DIFERENTES TOPOLOGIAS DE MAPAS COGNITIVOS FUZZY DINÂMICOS APLICADOS EM PROCESSOS INDUSTRIAIS E SISTEMAS ROBÓTICA COLETIVA

Data de aceite: 01/03/2023

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

Jhonatas Luthierry Barbosa dos Santos
Graduando em Engenharia Elétrica pela UTFPR-CP
Universidade Tecnológica Federal do Paraná
Cornélio Procópio, PR
http://lattes.cnpq.br/3040974349883206

Henrique Cavalieri Agonilha
Universidade Filadélfia (Unifil) Londrina
Graduação em Engenharia de Software
Londrina – PR
http://lattes.cnpq.br/9845468923141329

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

João Maurício Hypólito
Fatec – Centro Paula Souza
Ciência da Computação
Ourinhos – SP
http://lattes.cnpq.br/5499911577564060

Andressa Haiduk
Dimension Engenharia
Ponta Grossa - Pr
http://lattes.cnpq.br/2786786167224165

Fabio Rodrigo Milanez
Faculdades da Indústria - Senai Londrina
Departamento Engenharia Elétrica
Londrina-PR
http://lattes.cnpq.br/3808981195212391

Emerson Ravazzi Pires da Silva
Universidade Tecnológica Federal do Paraná
Departamento de Engenharia Elétrica Daele
Cornélio Procópio – PR
http://lattes.cnpq.br/0797649979829091

Luiz Francisco Sanches Buzachero
Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio – PR
http://lattes.cnpq.br/1747856636744006

Michelle Eliza Casagrande Rocha
Universidade Pitágoras Unopar Anhanguera
Engenheira Projetista
Londrina-PR
http://lattes.cnpq.br/4411484670091641

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

José Augusto Fabri
Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Computação (DACOM)
Cornélio Procópio – PR
http://lattes.cnpq.br/1834856723867705

Níkolas Catib Boranelli
Acadêmico - Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio – PR
http://lattes.cnpq.br/4632175422834777

Augusto Alberto Foggiato
Health Science Center - Dentistry, Paraná Northern State University – UENP, Jacarezinho, PR, Brazil.
São Leopoldo Mandic Dental Research Institute, Campinas, SP, Brazil.
http://lattes.cnpq.br/5947790201939557

Francisco de Assis Scannavino Junior
Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio – PR

Rodrigo Rodrigues Sumar
Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio – PR

André Luis Shiguemoto
Universidade Tecnológica Federal do Paraná
Departamento Acadêmico de Engenharia Elétrica (DAELE)
Cornélio Procópio – PR

Wesley Candido da Silva
Faculdade da Indústria SENAI Londrina
Departamento Acadêmico de Engenharia Elétrica- Londrina -PR

Vicente de Lima Gongora
Faculdade da Indústria SENAI Londrina
Departamento Acadêmico de Engenharia Elétrica- Londrina -PR

RESUMO: Neste trabalho, os autores apresentam diferentes configurações de Mapas Cognitivos Fuzzy (FCM) aplicados em diversos processos industriais e em um sistema multirrobôs. O primeiro processo analisado corresponde a um tanque fermentador alcoólico de quarta ordem (substrato, biomassa, produto e volume da mistura fermentada). As técnicas de controle empregadas (Controlador Lógico Fuzzy – FLC; Controlador FCM) tem seus resultados comparados. O segundo processo analisado é de um misturador (mixer) industrial. Nele, dois líquidos são inseridos no mixer, que verifica o produto através da massa específica do líquido resultante da mistura. Neste caso, um Mapa Cognitivo Fuzzy Dinâmico (DFCM) é utilizado para o controle das válvulas que controlam os fluxos de fluido no sistema. Neste processo, o DFCM tem atualização dos valores das relações causais através do algoritmo de aprendizagem de Hebb. Por fim, um DFCM é utilizado para controlar um sistema com quatro robôs autônomos auxiliados por feromônios artificiais repulsivos. Para atualizar os valores dos relacionamentos deste DFCM, é utilizada uma sequência de eventos descritos pelas condições do ambiente sensoriadas pelos robôs. Em todos os processos apresentados neste trabalho, a utilização de FCMs e suas variações se mostrou satisfatória tanto nos termos de complexidade computacional (de implementação mais trivial) quanto nos resultados, equivalentes (ou até superiores) aos de técnicas clássicas, como a Lógica Fuzzy.

PALAVRAS-CHAVE: Lógica Fuzzy. Mapas Cognitivos Fuzzy Dinâmicos. Fermentador alcoólico. Mixer Industrial. Sistema Multirrobôs.

DIFFERENT TOPOLOGIES OF DYNAMIC FUZZY COGNITIVE MAPS APPLIED IN INDUSTRIAL PROCESSES AND COLLECTIVE ROBOTICS SYSTEMS

ABSTRACT: In this work, the authors present different configurations of Fuzzy Cognitive Maps (FCM) applied in several industrial processes and in a multi-robot system. The first process analyzed corresponds to a fourth-order alcoholic fermenting tank (substrate, biomass, product, and volume of the fermented mixture). The control techniques used (Fuzzy Logic Controller – FLC; FCM Controller) have their results compared. The second process analyzed is an industrial mixer. In it, two liquids are inserted into the mixer, which checks the product through the specific mass of the liquid resulting from the mixture. In this case, a Dynamic Fuzzy Cognitive Map (DFCM) is used to control the valves that control fluid flows in the system. In this process, the DFCM updates the values of the causal relationships through the Hebb learning algorithm. Finally, a DFCM is used to control a system with four autonomous robots aided by repulsive artificial pheromones. To update the values of the relationships of this DFCM, a sequence of events described by the ambient conditions sensed by the robots is used. In all the processes presented in this work, the use of FCMs and their variations proved to be satisfactory both in terms of computational complexity (the most trivial implementation) and in the results, equivalent (or even superior) to those of classical techniques, such as Fuzzy Logic.

KEYWORDS: Fuzzy Logic. Dynamic-Fuzzy Cognitive Maps. Alcoholic fermenter. Industrial Mixer. Multi-robot System.

1 I 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; 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. In other words, Fuzzy cognitive maps (FCMs) are a very convenient, simple, and powerful tool for simulation and analysis of dynamics systems (MENDONÇA et al., 2020a; PEDRYCZ; GOMIDE, 2007a; STACH et al., 2005).

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).

In this sense, 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; YURKOVICH, 1998), such as the heuristic process used in this work.

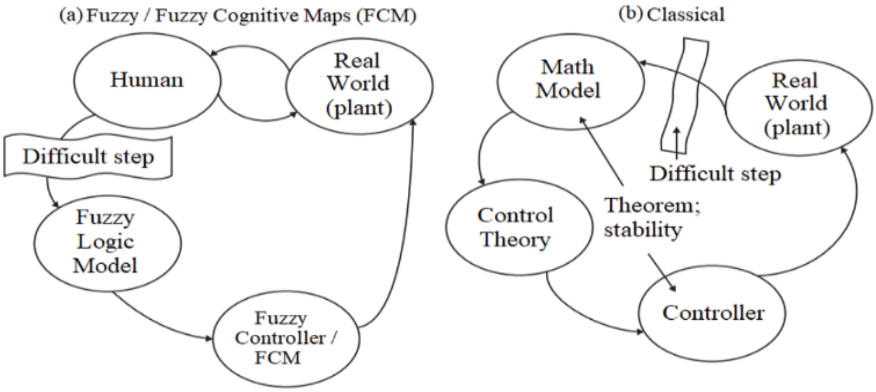

Figure 01 – (a) Fuzzy/FCM and (b) classical paradigm

Source: Adapted from (ROSS, 2010).

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 (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 classical methods, such as Fuzzy Logic. The authors present three examples of processes in this work. Intelligent control methods were used to control a fourth-order alcoholic fermenting tank (substrate, biomass, product and volume of the fermented mixture), an industrial mixer, in which two liquids are inserted into the mixer, checking the product through the specific mass of the liquid resulting from the mixture, and a system with four autonomous robots aided by repulsive artificial pheromones is controlled using a combination of DFCM and Ant Colony Optimization (ACO).

2 I BACKGROUND AND PROCESS DESCRIPTION

The first example of an FCM controller is a fermenter process. One aspect to be analyzed is the 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. 2 shows a real alcoholic fermenter (a) and the simulated one used in this work (b). In Fig. 2 (b), the *Fin* valve is responsible for the substrate flow in the tank, and *Fout* 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.

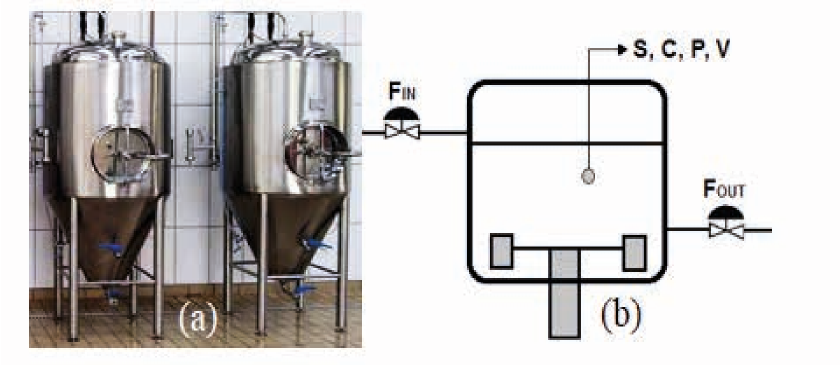

Figure 02 – (a) Real and (b) simulated alcoholic fermenters

Source: Adapted from (MENDONÇA et al., 2013).

The variables are the same as found in Mendonça et al. (2013).

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

$$\frac{dC}{dt} = \mu_c - \frac{F_{out}}{V}S \tag{2}$$

$$\frac{dP}{dt} = \frac{Y_{P/S}}{Y_{C/S}}\mu_c - \frac{F_{out}}{V}P \tag{3}$$

$$\frac{dV}{dt} = F_{in} - F_{out} \tag{4}$$

$$\mu_c = \mu_0 \frac{S}{K_s+Sa}\left(1 - \frac{P}{P_m}\right) \tag{5}$$

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, 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*.

The logic applied in the process was the Fuzzy, which was created by 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 μ_A:X→[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 (PEDRYCZ; GOMIDE, 2007b).

A Fuzzy Cognitive Map (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). FCMs introduced fuzziness to traditional Cognitive Maps (AXELROD, 1976), by using numeric descriptions (fuzzy binaries) of causal influences instead of positive or negative symbols.

In an 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 equation (6).

$$A_i^{(k+1)} = f\left(A_i^{(k)} + \sum_{\substack{j=1 \\ j \neq i}}^{N} A_j^{(k)} \cdot w_{ji}\right) \tag{6}$$

In (7), $f(.)$ is a sigmoid threshold function to squash the values within the range [0 1], as shown in equation (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.

$$f(x) = {}^{1}\!/_{(1 + e^{-\lambda x})} \tag{7}$$

In the first example, an alcoholic fermenter, the FCM controller was created at first, considering errors in the same way as seen in a PID controller: error (*Error*) and the differential error (*Errordiff*) for each iteration. Due to the low complexity of this system, it was unnecessary to use the integral error. System simulations were run in Matlab® 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. The authors designed an adaptive PID controller with FCM and Fuzzy adjustment mechanisms. The values of maximum tank volume (*V*) of 4.75 l and a minimum volume of 1 l. Accordingly, if the former case occurs, the Fin valve is completely closed, and if the latter case occurs, the valve *Fout* is closed.

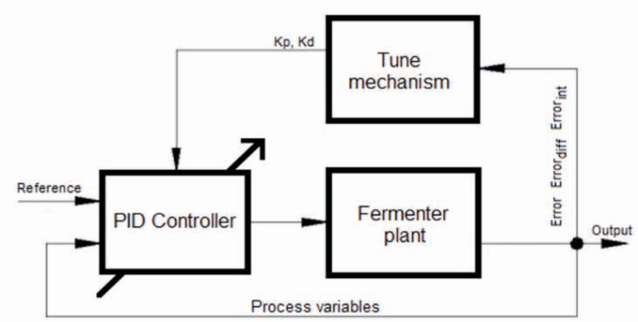

Figure 03 – Auto tune architecture

Source: Own authorship.

The architecture shown in Fig. 3 was used as a tuning mechanism for the both FCM-PID and Fuzzy-PID controllers presented. The variables *Error*, *Errorint*, and *Errordiff* 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 (*Kp*) and derivative (*Kd*) PID gains, adapting their values at each iteration. The initial parameters of the PID controller are *Kp*=2, *Kd*=4.95 and *Ki*=0.35, defined heuristically. The developed FCM is shown in Fig. 4, where concepts 4 and 5 correspond to the *Kp* and *Kd* gain multipliers to be applied in the PID. 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.

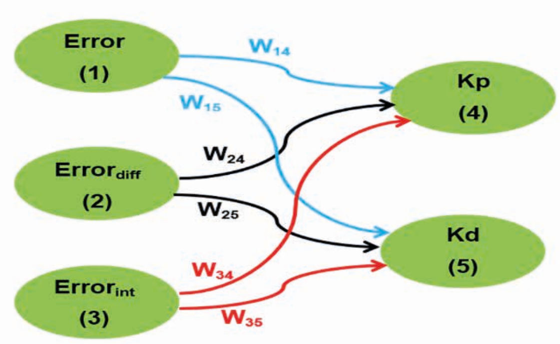

Figure 04 – FCM used in alcoholic fermenter process

Source: Own authorship.

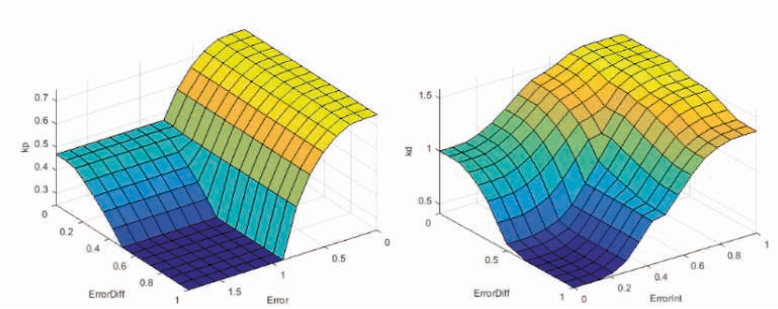

Figure 05 – Fuzzy surfaces – fermenter process

Source: Own authorship.

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 with 3 inputs (*Error*, *Errordiff* and *Errorint*), 2 outputs (*Kp* and *Kd* 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 Fuzzy surfaces obtained are shown in Fig. 5. The inputs range from 0 to 1, the *Kp* output range is [0 1.5] and *Kd* is [0 2], both adjusted heuristically.

Another proposal for control via FCM is an industrial mixer control that, due to the low complexity of FCM mathematics for its inference, allowed the controller to be embedded in a low-cost controller, such as Arduino and PIC. Figure 6 show the process, and the Adaptive FCM has the same structure seen in Fig. 4. However, has its weights adjusted dynamically with the Hebbian rule.

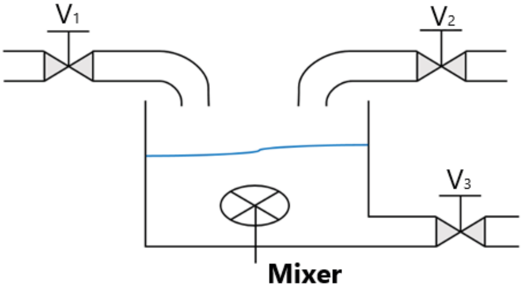

Figure 06 – Industrial mixer process

Source: Own authorship.

The similarity with the fermenter controller is highlighted by the authors. However, this controller has its weights adjusted offline by a genetic algorithm with selective population and online by Hebbian rule that tunes the weights according to the process error. This dynamic tuning can classify this controller as adaptive (POZO et al., 2011). In Fig. 7 it is possible to observe that we have three valves, two inlets (*V1* and *V2*) for the inlet of two different liquids, such as water and milk in a food process and one for outflow (*V3*). Two variables must be controlled by range, the weight and volume of the mixture; what makes it a Multiple Input, Multiple Output (MIMO) process. Figure 8 shows an example of a campaign with disturbances.

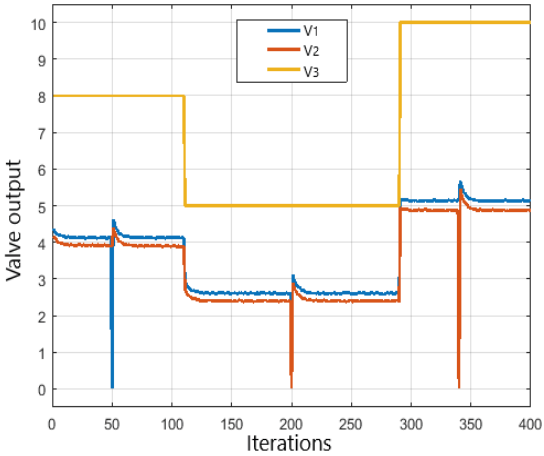

Figure 07 – Example of campaign with disturbances

Source: Own authorship.

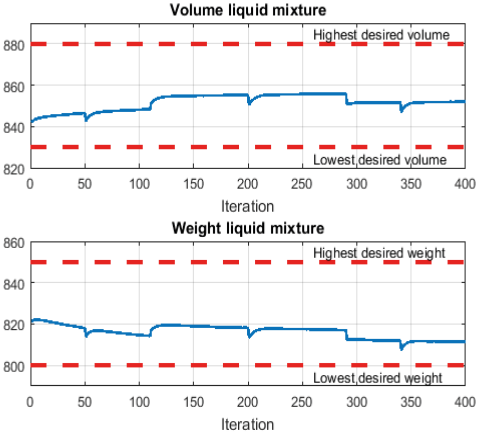

Figure 08 – Results – DFCM controller

Source: Own authorship.

3 I RESULTS AND DISCUSSION

In this section, we discuss the results of multi robot inspired in swarm robotics system to rescue victims. Inspired by the organization of social insects, such as ants, bees and termites, and the formation of schools of fish and birds in flight, swarm robotics is a field of study that seeks the best computational paths for robots to exchange information and act together, according to a common objective for which they were programmed. They are computational solutions that are in the field of study of several groups of researchers in the world.

Based on the concepts of repulsive artificial pheromones, this work presents an optimization of the robots' trajectory, thus increasing the search area without increasing the distance traveled. In other words, when a robot detects high concentrations of pheromones – whether they are left by the other robots or itself – it will deflect its course so as not to become trapped in relatively more difficult navigational zones such as narrow corridors. Swarm robotics has the prospect of use both in closed and open places, such as at sea, in the inspection and repair of underwater platforms, in maritime surveillance and in the air, with drones equipped with systems to monitor borders, for example (MCLURKIN, 2019).

This type of technology is getting cheaper and cheaper, but it is still not enough and there is a need for much research and development for the swarms of robots to be commercialized in the not-too-distant future, according to electrical engineer Marco Terra, coordinator of the Institute National Science and Technology (INCT) for Cooperative Autonomous Systems (InSAC), located at School of Engineering of São Carlos in University of São Paulo (EESC-USP). This category of robots to become popular, depends fundamentally on the cheapness of sensors and other components (NEDJAH; SILVA JUNIOR, 2019).

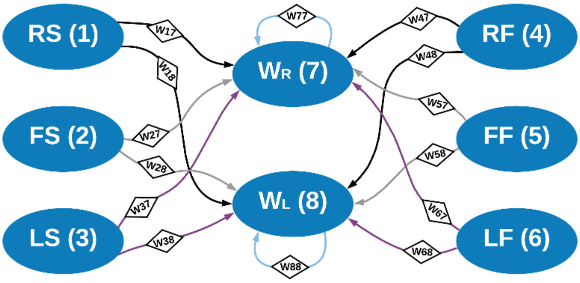

Figure 09 – DFCM-ACO controller applied in each robot

Source: Own authorship.

A summary of the authors' research is presented as follows. It initiated in 2016 in the field of autonomous mobile robotics by Mendonça et al. (2016), which implemented two navigation systems using Hybrid Dynamic Fuzzy Cognitive Maps (HD-FCM) and hierarchical Fuzzy logic controllers (FLC) in a single robot system. Nowadays, the research focusses on applying concepts of Ant Colony Optimization (ACO) for the evolution of the robot's trajectory. The first approach used one robot leaving pheromones along the way to the next ones (MENDONÇA et al., 2017).

The present work application uses a DFCM-ACO as a 4-robot system controller, as seen in Fig. 9. It can be classified as a multi-robot system with some characteristics of swarm robotics, such as the scalability. In other words, the system works in the same way with a larger number of robots (8, 16, 32 and so on). However, strictly to consider a Swarm Robotics technician it would be necessary to apply hundreds or even thousands of robots (GAZI; PASSINO, 2011).

The use of ACO reduces possible lost turns of some robots, i.e., in some situations hypothetically the robot number 1 would pass in a certain area and robot number 3 would consecutively pass again. With the use of the computational swarm intelligence technique (BONABEAU; DORIGO; THERAULAZ, 1999), an artificial pheromone is left by the previous robot and, due to this marking, the other robots that are searching for victims will not repeat the search in this place. Figure 10 shows the four robots starting, after 21 iterations, the search for victims in a virtual scenario. This type of technique could have been very useful in catastrophes such as building collapses.

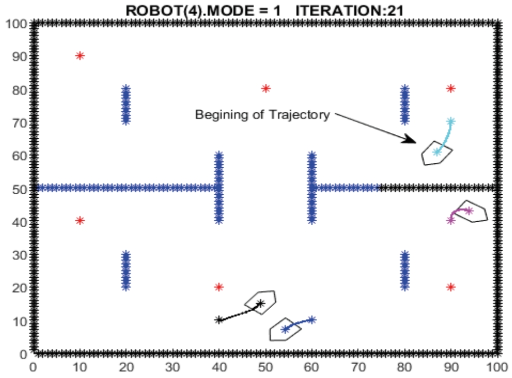

Figure 10 – Beginning of robots searches for scenario

Source: Own authorship.

It is observed in Fig. 10 that these robots are autonomous and only were not shown the successes in at least three scenarios to characterize autonomy (not the scope of this work). The objective was to show various applications of DFCM and, consequently, the versatility of application. However, in the articles cited in the development of the research, more than one scenario was presented and even comparisons with Fuzzy Mamdani were made. It should be noted that an article was submitted to WCCI 2020 with a comparison between Fuzzy Mamdani, DFCM and DFCM-ACO (MENDONÇA et al., 2020b).

Multi-robot strategy could be adapted for military application, for example, searching for mines or enemies. Or even applications in the industry in the search for parts, considering that autonomous robotics is one of the pillars of Industry 4.0 (MARIANI; BORGHI, 2019).

Figure 11 shows the end of the simulations, with all victims rescued.

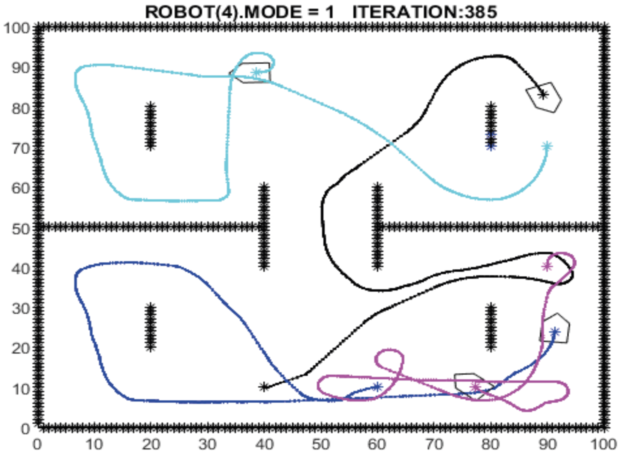

Figure 11 – End of robots searches with victims meeting

Source: Own authorship.

After 385 interactions, the mission was completed (Fig. 11). Figure 12 shows the areas searched by the robot group, which practically the entire search area was searched. The criterion for stopping the algorithm was when all the victims were found. Figure 13 shows a graph of the control pulses sent to the wheels of the robot # 1 and Fig. 14 shows a graph of the control pulses sent to wheels of robot # 3, according to the cinematic model used and similar to the presented by Soares et al. (2018).

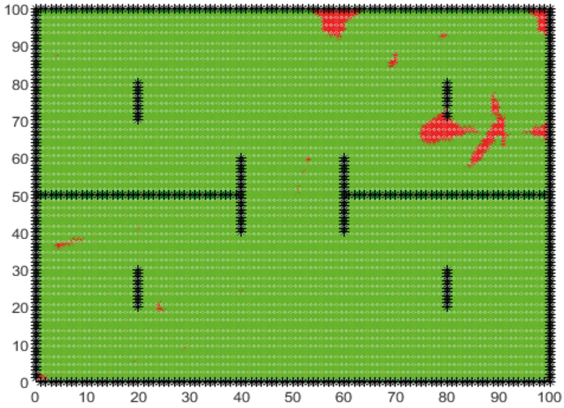

Figure 12 – Area searched by robots

Source: Own authorship.

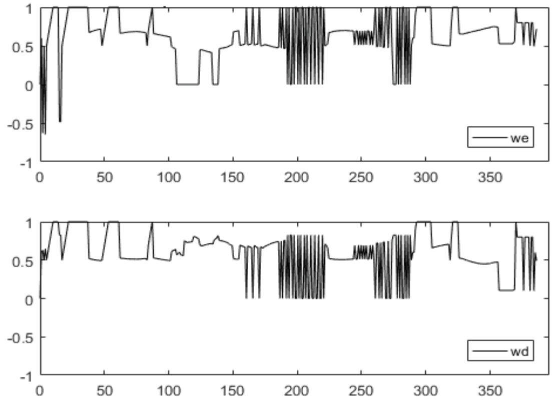

Figure 13 – DFCM-ACO control action pulses – robot #1

Source: Own authorship.

The inclusion of the DFCM-ACO algorithm, made the system with adaptive characteristics to the explore the environment due to the reduced number of lost maneuvers. For future work of this application, it could be tested a strategy of having a lead robot guided and the other autonomous follow the same.

Another experiment was done, aimed at testing the robustness of the system, to investigate whether the other robots would be able to accomplish the task if one of robots stopped. Figure 15 shows that at the beginning of the experiment, one of the robots stuck and stopped (green robot). Figure 16 shows that, even with this adverse condition, the group fulfilled the task of rescuing all victims.

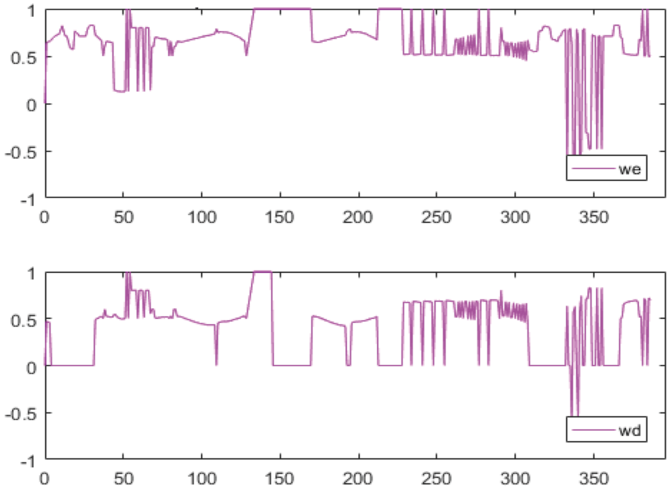

Figure 14 – DFCM-ACO control action pulses – robot #3

Source: Own authorship.

However, they used eight robots in two different scenarios to rescue victims (MENDONÇA et al., 2020b) and a comparison of a computational complexity metric was presented comparing Mamdani-type FLC, DFCM and DFCM-ACO. It is observed that the DFCM and the DFCM-ACO had similar complexity.

4 I CONCLUSIONS

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. In the control of the mixer, the results were satisfactory since the variables stayed within the desired ranges even with disturbances in the process.

Finally, the robot control with a DFCM-ACO controller showed that the system was able to explore almost the entire environment by approximately 95% and the results were significant. Time was not used as a parameter, but the number of iterations, because the experiments were simulated, and the computational base had a direct influence on it. However, despite showing only one scenario, the objective was achieved. It was possible to show the robustness of the system that managed to rescue the victims even with the stop of 1 of the 4 robots and, obviously, with a much larger number of iterations (655).

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.

REFERENCES

ÅSTRÖM, K. J.; WITTENMARK, B. **Adaptive Control**. 2. ed. USA: Dover Publications, 2008.

AXELROD, R. **Structure of decisions: the cognitive maps of political elites**. 1. ed. Princeton, NJ, USA: Princeton University Press, 1976.

BONABEAU, E.; DORIGO, M.; THERAULAZ, G. **Swarm Intelligence: From Natural to Artificial Systems**. 1. ed. New York, USA: Oxford University Press, 1999.

GAZI, V.; PASSINO, K. M. **Swarm stability and optimization**. 1. ed. Heidelberg: Springer Berlin Heidelberg, 2011.

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

LIMA, F.; SERRA, G. **Fuzzy PID controller multiobjective genetic design2015 IEEE 10th Conference on Industrial Electronics and Applications (ICIEA)**, 2015.

MAHER, M. **Modélisation et élaboration d'algorithmes d'estimation et de commande : application à un bioprocédé**. [s.l: s.n.].

MARIANI, M.; BORGHI, M. Industry 4.0: A bibliometric review of its managerial intellectual structure and potential evolution in the service industries. **Technological Forecasting and Social Change**, v. 149, n. December 2019, p. 1–24, 2019.

MCLURKIN, J. **Multi-Robot Systems Engineering**. Disponível em: <https://people.csail.mit.edu/jamesm/images/swarm/images/theswarm.jpg>. Acesso em: 2 out. 2019.

MENDONÇA, M. et al. A dynamic fuzzy cognitive map applied to chemical process supervision. **Engineering Applications of Artificial Intelligence**, v. 26, n. 4, p. 1199–1210, 2013.

MENDONÇA, M. et al. **Hybrid Dynamic Fuzzy Cognitive Maps and Hierarchical Fuzzy Logic controllers for Autonomous Mobile Navigation**. 2016 IEEE International Conference on Fuzzy Systems, FUZZ-IEEE 2016. **Anais**...Vancouver, BC, Canada: IEEE, 2016

MENDONÇA, M. et al. A cooperative architecture for swarm robotic based on dynamic fuzzy cognitive maps. **Engineering Applications of Artificial Intelligence**, v. 59, n. March, p. 122–132, 2017.

MENDONÇA, M. et al. **Multi-robot exploration using Dynamic Fuzzy Cognitive Maps and Ant Colony Optimization**. IEEE International Conference on Fuzzy Systems. **Anais**...Glasgow, UK: IEEE, 2020a

MENDONÇA, M. et al. **Multi-robot exploration using Dynamic Fuzzy Cognitive Maps and Ant Colony Optimization**. 2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE). **Anais**... Glasgow, United Kingdom: IEEE, 2020b

NEDJAH, N.; SILVA JUNIOR, L. Review of methodologies and tasks in swarm robotics towards standardization. **Swarm and Evolutionary Computation**, v. 50, n. October 2017, p. 1–26, 2019.

OGATA, K. **Modern Control Engineering**. [s.l: s.n.]. v. 17

PAPAGEORGIOU, E. I. (ED.). **Fuzzy Cognitive Maps for Applied Sciences and Engineering**. Heidelberg: Springer-Verlag Berlin Heidelberg, 2014.

PASSINO, K. M.; YURKOVICH, S. **Fuzzy Control**. 1. ed. Menlo Park, CA, USA: Addison Wesley, 1998.

PEDRYCZ, W.; GOMIDE, F. **Fuzzy Systems Engineering: Toward Human-Centric Computing**. 1. ed. Hoboken, New Jersey, USA: John Wiley & Sons, 2007a.

PEDRYCZ, W.; GOMIDE, F. **Fuzzy Systems Engineering Computing**. [s.l: s.n.].

POZO, A. et al. Computação Evolutiva. **Departamento de Informática, UFP**, p. 61, 2011.

ROSS, T. J. **Fuzzy logic with engineering applications**. 3. ed. New Mexico, USA: John Wiley & Sons, 2010.

SOARES, P. P. et al. **Group of Robots Inspired by Swarm Robotics Exploring Unknown Environments**. 2018 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE). **Anais**...Rio de Janeiro, Brazil: IEEE, 2018

STACH, W. et al. Genetic learning of fuzzy cognitive maps. **Fuzzy Sets and Systems**, v. 153, n. 3, p. 371–401, 2005.

ZADEH, L. A. Fuzzy Sets. **Information and control**, v. 353, p. 338–353, 1965.