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DISCRETIZATION OF FUZZY LOGIC CONTROLLERS ON MICROCONTROLERS

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Abstract. *One of the greatest advances of the development of control systems was the emergence of fuzzy logic, because it deals with imprecise information, which often is not seen by conventional controllers. Without the mathematical model of the system to be controlled, the fuzzy controller is a real and effective alternative for the control of non-linear process. The technology industry has grown in the creation of small-sized devices, and nowadays there are fuzzy controllers running inside of portable devices with microcontrollers. This technique is not well known and brings great advantages. This article describes a discretization of a fuzzy control system for a later deployment to a microcontrolled circuit.*

Keywords: *Control Systems, Discretization, Fuzzy Logic, Microcontroller*

1. INTRODUCTION

A control system is able to provide responses to a given input according to the process transfer function, responsible for the complete description of the dynamic characteristics of the system. Especially in non-linear processes, using this function (and/or trying to obtain it) may be impractical because of its complexity, which hinders the development of a control strategy through conventional techniques. In such cases, the Fuzzy Logic Controller (FLC) can be used successfully since it allows the use of linguistic expressions. In other words, a simple intuitive knowledge of human operators who know the system behavior can be encoded in control strategy.

Fuzzy logic is based on the theory of fuzzy sets (Zadeh, 1965) and was developed to deal with the void aspect of information. Today is a very versatile technology in developing control systems for sophisticated processes. It is much close in spirit to human thinking and natural language than traditional logic systems (Lee, 1990a). The use of fuzzy algorithms applied to control troubleshooting had its beginnings even in 70s (Mamdani, 1973) and later (Mamdani and Assilian, 1974) control rules were adopted such as "**IF** *A* **THEN** *B*", where *A* and *B* are values of linguistic variables. FLC is a control system that uses a subset of Artificial Intelligence and, unlike the classic controllers, dispenses knowledge of the mathematical model of the plant to be controlled. Traditional techniques may have difficulty and/or impossibility to achieve desired levels of efficiency, therefore this type of control is a practical alternative for a variety of challenging applications, since it provides a convenient method for building nonlinear controllers through heuristic information use.

Widely used in different kinds of control, microcontrollers are in summary computers with high performance encapsulated in a single integrated circuit (Wilmshurst, 2007). Programmable, equipped with processor and various computational resources, their use have as main advantages the low cost, small size and high processing capacity. Nowadays any device that interacts with the user carries internally a microcontroller.

Combining the versatility of the FLC to the portability of microcontrolled circuits, and also applying concepts regarding fuzzy logic, control systems, automation and electronics, this paper describes the construction of a prototype to control temperature in linear and nonlinear systems.

2. MATERIALS AND METHODS

2.1 Fuzzy Logic Fundamentals

The classic Boolean logic has its limits well defined, represented by only two values such as: true or false, 1 or 0, yes or no. If we were classifying persons by their height dividing them into an set *A* (tall people) and another set *B* (short people), after classified an individual could belong exclusively to only one set. If it is determined that the set *A* includes all individuals with stature bigger or equal 1.85 meters, a person with 1.84 meters height will belong to the set *B*. The truth of this information may be doubtful because analyzing more wisely, how can we say that a person 1.84 meters tall is exclusively low just being 1 cm below the stature of individuals classified as tall peaple? The limits of Boolean logic often generate uncertainties making difficult the resolution of some problems. Distinct from it, the fuzzy logic has no clear boundaries, in our example a person 1.84 meters tall would have a small participation (pertinence) in the set *B* and simultaneously large participation in the set *A*. In this logic one element may simultaneously belong to more than one set having different significance in each, specifically the variables can assume infinite values, so the uncertainty of the information is translated into a mathematical model establishing for each case participation levels or pertinence functions. In the fuzzy logic values are expressed linguistically and each term is interpreted as a fuzzy subset in the range between 0 and 1. The temperature in some control plant can be a linguistic variable that receives the values "low", "medium" and "high" described by fuzzy sets, represented by membership functions. Thus the quantification of each variable can receive sentences in a specific language ("high", "low", "small", "medium"), logical connectives ("not", "and", "or") and modifiers ("very", "little", "gently").

The fuzzy sets are used to represent or model inaccurate information in a simple manner with the purpose of simplifying the knowledge base. The characteristic function can be obtained so that the values assigned to the elements of the universal set *U*, belong to the range of real numbers including [0,1], according with Eq. (1).

$$\mu A: U \rightarrow [0,1] \qquad (1)$$

Each value set in this interval indicates the relevancy degree of the set *U* of elements in relation to the set *A*, that is what is the participation of an *x* element of *U* in the set *A*. Thus we define a membership function and the set *A* is a fuzzy set. Let us make an individual's classification according to the age group with the use of fuzzy sets: Be the universe set *U = {5, 10, 20, 30, 40, 50, 60, 70, 80}*, considering the following fuzzy sets: *A = {Children}*, *B = {Teens}*, *C = {Adults} and D = {Elderly}* for which we assign levels of participation (pertinence) of elements of the set U, according to Tab 1.

Table 1. Definition of relevancy degree in accordance with the age of individuals

Age	Child	Teenager	Adult	Elderly
5	1	0	0	0
10	0.7	0.3	0	0
20	0	0.3	0.7	0
30	0	0.1	0.9	0
40	0	0	1	0
50	0	0	0.6	0.4
60	0	0	0.2	0.8
70	0	0	0	1
80	0	0	0	1

Table 1 shows that a 20 years old person has little participation (0.3) in the group of adolescents and good participation (0.7) in the group of adults. In another way a 30 years old individual has almost no participation (0.1) in the group of adolescents and quite participation (0.9) in the group of people considered adults. Figure 1 graphically represents the significance level that is defined in the context of fuzzy sets. It is easy to see that part of a set is superimposed the other being that the elements found in this region have different participations in both.

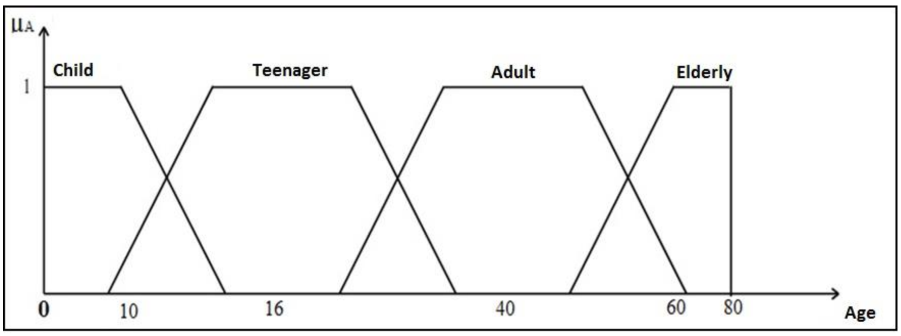

Figure 1. Graphical representation of fuzzy sets

2.2 Fuzzy Logic Controller Project

The FLC strategy is described by means of linguistic rules that connect, imprecisely, various situations and actions that can be taken where it is not necessary the mathematical model of the plant. Figure 2 shows the basic configuration of a fuzzy logic controller. Its project is basically divided into three stages: Fuzzyfication, fuzzy inference and defuzzyfication. In all of them Scilab® platform version 5.3.1 was used, which is a powerful free software and broad application use.

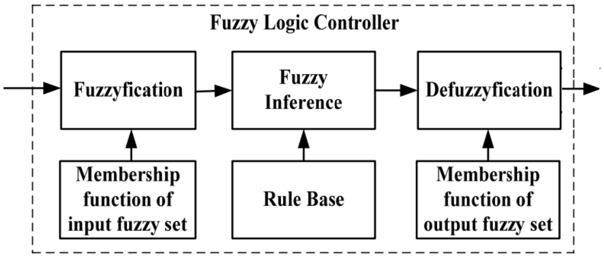

Figure 2. Block diagram of fuzzy logic controller (Source: Rosyadi, *et al*., 2012)

A basic control system requires four important variables: The set point (SP) indicating the desired output for the plant; The Process Variable (PV) which is responsible for the real time information from the output of the plant; Error (ER) which is the difference between what we want and what we actually have in the output; and the Manipulated Variable (MV) which is a signal generated by the controller acting on the process with objective to make that there is no difference between SP and PV (ER = 0).

The control model chosen for this study aimed to make the temperature control in both linear and nonlinear systems. The process variable (PV) is obtained from temperature sensors internally fixed to a wooden cabinet with dimensions 480 mm (length) x 240 mm (width) x 450 mm (height), this sensoring receives internal cabinet temperature, heated internally through four incandescent lamps of 60W each (not manipulated). The internal temperature control is done by the air flow generated by two fan coolers installed in the front and on the back of the cabinet (manipulated variable - MV), the set point (SP) is defined by the user through a keypad and the temperature range considered for this plant is between 20ºC and 80°C. The functioning is pretty simple: If the rotation speed of the coolers rises, the air flow increases and the internal temperature lowers, when the rotation speed decreases the air flow also decreases and the temperature increases. These decisions are taken through error calculation (ER) given in Eq. (2) and its behavior (DER).

$$ER = SP - PV \tag{2}$$

In a fuzzy controller there is a need to constant monitoring both the error as its behavior, in other words, if the error is decreasing, static or increasing. This variation, known as derivative of the error (DER), is given in Eq. (3) where is calculated the difference between the last measured error (LER) and the error previously measured (PER).

$$DER = \frac{d(error)}{dt} = LER - PER \tag{3}$$

Every possibility of error and its derivative should be treated in a special manner, and it is vital to the control's success. Table 2, essential for the controller project, summarizes the behavior of the control variables in a hypothetical situation with PV ranging from 20°C to 80°C and SP set at 50°C.

Table 2. Error (ER) and its derivative (DER) behavior

SP(ºC)	PV(ºC)	ER(ºC)	DER(ºC) (PV↑)	DER(ºC) (PV↓)
50	20	+30		+10
50	30	+20	-10	+10
50	40	+10	-10	+10
50	50	0	-10	+10
50	60	-10	-10	+10
50	70	-20	-10	+10
50	80	-30	-10	

2.2.1 Fuzzyfication Stage

The fuzzification comprises the process of transforming crisp values into grades of membership for linguistic terms of fuzzy sets (Rosyadi, *et al*., 2012). This stage is responsible for assigning degrees of membership to the input variables, making possible its use in the rule matrix of fuzzy controller. A universe vector X of 31 positions ranging from -15 to +15 was created in software using the Gaussian membership function (μgau) described in Eq. (4), where x

is element with pertinence level *µgau(x)*, *c* represents the center of the function and *s* determines the width of that function.

$$\mu gau(x,c,s) = e^{-\frac{1}{2}\left(\frac{(x-c)}{s}\right)^2} \quad (4)$$

With the conditions of the error and its derivative already known, six new functions were generated: **NER** (Negative error), **ZER** (Zero error), **PER** (Positive error), **NDE** (Derivative of the error negative), **ZDE** (Derivative of eh error zero) and **PDE** (Derivative of the error positive). Figure 3 graphically shows these functions.

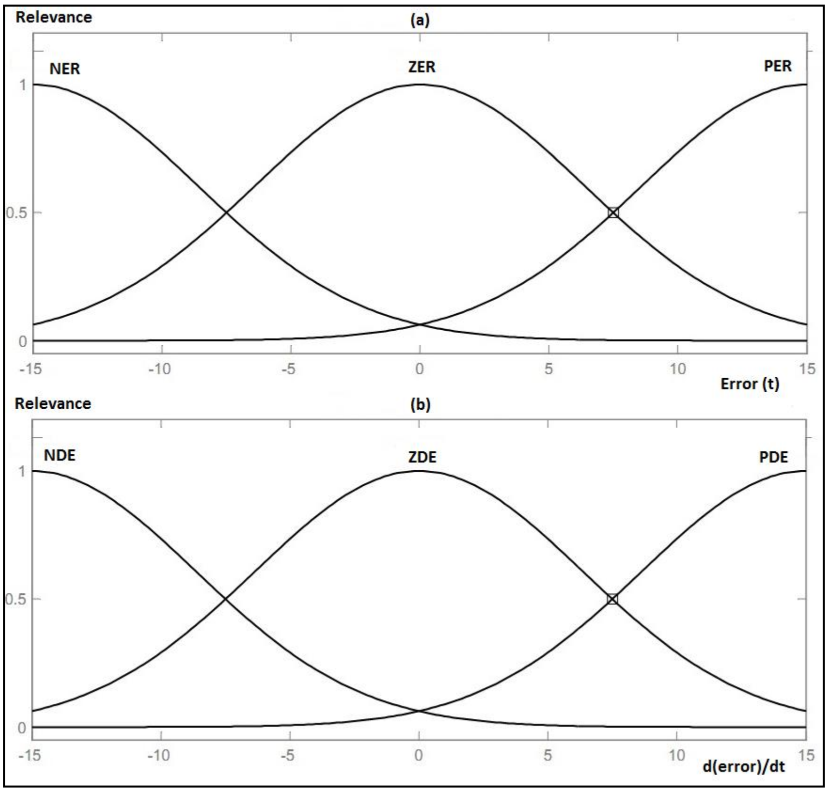

Figure 3. Graphs of the generated functions.
(a) ER (b) DER

2.2.2 Inference Fuzzy Stage

It is the application of technical knowledge, represented through rules defined by the operator, who has the knowledge of the operation and behavior of the plant to be controlled. Here are created control rules that will shape the system operation. The general form of a rule is: **IF** premise **THEN** consequence. Below is the modeling of the first rules dedicated to the project and the Tab. 3 shows the variables obtained from them.

- **If** the temperature is higher that desired **then** the rotation of coolers should be increased;
- **If** the temperature is correct **then** the rotation of coolers should not be changed;
- **If** the temperature is below that desired **then** the rotation of coolers should be decreased.

Table 3. Primary linguistic variables and their meanings

Linguist Variable	Meaning
INC	Increase cooler’s rotation (Temperature drops)
DON	Do nothing (Does not change cooler's rotation)
DEC	Decreases cooler's rotation (Temperature rises)

Table 4 shows that each linguistic variable is the result of three inferences, since we have to consider all conditions of error and its derivative. This gives us nine rules that, from now are able to control the process for all possible conditions.

Table 4. Primary linguistic variables and their inferences

Linguist Variable	Inferences
INC	INC1, INC2, INC3
DON	DON1, DON2, DON3
DEC	DEC1, DEC2, DEC3

The rules after using inferences device are:

- **If** ER is negative **and** DER is negative **then** INC2;
- **If** ER is negative **and** a DER is zero **then** INC1;
- **If** ER is negative **and** DER is positive **then** DON1;
- **If** ER is zero **and** DER is negative **then** INC3;
- **If** ER is zero **and** DER is zero **then** DON2;
- **If** ER is zero **and** DER is positive **then** DEC1;
- **If** ER is positive **and** DER is negative **then** DON3;
- **If** ER is positive **and** DER is zero **then** DEC3;
- **If** ER is positive **and** DER is positive **then** DEC2;

Applying Mamdani's max-min method according to the defined rules, using computational feature to model Fig. 4 and overlaying the three graphs generated for each linguistic variable, we can see the result of the fuzzy inference stage. It is possible to notice that, each coordinate input (X, Y), have a value (pertinence) on the output (Z).

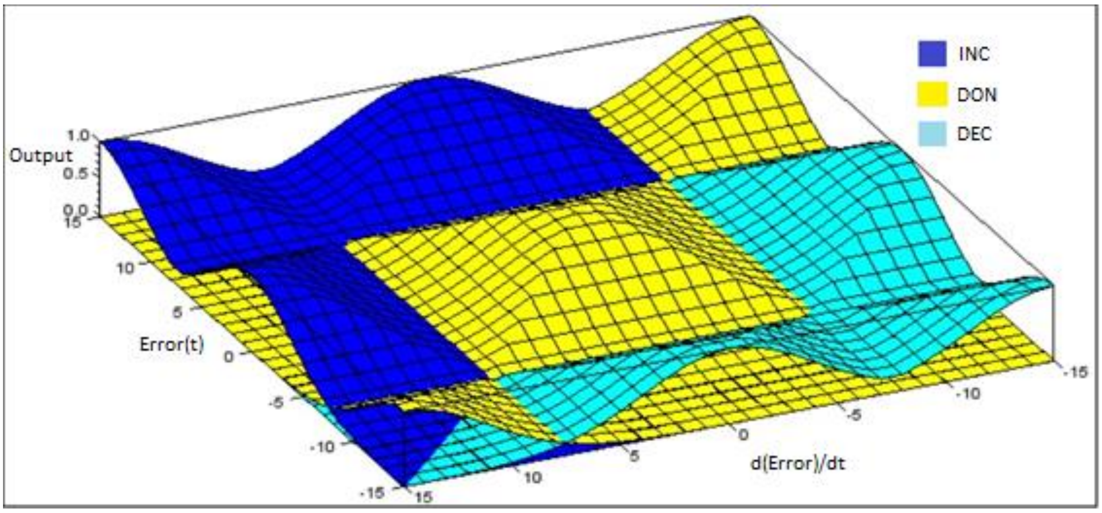

Figure 4. Linguistic variables overlaid on a 3D plane.

2.2.3 Defuzzyfication Stage

The deffuzification is a mapping from a space of fuzzy control actions defined over as output universe of discourse into a space of nonfuzzy control actions (Lee, 1990b). Responsible for converting the linguistic variables in numeric variables; this stage weighs the various responses provided by logical rules and assigns a numerical value to the output. This number will tell what is most relevant to do "Increases rotation, decreases rotation, or do nothing" and with what intensity. This consideration of responses may be performed by various methods, including "Max Criterion", "Mean of Maximum" and "Center of the Area". The method used in the project is the Mean of Maximum Method (MOM) that generates for the output array real numbers of pertinence now in the range [-1, + 1], since we control actions that will either increase (output ≥ 0) as decrease (Output <0) the rotation of coolers. This matrix has 31 lines and 31 columns and should be stored on the microcontroller memory, i.e. we have 961 different possibilities of control action provided for all conditions of the error and its derived.

Each real number generated by the output matrix must also be stored in a real variable, created in the microcontroller's software. But a single real variable occupies 32 bits in the microcontroller's memory and if we have 961 real values we need a memory with at least 3844 bytes of storage capacity only for the output matrix. The microcontroller chosen to control the process is the PIC18F4520® model manufactured by Microchip Technology©, has only 1536 bytes of data storage capacity, which would make its use impossible. The solution was multiplied by 100 all real numbers of the output matrix, round them to the nearest integer number and store them in a new created matrix that receives integer numbers, because each occupies only 8-bit memory, as can be seen in Figure 5.

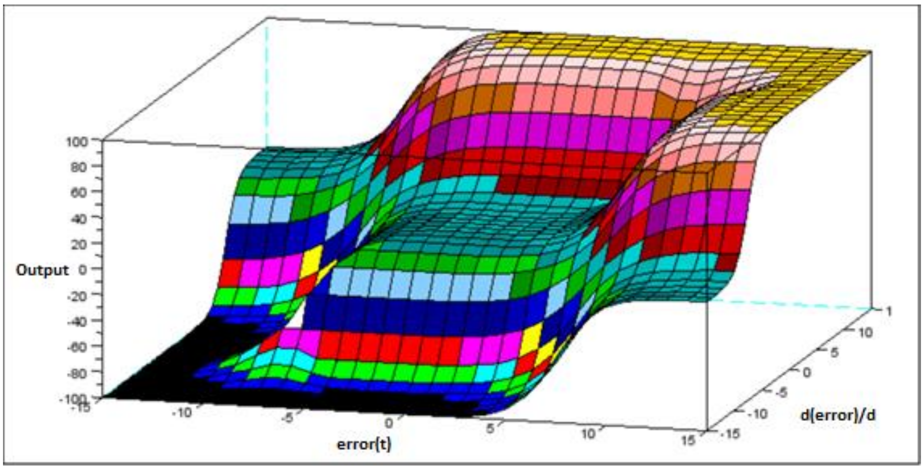

Figure 5. Output Matrix after defuzzyfication phase and suitable for storage in the microcontroller

3. RESULTS

The control strategy defined for the project and shown in Fig. 6, also includes actuators after the fuzzy controller already discretized. It is a gain block responsible for speed response of the controller and an integrator block to correct the offset error.

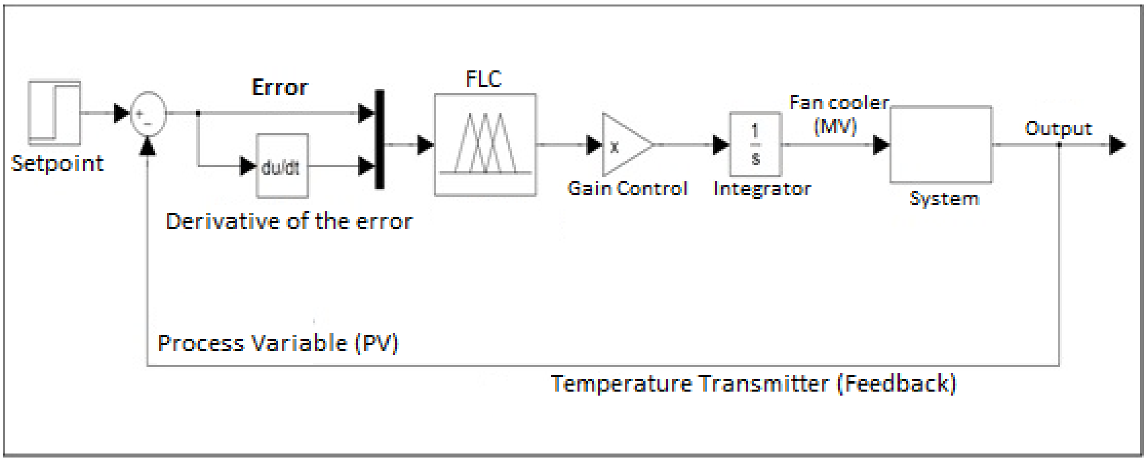

Figure 6. Representation in block diagram of the defined control system

The circuit shown in Fig.7 is pretty simple, with only the temperature sensing (LM35); an interface with LCD display; numeric keypad for data entry; one PIC18F4520® microcontroller responsible for the complete management system, and a TIP122 transistor that controls the rotation of coolers through the PWM signal sent by the microcontroller.

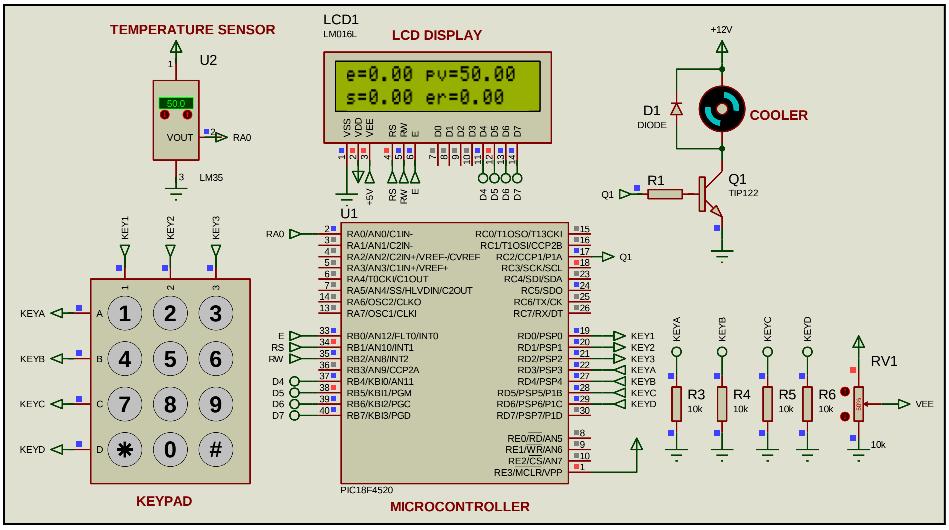

Figure 7. Circuit Diagram

In the prototype built, three tests were performed at room temperature 26°C and fixed gain. In the first, illustrated in Fig. 8, the temperature was controlled at 45°C in advance and the set point was changed to 48°C. Note that the PV starts to change about 5 seconds after changing the set point, as a result of reduction in rotational speed of coolers, being properly controlled after 154 seconds.

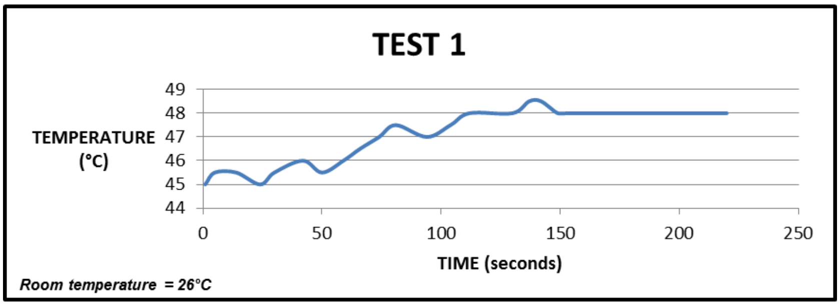

Figure 8. Test 1 - SP changed from 45°C to 48°C

In the same test, the temperature reaches the desired value for the first time 112 seconds after the start of control correction, but suffers a small "overshoot" of approximately 0.5°C which is quite normal and can be corrected by adjusting the gain of the controller. The second test was performed immediately after the first. With the temperature controlled at 48°C the SP was changed back to 45°C and the control was given according to Fig.9.

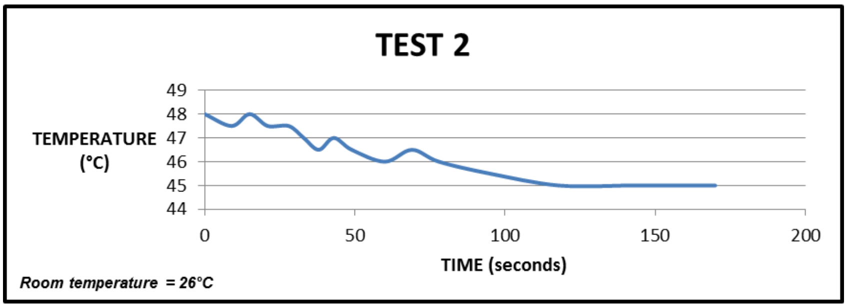

Figure 9. Test 2 - SP changed from 48°C to 45°C

Once again the process temperature starts to be modified about 5 seconds after the start of control correction in consequence of an increase in the speed of rotation of the coolers. Controlled in only 120 seconds, worth pointing out that this test does not have any "overshoot" and the temperature has stabilized firmly in 45ºC.

In both tests conducted so far, the process behaves pretty much linearly, and a conventional PID controller could be used successfully. As the purpose is also demonstrate the efficiency of this type of controller in nonlinear processes, after the second test was forced a non-linearity of the plant by removing part of the cabinet's upper cover (240mm x 240mm). This disturbance, now done in test 3, increased the flow of hot air out of the process and caused an almost instantaneous drop in internal temperature, shown in Fig. 10. Immediately after that perception, the controller began to reduce the cooler rotation so that the internal temperature could increase again.

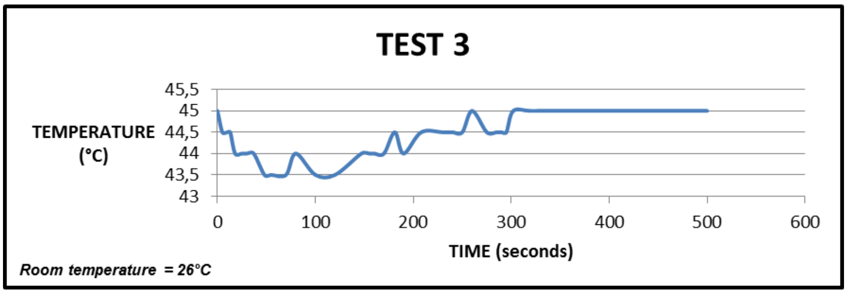

Figure 10. Test 3 - Alteration in the transfer function of process

Still analyzing Fig. 10, we find that the maximum error obtained after the change of the transfer function was 1.5°C, which was an excellent result and proves efficiency of this controller. With the continuous reduction of the rotation of the cooler, the temperature increased again 70 seconds after the change of the plant, reaching back into SP value and in time of 270 seconds was completely stabilized at 45ºC after the start of the disturbance. This is the main advantage of the fuzzy controller, even with the change of process transfer function; he was able to control the temperature at about 5 minutes without any intervention of the human operator or changing the control parameters. If this experiment were repeated on a conventional PID controller, new tuning parameters of the controller would be required, as they are calculated according to the process transfer function.

The intention of this paper is to describe a simple and direct way to discretization a fuzzy controller for implementation on a microcontroller circuit, pointing advantages and applications. The methods described herein are not rules, since there are various ways to perform fuzzification, inference and defuzzyfication in a fuzzy controller project. It was also not the objective of the labor detailing the routine developed and executed in dedicated software to microcontrollers.

The use of fuzzy logic provides a very effective alternative to building controllers able to operate in processes with floating parameters or difficult to being accurately modeled. Demonstrated with the result of the tests, it was possible to construct a reliable, compact and economically viable controller to be applied in various needs of nonlinear control.

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