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# A comparison of traditional and adaptive control strategies for systems with time delay

Craig W. Alexander [a,*], Russell E. Trahan Jr. [b,]

[a]Monsanto, 1788 Lovers Lane, Augusta, GA 30901, USA
[b]Department of Electrical Engineering, University of New Orleans, New Orleans, LA 70148, USA

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**Abstract**

A recently developed tuning method is compared to an adaptive Smith Predictor control strategy. The robustness of each method is considered for time-varying plant parameters. Examples with simulations are provided to compare the methods and present conclusions on the advantages and disadvantages of each. © 2001 Elsevier Science Ltd. All rights reserved.

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## 1. Introduction

The PID controller is the most widely used control algorithm in the process industries because it is robust and easily applied to many different types of systems [1,2]. Modern computers will allow almost any control method to be implemented, but the PID controller is still used for most process control applications. However, the three modes of the PID controller, proportional, integral, and derivative, are not clearly related to process model parameters. Therefore, it has been necessary to develop rules to simplify the adjustment of the controller settings [3].

Many controller tuning methods have been developed over the years. Among the most popular are the Ziegler–Nichols method developed in 1942 and the Cohen–Coon method developed in 1953. These methods seek to provide closed-loop oscillation with a quarter amplitude decay in response to step changes in set point or load [4,5]. Many modern controller tuning methods are based on the Ziegler–Nichols and Cohen–Coon methods [15]. Recently, Abbas has developed a tuning procedure that offers superior performance over both the Ziegler–Nichols and Cohen–Coon methods. This method seeks to control a first-order plus time delay (FOPTD) plant to have a closed-loop response with a specified overshoot [6].

One of the most difficult process dynamics to control is time delay [7]. When the system dead time grows large in relation to the time constant, the PID controller tuning methods may not provide adequate performance [8]. Furthermore, many plants exhibit dynamic properties such as variable dead time or time constant [9].

* Corresponding author.
*E-mail address:* craig.w.alexander@monsanto.com (C.W. Alexander).


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A traditional PID controller may show performance degradation or may even become unstable if plant parameters change enough. Adaptive controllers are often implemented to accommodate these changing situations [10]. There are a number of adaptive control methods available to process control engineers including pole-placement, generalized predictive control (GPC), relay feedback auto-tuning, and internal model control (IMC) [10–12]. One popular method is the adaptive Smith Predictor. This controller uses a digital form of the standard Smith Predictor along with the recursive least-squares system identification algorithm to provide continuously updating adaptive control [10].

The purpose of this paper is to compare various methods for adjusting controllers for plant conditions. The performance of the adaptive Smith Predictor will be compared to that provided by Abbas. Two examples will be developed and then used to compare the robustness of the two methods by introducing changes to the plants during the simulation.

## 2. Abbas tuning

The PID controller is by far the most used method of regulating chemical process systems [1]. A properly tuned PID controller can provide excellent, robust control of most process systems [2]. However, the proper setting of the three modes of a PID controller is not always intuitively obvious. Through the years, a number of rules and guidelines have been developed to help the plant control engineer make the right decisions when tuning controllers. Two of the best known tuning methods are Ziegler–Nichols and Cohen–Coon which both attempt to achieve a quarter amplitude decay [1,3]. However, in many situations they generally produce plant responses with more oscillation than is acceptable to operators. Also, the calculations do not allow the control system designer to specify a desired closed-loop response [6,13]. This often results in the tuning being modified, or even set to manual mode, to achieve an overdamped response which will be more acceptable to the operator [9].

Abbas has developed a tuning method that relates the controller coefficients to the characteristics of a FOPTD process model as well as the desired overshoot of the closed-loop system. For a PID controller,

$$K_c\left[e(t) + \frac{1}{\tau_I}\int e dt + \tau_D \frac{d}{dt}e(t)\right] \tag{1}$$

the Abbas method specifies the gains as:

$$K_c = \frac{\tau + \frac{\theta}{2}}{K_P(\lambda + \theta)} \tag{2}$$

$$\tau_I = \tau + \tfrac{\theta}{2} \tag{3}$$

$$\tau_D = \frac{\tau\theta}{2\tau + \theta}. \tag{4}$$

where $\tau$ is the open-loop time constant (s), $\theta$ is the plant time delay (s), $\lambda$ is the desired closed loop time constant (s), and $K_P$ is the proportional term of the plant. From Eqs. (2)–(4), we see that only the proportional term of the controller is affected by the desired closed-loop time constant $\lambda$. The integral and derivative terms are only affected by the time constant and time delay of the open-loop plant. $\lambda$ is chosen to achieve the desired closed-loop performance [6].

Abbas defines two parameters to be used to find the desired value for the loop gain, $K = K_c K_P$. The process model is considered by defining $R$ as the time delay to time constant ratio, and the closed-loop response is considered by defining the overshoot as $V$. $V$ is a fraction between 0 and 1; e.g. a 10% desired overshoot requires $V = 0.1$. Abbas obtained closed-loop step responses from many plants via simulation. The data was plotted for a range of $0.1 \leqslant R \leqslant 5$ and $0 \leqslant V \leqslant 0.20$. After curve-fitting a large number of plant results using the Marquardt–Levenberg optimization algorithm, the simplest equation that approximates the experimental data is

$$K = \frac{a + bR^c}{d + eV^f} \tag{5}$$

where the parameters *a, b, c, d, e,* and *f* are given in Table 1 for P, PI, and PID controllers [6]. The controller proportional gain $K_c$ is then obtained by simply dividing the gain obtained from Eq. (5) by the plant gain $K_P$.

## 3. Adaptive control

Control systems engineers have long recognized the difficulty of controlling processes with dead time. Standard PI or PID control may not be adequate for controlling processes with large time delays [8]. Dead time is a factor in many chemical and biomedical processes, so PI and PID controllers are often "detuned" to maintain overall stability [7]. Often, more advanced methods of control are required for this type of process in order to improve performance.

Industrial users first began to use adaptive control methods in the 1970s [16]. An adaptive controller has parameters that can be continuously adjusted in response to changes in process dynamics and disturbances [1]. A process plant is a dynamic environment, so it is not unusual for a process to undergo significant changes that may degrade the performance of a standard PID controller or even lead to instability [9]. An adaptive controller includes a mechanism to update its own control parameters based on feedback from the plant output [17].

One type of adaptive controller can be thought of as having two loops: a typical feedback control loop consisting of the plant and the controller and another loop which contains a controller parameter adjustment algorithm [17]. The parameter adjustment loop may include some type of system identification routine that follows a set of rules to generate parameter updates [10]. The parameters include both those that are related to the nature of the process and those that can be chosen by the control designer [18]. The on-line parameter adjustment mechanism makes the adaptive controller inherently non-linear [17].

There are many methods of recursive system identification available to control system engineers today. In the work reported here, the recursive least squares method, one of the most popular parameter estimation schemes, has been used [10]. In the least squares method the plant inputs and outputs are sampled and a curve is optimally fit to these samples. This curve fitting is performed by minimizing the sum of the squares of the difference between the sampled data and the curve [19]. It is important to note, however, that the model chosen for the system identification must be capable of representing the plant accurately. A best fit for an inaccurate model will be useless for the purposes of adaptive control [20].

For some plants with large dead time, a detuned PID controller may not provide satisfactory performance, and it may be necessary to implement a more advanced control strategy. One well-known strategy is the Smith Predictor that was introduced in 1957 [1]. The Smith Predictor is a model-based controller that uses the plant model parameters to control the system [14]. The resulting feedback signal will not show the effects of the time delay if the model accurately represents the plant [22].

Since the Smith Predictor is a model-based controller, it is very sensitive to the accuracy of the process model [14]. Theoretical calculations can show that the Smith Predictor provides great improvement in control over traditional methods. However, the practical improvement is limited because even small changes in the actual dead time of a tightly tuned process can lead to instability [23]. This can be overcome by only applying the Smith Predictor to systems with well known and constant gains, time constants, and dead times or by tuning the controller less aggressively to allow a greater inaccuracy in the model [14,23]. It has been shown that there will still be some improvement over PID control as long as the model parameters are within 30% of the actual values [14]. Even with this range of inaccuracy allowed, one must have some understanding of the process to

Table 1
Abbas gain calculation parameters [6]

| Controller | *a* | *b* | *c* | *d* | *e* | *f* |
|---|---|---|---|---|---|---|
| P | 0.127 | 0.247 | −1.050 | 0.918 | −0.838 | 0.295 |
| PI | 0.148 | 0.186 | −1.045 | 0.497 | −0.464 | 0.590 |
| PID | 0.177 | 0.348 | −1.002 | 0.531 | −0.359 | 0.713 |

be controlled before implementing a Smith Predictor.

If the process model parameters vary significantly with time, an adaptive control algorithm may be necessary [14]. A continuously self-adjusting controller can change the model parameters so that they maintain an accurate model. The plant parameter changes may be due to wear, temperature changes, production rate changes, or other factors that may or may not be measured [21]. Automatically adjusting for these plant changes will ease the implementation of the Smith Predictor since the model can be updated on-line to match the process. Therefore, the burden of developing an exact model and frequent retuning can be moved from the control engineer to the adaptive controller [10].

For this work, we have implemented a continuously updating adaptive controller based on the digital Smith Predictor. A second-order plant model was used, and system identification was performed using the recursive least-squares method. The controller was designed to achieve a specified closed-loop time constant $T_m$[10].

To implement the recursive least squares algorithm, we first describe the plant as a discrete transfer function, $G_P(z^{-1})$:

$$G_P(z^{-1}) = \frac{B_P(z^{-1})}{A_P(z^{-1})} z^{-d} \tag{6}$$

where

$$B_P(z^{-1}) = b_1 z^{-1} + b_2 z^{-2} + \cdots + b_m z^{-m}$$
$$A_P(z^{-1}) = 1 + a_1 z^{-1} + \cdots + a_n z^{-n} \tag{7}$$

The relationship between the plant output $y(k)$ and the plant input $u(k)$ can be written as

$$y(k) + \sum_{i=1}^{n} a_i y(k-i) = \sum_{j=1}^{m} b_j u(k-d-j) + e(k). \tag{8}$$

Eq. (8) can be written in the compact form

$$y(k) = \theta^T x(k) + e(k). \tag{9}$$

The vector $\theta$ contains the parameters that are estimated. It is of the form

$$\theta = [a_1\, a_2\, \cdots\, a_n\, b_1\, b_2\, \cdots\, b_m]^T \tag{10}$$

The data vector, $x$, is

$$x(k) = \Big[-y(k-1)\ -y(k-2)\ \cdots\ -y(k-n)\ \ u(k-d-1)\, u(k-d-2)\ \cdots\ u(k-d-m)\Big]^T [10]. \tag{11}$$

The estimation model of the process is

$$G_m(z^{-1}) = \frac{B_m(z^{-1})}{A_m(z^{-1})} z^{-d} \tag{12}$$

where

$$B_m(z^{-1}) = \hat{b}_1 z^{-1} + \hat{b}_2 z^{-2} + \ldots + \hat{b}_m z^{-m}$$
$$A_m(z^{-1}) = 1 + \hat{a}_1 z^{-1} + \ldots + \hat{a}_n z^{-n} \tag{13}$$

and the ^ symbol denotes an estimated parameter. The parameter estimates are compacted into a vector as

$$\hat{\theta} = \Big[\ \hat{a}_1\ \hat{a}_2\ \cdots\ \hat{a}_n\ \hat{b}_1\ \hat{b}_2\ \cdots\ \hat{b}_m\Big]^T \tag{14}$$

resulting in a model output of

$$\hat{y}(k) = \hat{\theta}^T x(k)\,[10]. \tag{15}$$

For the recursive algorithm to be able to update at each sample time, it is necessary to define an error. The model prediction error is defined as

$$\varepsilon(k) = y(k) - \hat{\theta}^T(k-1)x(k) \tag{16}$$

which is the difference between the plant output and the model output. This error is used to update the parameter estimate according to

$$\hat{\theta}(k) = \hat{\theta}(k-1) + G(k)\varepsilon(k) \tag{17}$$

where the estimator gain matrix is defined as

$$G(k) = \frac{P(k-1)x(k)}{\gamma + x^T(k)P(k-1)x(k)}. \quad (18)$$

The forgetting factor, $\gamma$, will be chosen by the designer as a value between 0 and 1 as described below. The covariance matrix $P$ is updated using

$$P(k) = \frac{1}{\gamma}\left[I - G(k)x^T(k)\right]P(k-1)[10]. \quad (19)$$

The forgetting factor in Eq. (18) allows new data to be weighted more heavily than old data when updating the parameters. Thus, a large transient in the past will be discounted as time goes by. This factor allows us to adjust the parameter estimate convergence speed as well as to filter out the effects of noise in the system. In general, choosing $0.98 \leqslant \gamma \leqslant 0.995$ gives a good balance between speed and noise susceptibility [10].

The initial values of P(k) and $\hat{\theta}$(k) are chosen as estimates and then allowed to settle to their final values as the program goes through several iterations [20]. There is no unique way to initialize the algorithm because it depends on knowledge of the process [17]. One suggestion is to set $\hat{\theta}(0)$ = zero and $P(0) = \alpha I$ where $\alpha$ is a large scalar [25]. For the examples presented here, the initial estimates were chosen to be zero and $P(k)$ is chosen to be *100I* [10,17].

For good performance, the system identification must be allowed to run before closing the control loop. This will initialize the controller to close estimates of the plant parameters. Also, it is necessary to pre-tune the controller. For this work, we have used the Abbas tuning method to calculate the initial tuning settings. This will give both controllers a common starting point and provide a more realistic comparison of performance when changes are introduced.

## 4. Robustness comparisons

Real processes are not static. They operate under conditions that change over time. Therefore, it is important to implement a robust control system. In this section, we will consider the performance of the Abbas tuning equations versus the adaptive Smith Predictor when faced with a changing plant. Two examples will be presented to show the effectiveness of the adaptive Smith Predictor. Each example will model a typical industrial chemical process as a second-order plus time delay (SOPTD) transfer function. These examples will be used to compare the performance of the adaptive Smith Predictor to static Abbas tuning for a time-varying plant. Recall that Abbas' method was developed for a FOPTD plant; the following examples, by being SOPTD, will demonstrate the limitations of this technique when applied to higher order plants.

### *4.1. Example 1: distillation column*

The transfer function relating the viscosity, $y(s)$, and the reflux flow, $u(s)$, for a high vacuum distillation column can be expressed as:

$$G_{\mathrm{P1}}(s) = \frac{y(s)}{u(s)} = \frac{0.57e^{-20s}}{(1+8.6s)^2} = \frac{0.57\mathrm{e}^{-20s}}{73.96s^2 + 17.2s + 1} \quad (20)$$

where the time delay is equal to 20 s [10]. A step response shows that the open-loop time constant of this system is about 20 s. The system is not dead-time dominant since the time constant and time delay are the same. The Abbas tuning calculations for this system, using $V = 0.1$, give the loop gain as $K = 1.14$. The process gain is 0.57, so the controller gain will be $K_c = 2.0$. The integral and derivative terms are $\tau_I = 30.0s$ and $\tau_D = 6.67s$.

We modified the plant by increasing the time delay when the simulation time reached 500 s. The setpoint was varied as a series of step functions. The plant output with no change in the plant as controlled by the adaptive Smith Predictor is shown in Fig. 1. The overshoot is just under 30%, the 2% settling time is 189 s, and the rise time is 24 s. The plant output with a 10% increase in the dead time is shown in Fig. 2. With a 20% increase in the dead time, the results are shown in Fig. 3. A 50% increase in dead time gave results as shown in Fig. 4. Even with a 30% change in the plant, the overshoot is under 50%. When the plant suddenly

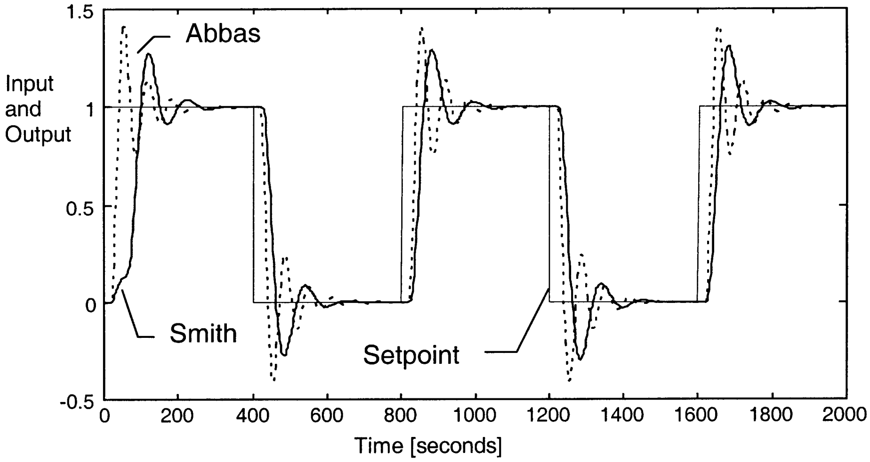


Fig. 1. Example 1 setpoint response, constant time delay.

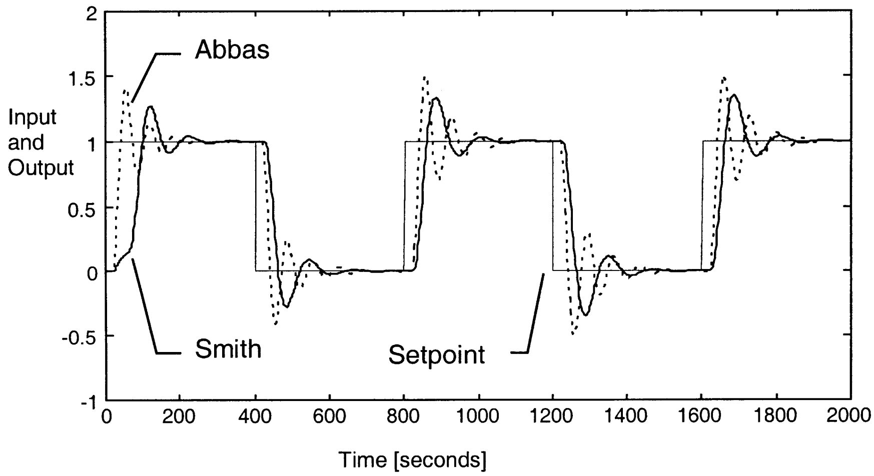


Fig. 2. Example 1 setpoint response, 10% change in time delay at 500 s.

changes by 50%, the controller still controls, but is becoming quite oscillatory. For this example, the adaptive Smith Predictor provides quite robust performance in the face of a changing time delay.

Using the Abbas tuning parameters, the plant output for a constant 20 s time delay is also shown in Fig. 1. The percent overshoot is 41.19% with a rise time of 13.8 s. The 2% settling time is 201 s. The ringing and large overshoot are attributed to the dependence of the Abbas tuning method on a FOPTD model. The oscillation is caused by the unmodeled second-order dynamics. Plant outputs for increases in time delay of 10%, 20%, and 50% are shown in Figs. 2–4, respectively. Note that the overshoot and the oscillations are greater for the Abbas technique even at the conditions used in calculating the tuning parameters. This degraded performance is attributed to the assumption of a first order plant in the Abbas development. Beyond a 10% change in the dead time, the overshoot is greater than 50%, which would be undesirable for most processes. Also, the increased oscillation of the system would cause undesirable process upsets.

The adaptive Smith Predictor provides the best control for this example. The controller reaches good performance fairly quickly, but the system

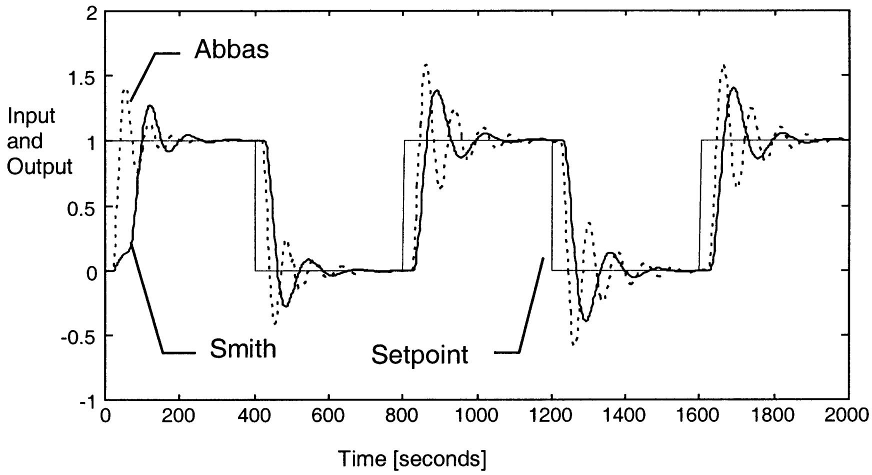


Fig. 3. Example 1 setpoint response, 20% change in time delay at 500 s.

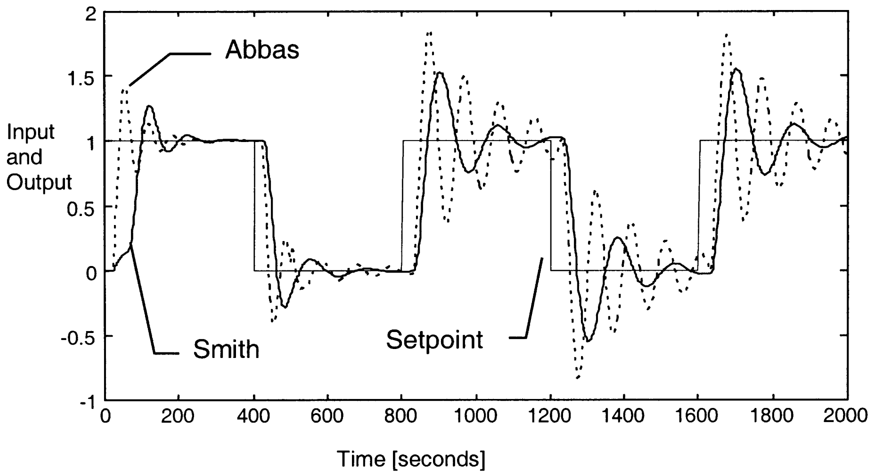


Fig. 4. Example 1 setpoint response, 50% change in time delay at 500 s.

must be able to handle the initial upset. This is taken into account by initializing the parameter estimates close to the correct values by pre-running the system identification. Abbas tuning is disappointing because of the unmodeled second order dynamics. When the gain is decreased, the performance is much better. This would add to the time to tune the controller but not as much as finding a reasonable second order model to use for parameter estimate initialization in the adaptive controller.

Next, the effects of load disturbances on the adaptive Smith Predictor controller for the distillation column were considered. A series of unit steps were introduced into the load and then the plant dead time is changed at a simulation time of 1000 s. The plant outputs and the load disturbances are shown in Figs. 5–8 for time delay changes of 0, 10, 20, and 50%, respectively. For all four cases, the controller performance is similar. The control is good with the maximum output deviation about 50% of the load disturbance. The

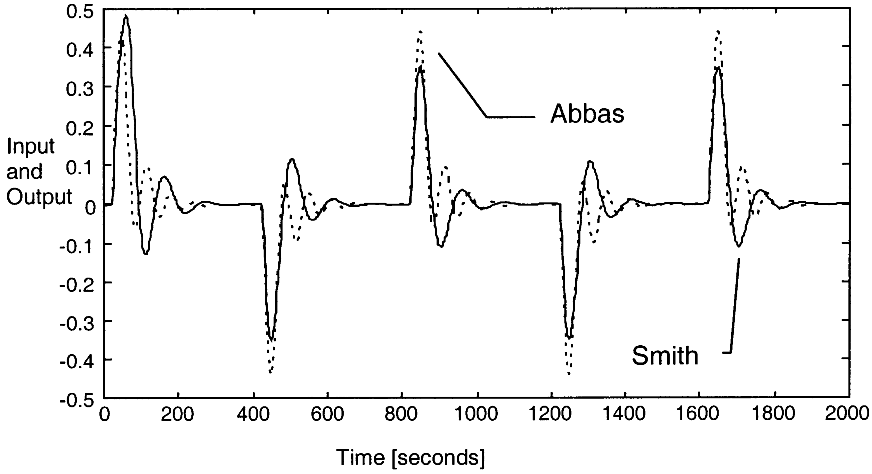


Fig. 5. Example 1 load response, constant time delay.

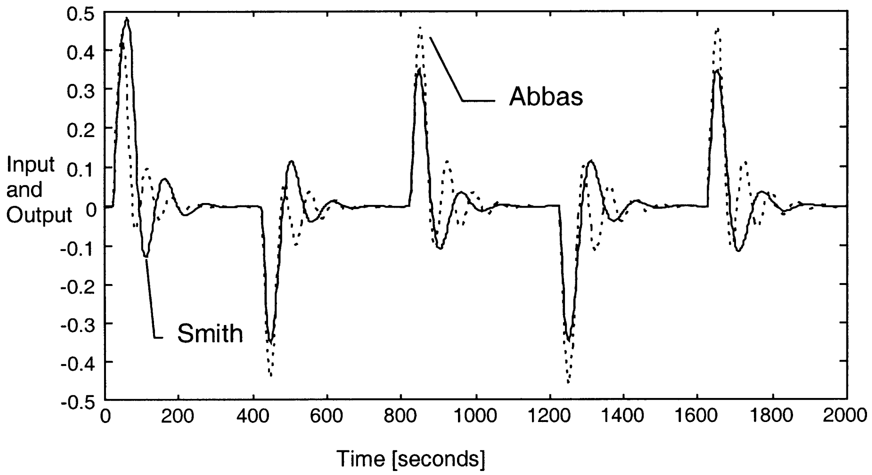


Fig. 6. Example 1 load response, 10% change in time delay at 500 s.

output settles back to zero with approximately quarter amplitude damping.

The amplitude of the output excursion due to the Abbas tuning is similar to that of the adaptive controller, but the settling time is much longer. The output oscillation is more noticeable even for a static plant. There is additional oscillation as the dead time grows more and more dominant, with the ringing approaching an unacceptable amount in Fig. 8. The Abbas-tuned controller is very sensitive to dead time changes. The controller settings may have to be detuned to get more robust performance.

For a load disturbance, the adaptive Smith Predictor again gave superior performance over the Abbas method. The difference in performance between set point change and load disturbance is found with the parameter initialization for the adaptive Smith Predictor. The adaptive controller seems to be relatively insensitive to parameter initial values in the presence of load changes. Thus, it is important to know whether a system

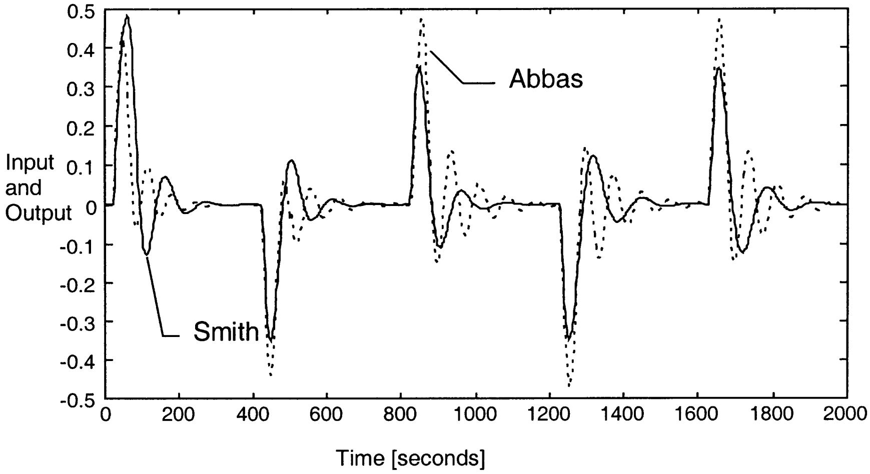


Fig. 7. Example 1 load response, 20% change in time delay at 500 s.

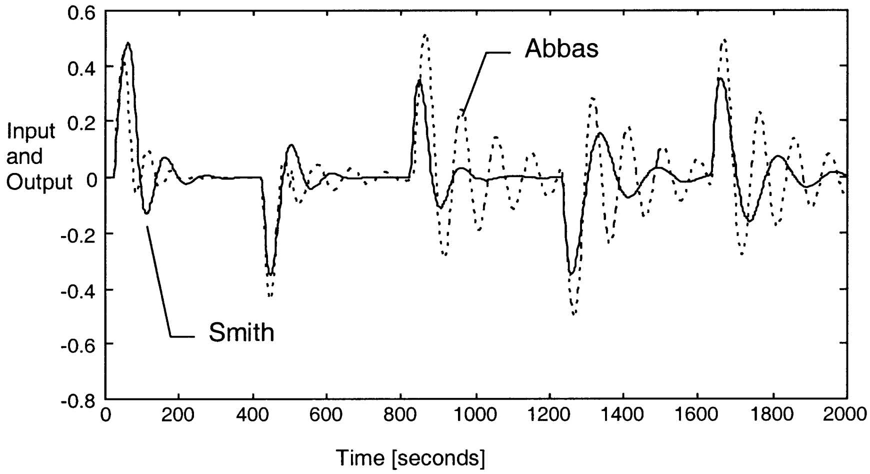


Fig. 8. Example 1 load response, 50% change in time delay at 500 s.

will see mostly set point changes or load deviations when selecting the proper control strategy.

### *4.2. Example 2: reactors in series*

This example considers two continuous reactors operated in series. The reaction takes place as component A reacts irreversibly to produce component B, the desired product. The parameters of the model include the flows into and out of each reactor and the concentrations in each reactor. It is acceptable that the volume of each reactor be different, but we have chosen to make them the same. The temperature and the density will remain constant across the system. The reaction is assumed to be a simple first-order reaction that takes place at a fixed reaction rate, $k$ [23].

The transfer function relating the concentration at the input of the first reactor to the concentration at the output of the second reactor is given by

$$C_{A2} = \frac{1}{[\tau_1 s + (k+1)][\tau_2 s + (k+1)]} C_{A0} \tag{21}$$

where the time constant $\tau_i$, $i=1,2$, is equal to the volume divided by the flow rate for each reactor. To make this a second-order plus time delay plant, a 20 s analyzer delay was added as follows

$$C_{A2} = \frac{e^{-20s}}{[\tau_1 s + (k+1)][\tau_2 s + (k+1)]} C_{A0} \, [23]. \quad (22)$$

The decomposition of ethyl chlorocarbonate is chosen as an example process. At a reactor temperature of 600 K, the rate of reaction is $k=0.02308 \text{ s}^{-1}$. This is a result of a frequency factor of $\alpha=9.2\times10^8 \text{ s}^{-1}$ and an activation energy of $E=29.1\times10^3$cal/mol [24]. A constant volume of 100 gallons (378.5 l), or 13.36 $ft^3$ (0.3785 $m^3$) is assumed for each reactor.

The effects of changing plant dynamics for the series reactor example can be investigated by changing the flow rate through the system to simulate a change in production rate. First, a 10% increase in the flow rates from 500 scfm (0.236 $m^3/s$) to 550 scfm (0.260 $m^3/s$) will be introduced when the simulation time reaches 500 s. The plant output for the adaptive Smith Predictor using a closed-loop time constant of five seconds when the flow is constant at 500 scfm (0.236 $m^3/s$) is shown in Fig. 9, and the plant output for a 10% increase in flow at 500 s is shown in Fig. 10. There is basically no difference between the two plots. At a flow change to 750 scfm (0.354 $m^3/s$), the plant yields results as seen in Figs. 11 and 12 shows a flow change to 1000 scfm (0.472 $m^3/s$). At 750 scfm (0.354 $m^3/s$), a 50% change in flow, there is some overshoot and some oscillation that quickly damps out. However, after three setpoint changes, the adaptive controller has returned to an overdamped response. Even at a flow change to 1000 scfm (0.472 $m^3/s$), the plant output returns to a smooth, overdamped curve following a large overshoot with lots of ringing for a few set point cycles.

The Abbas tuning for flows of 500 scfm (0.236 $m^3/s$) and a time constant of 3.55 s yields controller parameters of

$$K_c = 0.46 \qquad \tau_I = 13.55\text{s} \qquad \tau_D = 1.18\text{s}$$

for no overshoot, i.e. $V=0.0$. At a constant flow of 500 scfm (0.236 $m^3/s$), the plant output is shown in Fig. 9. The closed-loop time constant is 9.5 s and the settling time is about 71 s. For a 10, 50, and 100% increase in flow, the plant output is shown in Figs. 10–12, respectively. There is additional oscillation, but overall there is little change in the plant output. The controller is able to maintain the overshoot at zero as specified in the calculations. This system seems very robust with respect to large flow changes. The only drawback here is that the system will never adjust itself back to the original performance. The Smith Predictor

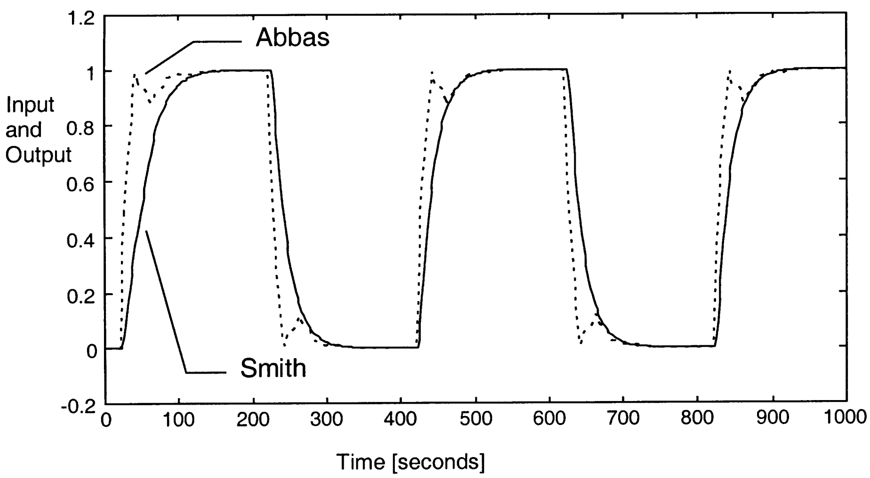


Fig. 9. Example 2 setpoint response, constant flow.

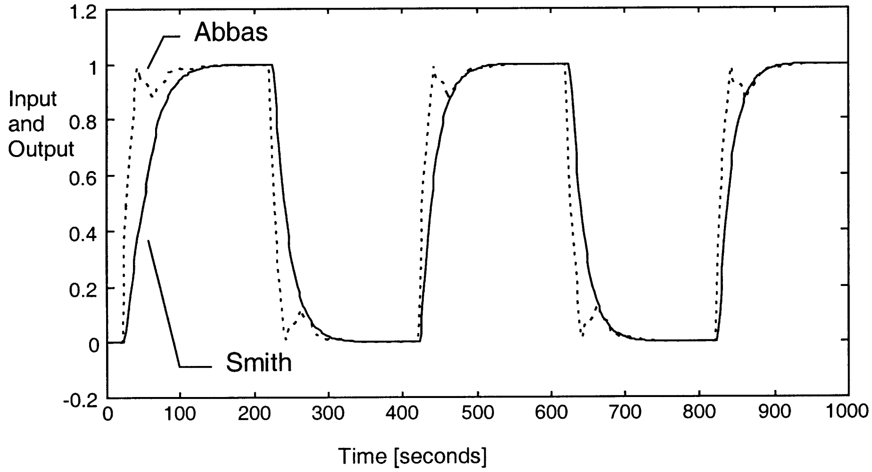


Fig. 10. Example 2 setpoint response, 10% flow increase at 500 seconds.

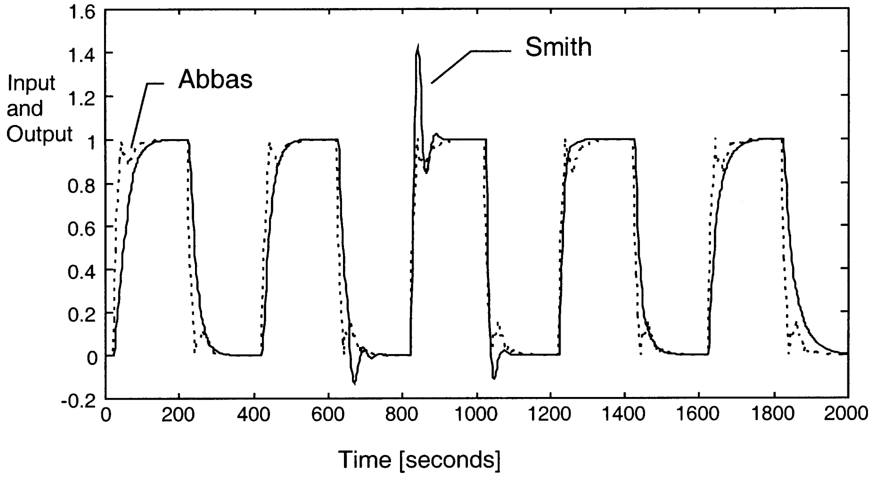


Fig. 11. Example 2 setpoint response, 20% flow increase at 500 s.

provided a smoother output after adjusting itself. However, since the Abbas tuning method requires much less effort and maintenance, it has shown to be an acceptable dead time compensation method.

From this example, we can see that if the system is dead time dominant, the adaptive Smith Predictor still requires a lot of a priori information about the system before starting the controller. A good guess of the system parameters is needed to keep the controller stable. This can be accomplished by running the system identification prior to closing the loop. However, the performance is excellent if the system is initialized correctly. By comparison, a quick step test allowed us to get good performance using the Abbas method. This performance is not as smooth as the adaptive Smith Predictor, but it required significantly less effort to produce.

Next, a series of load disturbances were applied to the system as controlled by the Abbas-tuned controller and the adaptive Smith Predictor. The effects of flow changes are studied in a similar manner to that described above. The plant outputs for the flow change are shown in Figs. 13–16. The performance of the adaptive Smith Predictor is very good for all cases. There is little difference in the plots except for a slight widening of the output deviation as the dead time to time constant ratio increases. The output deviates from steady state by less than the load change amplitude and returns to steady state very quickly.

The performance of the Abbas-tuned controller with $V=0.0$, i.e. no overshoot, for these same flow changes is shown in Figs. 13–16 as well. This system also gives good controller performance. The response is more erratic than the adaptive Smith Predictor, especially as the dead time to time constant ratio grows, but the output quickly returns to steady state with no overshoot. The adaptive Smith Predictor shows better performance for this example than Abbas. However, the Abbas performance is very good, only taking a slightly longer time to settle to steady state. This performance would probably be acceptable to plant personnel, especially in light of the complexity of implementing the adaptive controller.

Finally, note that these changes are probably much more harsh than those seen in an actual

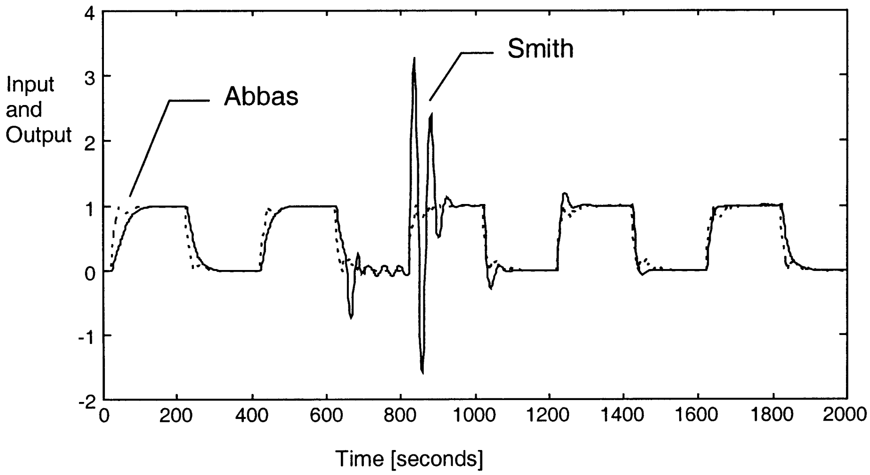


Fig. 12. Example 2 setpoint response, 50% flow increase at 500 s.

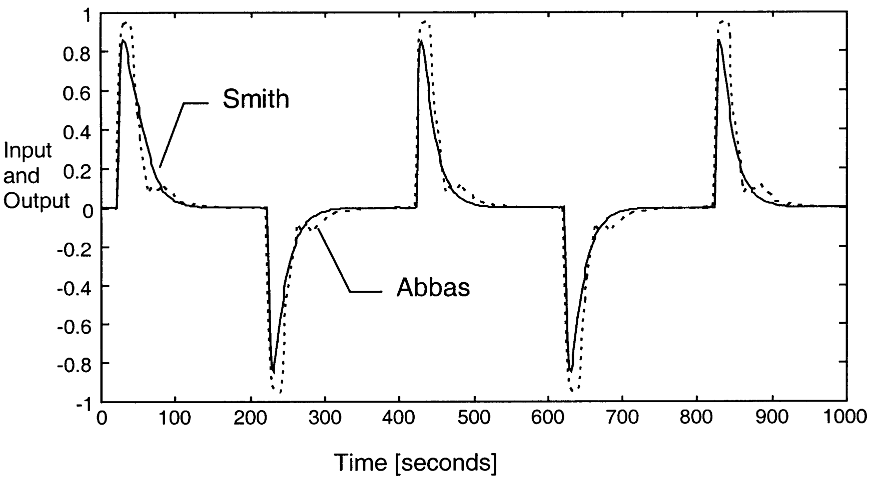


Fig. 13. Example 2 load response, constant flow.

plant situation. Even for a drastic change in production rate, the change would probably be introduced as a ramp or as a series of small steps. This would help the controller avoid the large upset seen at the flow change when the process is controlled by the adaptive Smith Predictor. In a real world situation, the adaptive Smith Predictor should be able to provide the smooth, overdamped response most of the time with occasional small upsets if the process change is larger than expected.

The Abbas tuning demonstrates good controller performance even for a large, sudden flow change. For ramps or a series of small step changes, control will degrade as seen in Figs. 9–12, however, the performance will still meet the control algorithm specification with respect to overshoot. The load disturbance response is comparable to that of the adaptive controller. The use of Abbas tuning would probably be preferred by most plant engineers for this system, since it requires the least implementation effort and the least long-term

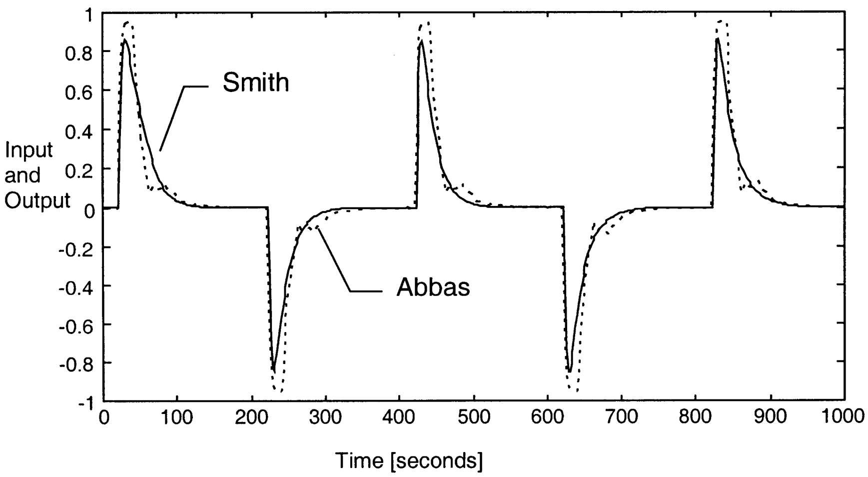


Fig. 14. Example 2 load response, 10% flow increase at 500 s.

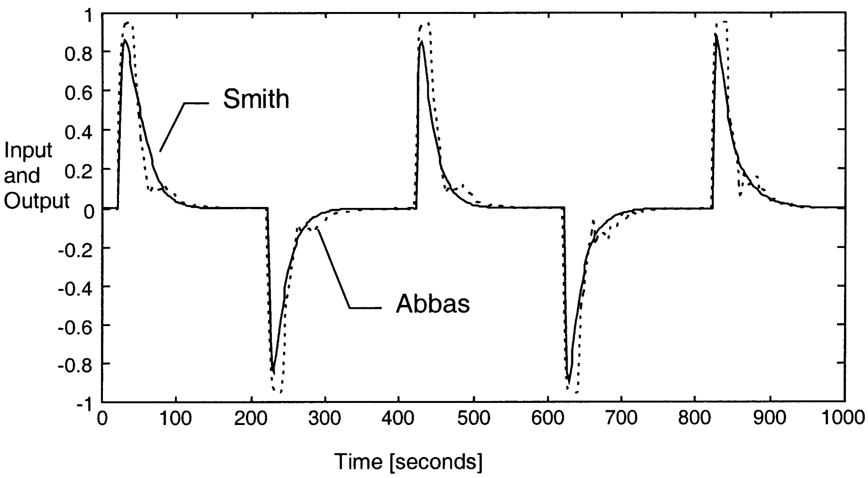


Fig. 15. Example 2 load response, 20% flow increase at 500 s.

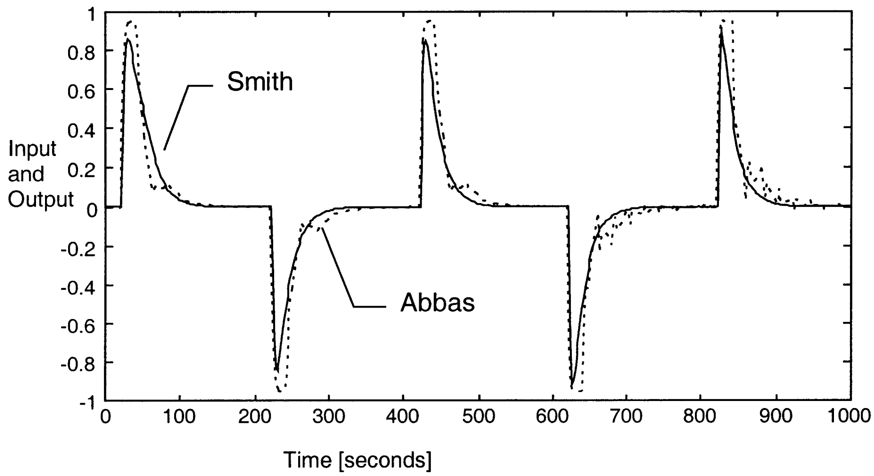


Fig. 16. Example 2 load response, 50% flow increase at 500 s.

attention. The distributed control system or programmable logic controller for the plant will have the standard PID controller as a standard feature. If necessary, gain scheduling could be implemented based on expected flow rates. An adaptive Smith Predictor will require a significant amount of programming as well as upkeep. Furthermore, the a priori knowledge needed to properly initialize the Smith Predictor may be a barrier to implementation.

## 5. Conclusions

The tuning method developed by Abbas is an improvement over traditional methods of PID controller tuning. The ability to specify closed-loop response performance offers a distinct advantage over the quarter amplitude decay methods of Zieger–Nichols and Cohen–Coon. The Abbas tuning method can provide performance that is more consistent over a wider range of dead time to time constant ratios than the older methods. The performance of a system with order greater than one suffers because of the unmodeled dynamics of the plant. However, the controller still provides a stable closed-loop system. Further research may allow the Abbas tuning method to be extended to include SOPTD systems similar to the method introduced in [13]. Otherwise, a technique could be developed to provide guidelines for detuning the controller settings provided by Abbas in the presence of higher order system response.

When the process to be controlled is known to change or when manufacturing conditions fluctuate frequently, it may be necessary to implement an adaptive controller. However, these controllers are much more complex than standard PID control. Therefore, one must be sure that an adaptive controller is really necessary. Furthermore, the adaptive Smith Predictor as shown in this paper requires a priori knowledge of the system in order to initialize the system to a reasonable estimate of the plant. The system identification should be allowed to run before the control is implemented, but this adds another layer of complexity to the system.

The adaptive Smith Predictor can outperform the Abbas tuning on a standard PID controller when a SOPTD plant has a varying time delay. As the time delay increases, the Abbas tuning begins to break down and the adaptive Smith Predictor is shown to exhibit superior performance. However, when the time constant varies while the dead time remains fairly constant, the Abbas tuning actually is superior in that its performance only degrades slightly while keeping the system output within specification. The adaptive Smith Predictor will be appropriate only if a smooth, overdamped response is required over a wide operating range of time delays. However, the system must be able to tolerate output transients during sudden, large changes in the process. Both methods demonstrated acceptable control for load disturbances. The adaptive controller showed some advantage in performance, but the Abbas control was not significantly worse.

The final answer is that there is no unique control method that is best for all processes. The tuning method developed by Abbas has been shown to be superior to more traditional tuning methods. However, even when using the Abbas tuning, a standard PID controller is not always the most efficient way to control a process. Adaptive control can be very effective in controlling a process but carries a significant cost penalty in complexity and time which must be weighed against the benefit. Abbas tuning parameters must be updated from time to time as conditions change and controller performance degrades, but adaptive controllers cannot simply be installed and forgotten either. The controls engineer must be knowledgeable in many types of control and should choose the simplest method that will provide acceptable control.

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**Craig W. Alexander** is a Senior Process Control Engineer with Monsanto in Augusta, GA. He recently transferred from the Luling, Louisiana plant where he had been since 1992. Craig holds a Bachelor of Electrical Engineering degree from Auburn University (1992) and a Master of Science in Engineering degree from the University of New Orleans (1999). He is a Senior Member of ISA and has been inducted into Tau Beta Pi, Eta Kappa Nu, and Sigma Pi Sigma. He is a registered professional engineer in control systems engineering.

**Russell E. Trahan Jr**. received the BS and MS degrees in Engineering Sciences from the University of New Orleans in 1970 and 1973, respectively. In 1977, he received a PhD in Electrical Engineering from the University of California, Berkeley, with a specialization in optimization and control. Since 1977 he has held a faculty position in the Department of Electrical Engineering at the University of New Orleans, and he now has the rank of Chevron USA Professor of Electrical Engineering and Department Chair. He has worked as a consultant to Litton Data Systems and the Naval Research Laboratory-Stennis Space Center, MS. His current research interests are in the areas of controls, optimization, and signal processing. Dr. Trahan is a member of ISA and IEEE.