Design of an Adaptive Controller with Online Identification Applied to a Pressure Tank

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Abstract

The objective is to design an adaptive controller for a pressure tank using online identification to obtain the mathematical model of the system. The method considered nonparametric and parametric identification recursive least squares to obtain a ARMAX model of the system dynamics. An adaptive controller for controlling auto-tuning pressure was developed. The simulation was carried out by two operating ranges.

The results show that it has reached a convergence time of 1 s., an identification with extended least squares, a settling time of 10 s. and steady-state error of 3% for the controlled variable. Based on the study, it is concluded that the controller has an acceptable performance against the nonlinearities of the process and does not require re-tune the controller to significant changes in the model or due to perturbance.

Key Words: Adaptive controller, parametric ID, recursive least squares, replacement of poles

Introduction

At present have been used different control algorithms to improve the performance of processes nonlinear nature and time-varying due to the uncertainties and disturbances, also in many cases modeling is difficult especially when the process parameters change frequently, then control requires an accurate knowledge of the process model. One solution is to design a self- tuning controller in response to variations in the dynamics of the process as the adaptive self-tuning controller with on-line identification (Rodriguez, F. and Lopez, M. 1996). Pressure control is critical because many industrial processes that exhibit a strongly nonlinear behavior due to changes in operating conditions and nature of the variation in time (Slotine, E. and Weiping, L. 1991).

Identification of dynamic systems is defined as obtaining a mathematical model using experimental data from measurements made at the input and output of the process, which reproduces the dynamics of the process and is presented as an iterative procedure to find the best model. When the identification is made at each sampling time, this identification is called online.

Algorithm Recursive Identification of Least Squares Estimation in line that has been used is based on the acceptance of an initial structure of the mathematical model (this model has been obtained from the nonparametric and parametric identification offline), which parameters for a work area are known. Knowledge of delay of the system reduces computational time.

Equipment and Materials

For data acquisition used a data acquisition card PCI 6024E DAQ of NI and a personal computer PIII.

The software package used was MatLab v6.5, Simulink and Real-Time Windows Target to generate executable code for real-time implementation. The figure 1 shows the equipment for data acquisition.

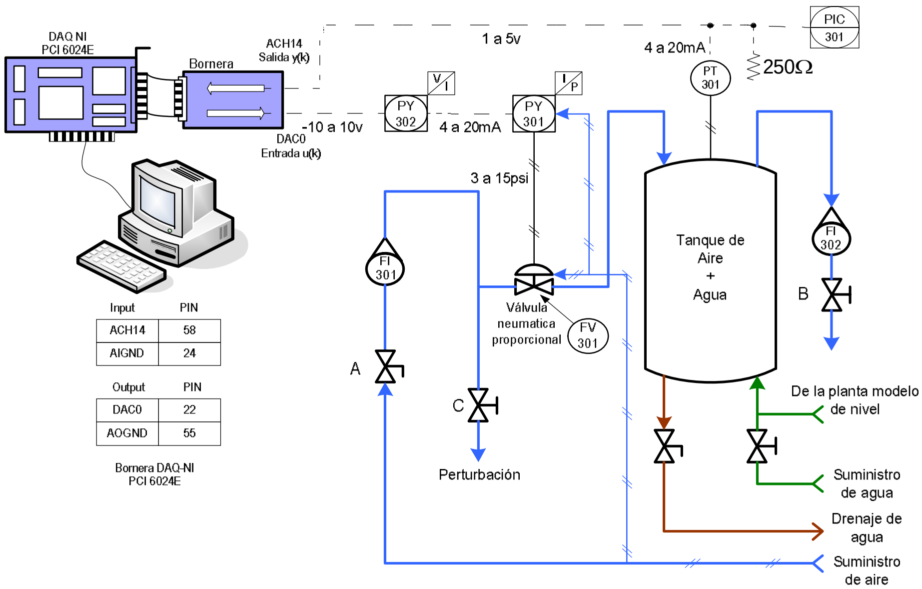

Figure 1. Diagram P&ID for Pressure Tank System.

Methodology

The experimental modeling considers the following steps:

-Nonparametric ID, to know the response to the step signal, the response to the sinusoidal signal, system appropriate sampling time, etc.
-Parametric ID, to know the response to the PRBS signal for obtaining the regression matrix input-output data with those obtained models plant considering disturbance.
-Recursive Online, to estimate model parameters in real-time identification, methods of least squares and extended least squares estimates for the parameters of the model were applied.

Experimental tests on the pressure tank was used to obtain the static characteristic, the nonparametric and parametric identification and identifying online where the parameter is updated in each sampling time. Before identification is necessary to analyze the recorded data and decide if they are the most appropriate for the estimation, especially if they have high frequency noise, those should be removed using Butterworth filters, etc. (Dávalos, J. 2005).

Non Parametric Identification

Spectral analysis was implemented by generating a sinusoidal signal of variable frequency in order to evaluate the response of the process for different frequencies (Aguirre, L. 2000).

Considering the response of frequency to the sinusoidal signal of system was determined when the power spectral density took a very small value with ω about 5 rad/s.

The static characteristic curve allowed a corresponding lift each scalar value of the manipulated variable in the whole area of control. This signal must be large enough to observe the limits of linearity of the process. For purposes of evaluation it considered two linear sections: a zone 1 from 5 to 30% of valve opening and a zone 2 from 35 to 50 % of valve opening.

The transient analysis was performed using step signals. The figure 2 shows the step response of the plant to an opening pressure of valve 5 to 20 % and also 36 to 42%.

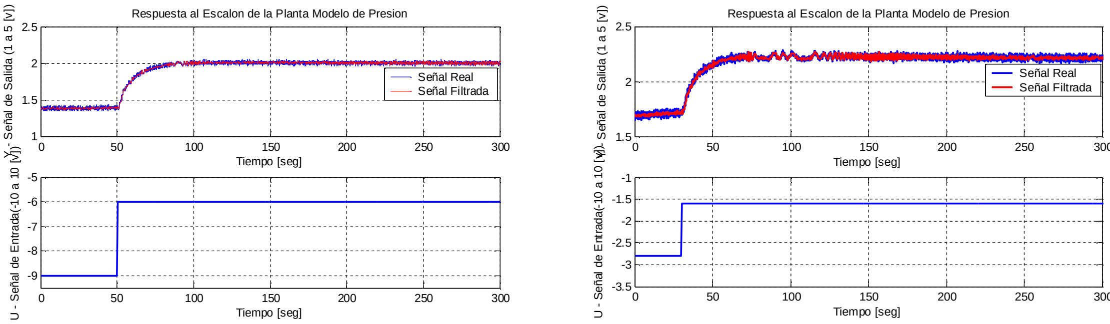

Figure 2. Step Response for valve opening of 5-20 % (Left) and 36-42 % (Right)

For the step response of the plant will approximate it possible for a first-order system, where the system considers estimated air valve (actuator), tank (plant) and the pressure transmitter (sensor). With the magnitudes of the signals and the time corresponding to 63.2% and 28.4% of the final steady state value, must be for the linear zone 1, the static gain K≈0.2262, the time delay L ≈ 0.5 s., constant time τ≈10.8 s. and the settling time ts≈30 s.

For linear zone 2, the static gain K≈ 0.4937, the time delay L≈ 0.5 s., the time constant τ≈11.85 s. and settling time ts≈ 30 s. Then, the non-parametric model of the system is:

$$G_P(s) = \frac{0.2262}{10.8s+1} e^{-0.5s} \tag{1}$$

Parametric Identification

Parametric identification is based on structured model as ARX, ARMAX, OE, BJ, etc., and finite structure parameters. For the parametric identification is necessary to generate a signal of pseudo-random binary sequence (PRBS), these signals are periodic in nature, relatively short periods that are close to white noise with constant spectral density over a wide range of frequencies (Ljung, L. 1987).

The response to a PRBS signal is designed to acquire data from input-output containing the best process information. Ten thousand samples were recorded with a time process of sampling 0.1 s, which are shown in figure 3. The PRBS signal amplitudes are defined by the ranges of valve opening. Previous knowledge of the process facilitates the choice of delay and order of system.

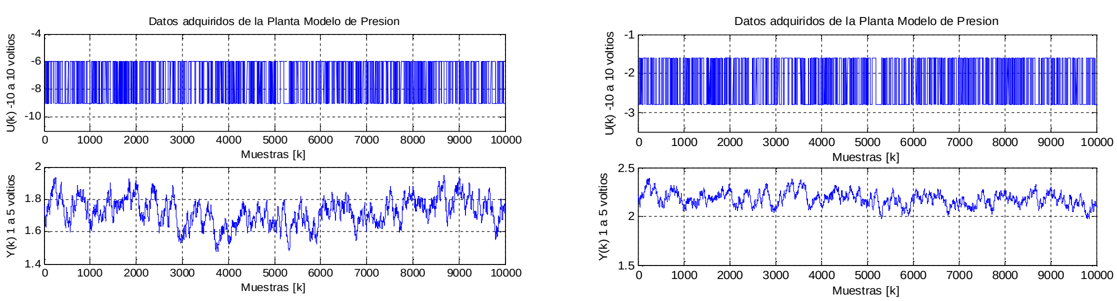

Figure 3. Response to PRBS for opening valve 5-20% (Left) and 36-42 %(Right)

The parametric identification was based on ARMAX model (Auto-Regressive Moving Average Controlled) that considers the deterministic and stochastic part of the process. The estimation or adjustment of parameters is formulated as an optimization problem where the criteria are the least squares to minimize the mean square error. We considered 70% of the acquired data for estimation and remaining 30 % for model validation. To estimate the model we have considered the 70 % of the acquired data. Figure 4 shows the measured output and the model output. The structure [2 2 2 5] is the most closely approximates the behavior of the system and the error in the estimate is 0.0036%.

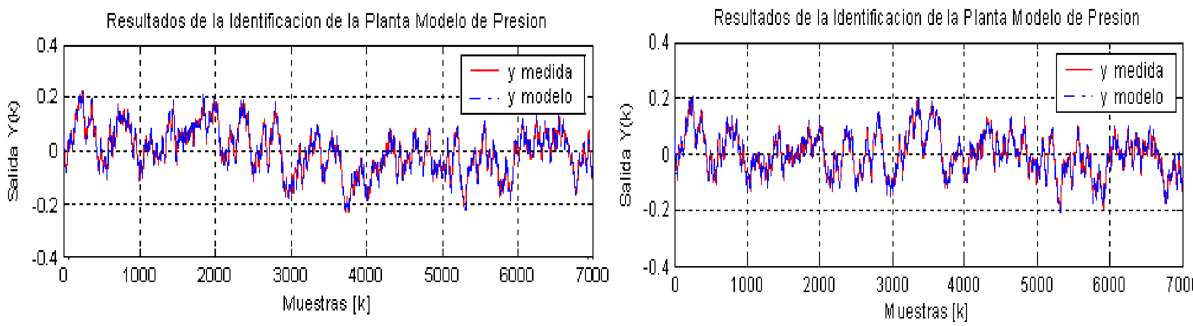

Figure 4. Outputs on the estimate for the linear zone 1(Left) and linear zone 2(Right)

The ARMAX model estimated for linear zone 1in transfer function pulse is:

$$y(k) = \left(\frac{-0.0008781\,z^{-1} + 0.001274\,z^{-2}}{1 - 1.833z^{-1} + 0.8348\,z^{-2}} \right) z^{-5}\,u(k) + \left(\frac{1 - 0.4448\,z^{-1} - 0.4229\,z^{-2}}{1 - 1.833z^{-1} + 0.8348\,z^{-2}} \right) e(k) \qquad (2)$$

The system has identified two real poles inside the unit circle (stable polar) and zero outside the unit circle, the system is non-minimum phase (Ogata, K. 1996).

The ARMAX model estimated for linear zone 2 in transfer function pulse is:

$$y(k) = \left(\frac{-0.002035\,z^{-1} + 0.003142\,z^{-2}}{1 - 1.802\,z^{-1} + 0.8043\,z^{-2}} \right) z^{-5}\,u(k) + \left(\frac{1 - 0.4718\,z^{-1} - 0.4460\,z^{-2}}{1 - 1.802\,z^{-1} + 0.8043\,z^{-2}} \right) e(k) \quad (3)$$

This last step is to determine if the model obtained satisfies the process dynamics considering a compromise between accuracy in steady state and the relative stability of the system. For validation of the model was considered 30% of the data acquired but not used in the estimation (cross-validation), this remaining information is compared by simulation with the measured output. The figure 5 shows the good approximation of the model output and the measured output to the linear zone 1, the validation error is 0.0043%. The same applies to the model output and the measured output for linear zone 2, the validation error is 0.0037%.

Residue analysis determines validity by graphics autocorrelation and cross correlation with the data obtained experimentally. This residue analysis is due to prediction errors obtained by calculating the difference between the observed and estimated output, these residues must be independent of the input. The range of confidence shows that the residuals are not entirely white.

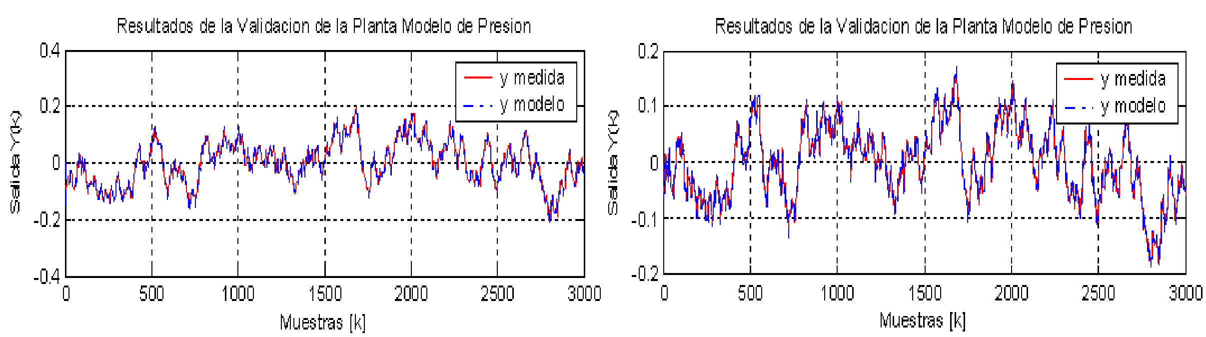

Figure 5.Outputs on validation for linear zone 1(Left) and linear zone 2(Right)

Recursive Identification Online

The online ID allows the calculation of the mathematical model at each sampling instant recursively without saving the data of the process, by constant updating of its parameters makes it possible to identify systems where the parameters vary in time (Soderstom, T. and Stoica, P. 1989).

The application of the method of recursive least squares (RLS) for ARX model and extended least squares method (RELS) for ARMAX model, dependent of perturbation model of white or colored noise, if that does not right should apply another method, especially if the relationship noise/signal is large. Recursive identification algorithm comprises a variable forgetting factor in the range from 0.96 to 1.

It included lower and upper bound of the covariance matrix for the lower bound, to the matrix is added a constant matrix R and the upper bound, the trace of the matrix. The recursive least squares method takes data at time k to estimate parameters at time k+1.

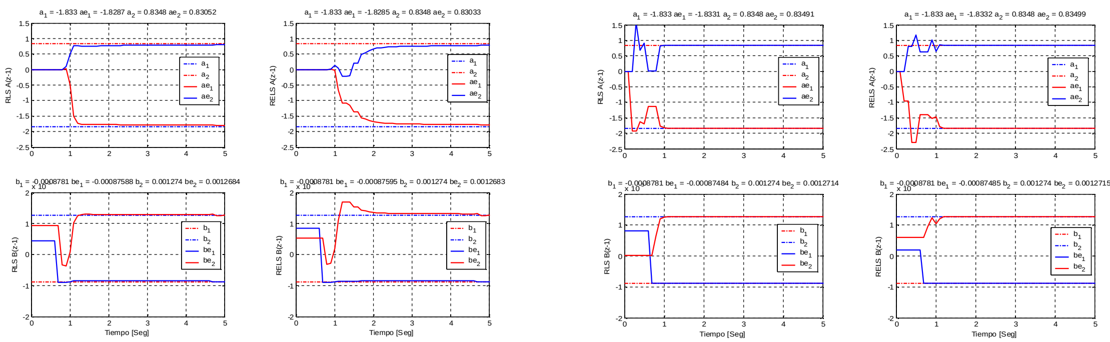

Figure 6: Parameters with RLS and RELS Algorithm in 36-42% of valve opening with Alpha 10^7(Left) and 10^{12}(Right).

The results of online simulations are shown, the convergence of the estimated parameters to the actual process. The figure 6 shows the results of online simulation: α =10^7, α_r =0.05, the initial forgetting factor is 0.98 and the minimum forgetting factor is 0.96. Furthermore, the maximum trace is 100000, the squared error ratio so is 0.000001 and variance of gaussian noise is nearly zero.

The recursive identification algorithm RLS converges faster than the RELS algorithm (RLS algorithm converges in 1s. and RELS in 2s). In addition, the adaptation of the estimated parameters is satisfactory, given that it's using a different point of operating. To verify the design of the recursive least squares identification with least squares RLS extended RELS was implemented. The figure 7 shows the actual data of the online identification with the initial conditions: PRBS signal with a range of initial operation of 15-35% of valve opening.

The following initial conditions for identifier is considered: theta, initial vector of parameters is zero , α=10^9, α_r = 0.05 , a factor of initial forgetting is 0.98, a factor of minimum missing 0.96, a peak trace of 100000 and the ratio of So squared error of 0.000001.

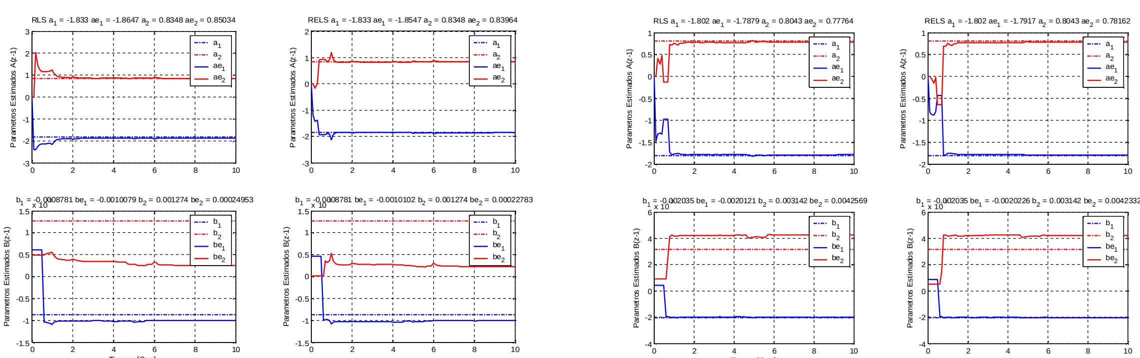

Figure 7.Online ID with a PRBS Signal for a valve opening of 15-35 %(Left) and 60-80 % (Right)

The figure 7 shows the parameters converge in approximately 2 s. in identifying the recursive least squares RLS and about 1 s. in the recursive least squares identification RELS extended. The speed of adaptation of parameters is about 1 s., this convergence does not necessarily have to converge to the actual values of the model, but if you find a system stability despite this uncertainty.

Adaptive Controller Design

The objective of the adaptive control of self -tuning is to maintain consistent process performance in presence of uncertainties or variations in the parameters of the plant. The control is performed adaptively because the behavior of the process is nonlinear and time-varying (Astrom, J. and Wittenmark, B., 1996), so enable the adaptive control to obtain appropriate linear approximations for the operating range of the process.

The figure 8 shows the block diagram of the adaptive controller of self- tuning by pole placement estimation applied to the plant.

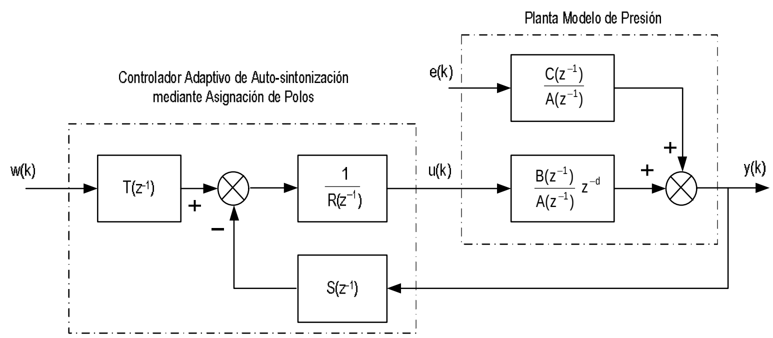

Figure 8.System Self-Tuning Adaptive Control by Pole Assignment

To develop the algorithm recursive least squares identification and RELS RLS have been based models offline identified (eq. 2 and 3). Is designed adaptive self- tuning controller with pole assignment (Dorf, R. 1989) forcing the entire resulting closed-loop system possesses a zero steady state error and stationary unit gain. The pole assignment method is intended that the closed-loop system considering the driver with specific dynamics.

The transfer function of the closed-loop is:

$$G_{LC}(z^{-1}) = \frac{T(z^{-1})B(z^{-1})z^{-d}}{A(z^{-1})R(z^{-1}) + B(z^{-1})S(z^{-1})z^{-d}} \quad (4)$$

The control law can be expressed by:

$$R(z^{-1})\ u(k) = T(z^{-1})\, w(k) - S(z^{-1})\, y(k) \qquad (5)$$

Results

We proceeded to simulate the behavior of the controller for case 1(equ. 3) and the following specifications: ζ damping factor of 0.8, tstime of settlement 10 s., $\omega_n$atural frequency of 0.5 rad/sec and the factor of the observer poles α=2.The figure 9 (left) shows the simulation results for the adaptive controller using the recursive least squares RLS identification, considering a desired path of 5 to 15% of desired pressure in the tank and a variance equal to 0.01 for generating the noise gaussian. The results of the simulation of case 1 show that the settling time is approximately 18s.The maximum percentage overshoot is about 5% and the steady-state error is 2%. The control law has a great control at the start, which is limited in magnitude in the program for implementation.
The control law is susceptible to tuning parameters (due to the poles of the controller and the observer).

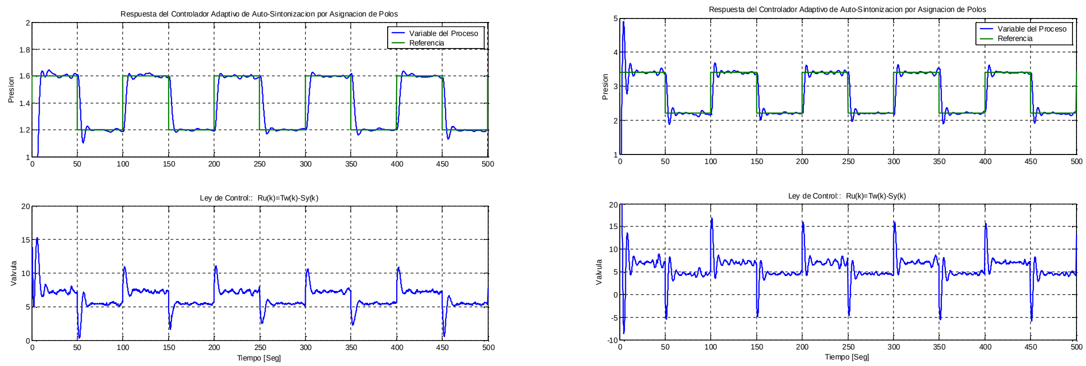

Figure 9.Response of controller for case 1 (Left) and case 2 (Right)

We proceeded to simulate the behavior of the controller for case 2 (equ.5) considering specification: ζ damping factor of 0.85 , ts settling time of 5 s., $\omega_n$natural frequency of 0.94 rad/sec and the factor observer poles is $\alpha = 1$. The figure 9 (right) shows the simulation results given a desired trajectory 30 to 60% of the desired pressure in the tank, the online identification algorithm used is RELS, gaussian noise variance is 0.05. The simulation of case 2 shows that the settling time is approximately 10s., the maximum overshoot of approximately 20% and the steady-state error is around 3%.

To test the adaptive controller design in the plant was implemented for a desired trajectory of 15 to 35% of pressure in the tank, income constant air flow at 40%, the tank is a 15cm water level and outlet valve slightly open. The following specifications are considered: ζdamping factor 0.85, ts settling time of 5 s.,ω_n natural frequency of 0.94 rad/seg. and factor of the poles of the observer is α=2. The pressure reaches the stability in about 10 s. as in the simulations, the steady state error in the pressure is 0.15% and the controller output (the control force) does not exceed to ±10v.

Conclusions

The adaptive self- tuning controller using the method of allocation of poles for pressure tank, provided acceptable behavior to the requirements and considering the nonlinearities of the process, Not required to re-tune the controller before significant changes in the desired value or due to the presence of disturbances, Simulations show that the methods of recursive least squares RLS identification and extended least squares RELS adapt quickly and the convergence of the parameters is satisfactory allowing to get the parameters of the model, updating the parameters in each sampling time, Convergence time 2s. parameters was obtained for the recursive least squares identification RLS 1s. for identification RELS extended least squares. A time of 10 s. was obtained to stabilize the pressure in the tank, the pressure control error is 0.15%, these results are for the entire operating range of the system. Besides the control law does not exceed the ±10v (no saturation) and is updated in each sampling period.

References

LuísAntônio Aguirre (2000). Introdução to identificaçãoSystems.Editora UFMG-BH www.editora.ufmg.br

Astrom Karl Johan and WittenmarkBjorn(1995). Adaptive Control.Addison-Wesley.

José Dávalos (2005). Identification of Processes Model Plants.Graduate School, PUCP-Peru.

Richard C. Dorf (1989). Modern Control Systems.Addison-Wesley.

Lennart Ljung (1987). System Identification.Theory for the User.Prentice Hall, New Jersey.

Katsuhiko Ogata (1996). Control Systems in Discrete Time. Prentice-Hall.

Francisco Rodríguez and López Manuel (1996). Adaptive and Robust Control. University of Seville, Spain.

Jean-Jacques E. Slotineand WeipingLi (1991).Applied Nonlinear Control.Prentice-Hall.

T.Soderstromand P. Stoica (1989). System Identification, Prentice Hall.