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AUTOMATION LEARNING ENVIRONMENT BASED ON FUZZY SYSTEMS

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Abstract. *The way of handling information and transmitting knowledge has led to substantial changes in the training of the engineering professional. Technological advancement and the adoption of teaching practices aligned with technological resources have played an important role in this new scenario. Thus, this proposal aims to present a practical learning environment using a nebulous logic that simulates the industrial environment with low cost and easy adaptability to existing environments. With this, the model can be implemented in any institution of higher education. Another important feature is that the model can be applied at the levels of technical, undergraduate and graduate education in the area of control and automation. The proposed model was conceived after a research with professors and students of undergraduate courses in control engineering and automation and electrical engineering from three universities of Rio de Janeiro (UERJ, PUC and UFRJ). Field research was also carried out to identify the mechanisms and instruments needed to build the models of the learning environment suggested by the interviewees. As a computational interface, LABVIEW was used for the easy applicability of controls and also for supporting a practical-industrial environment. The plant was constituted of typical elements for the practice of control and automation, as sensors, actuators, and electric motor, besides a computational platform. The tests were performed in three learning environments: (1) thermal system; (2) engine speed control; And (3) inverted pendulum. In all three cases, a fuzzy controller was used to characterize the academic-industrial activity.*

Keywords: *Learning environment, Automation and control, Fuzzy Systems, Practical Models*

1. INTRODUCTION

Models are abstractions of reality, in which unnecessary information for the analysis in question is overlooked and relevant aspects are described. Models describe the structure and behavior of real systems and can be used instead of real plants for different purposes (Silveira and Santos, 2008) and (Silveira, 2007). According to Silveira (2007), construction of models optimizes time and reduces project costs.

In the universities, they are used to speed up and decrease the number of prototypes to be built and are used in conjunction with simulators to reduce costs and improve time off. In order to perform a simulation or experiment, it is necessary to construct a computational model that responds to the real situation that it wishes to simulate.

To construct the models, some interviews with professors and students of the electrical, electronic and automation engineering courses were carried out with great universities of Rio de Janeiro (UERJ, PUC-RJ and UFRJ). The interviews suggested the use of models to facilitate the understanding of the contents taught in the Control and Automation disciplines. For some experiments performed using traditional control processes it was suggested the insertion of techniques using fuzzy systems. This task is now quite easy to simulate because it resides in the software used in this research, MATLAB (Matworks, 2016) and LABVIEW (NI, 2016).

The general model developed was classified into three stages of learning: (1) basic: which comprises the basic and general assembly of the system; (2) intermediate: which is an assembly directed to PID systems; and (3) Advanced: with an approach using fuzzy systems to: (1) thermal system; (2) speed control system of motors; and (3) a system to simulate an inverted pendulum. In this paper will be shown de advanced model – but applying fuzzy systems only to (1) and (2). The model to simulate an inverted pendulum will be presented in other work.

2. EXPERIMENTAL MODEL: ENVIRONMENT AND OPERATION PLANTS

The plant and the model originated three stages of learning: (1) basic level: it comprises the basic assembly on-off; (2) intermediate level: corresponds to an assembly focused on PID systems; And (3) advanced level: which makes an approach using fuzzy systems. In this paper we will present only the advanced model based on fuzzy logic. Therefore, in order to consult the other developed models, it is suggested the reading of (Medeiros Jr, 2011, Medeiros Jr *et al.*, 2016a, and Medeiros Jr *et al.*, 2016b).

The objective is to contribute to the teaching methods and procedures through a more realistic approach and with more possibilities to apply experiments in learning environment of control and automation. To achieve this goal, a computer interface developed with LABVIEW and Matlab was also constructed for the three experimental models

In order to implement the experimental models, a plant composed of a set of electro-electronic (Chassis) and computational components (hardware and software) was developed, as shown in figure 1 (a) and (b).

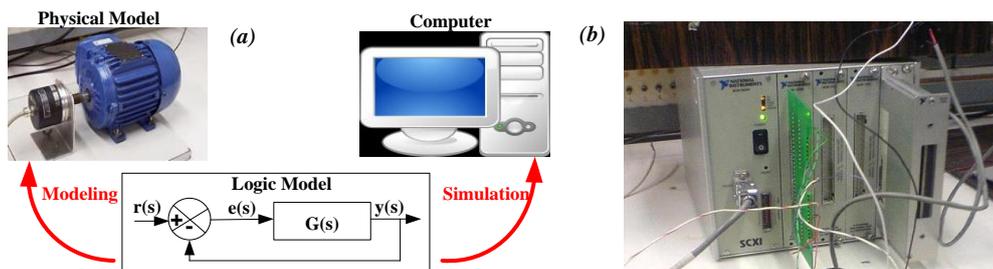


Figure 1. (a) Plant (model, simulation and experiment) (b) SCXI-1200 Module

The element responsible for interconnecting the input and output signals is the SCXI-2000 Chassis. The SCXI-2000 Chassis also contains the communication port with a computer to run LABVIEW and a SCXI-1200 module. The SCXI-1200 module features an analogical and digital (I/O) port spell that allows processing and control of the signals originated in the application.

2.1 The Thermal System Model

The thermal system is composed consists of two actuators: (1) the cooler; and (2) the other the heater, and an NTC (Negative Temperature Coefficient) sensor to monitor temperature variation and allow controller action. The NTC and the resistor are connected in series in order to construct a voltage divider. Thus the voltage of the resistor is directly proportional to the temperature variation of the NTC. The actuators can be connected to relays or to voltage regulators PWM (Pulse-Width Modulation) and control by TRIAC (Triode for Alternating Current), depending on the level of learning applied in the control.

The thermal system controller uses a set-point to maintain the temperature. A sensor reads the incoming analog signal and transmits it to a heater / cooler. The system is represented by the block diagram in figure 2.

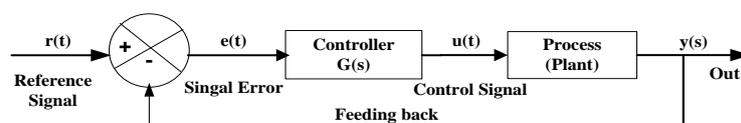


Figure 2. Thermal system model

The first order experimental model was built in the Electrical Engineering Laboratory (LEE), following the orientation of (Klerk, 2004), and it was quite didactic. The main components of this model are shown in figure 3.

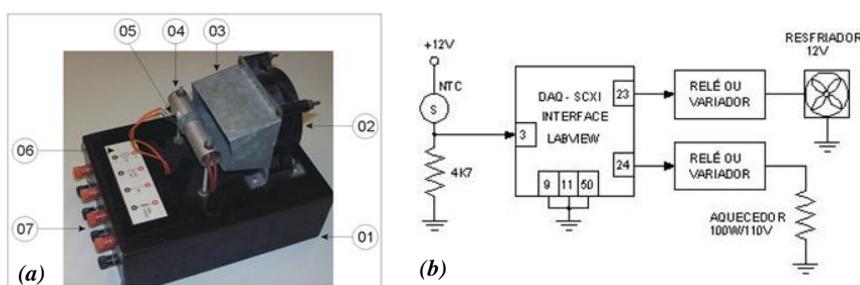


Figure 3(a). Model of the thermal system and (b) Connections Schema

Where: (1) Wooden support box (145x65x200mm - L x W x D); (2) Cooling fan type 12V DC; (3) AR concentrator (Galvanized sheet steel); (4) Heating resistance 100W (soldering iron); (5) Temperature Sensor (NTC 4K7); (6) Nameplate; and (7) Connectors.

The curve of system can be obtained by $(\theta \times Vr)$, where θ is the measured temperature in $^{\circ}C$ and Vr is the voltage in the resistor in volts, in a form suitable to be treated by the Fuzzy System. The curve obtained in this problem is equation (5) and the values of (θ) and (Vr) are shown in the Table 1.

$$\theta(Vr) = (12.7.Vr-65.3) \text{ } ^{\circ}C \quad (5)$$

Table 1. Voltage x Temperature

θ	29	32	41	48	57	72	82	88	97
Vr	6,6	6,9	8,0	8,7	9,6	10,3	10,8	11,1	11,2

2.2 Mathematical Model Of Thermal System (Plant and Controller)

The linear system of stable first order with delay, where we have as the transfer function of the plant (equation 1) and the functional description of the controller (equation 2).

$$\text{Plant} = \frac{K}{\tau s + 1} \quad (1)$$

$$\text{Controller} = f(e^{(ts)}) \quad (2)$$

From the equations (1) and (2) the following transfer function (3) can be modeled.

$$G(s) = \frac{Ke^{-T s}}{\tau s + 1} \quad (3)$$

Where: K is the system gain, T is the delay and τ is the system time constant.

Let $u(t)$ and $y(t)$ be the input and output signals of the system with the transfer function described in equation 2. Exciting the system with a degree of amplitude A , can be shown that the following output of the system:

$$y(t) = \begin{cases} K A \left[1 - e^{-\frac{1}{\tau}(t-T)} \right], & t \geq T \\ 0, & t < T \end{cases} \quad (4)$$

The parameters K , T and τ can then be identified by the equation above and represented graphically by Figure 4.

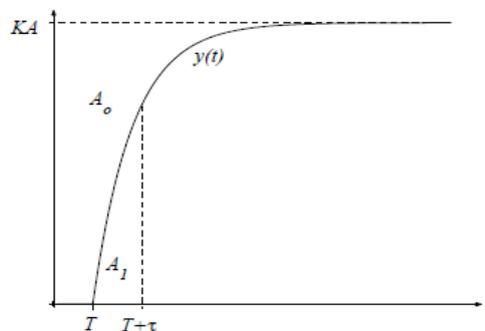


Figure 4. Methods of the areas to identify the parameters K , T and τ .

2.3 The Control Speed System Model

There are numerous industrial processes that use Three-phase Induction Motors (MIT) as mechanical drive and as a drive that can have its speed controlled and adjusted at a lower cost, that require little maintenance and also

constructively simpler and more robust. Electronic control systems are reliable alternatives and will soon replace conventional models. This justifies the insertion of the plant and the fuzzy model to control speed of motors in a teaching environment.

The experimental model designed for the speed control system corresponds to a model is first order with the following items: (1) a motor; And (2) an encoder (a speed sensor). Figure 5 shows the block diagram of the proposed model.

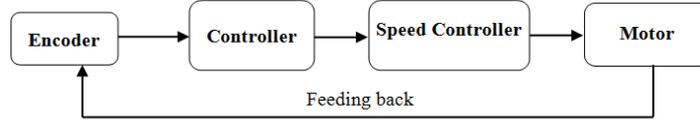


Figure 5. Block diagram of speed system control

Figure 6 shown the physical and logical model of the of speed systems control (plant), with an electrical motor (a) and a connection diagram.

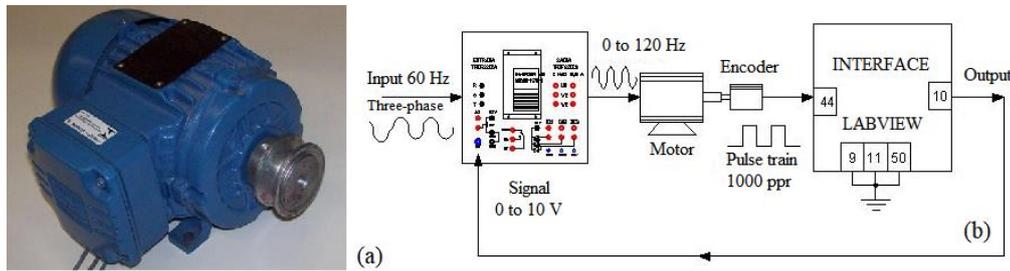


Figure 6 (a). Electrical motor and (b) Connection diagram

2.4 Mathematical Model Of Speed System Control

The dynamic mathematical model of the induction motor (Neto *at al.*, 1997) is shown in the voltage equations, in volts, of the rotor and stator:

$$V_i = R_i I_i + \frac{d\lambda_i}{dt} \quad (6)$$

Where: the index "i" represents the phases *a, b, c* of the stator and *A, B, C* of the rotor. The term λ represents the concatenated total flow (dispersion flow plus mutual flow). The matrices *R* and *I* are of stator and rotor resistance and current.

The electromagnetic torque (*T_e*) can be obtained by varying the magnetic co-energy *W* in relation to θ_{mec} (rad/sec) which is the mechanical angular displacement of the rotor with respect to a fixed reference (Neto et al., 1997), that is obtained by equation (7):

$$T_e = \left. \frac{\partial W'}{\partial \theta_{mec}} \right|_{i_{const}} \quad (7)$$

The oscillation equation (8) relating (*T_e*) to the charge torque (*T_c*), moment of inertia *J* (Kg.m²), angular position θ_{mec} (rad/sec) and coefficient of viscous friction *B*, can be written as:

$$T_e = T_c + J \frac{d\omega_{mec}}{dt} + B\omega_{mec} \quad \text{where: } \omega_{mec} = \frac{d\theta_{mec}}{dt} \quad (8)$$

The speed variation in the induction motors has a relation between the rotation, the feed frequency, the number of poles and the slippage of an induction motor, according to equation (9):

$$n = \left[\frac{120 f}{p} \right] \cdot (1 - S) \quad (9)$$

Where: *n* is speed in rpm, *f* the frequency in Hz, *p* the numbers of poles and *S* the slip.

Equation 9 indicates that it is possible to operate with three parameters to vary the speed:

1. Number of poles (p) - discrete variation (2, 4, 6, etc.) and causes an increase in the volume of the motor housing.
2. Slip (s) - variation is continuous; causes rotor losses and has a small variation range (this method can only be applied on motors with coiled rotors).
3. Frequency of the supply voltage (f) - continuous variation.

Currently the most efficient method to control the speed of the induction motors is the frequency control. this is done using frequency converters.

The speed of the motor is controlled by the frequency converter. This in turn is controlled by the LABVIEW Interface, which emits a control signal from 0 to 10 Volts.

To close the mesh we use a speed transducer, called encoder coupled directly to the motor shaft. This causes a pulse train to be produced which varies the intensity in proportion to the speed variation of the motor.

3. ENVINMONET LEARNING

In this section will be presented the learning environment for the two models proposed. The interface of the two environments was developed in LABVIEW.

3.1 Inference Rules

A fuzzy logic controller is composed of a set of inference rules to simulate decision processes (human actions) and translate them into fuzzy concepts (inference fuzzy rules).

The inference rules can be constructed on several models of fuzzy systems, such as the *Mamdani* model and the *Takagi-Sugeno* model (Mathworks, 2006). These two models were incorporated into the project because they are part of MATLAB. The rules constructed with the *Mamdani* model use fuzzy sets in antecedents and consequents (Teixeira and Assunção, 2007).

The rules constructed with the *Mamdani* model use fuzzy sets in the antecedents and the consequent e (Teixeira and Assunção, 2007). The expression (1) exemplifies the construction of the rules for the *Mamdani* model.

$$\text{If } x \text{ é } A \text{ and } y \text{ é } B \text{ then } z \text{ é } C \quad (1)$$

Where: A and B are fuzzy sets in the antecedent, C a fuzzy set in the consequent, x and y input linguistic variables and z an output linguistic variable.

The *Takagi-Sugeno* model consists of an inference system to accurately describe non-linear dynamic systems through a set of linear, locally valid dynamic systems, smoothly interpolated, non-linear and convex (Johansen *et al.*, 2000). Expression (2) exemplifies the construction of rules for this model.

$$\text{If } x_1 \text{ é } A_{1i} \text{ and } x_2 \text{ and } A_{2i} \text{ and } \dots \text{ and } x_n \text{ and } A_{ni}, \text{ then } y = f_i(x_1, x_2, \dots, x_n) \quad (2)$$

Where, $A_{1i}, A_{2i}, \dots, A_{ni}$ are fuzzy sets of antecedents while the consequent is a function of the input variables.

Was applied the same logic structure (fuzzy) for both environments, but with some small adaptations according to the specificity of each plant.

3.2 Input/Output of Thermal System

Due to the limitations of the Fuzzy Controller Module (FCM), the system output signal was configured with the signal varying from -5V to + 5V. Thus, we will have the positive voltage of the output for cooling and the negative voltage for heating.

The input / output variables¹ to define the linguistic terms of the “fuzzification” are given in Table 2.

Tabela 2. Input terms of thermal systems

Input Terms		
Variables	Temperature	Temperature Variation

¹ The acronyms of the terms Temperature and Temperature Variation represents the input and output in Portuguese of the inference machine (Fuzzy rules) for two cases (Thermal and speed systems).

Terms	Very Cold (MF) Cold (F) Bit Cold (PF) Lukewarm (M) Bit Hot (PQ) Hot (Q) Very Hot (MQ)	High Negative (NA) Medium Negative (NM) Low Negative (NB) Low Positive (PB) Medium Positive (PM) High Positive (PA) High Positive ⁺ (PA ⁺)
Values	Interval of temperature [0,60]	Interval of temperature variation [-8,8]
Propositions	Very cold temperature (MF) Cold temperature (F) Bit Cold temperature (PF) Lukewarm temperature (M) Bit hot temperature (PQ) Hot temperature (Q) Very hot temperature (MQ)	Temperature variation = (NA) Temperature variation = (NM) Temperature variation = (NB) Temperature variation = (PB) Temperature variation = (PM) Temperature variation = (PA) Temperature variation = (PA ⁺)
Output Terms		
Variables	Output	
Terms	High Heating (AA) Medium Heating (MA) Low Heating (BA) Zero (Z) Low Cooling (BR) Medium Cooling (MR) High Cooling (AR)	
Propositivos	Output = (AA) Output = (MA) Output = (BA) Output = (Z) Output = (BR) Output = (MR) Output = (AR)	

3.3 Fuzzification of Thermal System

The triangular and trapezoidal functions were used for the “fuzzification” process. Where we assemble the variables of temperature and temperature deviation, are called antecedents. The figure 7 and 8 shown the Fuzzy Set Editor to thermal system and set of variables to temperature and variation.

The most used “fuzzification” methods are: (1) center of mass; and (2) average of maxima. This work was used the method Center of Mass.

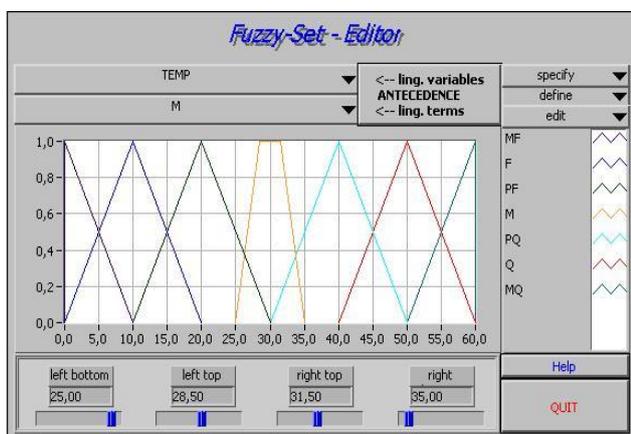


Figure 7. Linguistics variables of temperature

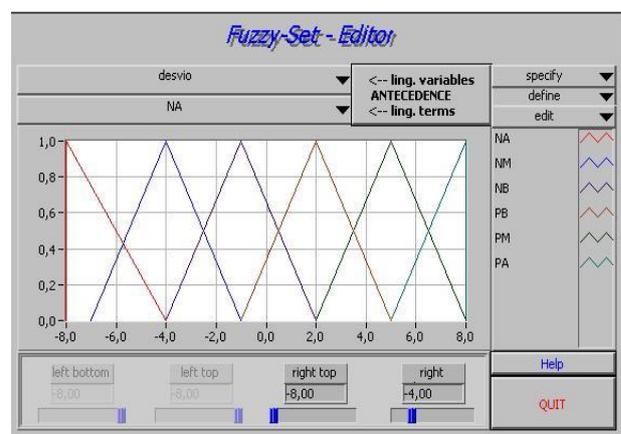


Figure 8. Linguistics variables of variation of temperature

Figure 9 presents the fuzzy inference rules adopted to control of the output of the thermal systems.

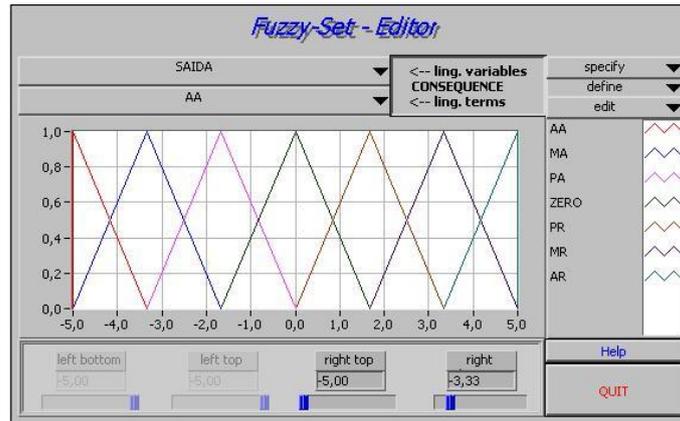


Figure 9. Output linguistic variables

The rules of inference did not meet all the quadrants because the thermal system is not able to meet all these quadrants, in this way it is unnecessary to activate all the rules. A total of seven quadrants were left without rules, as shown in table 3.

Table 3. Inference rules of thermal systems

Inference rules							
$\Delta T/T$	MF	F	PF	M	PQ	Q	MQ
NA	AA	AA	AA	MA	-	-	-
NM	AA	AA	MA	BA	-	PR	PR
NB	AA	MA	PA	Z	PR	MR	MA
PB	MA	MA	PA	Z	PR	MR	AR
PM	PA	PA	-	BR	MR	AR	AR
PA	-	PA	-	MR	MR	AR	AR

Figure 10 shows the system in operation on the block diagram screen, where the method center of mass was applied.

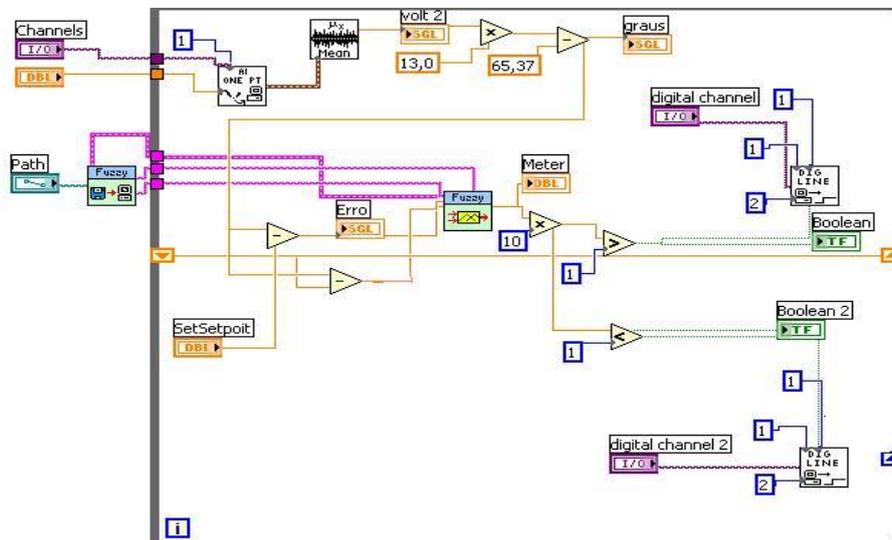


Figure 10. Block diagram and interconnections

We verified that the fuzzy control inserted in the experimental model worked within expectations. i.e., the inference engine worked correctly on the inputs of the thermal system, producing the expected outputs.

3.4 Fuzzification of Speed System

In this model we use as control the analogical signal 1 output of the frequency converter. This device has a frequency in the range (0 to 10Volts), Thus, to not exceed the maximum speed of motor, which is 1740 rpm, the application was restricted to interval 0 to 5 volts.

3.5 Input/Output of Speed System

The input and output variables used in the speed control system are shown respectively in Table 4.

Tabela 4. Linguistics input terms

Input Terms		
Variables	Error (e)	de/dt
Terms	Positive (VP) Normal (VM) Negative (VN)	High (TA) Normal (TM) Low (TB)
Input Values	Speed variation interval [-25,25]	Time variation interval [-3.5,3.5]
Input Terms		
Variables	Output	
Terms	Positive High (AP) Positive Medium (MP) Positive Low (BP) Zero (Z) Negative Low (BN) Negative Medium (MN) Negative High (AN)	
Output Values	Output range [0,5]	

For the “fuzzification” process of the speed control system, was used triangular and trapezoidal functions. In the fuzzy set editing interfaces of the LabVIEW, the input variables are called antecedents. Figures 11, 12 and 13 show the respective input and output variables for the speed control system.

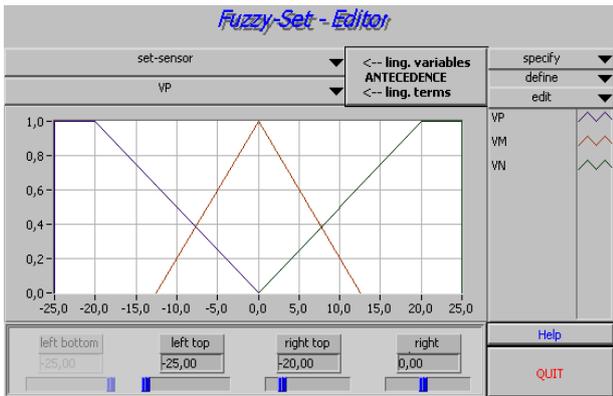


Figura 11 – Input linguistics variables - Triangular

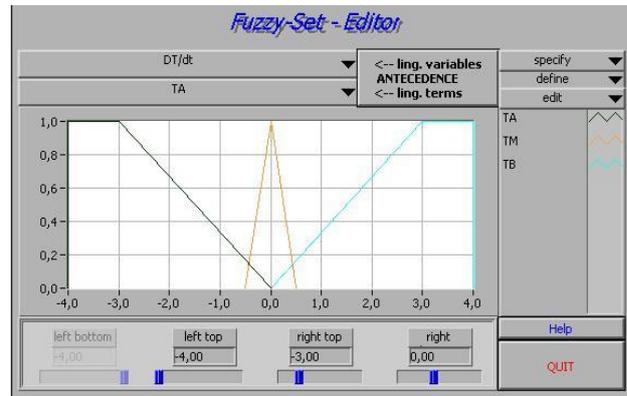


Figura 12 - Input linguistics variables - Trapezoidal

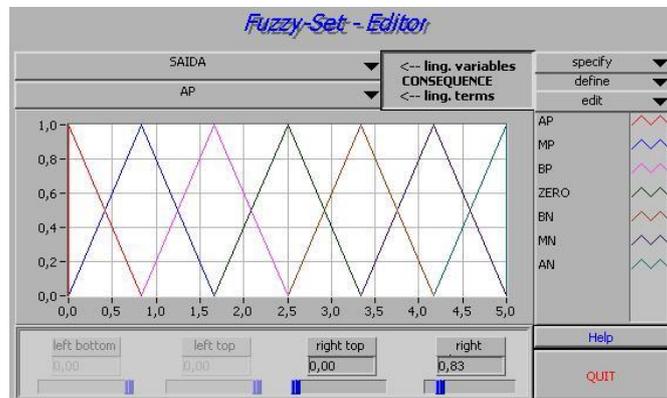


Figura 13. Output linguistics variables

Table 5 summarizes the inference rules used for the speed control system, where e is the error and de/dt are the variations of the time interval.

Table 5. Inference rules of speed systems

Inference rules			
$e/(de/dt)$	TB	TM	TA
VP	AP	BP	-
VM	MP	Z	MN
VN	-	BN	AN

For the “defuzzification” by the Mass Center method, the voltage level found for the output is 3.78V, so it has activated the speed controller to correct the rotation.

4. TESTE AND RESULTS

The plants of the two systems, as well as the operational platform, comprised of LABVIEW interfaces and the Inference machine, were tested to measure the functionality and performance of fuzzy controls.

With the goal of comparing the performance and stability of the implanted systems using fuzzy logic, a test scenario was modeled to the two systems with the following characteristics: (1) a test of system stabilization time from the disturbance in value; and (2) a comparative analysis with a PID system for temperature control and speed control.

Table 6 presents the results of comparative tests between the thermal system using Fuzzy logic with a traditional PIP system. In this test, the fuzzy system had a slight advantage over the PID system.

Table 6: Test applied to thermal systems (Fuzzy X PID)

Comprative Results – Thermal Systems (PID X Fuzzy)		
Controller	Disturbance	Accommodation Time
<i>PID</i>	<i>15°C</i>	<i>12 min</i>
<i>Fuzzy</i>	<i>15°C</i>	<i>10 min</i>

The second test applied to the speed control system presented the results with a subtle difference in relation to the test run for thermal system, as can be seen in Table 7.

Table 7: Test applied to speed systems (Fuzzy X PID)

Comprative Results – Speed Systems (PID X Fuzzy)		
Controller	Disturbance	Accommodation Time
<i>PID</i>	<i>100 rpm</i>	<i>1 min e 16 sec</i>
<i>Fuzzy</i>	<i>100 rpm</i>	<i>1 min e 22 sec</i>

The PID controller was faster than the Fuzzy system because the control system has a predominantly accelerating characteristic. The controller PID is more derivative than integrative, in this way the PID control recovers a little faster than the Fuzzy system.

5. CONCLUSIONS

The learning environment for the systems proposed in this work was made available for application in the teaching of the control and automation discipline of UERJ's electrical engineering faculty. The feedback was very positive since the model has contributed significantly to the improvement of teaching methods and experimental procedures in the area of control and automation of the course, mainly the model using nebulous logic.

Through the built models it was possible to propose practical improvements in the teaching of disciplines related to control and automation, mainly with: (1) the reformulation of the workbenches and laboratory work environment; (2) the creation of new prototypes that reflect industrial applications; And (3) reformulation of laboratory experiments including nebulous logic with simulations in MATLAB and LABVIEW.

The research present opportunities in the future the construction of new models and consequently more experiments in learning environment. Another perspective is the creation and expansion of laboratories in a multiuser and multidisciplinary environment that can allow creating new classes with new concepts, thus improving the practical process of learning.

6. ACKNOWLEDGEMENTS

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7. REFERENCES

- Johansen, T. A.; Shorten, R. Murray-Smith, R. (2000). On the interpretation and identification of dynamic Takagi-Sugeno models. *IEEE Transactions on Fuzzy Systems*, 8(3):297–313.
- Klerk, E.; Craig, I. K., A laboratory experiment to teach closed-loop system identification, *IEEE Transactions on Education* 47(2), 2004.
- Medeiros Jr, J.; Um ambiente de aprendizagem em automação e controle baseado em sistemas nebulosos; Dissertação de Mestrado; Faculdade de Engenharia Elétrica; UERJ; 2011.
- Medeiros JR, J.; Ribeiro, S. A.; Almeida, N. N.; Neto, L. B. Um Modelo para Montagem de Projetos de Sistemas Térmicos em Ambientes de Ensino de Controle e Automação (Parte 1): Uma Abordagem para Controles PID. *Anais COBENGE 2016*.
- Medeiros JR, J.; Ribeiro, S. A.; Almeida, N. N.; Neto, L. B. Um Modelo para Montagem de Projetos de Sistemas Térmicos em Ambientes de Ensino de Controle e Automação (Parte 2): Uma Abordagem com Lógica Nebulosa. *Anais COBENGE 2016*.
- Mathworks; *Fuzzy Logic Toolbox* (Design and Simulate Fuzzy Logic Systems) - 2016. Disponível em. <<<http://www.mathworks.com/products/fuzzy-logic>>>
- Neto I.M., Camacho J.R., Salerno C. H. E., Alvarenga B. P., Analysis of a Three-Phase Induction Machine Including Time and Space Harmonic Effects: The A, B, C Reference Frame, Artigo IEEE PE-154-EC-0-10-1997, *IEEE Transactions on Energy Conversion*, EUA, October 1997.
- NI - National Instruments; Labview - User Manual; North Mopac Expressway Austin, Texas 78759-3504 USA; 2016.
- Silvera, M. A., Enciclopédia de automática: controle automação, volume I, São Paulo, Editora Blucher, pp. 68-77, 2007.
- Silveira, P. R. da; Santos. W. E. Automação e controle discreto. São Paulo: Érica, 2008.
- Teixeira, M. C. M.; Assunção, E.; Extensões para sistemas não-lineares. In Aguirre, L. A., editor, Enciclopédia de Automática: Controle & Automação, volume 1, pp. 218–246. Blucher; 2007.

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