A NEW METHOTOLOGY FOR ADAPTIVE FUZZY CONTROLLER. COMPARISON PERFORMANCE AGAINST SEVERAL CONTROL ALGORITHMS IN A REAL TIME CONTROL PROCESS

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Abstract: This article presents a comparative study of various control algorithms. An adaptive fuzzy logic controller is set to prove its effectiveness against other conventional controllers in a simulated control process as well as in a real environment. Through a training board that allows us to control the temperature, we can compare the behavior of each used algorithm. The adaptive fuzzy logic controller will be required to present a real high performance in temperature control, having in mind that the adaptive algorithm starts with no rules set i.e., empty rule base or by assigning arbitrary values to the rules without any information off-line. The comparison of results clearly shows the great contribution that the policy of an adaptive algorithm brings; ease of implementation and high accuracy.

1 INTRODUCTION

An intelligent control system typically consists of two parts: the firstis the “knowledge base” which presents the necessary knowledge to control the plant, and the second is an “inference engine” which processes the knowledge through reasoning, possibly using a new set of data to obtain the decision. Our study uses intelligent control techniques based on fuzzy logic and PID controller structures. Several structures of controllers have been tested in this control process to demonstrate the profitability of our adaptive fuzzy controller.

During the past 30 years numerous studies have presented several examples of adaptive controllers. In the 70sE.H. Mamdani and his student S. Assilian (Mamdani and Assilian, 1975) to determine the responsible rule for the undesirable state of the plant and replace it with the appropriate value, these steps have initialized a new policy of adaptive fuzzy logic controllers it calling Self Organizing Control (SOC) system (Procyk, 1979). In most SOC approaches, this dependence is expressed using only the monotonicity sign of the plant (Cho, 2002; Fan, 2004; Hua, 2004; K.Lin, 2003; M.Lin, 2004; Park, 2005; Velagic, 2003; Velez-Diaz, 2004; Yi, 2002).

The main focus of this paper is to prove that our adaptive fuzzy controller is capable of achieving a high accuracy and a good robustness through modifying the consequents of the rules in real time, the controller determines in which sense the rules have to be moved i.e., auto-learning. The proposed methodology is robust against modification of the parameters of the plant (break-downs). It is important to note, that no initial knowledge about the control policy is required and therefore the fuzzy controller can start with a set of empty rules.

2 TEMPERATURE CONTROL: THE HARDWARE DESCRIPTION

In this paper we will try to simulate the control of temperature of a room using a training board with several intelligent control algorithms. Our goal is to maintain the temperature of the room at a desired value; the room is equipped with a temperature source that heats the environment and a fan for

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lowering the temperature in cases of over passing the set point. The controller will aim to generate the fan power signal and determining their performance rating regard to the difference between the sensed temperature inside the room and the required temperature.

3 DESIGN AND IMPLEMENTATION OF THE USED CONTROLLERS

3.1 Tuning the PID Controllers

The Ziegler–Nichols closed loop (Ziegler, 1942), tuning method is a heuristic method of tuning a PID controller. It is performed by setting the *I* (integral) and *D* (derivative) gains to zero. The *P* (proportional) gain is then increased (from zero) until it reaches the ultimate gain K_u, at which the output of the control loop oscillates with a constant amplitude. K_u and the oscillation period P_u are used to set the *P*, *I*, and *D* gains depending on the type of controller used.

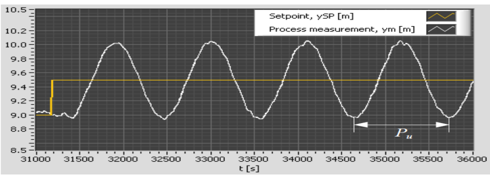

Figure 1: Ideal tuning phase of the Ziegler-Nichols closed loop method.

Table 1: Formulas for the controller parameters in the Ziegler-Nichols closed loop method.

Structures	Parameters		
	Kp	Ti	Td
P controller	0.5 Kp_u	∞	0
PI controller	0.45Kp_u	$P_u/1.2$	0
PID controller	0.6 Kp_u	$P_u/2$	$P_u/8$

3.2 Design of a Static Fuzzy Logic Controller

Due to its simplicity and stability we chose a TSK-0 fuzzy logic controller (static controller), with two inputs and one output. The controller inputs are the temperature error and its derivative (T*e*, T*ė*), the error is the difference between the required temperature Tsp and the temperature at instant i (T*i*), in fact the error equation is: *Te = Tsp – Ti*. The controller output is the tension that controls the fan operation. The inputs have a set of membership functions describing the state of these variables in their natural space, limited by its real extreme limits. The first input has seven and the second one has fife triangular membership functions covering the whole range of variation. The output is a set of scalar values (TSK-0 type controller).

3.3 Implementation of an Advanced (Adaptive) Fuzzy Logic Controller in Real Time

In this article, we used the product as T-norm for the fuzzy inference method and the ''centre of gravity'' with sum-product operator as the defuzzification strategy. Using the above notation, we can express the output of the fuzzy controller as follows:

$$\tilde{F}(\vec{x}^{k}) = \frac{\sum_{i_1=1}^{n_1}\sum_{i_2=1}^{n_2}\cdots\sum_{i_N=1}^{n_N}\left(R_{i_1 i_2\ldots i_N}\cdot\prod_{v=1}^{N}\mu_{X_v^{i_v}}(x_v^k)\right)}{\sum_{i_1=1}^{n_1}\sum_{i_2=1}^{n_2}\cdots\sum_{i_N=1}^{n_N}\left(\prod_{v=1}^{N}\mu_{X_v^{i_v}}(x_v^k)\right)} \quad (1)$$

where $\vec{x}^{k}$ is the N-dimensional input vector at instant *k*. The adaptive algorithm used, will be able to adapt the controller parameters using the information obtained from the current error in the output of the plant. The correction sense is deduced from the monotony of the plant.

In the algorithm subject of this study, coarse adaptation of the fuzzy rule consequents is achieved by evaluating the current state of the plant and proposing a correction of the rules responsible for the existence of such a state, either as a reward or as a penalty, in the following way:

$$\begin{aligned}\Delta R_{i_1 i_2\ldots i_N}(k) &= C\cdot\mu_{i_1 i_2\ldots i_N}(k-d)\cdot e_y(k) = \\ C\cdot\mu_{i_1 i_2\ldots i_N}&(k-d)\cdot\left(r(k-d)-y(k)\right)\end{aligned} \quad (2)$$

where: $\mu_{i_1 i_2\ldots i_N}$ is the strength or α-level of rule $R_{i_1 i_2\ldots i_N}$, and $e_y(k)$ is the error at instant k.

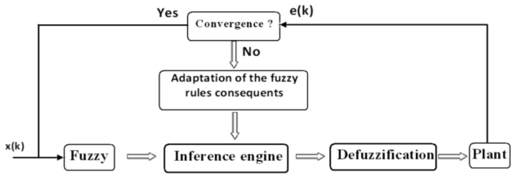

Figure 2: Adaptive fuzzy controller.

Since, as in (Rojas, 1999), the degree with which the rule was activated in achieving the control output u(k-d) was used proportionally with the modification adopted now being evaluated at instant *k*. In the aforementioned expression, d represents the time delay, r(k-d) is the required set point of the plant output at instant k-d and y(k) is the current plant output, it is very important to clear up that using r(k) would be incorrect, because the rules that are activated at instant k-d serve to achieve the desired value r(k-d) and not r(k). The determination of the absolute value of the coefficient C is calculated spent in off-line using the formula: $|C| = \Delta u/\Delta y$, where Δy is the operation range of the plant output , which must be estimated beforehand from the knowledge about the set points that we are going to use, and Δu is the operation range of the controller's actuator. In our case and after studying our plant we chose $|C|= 15$.

4 SIMULATION RESULTS

4.1 Real Simulation: Temperature Control

The MSE calculated in this study is not the MSE of the function approximation by the controller but it's the MSE between the set point and the plant output measured after *d* instants of time, being *d* the delay of the plant.

$$\mathrm{MSE} = \frac{\sum_{k=1}^{\mathrm{Num\_Epochs}} (r(k)-y(k+d))^2}{\mathrm{Num\_Epochs}} \quad (3)$$

4.1.1 Temperature Control Using a P, I and D Control Policy

- **The PD and PI Controllers**

The PD and PI controllers have been able to control the temperature, the MSE (mean squared error) for the last 40 iterations are respectively around 0.49 (Fig. 3) and 0.43 (Fig. 4).

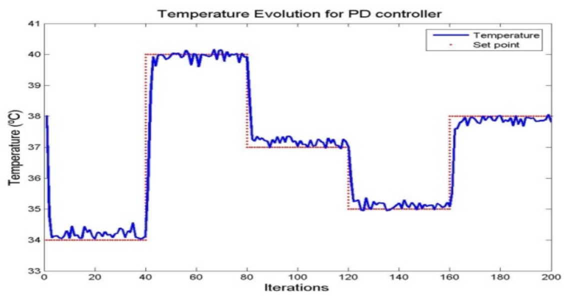

Figure 3: Control evolution with PD algorithm for various set points.

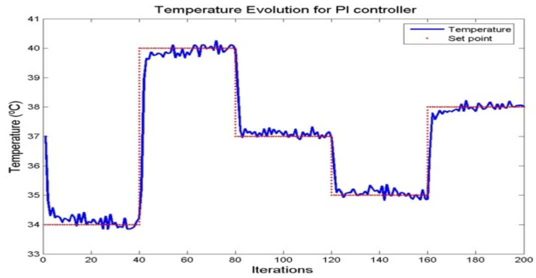

Figure 4: Control evolution with PI algorithm for various set points.

- **Using a Full PID Controller**

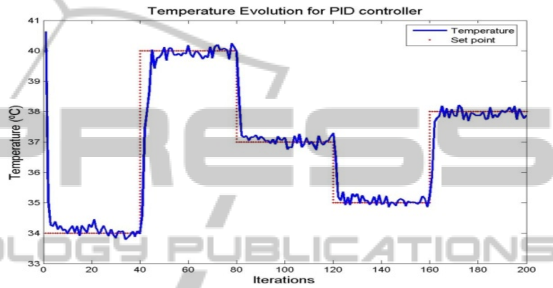

Figure 5: Control evolution with PID algorithm for various set points.

Fig. 5 clearly shows that our PID works well as a controller for various values of set points, guaranteeing the convergence around the set point with a 0.47 MSE in the last 40 iterations.

4.1.2 Temperature Control using a Static Fuzzy Logic Controller

Fig. 6 shows that the static fuzzy logic controller is performing well. The MSE for the last 40 iterations is 0.31.

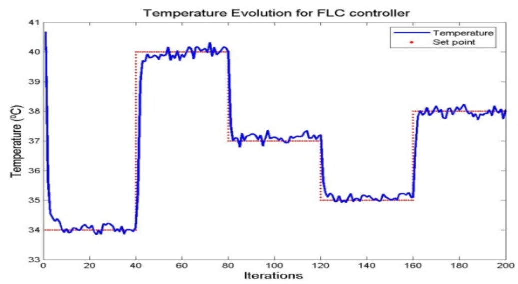

Figure 6: Control evolution with FLC algorithm for various set points.

4.1.3 Temperature Control using Adaptive Fuzzy Logic Controller

An analysis of the MSE in the last 40 iterations shows clearly the superiority of the latter compared with others; the adaptive algorithm has been able to reduce the error to almost 50%. The MSE in this case is 0.17.

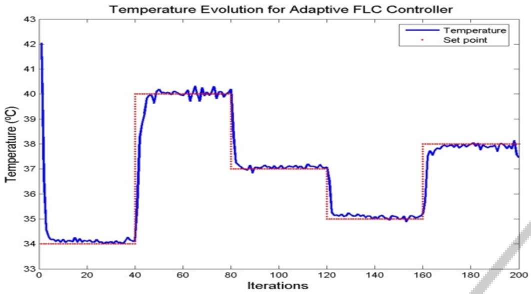

Figure 7: Control evolution with adaptive FLC algorithm for various set points.

4.2 Results Comparison

The graphical method consists in drawing the representing curve of the difference between the errors committed by two different algorithms at the same time interval and to achieve the same set point, i.e, represents the function defined as:

$$\text{Error difference} = E_{(\text{Algorithm 1})} - E_{(\text{Algorithm 2})} \quad (4)$$

If $E_{(\text{Algorihtm 1})} > E_{(\text{Algorithm 2})} \Rightarrow$ Error difference > 0
The graphical representation of the function Error difference is above zero.

If $E_{(\text{Algorithm 1})} < E_{(\text{Algorithm 2})} \Rightarrow$ Error difference < 0
The graphical representation of the function Error difference is under zero.

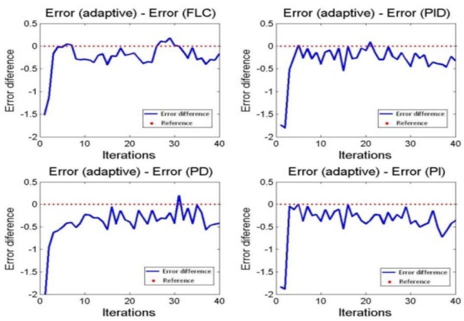

Figure 8: Differences between the error committed by the Adaptive FLC and the remaining algorithms.

The four cases presented in Fig. 8 show that the error difference curve is almost always under the zero line, mathematically this means that:

$$\text{Error difference} = E_{(\text{Algorithm 1})} - E_{(\text{Algorithm 2})} < 0$$

$$\Rightarrow E_{(\text{Algorithm 1})} < E_{(\text{Algorithm 2})}$$

In our case: $E_{(\text{Algorithm 1})}$ is $E_{(\text{Adaptive})}$.

The Error difference is almost always less than zero in the four cases, that means that the $E_{(\text{Adaptive})}$ is less than the rest of committed errors by others algorithms $E_{(\text{FLC,PID,PD,PI})}$.
The numerical comparison (Table 2) is based on the analysis of the MSE for each algorithm.

Table 2: Comparative performance indices for all used algorithms in real simulation.

MSE	Algorithms				
	PI	PD	PID	Classic FLC	Adaptive FLC
$MSE_{160 \rightarrow 200}$	0.43	0.49	0.47	0.31	0.17
$MSE_{100 \rightarrow 200}$	0.38	0.44	0.41	0.28	0.23
$MSE_{0 \rightarrow 200}$	0.84	0.89	0.85	0.78	0.67

The results presented in this table show the differences between the algorithms used. The adaptive controller has the best error reduction compared to the other, i.e., the adaptation presented and tested by I. Rojas et.al (Rojas, 2006) is a good alternative to replace the P, I, D controllers or a classical fuzzy logic controller for these kinds of plants.

4.3 The Perturbation Effects on the behavior Algorithm

Fig. 9 depicts the behavior of the algorithms (static FLC and Adaptive FLC) after a disturbance of 25% at iteration number 20. The disturbance used here is a simulation of a temperature decrease caused by a secondary fan and at the 65 iteration, we have caused a disturbance of 20% but this time we simulate a temperature increase caused by another source of temperature. The response of the plant after the disturbances for each algorithm can clearly explain the differences between every one of them.

Top of Figure 9 shows the behavior of static FLC in perturbation cases. We can notice how these disturbances can affect the control precision; the static FLC keeps the plant under control but with large error without over passing the perturbation effects.

In the bottom graph the adaptive FLC presents a very good performance against these disturbances. It can be clearly noticed that the control precision does not suffer big changes and that the adaptive algorithm can overcome the perturbation effects in few moments later.

Table 3 presents a numerical comparison between the error committed in 10 iterations before causing the disturbances and the error committed in

10 iterations with disturbance for each algorithm.

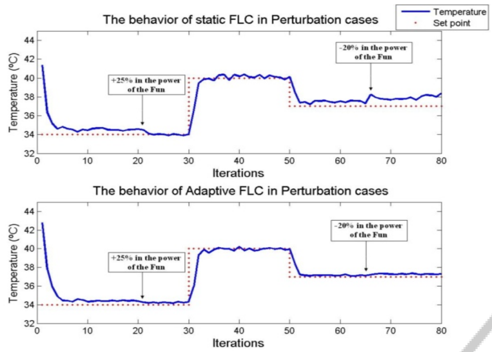

Figure 9: The perturbation effects on the control performance.

Table 3: Comparative performance indices before and after the perturbation.

MSE in 10 iterations	+ %25 in the power of the Fan		- %20 in the power of the Fan	
	FLC	Adapt FLC	FLC	Adapt FLC
Before perturbation	0.78	0.42	0.64	0.1
After perturbation	0.32	0.36	1.77	0.14

It is important to clear here that the error reduction in the first case of perturbation doesn't mean a control improvement, it's due to the new Fan added by simulation, adding a Fan with power more bigger signify big reduction in the error committed and maybe the error will change the sign if this Fan power was too much. The MSE presented in this table proves that the perturbation effects on the behavior of the adaptive algorithm are very small when compared with their effects on the behavior of the FLC algorithm.

5 CONCLUSIONS

This paper presents a comparative study between several control algorithms and an adaptive fuzzy logic controller. Both, the conventional fuzzy logic controller and the P, I and D controller structure show their capabilities to control the plant with a reasonable error. The adaptive algorithm without any off line pre-training and starting with no definite rule base has been able to improve the committed error during the control process. The adaptive algorithm does not need any complex mathematical models. It only needs a limited information from the plant.The monotonicity and the delay of the plant, were the only information used by the adaptive algorithm to optimize the error at the plant output. The results comparison can prove the superiority of the proposed adaptive FLC controller against the remaining of algorithms.

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