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APPROACH OF A FUZZY PID CONTROLLER INVOLVED IN RASPBERRY ARCHITECTURE PI AND PYTHON: A CASE STUDY OF A THERMAL PLANT

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Abstract. Computational intelligence has several techniques that are executed in several fields for learning, perception, prediction and control. We can use computational methods allied to fuzzy logic to obtain control meshes with a minimal degree of error. In this work we have developed a PID controller based on fuzzy logic written in Python programming language that can be applied to microcomputers such as Raspberry Pi for control with robustness, reliability and connectivity. The PID, or also known as proportional integral derivative controller is a method of control of processes that groups computational executions, generating minimum degree of error. This control was modeled in Python from object oriented programming and with mathematical and fuzzy libraries, executed in a microcomputer, that has GPIO's (General Purpose Input / Output) which are an interface of data input and output directly on the board and can be connected to sensors / actuators and M2M (Machine to Machine) communication, which facilitates the final application in industrial or residential plants, crossing concepts of IoT and Industry 4.0. The PID controller coupled with fuzzy logic produces a fuzzy-PID controller, robust and dynamic based on IF-THEN rules and pertinence functions, capable of working with linguistic variables that model physical media based on human cognition. The set of rules used in the code can be extended to various models and plants, such as in temperature control. The data obtained can be exported and analyzed in software such as MATLAB, SCILAB, thus obtaining graphs and analyzes in real time, being able to perform the parallelism with analysis and simultaneous control. We can apply the control algorithm in an electric thermal plant where the desired temperature and the current temperature are input data of the plant, these values are fuzzified and are processed mathematically based on the system rules, inference machine and the fuzzy-PID operation, the values where they are transformed into a PWM (Pulse-Width Modulation) control signal applied to an electric resistance. As one of the goals of control and automation is to try to minimize human interference in a machine or procedure, making the system more optimized, safe and efficient. The computational control establishes relations with the automation area in order to transform processes control as more "intelligent" and implement decision making so that their choices are progressively more reliable.

Keywords: Fuzzy Logic, Control Systems, Embedded systems, Thermal Plant,

1 Introduction

Control Engineering is present in the context of our society in several purposes, optimizing routines and providing cost reduction. As well as the other areas of Science and Technology, it plays an important role in current technological advances, ensuring the accuracy, reliability and consistency of several processes that were once susceptible to human failure. For Bartoszewicz [1] the main focus of Control Engineering is to design control systems that are robust in relation to external disturbances as well as modeling in the face of uncertainty.

One of the main control techniques based on mathematical modeling is through Proportional, Integral and Differential (PID) operations. According to Ogata [2] we can apply this technique when the mathematical model of the plant is not known and, therefore, analytical design methods cannot be used, PID controls are the most useful.

According to Leite [3], the modeling of robust control systems has been increasingly challenging due to the advancement in plant complexity, which makes the use of new technologies necessary. With all the advances in Computational Intelligence techniques, exploration and use in the field of industrial process control have been gaining prominence for their effectiveness, especially fuzzy control.

In the words of Camboim [4] there are limits to the performance of processes that have a high complexity when using classical control. However, Fuzzy Control is a decision manager that has been widely used in several models that deal with imprecision. It deals with indeterminate convictions, being a methodology of description of categories that does not establish resistant measures between them. Its use is chosen whenever one works with fluctuation, ambivalence and subjectivity in mathematical or theoretical paradigms of practical experiments.

A thermal plant can be modeled using fuzzy heuristic methods in a more simplified and adaptable way, since temperature control systems require fine adjustments for reliable operation. In this work it was approached a methodology that aggregates techniques of fuzzy control through the rules base, listed to the use of embedded devices in order to obtain a dynamic model that adjusts the thermal plant generating a tiny degree of error with the use of embedded device in which will act as a controller having GPIO output interface for direct communication with sensors and actuators which makes the process more dynamic and fast.

2 Problematic

Traditional control techniques are based on the mathematical modeling of the proposed system. This technique produces a characteristic equation called the transfer function which models the entire system. To obtain this equation it is necessary that some adjustments, assumptions and restrictions are made. For example, assuming in many cases that the system addressed is linear or ignoring some physical and chemical phenomena by underestimating external disturbances and the imprecision of values. This approach allows the transfer function to generate discrete or continuous values in relation to time by returning a large volume of data to be treated.

Thermal systems are complex in their modeling, need accuracy of controlled values and are susceptible to changes influenced by the external environment. The modeling of this system can be complex and not very adaptive to changes and alterations, as well as requiring a continuous analysis of the collected data requiring a new approach that reduces failures, costs and that is modeled from heuristic methods in which it approaches the human reasoning.

3 Theoretical background

3.1 Fuzzy Sets and Logic

Traditional binary logic has large studies based on the dichotomy of states that can be applied in various situations of nature where we need to deal with contrary situations clearly and precisely.

However, in contrast to classical logic, there is the logic of fuzzy sets, a term defined by Zadeh [5] as a class of objects with a continuum of association notes that is characterized by an association function (characteristic) that assigns to each object a degree of association that varies between zero and one. Where some traditional concepts of union, intersection, complement, relationship, convexity, etc., are extended so that they undergo only a few adaptations. According to Jang [6] Fuzzy Set, as the name indicates, is a set without a clear border with a transition zone between pertinences, where this transition can be modeled according to the situation through fuzzy functions in modeling with the use of common linguistic expressions and their modifiers as "water is hot" or "temperature is high".

In our daily lives we find many classes that do not have a defined mathematical representation, such as examples, class of tall men and class of tall women. Class distribution is part of the human cognitive set. The values used in fuzzy logic can be presented through linguistic sentences according to the imposed question.

Fuzzy logic is used in the resolution of issues where doubt and lack of clarity are complex factors that hinder the action of putting into practice standardized models. Often the objects found in the real world do not have such precise associations, the traditional logic works with precise values having only two states, and may also be values of a limited and intrinsic range. Fuzzy logic operates with values that are commonly not well determined by numbers.

3.2 Membership Function - MF

According to Simões [7] can be considered the main feature of fuzzy logic. The pertinence function relates the physical values and returns values between 0 and 1, which means that an element can partially belong to a set having a fractional pertinence value among the already mentioned interval. The transition zone between pertinence is made gradually following the characteristics of the adopted function. The transition zone can be approached in a probabilistic way, that is, the sum of the pertinences always returns the value 1. There are several functions of pertinences that have different properties in which you choose the one that best fits the problem. For Jang [6] a fuzzy set can be completely described through its pertinence functions, we can list all the points that define an association function in a convenient and concise way through a mathematical formula. Below are some functions of a dimension that represent only one state.

- ***Triangular Membership Function***
  A triangular function is specified by the parameters a, b and c. The three parameters represent, respectively, the beginning, the peak and the end of the pertinence function according to the Eq. (1).

$$\mu(x) = \begin{cases} 0 \;\; x \leq \;\; a \\ \frac{(x-a)}{(b-a)} \;\; x \in [a, b] \\ \frac{(c-x)}{(c-b)} \;\; x \in [b, c] \\ 0 \;\; x \geq \;\; c \end{cases} \tag{1}$$

- ***Trapezoidal Membership Function***
  A trapezoidal function is specified by the parameters a, b, c and d according to the Eq. (2).

$$\mu(x) = \begin{cases} 0 \;\; x \leq \;\; a \\ \frac{(x-a)}{(b-a)} \; x \in [a, b] \\ 1, \;\; x \in [b, c] \\ \frac{(d-x)}{(d-c)} \; x \in [c, d] \\ 0 \;\; x \geq \;\; d \end{cases} \tag{2}$$

Due to the fact that their formulas are simple both MF above have great computational efficiency which makes them widely used in real time applications. However, due to their simplistic nature composed of not very smooth straight lines, they are not applied in cases where a smooth transition is needed. Below we have the Fig. 1 that shows two other examples of pertinence function with smoother and non-linear curves that are the **c) Gaussian** and **d) Bell**.

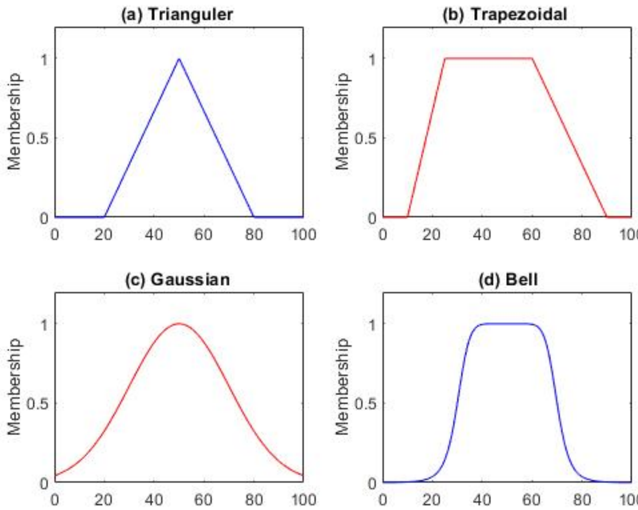

Figure 1. Parameterized MF Examples a) Triangle (20,50,80), b) Trapezoidal (10,25,60,90), c) Gaussian (50,20), d) Bell (24,4,50)

3.3 Linguistic Variables

We usually divide an X-space into several nebulous clusters. Those diffuse sets that usually take names that fit adjectives that appear in our daily use, such as ”large”, ”medium”, or ”small”, are called linguistic values. As pointed out by Jang [6] as soon as complexity of a system increases, the difficulty of making accurate but meaningful statements about its behavior decreases until it reaches a threshold beyond which accuracy and significance become almost mutually exclusive characteristics.

The concept defined by Jang [6] denotes that a linguistic variable is characterized by a fivefold in accordance with Eq. (3).

$$(x, T(x), X, G, M) \tag{3}$$

Where x is the name of the variable; $T(x)$ is the set of x terms, that is, the set of its linguistic values or linguistic terms; X is the universe of discourse; G is a syntactic rule that generates the terms in $T(x)$; and M is a semantic rule that associates with each language value A its meaning $M(A)$, where $M(A)$ denotes Fuzzy set in X. Let's take as an example the age of a person, we can observe that the linguistic variable in question is age - $T(Age)$, the primary linguistic values that this variable can receive are, **New, Young, Elderly**, as well as the values with linguistic complements, **Very new, Not very new, Not very new, Not very old, Elderly**, etc. These terms are linked to linguistic age variable.

3.4 Fuzzy IF-THEN Rules

Human reasoning can be represented through logical propositions; we represent this reasoning in terms of Fuzzy IF-THEN rules. A fuzzy IF-THEN rule is a conditional statement expressed as in Eq. (4).

$$IF < fuzzyproposition >, THEN < fuzzyproposition > \tag{4}$$

So we need to understand what a fuzzy proposition is. According to Wang [8] there are two types of fuzzy propositions:

- Atomics - These are single-state propositions

$$x\ is\ A \tag{5}$$

- Compounds - These are propositions that use "and", "or" and "not" type connectors that represent fuzzy intercession, Fuzzy union and Fuzzy complement.

$$x\ is\ A\ or\ x\ is\ not\ M \tag{6}$$

The key question now is how to interpret the IF-THEN operation, there are several interpretations and the most used in Fuzzy systems, according to Wang [8], is the Mamdani Implication.

3.5 Fuzzy Control

According to Wang [8] Fuzzy systems are rule-based. The heart of a fuzzy system is the knowledge base that consists of the so-called IF-THEN Fuzzy rules. IF-THEN rules are statements in which linguistic variables are characterized by functions of relevance. According to Gomide [9] Fuzzy systems are composed of :

- Fuzzifier: The fuzzyfication interface is designed to add a linguistic term to each numerical input value.
- Rule Base: Interference performs the task of interference between input linguistic variables and output linguistic variables, that is, it discerns the rules that are active in the knowledge base.
- Inference System: The knowledge base consists of a mass of data and rules. The data are numerical and the rules govern the functioning of the system. It is generated by an expert in the field.
- Defuzzifier: The defuzzyfication interface converts the output language variables into numerical values that will be sent to the actuators.

3.6 Raspberry PI and Python

Raspberry Pi is a low-cost computer with GPIO (General Purpose Input Output) pins, launched in England in 2012. Designed to be a digital inclusion tool and based on a large number of free software options (free software), it allows children and adults to have a first contact with computer concepts, programming logic and algorithms.

This versatile platform also offers easy access to its input and output system allowing easy connection of circuits and electronic modules and, thus, Raspberry is an excellent tool for learning the development of the concept of Electronics, Computing, Physics and Internet of Things. It can be used for small or large projects, either for beginners or hobbyists, or for professionals in the areas of Computing, Electronics and Automation.

Python is a programming language of high level, interpreted, script, imperative, object oriented, functional, dynamic and strong typing. It was released by Guido van Rossum in 1991. Currently it has a community development mode, open and managed by the non-profit organization Python Software Foundation. It has a specific library (SciKit-Fuzzy) to use fuzzy logic, through which we were able to generate a PID control algorithm that was able to generate satisfactory results. The Matplotlib library was also used to generate the graphics.

3.7 PWM - Pulse Width Modulation

For Oliveira [10] pulse width modulation transforms an analog value into a set of digital signals sent over a given period of time. Taking into account a long period of time we observe that the shape of the resulting signal is a square wave that alternates between high and low logic level. The ratio of high time to total wave period is the Duty Cycle (DC) which is the applied signal strength indicator. This signal can be obtained at the GPIO output of Raspberry Pi where we can control it. PWM signals are widely used in motor speed control, in resistances in order to control temperatures and in brightness control.

4 Methodology

The cloud controller follows a few steps in its own. The first step is to identify the input variables of the system, then design the pertinence functions with the zone of uncertainty according to the plant in which we want to control, then the Fuzzy rules block is established according to the environment and the linguistic variables used in the system. Next, the control algorithm is implemented in an embedded device that will be responsible for concentrating the processing, measurement and performance tasks.

4.1 Control Variables

The choice of variables is made through the analysis of the plant identifying the process to be controlled and its main features. For our case study applied to a thermal plant the main control variable will be the temperature, in which we will compare the output of the system with the input, thus obtaining the error value. For a more precise and robust control we will use the variation rate of this error as the second variable to be taken into account, since environmental disturbances and abrupt variations impact on our plant.

By choosing the variables below we define your speech universe, i.e., the Error variable can be given Eq. (7), and it varies between [-30, 30] with about 200 points which was defined in Python code. The Eq. (7) is an equation as a function of time because it varies with it.

$$Erro(t) = Set(Target)\ temperature - Measured\ temperature \tag{7}$$

When the 'error' is lower or higher we will opt for the extremes in the actuators since it would overload the controller and thus generate greater accuracy and speed for application in real time. The error variation rate variable can be given by the Eq. (8) which is equal to the current system error minus the previous error. The universe of speech of this variable is [-3,3]. The range of values can be considered small compared to the other variables, however this variable is the result of a rate of change that are usually small values between 0 and 5.

$$\Delta Erro = Erro(t) - Erro(t-1) \tag{8}$$

From the variables and Eq. (7) and Eq. (8) we can model a proportional and differential controller, because we know that at $Erro(t)$ negative represents a temperature at the output of the system higher than the desired one, whereas $Erro(t)$ positive represents the temperature at the output of the system lower than the desired one.

The error variation rate tells us how the system is reacting at each moment, if $\Delta E(t)$ is positive the error is increasing due to some external factor or failure and the system must react, otherwise, if $\Delta E(t)$ is negative the error is being corrected and the system approaches its desired temperature.

The next variable to be treated will be the PWM output variable, this variable is of paramount importance because it will be responsible for acting on the temperature increase in the electrical resistance. The PWM output has values in the range of [0,100] which corresponds to the Duty-Cycle.

4.2 Membership Function(MF) of linguistic variables

By defining the universe of discussion of each variable we can model the functions of pertinences. ***Temperature Error:*** This variable has seven linguistic values in which they are divided in the discourse universe through functions of triangular relevance, as shown in the Fig. 2, where the acronyms represent the following linguistic values: **MUN** : Very Negative Error, **MEN** : Mean Negative Error, **PN** : Little Negative Error, **ZE** : Zero Error, **PP** : Low Positive Error, **MEP** : Mean Positive Error, **MUP** : Very Positive Error,

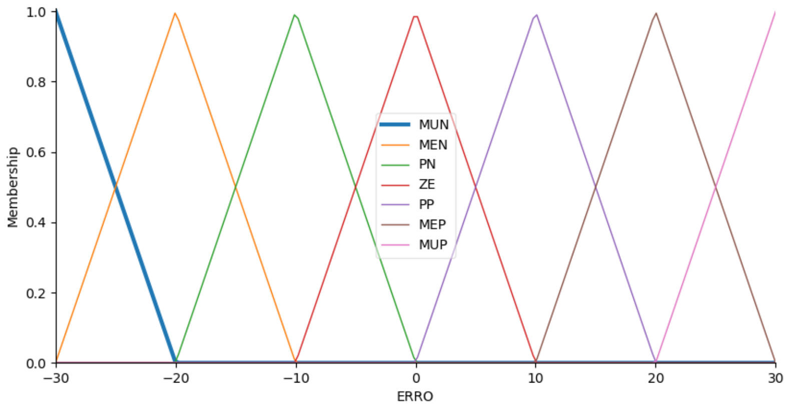

Figure 2. MF of variable Erro

Δ ***Erro:*** The variable also has seven linguistic values distributed in the discourse universe [-5 5], according to the Fig. 3, through triangular functions where the acronyms represent the following linguistic values: **CMU** : Falling a Lot **CME** : Falling Average, **CP** : Falling Little, **ZE** : Zero , **SP** : Rising Little, **SME** : Rising Average, **SMU** : Rising a Lot,

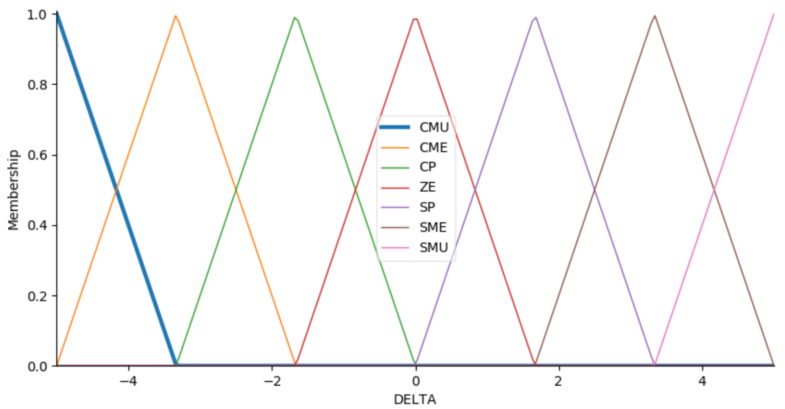

Figure 3. MF of variable ΔE

PWM Out: The output variable that will result from the relationship between the other two variables will be the PWM-Out that has five functions of triangular pertinence distributed in the discourse universe of [0 1] as shown in the Fig. 4. The acronyms represent the following linguistic values: **ZPWM** : Zero PWM **BPWM** : Low PWM, **MPWM** : Average PWM, **APWM** : High PWM , **AAPWM** : Very High PWM,

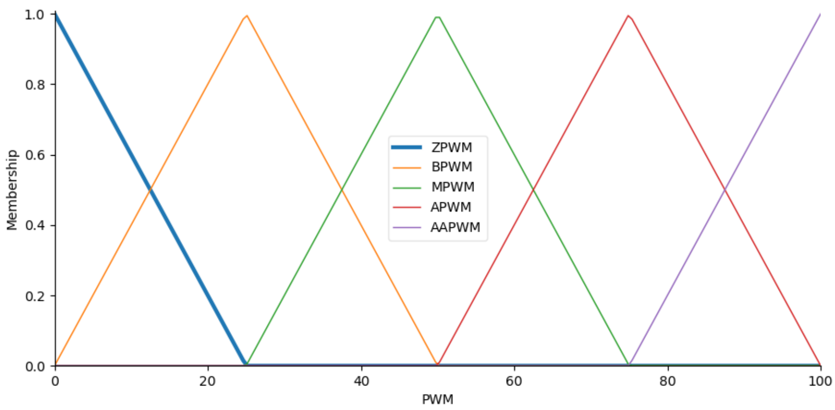

Figure 4. MF of variable Out-PWM

4.3 Fuzzy rules base and control algorithm PID

The system rules are the central part of all transactions, they are based on IF-ELSE, where there are the previous and consequential rules. The antecedents are the input variables, while the consequent ones are the output variables. For this project, 49 control rules have been elaborated, some of which are listed below.

IF error= MUN and Delta = ZE , **THEN** output = ZPWM;
IF error= ZE and Delta = SP , **THEN** output = BPWM;
IF error= MEP and Delta = SP , **THEN** output = MPWM;
(...)
IF error= pp and Delta = SME , **THEN** output = APWM;
IF error= MUP and Delta = CP , **THEN** output = AAPWM;

Basically we can explain the logic in these rules using some control concepts. There are situations where the output is inevitably the value of Zero PWM - ZPWM, which is when the value of the Error is Very negative - MUN, that is, from the Eq. (7) we know that the temperature needs to decrease.

On the other hand when the Error is Very Positive - MUP the output must be different from Zero - PWM because with the Eq. (7) we know that the temperature must increase to reach the expected value, the way this increase must be implemented is related to our second input variable the ΔE that shows how the variation is occurring, either subtly or abruptly, this second value is closely linked to external influences.

The parameterization and PID tuning of the variables Kp (proportional gain), Ki (integral gain) and Kd (derived gain) are generated from an algorithm contained in the Python Sci-Fuzzy library where the values are continuously adapted for a better response to the system.

4.4 Embedded device and control signal

The control system is executed through the Raspberry PI where the algorithm that runs in Python 3, this system includes since the acquisition of data through the sensors until the performance through the control signal generating an output in pulses (PWM) that can amplified by an external circuit coupled for large applications. With this we get a scheme as summarizes the Fig. 5, with the Raspberry Pi as centralizer of tasks of decision and performance through the GPIO, where a supervisor can be embarked on it. The communication with other embedded devices remotely can also be implemented because the Raspberry PI has Wi-Fi and Bluetooth connectivity.

The acquisition of data for analysis in computational software such as MATLAB and SCILAB can be done through the code that can also reuse these data and analysis to improve its accuracy.

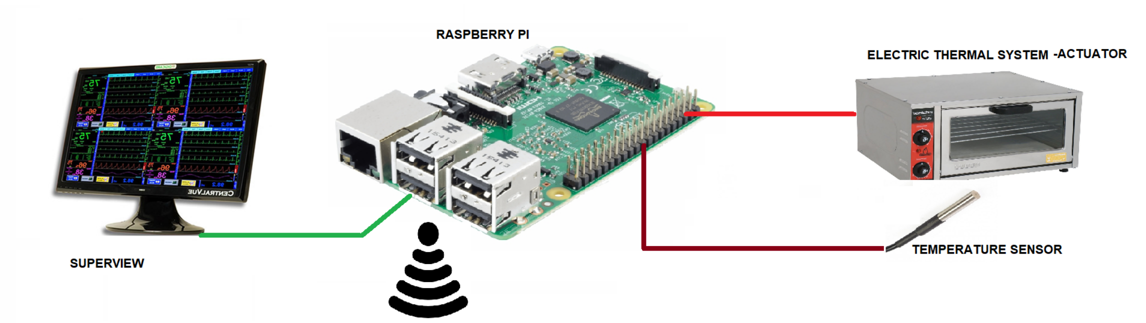

Figure 5. Thermal plant control scheme with Raspberry PI and supervisory

5 Results observed

The computed control space is in the Fig. 6 and where we can observe the universe of speech, this surface is given according to the block of control rules in it we can visualize the combination for the input values and their respective outputs, thus producing a control surface. The yellow part of the graph is where we have the PWM saturation zone, which is when the system needs to quickly increase the temperature, for this operating at a high Duty-Cycle value. The dark blue zone is where the system needs to decrease the temperature for this by operating at a low Duty-Cycle value.

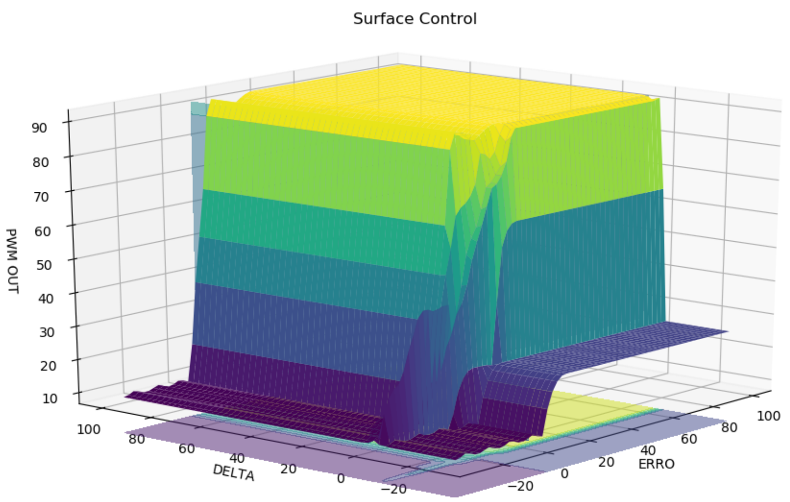

Figure 6. Surface Control

As observed in the Fig. 6 the curves present smoothness due to the defuzzyfication methodology adopted by the system. Which is responsible for interpreting the cloudy data and transforming it into physical data. This interpretation is adjusted according to the plant to be controlled.

The fuzzy control algorithm was simulated obtaining the result shown in the Fig. 7, where it is possible to observe the accuracy and the error that occurs in the change. The very common overshoot in several control systems happens in a subtle way being corrected soon after. The amplitude of errors being positive and negative is according to the Eq. (7). In practice, the system should be very close to this model because the same as we have seen is capable of adapting to external disturbances.

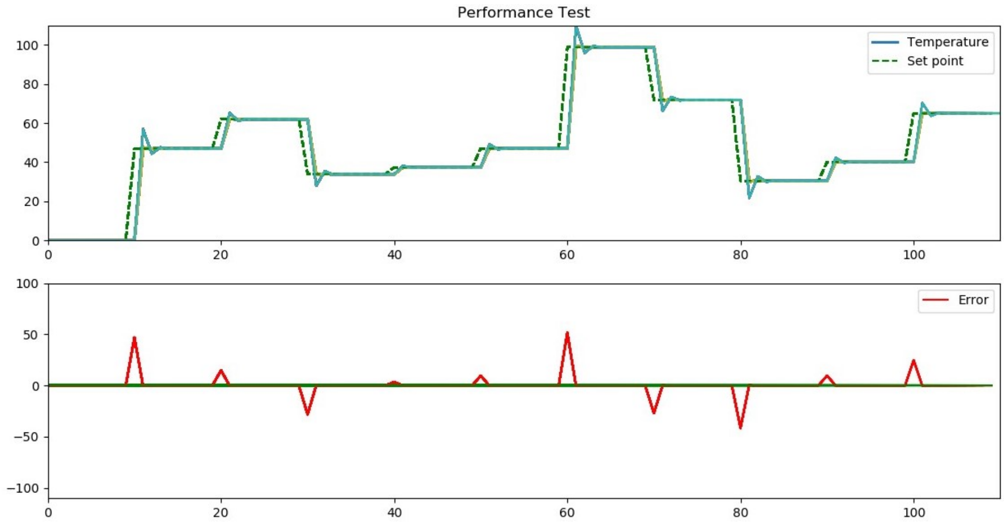

Figure 7. Computational simulation: Temperature x Time, Error x Time

6 Conclusion

The simulations performed in Python3 programming language, produces a fast response for applications in real time as well as allows integration with other platforms of computational analysis. This study uses control methodologies with fuzzy logic applied to a dynamic environment, which is our microcomputer that can be integrated into a network connecting to other control devices. This application can be expanded to other control plants being only necessary an adjustment in the Fuzzy controller rules base.

A physical simulation was not possible due to scarcity of resources, among other factors, as it would be important to assemble a prototype. This project can be expanded to applications in devices with RTOS (Real-Time Operational System) and can be applied to concomitant multiplant operations. The project has a lot of potential for large scale application for several industrial plants as well as its implementation has a lower cost of application and a more intuitive control programming.

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