniques to an industrial mixing process. The proposed controller designed based on a Hebbian adaptation of the Fuzzy Cognitive Map (FCM) learning mechanism, which results in a Dynamic Fuzzy Cognitive Map (DFCM) model. The research develops and validates this DFCM using Hebbian learning algorithms to improve adaptability and robustness in nonlinear industrial systems. To ensure reliability, a classical fuzzy controller and a standard Proportional-Integral-Derivative (PID) controller implemented as benchmarks to validate the simulation results of the DFCM-based control for the industrial mixer. Extensive simulation experiments conducted to compare the performance of the controllers. The results demonstrate that the proposed DFCM provides superior performance in adaptability and robustness compared to the benchmarks, while also suggesting low computational complexity for practical implementation.

Keywords: Fuzzy Cognitive Maps, Hebbian Learning, Process Control, Fuzzy Logic, Artificial Neural Network.

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; o 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 significantly influenced by the selection of the set points for the process variables, as they fundamentally impact product quality characteristics and process performance metrics (Marchal; García; Ortega, 2017).

This work serves as a direct evolution of the study presented by Mendonça *et al.* (2017). While the previous work established and validated the DFCM (Dynamic Fuzzy Cognitive Map) controller, the proposal of this new article is to significantly expand that analysis. The main contributions of this evolution are: (1) the introduction of a Genetic Algorithm (GA) for the offline optimization of the controller's initial weights, and (2) a more robust benchmarking analysis, comparing the DFCM's performance not only against Fuzzy-ANN controllers but also notably against a classic Proportional--Integral-Derivative (PID) controller, which serves as a standard industrial benchmark

The article proposal is to use a different setup, specifically the initial state and a comparison with a new controller using Fuzzy-Logic with ANN (artificial neural network). The motivation for this research is the development of optimal control theory, robust Control, and adaptive Control, which significantly expands the automation concept and studies the feasibility of 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 manage complex processes based on inaccurate and/or approximate information. The strategy adopted by them is also imprecise in nature and can usually expressed in linguistic terms. Thus, by means of Fuzzy Logic concepts, it is possible to model this type of information (Zadeh, 1992).

Previous works that used Fuzzy techniques can cited, such as Fabro and Arruda (2003), which applies a Fuzzy-Neuro predictive control tuned by Genetic Algorithms (GA) on a fermentation process. A Proportional Derivative Fuzzy Logic Controller (Fuzzy-PD) initially used to control the process, a nonlinear system with non-minimal phase and ample accommodation time.

More recently, Yesil, Kumbasar and Karasakal (2013) presented an FCM used to tune the parameters of PI controllers on a nonlinear system. These controllers cannot achieve satisfactory results in this type of system due to the difference in their static and dynamic properties.

There is also Mendonça *et al.* (2012), where new types of concepts and relations, not restricted to cause-effect ones, added to the model, resulting in a dynamic fuzzy cognitive map (DFCM). In this sense, a supervisory system developed to control the fermentation process.

BACKGROUND

Fuzzy Cognitive Maps (FCM) introduced by Kosko's work, which added Fuzzy values to the causal relationships of Axelrod's Cognitive Maps paper. In fact, FCMs are system models that represent a graph form, where the nodes represent concepts related to the problem, and the lines connecting them represent the causal relationships between these concepts. An FCM is a 4-tuple, as described in works as Stach *et al.* (2005) and Arruda *et al.* (2016). It is used to study the dynamics of systems due to its mathematical simplicity. The relationship's influence is calculated using normalized states and matrix multiplications.

The system's dynamics may converge into a steady state, a limit cycle of states, or even a chaotic state Kosko (1992) and Lee (2003). Every concept's activation level is based on its own previous iteration and the propagated weighted values of all the concepts connected to it (it means all concepts that influence it).

In the literature, numerous examples of FCMs exist that utilize monotonic and symmetric cause-and-effect relationships between concepts. Although these relationships may be effective in controlled environments, they cannot apply in the real world due to their dynamic aspects. To bring FCMs to more realistic environments, several techniques can be employed, such as using Fuzzy rules and feedback mechanisms Carvalho and Tome (2009) or algebraic equations to define causal relationships when the real system has modeled using crisp relations Aguilar (2004).

In general, a Fuzzy Cognitive Map (FCM) is a tool for modeling human knowledge and understanding. It can obtain through linguistic terms inherent to Fuzzy Systems, which have a structure like Artificial Neural Networks (ANN), facilitating data processing and enabling capabilities for training and adaptation. FCM is a technique based on knowledge that inherits characteristics of Cognitive Maps and Artificial Neural Networks (Kosko, 1986; Kosko 1992), with applications in different areas of knowledge (Lee, 2003; Mendonça *et al.*, 2017).

In addition to the advantages and characteristics inherited from these primary techniques, FCM initially proposed as a tool for building 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 construction to human reasoning.

Dynamic Fuzzy Cognitive Maps (DFCM) need to develop into a model that can manage the behaviors of nonlinear, time-dependent systems, and sometimes in real-time. Examples of different variations of the classic FCMs can found in recent literature, e.g., (Papageorgiou, 2013).

This paper has two objectives. The first objective is to develop two controllers using an acyclic DFCM, with the same knowledge as a Fuzzy and Fuzzy Neural controller, and with similar heuristics, thus producing comparable simulated results.

To achieve the goals, we initially used a similar DFCM proposed initially in Mendonça *et al.* (2013) to control an industrial mixing tank. The Hebbian algorithm used to dynamically adapt the DFCM weights. To validate the DFCM controller, its performance compared with that of a Fuzzy Logic controller. This comparison conducted using simulated data.

Previous work by Mendonça *et al.* (2013) applied a DFCM to this same industrial mixer problem, laying the groundwork for the present study. In that approach, the controller's initial weights optimized using Simulated Annealing, and dynamic adaptation explored using both Hebbian Learning and a rule-based selection mechanism (DT-FCM). This paper builds upon that foundation by introducing a Genetic Algorithm (GA) for offline optimization and focusing on a refined Hebbian algorithm for dynamic adaptation, comparing its performance against a wider range of benchmarks, including a classic PID.

DEVELOPMENT

To demonstrate the proposed technique, this study utilizes a well-known case study from the literature: an industrial mixer process. This case was selected to illustrate the need for refining a model based on Fuzzy Cognitive Maps (FCM) that was initially built exclusively with expert knowledge.

Case Study: The Industrial Mixer Process

The process consists of a tank with two inlet valves (V1 and V2) for different liquids, a mixer, an outlet valve (V3) for removing the final product and a specific gravity meter that measures the specific gravity of the liquid produced. For this study, the two liquids are water (specific gravity of 1.0) and soybean oil (specific gravity of approximately 0.9).

Valves V1 and V2 introduce the two different liquids into the tank. During the reaction, a new liquid with a unique specific gravity is produced. The outlet valve, V3, empties the tank according to a predetermined campaign output flow, ensuring the final mixture meets specified volume and specific gravity levels. Although simple, this process is a Two-Inputs and Two-Outputs (TITO) system with coupled variables. To monitor the quality of the fluid, a weighting machine in the tank measures its specific gravity.

DOI https://doi.org/10.22533/at.ed.3175825011014

Process Modeling and Control Objectives

The objective of control is to maintain the mixture's volume (V) and mass (G) within their specified operating ranges. The desired mixed liquid is ready when its mass falls within the range $[G_{min}, G_{max}]$ and it can only be removed when its volume is within the range $[V_{min}, V_{max}]$.

The operational constraints are defined as:

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

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

In this study, the target range for mass is 810 to 850 mg, and for volume, it is 840 to 880 ml. The initial values are 800 mg for mass and 850 ml for volume.

Following the methodology of Papageorgiou et al. [23], experts can define key concepts related to the physical process. The concepts for the cognitive model are:

- Concept 1: State of valve V1 (closed, open, or partially open);
- Concept 2: State of valve V2 (closed, open, or partially open);
- Concept 3: State of valve V3 (closed, open, or partially open);
- Concept 4: Quantity of mixture (volume) in the tank, dependent on the state of valves V1, V2, and V3.
- Concept 5: Value of the specific gravity measured by the G sensor.

The process model is derived from the principle of mass conservation in an incompressible fluid, resulting in a set of differential equations. The initial volume plus the inflow from valves V1 and V2, minus the outflow from valve V3, determines the tank volume. The mass of the tank follows the same principle, where the specific gravities for the liquids from V1 () and V2 () are 1.0 and 0.9, respectively.

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

$$Weight_{tank} = M_i + \left(V_1 \cdot me_1 + V_2 \cdot me_2\right) - M_{out} \quad (4)$$

Proportional-Integral-Derivative (PID) Controller Development

In addition to the intelligent controllers, a classic Proportional-Integral-Derivative (PID) controller was implemented to provide a standard industrial benchmark. The strategy employs a decoupled control architecture using two independent PID controllers to manage the TITO system.

1. **Level Controller (PID-L):** This regulates the total mixture volume (V) by controlling the sum of the inlet flows ($u_{\sum}$ ¿$=V_1+V_2$¿). It uses the volume error ($e_L = V_{ref} - V$) and includes a feedforward term to reject the outlet flow (V_3) disturbance.
2. **Density Controller (PID-R):** This regulates the specific gravity (ρ) by controlling the difference between the inlet flows ($u_{diff} = V_1 - V_2$)It uses the density error ($e_R = \rho_{ref} - \rho$).

The outputs are mapped to the individual valves ($V_1=0.5\ (u_{\sum ¿+u_{diff}¿})$; $V_2=0.5(u_{\sum ¿-u_{diff}))¿}$ .A back-calculation anti-windup mechanism was applied to both controllers to manage saturation.

Logical Reasoning of the Heuristic Control Strategy

This section details the core logical reasoning; that defines the heuristic control strategy for the industrial mixer. This logic serves as the fundamental basis for both the benchmark Fuzzy controller and the proposed DFCM controller, ensuring the subsequent comparison is based on the same underlying control principles.

To formally implement this logic as a benchmark, a standard Fuzzy controller developed would be a process controller. Fuzzy logic is well-suited for creating effective nonlinear controllers, even with imprecise plant models, and has a long history of application in process control.

While a detailed discussion of the Fuzzy controller's specific implementation is outside the scope of this paper, its key features include triangular and trapezoidal membership functions and a rule base with nine rules. As noted, this rule base (shown below) encapsulates the shared logical reasoning for both controllers. The rules are symmetrical, making the control surface for valve V1 identical to that of valve V2.

- If (Level is low) then (V_1 is medium) (V_2 is medium) (1)
- If (Level is medium) then ($V_1$is low) (V_2 is low) (1)
- If (Level is high) then (V_1 is low) (V_2 is low) (1)
- If (Weight is low) then (V_1 is high) (V_2 is high) (1)
- If (Weight is medium) then (V_1 is low) (is low) (0.5)
- If (Weight is high) then (V_1 is low) ($V_2$is low) (1)
- If (ValveOut is high) then (V_1 is high) ($V_2$is high) (0.5)
- If (ValveOut is medium) then (V_1 is medium) ($V_2$is medium) (0.5)
- If (ValveOut is low) then (V_1 is low) ($V_2$is low) (0.5)

This logic forms the complete definition for the Fuzzy Logic benchmark controller. The subsequent section will detail how this same heuristic strategy translated into the causal structure of the Dynamic Fuzzy Cognitive Map (DFCM).

Hybrid Fuzzy-ANN Controller

Another benchmark would be a sequential hybrid model also created by connecting two subsystems in series. A Fuzzy-ANN cascade controller was developed where an Artificial Neural Network (a multilayer perceptron) was trained using the output data from the Fuzzy controller. The network topology was selected empirically, resulting in a single hidden layer with two hundred neurons. The training dataset consisted of 6,000 points from within the control region, Fuzzy Logic, and this controller we simulated, or the model simulates.

Dynamic Fuzzy Cognitive Map (DFCM) Controller Development

A DFCM is used to control the mixer, with the objective of maintaining volume and mass within the specified limits. The development of the DFCM controller was conducted in three distinct stages.

Stage 1: Structural Definition

First, the DFCM structure was defined with concepts and causal relationships, like a classic FCM. The concepts correspond to process variables (sensors) and control actions (actuators). The control heuristic is like the Fuzzy controller: if the outflow from V3 increases, the inflow from V1 and V2 also increases (a positive relationship). Conversely, if the mixture's volume or weight increases, the inflow from V1 and V2 decreases (a negative relationship).

Stage 2: Initial Weight Optimization via Genetic Algorithm (GA)

- While previous iterations on this problem utilized Simulated Annealing for weight optimization, this study employed a Genetic Algorithm (GA) to determine the initial values of the causal relationships (weights) offline. The GA parameters were.
- Recombination Method: Single--point crossover.
- Mutation Method: Randomly chosen.
- Selection Method: Tournament.
- Population Size: thirty chromosomes.
- Fitness Function E(i): The function considers the overall error of the two desired outputs over 15 generations. It is given by:

$$E_i=\sqrt{(0.44- A_{3(k+1)})^2+(0.42- A_{4(K+1)})^2} \quad (5)$$

The GA stabilizes and finds an initial solution for the valve openings at approximately 44% for V1 and 42% for V2. The initial weights obtained are shown in Table 1.

Initial Causal Relationship Weights	
W13	*-0.2647*
W14	*-0.324*
W23	*-0.2831*
W24	*-0.3339*
W53	*0.2648*
W54	*0.2754*

Table 1: Initial Causal Relationship Weights

Stage 3: Dynamic Tuning with Hebbian Learning

The third stage involves refining the model for dynamic response. When a set point changes, the weights are dynamically adjusted using an adaptation of the classic Hebbian learning algorithm. This algorithm provides online control actions: if the mixture's weight or volume increases, the negative causal relationship for the inlet valves is intensified, causing them to close faster. Conversely, if the weight or volume decreases, the relationship is positively intensified. The update rule is:

$$W_i(k)= W_{ijk-1}\pm \gamma\Delta A_i \quad (6)$$

Where: is the concept variation resulting from a causal relationship given by , and is the learning rate at iteration . An adapted version of this rule was applied in this work:

$$W_{ik}= k_p\cdot(W_{ijk-1}- \gamma\Delta A_i) \quad (7)$$

Here, $\gamma = 1$ for all, and k_p is a proportional gain determined empirically for each weight pair. The values are $k_p = 40$ for (W_{14}; W_{23}), $k_p = 18$ for (W_{13}; W_{24}), and $k_p = 2.36$ for (W_{53}; W_{54}), with normalized values.

This causal structure is visually represented in Figure 1. The diagram illustrates the five key concepts defined for the controller: the process variable inputs 'Volume' (Concept 1), 'V3' (Concept 2), and 'Weight' (Concept 5), which represent the sensors, and the control action outputs 'V1' (Concept 3) and 'V2' (Concept 4), which represent the actuators. The connections (e.g., W23–hebb, W14–hebb) represent the causal weights between these concepts, which are dynamically tuned by the Hebbian learning algorithm detailed in Stage 3.

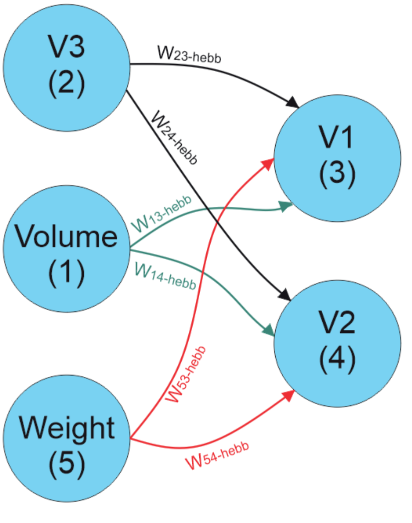

Fig. 1. DFCM Structure

DFCM Inference and Stability

The inference mechanism for the DFCM is identical to that of a classic FCM, using the following equations:

$$A_i = \sum_{j=1, j \neq i}^{n} A_j \cdot W_{ji} \qquad (8)$$

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

The use of the sigmoid transfer function helps ensure the system's stability, as the calculated values converge toward a specific value. Initial stability analyses for this type of system have been presented in previous works, often using methods like the contraction mapping theorem or by identifying a Lyapunov energy function. Since the DFCM uses the same core equations as a stable FCM but with dynamic tuning, the experimental results also demonstrate stability.

SIMULATED EXPERIMENTAL RESULTS

This chapter details the performance of the proposed DFCM controller and compares it against three benchmarks: a classic Fuzzy Logic controller, a hybrid Fuzzy-ANN controller, and a standard industrial PID controller. The analysis is based on the quantitative results from two distinct operational campaigns, one without disturbances (Table 2) and one with disturbances (Table 3), as well as the qualitative performance of the PID benchmark (Figures 1-3).

Quantitative Analysis

Tables 2 and 3 provide a comprehensive quantitative comparison of the four distinct control architectures evaluated in this study: the DFCM, Fuzzy Logic, Fuzzy-ANN, and classic PID. The simulated results clearly indicate that the performance of the Dynamic Fuzzy Cognitive Map (DFCM) controller is superior to that of the other conventional controllers.

To evaluate performance, two key metrics were established: "Volume mix (mL) Max-min" and "Weight mix (mg) Max--min". These metrics represent the total range of variation (i.e., oscillation) observed for each controlled variable throughout the entire simulation campaign. A lower numerical value in these columns is desirable, as it corresponds to a higher degree of control precision and system stability, indicating that the controller successfully minimized deviation from the setpoint.

The controllers were evaluated across two distinct scenarios. Table 2 presents the baseline performance of each controller under ideal, predictable operating conditions. Following this, Table 3 evaluates their comparative robustness and performance under the introduction of simulated process disturbances.

DFCM Performance Analysis

The Dynamic Fuzzy Cognitive Map (DFCM) controller, the primary contribution of this study, was designed to provide a robust and adaptive solution for the industrial mixer process. Its performance was evaluated across two operational campaigns, both in a baseline scenario (Table 2) and in a more challenging scenario introducing disturbances (Table 3). The analysis of these quantitative results demonstrates a substantial performance advantage over all implemented benchmarks.

In the baseline simulation without disturbances (Table 2), the DFCM controller demonstrated superior precision in the critical weight-control metric. The DFCM maintained the mixture weight within a 10.74 mg range (Campaign 1) and volume within a 14.07 mL range. For comparison, the Fuzzy Logic controller's weight variance was significantly higher at 22.87 mg, and the Classic PID controller had the weakest precision at 45.24 mg.

The most critical test, however, was the controller's performance under disturbances (Table 3). This scenario highlights the core advantage of the DFCM's adaptive nature. When disturbances were introduced, the simulated DFCM's weight range remained highly precise at 14.69 mg (Campaign 1). In sharp contrast, the non-adaptive Classic PID controller's performance degraded significantly, with its weight range increasing to 52.50 mg (Campaign 1), demonstrating its lack of robustness.

In addition to the quantitative data, Figures 2 through 5 provide a qualitative visualization of the DFCM controller's performance during one of the operational campaigns. Figure 2 details the control action, showing the smooth adjustment of the inlet valves (V1 and V2) as they respond to the stepped changes in the outlet valves (V3) campaign flow.

Figure 3 and Figure 4 illustrate the controller's effective response for the primary variables, showing the Volume and Mass being steered from their initial states to their respective setpoints, where they are maintained stably within the operational bands. Figure 5 shows the corresponding successful stabilization of the specific gravity (ρ).

This adaptive capability stands in stark contrast to the non-adaptive controllers. The classic PID, while stable, saw its performance degrade significantly under dis-

Controller	Campaign	Volume mix (mL) Max-min	Weight mix (mg) Max-min
DFCM	1	14.07	10.74
	2	13.52	10.68
Fuzzy Logic	1	35.55	22.87
	2	38.20	16.65
Fuzzy-ANN	1	36.69	25.31
	2	38.11	25.28
Classic PID	1	39.07	45.24
	2	37.62	44.43

Table 2: Quantitative Results without Disturbances

Controller	Campaign	Volume mix (mL) Max-min	Weight mix (mg) Max-min
DFCM	1	13.82	14.69
	2	14.79	14.31
Fuzzy Logic	1	35.51	28.02
	2	38.12	20.64
Fuzzy-ANN	1	36.69	25.28
	2	38.10	25.29
Classic PID	1	39.06	52.50
	2	37.61	51.80

Table 3: Quantitative Results with Disturbances

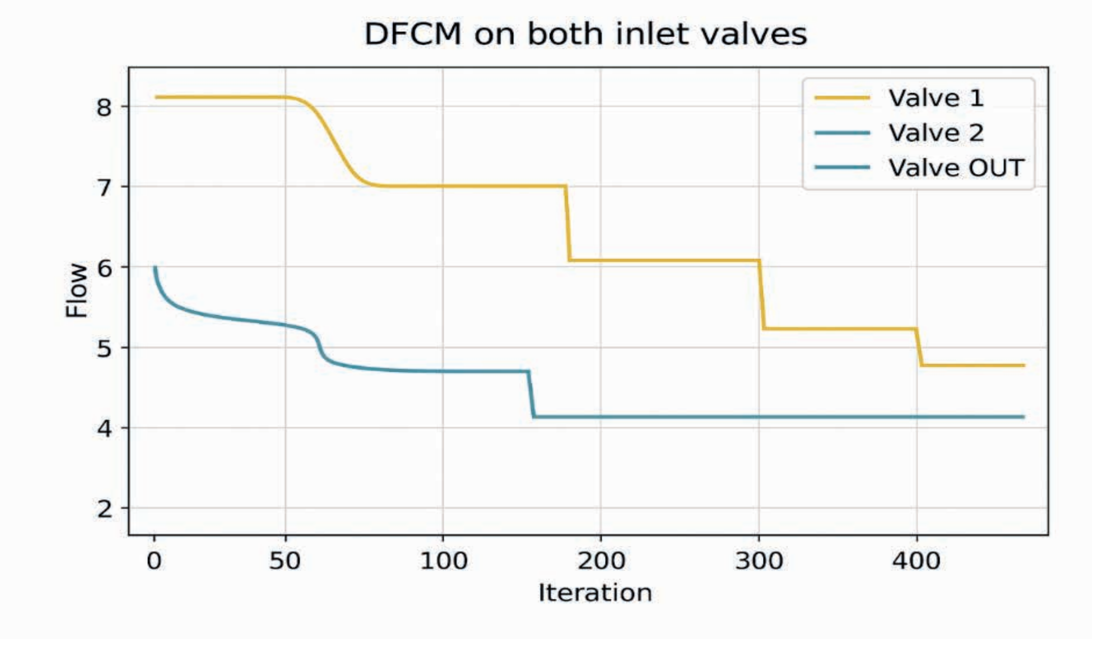

Fig. 2. DFCM on both inlet valves

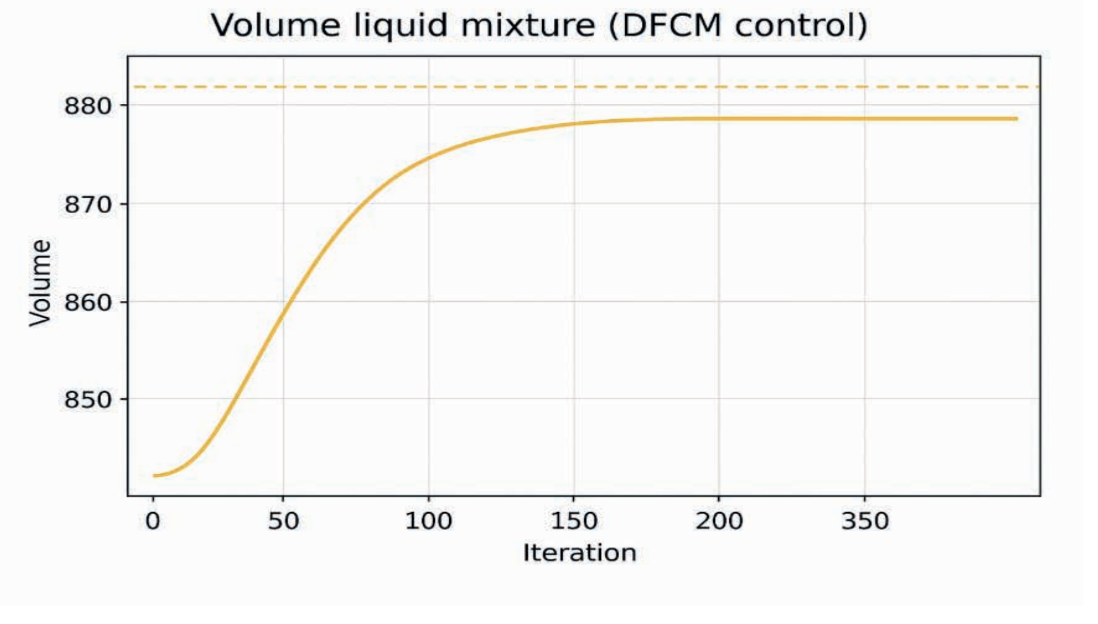

Fig. 3. Volume Liquid Mixture.

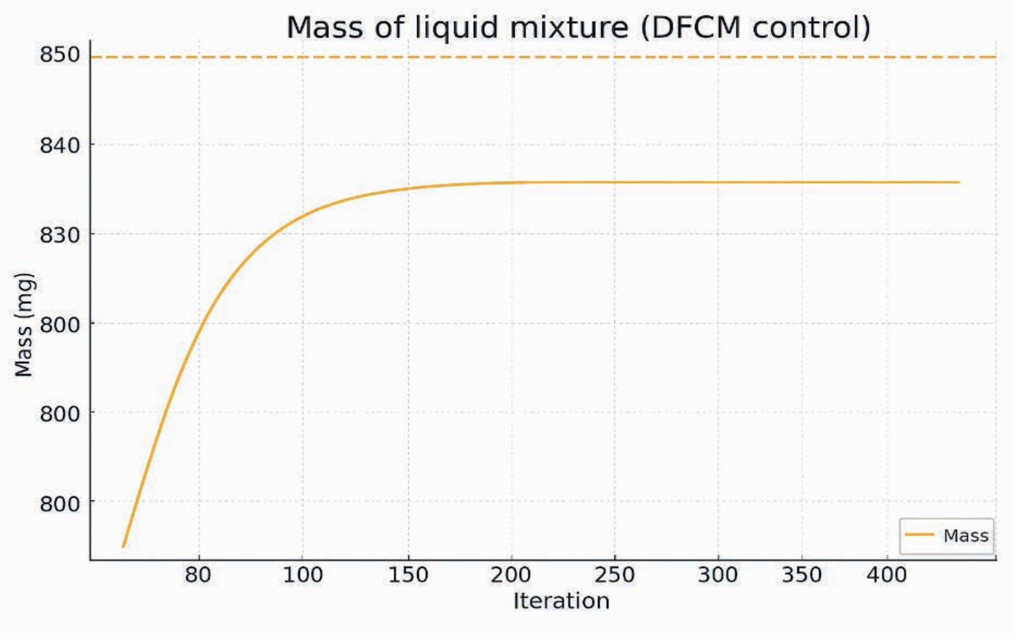

Fig. 4. Mass of liquid mixture in DFCM Control

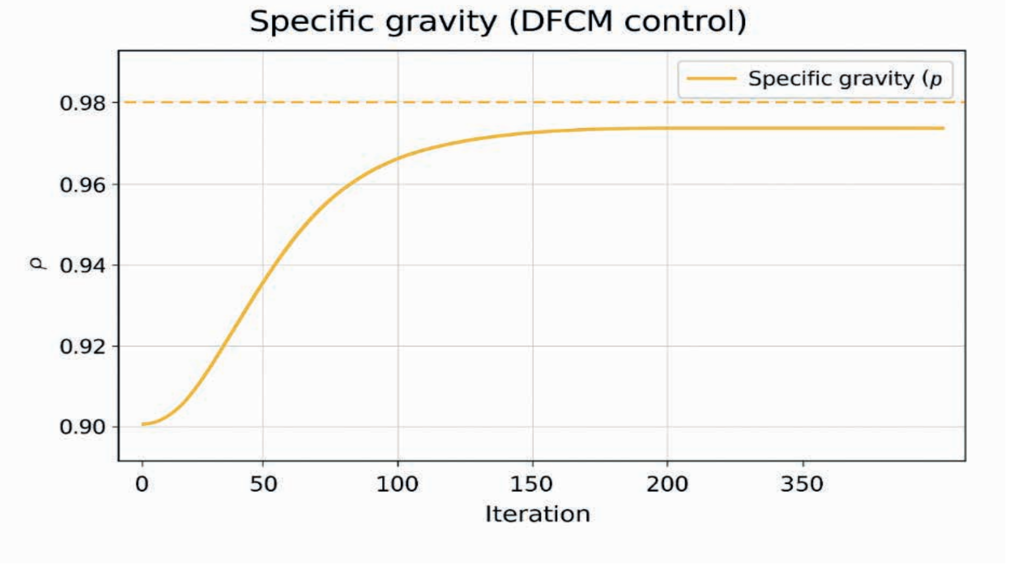

Fig. 5. Specific gravity in DFCM Control

turbance. As shown by comparing Table 2 and Table 3, the PID's weight control error (Max-min) increased from 45.24 mg to 52.50 mg.

Fuzzy Logic and Fuzzy-ANN Performance Analysis

To emphasize advantages of the applying AI controllers according to previous cited articles, a robust validation for the proposed DFCM, a standard Fuzzy Logic controller was implemented as a key intelligent benchmark. This controller was developed using the same heuristic control strategy and operational conditions as the DFCM to ensure a fair and direct comparison. Additionally, a hybrid Fuzzy-ANN controller was developed by training a neural network on the output data of the Fuzzy controller.

The quantitative results show that while the standard Fuzzy Logic controller provides stable control, it lacks the high precision of the DFCM. In the baseline simulation without disturbances (Table 2), the Fuzzy controller's volume variation (Max-min) was 35.55 mL in Campaign 1 and 38.20 mL in Campaign 2. These values are more than double the variation exhibited by the DFCM (14.07 mL and 13.52 mL, respectively), indicating a much larger oscillation around the desired setpoints.

When subjected to disturbances (Table 3), the Fuzzy controller maintained its operational stability, with its volume variation remaining consistent at 35.51 mL and 38.12 mL. However, unlike the adaptive DFCM which actively rejected the disturbance, the Fuzzy controller's weight control precision degraded, increasing from 22.87 mg to 28.02 mg in Campaign 1. This demonstrates that, as a non-adaptive intelligent controller, it is more precise than the classic PID but is still susceptible to unmodeled dynamics and cannot match the robustness of the Hebbian-tuned DFCM.

Furthermore, the sequential hybrid Fuzzy-ANN controller did not offer a significant performance improvement over the standard Fuzzy controller, producing identical quantitative results in both baseline and disturbance scenarios (Tables 2 and 3). This reinforces the conclusion that the adaptive mechanism of DFCM provides a unique performance advantage that is not present in these other intelligent benchmarks.

PID Control Performance Analysis

The performance of the classic PID controller, implemented as an industrial benchmark, is shown in Figures 6 through 9. Figure 6 details the action of the inlet valves (V1 and V2), which correctly adjust their flow rates in response to the stepped disturbances from the outlet valve (V3).

Figure 7 shows the volume control, which successfully brings the mixture from its initial state (approx. 830 ml) to the 870 ml setpoint, maintaining it firmly within the [840, 880] ml operational band.

Figure 8 and Figure 9 demonstrate the control of the mixture's properties, steering Mass and Specific Gravity (ρ) from their initial states (800 mg and 0.94, respectively) to their setpoints, where they are held within their required operational bands.

A direct qualitative comparison between the two sets of figures (Figures 2-5 for

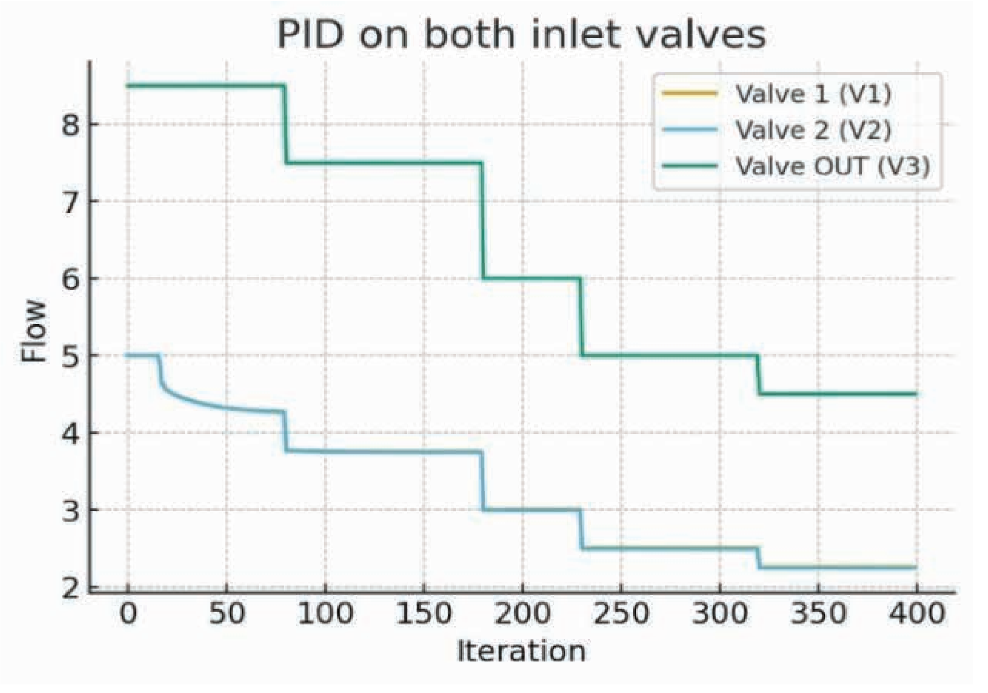

Fig. 6. PID on both inlet valves

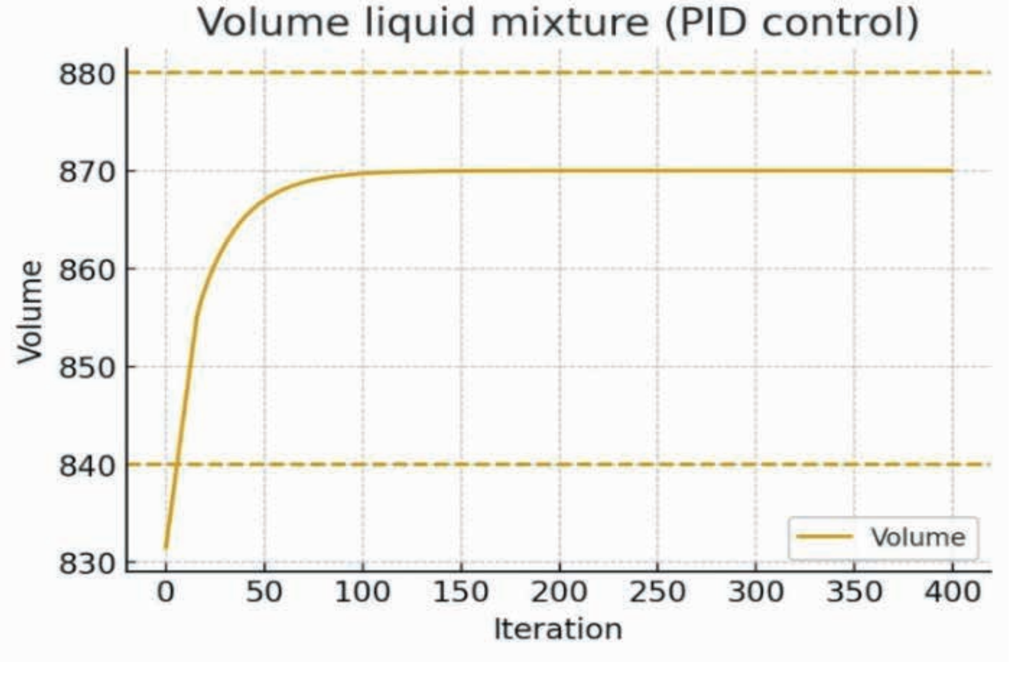

Fig. 7. Volume Liquid Mixture in PID Control

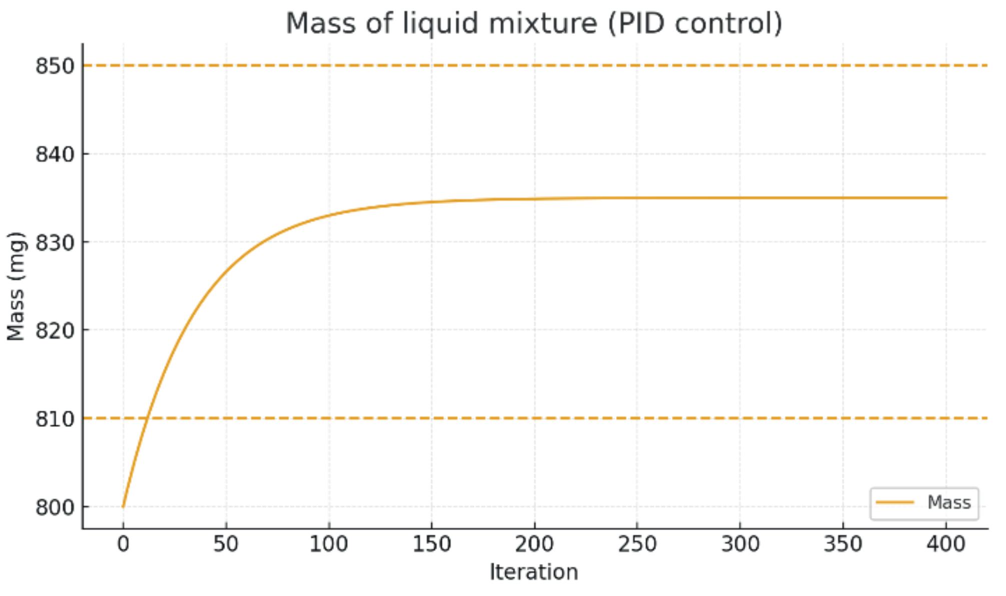

Fig. 8. Mass of Liquid Mixture in PID Control

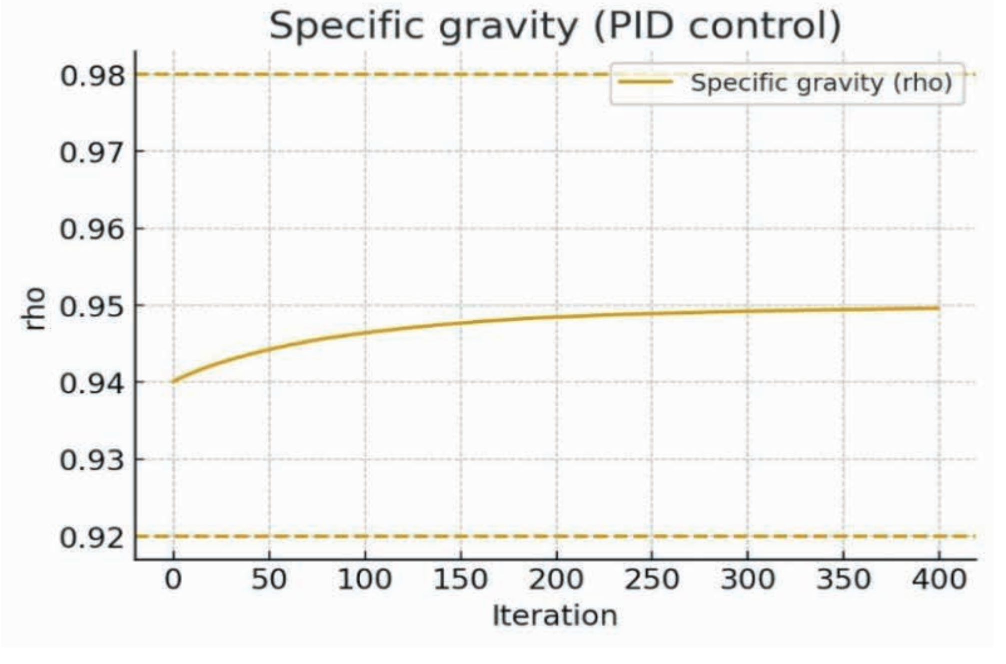

Fig.9. Specific Gravity PID Control.

the DFCM and Figures 6-9 for the PID) provides an initial validation of the proposed controller. While both systems successfully steer the process variables to their respective setpoints and maintain stability, the control action of the DFCM (Figure 2) demonstrates a smoother, more continuous adjustment of the inlet valves. This contrasts with the stepped, discrete actions of the classic PID (Figure 6). This visual evidence, which suggests a more refined and stable response from the DFCM, is quantitatively confirmed in the following section, where the controllers are rigorously benchmarked for precision and robustness using the data from Tables 2 and 3.

Comparative Performance Evaluation

According to 4.3 comprehensive evaluation of the controllers, based on the quantitative data presented in Tables 2 and 3, was performed to benchmark the proposed DFCM against the Fuzzy Logic, Fuzzy-ANN, and classic PID controllers. The analysis focused on two primary metrics: control precision under baseline conditions and performance robustness under the introduction of disturbances.

Regarding control precision (Table 2), the DFCM exhibited the lowest maximum-minimum (Max-min) variation for both process variables across both campaigns. In Campaign 1, the DFCM's weight variation was 10.74 mg. This value contrasts significantly with the Fuzzy Logic controller, which registered a variation of 22.87 mg, and the classic PID, which demonstrated the highest variation at 45.24 mg. This quantitative data indicates a superior steady-state accuracy and lower oscillation for the DFCM model.

The most critical distinction, however, was observed in the robustness analysis (Table 3). When subjected to disturbances, the DFCM's performance remained exceptionally consistent, with its weight variation (14.69 mg in Campaign 1) showing only a marginal deviation from the baseline. This stability is attributed to its adaptive Hebbian learning mechanism, which actively compensates for unmodeled process dynamics in real-time. Conversely, the non-adaptive benchmarks exhibited measurable performance degradation. The classic PID controller's weight control error increased to 52.50 mg, while the static Fuzzy Logic controller's error also rose, increasing to 28.02 mg.

In summary, the simulation data indicates that the proposed DFCM controller provides superior performance in both precision and robustness when compared to the implemented static-intelligent (Fuzzy, Fuzzy-ANN) and classic industrial (PID) benchmarks for this process.

Performance Metrics and Computational Complexity

In addition to control performance, metrics related to the computational load of the intelligent controllers were evaluated. The total simulation processing time was recorded on the same computer to provide a comparative baseline.

The results indicated that the processing times for the Fuzzy Logic and DFCM controllers were highly comparable. A slight, consistent advantage was observed for the DFCM, which completed the simulations marginally faster than the Fuzzy Logic controller. This finding is consistent with the theoretical structure of the controllers; the DFCM's inference relies primarily on

DOI https://doi.org/10.22533/at.ed.3175825011014

simple matrix multiplication and a sigmoid function, whereas the Fuzzy Logic controller must evaluate a rule base.

As noted, a formal quantitative analysis of the algorithm's computational complexity was not within the scope of this study.

CONCLUSIONS

This study makes a notable contribution by applying Dynamic Fuzzy Cognitive Maps to an industrial control problem. The results, based on extensive simulation, indicate that the Dynamic Fuzzy Cognitive Map (DFCM) controller performs better than the other controllers evaluated: Fuzzy Logic, Fuzzy-ANN, and the classic Proportional-Integral-Derivative (PID) controller.

A key finding is the superior robustness of the adaptive DFCM. The quantitative analysis showed that while the DFCM maintained consistent, high-precision performance in scenarios with and without disturbances, the classic PID controller's performance degraded significantly when faced with the same disturbances. This highlights the practical advantage of the DFCM's Hebbian learning mechanism in adapting to unmodeled dynamics, a critical weakness of the non-adaptive PID. While the Fuzzy-ANN controller did not offer a significant improvement over the standard Fuzzy controller, it did provide a slight reduction in noise. Furthermore, the simplicity of the DFCM's inference process suggests low computational complexity.

Future research will focus on a formal quantitative analysis of the DFCM's computational complexity to draw more generalized conclusions. Additionally, we plan to obtain and analyze results from a real-world prototype to validate these simulated findings. This would leverage advanced machine learning libraries, improve the reproducibility of experiments, and facilitate more complex simulation scenarios.

ACKNOWLEDGE

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001.

REFERENCES

AGUILAR, J. *Dynamic random Fuzzy cognitive maps. Computación y Sistemas*, v. 7, n. 4, 2004.

ARRUDA, L. V. R.; MENDONÇA, M.; NEVES JR., F.; CHRUN, I. R.; PAPAGEORGIOU, E. I. *Artificial Life Environment Modeled by Dynamic Fuzzy Cognitive Maps. IEEE Transactions on Cognitive and Developmental Systems*, v. PP, n. 99, p. 1–1, 2016.

CARVALHO, J. P.; TOME, J. A. *Rule Based Fuzzy Cognitive Maps in Socio-Economic Systems.* In: EUROPEAN SOCIETY FOR FUZZY LOGIC AND TECHNOLOGY CONFERENCE, 2009. Proceedings. EUSFLAT, 2009.

FABRO, J. A.; ARRUDA, L. V. R. *Fuzzy-neuro predictive control, tuned by genetic algorithms, applied to a fermentation process.* In: IEEE INTERNATIONAL SYMPOSIUM ON INTELLIGENT CONTROL, 2003, Houston. Proceedings. Houston, TX: IEEE, 2003. p. 194–199.

LEE, K. C.; LEE, S. *A cognitive map simulation approach to adjusting the design factors of the electronic commerce web sites. Expert Systems with Applications*, v. 24, n. 1, p. 1–11, 2003.

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*, v. PP, n. 99, p. 1–12, 2017.

MENDONÇA, M.; ANGÉLICO, B.; ARRUDA, L. V. R.; NEVES JR., F. *A dynamic fuzzy cognitive map applied to chemical process supervision. Engineering Applications of Artificial Intelligence*, v. 26, p. 1199–1210, 2013.

MENDONÇA, M.; CHRUN, I. R.; NEVES JR., F.; ARRUDA, L. V. R. *A cooperative architecture for swarm robotic based on dynamic fuzzy cognitive maps. Engineering Applications of Artificial Intelligence*, v. 59, p. 122–132, 2017.

MENDONÇA, M.; MATSUMOTO, D.; ARRUDA, L. V. R.; PAPAGEORGIOU, E. I. Intelligent Systems Applied to the Control of an Industrial Mixer. In: ARTIFICIAL INTELLIGENCE APPLICATIONS AND INNOVATIONS (AIAI), 8., 2013, Paphos. Proceedings […]. Paphos, Greece: Springer, 2013. p. 537-546.

MENDONÇA, M.; NEVES JR., F.; ARRUDA, L. V. R.; PAPAGEORGIOU, E. I.; CHRUN, I. R. *Embedded Dynamic Fuzzy Cognitive Maps for Controller in Industrial Mixer.* In: INTERNATIONAL KES CONFERENCE ON INTELLIGENT DECISION TECHNOLOGIES – KES-IDT-16, 8., 2016, Tenerife. Proceedings […]. Tenerife: KES-IDT, 2016. p. 1–10.

MENDONÇA, Márcio; SOUZA, L.B. ; SOARES, P.P. ; PAPAGEORGIOU, E. I. ; BARROS, R.V..D. . Dynamic Fuzzy Cognitive Maps Embedded and Intelligent Controllers Applied in Industrial Mixer Process. INTERNATIONAL JOURNAL ON ADVANCES IN SYSTEMS AND MEASUREMENTS, v. 10, p. 222, 2017.

PAPAGEORGIOU, E. I. *Fuzzy Cognitive Maps for Applied Sciences and Engineering: from Fundamentals to Extensions and Learning Algorithms.* Heidelberg: Springer, 2013.

STACH, W.; KURGAN, L.; PEDRYCZ, W.; REFORMAT, M. *Evolutionary Development of Fuzzy Cognitive Maps.* In: IEEE INTERNATIONAL CONFERENCE ON FUZZY SYSTEMS, 14., 2005, Reno. Proceedings […]. Reno, NV: IEEE, 2005. p. 619–624.

YESIL, E.; KUMBASAR, T.; KARASAKAL, O. *Self-tuning interval type-2 fuzzy PID controllers based on online rule weighting.* In: IEEE INTERNATIONAL CONFERENCE ON FUZZY SYSTEMS (FUZZ-IEEE), 2013, Hyderabad. Proceedings […]. Hyderabad: IEEE, 2013. p. 1–6.

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