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Process Identification using Nonideal Step Inputs

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Abstract: Methods to estimate the parameters and the time delay of continuous time transfer function models using different nonideal step inputs are presented. By nonideal step inputs we refer to excitation signals that initially change gradually or in smaller steps to a final value unlike the ideal step that requires a sudden jump equalling the size of the step. Many different forms of such input signals can be designed. We consider four types namely the saturated ramp, the staircase input, the saturated sinusoid and the filtered step input. Two approaches are taken for the parameter estimation. First, estimation equations are directly obtained for the particular inputs and second, equivalent ideal step responses are generated from the nonideal step responses and step response method is used to estimate the parameters. The estimation equations are based on the integral equation approach. The necessary mathematical derivations are provided taking a first order plus time delay model as an example. Simulation results for both first and second order models are presented to demonstrate the efficacy of the proposed methodologies.

Keywords: Step input, time delay, nonideal step, integral equation;

1. INTRODUCTION

Over the last decade, some interesting developments in the field of identification from step response have been reporetd. In fact, a considerable research effort in the field of system identification is devoted to identification from step response and over the last few years there has been a renewal in interest in this topic. This is partly because the step might be the most commonly used input signal in process industries. From the design aspect, it might be the simplest input to design. Also it offers unique advantages in the parameter estimation step. With the new developments in the integral equation approach, the coefficients of transfer function models along with their time delay can be estimated simultaneously from the step response [Wang and Zhang (2001)]. Different practical issues, for example the unsteady initial conditions [Ahmed et al. (2008); Hwang and Lai (2004); Liu et al. (2007)] and the presence of disturbances [Ahmed et al. (2009a)] have also been dealt. Other developments in this field have been reported in [Li et al. (2005); Mei et al. (2005); Wang et al. (2004)].

Choice of the input signal plays an important role on the quality of the estimated model and it has been an active area of research [Doraiswami et al. (1986); Kalafatis et al. (2005); Zaremba and Pavlov (2002); Antoulas and Andersen (1999); Iwase and Shigi (2005)]. While the step response has been subject to extensive studies, its variants have not been considered explicitly although in real life applications, the ideal step input is not always applicable. In this article, we introduce some variants of the step input that are already in use in industrial applications. We name the variants of the ideal step to be nonideal steps as they do not change instantaneously.

1.1 Nonideal step inputs

Step input requires an instantaneous change of the corresponding variable from one operating point to another. For some variables, it might be possible to make such a sudden change. For example, flow rates can be changed almost instantaneously over some operating range. However, for some other variables, a sudden change may not be feasible. Even when a sudden change is possible, there might have a risk of process upset. For such a case, variables are often increased gradually during the initial stage. For example, to make a change in a column pressure it is a common practice to initially increase the pressure gradually until it reaches the desired operating point and then it is kept constant. In some cases, the desired change is attained in two or more steps instead of one, resulting in a staircase type of input. Also, step changes are often made in both positive and negative directions to capture the nonlinearities in processes giving pulse type inputs. Sometimes the step signal is passed through a filter and the filtered step is applied. All these result in, what we call, nonideal step inputs. Figure 1 shows a few of such input signals commonly used in process industries.

As the nonideal step inputs do not require an instantaneous large change in the variable, they are not limited in application. Another advantage of the use of nonideal step input might be the comparatively moderate change in the output response. For example, processes having an underdamped dynamics may exhibit a high overshoot when an ideal step is applied. However, if a nonideal step, such as a filtered step or a saturated sinusoid is applied, the overshoot may be much less. Figure 2 shows the responses to an ideal step input and a saturated sinusoid input

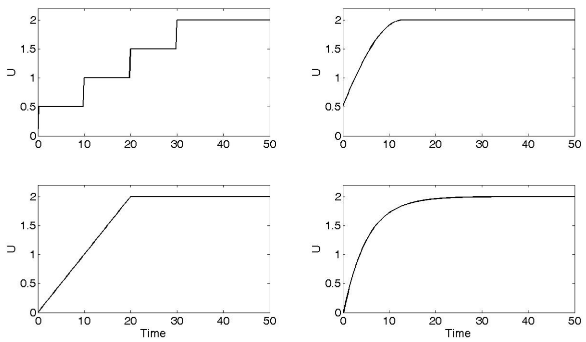

Fig. 1. Nonideal step inputs: 1. staircase (top-left) 2. saturated sinusoid (top-right) 3. saturated ramp (bottom-left) 4. filtered step (bottom-right)

of a process with underdamped and nonminimum phase dynamics. It can be seen that both the inverse response and the overshoot are considerably less in the case of the sinusoidal input. Thus in the test stage, the required response is obtained without disturbing the process to a large extent.

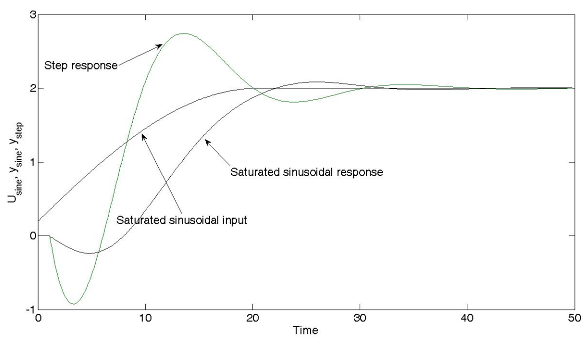

Fig. 2. Response of a process with underdamped dynamics and inverse response due to ideal step input and a saturated sinusoidal input.

Certain types of these inputs have been considered under different titles. The saturated ramp has been considered by Hwang and Lai (2004) under the title of pulse inputs. However, the method by Hwang and Lai (2004) involves a two step solution procedure and each step requires sufficient good quality data. The staircase inputs have been considered under the banner of piecewise step inputs by Liu et al. (2007). We include the staircase input signal in this study to complete the set of inputs. The mathematical procedure for the staircase input is similar to that of [Liu et al. (2007)]. New estimation equations are provided for the saturated ramp and the filtered step that involve a single stage simultaneous solution of parameters and the delay. For the saturated sinusoidal input, equivalent step response is generated from the sinusoidal response and a step response method is used to obtain the model.

The following sections of the article has been organized as follows: section 2 outlines the necessary mathematical formulation to describe the identification methodology for the integral equation approach for both ideal and nonideal step inputs. Section 3 presents the simulation results and finally in section 4, concluding remarks are provided.

2. MATHEMATICAL FORMULATION

First the general formulation of the integral equation method is outlined. This is followed by the derivation of the estimation equations for the different types of the input. For the purpose of simplicity in the presentation, we discuss the methods using an example of a first order plus time delay model. However, the methods are not limited in application to first order processes and the estimation equations are readily extendable to general n-th order models.

2.1 The Integral Equation Approach

Let us consider a first order model described by the following differential equation

$$\frac{dy(t)}{dt} + ay(t) = bu(t) + e(t) \tag{1}$$

Here, $y(t)$ and $u(t)$ are the process output and input, respectively, and $e(t)$ is the error term, evolving from the measurement noise. The objective of identification is to obtain an estimate of the parameter vector, $[a\ \ b]^T$, from a given set of input and output data $[u(t)\ y(t)]$ for $t = t_1, t_2, \cdots t_N$, with N being the length of the data set.

In the integral equation approach, the differential equation is integrated to express the model equation in terms of the integrals of the signals instead of their derivatives. While the derivative operation magnifies the noise, the integrator acts as a filter for the noise. Integration of eqn(1) once assuming an initial steady state of the output gives

$$y(t) + ay^{[1]}(t) = bu^{[1]}(t) + e^{[1]}(t) \tag{2}$$

For a signal $x(t)$, $x^{[1]}(t)$ is its first order integral, i.e. $x^{[1]}(t) = \int_0^t x(\tau)d\tau$. The estimation equation is then obtained as

$$y(t) = \begin{bmatrix} -y^{[1]}(t) & u^{[1]}(t) \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} + e^{[1]}(t) \tag{3}$$

Or equivalently

$$\gamma(t) = \phi^T(t)\theta + \xi(t) \tag{4}$$

where, $\gamma(t) = y(t)$, $\phi^T(t) = \begin{bmatrix} -y^{[1]}(t) & u^{[1]}(t) \end{bmatrix}$, $\theta = \begin{bmatrix} a \\ b \end{bmatrix}$, $\xi(t) = e^{[1]}(t)$. Equation (4) can be written for $t = t_1, t_2 \cdots t_N$ and combined to give the estimation equation

$$\Gamma = \Phi\theta + \xi \tag{5}$$

with

$$\Gamma(t) = \begin{bmatrix} \gamma(t_1) \\ \gamma(t_2) \\ \cdots \\ \gamma(t_N) \end{bmatrix}, \quad \Phi(t) = \begin{bmatrix} \phi(t_1) \\ \phi(t_2) \\ \cdots \\ \phi(t_N) \end{bmatrix}^T \tag{6}$$

The parameter vector θ is then obtained as the least squares solution

$$\theta = (\Phi^T\Phi)^{-1}\Phi^T\Gamma \tag{7}$$

So far we have considered a general input signal and the methodology is valid for any type of input. However, the step input offers a unique advantage in the estimation of time delay.

Consider a first order model with delay described by

$$\frac{dy(t)}{dt} + ay(t) = bu(t-\delta) + e(t) \tag{8}$$

where, δ is the time delay. If we follow the above integration approach, we end up with an estimation equation

$$y(t) + ay^{[1]}(t) = bu^{[1]}(t-\delta) + \xi(t) \tag{9}$$

It has been shown by Wang and Zhang (2001) that if the input is a step, the integral of the delayed input term can be decomposed to give an explicit appearance of the delay. For a step input of size h, the integral of the delayed signal can be expressed as

$$u^{[1]}(t-\delta) = ht - h\delta \text{ for } t > \delta \tag{10}$$

Equation (9) can be written as

$$y(t) + ay^{[1]}(t) = bht - bh\delta + \xi(t) \tag{11}$$

Then the following estimation equation would give the parameters along with the delay.

$$y(t) = \begin{bmatrix} -y^{[1]}(t) & ht & -h \end{bmatrix} \begin{bmatrix} a \\ b \\ b\delta \end{bmatrix} + \xi(t) \tag{12}$$

Equation (12) can be written for $t = t_{d+1}, t_{d+2} \cdots t_N$ as in eqn (6) and combined to give the set of estimation equation

$$\Gamma = \Phi\theta + \xi \tag{13}$$

Here, d is the time delay in terms of number of sampling intervals (Δt), i.e. $d = \frac{\delta}{\Delta t}$ and N is the total number of samples available. When the time delay is not an integer multiple of the sampling interval, d is chosen as the nearest integer in the positive direction. From the solution of (13) we get θ that gives estimates of a, and b directly. The delay is then obtained as $\delta = \theta(3)/b$.

So far we have described the methodology for the ideal step input. Next sections describe how we can get the estimation for different nonideal step inputs.

2.2 Saturated ramp

When an input is initially changed linearly and then kept at a constant value, we get the so called saturated ramp. Such an input can be expressed as a combination of two ramps and can be presented mathematically as

$$u(t) = \sum_{i=0}^{1} p_i \left[t - L_i\right] \Omega(t - L_i) \tag{14}$$

where $p_0 = \frac{h}{L_1}$, $p_1 = -p_0$ and $L_0 = 0$. h is the value of the ramp signal at its saturation, L_1 is the time of the input to reach saturation and Ω is the unit step input defined as

$$\Omega(t - L_i) = \begin{cases} 0 \text{ for } t < L_i \\ 1 \text{ for } t \geq L_i \end{cases} \tag{15}$$

So, we can express $u(t-\delta)$ as

$$u(t-\delta) = \sum_{i=0}^{1} p_i \left[t - L_i - \delta\right] \Omega(t - L_i - \delta) \tag{16}$$

As shown earlier for a process initially at a steady state, the estimation equation can be expressed as in eqn (9)

$$y(t) + ay^{[1]}(t) = bu^{[1]}(t-\delta) + \xi(t) \tag{17}$$

The first order integral of the delayed saturated ramp signal then becomes

$$u^{[1]}(t-\delta) = \sum_{i=0}^{1} \frac{p_i}{2} \left[t - L_i - \delta\right]^2 \Omega(t - L_i - \delta) \tag{18}$$

The estimation eqn (17) can then be written as

$$\begin{aligned} y(t) = & -ay^{[1]}(t) + b\sum_{i=0}^{1} \frac{p_i}{2} \left[t - L_i\right]^2 \Omega(t - L_i - \delta) \\ & + b\delta \sum_{i=0}^{1} -p_i \left[t - L_i\right] \Omega(t - L_i - \delta) \\ & + b\delta^2 \sum_{i=0}^{1} \frac{p_i}{2} \Omega(t - L_i - \delta) + \xi(t) \end{aligned} \tag{19}$$

Or equivalently

$$\gamma(t) = \phi^T(t)\theta + \xi(t) \tag{20}$$

where,

$$\gamma(t) = y(t) \tag{21}$$

$$\phi(t) = \begin{bmatrix} -y^{[1]} \\ \sum_{i=0}^{1} \frac{p_i}{2} \left[t - L_i\right]^2 \Omega(t - L_i - \delta) \\ \sum_{i=0}^{1} -p_i \left[t - L_i\right] \Omega(t - L_i - \delta) \\ \sum_{i=0}^{1} \frac{p_i}{2} \Omega(t - L_i - \delta) \end{bmatrix} \tag{22}$$

$$\theta = \begin{bmatrix} a & b & b\delta & b\delta^2 \end{bmatrix}^T \tag{23}$$

From θ we directly get $a = \theta(1)$ and $b = \theta(2)$. δ can be obtained in a number of ways. On the basis of the simulation results, we suggest to estimate it as $\delta = \theta(3)/\theta(2)$.

2.3 The staircase input

As mentioned earlier, the mathematical derivation for the staircase input follows that of the piecewise step input as described by Liu et al. (2007). We present here for the sake of completeness of the set of inputs. The staircase input can be expressed as

$$u(t) = \sum_{i=0}^{I} h_i \Omega(t - L_i) \tag{24}$$

where $t_0 = 0$. We can express $u(t-\delta)$ as

$$u(t-\delta) = \sum_{i=0}^{I} h_i \Omega(t - L_i - \delta) \tag{25}$$

As shown earlier the estimation equation can be expressed as in eqn(17) and the first order integral of the delayed staircase signal then becomes

$$u^{[1]}(t-\delta) = \sum_{i=0}^{I} h_i \left[t - L_i - \delta\right] \Omega(t - L_i - \delta) \tag{26}$$

The estimation eqn(17) can then be written as

$$\begin{aligned} y(t) = & -ay^{[1]}(t) + b\sum_{i=0}^{I} h_i \left[t - L_i\right] \Omega(t - L_i - \delta) \\ & + b\delta \sum_{i=0}^{I} -h_i \Omega(t - L_i - \delta) + \xi(t) \end{aligned} \tag{27}$$

Or equivalently

$$\gamma(t) = \phi^T(t)\theta + \xi(t) \tag{28}$$

where,

$$\gamma(t) = y(t) \tag{29}$$

$$\phi(t) = \begin{bmatrix} -y^{[1]} \\ \sum_{i=0}^{I} h_i [t - L_i] \Omega(t - L_i - \delta) \\ \sum_{i=0}^{I} -h_i \Omega(t - L_i - \delta) \end{bmatrix} \tag{30}$$

$$\theta = [\, a \;\; b \;\; b\delta \,]^T \tag{31}$$

2.4 Saturated sinusoid

For the saturated sinusoid, we take the approach to estimate the step response from the sinusoidal response and use the integral equation based step response method to obtain the model. This approach has been outlined for single and multiple sinusoidal inputs in [Ahmed et al. (2009b)]. We show that the input can be changed initially in a sinusoidal way and then kept constant to result in the so called saturated sinusoid and we provide the methodology to obtain the step response from the response due to a saturated sinusoid that can be expressed as

$$u(t) = \sum_{i=0}^{2} q_i \sin[\omega(t - L_i) + \nu_i] \Omega(t - L_i) \tag{32}$$

A saturated sinusoid as in Fig. 1 whose saturation value is h and the time to reach the saturation is L, can be represented by the above equation for a set of values $q_0 = -q_1 = q_2 = h$, $\omega_0 = \omega_1$, $\omega_2 = 0$, $L_0 = 0$, $L_1 = L_2 = L > 0$, $\nu_0 < \pi/2$ and $\nu_1 = \nu_2 = \pi/2$. The input can be expressed in the Laplace domain as

$$U(s) = \sum_{i=0}^{2} q_i \frac{\beta_i s + \mu_i}{s^2 + \omega_i^2} e^{-L_i s} \tag{33}$$

where $\beta_i = \sin(\nu_i)$, $\mu_i = \omega \cos(\nu_i)$. For the above values of the parameters, the input expression simplifies to

$$U(s) = h\frac{\beta s + \mu}{s^2 + \omega^2} + \frac{h\omega^2}{s(s^2 + \omega^2)} e^{-Ls} \tag{34}$$

where $\omega = \omega_0$, $\beta = \beta_0$, $\mu = \mu_0$, $L_1 = L_2 = L$.

To obtain the step response from response due to other inputs, we express the input output relation for a process as

$$Y(s) = G(s)U(s) \tag{35}$$

Here, $G(s)$ is the process transfer function. If the input is a unit step, we have $U(s) = \frac{1}{s}$ and the unit step response, $Y_{step}(s)$, can be obtained as

$$Y_{step}(s) = G(s)\frac{1}{s} \tag{36}$$

Comparing (35) and (36) we get the relation to obtain the unit step response from output data due to other type of excitation signal

$$Y_{step}(s) = \frac{Y(s)}{sU(s)} \tag{37}$$

In the case of the saturated sinusoid, from eqn (37) we get

$$\begin{aligned} Y(s) &= sU(s)Y_{step} \\ &= \left[h\frac{s(\beta s + \mu)}{s^2 + \omega^2} + \frac{h\omega^2}{(s^2 + \omega^2)} e^{-Ls}\right] Y_{step}(s) \end{aligned} \tag{38}$$

To give

$$Y_{step}(s) = \frac{s^2 + \omega^2}{hs(\beta s + \mu)} Y(s) - \frac{\omega^2 e^{-Ls}}{s(\beta s + \mu)} Y_{step}(s) \tag{39}$$

From the above equation we see that the sinusoidal response can be passed through a filter and added to the delayed step response to get the step response of the process. As shown in Fig. 3, Simulink can be used for this purpose where the filters are $\frac{1}{F1(s)} = \frac{s^2+\omega^2}{hs(\beta s+\mu)}$ and $\frac{1}{F2(s)} = \frac{\omega^2}{s(\beta s+\mu)}$ The parameters and the delay then can

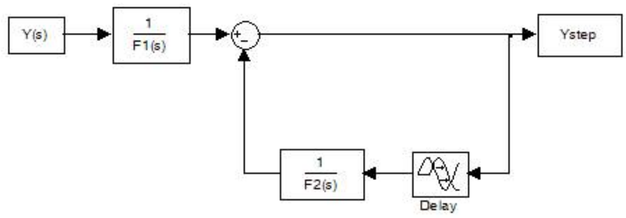

Fig. 3. Simulink model to obtain the step response from the saturated sinusoidal response.

be obtained by using the estimation equation (5) for the step response method by replacing $y(t)$ by $y_{step}(t)$ and with $h = 1$.

2.5 Filtered step

A filtered step can be expressed in the Laplace domain as

$$U(s) = \frac{1}{\lambda s + 1}\frac{h}{s} \tag{40}$$

So the estimation equation for this input becomes

$$Y(s) = \frac{b}{s + a}\frac{1}{\lambda s + 1}\frac{h}{s} e^{-\delta s} \tag{41}$$

After rearrangement

$$\lambda Y(s) + \frac{Y(s)}{s} + a\lambda\frac{Y(s)}{s} + a\frac{Y(s)}{s^2} = b\frac{h}{s^3} e^{-\delta s} \tag{42}$$

The equation in the time domain can be obtained as

$$\lambda y(t) + y^{[1]}(t) + a\lambda y^{[1]}(t) + a y^{[2]}(t) = bh\frac{(t - \delta)^2}{2} \tag{43}$$

Or equivalently

$$\gamma(t) = \phi^T(t)\theta + \xi(t) \tag{44}$$

where,

$$\gamma(t) = y(t) + y^{[1]}(t)$$

$$\phi(t) = \begin{bmatrix} -\lambda y^{[1]}(t) - y^{[2]}(t) \\ \frac{ht^2}{2} \\ -ht \\ \frac{h}{2} \end{bmatrix}$$

$$\theta = [\, a \;\; b \;\; b\delta \;\; b\delta^2 \,]^T$$

2.6 Implementation issues

Different issues related to the industrial application of the step response has been studied in the literature. The presence of unsteady initial conditions has been studied by Ahmed et al. (2008); Hwang and Lai (2004); Liu et al. (2007). The effect of disturbances has also been studied [Ahmed et al. (2009a)]. The methods proposed in this paper can be readily extended to apply to step response with transient initial state and in the presence of disturbances.

The estimation equation (13) is valid for $t > \delta$. So, to formulate it we need the unknown δ. To overcome this problem an initial guess of the delay is used and the estimation equation is solved. If the initial guess is far away from the real delay, this procedure may have to be repeated. For the initial guess, process knowledge can be used. In the absence of process information we suggest choosing a small time delay. Extensive simulation results show that even when the initial guess is much smaller than the real delay, the estimation procedure needs to be repeated only $4-5$ times to get a convergent result.

The least squares solution for the estimation equation (13) is given by

$$\theta^{LS} = (\Phi^T\Phi)^{-1}\Phi^T\Gamma \tag{45}$$

The properties of the estimated θ^{LS} depend on the error term ξ in (13) that evolves due to the noise in the output measurements. Typically, the measurement noise is considered to be zero mean white noise or filtered white noise. In the presence of a colored noise, the least squares solution may not be unbiased. Even if the measurement noise is assumed to be white with zero-mean, the integration operation results in a colored error term. So, the LS solution is not unbiased even for a white measurement noise and we need a bias elimination scheme. To get an unbiased estimate of the parameters, different techniques can be used. We use the instrumental variable (IV) method proposed by Young (1970) which is commonly used in continuous-time identification; see e.g. Ahmed et al. (2007) and Garnier et al. (2003). To generate the instruments, the least squares solution is used to get the predicted values of the output. The instrument matrix is then derived by replacing $y(t)$, in the regressor by their predicted values, $\hat{y}(t)$ i.e. for the first order process, the instrument vector equivalent to the regressor in eqn(12) is given by

$$\psi(t) = \left[\, -\hat{y}^{[1]}(t) \;\; ht \;\; -h \,\right]^T$$

The instrument matrix is then obtained in the same way as the regressor is obtained by (6). The instrumental variable estimate of the parameters is given by

$$\theta^{IV} = (\Psi^T\Phi)^{-1}\Psi^T\Gamma \tag{46}$$

The IV procedure can be repeated. However, no additional step is necessary as the repetition can be embedded within the updating steps for δ.

3. RESULTS

In this section we present identification results obtained using the nonideal step input signals. For this simulation study first and second order processes are considered. Simulink is used to generate the data and to filter the output signals. In simulink, processes and filters are represented by the continuous-time transfer function blocks and variable-step ode45 is used as the solver. In generating noise corrupted data, the sampled noise free outputs are corrupted with discrete-time white noise sequences. The noise to signal ratio(NSR) is defined as the ratio of the variance of the noise to that of the noise free signal. Monte Carlo simulations are carried out by changing the random noise sequences which is done in MATLAB by changing the seed. A total of 500 data points are used for each cases. The end time of data collection is chosen as the settling time of the processes. The instrumental variable method is used for the simulation study. The initial guesses of the delay were equal to one sampling intervals.

3.1 First order modeling

Figure 4 shows the estimation results of a process having the following transfer function

$$G(s) = \frac{1.25}{20s+1}e^{-7s} \tag{47}$$

The parameter vector in terms of gain, time constant (τ) and time delay for the process is $[\tau\ K\ \delta] = [20\ 1.25\ 7]$ whose equivalent in terms of the parameter vector of the estimation equation is $[a\ b\ \delta] = [0.05\ 0.0625\ 7]$. Although parameters are estimated as $[a\ b\ \delta]$, we present them in terms of $[\tau\ K\ \delta]$. Here the mean values of the parameters from 100 Monte Carlo simulations are plotted along with their standard deviation. The dotted lines show the true value of the corresponding parameters. The NSR for this case is 10%. The estimation results show that for the

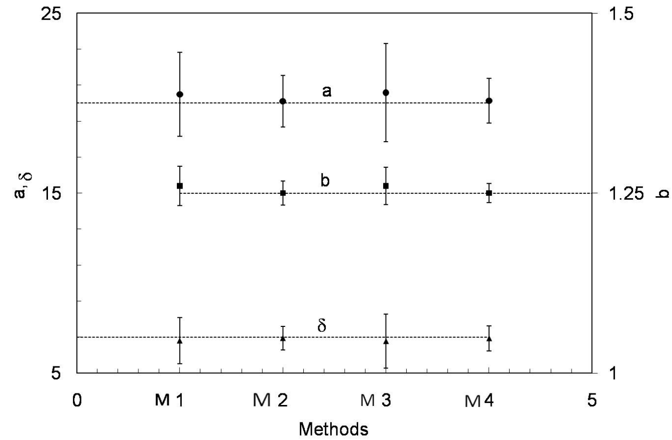

Fig. 4. Parameter estimation results using the different input. M1- staircase, M2- saturated sinusoid, M3-saturated ramp, M4- filtered step .

particular process and for the set of input signals, the saturated sinusoid and the filtered step performed better than the staircase and the saturated ramp in terms of the bias and variance of the estimates. Detailed study of the effect of the signal parameters on the estimation results and a comparative study of the different types of inputs are to be investigated further.

Figure 5 shows the effect of noise on the parameter estimates for the above example where the filtered step input is used. It is seen that for a wide range of noise to signal ratio, satisfactory estimates can be obtained.

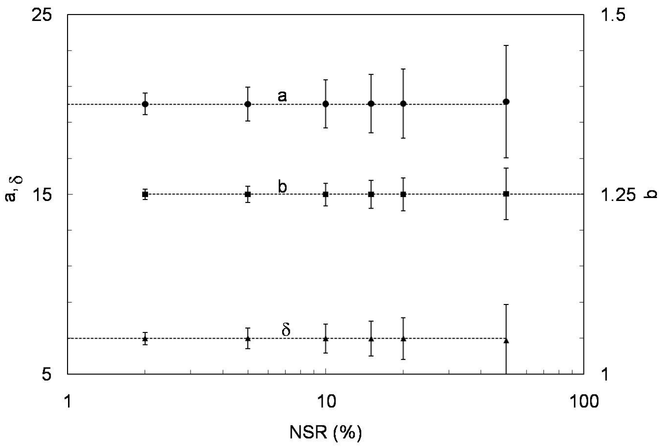

Fig. 5. Effect of noise on parameter estimates. Input-filtered step .

3.2 Second order modeling

Identification results for a number of second order processes are presented in Table 1. The parameters are the mean values of 100 estimates. The numbers in the parentheses are their standard deviations. We consider both underdamped and overdamped processes. Processes with a zero are also considered. The examples include both minimum phase and non-minimum phase processes. The input signal used for this study is a saturated sinusoid. The NSR for each of these cases is 10%.

Table 1. True and estimated models of different second order processes.

True model	Estimated model
$\frac{1.25e^{-0.6s}}{9s^2+2.4s+1}$	$\frac{1.25(\pm0.005)e^{-0.58(\pm0.27)s}}{9.07(\pm0.81)s^2+2.42(\pm0.25)s+1}$
$\frac{(2s+1)e^{-1s}}{9s^2+2.4s+1}$	$\frac{(1.97(\pm0.78)s+1(\pm0.004))e^{-1(\pm0.4)s}}{9.02(\pm0.65)s^2+2.45(\pm0.35)s+1}$
$\frac{(-5s+1)e^{-1s}}{9s^2+2.4s+1}$	$\frac{(-4.9(\pm0.3)s+1.2(\pm0.01))e^{-0.97(\pm0.3)s}}{9(\pm0.74)s^2+2.43(\pm0.2)s+1}$
$\frac{1e^{-0.2s}}{0.25s^2+0.7s+1}$	$\frac{1(\pm0.01)e^{-0.205(\pm0.09)s}}{0.26(\pm0.1)s^2+0.71(\pm0.12)s+1}$

4. CONCLUDING REMARKS

A set of excitation signals described as nonideal step inputs are introduced for identification of continuous time models. The corresponding estimation equations that allow the simultaneous estimation of the model parameters and the delay are derived. These inputs are applicable to variables that cannot be changed instantaneously in a step manner. By applying such inputs, large deviation of the process outputs can also be avoided. A set of such inputs are introduced offering the user to choose from a number of options that suits to their specific variables. Simulation results are presented for first and second order processes and the estimated model parameters demonstrate the efficiency of the proposed methods in terms of their accuracy and consistency.

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