An Indirect Self-Tuning Control Scheme based on Recursive Least Square Estimation and Pole Placement Design

Article · January 2008

2 authors:


Prasheel Suryawanshi
Avantika University, Ujjain


Sudhir Agashe
College of Engineering, Pune

International J. of Engg. Research & Indu. Appls. (IJERIA).
ISSN 0974-1518, Vol.1, No. V (2008), pp 307-322

AN INDIRECT SELF-TUNING CONTROL SCHEME BASED ON RECURSIVE LEAST SQUARES ESTIMATION AND POLE PLACEMENT DESIGN

PRASHEEL V. SURYAWANSHI AND SUDHIR D. AGASHE

Abstract

Process control has become increasingly important in the process industries as a consequence of global competition, rapidly changing economic conditions and more stringent environmental and safety regulations. The severity of the non-linearities in chemical and biochemical processes influences the selection of control algorithms for successful control of a process. An adaptive system is one that can modify its parameters or behavior in response to the changes in the dynamics of the process and the character of the disturbances. By increasing our understanding of these systems it may be possible to derive considerable benefit, in terms of reduced product variability and optimal resource utilization, and this work is a step in that direction.

The concept of Self-Tuning Regulators (STR) is introduced. A nonlinear bioreactor is used to illustrate the theory and utility of the said control philosophy. The paper aims at development of an indirect self-tuning approach based on recursive least square (RLS) estimation and minimum degree pole placement (MDPP) design. The process performance is investigated for the designed control strategy. The substantial advantage of adaptive control over the conventional PI Control, in meeting a particular performance criterion is demonstrated in the presence of all the complexities associated with the real process. The simulation is tested in MATLAB – SIMULINK environment. The conception of control presented in this paper will be of assistance in the adjustment of existing controller applications and in the design of new installations.

1. INTRODUCTION

An adaptive system is one that can modify its parameters or behavior in response to the changes in the dynamics of the process and the character of the disturbances. Adaptive Control is a technique *with adjustable parameters and a mechanism for adjusting the parameters*. The controller becomes non-linear because of the parameter adjustment mechanism. An adaptive control system can be thought of having two loops. One loop is a normal feedback with the process and the controller. The other is the parameter adjustment loop [1], [2], [3], [4].

An adaptive control system provides a means of continuously monitoring the system's performance in relation to the optimum condition and a means of automatically modifying the system parameters to approach this optimum. Performance quality is evaluated by considering the speed of process recovery from a disturbance or set-point change with constraints on process overshoot and ringing.

Depending on the manner in which, adaptation is performed, there are different types of adaptive schemes. The concept of Self-Tuning Regulators is discussed in Section 2. A nonlinear bioreactor is used to illustrate the theory and utility of adaptive technique. Section 3 presents an overview of a bioreactor along with its mathematical model. The estimator and controller development are discussed next. An RLS estimator is presented and the parameters of the process model are obtained. The development of the pole placement control formulation to track the reference in a closed-loop implementation is presented. The stability and robustness analysis of the convergent adaptive controller is discussed. The simulation results are presented and a comparative analysis is carried out with PI control algorithm.

2. SELF-TUNING REGULATOR

A *Self Tuning Regulator* is an adaptive scheme in which the estimates of the process parameters are updated and the controller parameters are obtained from the solution of a design problem using the estimated parameters. As usual, the adaptive controller comprises of two loops. The inner loop consists of the process and an ordinary feedback controller. The parameters of the controller are adjusted by the outer loop, which is composed of a recursive parameter estimator and a design calculation [3], [11].

In self-tuning control, the parameters in the process model are updated as new data are acquired (using online estimation methods), and the control calculations are based on the updated model. Self-tuning controllers generally are implemented as shown in **Fig. 1**.

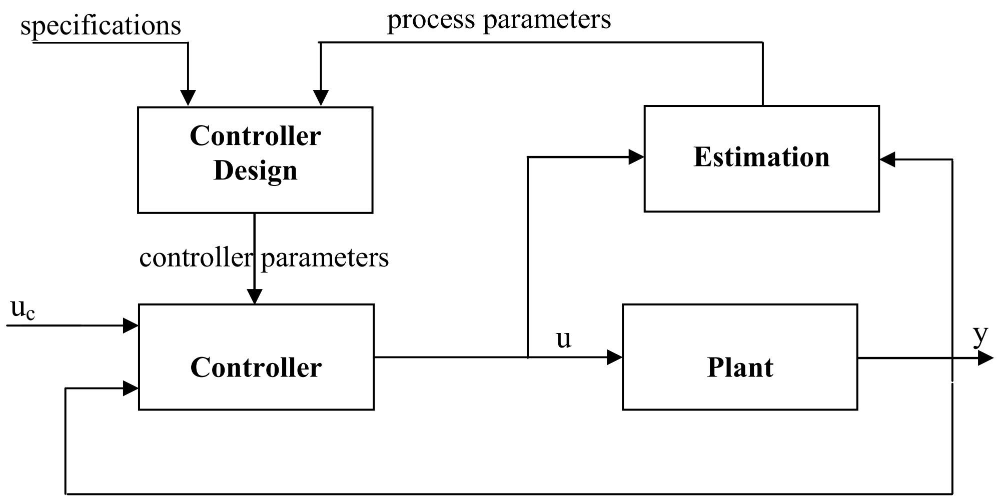

Fig. 1: Block diagram of Self Tuning Regulator [1]

In this figure 3-sets of computations are employed:

- Estimation of the model parameters
- Calculation of the controller settings
- Implementation of the controller output in the feedback loop

A controller of this construction is called *Self Tuning Regulator* to emphasize that the controller automatically tunes its parameters to obtain the desired properties of the closed loop system [1]. The controller shown is thus a very rich structure and gives an *Indirect Adaptive Algorithm*. The controller parameters are not updated directly, but rather indirectly via the estimation of the process model as if estimates were correct (*The Certainty Equivalence Principle*).

3. BIOREACTOR

A non-linear fermenter in fed-batch mode is used to illustrate the theory and utility of developed Adaptive algorithm. Biotechnological processes are characterized for their complex dynamic response as, for example, inverse response, dead time, time delay in the measurements, presence of parameters that vary with time and high non-linearities involving the variables. For these reasons modeling, simulation and control of these systems is still not a totally resolved problem. As the literature has been showing [5], [6], [9], [15], [18], [21] it is necessary to develop control algorithms based on advanced control concepts to obtain system's operation at high performance levels harmonized to safe conditions for the microorganisms.

The process considered in this work is an aerobic fed-batch bioreactor growing ***Saccharomyces cerevisiae*** on glucose and is depicted in Fig. 2 for reference.

The other features are,

Substrate	– Glucose
Product	– Ethanol
Growth Model	– Structured, Multiscale

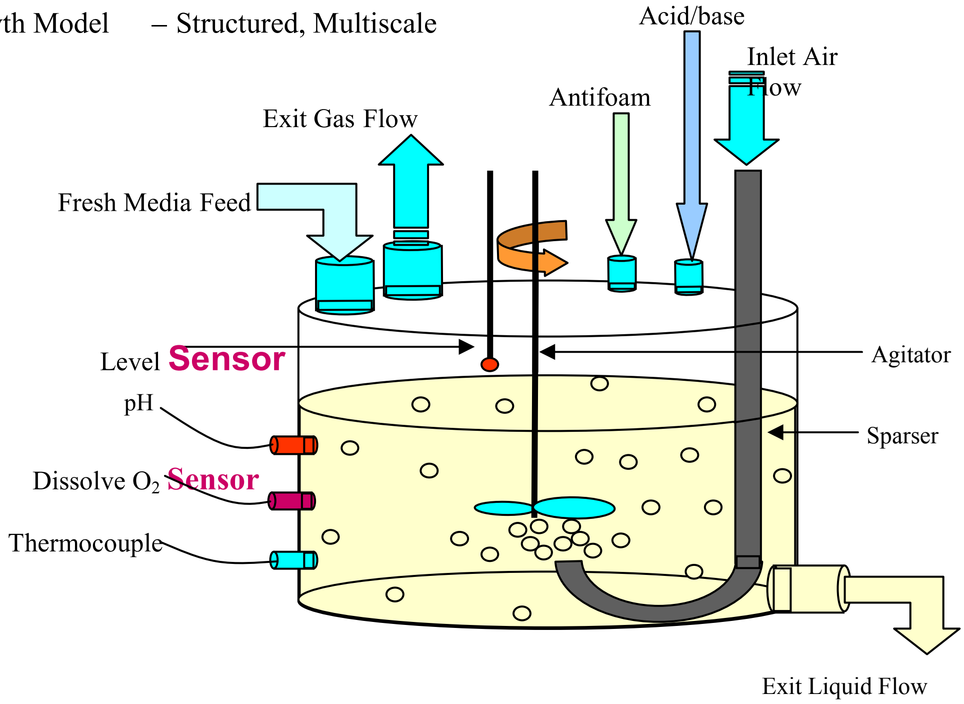

Fig. 2: Aerobic Fermenter

3.1 Bioreactor Model Description

The model considered here was described by Enfors and co-workers [22]. The process model includes a description of the state variables, biomass (X), glucose (S), ethanol (E), volume (V), and dissolved oxygen tension (DOT).

$$\frac{dX}{dt} = \mu X - \frac{F}{V} X \tag{1}$$

$$\frac{dS}{dt} = \frac{F}{V}(S_i - S) - X qS \tag{2}$$

$$\frac{dV}{dt} = F \tag{3}$$

$$\frac{dDOT}{dt} = KLa(100 - DOT) - 14000 X qO \tag{4}$$

$$\frac{dE}{dt} = X(qE_p - qE_c) - \frac{F}{V} E \tag{5}$$

The equations for biomass, substrate, and ethanol consist of two terms. A positive, growth or accumulation term whereas the second term containing the factor *F/V*, is due to the dilution of these components as feed is added during the reactor operation. The concentration of substrate in the feed is *Si*, and it is assumed that the feed is sterile, i.e. it does not contain any biomass. *KLa* is the liquid side mass transfer coefficient in the balance equation for dissolved oxygen.

4. ESTIMATION

The control scheme for the fed-batch bioreactor is implemented in two stages, and the substrate feed rate serves as the manipulated variable. Initially, a *Recursive Least Squares Estimator* is used to continuously and recursively update the parameters of a process model on-line. The next step involves update of the controller transfer functions based on the parameter estimates, to track the reference trajectory in closed-loop operation.

Recursive estimation algorithm is desirable in adaptive control systems as the observations are obtained sequentially in real time [7], [12], [14], [26]. It saves the computation time by using the results obtained at time (t–1) to get the estimates at time t. The estimation update is of the feedback form:

$$\begin{bmatrix} current \\ parameter \\ estimate \end{bmatrix} = \begin{bmatrix} previous \\ parameter \\ estimate \end{bmatrix} + \textit{(estimator gain) x (prediction error)}$$

4.1 RLS Algorithm

Recursive parameter estimation aims at generating a better estimate $\hat{\theta}(k)$ by an updating strategy that provides a correction based on the current prediction error as,

$$\hat{\theta}(k) = \hat{\theta}(k-1) + G(k)\,\varepsilon(k) \tag{6}$$

Here the estimator gain G(k) is a gain matrix chosen to improve the estimation, while the form of G(k) is determined by criterion that the estimation procedure seeks to optimize. The RLS method with a exponential forgetting factor λ, where 0 < λ < 1, chooses the model parameters such that the weighted sum-of-squares of the prediction error,

$$J_{WLS} = \sum_{j=1}^{k} \lambda^{k-1}\,\varepsilon(j)^2 \tag{7}$$

is minimized. This is achieved when the gain vector G(k) is chosen as,

$$G(k) = \frac{P(k-1)x(k)}{\lambda + x^T(k)P(k-1)x(k)} \tag{8}$$

where the covariance matrix P(k) is updated as,

$$P(k) = \frac{1}{\lambda}\left[I - G(k)x^T(k)\right]P(k-1) \tag{9}$$

Thus, the implementation of RLS parameter estimator consists of just iterating the four equations (6 – 9) at every time instant ‘k’.

The inclusion of forgetting factor provides a weighting on the data used for the estimation, with the importance of the data declining exponentially over time. Thus new data are given relatively high weighting, while data from many samples in the past are given lower weightings.

4.2 Results from Estimation

As the plant to be estimated is in discrete transfer function form, the non-linear modeling equations described in section 3.1 are first linearized to find the state space form. This is then converted to transfer function, which is then discretized using a zero order hold. The readers are advised to refer [19], [20] for more details on this transformation.

The parameters estimated by RLS estimator are shown in Table 1

Table 1: Parameter estimates of the plant by RLS Algorithm

Initial parameter vector, $\theta = \begin{bmatrix} 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \end{bmatrix}^T$

Initial covariance matrix, $P = 1000\ x\ I_4$

Forgetting factor, $\lambda = 0.98$

Parameters	b0	b1	b2	a1	a2	a3
True value	1	1.2	0.27	-1.1	0.09	0.445
Time = 20s	1	1.2	0.27	-1.1	0.09003	0.445
Time = 100s	1	1.2	0.27	-1.1	0.09003	0.445

The parameter estimates for the plant are also shown in Fig. 3.

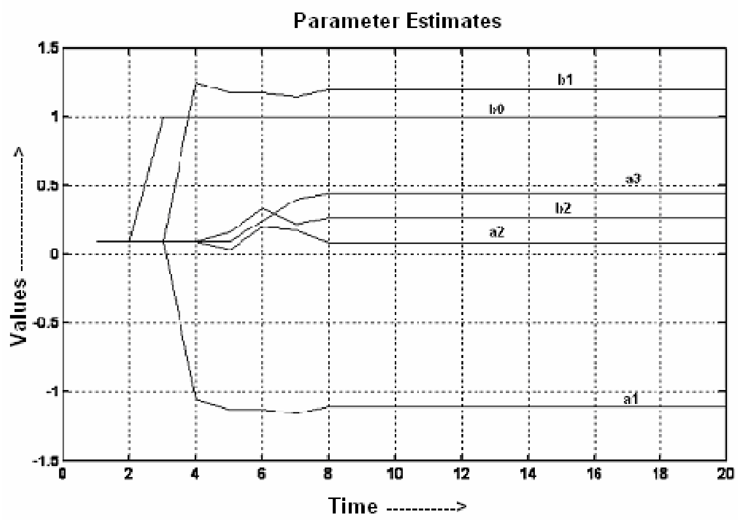

Fig. 3 Parameter estimates of the plant by RLS Algorithm

It is observed that the RLS algorithm is able to accurately estimate the parameters of the process model, which forms the basis for control design, discussed in next section. The RLS provides consistent estimates and fast convergence. It enables tracking of changes and are computationally simple.

5. CONTROL

This section deals with the controller design and controller blocks of self-tuning regulator shown in Fig. 1. The block labeled "Controller Design" contains computations that are required to perform a design of a controller with a specified method and a few design parameters that can be chosen externally. The design method considered in this work is deterministic pole-placement [1], [2], [11]. The basic idea in pole placement control is to determine a controller that gives the desired closed loop poles. The block labeled "Controller" is an implementation of the controller whose parameters are obtained from the control design.

The parameters estimated by the RLS estimator are fed as input to the design block. The values obtained for the controller parameters based on MDPP design are shown in Table 2.

Table 2: Controller parameters obtained by MDPP Design

Reference model polynomial, $A_m = \left[1 \; -1 \;\; 0.28 \;\; 0.104\right]$

Observer polynomial, $A_O = \left[1 - 0.4 \;\; -0.32\right]$

Parameters		Analytical value	Practical value
R	R0	1	1
	R1	– 0.6419	– 0.6419
	R2	– 0.2460	– 0.246
S	S0	0.3419	0.3419
	S1	– 0.6003	– 0.6003
	S2	0.2822	0.2822
T	T0	0.1555	0.1555
	T1	– 0.0622	– 0.06219
	T2	– 0.0498	– 0.04975

It is observed that the design block using pole placement design is able to accurately determine the controller parameters for the process model, based on the estimates obtained by RLS. These parameters are then used to compute the control law in the RST controller; which takes 2 inputs in the form of reference and plant output.

A general controller can be described by,

$$R(z^{-1})u(t) = T(z^{-1})u_c(t) - S(z^{-1})y(t) \tag{10}$$

where, R, S and T are polynomials. This control law represents a negative feedback with transfer function operator –S/R and a feed-forward with transfer function operator T/R. The unit step response for the convergent adaptive controller is shown in Fig. 4.

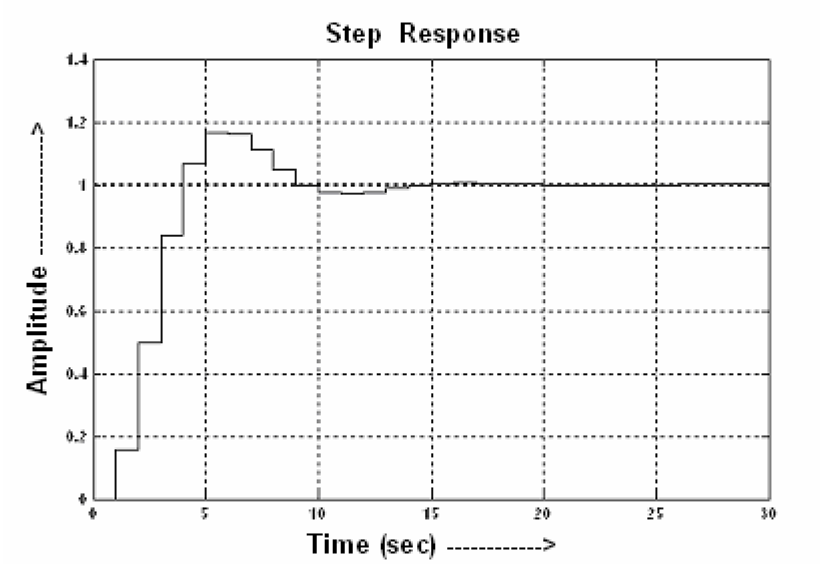

Fig. 4: Step Response of the plant under Adaptive Control

The simulation thus demonstrates the validity of the MDPP algorithm with Controller implementation.

6. RESULTS AND ANALYSIS

This section focuses on the results obtained for the convergent adaptive controller applied to the multi-scale, fed-batch bioreactor considered in this work and described by the model in Section 3.1. The step response of the plant under the designed adaptive controller is presented first and the controller is also analyzed for servo-performance. Next, the stability and robustness for noise contamination is tested.. A comparison of the resultant adaptive controller with a conventional PI algorithm concludes the section.

6.1 Control Performance

The behavior of the fed-batch system of alcoholic fermentation is investigated under adaptive controller action. The control loop regulates the ethanol concentration in the reactor, by handling the feed flow rate of syrup. The step response of the convergent adaptive controller with the performance measures is shown in Fig. 5, whereas, Fig. 6 shows the performance of the STR in servo problems where several set points are set during simulation.

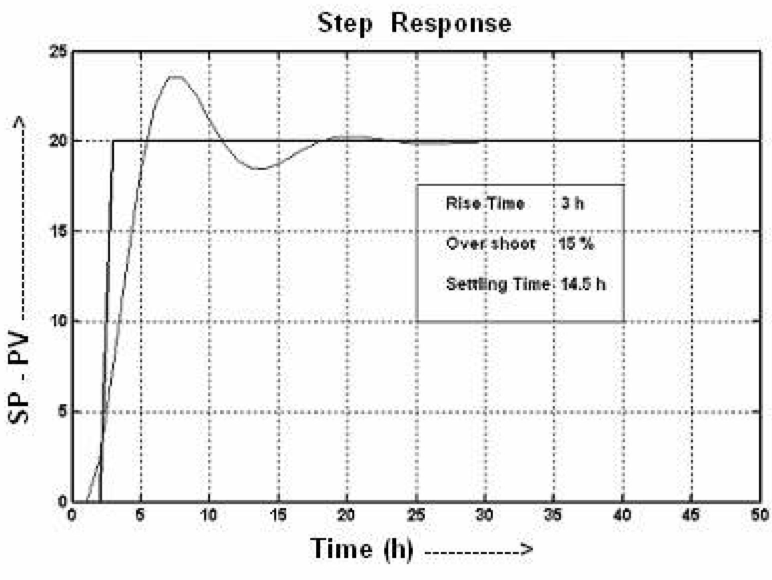

Fig. 5: Step Response of the plant with the designed STR Algorithm

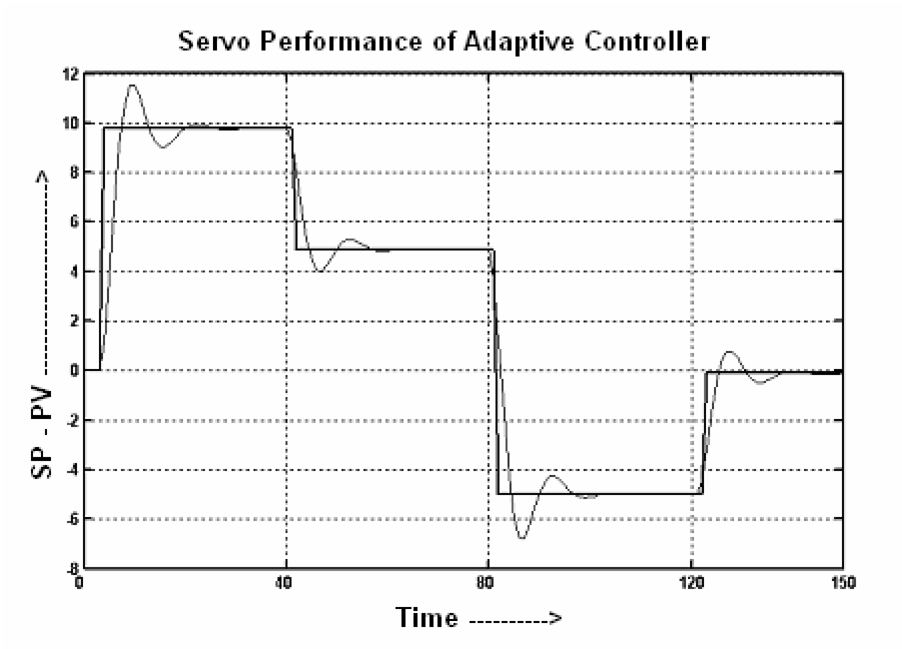

Fig. 6: Servo Performance of STR Algorithm developed for the system

6.2 Frequency Analysis

Frequency response concepts and techniques play an important role in control system design and analysis; particularly for stability and robustness analysis. The Bode stability criterion is utilized here to examine the stability margin of the system. The bode plot is obtained using *Control System Toolbox* of *MATLAB* [8] for the said system with feed forward part omitted and included.

The gain margin and the phase margin are tabulated in Table 3.

Table 3: Performance measures for stability analysis

System	Gain Margin (dB)	Phase Margin (deg)
Feed forward omitted	12.9	67.1
Feed forward included	9.31	67.2

6.3 Robustness Analysis

Robustness is an important issue in control design. That is, the control system designed must be capable of achieving the *a priori* specified performance objectives (and of course stability) despite the model parametric uncertainty, which is also established *a priori* [23].

The basic idea of adaptive controller design is to estimate the plant on-line, so that the controller can change its parameters to adapt to the changing environments. Therefore a robust estimator in an adaptive control system plays a key role. In this section, the convergence and accuracy of estimation is tested by adding a noise signal to the estimator developed in this work. The noise signal, in the form of a random number generator, which generates normally distributed random numbers, is added at the estimator input and the plant output. The estimated parameters for different values of mean are shown in Table 4 and Table 5.

Table 4: Parameter estimates with noise addition at estimator input

Parameters/ Noise (Mean)	b0	b1	b2	a1	a2	a3
True value	1	1.2	0.27	-1.1	0.09	0.445
0	1	1.2	0.27	-1.1	0.09003	0.445
0.05	0.9943	1.2	0.2711	-1.1	0.09	0.445
0.1	0.9886	1.199	0.2722	- 1.1	0.09	0.445
0.2	0.9772	1.198	0.2744	- 1.1	0.09	0.445
0.4	0.955	1.196	0.2789	- 1.1	0.09	0.445
1.0	0.8912	1.19	0.2926	- 1.1	0.08933	0.4454

Table 5: Parameter estimates with noise addition at process output

Parameters/ Noise (Mean)	b0	b1	b2	a1	a2	a3
True value	1	1.2	0.27	-1.1	0.09	0.445
0	1	1.2	0.27	-1.1	0.09	0.445
0.05	0.9998	1.2	0.2711	-1.1	0.09	0.445

0.1	0.9995	1.2	0.2722	-1.1	0.09	0.445
0.2	0.999	1.201	0.2744	-1.1	0.09	0.445
0.4	0.998	1.202	0.2789	-1.1	0.09	0.445
1.0	0.995	1.204	0.2922	-1.1	0.09	0.445

The results here show that the error is very small and the influence of noise contamination on the estimation accuracy is very small.

6.4 Comparison with PI Control

The step response of the plant with PI control is shown in Fig. 7.

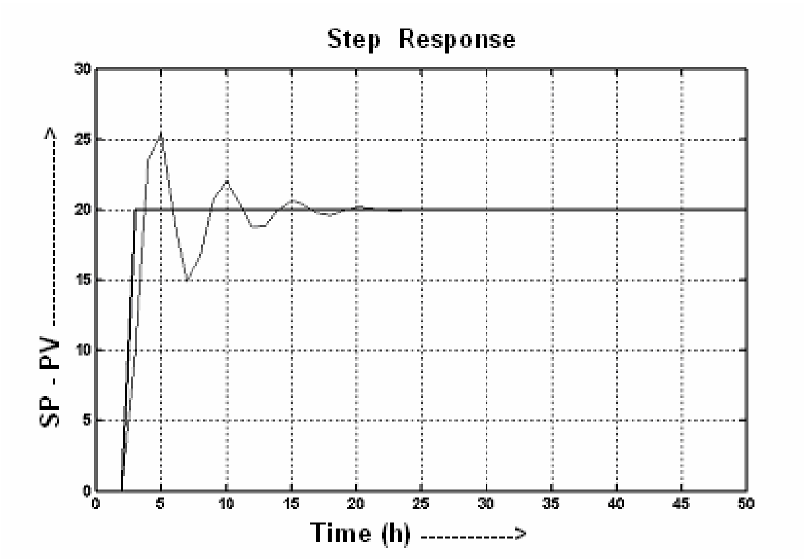

Fig. 7: Step Response of the plant with PI Control Algorithm

Table 6 presents the comparative performance of the designed self-tuning strategy with the conventional PI control.

Table 6: Comparison of performance for different control strategies

Parameters	Adaptive Control	PI Control
Rise Time (h)	3	2.4
Overshoot (%)	16	27.5
Settling Time (h)	13	16

The comparison thus demonstrates the role of adaptive strategy in enhancing the system performance by automatically optimizing the control law. The speed of process recovery from a disturbance or set-point change is improved. The overshoot and ringing are within constraints.

CONCLUSION

In this work, the problem of Indirect Self-Tuning Control is addressed. A non-linear fermenter in fed-batch mode is used to illustrate the theory and utility of developed Adaptive algorithm.

The bioreactor operation is highly nonlinear at both a microscopic cellular scale and a macroscopic reactor scale; with reactions at these scales occurring at different times, the bioreactor system is multi-scale both temporally and spatially. A model structure that recognizes the multi-scale nature of the system is utilized to describe the fermentation of *Saccharomyces Cerevisiae* on glucose to produce ethanol as a product.

The controller design philosophy is based on continuously estimating a linear parameterized model of the process; this is then used to update the controller transfer functions. An RLS Estimator is first developed in order to estimate the parameters of the plant. In the next step, a control philosophy is designed based on the parameter estimates to track the reference trajectory. The controller design also include explicit constraints on both the state and manipulated variables and perform an excellent job of tracking the reference trajectory, while attaining the end of batch ethanol concentration.

The performance of the STR is investigated through process computer simulation under industrial operating conditions. The substance of this advanced control is demonstrated by comparison with the conventional PI control algorithm.

The STR developed can be described as a control structure and a relationship between the plant's parameters and the controller's parameters. The salient features of the control algorithm developed can be summarized as, closed-loop stability, good disturbance rejection (without excessive control action), fast set point tracking (without excessive control action) and low sensitivity to measurement noise

The subject of adaptive control continues to be of considerable interest. However adaptive control has tended to be a niche application rather than being used pervasively in industrial applications. In the future it is expected that control products that use some form of adaptation will become more common as algorithms improve and process knowledge increases.

REFERENCES

[1] Astrom Karl J, Wittenmark Bjorn, "Adaptive Control", 2nd Edition, Pearson, Delhi (2001)

[2] Astrom Karl J, Wittenmark Bjorn, "Computer Controlled Systems – Theory and Design", 2nd Edition, PHI, New Delhi (1994)

[3] Astrom K.J, Wittenmark B., "On self tuning regulators" in Automatica, Vol.9, pp. 185-199, Pergamon, Great Britain (1973)

[4] Astrom K.J, "Theory and Applications of Adaptive Control – A Survey" in Automatica, Vol.19, No.5, pp. 471-486, Pergamon, (1983)

[5] Bastin G, D. Dochain, "On-line Estimation and Adaptive Control of Bioreactors – Process Measurement and Control" in Automatica, Vol. 29, No. 3, pp. 797-805, Pergamon, Great Britain (1993)

[6] Bingjun Guo, Aiping Jiang, Xiangming Hua, Arthur Jutan, "Nonlinear Adaptive control for multivariable chemical processes" in Chemical Engineering Science, Vol. 56, pp. 6781-6791, Pergamon, (2001)

[7] Hang Chang C., Lee Tong H., Weng K. Ho, "Adaptive Control", ISA, North Carolina (1993)

[8] "Control System Toolbox for use with MATLAB", Version 5, The Mathworks Inc., Natick, M.A. (September 2000)

[9] Dochain Denis, "On-line Parameter Estimation, Adaptive State Estimation & Control of Fermentation Processes", France (1986)

[10] "External Interfaces", Ver. 6, The Mathworks Inc. (2000)

[11] Fortescue T. R., Kershenbaum L. S., Ydstie B. E., "Implementation Of Self-Tuning Regulators with Variable Forgetting Factors" in Automatica, Vol. 17, No. 6, pp. 831-835, Pergamon, Great Britain (1981)

[12] Giri F, Dion J.M., Dugard L., M'saad M., "Parameter Estimation Aspects In Adaptive Control" in Automatica, Vol. 27, No. 2, pp. 399 – 402, Pergamon, Great Britain (1991)

[13] Gundala R, Hoo K., Piovoso M., "Multiple Model Adaptive Control Design for a MIMO Chemical Reactor" in Ind. & Eng. Chem. Res. Vol. 39, pp. 1554-1563 (2000)

[14] Rolf Isermann, "Parameter Adaptive Control Algorithms – A Tutorial" in Automatica, Vol. 18, No. 5, pp. 513-528, Pergamon, Great Britain (1982)

[15] Johnson A, "The control of fed-batch fermentation processes - A survey", in Automatica, Vol. 23, pp. 691-75, Pergamon (1987)

[16] Katarov, Vinarov, Gordeev, “Modeling of Bioreactors”, in International Chemical Engineering, Vol. 27, No. 4, pp. 615 – 637 (1987)

[17] Kosanovich Karlene A, Michael J. Piovoso, Vadim Rokhlenko, AIIon Guez, “Nonlinear adaptive control with parameter estimation of a CSTR” in Journal of Process Control, Vol. 5, No. 3, pp. 137-148, Butterworth–Heinemann, (1995)

[18] Meleiro L.A.C., Filho R. Maciel, “A self-tuning adaptive control applied to an industrial large scale ethanol production” in Computers and Chemical Engineering, Vol. 24, pp. 925-930, Elsevier (2000)

[19] Nise Norman S, “Control System Engg.”, 3rd Edition, Wiley, Newyork (2000)

[20] Ogata Katsuhiko, “Discrete Time Control Systems”, 2nd Edition, Pearson, New Delhi (2001)

[21] Parulekar S. J, H.C.Lim, “Modeling, optimization, and control of semi-batch bioreactors”, in Adv. Biochem. Engg. Biotech, Vol. 32, pp. 207-258 (1985)

[22] Pham H.T.B, Larsson G., and Enfors S.O., “Growth and energy metabolism in aerobic fed-batch cultures of Saccharomyces cerevisiae: Simulation and model verification”, in Biotech. & Bioeng., Vol. 60, pp. 474 – 482 (1998)

[23] Rohrs C.E, Alavani L., Thans M. and G. Tein, "Robustness of Continuous Time Adaptive Control Algorithms in the Presence of Unmodeled Dynamics", in IEEE Trans. on Auto. Control, Vol. 30, pp. 881 – 889 (1985)

[24] Soni Abhishek, “A Multi-Scale Approach To Fed-Batch Bioreactor Control”, PhD Thesis, University of Pittsburgh (2002)

[25] “Using Simulink”, Ver. 4, The Mathworks Inc., Natick, M.A. (2000)

[26] Waghmare L.M, Metkar Abhirraj N., Mateenuddin H. Quazi, “Recursive Identification Methods and effect of variation of Initial values and Forgetting Factor on the Identified Estimates” International Conference on Instrumentation (INCON 2004), Pune, India (December 2004)

Prasheel V. Suryawanshi
Maharashtra Academy of Engineering
Alandi (D), Pune, INDIA
E-mail : prasheels@mitpune.com

Sudhir D. Agashe
College of Engineering,
Pune, INDIA
E-mail : sda@instru.coep.org.in