Preprints of the 10th IFAC International Symposium on Dynamics and Control of Process Systems
The International Federation of Automatic Control
December 18-20, 2013. Mumbai, India

Identification of integrating processes with time delay

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Abstract: A set of methods for identification of continuous-time transfer function models for integrating processes with time delay is proposed. The step, piecewise constant and piecewise linear inputs are considered which indeed cover most of the input signals commonly used in industries. For all of the three types of input signals, estimation equations to simultaneously obtain model parameters and the time delay are derived. The final parameter estimation equations are in a form suitable for the least-squares solution. Mathematical formulation of the methods is presented using the example of an integrating process with a first order lag dynamics and a zero which can be extended for other structures. An instrumental variable method to deal with the bias issue in least-squares solutions is used. Simulation results are presented to demonstrate the efficacy of the algorithms and their relative performance.

Keywords: Integrating process, time delay, identification, input signals.

1. INTRODUCTION

Integrating processes, characterized by the presence of a root of the characteristic equation at the origin of the s-plane, are difficult to identify and control. An example of such a system is the motor drive present in a remote position control system (Thaler (1989)). Here, in open-loop, a bounded step input usually produces an unbounded output. An equally common but different problem that occurs in the process industries, is the control of water level in a steam boiler drum and applications involving surge tanks (Panda et al. (2011)). More basic examples involving liquid level are considered in (Wang and Cluett (1997)). Other cases cited in the literature include the control of processes involving the heating and cooling of closed batch reactors (Huzmezan et al. (2002)) which tend to have an integrating response due to the circulation of the heating and cooling fluids through coils and jackets.

In order to understand the behaviour of such complex systems simulation plays an important part. Astrom and Bell (2000) developed from first principles a nonlinear dynamic model for a natural circulation drum boiler. As pointed out by Pai et al. (2010), such a model whilst informative is not suitable to be used for control system design. Further, because of the non-minimum performance of this and many other similar processes, the authors agreed that a more useful representation was the open-loop structure proposed by Luyben (2003) with the transfer function

$$G_p(s) = \frac{K_p(1 - sT_1)}{s(1 + sT_2)} e^{-sL} \tag{1}$$

Luyben (2003) also presented a curve fitting procedure using MATLAB software to determine the system parameters based on the open loop step response. Several papers have been presented using auto-tuning feedback to identify low order integrating plus time delay models. Examples include the paper by Liu and Gao (2008) and the references included. Panda et al. (2011) also exploited relay feedback but their models incorporated an extra pole and zero in the transfer function. Gu et al. (2006) proposed a graphical method for identification of non-minimum phase integrating processes with time delay.

In this paper we propose a set of identification methods to estimate the parameters and the delay of continuous-time transfer function similar to the structure (1). The new approach has the ability to identify both minimum and non-minimum phase processes. The advantages of the procedures include that the input signal is not restricted to being a step function but methodologies for piecewise constant and piecewise linear inputs are also developed. Further desirable properties are the system can be in a non-steady state condition when the input is applied and the system response can be noise contaminated. The following section describes the proposed methodologies.

2. METHODOLOGY

The mathematical formulation is described using the following model as an example; however, the methods are applicable to models with other numerator and denominator orders.

$$G(s) = \frac{b_1 s + b_0}{s(s + a_0)} e^{-\delta s} \tag{2}$$

Where $G(s)$ is the transfer function between the input, $U(s)$ and the output $Y(s)$; $[a_0 \;\; b_1 \;\; b_0]$ are the model parameters and δ is the time delay. Considering that the

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process output is initially at a transient state, $y(0)$, when the input signal is applied, the input-output relation can be expressed in the equation error form as

$$s^2Y(s) - sy(0) - y'(0) + a_0\left[sY(s) - y(0)\right] \\ = (b_1 s + b_0)\, e^{-\delta s}U(s) + E(s) \quad (3)$$

With further rearrangement the equation is written as

$$(s^2+a_0 s)Y(s) = (b_1 s + b_0)e^{-\delta s}U(s) + c_1 s + c_0 + E(s) \quad (4)$$

where $E(s)$ is the error term resulting from the measurement noise in the output signal and

$$c_1 = y(0) \quad (5)$$

$$c_0 = a_0 y(0) + y'(0) \quad (6)$$

Integrating Eq. (4) twice which is equivalent to multiplying both sides of the equation by $\frac{1}{s^2}$ and expressing the resulting equation in the form of an estimation equation

$$Y(s) = -a_0\frac{Y(s)}{s} + b_1\frac{U(s)}{s}e^{-\delta s} \\ +b_0\frac{U(s)}{s^2}e^{-\delta s} + \frac{c_1}{s} + \frac{c_0}{s^2} + E_1(s) \quad (7)$$

Taking inverse Laplace transform the following time domain equation can be obtained.

$$y(t) = -a_0 y^{[1]}(t) + b_1 u^{[1]}(t-\delta) \\ +b_0 u^{[2]}(t-\delta) + c_1 + c_0 t + e_1(t) \quad (8)$$

where, for any signal $x(t)$, $x^{[i]}(t)$ is its i-th order integral. Equation (8) is valid for any bounded input sinal $u(t)$. In the above equation, the time delay term remains as an implicit parameter which cannot be directly estimated. Also to estimate other parameters, the time delay should be known. In the following sections, estimation equations are derived from Eq. (8) which allow simultaneous estimation of the model parameters and the delay term. Also the initial conditions can be obtained as part of the solution.

2.1 Method 1: Identification from step response

If the input is a step of size h and is applied at time $t = 0$, the following integral holds for $t \geq \delta$.

$$u^{[i]}(t-\delta) = \frac{h[t-\delta]^i}{i!} \quad (9)$$

For a step input the estimation equation Eq. (8) becomes

$$y(t) = -a_0 y^{[1]}(t) + b_1 h[t-\delta] + b_0 h\frac{[t-\delta]^2}{2} + c_1 + c_0 t + e_1(t) \quad (10)$$

which can be rearranged to give

$$y(t) = -a_0 y^{[1]}(t) + b_0\frac{ht^2}{2} + (b_1 h - b_0 h\delta + c_0)t \\ +(-b_1 h\delta + b_0 h\delta^2/2 + c_1) + e_1(t) \quad (11)$$

In the least-squares form the equation is written as

$$\gamma_1(t) = \phi_1(t)\theta_1 + e_1(t) \quad (12)$$

where,

$$\gamma_1(t) = y(t), \quad \phi_1(t) = \begin{bmatrix} -y^{[1]}(t) & \frac{ht^2}{2} & t & 1 \end{bmatrix}$$

$$\theta_1 = \begin{bmatrix} a_0 \\ b_0 \\ b_1 h - b_0 h\delta + c_0 \\ -b_1 h\delta + \frac{b_0\delta^2}{2} + c_1 \end{bmatrix}$$

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

$$\Gamma_1 = \Phi_1\theta_1 + E_1 \quad (13)$$

with

$$\Gamma_1(t) = \begin{bmatrix} \gamma_1(t_{d+1}) \\ \gamma_1(t_{d+2}) \\ \cdots \\ \gamma_1(t_N) \end{bmatrix}, \quad \Phi_1(t) = \begin{bmatrix} \phi_1(t_{d+1}) \\ \phi_1(t_{d+2}) \\ \cdots \\ \phi_1(t_N) \end{bmatrix}$$

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 the above equation the parameters a_0 and b_0 can be obtained directly. However the parameter b_1 and the time delay δ cannot be obtained as they are aggregated with c_0 and c_1. Ahmed et al. (2008) showed that using higher order integration of the model equation an estimation equation can be formulated to give all the unknowns. The idea behind this approach is that the higher order integrals of the delayed input terms can be decomposed into more terms to yield as many parameters, individual and aggregated, in the parameter vector as the number of unknowns. One more step of integration would give

$$y^{[1]}(t) = -a_0 y^{[2]}(t) + b_1 h\frac{[t-\delta]^2}{2} \\ +b_0 h\frac{[t-\delta]^3}{3!} + c_1 t + c_0\frac{t^2}{2} + e_2(t) \quad (14)$$

Or in the least-squares form

$$\gamma_2(t) = \phi_2(t)\theta_2 + e_2(t) \quad (15)$$

where,

$$\gamma_2(t) = y^{[1]}(t), \quad \phi_2(t) = \begin{bmatrix} -y^{[2]}(t) & \frac{ht^3}{3!} & \frac{t^2}{2} & t & 1 \end{bmatrix}$$

$$\theta_2 = \begin{bmatrix} a_0 \\ b_0 \\ b_1 h - b_0 h\delta + c_0 \\ -b_1 h\delta + \frac{b_0\delta^2}{2} + c_1 \\ \frac{b_1 h\delta^2}{2!} - \frac{b_0 h\delta^3}{3!} \end{bmatrix} = \begin{bmatrix} \theta_1 \\ \frac{b_1 h\delta^2}{2} - \frac{b_0 h\delta^3}{3!} \end{bmatrix}$$

The parameter vector θ_1 is a subset of θ_2. $\gamma_2(t)$ and $\phi_2(t)$ can be written for $t = t_{d+1}, t_{d+2} \cdots t_N$ and combined to give Γ_2 and Φ_2. The additional element of θ_2 can be obtained as

$$\underline{\theta}_2\mathbf{1} = \Gamma_2 - \tilde{\Phi}_2\theta_1 \quad (16)$$

where, $\mathbf{1}$ is a unit vector of length $N-d$. Using the notations

$\underline{\theta}_n$: the last element of θ_n

$\tilde{\Phi}_n : \Phi_n$ with its last column removed

The last element of θ_2 can be obtained as $\underline{\theta}_2 = \left(\mathbf{1}^T\mathbf{1}\right)^{-1}\mathbf{1}^T\left[\Gamma_2 - \tilde{\Phi}_2\theta_1\right]$ which is the mean value of the elements of $\left[\Gamma_2 - \tilde{\Phi}_2\theta_1\right]$. Follwing the above procedure, two further steps of integration will give

$$\gamma_3(t) = \phi_3(t)\theta_3 + e_3(t) \tag{17}$$

$$\gamma_4(t) = \phi_4(t)\theta_4 + e_4(t) \tag{18}$$

where,

$$\gamma_3(t) = y^{[2]}(t), \quad \gamma_4(t) = y^{[3]}(t)$$

$$\phi_3(t) = \begin{bmatrix} -y^{[3]}(t) & \frac{ht^4}{4!} & \frac{t^3}{3!} & \frac{t^2}{2} & t & 1 \end{bmatrix}$$

$$\phi_4(t) = \begin{bmatrix} -y^{[4]}(t) & \frac{ht^5}{5!} & \frac{t^4}{4!} & \frac{t^3}{3!} & \frac{t^2}{2} & t & 1 \end{bmatrix}$$

$$\theta_3 = \begin{bmatrix} \theta_2 \\ -\frac{b_1 h\delta^3}{3!} + \frac{b_0 h\delta^4}{4!} \end{bmatrix}, \quad \theta_4 = \begin{bmatrix} \theta_3 \\ \frac{b_1 h\delta^4}{4!} - \frac{b_0 h\delta^5}{5!} \end{bmatrix}$$

The additional elements of θ_3 and θ_4 can be obtained from

$$\underline{\theta}_3\mathbf{1} = \Gamma_3 - \tilde{\Phi}_3\theta_2 \tag{19}$$

$$\underline{\theta}_4\mathbf{1} = \Gamma_4 - \tilde{\Phi}_4\theta_3 \tag{20}$$

From the above solutions we get the the following set of equations

$$\frac{b_1 h\delta^2}{2} - \frac{b_0 h\delta^3}{3!} = \underline{\theta}_2 \tag{21}$$

$$-\frac{b_1 h\delta^3}{3!} + \frac{b_0 h\delta^4}{4!} = \underline{\theta}_3 \tag{22}$$

$$\frac{b_1 h\delta^4}{4!} - \frac{b_0 h\delta^5}{5!} = \underline{\theta}_4 \tag{23}$$

The solution for δ from this set of equations is

$$\delta = \frac{-4\underline{\theta}_3 \pm 2\sqrt{4\underline{\theta}_3^2 - 5\underline{\theta}_2\underline{\theta}_4}}{\underline{\theta}_2} \tag{24}$$

Of the two solutions of δ, one has to choose the one corresponding to the " + " sign for non-minimum phase processes whereas for minimum phase processes the one corresponding to the "−" sign should be chosen. Using the estimated value of δ and the estimate of b_0 obtained from θ_2, one can get the parameter b_1 from any of the equation set (21)-(23). Using the estimated δ, b_0 and b_1 one can get c_0 and c_1 from the last two elements of θ_2. Finally the initial conditions $y(0)$ and $y'(0)$ can be retrieved using the estimate of a_0 and the relations (5)-(6).

2.2 Method 2: Identification using piecewise constant input signals

A step input may not be always applicable to a process with integrating dynamics. As an alternative, pulse type input signals can be applied. Also binary input signal or relay type input can be used. All these signals can be characterized as piecewise constant signals which can be mathematically expressed as

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

Here, i corresponds to the sampling instants, h_i is the step change of the input signal at the i-th sample point i.e. $h_i = u_i - u_{i-1}$ and $L_i = t_{i-1}$. Ω is the unit step signal i.e.

$$\Omega(t - L_i) = \begin{cases} 0 \text{ for } (t - L_i) < 0 \\ 1 \text{ for } (t - L_i) \geq 0 \end{cases} \tag{26}$$

For any $t = t_k$, where t_k is the k-th sampling time, in Eq. (25), for all the terms with $i > k$, $\Omega(t - L_i) = 0$. So for $t = t_k$ we have

$$u(t) = \sum_{i=0}^{k} h_i\Omega(t - L_i) \tag{27}$$

For such an input the delayed signal can be expressed as

$$u(t - \delta) = \sum_{i=0}^{k} h_i\Omega(t - L_i - \delta) \tag{28}$$

For simplicity in the presentation the notation $\Omega_i = \Omega(t - L_i - \delta)$ will be used. Using this notation, the integral of the delayed input signal can be expressed as

$$u^{[i]}(t - \delta) = \sum_{i=0}^{k} h_i\frac{[t - L_i - \delta]^i}{i!}\Omega_i \tag{29}$$

The estimation equation (8) then becomes

$$y(t) = -a_0 y^{[1]}(t) + b_1\sum_{i=0}^{k} h_i\left[t - L_i - \delta\right]\Omega_i$$

$$+ b_0\sum_{i=0}^{k} h_i\frac{[t - L_i - \delta]^2}{2!}\Omega_i + c_1 + c_0 t + \xi(t) \tag{30}$$

Or equivalently

$$\gamma_c(t) = \phi_c^T(t)\theta_c + \xi(t) \tag{31}$$

with

$$\gamma_c(t) = y(t)$$

$$\phi_c(t) = \begin{bmatrix} -y^{[1]} \\ \sum_{i=0}^{k} h_i\frac{[t - L_i]^2}{2}\Omega_i \\ \sum_{i=0}^{k} h_i\left[t - L_i\right]\Omega_i \\ \sum_{i=0}^{k} h_i\Omega_i \\ t \\ 1 \end{bmatrix}, \theta_c = \begin{bmatrix} a_0 \\ b_0 \\ b_1 - b_0\delta \\ -b_1\delta + b_0\delta^2/2 \\ c_0 \\ c_1 \end{bmatrix}$$

$\xi(t) = e^{[1]}(t)$. Equation (31) can be written for $t = t_{d+1}, t_{d+2} \cdots t_N$ and combined to give the estimation equation.

$$\Gamma_c = \Phi_c\theta_c + \xi \tag{32}$$

From the solution of Eq. (32) the model parameters a_0 and b_0 as well as the initial condition parameters c_1 and c_0 can be obtained directly. To get b_1 and δ, the elements of θ can be used as

$$\delta = \frac{-\theta_c(3) \pm \sqrt{\theta_c(3)^2 - 2\theta_c(2)\theta_c(4)}}{\theta_c(2)} \tag{33}$$

$$b_1 = \theta_c(3) + \theta_c(2)\delta \tag{34}$$

2.3 Method 3: Identification using piecewise linear input signal

A number of input signals cannot be approximated as piecewise constant because of their piecewise linear nature. This section outlines the mathematical formulation for input signals with piecewise linear characteristics which can be mathematically expressed as

$$u(t) = \sum_{i=0}^{N} \alpha_i \left[t - L_i\right] \Omega(t - L_i) \tag{35}$$

Here, i corresponds to the sampling instant, α_i is the rate of change of the slopes of the input signal at the i-th sample point and $L_i = t_{i-1}$. Ω is the unit step signal. For any $t = t_k$, where t_k is the k-th sampling time, in Eq. (35), for all the terms with $i > k$, $\Omega(t - L_i) = 0$. So for $t = t_k$ one gets

$$u(t) = \sum_{i=0}^{k} \alpha_i \left[t - L_i\right] \Omega(t - L_i) \tag{36}$$

For such an input the delayed signal can be expressed as

$$u(t-\delta) = \sum_{i=0}^{k} \alpha_i \left[t - L_i - \delta\right] \Omega(t - L_i - \delta) \tag{37}$$

For simplicity in the presentation the notation $\Omega_i = \Omega(t - L_i - \delta)$ will be used. Using the notation, the integral of the delayed input signal can be expressed as

$$u^{[i]}(t-\delta) = \sum_{i=0}^{k} \alpha_i \frac{\left[t - L_i - \delta\right]^{i+1}}{(i+1)!} \Omega_i \tag{38}$$

The estimation equation then becomes

$$\begin{aligned} y(t) = & -a_0 y^{[1]}(t) + b_1 \sum_{i=0}^{k} \alpha_i \frac{\left[t - L_i - \delta\right]^2}{2!} \Omega_i \\ & + b_0 \sum_{i=0}^{k} \alpha_i \frac{\left[t - L_i - \delta\right]^3}{3!} \Omega_i + c_1 + c_0 t + e_1(t) \end{aligned} \tag{39}$$

Or equivalently

$$\gamma_l(t) = \phi_l^T(t)\theta_l + \xi(t) \tag{40}$$

with

$$\gamma_l(t) = y(t)$$

$$\phi_l(t) = \begin{bmatrix} -y^{[1]} \\ \sum_{i=0}^{k} \alpha_i \frac{\left[t - L_i\right]^3}{3} \Omega_i \\ \sum_{i=0}^{k} \alpha_i \frac{\left[t - L_i\right]^2}{2} \Omega_i \\ \sum_{i=0}^{k} \alpha_i (t - L_i) \Omega_i \\ t \\ 1 \end{bmatrix}, \theta_l = \begin{bmatrix} a_0 \\ b_0 \\ b_1 - b_0\delta \\ -b_1\delta + b_0\delta^2/2 \\ \frac{b_1\delta^2}{2} - \frac{b_0\delta^3}{3!} \\ c_0 \\ c_1 \end{bmatrix}$$

Equation (40) can be written for $t = t_{d+1}, t_{d+2} \cdots t_N$ and combined to give the estimation equation.

$$\Gamma_l = \Phi_l \theta_l + \xi \tag{41}$$

The first four elements of θ_l are the same as θ_c. Also these are the elements that contain the model parameters and the delay. hence we can use Eqs. (33) and (34) to retrieve the terms δ and b_1 for this case. The parameters a_0, b_0 and the initial condition terms c_0 and c_1 can be obtained directly.

2.4 Bias elimination

The properties of least-squares solution of an equation $\Gamma = \Phi\theta + \xi$ is given by (42) and depend on the error term ξ.

$$\theta^{LS} = (\Phi^T\Phi)^{-1}\Phi^T\Gamma \tag{42}$$

The error evolves due to the presence of noise in the output measurements which is generally zero mean white noise or filtered white noise. However, the integration operation performed on the output signal results in a colored error term even if the measurement noise is assumed to be white with zero-mean. So, the LS solution is not unbiased even for a white measurement noise and we need a bias elimination scheme. 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). The instrument vector, $\Psi(t)$ is derived by replacing the terms related to the output, $y(t)$, in the regressor by their predicted values, $\hat{y}(t)$. The LS solution is used for prediction. The instrumental variable estimate of the parameters is given by

$$\theta^{IV} = (\Psi^T\Phi)^{-1}\Psi^T\Gamma_n \tag{43}$$

3. SIMULATION RESULTS

The proposed methodologies are applicable to models with different lag and lead dynamics. For the simulation study the following model is used

$$G(s) = \frac{K}{s(\tau s + 1)} e^{-\delta s} \tag{44}$$

with $[K \ \tau \ \delta] = [1.25 \ 20 \ 7]$ which is equivalent to $G(s) = \frac{0.0625}{s(s+0.05)} e^{-7s}$ in the notations used in Sec. 2 with $[a_0 \ b_0 \ \delta] = [0.05 \ 0.0625 \ 7]$. Although the parameters are estimated as $[a_0 \ b_0 \ \delta]$, they are represented as $[K \ \tau \ \delta]$ in the results presented in this section as this gain and time constant representations are more common in use.

Three input signals were used for the three methodologies; namely a step signal for method 1, a pulse signal for method 2 and a multiple frequency sinusoid signal for method 3. Simulink was used to generate data and all calculations were carried out using Matlab. Noise free output signals were corrupted with white measurement noise with different noise to signal ratio (NSR) defined as the variance of the noise to that of the noise free signal. Monte Carlo simulations (MCS) were performed by changing the seed of the noise. For all simulations the end time of experiment, t_N, was chosen as 100 and the sampling time varied according to the choice of data length, N. The output was maintained at a initial steady state $[y(0) \ y'(0)] = [0.1 \ 0.1]$.

3.1 Effect of noise

To study the effect of noise on the performance of the three methods, noise with different NSRs were added and the model parameters were obtained for 100 MCS by changing the seed. Figures 1-3 present the identification results for the step, pulse and sinusoidal input signal, respectively. The mean values of 100 estimates are presented along with their standard deviations. The number of data points used for identification was 500 for each case.

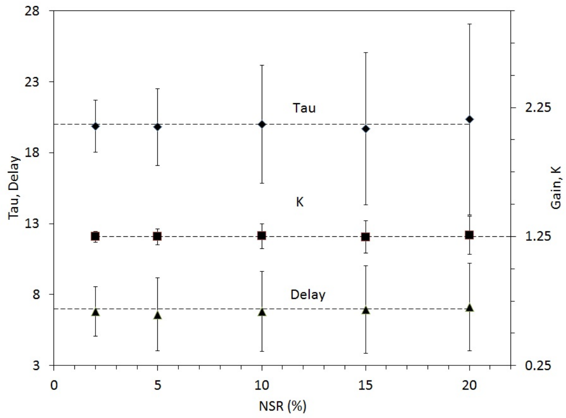

Fig. 1. Effect of NSR on parameter estimates for the step input.

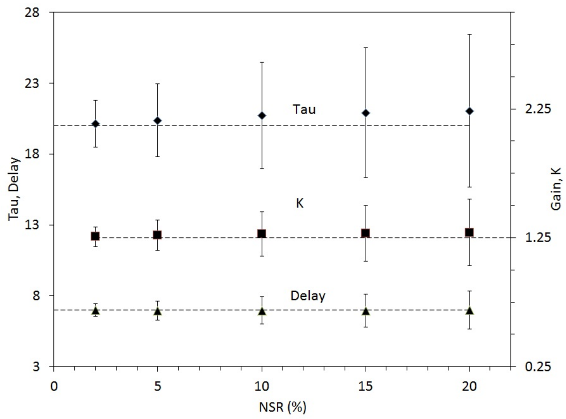

Fig. 2. Effect of NSR on parameter estimates for the pulse input.

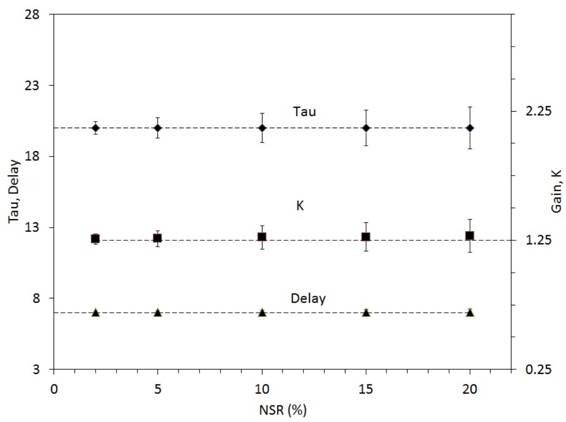

Fig. 3. Effect of NSR on parameter estimates for the sinusoidal input.

3.2 Effect of data length

To study the effect of data length on the performance of the three methods, identification exercise were carried out for all of the three methods keeping the NSR at 10%. Figures (4)-(6) present the the results of 100 MCS.

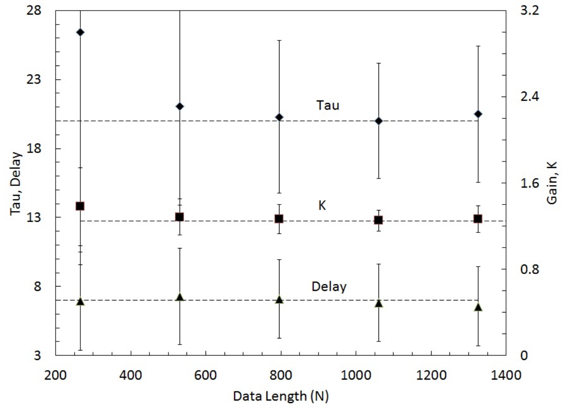

Fig. 4. Effect of data length on parameter estimates for the step input.

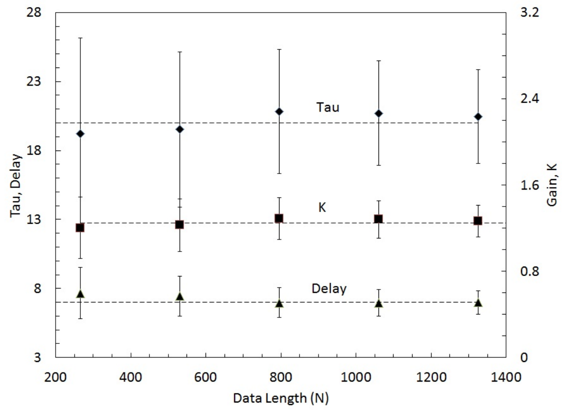

Fig. 5. Effect of data length on parameter estimates for the pulse input.

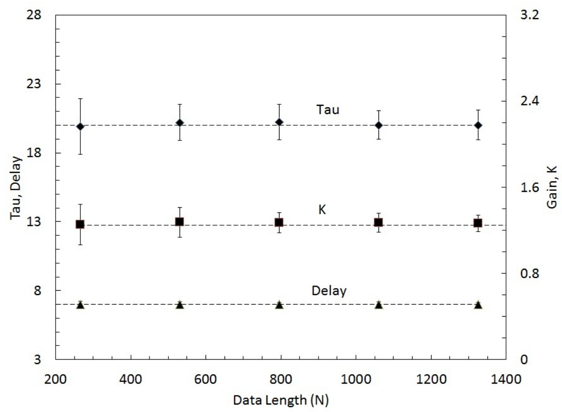

Fig. 6. Effect of data length on parameter estimates for the sinusoidal input.

3.3 Comparative performance of the three methods

To compare the performance of the three methods using a single index a total error criterion is defined which is a combined measure of bias and variance and is denoted by E_{total}.

$$E_{total} = \frac{1}{N_\theta} \sum_{i=1}^{N_\theta} \frac{(\hat{\theta}(i) - \theta(i))^2 + \text{var}(\hat{\theta}(i))}{\theta(i)^2} \qquad (45)$$

where, $\theta(i)$ represents the true values of the $i - th$ parameter and $\hat{\theta}(i)$ is its estimated value. N_θ is the number of parameters.

As seen from the results in the above sections and the results presented in Figures (7)-(8), although all of the three methods give satisfactory results for different NSR and data lengths, the methodology for piecewise linear signal gives better performance compared to the other two methods in terms of the properties of the estimated parameters.

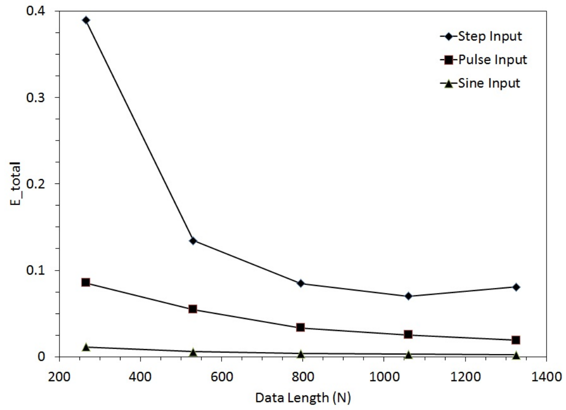

Fig. 7. Total error in the parameter estimates for the three input signals with different data length and 10% NSR.

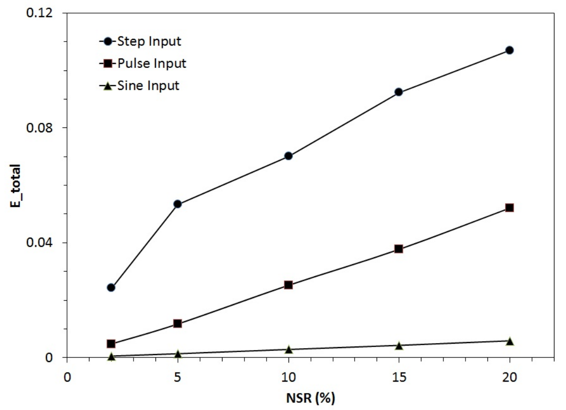

Fig. 8. Total error in the parameter estimates for the three input signals with different NSR and data length of N=1060.

4. CONCLUDING REMARKS

Input signals used for system identification are either piecewise constant or piecewise linear. The step input is also commonly used for identification. This article presents methodologies for identification of integrating processes using all of the above mentioned input signals. Through simulation study it has been demonstrated that the methods are capable of estimating model parameters for a wide range of NSR and data length. In terms of the properties of the estimated parameters, the sinusoidal input which is considered a piecewise linear signal, showed better performance compared to the other two signals namely the step and the pulse. The proposed methodologies, although derived taking a process with a first order lag dynamics as an example, are applicable to models with higher order dynamics as well.

ACKNOWLEDGEMENTS

The first and third author would like to acknowledge the financial support from Research and Development Corporation (RDC), Newfoundland and Labrador.

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