ADAPTIVE PID CONTROLLERS TUNING: LMS GAIN SCHEDULING TRAINING AND INDUSTRIAL PROGRAMMABLE LOGIC CONTROLLERS

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Abstract— The main issue of this article is the blending of *LMS* training with the artificial neural network theory for design and improvement of *PID* type controllers tuning. The *LMS* method and the neural theory contribute for the gain adjustments and to establish the plant-activation function, respectively. Thus, the Plant-*PID* dynamic system is seen as a single entity, providing the base of the proposed method for controllers design through *ANNs*. The proposed method is based on a stochastic optimization structure which puts together the target variables and its restrictions. This structure is solved according to an extension of the *LMS* method, taking into account the adapting controller design of programmed type. These models form the base for the development of logarithms to be implemented in the programmable logic controllers. The *PID* adaptive control system is synthesized in industrial programmable logic controllers due to its high computing power. The gain adjustments via *LMS* training is used to evaluate the *DC* motor speed control performance of the method.

Keywords— Artificial Neural Network, PID tuning, Industrial Process, PLC, LMS and DC electrical motor.

1 Introduction

The importance of PID Controllers can be proved not only by its industrial application, but also by the large amount of research documentation available in technical and scientific congress annals and journals. It could be said that the induction motor is the industry main drive and the PID control systems are the main structures of the industrial controllers.

The PID controllers originally appeared in the XXs, (Datta et al., 2000), despite of easily comply with its digital version, its gaining tuning problem, (Yu, 1999), it still remains as a challenge for the designer, (Pedret et al., n.d.). In industry, the PID synthesis is associated by Programmable Logic Controllers (PLC); these are semiconductor devices using integrated circuits instead of electromagnetic devices to implement the control.

The PLCs general features are high logic capability and functionality, in a way that they are able to execute instructions, such as, timing, counting, arithmetic, communication and data manipulation to control industrial machines and processes (Hackworth and D.Hackworth, 2001) and (Ioannides, 1997).

This work is formed by Sections which comprise the controller tuning method of differential and integral proportional type (PID). Initially, we have introduced the PID controller tuning, Section 2, by means of *Ziegler-Nichols*, artificial intelligence (AI) and linear quadratic regulator (LQR) methods, so as to show and comment the procedures of these two trends in order to adjust its gains. The development of the method for PID-least mean square (PID-LMS) tuning is presented in Section 3, focus on the association of the proposed method with the LMS gains adjustment theory and with the artificial neural networks (ANN). In Section 4, gain-scheduling PID design is developed in terms of PID tuning so as to improve the control system performance, which are designed for a Direct Current (DC) servomotor speed control. The technical feasibility assessment for adapting PID implementation of programmable gain is discussed in real time for PLC, Section 5, the adaptive PID programmable gain algorithm is synthesized in a ladder language diagram. The conclusions and trade-offs are discussed in the last section. The servomotor board data and PLC are addressed in Appendix A.

2 PID controller Tuning

Due to its control actions, the PID controller has been surviving to radical technological advances in the 20th century. This can be proved in (Datta et al., 2000) who considers PID the most important thing when it comes to industrial processes. Until 2000, (Yu, 1999), 90% of the controllers in industrial processes were the PID type and performed PI. The need for its use until the end of the 20th is represented by the investigation of new method of PID synchronization. The authors stress the controller deficiency in terms of the industrial sectors classification and the internal hierarchy in terms of operational behavior associated with project value figures and/or gain adjustments.

The PID controllers' adjustments have been done by methods based on time and frequency. The time approach considers the dynamic system stimulated by degrees or pulses and, according to the process response particularities, the process standard parameters are calculated. These tests are conducted using open or close filter, as the first is sensible to load disturbances and the latter represents time reduction. The chosen controllers provoke oscillations in the responses. As a consequence, the process is close to a lessen behavior. The most common method is the *Ziegler-Nichols*, (Yu, 1999), and is considered as an experimental type that uses a identification systems theory/procedures for gain adjustment.

Other methods used to perform gains adjustments are based on artificial intelligence (AI) and linear quadratic regulator (LQR). The artificial neural networks, (Kato et al., 2005) and (MYao Zhang Sen, 1995), genetic algorithms, (Herrero et al., 2002), and fuzzy logic, (Kim, 2001) are the new approaches developed to tune the gain of PID controllers family.

2.1 LQR Adjustment

The LQR controller adjustment method developed by (Ferreira et al., 2003) has as base, the location of auto structures and genetic algorithms. The PID tuning against the artificial neural network is represented as a proposal for the gain determination. The tuning of the LQR optimal controller is developed in patterns in the space of the dynamic system condition. The tuning of its controllers has been explored. These values uses approximate changes in potential series that are derived from an LQR canonic formulation. Recent results certify the viability for the controllers' synthesis by an optimum controller technique, not only for gain adjustments but for the LQR robust filter recover, after the insertion of state observers. The main suggestions proposed by these authors are models of evolutionary computation of genetic algorithm type.

3 PID-LMS Tuning

The PID controller gain adjustment is based on a neural structure of perceptron type of Figure 1, the error signal is pre processed, the linear combiner representing PID gain structure and activation function that represents the drive. The gain adjustment is seen as a neural unit in the Rosenblat sense that is performed by the LMS method.

The adaptive adjustment mechanisms has its foundations in the recursive least squares (RLS)

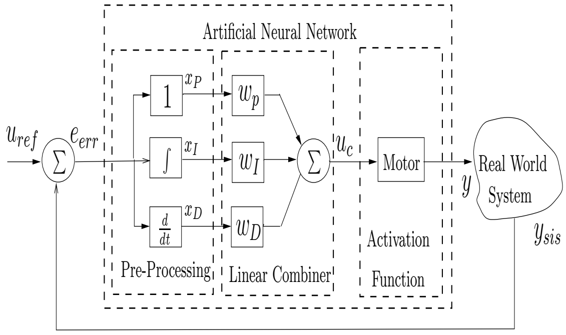

Figure 1: General Diagram representing the PID-Plant-ANN.

family. Specifically, the LMS method to minimize feedback errors.

$$
\begin{aligned}
min_e &= E\{(u_{ref}(t) - y(t))^2\} && (1)\\
\text{sa} & \\
w_{PL} &< w_P < w_{PU} && (2)\\
w_{IL} &< w_I < w_{IU} \\
w_{ID} &< w_D < w_{DU}
\end{aligned}
$$

The *Wiener-Hopt* equations, (Haykin, 1994), for PID gain adjustment,

$$
\begin{aligned}
\omega_P\Gamma_x(P,P) + \omega_I\Gamma_x(I,P) + \omega_D\Gamma_x(D,P) &= \Gamma_{xref}(P)\\
\omega_P\Gamma_x(P,I) + \omega_I\Gamma_x(I,I) + \omega_D\Gamma_x(D,I) &= \Gamma_{xref}(I)\\
\omega_P\Gamma_x(P,D) + \omega_I\Gamma_x(I,D) + \omega_D\Gamma_x(D,D) &= \Gamma_{xref}(D).
\end{aligned} \tag{3}
$$

where $\Gamma_{j,k}$is the the auto-correlation function of the proportional, integral and derivative errors signals. $\Gamma_{x\phi}(x)$ is the function of the correlation between the reference value and the PID time input signal. Figure 2 shows the LMS adaptive controller.

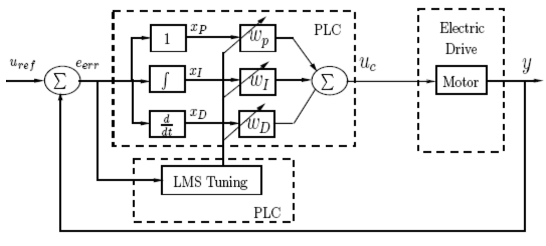

Figure 2: Adaptive *LMS* Controller

Given the vectorial structure,

$$
\begin{bmatrix} \Gamma_{xref}(P) \\ \Gamma_{xref}(I) \\ \Gamma_{xref}(D) \end{bmatrix} =
$$

$$\omega_P \begin{bmatrix} \Gamma_x(P,P) \\ \Gamma_x(P,I) \\ \Gamma_x(P,D) \end{bmatrix} + \omega_I \begin{bmatrix} \Gamma_x(I,P) \\ \Gamma_x(I,I) \\ \Gamma_x(I,D) \end{bmatrix} + \omega_D \begin{bmatrix} \Gamma_x(D,P) \\ \Gamma_x(D,I) \\ \Gamma_x(D,D) \end{bmatrix} \quad (4)$$

where ω_P, ω_I, ω_D are the PID controller gains that are adjusted every interval Δt. The cross variances are symmetric,

$$\omega_{OP}\Gamma_{Px} + \omega_{OI}\Gamma_{Ix} + \omega_{OD}\Gamma_{Dx} = \Gamma_x, \quad (5)$$

where Γ_{Px}, Γ_{Ix} and Γ_{Dx} are the stochastic basis vectors that generates the command signal $u_c(t)$,

$$u_c(t) \;=\; \hat{\omega}_P(t)x_P(t) + \hat{\omega}_I(t)x_I(t) + \hat{\omega}_D(t)x_D(t) \quad (6)$$

where $x_P(t)$, $x_I(t)$ and $x_D(t)$ are the neuronal inputs that are weighted by $\hat{\omega}_P(t)$, $\hat{\omega}_I(t)$ e $\hat{\omega}_D(t)$, respectively. Corresponding to the PID gains, with this purpose, it is considered that the controllers' adjustments are performed during Δt time intervals associated with parameter variations. A set of optimal gains are defined for several operational conditions that are established load variations or parameter variations.

The adaptive digital PID controller in its first abstraction is represented by the functional units of the PID control law,

$$u_c = \sum_{i=1}^{(P,I,D)} \omega_i x_i, \quad (7)$$

where ω_i is the controller gain and x_i is delayed inputs. The second part represents the gain adjustment, (Haykin, 1994), for the design operational conditions,

$$\hat{\omega}^k_{PID}(t+1) = \hat{\omega}^k_{PID}(t) + \eta_{PID}e^k(t)\hat{x}^k_{PID}(t), \quad (8)$$

where $\hat{\omega}^k_{PID}$ is the estimation for the u^k_{ref} operation condition, represented in Figure 2, and η_{PID} is the learning rate. The Eqs (7) and (8) constitute the digital controller core and the relations between these equations.

The developed method to tune the PID controller in real time, based on structure the artificial neural PID controller of Figure 3, has the pre processing, linear combiner and LMS training units implemented in a PLC. This implementation have performed by some researchers using on shelf micro controllers. An implementation using the PIC controller can be seen in (Turibe, 2006.).

The advantage of using a industrial PLC, Appendix A, are the flexibility and pre defined functions, such as PID control. In the case of applications using micro controllers the the routines must be be developed (Turibe, 2006.).

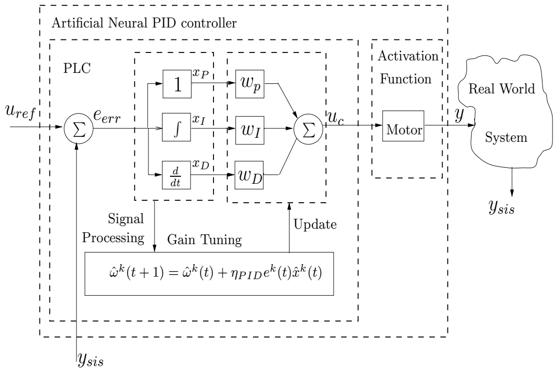

Figure 3: *LMS* Adjustment Unit.

The artificial neural PID adaptive controller, Figure 3, is established by the processing unit that performs integration and derivation of the error signal. The linear combiner unit gives the u_c control signal that has two inputs: the signal from the pre processing and updated weights from the LMS training units. The activation function is based on the control actuator model, in our case is the DC motor.

4 Gain-Scheduling PID Design

A design methodology for the gain-scheduling controllers, a type of adaptive controller, (Astrom and Wittenmark, 1989), is presented in terms of the PID controller tuning to support several operational conditions. These controllers are designed to control the speed of a DC motor, with independent excitation, based on the theory developed in Section 3.

4.1 Digital PID Controller

The PID digital controller structure in the time domain,

$$u^{PID}_k \;=\; K_P e_k + K_I \sum_i^{k-1} e_k + K_D \frac{e_k - e_{k-1}}{T_s} \quad (9)$$

where u^{PID}_k is the k-th control signal for interval sampling of T_s seconds.

4.2 Plant Dynamic Model

This topic focuses on the model equations which rules the plant behavior and are fitted for the PID controller design. The reference (Krause et al., 1995) shows details of the DC machines theory focusing on the speed control. Applying *Laplace* transformation in these equations,

$$
\begin{aligned}
V_a(s) &= R_a I_a(s) + L_a s I_a(s) + K_v \Omega_r & (10)\\
T_e(s) &= J s \Omega_r(s) + b_p \Omega_r(s) + T_l. & (11)
\end{aligned}
$$

Then,

$$
\begin{aligned}
I_a(s) &= \frac{1}{R_a + sL_a}(V_a(s) - K_V \Omega_r(s)) & (12)\\
\Omega_r(s) &= \frac{1}{Js}(T_e - T_l - b_p \Omega_r(s)) & (13)
\end{aligned}
$$

Figure 4 shows a block diagram of the machine model. This diagram is composed by two models: the first represents the armature and the second represents the mechanic model. Both of them are directly connected through an Eq. (19) and through the re-feeder of the velocity by the constant K_V. The block diagram that represents the armature has the following transfer function,

$$
\frac{I_a}{V_a - K_V \omega_r - R_a} = \frac{1}{L_a s}
$$

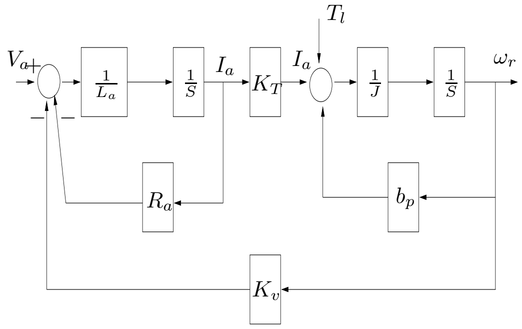

Figure 4: DC Motor block diagram for PID controller design.

The DC machine block diagram, Figure 4, can be represented by transfer functions,

$$
\begin{aligned}
g_1(s) &= \frac{1}{L_a s + R_a} & (14)\\
g_2(s) &= \frac{1}{Js + b_p}, & (15)
\end{aligned}
$$

The armature terminal voltage equation,

1

$$
V_a = R_a I_a + L_a \frac{dI_a}{dt} + E_a. \qquad (16)
$$

The armature voltage,

$$
\begin{aligned}
E_a &= K_a \phi \omega_r & (17)\\
& & (18)
\end{aligned}
$$

and

$$
T = K_T I_a, \qquad (19)
$$

If $T_L = 0$, Figure 4, is obtained easily a new simplification for describing the DC machine as transfer functions,

$$
\frac{\Omega_r(s)}{V_a(s)} = \frac{\frac{K_T}{JL_a}}{s^2 + (\frac{R_a}{L_a} + \frac{b_p}{J})s + \frac{R_a b_p + K_v K_T}{JL_a}} \qquad (20)
$$

4.3 LMS gain adjustment

Figure 5 represent the rotor speed behavior of the DC motor for the PID first tuning controller. The gain was obtained by try and error in order to obtain a small overshot and accommodation time. The PID can be understood as plate dates and the motor CC values parameters contained in Appendix A.

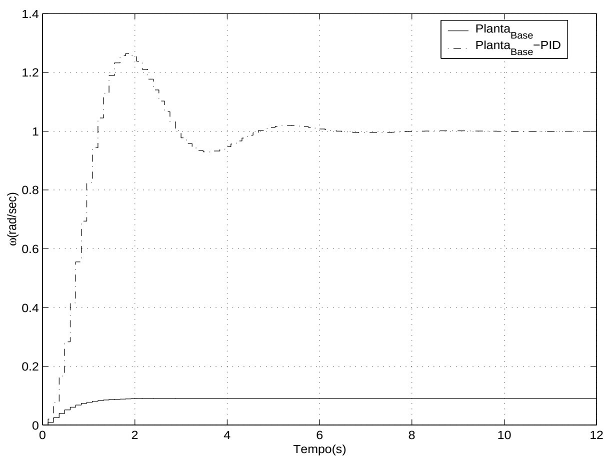

Figure 5: Plant's Behavior and Actions Performance of the base PID Controller.

4.3.1 The Adjustment Problem

The variations of electrical, mechanical, and/or operational parameters of the machine lead to a performance loss. These occurrences trigger a reduction of the equipment's useful time due to the stresses and caused during energizing and/or operation. Consequently, there is a reduction of productivity that is compromised with the cost/benefit relation during the acquisition process and motor commissioning to operate according to a given scheduling.

The variations of these parameters or operation points are called $Plant_1$, $Plant_2$, …, $Plant_n$. In Figure 6 is illustrated the velocity behavior by means of parametric variations in K_t, b, R_a and K_e parameters. The design of programmable control gains, (Astrom and Wittenmark, 1989), that

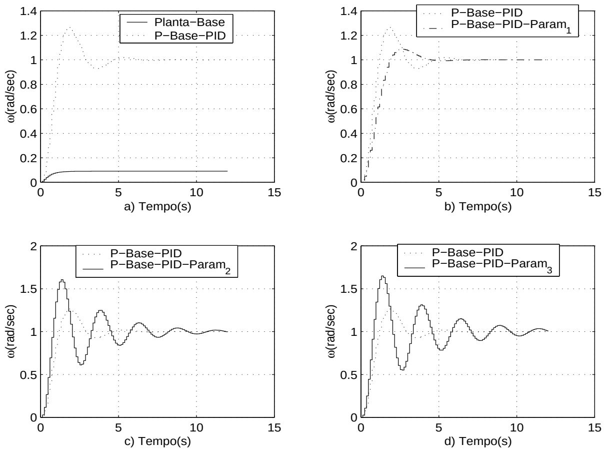

Figure 6: Actions of the base PID Controller for Parametric Variations.

Table 1: Plant Parameter variations.

$Plant_i$	Parameters				
	R	L	K_t	J	b
base	1	0.5	0.01	0.01	0.10
1	1.1	0.55	0.011	0.011	0.11
2	0.9	0.45	0.009	0.009	0.09
3	0.40	0.01	0.0060	0.0060	0.09

are related to the parametric variations shown in Table 1.

The error signals of parametric variations, Figure 7, show the divergence between the specified speed signal and the value measured in the plant. This divergence must be corrected by the optimization structure, Eqs. (1) and (2), due to the PID gains.

4.3.2 LMS Training

The LMS algorithm takes into accounting the evolutions of the adjustment stages in the diagrams of Figures 2 and 3 that represent the abstractions to obtain the error signal processing and the gain adjustment, respectively. The LMS training for determining the gains vector $[\ K_d \quad K_I \quad K_D\ ]$ is based on the relation (8). The error of reference and output signal of the plant, input signals of the linear combiner, Eq. (7), and the learning coefficient η_{PID} must be pre-processed and evaluated in a heuristic way.

The training is carried out off-line; the error signals of Figure 7 are pre-processed in its proportional, integral, and differential forms to satisfy the structure of the digital PID controller, Eq. (9). The behavior of the combiner inputs, Eq. (7), in its proportional, integral, and differential forms to carry out the LMS adjustment that are performed by based on Eq. (8), are shown in Figure 8.

The learning coefficients are adjusted empirically according to the values shown in Table 2. Initially, it assumes the beginning values 1 (one) for η_P, η_I and η_D.

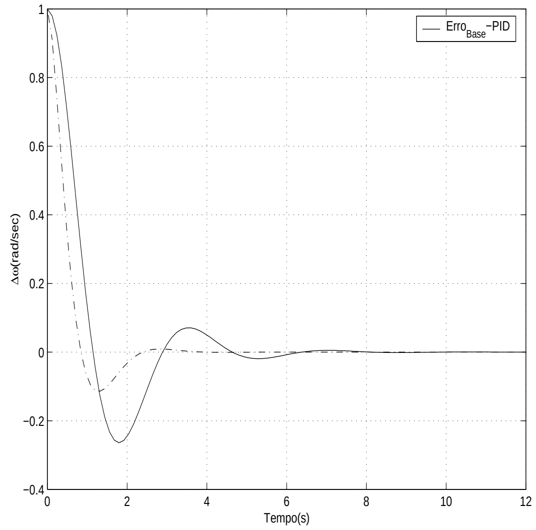

Figure 7: Rotor Speed Error Signals.

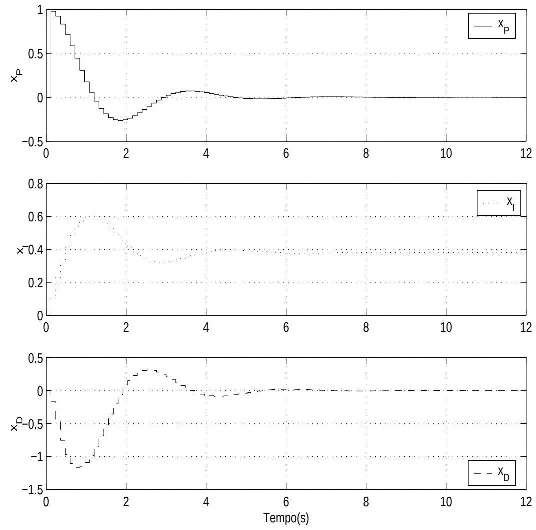

Figure 8: Input Signals for LMS Adjustment.

The evolution of the gain training, Figure 9, or weights show that stability was reached around 0.01 seconds, according to the LMS model, Eq. (8).

The behavior of the velocity signal error, Figure 10, shows an exponential rate decrease relatively slow to reach standard value. That is, the accommodation and ascending times are predominant, but, on the other hand, we do not have the oscillation problems.

Table 2: LMS Method Learning Coefficients.

Plant	η_P	η_I	η_D
ref-LMS	2.0000	30.0000	-0.0001
1	5.0000	24.0000	-0.0001
2	3.0000	28.0000	-0.0001
3	4.0000	25.0000	-0.0001

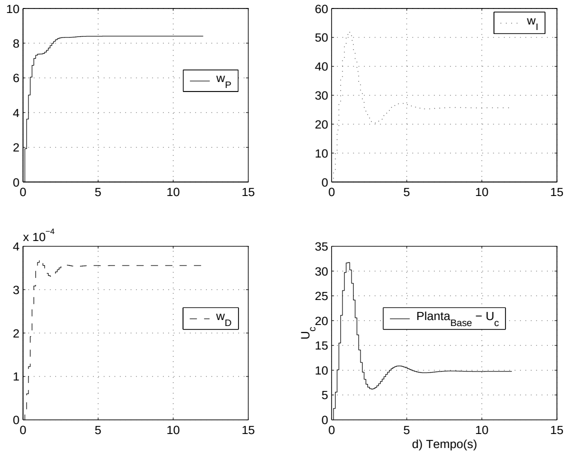

Figure 9: Gains Evolution of the LMS Adjustment.

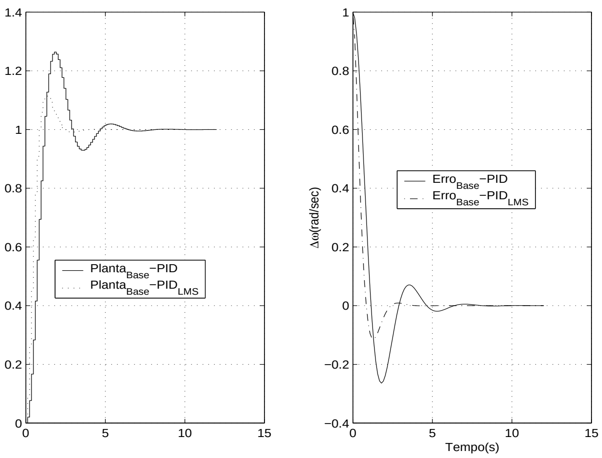

Figure 10: Performance of PID-LMS and reference Controller.

In Figure 10, one has a qualitative view of the PID controllers' performance that are designed through the *Ziegler-Nichols* (ZN) and LMS-neural methods. The LMS accommodation and ascending times are fast as compared to ZN.

4.3.3 LMS Gains Scheduling

Table 3 shows the gains and time constants for the PID that are adjusted according to the LMS model, Eq. (8), that solves the optimization structure, Eqs. (1) and (2).

Table 3: PID Controllers' Programmed Gains.

PID Project	Gains		
Plants	K_P	K_I	K_D
$Base - LMS$	8.0252	26.7313	0.0003
1	25.2038	64.8360	0.0004
2	15.6226	11.8956	0.0002
3	24.1028	11.9151	0.0002

By observing Figures 6 and 11, one verifies a LMS-neural controllers' satisfactory performance. The comparison of LMS error, Figure 12, allows an evaluation of the control objective.

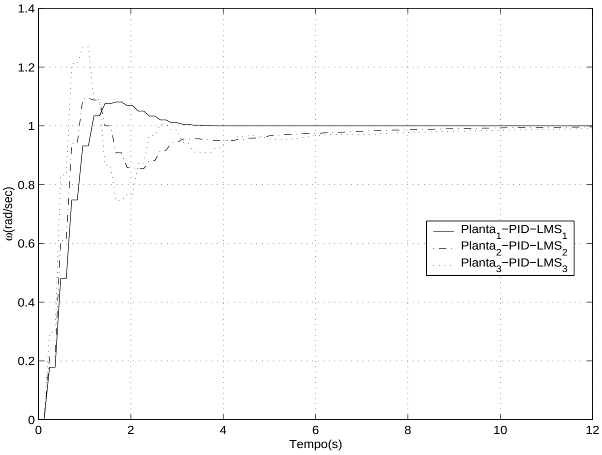

Figure 11: Performance of reference PID-LMS Controller.

5 PLC PID-LMS Real Time Design

The PLC's are electronic equipment used in a flexible automation system. They are very useful and versatile work tools for applications in drive and control systems, and because of that, they are observed in large scale in the industrial environment. They allow an easily altering of the logic output drives by virtue of the inputs, according to the needs pointed out by the process in which it is inserted. Consequently, we can combine several input signals to control several activators connected to the output points. Currently, the PLC has important characteristics that make it the most used device for process control in industrial plants. Some of the most relevant characteristics are described below:

- High level programming language.

- Simplification of the electrical boards.

- Operational Confidence

- Advanced functions, including dynamic control functions and A/d and D/A conversion.

- Communication in industrial and probabilistic nets.

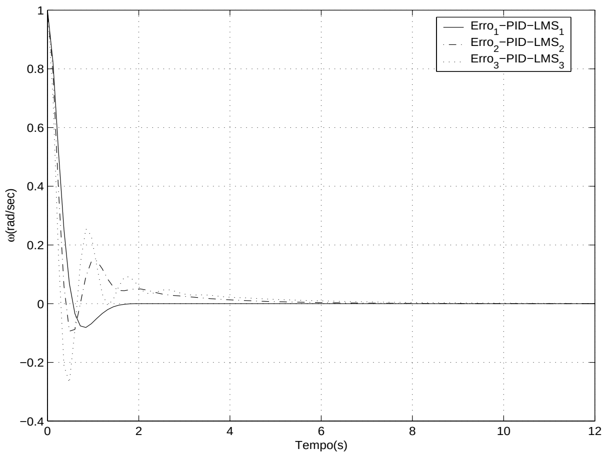

Figure 12: LMS Controllers Signal Errors.

In order to demonstrate the technical viability of programmable gain adaptive PID controllers one suggests the application in a PLC through the synthesized control algorithm in a Ladder language diagram. The control algorithm performs a particular function, the self- adjustable control system, Figure 13, and the gain values are obtained from the programmable gain table. That is, in this application, the coefficients belonging to the PLC's PID block are modified according to the LMS-neural method seen in Section 4.

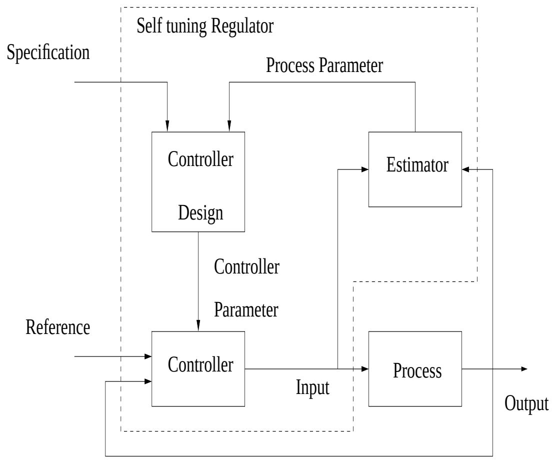

Figure 13: Self-Adjustable Controller Block Diagram.

The development of a control application in the PLC with a PID-type controller is easily implemented with the use of a logic block belonging to the set of functions located in the PLC's processing unit, besides analogical inputs and outputs that receive process information to be controlled.

Figure 14 shows an algorithm that synthesizes this application. In this algorithm is shown the process used to implement the gain scheduling on PLC. First, the gain scheduling was made off-line using LMS-neuronal method, described in Section 4.3. The second step is an on-line procedure, using a PLC loop scan, that the input signal (from sensors) is read and processed. According to reference read from input, like speed motor, the P, I and D gains are selected from gain scheduling. The last step is to process the PLC PID block and to update the output.

In Figure 14 is shown an algorithm that synthesizes this application that was used is this design. The instruction PID was implemented on SLC 500 using the PID block; the reference, process variable and control variable was scaled using the SCP instruction. The gain scheduling was stored in a float data file.

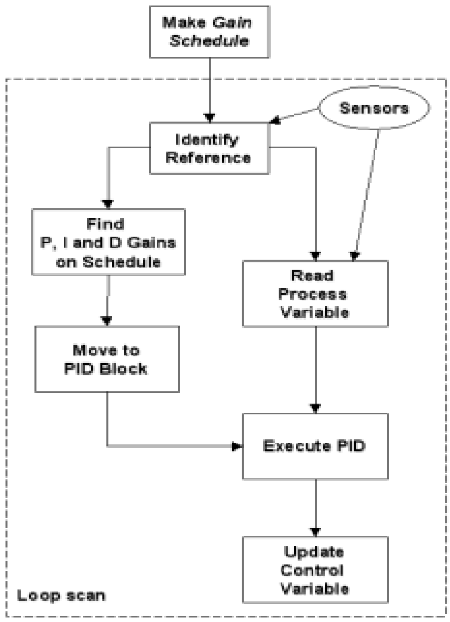

Figure 14: Gain Schedulling PID-PLC Logic Diagram.

6 Conclusion

In general, an artificial neural network approach associated with the PID structure, electric drive and plant to tune the controller gains had been developed and evaluated in the context of design method, control specifications and its synthesis in a PLC.

It had been presented and discussed a method for PID controllers' tuning that is based on the general RLS parameters estimation and artificial neural networks theories. Specifically the artificial biological approach associated with its artificial representations, the training method is the LMS, the PID structure is the linear combiner and the DC drive is the activation function, in this way, the control system (PID structure and DC drive) is seen as a neuron of perceptron type.

The design analysis has shown satisfactory results for real world implementation of the gain scheduling control. The synthesis of PID controllers in PLCs has shown that these devices are flexible and suitable for application on adaptive control systems based on gain scheduling. The LMS method as training rule can be associates a good control results, considering the proposed optimization structure.

A Plate And Parameters Data

The motor and PLC are the main control equipment and devices used to synthesize the control system. The Plate and Parameters data of this control element are shown in Table 4.

Table 4: Electric DC motor Parameters.

Parameter	Value
R	1 Ω
L	0.5 H
Kt	0.01 Nm/Amp
J	0.01 $kg.m^2$
b	0.1 $N - m/rad$

The PLC utilized was the SLC 500 processor 5/05 of Rockwell Automation. The program used to develop this application were the RS Logix 500 and the RS Linx.

Acknowledgements

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