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Robust Fuzzy Digital PID Controller Design Based on Gain and Phase Margins Specifications

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***Abstract*— A robust fuzzy digital PID control methodology based on gain and phase margins specifications, is proposed. A mathematical formulation, based on gain and phase margins specifications, the Takagi-Sugeno fuzzy model of the plant to be controlled, the structure of the digital PID controller and the time delay uncertain system, was developed. A multiobjective genetic strategy is defined to tune the fuzzy digital PID controller parameters, so the gain and phase margins specified to the fuzzy control system are get. An analysis of necessary and sufficient conditions for fuzzy digital PID controller design with robust stability, with the proposal of the two theorems, is presented. Experimental results show the efficiency of the proposed methodology, applying on a platform control in real time of a thermic plant through tracking of the reference and the gain and phase margins keeping closed of the specified ones.**

I. INTRODUCTION

Since 1980, fuzzy systems have been applied in modeling and control of dynamic systems. Among several types of fuzzy systems, there is a very important class called Takagi-Sugeno (TS). Recently, it became a powerfull tool applyied to modeling and control [1]–[3]. This is due to structure based on rules that allows approximation of functions, nonlinearities and uncertainties as well [4]–[6].

The fuzzy PID controller is proposed in this paper. Conventional PID controller is very applyied yet due its structure relatively simple, and parametrics adjustement for guaranteed stability and confiability in several applications [7][8]. However, in industrial processes with nonlinearities, parametrics variations and uncertainties, the adjustement of PID controller parameters becomes dificult, so the robustness requirements are not attended. Due that, the fuzzy PID controller became as alternative for control systems design so guarantee robustness and high performance requirements, once its rules structure allows treatment of dynamic complexities in the process to be controlled [9]–[14].

The proposed methodology in this paper consists in a model based fuzzy robust digital PID controller design from the gain and phase margins specifications. The mathematical formulation based on fuzzy Takagi-Sugeno structure and PDC strategy, is presented. From a multiobjective genetic algorithm, the PID subcontrollers parameters are obtained according to the gain and phase margins specifications and the fuzzy model parameters of the process to be controlled. The necessary and sufficient conditions for fuzzy digital PID controller design, from robust stability criteria, with proposal of two theorems, as well as experimental results for real time robust fuzzy PID control of a thermic process, are presented.

This paper is organized as follows: in section II, the proposed methodology for fuzzy model based robust digital PID controller, is presented; and, the TS fuzzy modelling based on Fuzzy C-Means (FCM) clustering algorithm and least squares algorithm, from experimental data of the process to be controlled, is formulated. The proposed methodology for the digital PID controller design based on fuzzy robust model, from the gain and phase margins specifications, the Takagi-Sugeno fuzzy model of the process to be controlled, the robust fuzzy digital PID controller, are observed in section III. From the robust stability analysis, two theorems containing the necessary and sufficient conditions for the robust fuzzy digital PID controller design, are proposed in section IV. In section V, a multiobjective genetic strategy to obtain the gain and phase margins specifications, for controller design is also presented. In section VI, the experimental results for real time robust fuzzy digital PID control of the thermic process, are outlined. Finally, section VII concludes the paper.

II. IDENTIFICATION OF TS FUZZY MODEL BASED ON CLUSTERING ALGORITHM

A. Antecedent parameters estimation

In this paper, the TS fuzzy model antecedent parameters are estimated by Fuzzy C-Means (FCM) clustering algorithm, which is based on minimizing the functional given by:

$$J(Z;U,V) = \sum_{i=1}^{c}\sum_{k=1}^{N}(\mu_{ik})^m \left\|z_k - v_i\right\|_A^2 \quad (1)$$

where

$$U = [\mu_{ik}] \in M_{fc} \quad (2)$$

is a fuzzy partition matrix of Z,

$$V = [v_1, v_2, ..., v_c]\,, v_i \in \Re^n \quad (3)$$

is a vector of cluster prototypes (centers), determined by:

$$D_{ikA}^2 = \left\|z_k - v_i\right\|_A^2 = (z_k - v_i)^T A\,(z_k - v_i) \quad (4)$$

which is a squared inner-product distance norm, where z_k represents the elements of each column of the data matrix

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Z and v_i is associated with the coordinates of the clusters centers.

The FCM algorithm is realized using the following steps: given the data set Z and the initial partition matrix $U^{(0)} \in M_{fc}$, choose the number of clusters $1 < c < N$, the tolerance $\epsilon > 0$ and the weighting exponent $m > 1$.

Repeat for *l=1,2,...*

1- Compute the cluster prototypes (means):

$$v_i^{(l)} = \frac{\sum_{k=1}^{N} \mu_{ik}^{(l-1)} z_k}{\sum_{k=1}^{N} \left(\mu_{ik}^{(l-1)}\right)^m}, 1 \leq i \leq c \quad (5)$$

2- Compute the distances:

$$D_{ikA}^2 = \left(z_k - v_i^{(l)}\right)^T A \left(z_k - v_i^{(l)}\right), 1 \leq i \leq c, 1 \leq k \leq N \quad (6)$$

3- Update the partition matrix:
If $D_{ikA} > 0$ for $1 \leq i \leq c, 1 \leq k \leq N$,

$$\mu_{ik}^{(l)} = \frac{1}{\sum_{j=1}^{c} (D_{ikA}/D_{jkA})^{2/(m-1)}}, \quad (7)$$

otherwise
$\mu_{ik}^{(l)} = 0$ if $D_{ikA} > 0$, and $\mu_{ik}^{(l)} \in [0,1]$ with $\Sigma_{i=1}^{c} \mu_{ik}^{(l)} = 1$.
Until $||U^{(l)} - U^{(l-1)}|| < \epsilon$.

B. Consequent parameters estimation

Consider the transfer function $G_P^i(z)$ as *i*-th rule consequent sub-model of the TS fuzzy inference system, given by:

$$G_P^i(z) = \frac{b_0^i + b_1^i z^{-1} + \ldots + b_\beta^i z^{-\beta}}{1 + a_1^i z^{-1} + a_2^i z^{-2} + \ldots + a_\alpha^i z^{-\alpha}}, \quad (8)$$

where:

- z is a complex variable, based on Z-transform;
- $a^i_{1,2,\ldots,\alpha}$ and $b^i_{1,2,\ldots,\beta}$ are the *i*-th sub-model parameters;
- α and β are the orders of the numerator and denominator of $G_P^i(z)$, respectively.

The TS fuzzy dynamic model presents the following structure:

$$\begin{aligned}\tilde{y}(k) = \sum_{i=1}^{l} \gamma^i(k)[b_0^i u(k) + \ldots + b_\beta^i u(k-\beta) - \\ + a_1^i y(k-1) - a_2^i y(k-2) - \ldots - a_\alpha^i y(k-\alpha)]\end{aligned} \quad (9)$$

In matricial form, results:

$$\widetilde{\mathbf{Y}}(\mathbf{k}) = \Gamma^1 \mathbf{X}(\mathbf{k}) \Theta^1 + \ldots + \Gamma^i \mathbf{X}(\mathbf{k}) \Theta^i \quad (10)$$

where:

$$\begin{aligned}X(k) = [u(k)|u(k-1)|\ldots|u(k-\beta)|y(k-1)| \\ |-y(k-2)|\ldots|-y(k-\alpha)]\end{aligned} \quad (11)$$

is called the regressors matrix ,

$$\Theta^i = \begin{bmatrix} b_0^i \\ b_1^i \\ \vdots \\ b_\beta^i \\ a_1^i \\ a_2^i \\ \vdots \\ a_\alpha^i \end{bmatrix} \quad (12)$$

is the vector of the submodel parameters in i-th rule,

$$\Gamma^i = \begin{bmatrix} \gamma^i(0) & 0 & \ldots & 0 \\ 0 & \gamma^i(1) & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & \gamma^i(N) \end{bmatrix} \quad (13)$$

is the diagonal weighting matrix of i-th rule,

$$\widetilde{\mathbf{Y}}(\mathbf{k}) = \begin{bmatrix} \tilde{y}(0) \\ \tilde{y}(1) \\ \vdots \\ \tilde{y}(N) \end{bmatrix} \quad (14)$$

is the output vector of fuzzy model.

Considering the output vector of the uncertain dynamic system as

$$\mathbf{Y}(\mathbf{k}) = \begin{bmatrix} y(0) \\ y(1) \\ \vdots \\ y(N) \end{bmatrix} \quad (15)$$

applying the least squares algorithm in order to reduce the approximation error between the outputs of the fuzzy model and the uncertain dynamic system, the parameters vector of the sub-models in the consequent space can be estimated as follow:

$$\begin{aligned}\Theta^1 &= (\mathbf{X}'\Gamma^1\mathbf{X})^{-1}\mathbf{X}'\Gamma^1\mathbf{Y(k)} \\ \Theta^2 &= (\mathbf{X}'\Gamma^2\mathbf{X})^{-1}\mathbf{X}'\Gamma^2\mathbf{Y(k)} \\ &\vdots \\ \Theta^l &= (\mathbf{X}'\Gamma^l\mathbf{X})^{-1}\mathbf{X}'\Gamma^l\mathbf{Y(k)}\end{aligned} \quad (16)$$

III. Strategy for robust fuzzy digital PID controller design

A. Tuning formulas for model based control via gain and phase margins specifications

The Takagi-Sugeno (TS) fuzzy inference system to be used as model of the uncertain dynamic system, presents the $i|^{[i=1,2,\ldots,l]}$-th rule given by:

$R^{(i)}$: IF $\widetilde{y}(k-1)$ IS $F^{i}_{k|\widetilde{y}(k-1)}$ THEN

$$G^{i}_{P}(z) = \frac{K^{i}_{1}z + K^{i}_{2}}{a^{i}z^{2} + b^{i}z + c^{i}}$$

where a^{i}, b^{i}, c^{i}, K^{i}_{1}, and K^{i}_{2} are the parameters to be estimated by least square algorithm. The variable $\widetilde{y}(k-1)|^{[t=1,2,\ldots,n]}$ belongs to fuzzy set $F^{i}_{k|\widetilde{y}(k-1)}$ with a value $\mu^{i}_{F_{k|\widetilde{y}(k-1)}}$ defined by a membership function $\mu^{i}_{\widetilde{y}(k-1)} : R \rightarrow [0,1]$, with $\mu^{i}_{F_{k|\widetilde{y}(k-1)}} \in \mu^{i}_{F_{1|\widetilde{y}(k-1)}}$, $\mu^{i}_{F_{2|\widetilde{y}(k-1)}}$, $\mu^{i}_{F_{3|\widetilde{y}(k-1)}}$, ... ,$\mu^{i}_{F_{p_{\widetilde{y}(k-1)}|\widetilde{y}(k-1)}}$, where $p_{\widetilde{y}(k-1)}$ is the partitions number of the universe of discourse related to linguistic variable $\widetilde{y}(k-1)$ [15]–[17]. The TS fuzzy digital PID controller, according to Parallel Distributed Compensation (PDC), presents the $j|^{[j=1,2,\ldots,l]}$-th rule given by:

$R^{(j)}$: IF $\widetilde{y}(k-1)$ IS $F^{j}_{k|\widetilde{y}(k-1)}$ THEN

$$G^{j}_{c}(z) = \frac{\alpha^{j}z^{2} + \beta^{j}z + \gamma^{j}}{z^{2} - z}$$

where:

$$\alpha^{j} = K^{j}_{P} + \frac{K^{j}_{I}T}{2} + \frac{K^{j}_{D}}{T} \tag{17}$$

$$\beta^{j} = \frac{K^{j}_{I}T}{2} - K^{j}_{P} - \frac{2K^{j}_{D}}{T} \tag{18}$$

$$\gamma^{j} = \frac{K^{j}_{D}}{T} \tag{19}$$

where K^{j}_{P}, K^{j}_{I},and K^{j}_{D} are proportional, integral, and derivative fuzzy controller gains, and T is the sample time, respectively [18].

In the direct path of closed-loop control system, considering the TS fuzzy model, the time delay z^{-m}, and the fuzzy digital PID controller, it has:

$$\begin{aligned} G_{c}(\widetilde{y}(k-1),z)G_{p}(\widetilde{y}(k-1),z) &= \sum_{j=1}^{l}\sum_{i=1}^{l}\gamma_{i}(\widetilde{y}(k-1))\times \\ &\times\gamma_{j}(\widetilde{y}(k-1)) \times \left(\frac{\alpha^{j}z^{2} + \beta^{j}z + \gamma^{j}}{z^{2}+z}\right) \times \\ &\times\frac{K^{i}_{1}z + K^{i}_{2}}{a^{i}z^{2} + b^{i}z + c^{i}}z^{-m} \end{aligned} \tag{20}$$

The gain and phase margins of the fuzzy control system are given by:

$$arg[G_{c}(\widetilde{y}(k-1),e^{j\omega_{p}})G_{P}(\widetilde{y}(k-1),e^{j\omega_{p}})] = -\pi \tag{21}$$

$$A_{m} = \frac{1}{|G_{c}(\widetilde{y}(k-1),e^{j\omega_{p}})G_{P}(\widetilde{y}(k-1),e^{j\omega_{p}})|} \tag{22}$$

$$|G_{c}(\widetilde{y}(k-1),e^{j\omega_{g}})G_{P}(\widetilde{y}(k-1),e^{j\omega_{g}})| = 1 \tag{23}$$

$$\phi_{m} = arg[G_{c}(\widetilde{y}(k-1),e^{j\omega_{g}})G_{P}(\widetilde{y}(k-1),e^{j\omega_{g}})] + \pi \tag{24}$$

where the gain margin is given by (21) and (22), and the phase margin is given by (23) and (24), respectively. The ω_{p} is called phase crossover frequency and ω_{g} is called gain crossover frequency [19][20].

IV. Robust Stability Analysis

For the robust fuzzy PID digital controller design, based on the gain and phase margins specifications, the following theorems are proposed:

Theorem 1: Each robust digital PID sub-controller, $G^{j}_{c}(z)|^{[i=1,2,\ldots,l]}$, in the rule base consequent of the TS fuzzy PID controller, guarantees stability to the respective linear submodel $G^{i}_{p}(z)|^{[i=1,2,\ldots,l]}$, in the rule base consequent of the TS fuzzy model of the plant to be controlled, i. e., with $i=j$.

Proof: The proof of this theorem is not shown once there is no space enough in this paper [21].

Theorem 2: The robust fuzzy digital PID controller, $G_{c}(\widetilde{y}(k-1),e^{j\omega T})$, guarantees the gain and phase margin specifications to fuzzy control system.

Proof: The proof of this theorem is not shown once there is no space enough in this paper [21].

V. Multiobjective Genetic Strategy for Controller Tuning

The proposed genetic strategy considered to optimize the parameters α^{j}, β^{j} and γ^{j} of fuzzy digital PID controller in the *j*-th rule from the gain and phase margins specifications, presents the cost function given by:

$$Cost = \delta_{1}f_{c1} + \delta_{2}f_{c2} \tag{25}$$

with

$$f_{c1} = |A_{mc} - A_{me}| \tag{26}$$

$$f_{c2} = |P_{mc} - P_{me}| \tag{27}$$

$$\delta_{1} + \delta_{2} = 1 \tag{28}$$

where A_{mc} and P_{mc} correspond to gain and phase margin computed; A_{me} and P_{me} correspond to gain and phase margin specified, respectively; and, $\delta_{1} = \delta_{2} = 0.5$. The crossover between two chromosomes generates two new offspring by a simple crossover operator, which performs a weighted sum between the parents in order to generate the offspring, as follow:

$$\begin{aligned} chromosome_{1} &= [p_{m1}, p_{m2}, p_{m3}..., p_{mn}] \\ chromosome_{2} &= [p_{p1}, p_{p2}, p_{p3}..., p_{pn}] \\ d_{new1} &= \eta * p_{mn} + (1-\eta) * p_{pn} \\ d_{new2} &= \eta * p_{pn} + (1-\eta) * p_{mn} \end{aligned} \tag{29}$$

where the terms p_{mn} and p_{pn} represent the n genes of mother chromosome ($chromosome_1$) and genes of father chromosome ($chromosome_2$) respectively, d_{new} is the new offspring generated from two chromosomes and η is a random value between 0 and 1. The mutation operator selects randomly a gene from the chromosome of the population and changes its value to any other, within the range of possible values that the gains of the fuzzy controller can take. The best chromosome of the previous generation is keeped for the next generation, which is complemented by offspring and the result of the mutation on them. The stages of evaluation, classification, partner selection, crossover, mutation, and formation of the new population are repeated at each iteration of the algorithm [22]–[24].

VI. Experimental Results

A. Description of the platform for real time control of a thermic process

The platform for real time control is composed of the thermic process, the software *LabVIEW*, the *CompactRIO 9073*, the analog input module *NI 9219*, the analog output module *NI 9263*, the temperature sensor *LM 35* and the actuator based on *CI TCA 785*. The thermic process consists in an AC 220Volts monophasic toaster, with functional temperature in the interval from 25°C to 265°C. The *LabVIEW* is a graphical programming language in which the supervisory system will be developed for real time analysis of the closed loop control: the temperature signal is received by sensor from the data acquisition system, which is compared to reference temperature; the error signal is processed by robust fuzzy PID controller and the control signal is sent to the thermic process. The acquisition data platform for real time robust fuzzy PID control of the thermic process is shown in the Fig. 1.

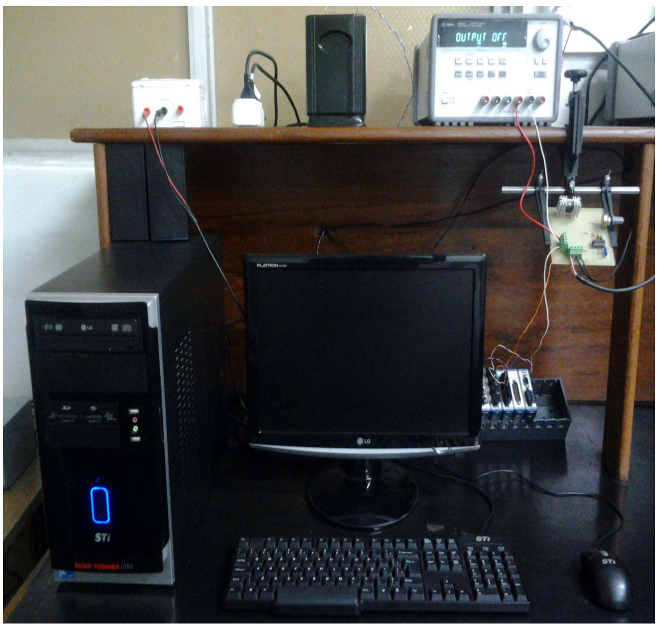

Fig. 1. Platform control system of the thermic process

B. TS Fuzzy modeling for thermic process

In the identification procedure, it was used the input and output signals of the uncertain dynamic system, as shown in Fig. 2 . The time delay was estimated by computing sample cross-correlation function between the input and the output signals, resulting in a time delay of 1360 samples, considering the sample time of 17ms, corresponding to 2.312 seconds [25], as shown in Fig. 3.

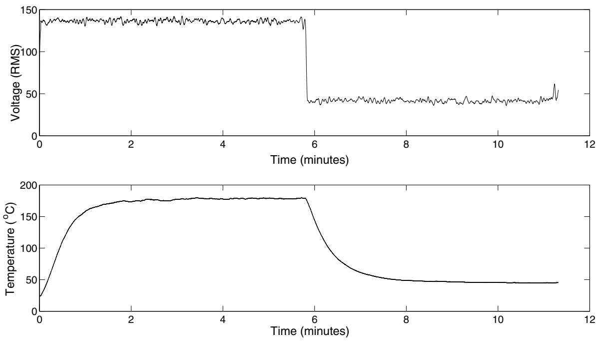

Fig. 2. System identification - input (voltage) and output (temperature) signals

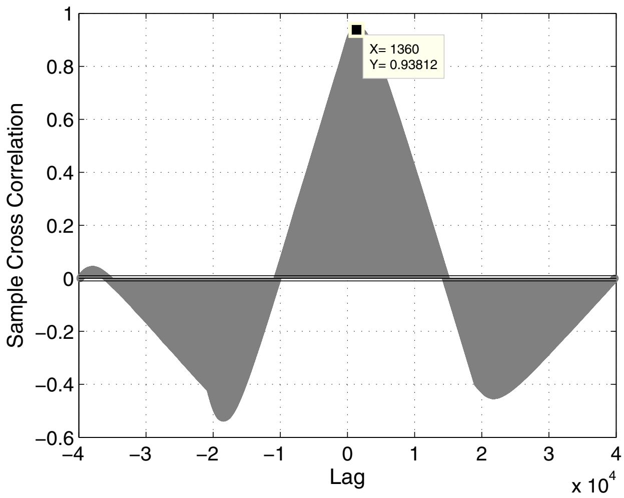

Fig. 3. Cross correlation function between input and output signals

In order to estimate the fuzzy sets, the FCM (Fuzzy C-Means) algorithm was implemented for 2 clusters, weighting exponent $m = 1.2$ and tolerance $\epsilon = 0.01$. The fuzzy sets obtained are shown in Fig. 4. It is observed that two submodels contribute to process behavior: for temperature under 80°C the process behavior corresponds to first submodel, above 140°C corresponds to second submodel, and between 80°C e 140°C, two submodels from membership degree contribute to process behavior.

From the data input and output of the uncertain dynamic system, taking into account the weights of fuzzy sets, the least squares algorithm was applied for parameter estimation of the consequent submodels, resulting in the fuzzy model structure of the uncertain dynamic system to be controlled. However, the identified TS fuzzy model was submitted to optimization procedure by genetic algorithm to improve DC gains to submodels. The gains obtained were $g_1 = 0.0055$ and $g_2 = 0.72$, corresponding to submodels G_p^1 and G_p^2, respectively. A comparative analysis for the temporal response performance of the thermic process, TS fuzzy model optimized and identified is shown in Fig 5. The identified TS fuzzy model after optimization procedure is given by (30) and (31).

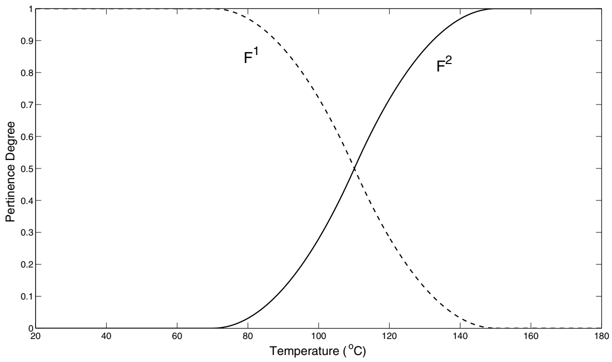

Fig. 4. Estimated membership functions by FCM algorithm

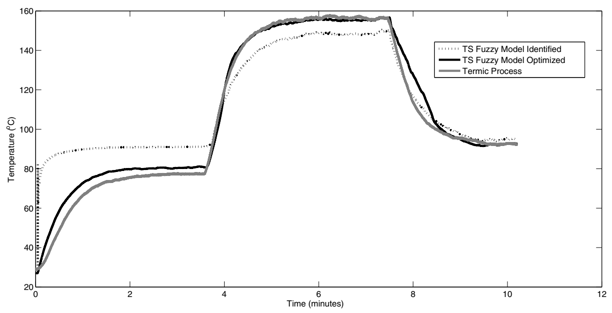

Fig. 5. Fuzzy modeling of the thermic process: identified TS fuzzy moc (dotted line), thermic process (gray line), optimized TS fuzzy model (black line)

$$R^1 : IF\ Temperature \text{ is } F^1 \text{ , THEN}$$

$$G_p^1(z) = 0.0055 \frac{0.0513z + 0.0504}{z^2 - 0.5815z - 0.4177} z^{-136} \tag{30}$$

$$R^2 : IF\ Temperature \text{ is } F^2 \text{ , THEN}$$

$$G_p^2(z) = 0.72 \frac{0.1344z - 0.1334}{z^2 - 0.5921z - 0.4072} z^{-136} \tag{31}$$

where:

$$F^1(a,b)\,|^{a=70;b=150.2} \tag{32}$$

$$\begin{cases} 1, Temperature \leq a \\ 1 - 2\left(\frac{Temperature - a}{b-a}\right)^2, a \leq Temperature \leq \frac{a+b}{2} \\ 2\left(b - \frac{Temperature}{b-a}\right)^2, \frac{a+b}{2} \leq Temperature \leq b \\ 0, Temperature \geq b \end{cases}$$

and $F^2 = 1 - F^1$.

From the multiobjetive genetic strategy proposed in this paper, specifying the appropriate gain and phase margins for the fuzzy control system, and considering the fuzzy model of the uncertain dynamic system with time delay of $m = 136$, the parameters of the fuzzy digital PID controller were obtained, according to Tab. I. It can be seen the eficiency of the proposed methodology in the model based PID controller design, since the gain and phase margins obtained of the fuzzy control system keeping closed of the specified ones. The Bode Diagram of $G_p^1 G_c^1 z^{-\tau/T}$ and $G_p^2 G_c^2 z^{-\tau/T}$ are shown in Fig. 6 and Fig. 7, respectively.

TABLE I

PARAMETERS OF PID CONTROLLER AND GAIN AND PHASE MARGINS OBTAINED TO SUB-MODELS ($A_{me} = 2.5, P_{me} = 60°C$)

Submodel	(A_{mc}, P_{mc})	PID parameters (α, β, γ)
G_p^1	$(2.9643, 63.8115°C)$	$(10.24, -10.47, 0.2353)$
G_p^2	$(2.5936, 62.6088°C)$	$(2.297, -2.368, 0.07442)$

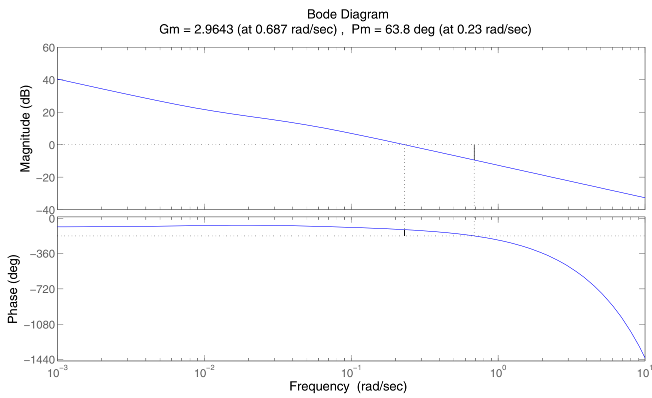

Fig. 6. Bode Diagram of $G_p^1 G_c^1 z^{-\tau/T}$

The multiobjective genetic algorithm used the following parameters: 300 generations, random initial population of 100 chromosomes, selection rate of 50% and mutation rate of 12%. The performance of the multiobjetive genetic strategy to minimize the multiobjetive cost function, according to the number of generations and the possible solutions computed by GA (Pareto region), is shown in Fig. 8 and Fig. 9, respectively. In Fig. 9, the best solution is in red.

The parameters of fuzzy digital PID controller obtained by the multiobjetive genetic strategy proposed was compared to Ziegler-Nichols Method [18]. The temporal response performance of the proposed methodology is shown in Fig. 10. The initial condition for temperature set point was of 100°C. The changing to 150°C in the temperature set point was applied

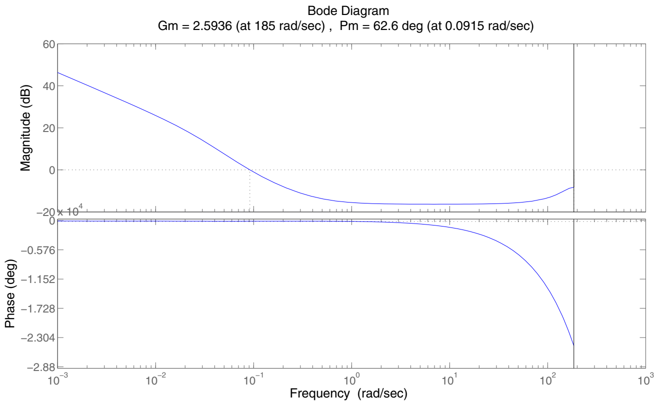

Fig. 7. Bode Diagram of $G_p^2 G_c^2 z^{-\tau/T}$

at 425 seconds. A gain variation was applied to the termic process at 212 seconds.

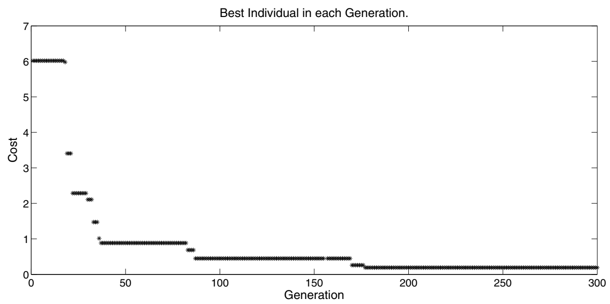

Fig. 8. The cost of the best individual in each generation

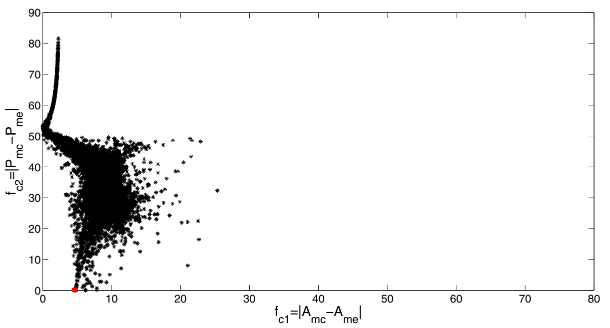

Fig. 9. Pareto region computed by multiobjective GA. The best solution is in red.

Control action obtained with the robust fuzzy digital PID controller and de Ziegler-Nichols controller, and instantaneous gain and phase margins obtained with the robust fuzzy PID controller, as shown in Fig. 11 and Fig. 12, respectively. Instantaneous membership values of fuzzy controller is show in Fig. 13.

VII. Conclusions

The proposed robust fuzzy digital PID controller, during the process, ensured values close to the gain and phase

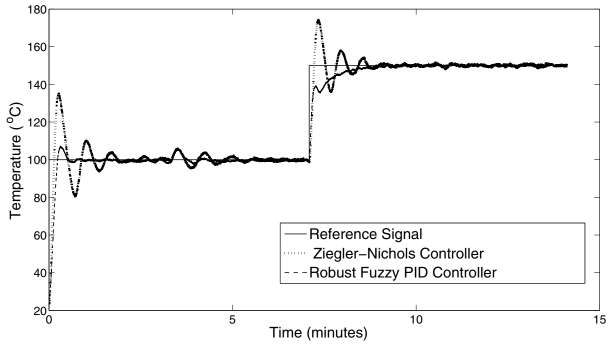

Fig. 10. Temporal response performance of the Ziegler-Nichols controller and robust fuzzy PID controller

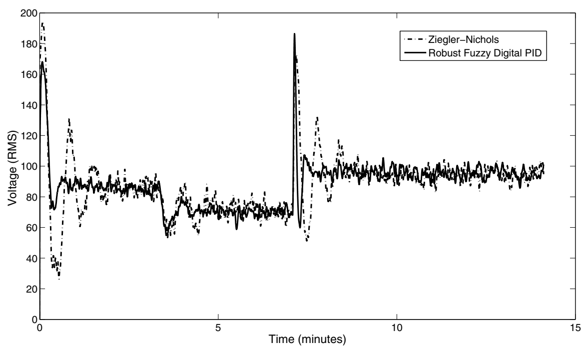

Fig. 11. Control action from the robust fuzzy digital PID controller and the Ziegler-Nichols PID controller

margins specified in the controller design by multiobjective genetic strategy applied to the thermic process showed robustness and stability.

Furthermore, it was efficient to the tracking of the reference trajectory, compared to a classic PID controller (Ziegler-Nichols), despite of dynamics that interfere the process behavior, such as nonlinearities, uncertainties and time delay, proving the efficiency of the proposed methodology as well as the experimental proof of the theorems proposed.

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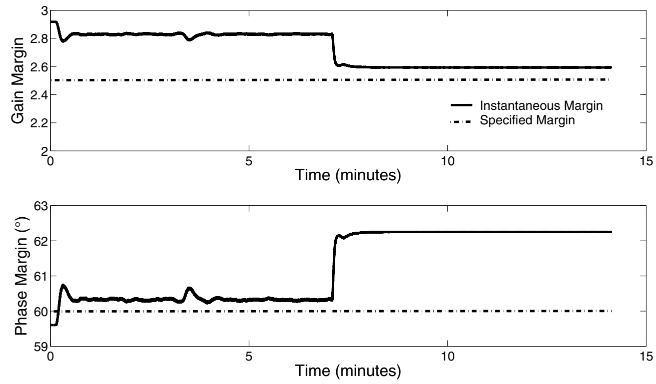

Fig. 12. The instantaneous gain and phase margins for the robust fuzzy PID control system

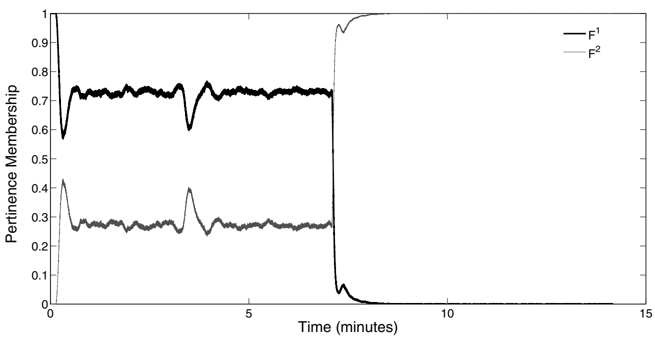

Fig. 13. Instantaneous membership degrees of the robust fuzzy PID controller

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