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Classic And Fuzzy PI Controller For A DC-DC Boost Converter

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Abstract
The present work uses classical and fuzzy design to control a DC-DC Boost converter. The advantages and disadvantages of the proposed control strategy are analyzed. One of the main features of the ANFIS architecture in MATLAB is the possibility of using a hybrid learning algorithm to tune the parameters of the adaptive system (FIS). In conclusion, for the DC-DC boost converter, the optimization method used for training was the hybrid method because the algorithm tends to minimize the error to the smallest possible value.

Keywords: Fuzzy, PI controller, Boost converter.

I. INTRODUCTION

DC/DC converters are electronic power systems that transform a voltage level at your input to another level at your output by exchanging solid-state devices. They are used in various applications, such as power sources for personal and portable computers, consumer electronic device adapters, and aerospace power systems. The importance of the study of DC/DC converters lies in their nonlinear nature and the fact that their practical operation is far from their theoretical prediction due to problems associated with parasitic resistances and capacitances and leakage inductance components (Atacak, 2012).

Diffuse control is one of the most successful applications of Zadeh's fuzzy set theory. It has proven to be a valuable tool in real-time industrial process control, in which it isn't easy to obtain the mathematical model of the system. However, a fuzzy controller's performance depends on experts' experience and knowledge. A test and error process is applied to adjust the base parameters of rules and member sets. This implies that these parameters can change from one expert to another so that controller efficiency can be affected (Zadeh, 1965) (Lee, 1990). Neural-diffuse control designs diffuse logic-based controllers that employ neural network techniques to adapt and establish control objectives (Brown, 1994).

Numerous control techniques have been applied to DC/DC converters. For example, in a PID controller, appropriate tuning is essential so that any change in operating conditions is not reflected in the system output; however, it is expected that when modifying some parameters, the efficiency is reduced (Cheng, 2010). An innovative option in process control is to employ heuristic reasoning based on the experience of a system expert. This experience is usually collected in the form of language declarations and rules. In this case, it is not necessary to establish a model. Still, the complete design of the controller is reduced to the "conversion" of a set of language rules within an automatic control algorithm. Fuzzy logic provides this conversion mechanism required for controller design (Cheng, 2010) (So, 1996).

Fuzzy control of PI, PD, and PID

PI, PD, and PID controllers remain the most widely used industrial control circuits worldwide because they have simple structures, can be efficiently designed, and offer good control system performance at an acceptable cost(Astrom, 2001) . However, The PI, PD, and PID controllers may not guarantee satisfactory performance of the control system if the mathematical model of the process controller is highly nonlinear and subject to parameter variations or uncertainties. So, the theory of diffuse control is proposed to improve the performance of the pi, PD, or PID c Control system (Guzelkaya, 2003) (results, 2007) .

Control systems with Mamdani fuzzy controllers

O design de sistemas de controle difuso com Mamdani é geralmente realizado por meios heurísticos, incorporando habilidades e experiência humana. Embora os índices de desempenho de tais sistemas de controle sejam geralmente satisfatórios, um grande problema é a análise das propriedades estruturais do FCS, que incluem estabilidade, controle, sensibilidade paramétrica e robustez (Jantzen, 2007) (Sala, 2005). As tendências atuais usam a abordagem de Lyapunov (Sugeno, 2004), a abordagem de Krasovskii (Tian, 2006), o método de descrição da função (Michels, 2007), o teorema invariante de Krasovskii-LaSalle (Precup, 2008) , o teorema do pequeno ganho (Mohan, 2008).

The design of diffuse control systems with Mamdani is usually carried out by heuristic means, incorporating skills and human experience. Although the performance indices of such control systems are generally satisfactory, a significant problem is the analysis of the structural properties of FCS, which include stability, control, parametric sensitivity, and robustness (Jantzen, 2007) (Sala, 2005). Current trends use Lyapunov's approach (Sugeno, 2004), Krasovskii's approach (Tian, 2006), the whole of function description (Michels, 2007), the invariant theorem of Krasovskii-LaSalle (Precup, 2008) , the theorem of the small gain (Mohan, 2008).

The automotive industry is a particular area of success for Mamdani. The control of hybrid electric vehicles is addressed (Schouten, 2002), and the complexity of all related control strategies is emphasized (Salmasi, 2007). Mamdani proposed the first fuzzy controller in the seventies and comprised the following basic procedure:

- The error is the difference between the desired value and the variable's actual value to be controlled: $\varepsilon = V_{Desired} - V_{real}$, the join functions that will perform the defuzzification will be selected.
- The rules are established from conditional propositions, and the inference device will be a max-min composition previously defined as:

$$X_T(x, z) = \vee_{y \varepsilon Y} \left(X_R(x, y) \wedge X_s(y, z)\right) \quad (1)$$

- The binding functions are selected for the dulcification and the method to use to find the output value, usually the centroid method:

$$\frac{\sum \mu(x).x}{\sum \mu(x)} \text{ (discreet)} \qquad \frac{\int \mu(x).xdx}{\int \mu(x)dx} \text{ (continuous)} \quad (2)$$

Sistemas de controle com controladores fuzzy Takagi-Sugeno.

Diffuse T-S models represent diffuse dynamic models or diffuse systems. That brings a double advantage. First, any model-based technique (including a nonlinear one) can be applied to diffuse dynamic models. Second, the controller itself can be considered a diffuse system. Since the diffuse nonlinear process model is usually based on a set of local linear models that are smoothly fused by the fuzzy model structure, a natural and direct approach is to design a local controller for each local process model (Cao, 199) (Koczy, 1996) (Room A. a., 2005).

In data-based identification, the model due to Takagi and Sugeno became popular. In this model, the antecedent is defined from the same linguistic variables, while the consequent is a linear function of the input variables:

$$R_i\text{: if x is } A_i \text{ then } y_i = a_i^T x + b_i \quad (3)$$

Where a_i is the resultant parameter vector, b_i is a change to climb e i = 1,. . K., K. This model combines a linguistic description with standard functional regression: the antecedents describe diffuse regions in the input space where the consequent functions are valid. The result is calculated by taking the weighted average of the contributions of the individual rules.

$$y = \frac{\sum_{i=1}^{k} \beta_i(x) y_i}{\beta_i(x)} = \frac{\sum_{i=1}^{k} \beta_i(x)(a_i^T x + b_i)}{\sum_{i=1}^{k} \beta_i(x)} \quad (4)$$

Where βi (x) is the degree of conformity of the i-th rule, for rule (4), βi (x) = μAi (x), but it can also be a more complicated expression, as shown below. The historical fuzzy sets are usually defined to describe distinct and partially overlapping regions in the input space. The parameters a_i then (approximated) local linear models of the nonlinear system. The TS model can be considered a partial linear approximation of a nonlinear function or a parameter programming model. Note that the variables before and after may be different.

Neuro-Diffuse modeling.

At the computational level, a diffuse system can be seen as a layered structure (network), similar to artificial neural networks. To optimize the parameters in a diffuse system, one can employ known descending gradient training algorithms of the area of network neurons. For this same part, this approach is generally known as neuro-diffuse modeled (Jang J.-S. a.-T., 1993)(Brown, 1994) (Jang J. a., 1997).

Prior knowledge and process data can be used to build neuro-diffuse systems. Previous knowledge can be approximate (qualitative, heuristic) (Babuvska, 2003).

- Specialized knowledge is formulated as a collection of if-then rules. In this way, an initial template is created. The parameters of this model (the member functions, consequent parameters) are then adjusted using process data.
- Using numeric data, fuzzy rules (including associated parameters) are constructed from scratch. In this case, the advantage of using a neuro-diffuse model is the possibility of interpreting the obtained result (which is not possible with truly black structures such as neural networks). An expert can confront the information stored in the rule base with his own knowledge, modify the rules, or provide others to extend the model's validity, etc.

This study aims to understand the advantages of fuzzy logic to quickly design control systems based on heuristic knowledge and system data, in addition to expanding the knowledge and use of Mandani and ANFIS controllers in different electronic, electrical, telecommunications, and other applications.

II. METHODOLOGY

The Boost converter is a voltage-boosting circuit that uses the characteristics of the inductor and capacitor as energy storage elements to increase the power supply current and inject it into the capacitor, producing higher d and voltage levels in the load than those of the source. The switch on the diagram (Figure 1) consists of two elements: a fast switching element, such as a BJT transistor, a MOSFET or the most used IGBT, and the other, a diode with a much shorter recovery time than the control signal period; the function of the latter is to prevent the condenser discharge current from being returned, because it is desirable that when the source is disconnected from the capacitor and load resistance to store energy in the coil, the current is supplied to the load by the capacitor discharge.

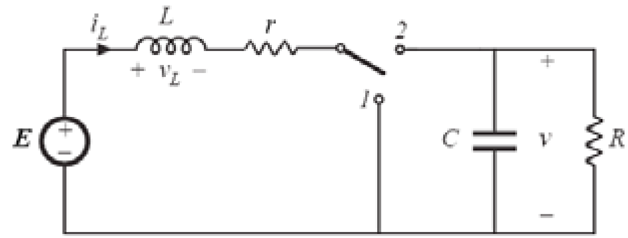

Figure 1. Boost converter circuit

When the transistor is conductive (switch in 1), the inductance stores energy and then delivers it simultaneously to the load and capacitor at another voltage level at the intervals where the transistor is in a cutout (switch in 2). The switch at position 1 of the physical circuit (Figure 2) indicates that the transistor is in saturation, so the diode anode is short-circuited to the ground; the diode is polarized to inverse and behaves like an open circuit breaker.

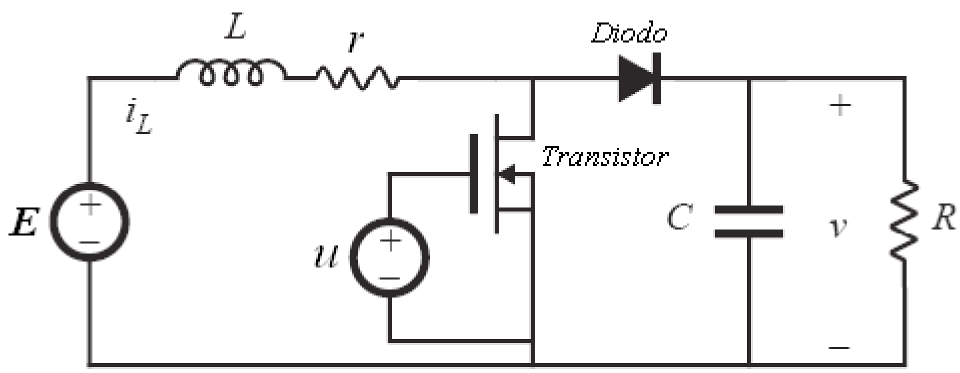

Figure 2. Real converter with transistor and diode

Table 1 shows the most important aspects of the system used to model the elevator button and the parameters and variables presented in the system.

Table 1. Most essential parameters of the voltage lift.

Parameters	**Model**
Entry	A control signal (u)
Output	Voltage (v)
Disorders	Changes in energy supply Mudanças in load resistance
Subsystem	Control Switch

	Power circuit Load
Classification	The system is dynamic and has a nonlinear model

We obtain the model in state variables that correspond to the current in the inductance (i) and the voltage in the load (v), the input to the system is the u parameter that determines the output voltage level because it controls the conduction time of the transistor.

$$\begin{bmatrix} \frac{di}{dt} \\ \frac{dv}{dt} \end{bmatrix} = \begin{bmatrix} -\frac{r}{L} & 0 \\ 0 & -\frac{1}{RC} \end{bmatrix} \begin{bmatrix} i \\ v \end{bmatrix} + \begin{bmatrix} \frac{-v}{l} \\ \frac{i}{c} \end{bmatrix} u + \begin{bmatrix} -\frac{E}{L} \\ 0 \end{bmatrix} \quad (5)$$

III. SIMULATION AND DISCUSSION OF THE RESULT

The values of the elements used in the circuit to develop the simulations are chosen with the circuit that operates in a steady state. The equations that define the l and c values are defined in table 2.

Table 2. circuit elements values

Element	**Description**	**Value**
R	Load resistor	50Ω
C	Capacitor	25uF
L	Inductor	400uH
r	Inductor resistor	0.1Ω
E	Power voltage	100V

From equation 5, the nonlinear model was obtained in Simulink / Matlab figure 3.

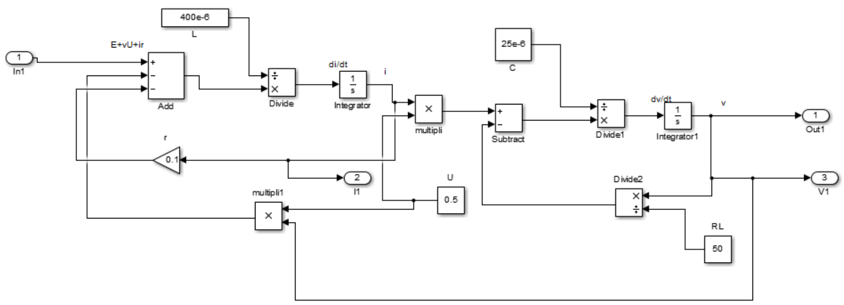

Figure 3. Model on lineal Simulink

Figure 4 shows the system response to two inputs, the duty cycle set value for the desired output (0.5), and this input amplified 1.5 times, i.e., 0.75. With this graph, the non-linearity of the system is verified, the curves have the same shape, but they do not comply with the principles of homogeneity and overlap; as the input increases, the output decreases.

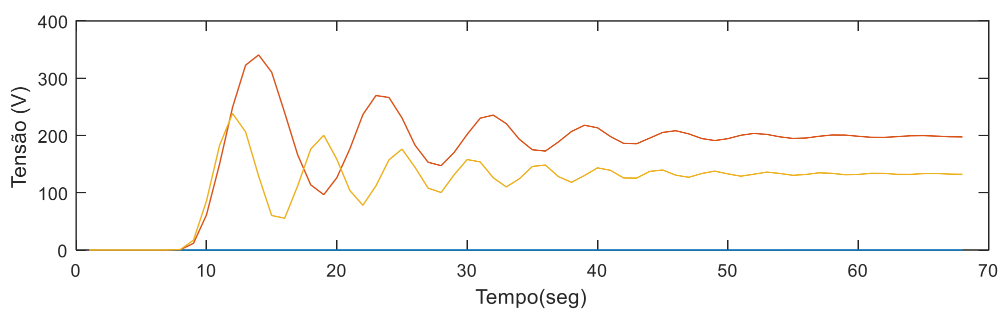

Figure 4. Resposta do sistema a duas entradas.

The equilibrium points are found to determine a linear model from the equations that describe the system. The balance occurs when:

$$\bar{u}\bar{I} + \frac{V}{R} = 0 \quad \text{and } E - \bar{I}r - \bar{u}\bar{V} = 0 \quad (6)$$

It has been defined $\bar{u} = 0.5$ replacing in equation 6 we get: $\bar{V} = 198{,}412V$; $\bar{I} = 7{,}936A$

Using the Simulink file with the nonlinear model and equilibrium points, the linear model is calculated through the MatLab linmod function resulting in:

$$A = 10^4 \begin{bmatrix} -0.025 & -0.125 \\ 2 & -0.080 \end{bmatrix}$$

$$B = 10^5 \begin{bmatrix} -5 \\ 3.2 \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$D = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Mandani control Conversor DC DC

Starting from the system's response to a gain step entry 'r' in Figure 7, which is the desired value of the system, and with pertinence functions for fuzzification and defuzzification triangular type, with three terms and the same labels, it is possible to project the rule matrices for each type of controller according to their actions: P controller, PD controller, PI controller, and PID controller.

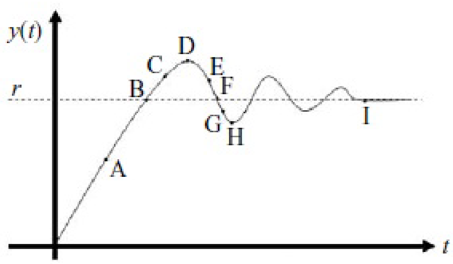

Figure 5. Answer a Step r

Rules for fuzzy sets are called negative (N), zero (Z), and positive (P). The PI control action is presented in Table 3 (Pedro, 2010).

Table 3. Fuzzy ruleset

			Error		
			N	**Z**	**P**
		N	N	Z	P
derived from error	**Z**		N	Z	P
		P	N	Z	P

The following fuzzy rule set is defined:

R1= If X1 is N and X2 is N then Y is N.

R2= If X1 is N and X2 is Z then Y is Z.

R3= If X1 is N and X2 is P then Y is P.

R4= If X1 is Z and X2 is N then Y is N.

R5= If X1 is Z and X2 is Z then Y is Z.

R6= If X1 is Z and X2 is P then Y is P.

R7= If X1 is P and X2 is N then Y is N.

R8= If X1 is P and X2 is Z then Y is Z.

R9=If X1 is P and X2 is P then Y is P.

Se defined the following operators for the fuzzy reasoning of the model:

- Composition sup-t = sup-min
- Background Aggregation = Min
- Semantics of rules (or implication) = Min (Mamdani rule)
- Aggregation of Rules = Max
- Defuzzification Method = Centroid

The linguistic variables of the Mamdani control system are as follows: figure 6 shows error input and derived from error, and figure 7 Shows output.

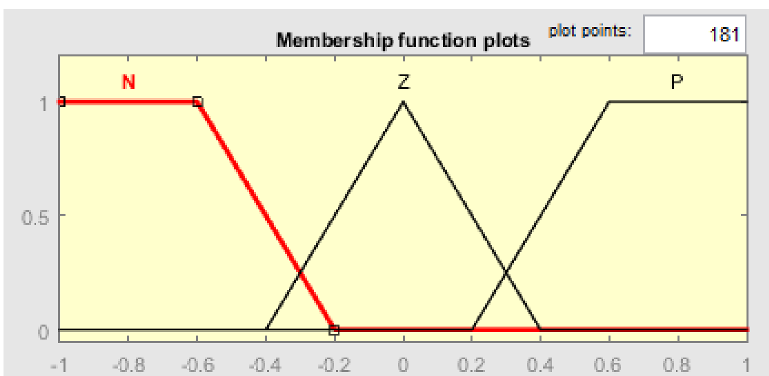

Figure 6. Linguistic variables error and derived error

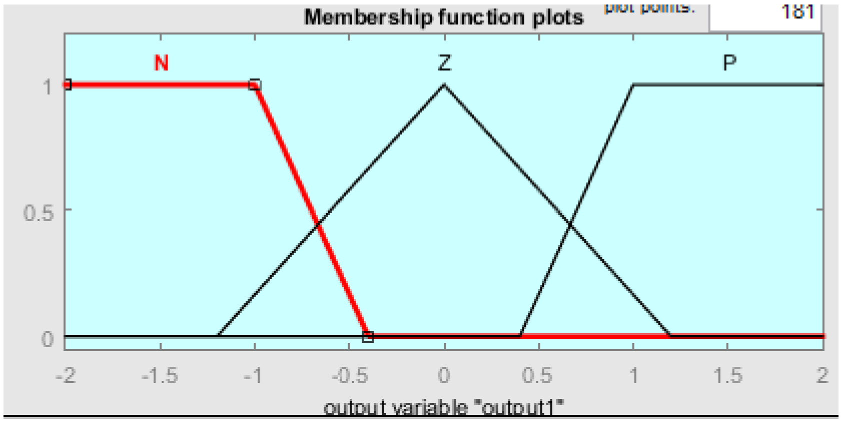

Figure 7. *Linguistic variables control output.*

Neuro-Fuzzy Control DC-DC Converter

The inputs must be placed in the first columns to form the training matrix, and the last column corresponds to the output in MATLAB.

- datostrn = [error2 derror2 out2].

To start training, enter the ANFIS Editor by typing the following instruction:

Neuro-FuzzyDesigner: To upload the data, select the option "Training" and "workshop" and then click the "Load data... button," and the following screen will appear (Figure 8) where the name corresponding to the data array:

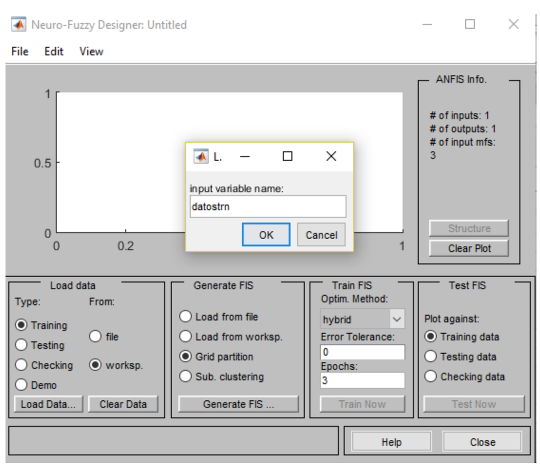

Figure 8. Training data entry matrix

In the drawing region, the distribution of the training data was obtained with the PI controller type figure 9.

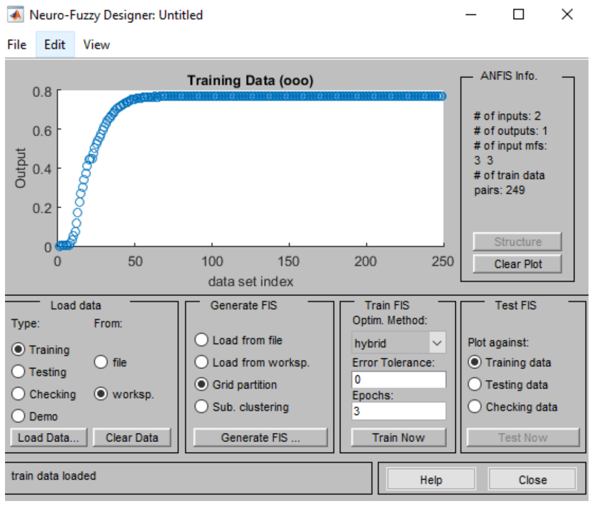

Figure 9. Training data obtained from the controller.

Então o FIS inicial deve ser gerado, (Selecione " "Grid Partition"). Para configurar a estrutura FIS inicial, clique no botão "Gerar FIS", obtendo a tela mostrada na Figura 10.

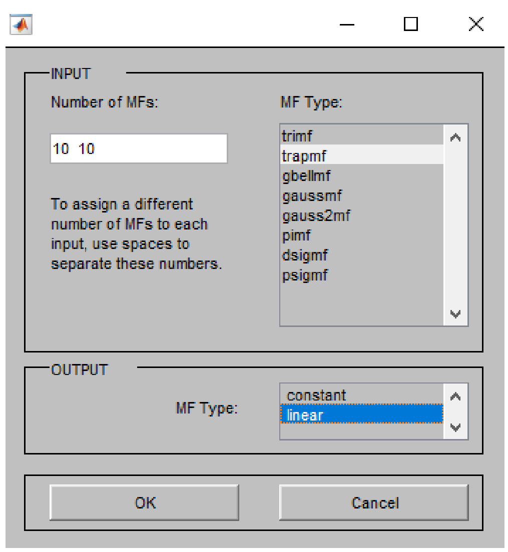

Figure 10. Initial FIS structure

To obtain the FIS controller, each controller has been trained with ten functions trapmf for each input, with 249 data and 50 Epochs for the PI controller. Now shows the control system generated by ANFIS figure 11.

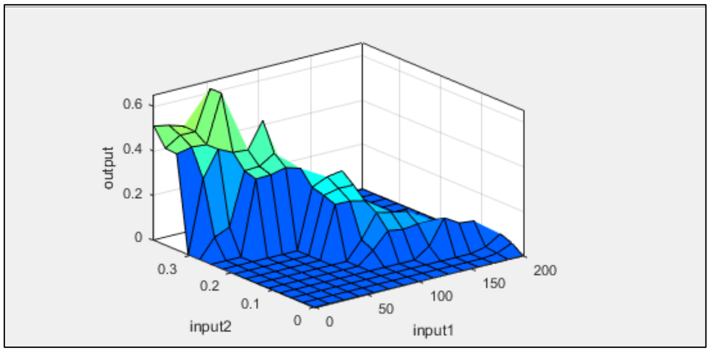

Figure 11. Control generated by ANFIS

DC-DC converter simulation

For the first application, the Mandani diffuse control methodology optimally DC_DC Boost type converter. It is shown in Figure 12.

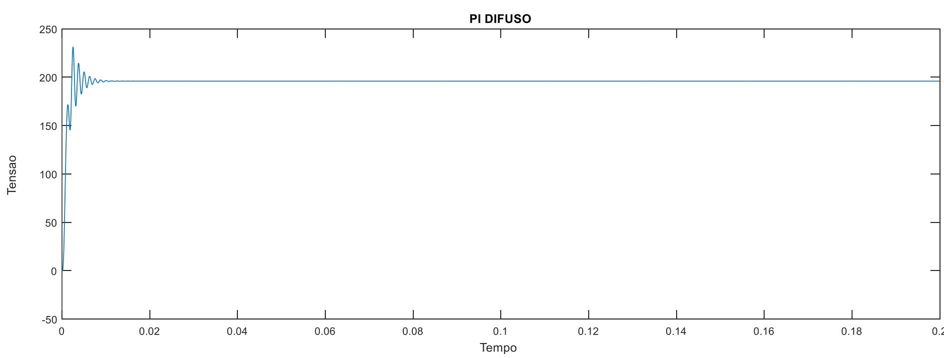

Figure 12. Controle Difuso PI

When we vary the break-even point, we compared the outputs of the fuzzy controller and classic PI controller to a 180V voltage.

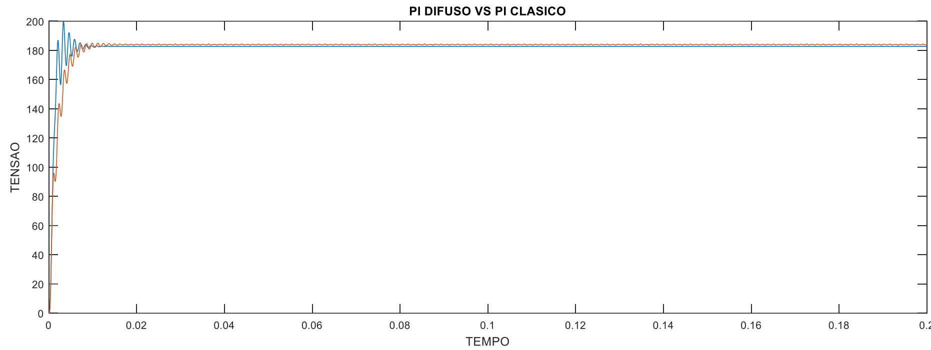

Figure 13. PI DIFFUSE VS PI CLASICO 180 V

The second neuro-diffuse controller is simulated with the plant, and com can't the results with the classic PI (see figure 14)

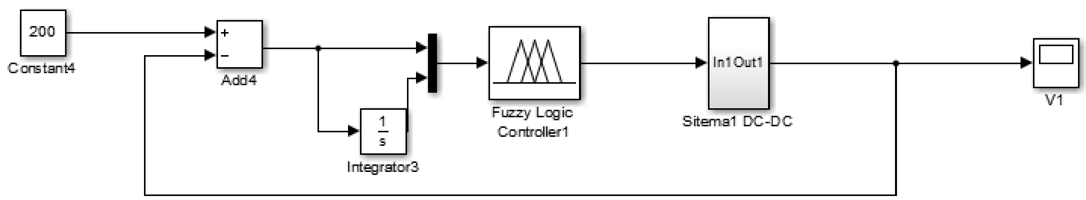

Figure 14. Controlador fuzzy.

Graph 20 shows how diffused PID is adapted to conventional PI.

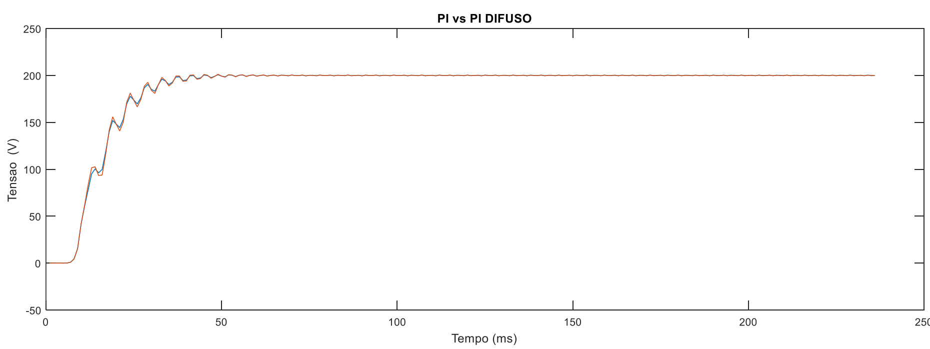

Figure 15. PI vs PI fuzzy (180V)

When we vary the break-even point, we observe how the fuzzy controller behaves:

- First voltage, 190 V shown in figure 16.

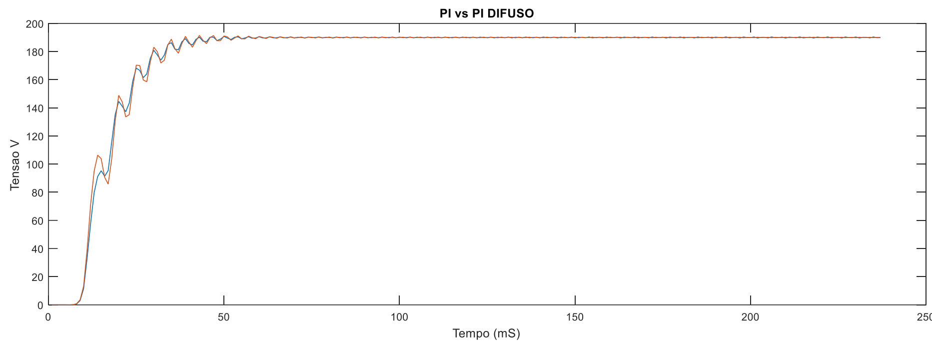

Figure 16. PI vs. PI fuzzy (190V)

- Second, a voltage of 180 V is shown in figure 17.

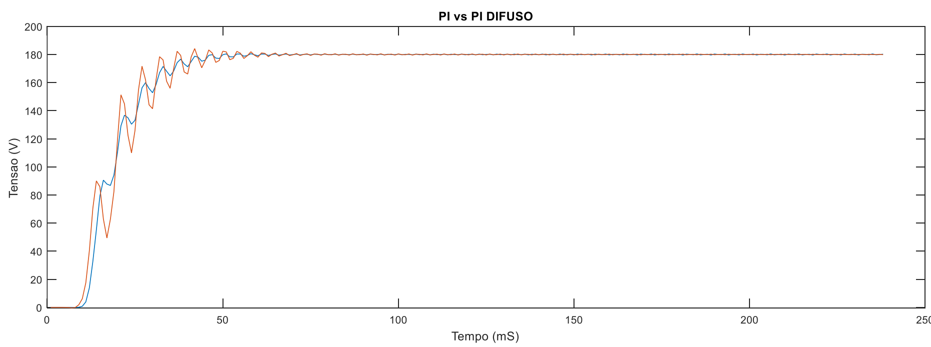

Figure 17. PI vs PI fuzzy (190V)

The fuzzy controller meets the design conditions and adapts to changes in voltage. as it was exposed in figure 16 and figure 17.

IV. CONCLUSIONS

Fuzzy systems incorporate the knowledge of experts in the form of rules of the type if ... then, together with the ownership of neural networks, which makes them adaptable and thus can adjust the values of the parameters of their antecedents or their consequences based on a set of input/output data pair. These characteristics make them very suitable for mimicking the behavior of systems whose mathematical models cannot be easily obtained.

One of the main features of the ANFIS architecture in MATLAB is the possibility of using a hybrid learning algorithm to adjust the parameters of the adaptive system (FIS). This algorithm is very efficient in minimizing the measurement of system output error when the parameters of its functions are adjusted.

When selecting the number of inputs and outputs that need to be sampled for training, an ANFIS architecture mimics the original system's behavior; it is necessary to consider the system's complexity because, in many cases, selecting input and output can be enough to train. However, in this work, it was observed that, with more complex systems, it is necessary to select two inputs with an output so that the system obtained after training imitates the behavior of the plant with less error. For the DC-DC boost converter, the optimization method used for the training was the hybrid method because the algorithm tends to minimize the error at the lowest possible value.

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