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A Closed Loop Deadtime/ Parameter Estimator for Self-Tuning Process Control

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Abstract

Processes with large deadtime to time constant ratios have traditionally proven difficult to control effectively. In practice, PID controllers (tuned to assure robustness at the expense of performance) are generally employed for the control of these processes. Conceptually better performance is achievable through deadtime compensation using a Smith Predictor or Model Based Controller. Unfortunately these techniques are rarely used in practice due, in part, to unfamiliarity of technicians and operators with the tuning of these controllers. Recent work in self tuning control has had little impact on the control of large deadtime processes. This can be attributed to reliance of most self tuning controllers on the PID algorithm and the absence of techniques for the identification of process deadtime.

This paper describes a model based control algorithm that directly incorporates deadtime compensation and a novel closed loop process identification technique capable of identifying process deadtime directly. This combination provides an effective system for the control of large deadtime process. The resulting controller is easy to implement and commission. Its auto tuning feature provides a simple mechanism for retuning the controller on a periodic basis. Extensive simulation results and preliminary field test results are presented in addition to a brief description of the controller and auto tuner.

Introduction

The application of self tuning controllers to processes with large, unknown or time varying deadtimes, has been the goal of much research. A majority of research in this area has attempted to extend recursive least squares parameter estimation to include deadtime identification. 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.

Itakura [4] and Nishikawa, et al [5] describe a technique for estimating process parameters including deadtime for systems operating in closed loop. This technique, henceforth referred to as a deadtime/parameter estimator (DPE), calculates time integrals of system variables reacting to a step or impulse input. Proper selection of these integrals (contr areas) results n a set o non near ecuat ons solve e r the process r mete s e DPE ident fies the complete dynam c cha acter st cs c p cesses es they pe te e se e t v e n effective base for the imp ementat o o an aut tu ing contr c

Th s paper describes an auto tun ng imp eme itatio i us ng the DPE n conjunct o w h e m dc se le e

o First the details of the mode based control er are rev ewed

o Second, the derivation of the control area parameter est mat or o the m de based c ntr er is reviewed A r gorous descr pt on can be found in [6]

o Last, simulation results are presented t s pp rt he se ect on c var us p me e s sed s algorithm and illustrate the strengths and imitations of this tech ique

Model Based Controller Description

The initial implementation of the DPE auto tuner is based n a m del ased c nt e e m de se controller was selected over a more conventional PID controller for two reasons The pr m ry eas n w s th controller's ability to compensat for the effects of process deadtime Th s a ows t e u e t e e e pp e to a m re general c ass o processes than the c ass o processes st tab e PID c ntr A sec nd v e of the model based contrc er is the use o a separate parameter r spec y g c se d c p c n e contrast, PID parameter selecti n requires c sed c p per ormance t e e red nt e s e e tuning parameters

Figure 1 presents a block diagram of the model based contr le and (1) de nes t t ans e unct n

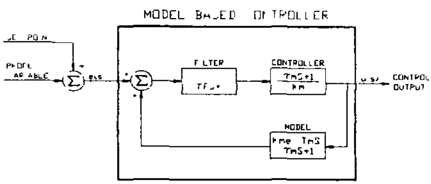

FIGURE 1 MODEL BASED CONTROLLER

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

This particular formulation assumes that the controlled process can be approximated by a first order lag with deadtime. 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 to a change in setpoint or to a disturbance.

Deadtime/Parameter Estimation Technique

The use of the previously described model based controller requires knowledge of the dynamic characteristics of the controlled process. To extend the applicability of this system to processes with unknown or time varying dynamics, a feature based parameter estimation technique is employed. This technique has the advantage of estimating all process parameters, including deadtime, in closed loop. The technique selected for this work parallels that described by 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 nonlinear equations for the process parameters.

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

- o 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.

- o The setpoint to the controller is increased (decreased) by a prescribed amount to start the estimation procedure.

- o The integrals in (2) and (3) 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 0 to t_{ss}. Figure 2 illustrates the calculation of these integrals.

- o 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.

- o 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.

- o After observing the process response to a step setpoint change, (4) and (5) 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 term of (5) using a successive substitution technique and starting from an initial τ_{est} of 0.

$$I_1 = \frac{1}{SP}\int_0^\infty \left[m_{ss} - m(t) \right] dt \tag{2}$$

$$I_2 = \frac{1}{SP}\int_0^\infty \left[m_{ss} - m(t) \right] e^{\alpha t}\, dt \tag{3}$$

$$k_{est} \quad \frac{SP}{m_{ss} \quad m_{init}} \tag{4}$$

$$\tau_{est} \quad z + \frac{1}{\alpha} \ln \left[\frac{a\tau_{est} \quad b}{c} \right] \tag{5}$$

$$T_{est} \quad z \quad \tau_{est} \tag{6}$$

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

SP Change in Setpoint

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

$k_m, \tau_m \; T_m \; \tau_f$ Controller Parameters

α weighting parameter $(\tau_m + T_m)$

and

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

$$a \quad \left[\alpha(\tau_f \alpha + 1 + e^{\,T m \alpha}) + \frac{k_{est} \alpha (\tau_m \alpha + 1)}{k_m (k_{est} I_2 \alpha \;\; 1)} \right]$$

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

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

Simulation Results

Simulation testing was conducted using a Bailey Controls Multi function Controller (MFC03) The DPE algorithm was implemented as a C program, the existing model based controller was used and two generic processes were simulated using standard function code logic The generic processes used for the simulation testing, consisted of a third order lead lag network with deadtime and a second order polynomial with deadtime specified in terms of natural frequency and damping ratio Both linear processes were designed to operate 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 with deadtime process to determine the effects of the ratio between process time constant and deadtime and selection of the model based controllers filter time constant on estimator performance Table 1 summarizes the results of initial testing by showing the worst estimates generated for first order processes with deadtime to time constant ratios of 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

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

τ_p	T_p	τ_{est}	T_{est}	τ_f(worst case)
60	10	59 18	10 41	45
30	30	32 10	27 98	90
30	60	32 50	58 07	90
30	120	36 70	113 79	90
30	5	31 50	3 61	90

Table 1 shows that smaller values of the filter time constant resulted in improved estimator performance down to the point at which controller saturation occurs in response to the required setpoint change For small filter time constants, the value of $e^{-\alpha t}$ remains large for a greater percentage of the total process response increasing the amount of information captured by the integral I_2 and 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 0 25 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 assumed that the type of noise present and the magnitude of the noise with respect 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 DPE identified both the process time constant and deadtime to within ±1.5 seconds or 5%. For cases with either the model time constant or the model deadtime of the model based controller set significantly larger than the correct value and with a small filter time constant, no estimates were obtained. Observation of the closed loop response for these cases revealed marginal stability or instability of the closed loop system, preventing convergence of the integral I_1

The above simulation studies validated the performance of the DPE 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 was tuned during the course of the closed loop test or when the initial controller tuning resulted in a highly oscillatory or unstable closed loop system.

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

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

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

The DPE 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 evoking a stable closed loop response the estimator approximated the high order process with

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

Figure 3 shows the open loop response of this estimated process, $G_{1est}(s)$, superimposed over the open loop response of the process it approximates, $G_1(s)$. Figure 4 shows the closed loop response of the process $G_1(s)$ under the control of the model based controller using the estimated model to establish its tuning and using a filter time constant of 60.0 seconds.

This series of tests clearly shows that the DPE is capable of approximating high order overdamped process dynamics with a first order model, even in the presence of numerator dynamics. Further, these closed loop tests show that using the estimated parameters to tune the model based controller provides excellent closed loop control of high order processes.

Simulation testing with the process $G_2(s)$ revealed an inability of the DPE to approximate underdamped systems using a first order model. Specifically, the estimator provided 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 too of tuning resulted in sluggish closed loop performance. Clearly, neither the DPE nor the first order model based controller are well suited for use with highly underdamped processes.

Conclusion

Bailey Controls is developing a powerful autotuning controller, using a deadtime/parameter estimator algorithm to identify process characteristics and a model based controller to provide deadtime compensated closed loop control. Simulation results show that this autotuner is applicable to a wide range of industrial processes. Currently, this autotuner is undergoing further evaluation at several field test locations. In its current configuration, the DPE portion of the autotuner is able to respond to naturally occurring step setpoint changes. Also, an external triggering mechanism can be used to force the DPE to reidentify the process.

The development of the autotuning controller is nearing completion. After validation of the algorithm implementation and documentation through field testing, the DPE will be added to Bailey's library of standard function codes. Nevertheless, several areas of interest have been identified as targets for continuing development. First, simulation results suggest that the DPE is not applicable to processes that exhibit highly oscillatory closed loop responses. Fortunately, one can often stabilize closed loop responses by increasing the filter time constant of the model based controller. Therefore, a first goal of continuing research will be to identify a mechanism for automatically increasing the filter time constant of the model based controller to stabilize closed loop system response and allow identification of process characteristics. Second, PID controllers are currently used in a majority of applications. Initial development of the DPE identified and validated equations for process identification for use with PID controllers. Therefore, a second goal of continuing research will be to implement a version of the DPE for use with a PID controller.

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