A Two Step Closed Loop Parameter Estimation Technique for Self-Tuning Process Control

John D Lane
Senior Applications Engineer
Bailey Controls Company

Tom J Scheib
Chief Application Engineer
Bailey Controls Company

M A Keyes IV
Senior Group V P
McDermott International

Presented at
The AIChE Annual Meeting
Washington, D C
Nov 27 Dec 2, 1988

Technical Paper

TP88-24

Bailey Controls
Babcock & Wilcox

A Two Step Closed Loop Parameter Estimation Technique

for

Self-Tuning Process Control

John D. Lane
Senior Application Engineer
Bailey Controls Company

Tom J. Scheib
Chief Application Engineer
Bailey Controls Company

M.A. Keyes IV
Senior Group V.P.
McDermott International

Abstract

A general purpose closed loop parameter estimation technique has been developed for self tuning process control applications. This technique is applicable to a wide class of industrial control problems including those with large unknown and time varying process delays. This technique works by combining the continuous identification and parameter tracking attributes of a recursive least squares algorithm with periodic deadtime estimation.

The two step parameter estimator is coupled with a model based control algorithm as a self tuner/auto-tuner. This configuration offers tight control for a wide variety of processes through inherent deadtime compensation. Design and simulation testing have validated this methodology in conjunction with a PID algorithm.

This paper provides a description of the individual components of the self tuning controller along with a description of the special considerations required to integrate the two independent parameter estimators. Results of simulation studies are presented.

Introduction

Industrial processes with large unknown and/or time varying process delays rank among the most difficult to control. Self tuning in its present form is largely inapplicable to this class of processes due to a reliance on recursive least squares parameter estimation and the PID control algorithm. Recursive least squares parameter estimation, the basis for a majority of self tuning controllers, fails because of a requirement for explicit knowledge of the process deadtime. Likewise control systems comprised of a PID controller are unable to directly compensate for process deadtime. To maintain loop stability these control systems must be detuned, degrading overall controller performance.

One mechanism for extending self tuning control to this class of processes is to couple a recursive least squares parameter estimation algorithm with a deadtime estimator and augment the control function with deadtime compensation. Two particular methods, one employing a bank of estimators with different assumed values for the deadtime [1] and a second employing a single estimator to identify a set of parameters extended over the time horizon in the neighborhood of an assumed deadtime [2], have received much attention. Unfortunately these techniques, along with other signal processing applications, see [3] for a survey, have proven impractical for general purpose application in an industrial setting.

Recent work by Itakura [4] and by Nishikawa et al [5] describes a technique for estimating process parameters including deadtime for systems operating in closed loop. This technique uses time integrals of system variables each ... to a step or impulse input. Proper selection of these integrals (control areas) results in a set of equations solvable for the process parameters. Employing control areas for parameter estimation allows direct identification of process deadtime. Additionally the smoothing effects of integration attenuates the effects of process noise on the parameter estimates.

Herein, a self tuning/auto-tuning control technique is described that incorporates both a recursive least squares and a control area algorithm for parameter estimation. This novel formulation enjoys the continuous parameter tracking benefits of a recursive least squares algorithm and is able to maintain performance on processes with varying or unknown deadtime.

The initial implementation of the two step closed loop parameter estimator is for a model based controller structure [6]. This combination was selected because of the deadtime compensation feature of model based controllers. A comparable formulation exists for a commonly used PID control algorithm and initial simulation testing has validated the feasibility of this approach.

The following discussion deals only with the two step parameter estimator formulation for a model based controller. This discussion is organized as follows:

- o First, the details of the model based controller and the recursive least squares parameter estimator are reviewed. Both of these elements are described elsewhere, e.g. Lane [7].
- o Second, the derivation of the control area parameter estimator for the model based controller is described. Simulation results are presented to support the selection of various parameters used by this algorithm and illustrate the strengths and limitations of this technique.

c. Third implementation details describing the logic and methodologies through which the two estimation techniques interact are discussed.

Basic Self-Tuning Controller Description

Initially, the two step closed loop parameter estimator was coupled with a model based controller as a self tuner/auto-tuner. The model based controller was selected over a more conventional PID controller for two reasons. The primary reason was this controllers ability to compensate for the effects of process deadtime. This allows the self tuner/auto-tuner to be applied to a more general class of processes than the class of processes suitable for PID control. A second advantage of the model based controller is the use of a separate parameter for specifying closed loop performance. In contrast, PID parameter selection requires closed loop performance to be factored into the specification of all tuning parameters.

Figure 1 presents a block diagram of the model based controller and (1) defines its transfer function.

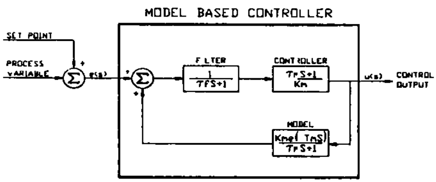

Figure 1. Model Based Controller

$$\frac{U(s)}{e(s)} = \frac{1}{k_m}\left[\frac{\dfrac{\tau_m S + 1}{\tau_f S + 1}}{1 - \dfrac{e^{-T_m S}}{\tau_f S + 1}}\right] \qquad (1)$$

This particular formula assumes that the controlled process can be approximated by a first order lag with dead time. The controller is tuned in terms of the observed process gain, lag time constant, and deadtime. A fourth tuning parameter, the filter time constant, specifies the desired time response of the process variable to a change in setpoint or to a disturbance.

The properties of this model based controller are described in the literature, see for instance [8], [9] and [10].

The basic self tuning control system couples a variable forgetting factor version of recursive least squares parameter estimation with the model based controller. This algorithm addresses many of the practical difficulties associated with the application of self tuning control. In addition, the parameter estimation algorithm includes a significant rule base developed to supervise its operation. This rule base compensates for discrepancies between theoretical assumptions and the realities of an industrial setting.

The recursive least squares parameter estimation technique used for this work, estimates parameters based on an assumed plant form shown in (2). (3) through (7) define the algorithm used. Further details of this algorithm and the mapping between estimated and controller parameters can be found in Lane [7].

$$y(t) = a_1 y(t-1) + b_0 u(t-k) + c \qquad (2)$$

where $y(t)$ = current process variable
$y(t-1)$ = previous process variable
$u(t-k)$ = control output delayed by k
a_1, b_0, c = model parameters

$$e(t) = y(t) - \theta'(t-1)\Phi(t) \qquad (3)$$

$$w(t) = \Phi'(t)P(t-1)\Phi(t) \qquad (4)$$

$$\theta(t) = \theta(t-1) + \frac{P(t-1)\Phi(t)e(t)}{1 + w(t)} \qquad (5)$$

$$\lambda(t) = \frac{\eta[1 + w(t)]}{\eta[1 + w(t)] + e^2(t)} \qquad (6)$$

$$P(t) = \frac{P(t-1)}{\lambda(t)}\left[I - \frac{\Phi(t)P(t-1)\Phi'(t)}{\lambda(t) + w(t)}\right] \qquad (7)$$

where $\theta'(t) = [a_1, b_0, c]$

$\Phi'(t) = [y(t-1), u(t-k), 1.0]$

η = Time horizon for forgetting factor.

The basic self tuning controller also incorporates an open loop initialization routine for automatically selecting controller tuning parameters and tailoring the recursive least squares estimator to the actual process. See Lane [11] for further details.

Deadtime/Parameter Estimation Technique

The use of the previously described self tuning control system is constrained to processes with a known and fixed process delay or to processes where the delay can be measured or inferred online. To extend the applicability of this system to processes with unknown or time varying deadtime, a feature based parameter estimation technique was developed. This technique has the advantage of estimating all process parameters including deadtime in closed loop. The technique selected for this work parallels the work of Itakura [4] and Nishikawa [5]. The basic idea is that certain quantitative measures of the system response to a step setpoint change can be directly related to the process parameters. Using various control areas involving the process output, one can develop and then solve a set of non linear algebraic equations in the process parameters.

The following steps describe the procedure used for estimating the deadtime and process parameters of a first order near system using the controller (1)

- The maximum deviation of the process variable from setpoint is determined over a fixed time horizon along with the average value for the controller output. This information is used to determine when the process has reached steady state and to provide an initial value of the control output.
- The setpoint to the controller is increased (decreased) by a prescribed amount to start the estimation procedure.
- The integrals in (8) and (9) are calculated numerically as the process responds to the setpoint change. Note that the values of both of these integrals converge as the process output approaches the new setpoint. Therefore these integrals can be calculated over the finite time horizon from $t = 0$ to $t = t_{ss}$. Figure 2 illustrates the calculation of these integrals.
- The process is considered to have achieved steady state conditions when the error between the process variable and the new setpoint is less than twice the maximum deviation measured in step 1 for a fixed amount of time.
- The final value of the control output is calculated by averaging over a fixed time horizon. This minimizes the effects of process noise on the test.
- After observing the process response to a step setpoint change (10) through (12) are used to estimate the process parameters. Clearly τ_{est} and T_{est} cannot be computed directly from these equations. Excellent results, nevertheless, have been obtained by solving the exponential form of (11) from an initial τ_{est} of 0.0 using a successive substitution technique.

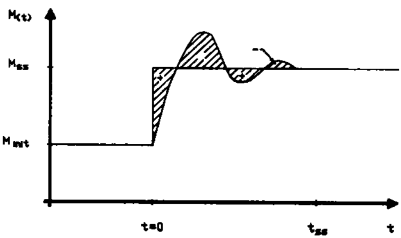

Figure 2 - I_1 Calculation

$$I_1 = \frac{1}{\Delta SP}\int_0^\infty \left[m_{ss} - m(t) \right] dt \qquad (8)$$

$$I_2 = \frac{1}{\Delta SP}\int_0^\infty \left[m_{ss} - m(t) \right] e^{\alpha t} dt \qquad (9)$$

$$k_{est} = \frac{\Delta SP}{m_{ss} - m_{init}} \qquad (10)$$

$$\tau_{est} = z + \frac{1}{\alpha} \ln \left[\frac{a\tau_{est} - b}{c} \right] \qquad (11)$$

$$T_{est} = z - \tau_{est} \qquad (12)$$

where

I_1, I_2 Control Area Integrals

m_{ss} Final Value, Control Output

m_{init} Initial value, Control Output

$m(t)$ Control Output at time t

ΔSP Change in Setpoint

$k_{est}, \tau_{est}, T_{est}$ Estimated Parameters

k_m, τ_m, T_m, τ_f Controller Parameters

α weighting parameter $(\tau_m + T_m)^{-1}$

and

$$z = \frac{k_m}{k_{est}} (\tau_f + \tau_m) - k_{est} I_1$$

$$a = \left[\alpha(\tau_f \alpha + 1 + e^{T_m \alpha}) + \frac{k_{est}\alpha(\tau_m \alpha + 1)}{k_m (k_{est} I_2 \alpha - 1)} \right]$$

$$b = \frac{a}{\alpha}$$

$$c = \frac{k_{est}}{k_m} (\tau_m + 1)$$

Simulation Results

A computer simulation of the model based controller, deadtime/parameter estimator and two generic processes was used to examine the capabilities and limitations of the deadtime/parameter estimator. The simulation of the model based controller was designed to closely parallel the implementation of this controller in Bailey's NETWORK 90® equipment. This required the approximation of the deadtime within the controller through the use of a finite element buffer and linear interpolation between these buffered values. Two generic processes were used for the simulation testing: a third order lead lag network with deadtime and a second order *system with deadtime specified in terms of static gain, natural* frequency, and damping ratio. Both linear processes operated around a bias of 50.0 and with a gain of 1.0. Zero mean, Gaussian white noise with a specified standard deviation was added to the output of each process. The simulation was designed to run the process at a sampling rate 3 times that of the controller to approximate the behavior of a digital controller operating on an analog process. A supervisory program controlled each simulation run to assure repeatability and consistency between all tests.

Preliminary simulations used a first order lag process with deadtime to determine the effects of the ratio between process time constant and deadtime and the model based controllers filter time constant on estimator performance. These tests were also used to validate the estimators robustness to the sign of the setpoint change used and the ability of the estimator to identify the characteristics of processes with both positive and negative gains. Table 1 summarizes the results of initial testing by showing the worst estimates generated for 5 first order processes with deadtime to time constant ratios ranging from 1/6 to 4. The controller parameters were specified to match those of the actual process with filter time constants ranging between 10.0 and 90.0 seconds. The filter time constant τ_f used by the controller that produced the worst case estimates is also tabulated.

Table 1 Estimator performance for first order process with *controller/process matching and no noise*

τ_p	T_p	τ_f	τ_{est}	T_{est}
60	10	45.0	59.18	10.41
30	30	90.0	32.10	27.98
30	60	90.0	32.50	58.07
30	120	90.0	36.70	113.79
30	5	90.0	31.50	3.61

Smaller values of the filter time constant typically resulted in improved estimator performance down to the point at which controller saturation occurs for the required setpoint change. For small filter time constants the value of $e^{\alpha t}$ in (9) remains large for a greater percentage of the total process response, increasing the amount of information captured by the integral I_2, thus improving estimator accuracy.

The error between the estimated and actual parameters increases as a function of the deadtime value used in the controller results from inaccuracy in the controllers implementation of the deadtime. When estimated parameters were implemented in the controller, this error was found to have no impact on the overall performance.

Additive output noise with a standard deviation of less than 2.5% of the magnitude of the setpoint change had minimal impact on estimator performance. The impact of noise however, cannot be fully understood by analyzing the results of simulation testing alone. It is reasonable to expect that the type of noise present and the magnitude ratio of the noise to the size of setpoint change used for estimation and the process gain will affect estimator performance in ways that can only be understood through field testing.

A second set of simulation tests were used to determine the effect of initial parameter estimates on estimator performance. A first order plus deadtime process with τ_p = 30.0 seconds and T_p = 30.0 seconds was used. Controller parameters were varied as follows:

τ_m = 10.0 – 60.0 seconds

T_m = 10.0 – 60.0 seconds

τ_f = 15.0 – 60.0 seconds

The deadtime/parameter estimator identified both the process time constant and deadtime to within ±1.5 seconds or 5% of actual process values. For cases when either the model time constant or the model deadtime of the controller were significantly larger than the correct value, a small filter time constant led to closed loop instability and no estimates were obtained. The Integral measure I_1 did not converge in this situation.

The above simulation studies validated the performance of the deadtime/parameter estimator for the identification of parameters of first order processes. Excellent results were obtained independent of initial controller settings and in the presence of moderate levels of process noise. The estimator experienced difficulty only when the controller saturated during the course of the closed loop test or when the initial controller tuning resulted in a marginally stable or unstable closed loop system response.

Further simulation testing was conducted to explore the ability of the deadtime/parameter estimator to approximate high order dynamic systems with a first order process model. Two processes were used for this testing:

$$G_1(s) = \frac{(10s - 1)}{(30s + 1)^3} e^{-30s}$$

$$G_2(s) = \frac{w_n^2}{s^2 + 2\varsigma w_n s + w_n^2} e^{-Ts}$$

The deadtime/parameter estimator was tested on $G_1(s)$ using *controller settings*

τ_m = 30.0 – 90.0 seconds

T_m = 30.0 – 90.0 seconds

τ_f = 30.0 – 120.0 seconds

For all controller settings giving a stable closed loop response, the estimator approximated the third order process with

$$G_{1est}(s) = \frac{e^{-75s}}{55s + 1}$$

Figure 3 shows the open loop response of this estimated process, $G_{1est}(s)$ compared with the open loop response of the process $G_1(s)$. Figure 4 shows the closed loop response of the process $G_1(s)$ using the model based controller based on G_{1est} and a filter time constant of 15.0 seconds.

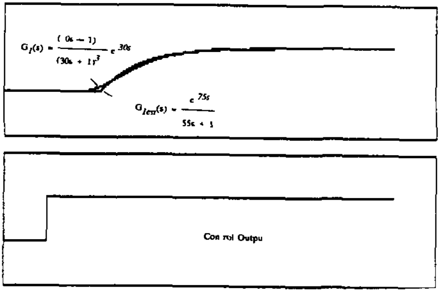

Figure 3 Open Loop Step Responses

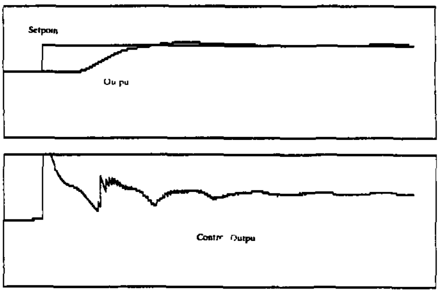

Figure 4 Closed Loop Response

This series of tests illustrates that the deadtime/parameter estimator provides a reasonable 1^{st} order model approximation for high order overdamped processes even in the presence of numerator dynamics. Furthermore this series of tests show that using the estimated parameters to tune the model based controller provides excellent closed loop control of the processes.

Simulation testing with the process $G_2(s)$ revealed an inability of the deadtime/parameter estimator to approximate most underdamped systems using a first order model. Nevertheless the estimator did provide suitable approximations for processes with a damping ratio above 0.8. Similarly, the first order model based controller provided stable closed loop response on processes with a damping ratio below this value only with the use of a large filter time constant. This type of tuning resulted in sluggish closed loop performance.

Implementation Details

The deadtime/parameter estimator is designed to detect naturally occurring step setpoint changes and to estimate process parameters when they occur. The estimator continually calculates the average of the process variable over a fixed time horizon using a first order filter. When a setpoint change is detected, the estimator compares this average with the old setpoint to determine if the process was at steady state conditions. If so, the estimation algorithm is run. Should a second setpoint change occur before completion the estimation is aborted. For reasons of practicality the estimator will treat ramp setpoint changes of less than 5 second duration as a step setpoint change. Use of a ramp setpoint change will lead to a slight degradation of the deadtime estimate.

In addition, the user may select to have the algorithm run on demand from the operator or on an event or time dependent basis. In these additional modes of operation, the user specifies the direction and magnitude of the setpoint change to be used for the test. Triggering the estimation algorithm results in the following sequence of events:

- The estimator waits until it determines that the process is at steady state conditions.
- The setpoint is changed by the user specified amount.
- Parameters are estimated to characterize the process from observation of the closed loop response. If the estimation algorithm fails to converge during this test the estimator doubles the value of its suggested filter setting. This output can be set to automatically change the filter time constant in the model based controller. The increase in the filter time constant will stabilize the process response allowing the estimator to obtain a valid model of process dynamics. After validation of the parameter estimates they are made available for automatic or manual updating of the control algorithm.
- The setpoint is returned to its pre test value.
- A second set of parameters are estimated to characterize the response of the process moving in the opposite direction of the first test. The second test helps to identify overall process response so as to diminish effects caused by nonlinearities.
- The deadtime/parameter estimator outputs the average of the estimates obtained during the two tests. If the filter output was changed after the first test, it is returned to its original pre test value.

The parameter estimates obtained in response to both natural and induced setpoint changes can be used to automatically update the model based controller or can be presented to the operator for review and manual updating.

Many questions still remain to be answered about when the *deadtime/parameter est mator should be run and how this* est mator shou d interact with Bailey s exist ng self tuning contro er Current deve opment efforts are focuss ng on the fo owing top cs

o Development of an a gorithm to mon tor the stability of the closed loop system Th s informat on will a ow the adjustment of the f lter t me constant to stab l ze the system unt new estimates of the process parameters are obta ned

• Development of a general measure of process performance Th s informat on will a ow the estimat on a gorithm to mon tor the process and to run automat ca y when the c osed oop performance degrades below a spec fied threshold

o Integrat on of the deadt me/parameter est mator with Ba ley s exist ng se f tun ng controller This will provide the con nuous parameter tracking of a recurs ve east squares a gor thm with an accurate deadt me est mate supp ed from the deadt me/parameter est mator

Conclusion

Th s paper presented mp ementat on and simulat on study details of a new technique for est mat on of process parameters ncluding deadtime It was shown that this techn que

o s arge y insens t ve to t a est mates for the parameters

o s large y nsens t ve to process no se

o s ab e to deve p a f rst order process mode that adequate y approx mates h gher order dynam c system for the purposes of contro Th s does not inc ude processes with underdamped open oop responses for wh ch the descr bed contro er structure s nadequa e

Acknowledgement

The contribut ons toward th s work of M Buchner and K Loparo of CWRU s Systems Enginee ring Department are gra ef y acknow edged They are respons b e for the dent ficat on of the deadt me est mation techn que employed and for pre minary derivat on and s mu at on testing of th s a gorithm n conjunction with the model based contro er

References

1 R. Chen, "Ident fication of T me Delays in Linear Stochastic Systems," M S Thesis, CWRU 1985

2 H Kurz and W Goedecke, "D gita Parameter Adaptive Control of Processes with a Slowly Varying Dead Time," *Automatica*, 17(1), 1981

3 De Souza E, Goodwin G, Mayne D, and Palaniswam M, "An Adaptive Control Algorithm for Linear Systems Having Unknown Time Delay" *Automatica*, 24(3), 1988

4 H Itakura, "Parameter Identification n a Process Control System," *IEEE Transactions on Automatic Control*, AC 31(12) 1986

5 Y N sh kawa et a, "A Method for Auto-Tuning of PID Control Parameters" *Automatica*, 20(3) 1984

6 T Matsko "Interna Model Contro for Chem ca Recovery," *Chemical Engineering Progress*, 1985

7 J Lane, "Descrip ion of a Modular Self Tun ng Control System," *Proceedings of the American Control Conference* 1986

8 J Parish, "The Use of Model Uncertainty n Contro System Des gn with Appl cation to a Laboratory Hea Exchange Process" M S Thesis CWRU 1982

9 Pop el L Matsko T and Brosilow C "Coordinated Control", *Chemical Process Control CPC III* 1986

10 Parish J, and Bros ow C, "Inferential Contro Applications," *Automatica*, 21(5), 1985

11 J Lane, "Se f Tun ng Control,", *Bailey Controls Co Application Guide*, AG-0000-953-01, 1987

00 20 35 04 11 07

00 20 36 04 11 07

00 20 37 04 11 07

Bailey Controls

Babcock & Wilcox, a McDermott company

29801 Euclid Avenue Wickliffe Ohio 44092 Phone (216) 585 8500

Litho in U.S.A. 1188