Determination of Dynamic Model Parameters Using Correlation Techniques for Smith Predictor

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***Abstract*- Smith predictor (SP) and modified Smith predictors are known as the most appropriate compensation techniques for the control of the processes with dead time. The stability and performance of the control scheme is directly linked to the coupling between the plant being controlled and its mathematical model. In case of uncertain or variable system parameters, SP fails to maintain the stability as well as the performance of the control. Accurate or close to accurate parameter estimation for these class of processes is very important for stability, control and optimization. There is a quite rich literature on the topic of dead time process control and parameter estimation, yet new approaches and methods are necessitated to improve the control scheme. In order to determine both the dead time and plant pole of the first order plus dead time plant for SP tuning, an on-line correlation algorithm is proposed to maintain the stability and performance of the control loop. Our approach utilizes a random Dither signal injected into the manipulated variable of the closed loop control system so that cross correlation between manipulated and controlled variable renders dead time and time constant of the plant. To illustrate the procedure, the processes with uncertain dead times and time constants are simulated using Matlab/Simulink pair and the results are presented.**

Keywords- Dead Time Compensation; Smith Predictor; Auto and Cross Correlation Techniques; Systems Identification

NOMENCLATURE

$G(s)$:	Transfer Function
$x(t), y(t)$:	Random Signals
$R_{xx}(\tau)$:	Auto Correlation Function
$R_{xy}(\tau)$:	Cross Correlation Function
$G_{xx}(f)$:	Power Spectral Density (V^2/Hz)
P_{av}:	Average Power (V^2) $[= \int_{-\infty}^{\infty} G_{xx}(f)df]$
$h(\tau)$:	Unit Impulse Response of a Linear Dynamic System
ω_0:	Cut Off Frequency (Rad/Sec)
$1/\alpha$:	Pole Position
B:	Signal Bandwidth (Rad/Sec)
p_0:	Power Magnitude
L:	Dead Time
CCF:	Cross Correlation Function
ACF:	Auto Correlation Function

I. INTRODUCTION

The dead time or transportation delay is a result of the process layout causing a delay between the application of control effort and its first effect on the process variable. In such processes, the transfer function representing the plant has an exponential Laplace term as given in Eq. 1.

$$G_p(s) = G(s)e^{-Ls} \tag{1}$$

where L is the dead time or the transportation delay.

Dealing with dead time or transportation delay has been one of the fundamental problems in the field of control engineering since it yields an irrational function which does not fit into standard theories and causes a large amount of phase shift in practice. Delay in general, dead time in particular, limits the range of control and leads the feedback loop to instability easily. The transfer functions for input and disturbance are given in Eq. 2 and 3, respectively. The characteristic equation of the closed loop control system given in Fig. 1 includes an exponential component making the characteristic equation quasipolynomial whose infinite number of roots determines the behavior of the system.

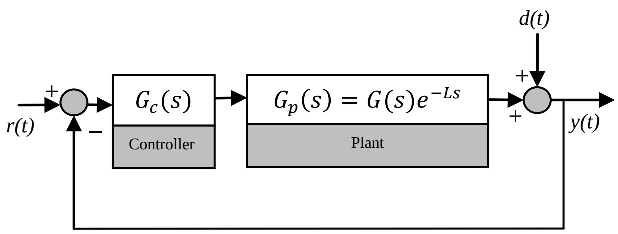


Fig. 1 Closed loop control system plant with dead time

$$T_R(s) = \frac{Y(s)}{R(s)} = \frac{G_c(s)G(s)e^{-Ls}}{1 + G_c(s)G(s)e^{-Ls}} \tag{2}$$

$$T_D(s) = \frac{Y(s)}{D(s)} = \frac{1}{1 + G_c(s)G(s)e^{-Ls}} \tag{3}$$

O.J.M.Smith [1,2] showed how to construct a feedback structure that effectively removes the dead time (L) out of the feedback loop and allows a feedback design based on $G(s)$ alone, which then accepts standard compensation methods. This compensation technique is known as Smith Predictor (SP) and is shown in Fig. 2. This is basically an internal model control (IMC) scheme since process model appears in the control structure. The plant transfer function for input and disturbance are given in Eq.4 and 5, respectively.

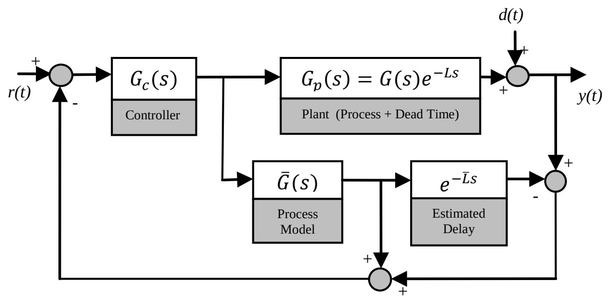


Fig. 2 Basic Smith predictor control scheme

$$T_R(s) = \frac{G_c(s)G(s)e^{-Ls}}{1 + G_c(s)G(s)e^{-Ls} + G_c(s)\bar{G}(s) - G_c(s)\bar{G}(s)e^{-\bar{L}s}} \quad (4)$$

$$T_D(s) = \frac{1+G_c(s)\bar{G}(s) - G_c(s)\bar{G}(s)e^{-\bar{L}s}}{1 + G_c(s)G(s)e^{-Ls} + G_c(s)\bar{G}(s) - G_c(s)\bar{G}(s)e^{-\bar{L}s}} \quad (5)$$

Assuming the process model and dead time estimation perfectly match with the actual values as; $G(s) = \bar{G}(s)$ and $L = \bar{L}$, we obtain Eq. 6 for the characteristic equation of the compensated system as:

$$1 + G_c(s)\bar{G}(s) = 0 \quad (6)$$

It is apparent from Eq.6 that the characteristic equation lends itself to a manageable form since there exists no exponential term in the characteristic equation. This basic principle has become the backbone of the dead time compensation in the field.

Modifications to standard Smith predictor have been proposed to overcome various control problems such as stability, robustness, disturbance rejection and auto tuning. Many researchers have contributed for further improvements by advising many form of so called 'Modified Smith Predictor'. Watanabe and Ito [3], Astrom *et al.* [4] and Datsych [5], Matausek and Kvascev [6] are among the few researchers offering modifications for some special cases and adaptive control methods. Hang *et al.* [7], Hagglund [8], Dumont *et al.* [9], Rad *et al.* [10] have applied on-line parameter estimation of the predictive model. Later, Kaya [11,12] has offered an automatic tuning of controller parameters using relay feedback approach in a modified SP configuration. These modifications, however, do not explicitly address the control problem of variable dead time processes. SP or modified SP configuration requires model dead time to follow the process dead time to encompass both stability and robustness of the closed loop.

The main motivation of this paper is to estimate dead time and plant parameter continuously on-line and tune the SP accordingly. Off-line determination of dead time has been dealt with by some researchers, see for example, [13, 14] for model parameter estimation and Meyr and Spies [15], Normay-Rico [16] and Bozorg and Davison [17] for dead time estimation and O'Dwyer [18] for a classification of estimation techniques. On-line determination of dead time was addressed as one of the open problems in connection with the delayed systems in a survey paper of Richard [19]. For a fast on-line determination of dead time Tian and Gao [20] proposed average magnitude difference function (AMDF) and reported that the function suits well for two typical processes.

Here, in this paper, we propose correlation techniques estimating both dead time and process parameter for the first order systems. The applications of correlation techniques have a long track record especially in the field of signal processing, communication and measurement, see for example [21,22]. It is shown, throughout this study, that auto and cross correlation techniques can well be used to determine process parameter and dead time of a stable first order plus dead time (FOPDT) plant.

Outline of this paper is as follows: the next section presents up to certain details, sufficient for the proper perspective on the topic of concern, the correlation functions and their use as a system parameter evaluation tool. The third section presents the application of correlation techniques to control loop. Section four presents the results and discussions. The final section concludes the paper.

II. CORRELATION FUNCTIONS AS SYSTEM PARAMETERS ESTIMATION TOOL

The power of correlation techniques lies in its ability to eliminate the independent disturbances and noise that naturally occur in systems. In this paper, we show that auto and cross correlation techniques can be used for determining systems' impulse response whereas cross correlation technique has advanced features for the determination of dead time.

The possible correlation or statistical dependence between two different random signals *x(t)* and *y(t)* is expressed by the auto and cross correlation function $R_{xx}(\tau)$ and $R_{xy}(\tau)$, respectively.

$$R_{xx}(\tau) = \lim_{T\to\infty} \frac{1}{T}\int_0^T x(t-\tau)x(t)dt \quad (7)$$

$$R_{xy}(\tau) = \lim_{T\to\infty} \frac{1}{T}\int_0^T x(t-\tau)y(t)dt \quad (8)$$

The cross correlation function given in Eq.8 can specifically be used to determine dead time when *x(t)* and *y(t)* are dependent random signals as shown in Fig. 3. Even if *y(t)* is contaminated by other independent noise, $R_{xy}(\tau)$ successfully yields the transportation delay. This feature of cross correlation function is the key merit to determine dead time in the plant transfer function.

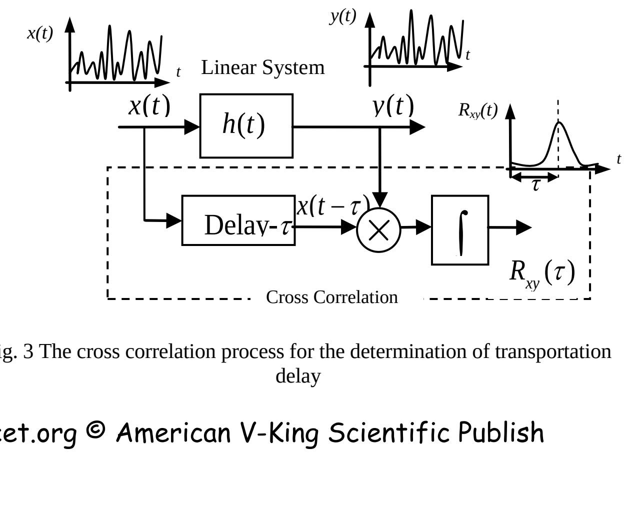


Fig. 3 The cross correlation process for the determination of transportation delay

There exists an important relationship between the auto correlation function and the power spectral density function known as Wiener-Khintchine theorem stating that $R_{xx}(\tau)$ and $G_{xx}(f)$ form a set of Fourier transform pairs [23] given by,

$$G_{xx}(f) = \int_{-\infty}^{+\infty} R_{xx}(\tau) e^{-j\omega\tau} d\tau \qquad (9)$$

$$R_{xx}(\tau) = \int_{-\infty}^{+\infty} G_{xx}(f) e^{j\omega\tau} df \qquad (10)$$

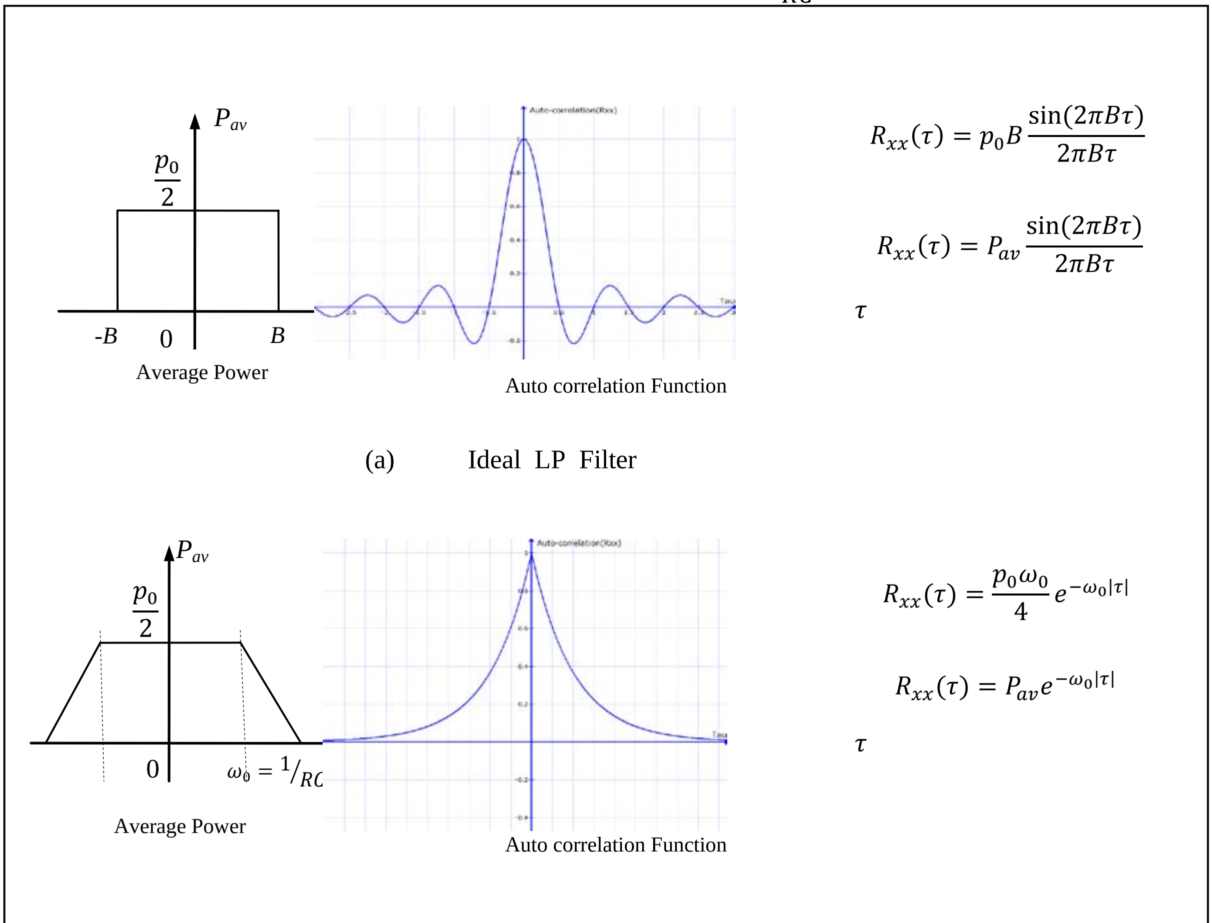
Eq.9 and 10 imply that auto correlation function provides some spectral properties of the random signals. As an example, when we consider an ideal band limited white noise as shown in Fig. 4a, it can be shown that the auto correlation function yields,

$$R_{xx}(\tau) = p_0 B \frac{\sin(2\pi B\tau)}{2\pi B\tau} \qquad (11)$$

where B is the signal bandwidth, $p_0/2$ is signal average power and the first zero is found at $\tau = {}^{1}/_{2B}$. Similarly, when an RC network is used as a low pass filter, the auto correlation function yields (Fig. 4b)

$$R_{xx}(\tau) = \frac{p_0\omega_0}{4} e^{-\omega_0|\tau|} \qquad (12)$$

where $\omega_0 = {}^{1}/_{RC}$



(a) Ideal LP Filter

(b) RC LP Filter

Fig. 4 Band limited white noise and corresponding auto correlation functions

A passive RC network structure conveys the same information as the first order plant dynamics. The auto correlation function given in Eq.12, therefore, enables us to find the cutoff frequency of a first order plant.

Perusal of Fig. 4b shows that the pole of a first order system which, in essence, is a low pass filter can be determined from auto correlation function. It shows that when a random signal passes through a low pass filter, the cutoff frequency can be extracted from ACF by measuring the rate of decay.

In addition to establishing dead time, the cross correlation function can also serve to find the unit impulse response of a linear system. It can be proven that the cross correlation function includes the unit impulse response of the system when a white noise is applied to the input [24].

$$R_{xy}(\tau) = \frac{1}{2} h(\tau) G_{xx}(0) \qquad (13)$$

$G_{xx}(f)$ is physically realizable, one sided power spectral density and $G_{xx}(0)$ is the power density of the white noise spectrum in $(\text{volt})^2$/Hz at very low frequencies. $h(\tau)$ is the impulse response of the system under test. For $R_{xy}(\tau)$ to give a direct measure of $h(\tau)$, $G_{xx}(0)$ must be flat i.e. much wider than a pass band of the system under test.

In most practical situations *y(t)* is contaminated by an independent background noise, *n(t)*, as shown in Fig. 5. *z(t)* is the only signal available for analysis which is contaminated by the noise.

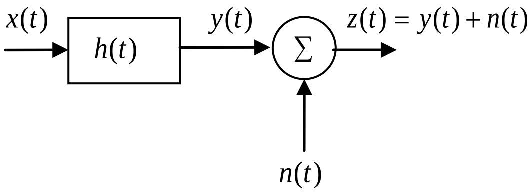


Fig. 5 Noise effect

The cross correlation function measured between *x(t)* and *z(t)* can, therefore, be proven to be

$$R_{xz}(\tau) = \frac{1}{2}h(\tau)G_{xx}(0) + R_{xn}(\tau) \quad (14)$$

where $R_{xn}(\tau)$ is the cross correlation function between *x(t)* and *n(t)* and $R_{xn}(\tau) = 0$ when *n(t)* and *x(t)* are uncorrelated or independent. Under these conditions, the measurement is unaffected by the presence of background noise and demonstrates the ability to extract accurate information from a noisy system. The background noise increases the variance of the result but the statistical errors can be reduced by increasing the averaging time.

III. APPLICATION OF CORRELATION ANALYSIS TO SMITH PREDICTOR TUNING

The present study is involved with the stable first order plus dead time (FOPDT) system model which is frequently encountered in the process industry and is considered to capture the dynamics of real plants sufficiently well for many applications (see examples [11][12][14]). The FOPDT process transfer function is identified as,

$$G(s) = \frac{1}{\alpha s + 1} e^{-Ls} \quad (15)$$

where α is the plant time constant (i.e. system pole or cutoff frequency is at $\frac{1}{\alpha}$ radsec^{-1}) and L is the dead time.

As discussed in the preceding sections, the correlation functions of random signals shall be used to determine α and L for SP tuning. As such, we implemented a random dither signal generator as the test signal source together with SW1 and SW2 switches, and the blocks which are responsible for the execution of correlation functions are termed as correlator as shown in Fig. 6.

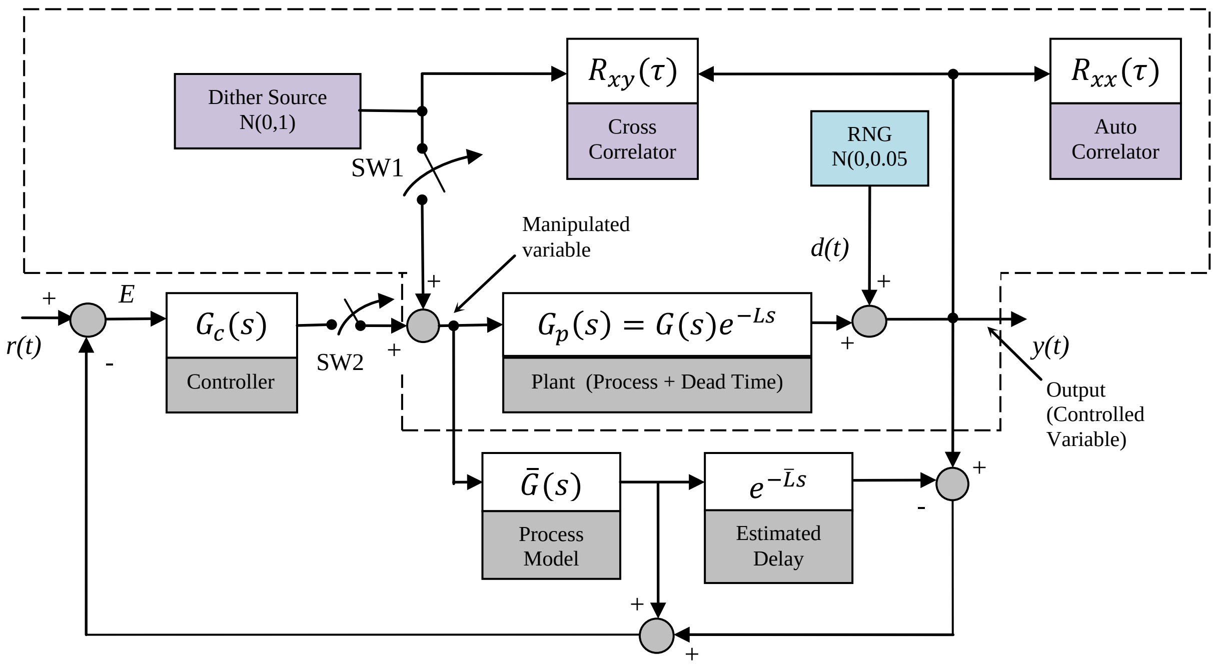


Fig. 6 Correlator application to Smith Predictor control scheme

SW2 switch is used for opening and closing the control loop. When SW2 is open, the plant is isolated from the other building blocks so that the manipulated variable is due exclusively to the signal generated by dither source when SW1 is closed. This state of operation is called open loop. The SW1 is, therefore, serves to inject dither signal to the plant when closed. When SW2 is closed, feedback loop is closed and the manipulated variable is the sum of controller output and dither signal available when SW1 is closed. The structure shown in Fig. 6, therefore, facilitates the determination of system parameters in open and closed loops as follows:

- Open loop operation (SW2 open /SW1 closed): The purpose of this operation is to determine initial system parameters before the loop is closed. This will allow assigning the process parameters required for process model and delay building blocks at the outset. In this operation scheme, the cross correlator will give the initial dead time while auto correlator will provide the cutoff frequency.

- Closed loop operation (SW2 closed): Closed loop operation is assumed to be a continuous on-line operation. Keeping SW2 closed, SW1 switch is closed at certain intervals, the periods of which are to be determined by the plant dynamics and correlation execution time requirements. Closed loop operation will employ merely the results of cross correlator for the determination of both parameters.

Dither source is chosen to be normal distribution random noise, bandwidth of which is selected as 1kHz. For the validity of Eq. 12, 13 and 14, the source bandwidth needs to be much wider than that of the cutoff frequencies of the plant under consideration so that the dither source can be assumed to be the white noise source. Plant cutoff frequencies are practically much lower than 1kHz. Here, the plant cutoff frequency is chosen between 0.5 and 10 radsec^{-1} corresponding to 0.0796Hz and 1.5915Hz. The system given in Fig.6 is simulated using Matlab/Simulink under various plant cutoff frequencies and dead times. It must be noted that this work is confined with the pursuit of accurate calculation of key plant parameters. The controller selection or optimal tuning is left outside the topic of concern.

IV. SIMULATION AND RESULTS

We have used Matlab/Simulink pair to conduct simulations for open and closed loop operations.

A. *Open Loop Operation Simulation*

During open loop operation, the plant is isolated from the control loop by opening SW2 and no distortion is applied to the system since distortion normally assumed to occur during normal closed loop operation. The purpose of this operation is to determine the plant parameters so that these parameters would be implemented before the loop is closed. The simulation algorithm is basically a dynamic system identification using correlation techniques as depicted in Fig. 7.

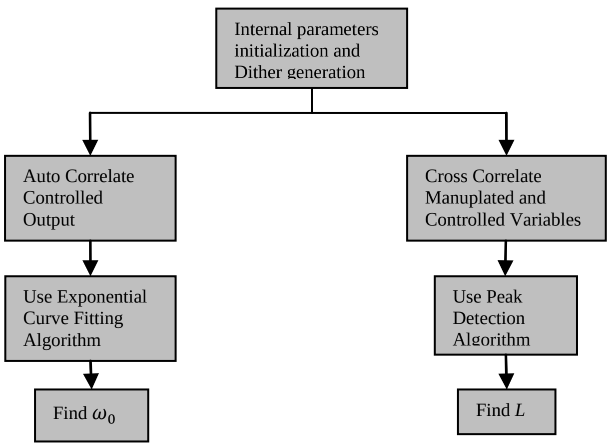
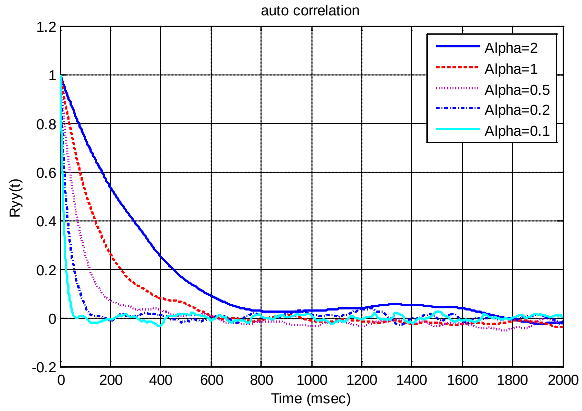
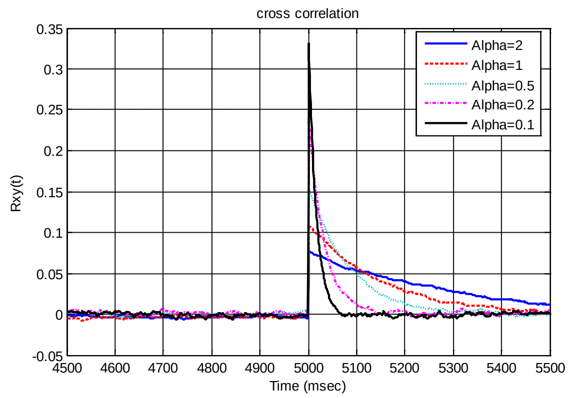


Fig. 7 Open loop correlation algorithm

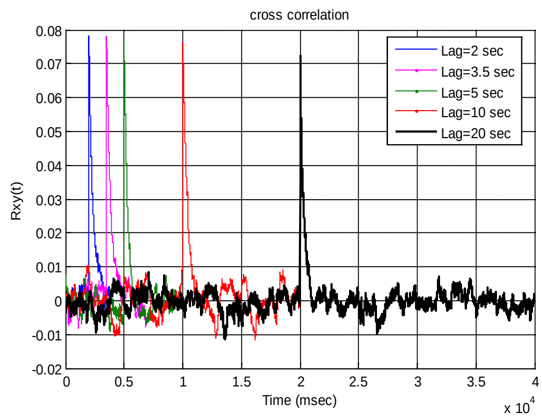
The correlation functions obtained from the open loop simulation are illustrated in Fig. 8. The results are consistent with the theoretical expectations introduced in the Section 2. Our plant, given in Eq. 12, is a simple low pass filter similar to the equation shown in Fig. 4b LP RC filter. Auto correlation function is therefore governed by Eq.12 which needs to be studied further to extract ω_0 corresponding to $1/\alpha$. Fig 8a shows the ACF of controlled variable when 1000Hz bandwidth of dither applied and dead time is assumed to be 5s. The ACF is not affected by the dead time but pole position (cutoff frequency) of the plant is. In order to determine exponential decay that would be used for the estimation of α, we employed exponential fitting algorithm. The measurement results for α including standard measurement error are given in Table 1 where the auto correlation functions are executed for a period of 180 seconds. As for the CCF, Fig. 8b shows constant dead time of 5s whereas Fig. 8c presents the results of CCF when dead time varies from 2 to 20s. Our simulation showed that the cross correlation between input and output functions gave almost accurate dead time under these favorable conditions. The cross correlation function required, however, a peak finding algorithm to determine the precise location of dead time in case of flat cross correlation functions.



(a) Normalized auto correlation for various pole positions



(b) Normalized cross correlation of the system in part (a) with 5sec. of dead time



(c) Cross correlation of the system with different dead times while the plant pole is at α =1

Fig. 8 Auto and cross correlation functions for various cutoff frequencies and dead times

These results, particularly in plant time constant calculation, pose some errors, magnitude of which increases in proportion to the plant time constant. Several error measures are given in Table 1 as α varies. Fig. 9 depicts the relative changes of errors with respect to mean value.

Among other error qualities MAPE gives more significant measure of error. From Table 1 and Fig. 9 it is obvious that when α gets larger i.e. time constant increases, the ACF for the measurement of α exhibits greater error. This is simply because of the decreasing bandwidth of the correlated signals.

The cross correlation function in Fig. 8c directly gives the dead time where the CCF peak appears. Our simulation showed that the cross correlation between input and output functions gave almost accurate dead time detection. The cross correlation function required, however, a peak finding algorithm to determine the precise location of dead time in case of flat cross correlation functions.

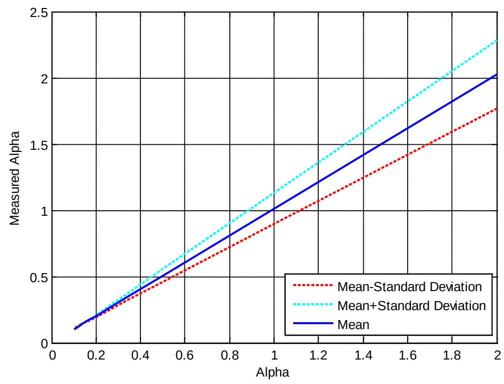


Fig. 9 Graphical representation of errors given in Table 1

TABLE I CALCULATED PLANT POLE AND ASSOCIATED ERRORS

Pole $(1/\alpha)$	α	Measured Mean $\alpha^{(*)}$	STD	MAD	MAPE	RMS
0.5	2	2.023166521	0.274634713	0.223583	11.17914	0.261569
1	1	1.021057626	0.084854783	0.076095	7.609496	0.083209
2	0.5	0.516514292	0.039270480	0.031721	6.344241	0.040751
3	0.333333	0.339627950	0.016333760	0.014269	4.280784	0.016725
4	0.25	0.245050989	0.011893074	0.010532	4.212749	0.01232
5	0.2	0.203529825	0.007283602	0.006305	3.152326	0.007759
6	0.166667	0.166562195	0.007122064	0.005815	3.488986	0.006757
7	0.142857	0.143397067	0.009925779	0.008182	5.727450	0.009432
8	0.125	0.123776435	0.003673817	0.003101	2.480563	0.003694
9	0.111111	0.111430369	0.003356996	0.002786	2.507724	0.003201
10	0.1	0.099436211	0.002150587	0.001895	1.894991	0.002117

(*) Mean of 10 regression each lasts 180 sec

STD : Standard Deviation

MAD : Mean Absolute Deviation

MAPE : Mean Absolute Percentage Error

RMS : Root Mean Square

B. *Closed loop Operation Simulation*

The closed loop simulation assumes that SW2 is kept closed as SW1 switch (see Fig. 6) is closed with certain periodic intervals, the period of which is to be determined by both the plant dynamics and correlation execution time requirements. The correlation analysis is carried out during the period when SW1 is kept closed. Here the auto correlation analysis cannot be used for the determination of plant pole as it was in the open loop operation since the auto correlation of plant output contains the total closed loop transfer function. It is therefore the cross correlation function between the signal source as plant input, and the plant output is required for the determination of the system parameters since cross correlation isolates the plant from the rest of the closed loop transfer function.

The closed loop is tuned using a PD controller of which proportional gain and derivative gain are selected as 100 and 0.075, respectively. The controller transfer function is therefore given as,

$$G_c(s) = 100 + 0.075s \quad (16)$$

and the system is assumed to be subjected to a normal random distortion signal having a bandwidth of 0.01Hz. Under these conditions simulation is conducted for different dead time values (2, 3.5, 5, 10 and 20s) and different α values (0.1, 0.2, 0.5, 1 and 2). The simulation algorithm for closed loop operation is given in Fig. 10.

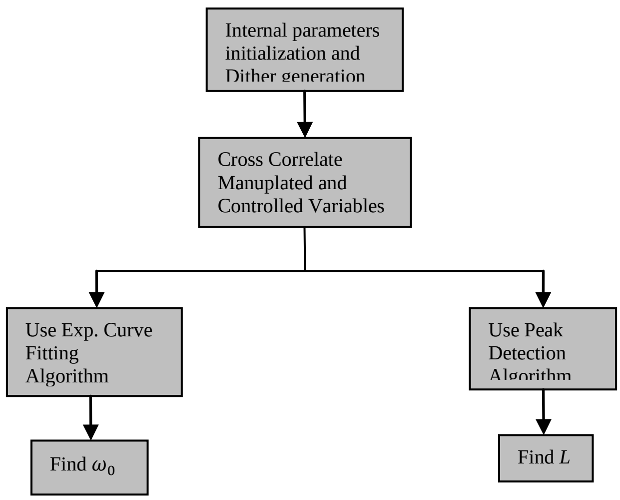


Fig. 10 Closed loop correlation algorithm

The simulation results are shown in Fig. 11 and 12. Dead time is measured as the time elapsed between zero and where the positive peak occurs as shown in Fig. 11. The peak is determined precisely through the peak detection algorithm. Fig. 12 is the result of different pole positions when dead time is kept constant. It is obvious that when pole $(1/\alpha)$ is large, the decay is slow, consequently pole determination is prone to large errors. The pole position and associated errors are presented in Table 3.

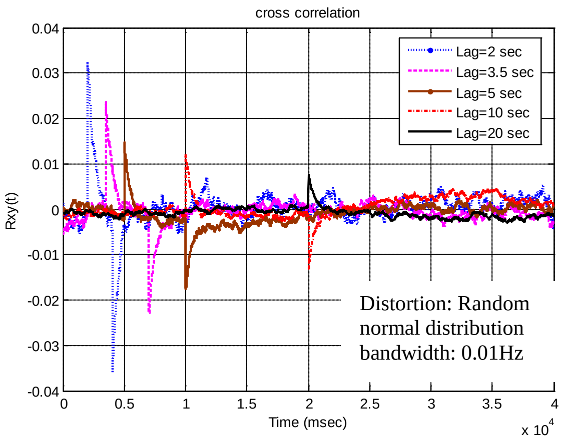


Fig. 11 Closed Loop cross correlation functions for various dead times

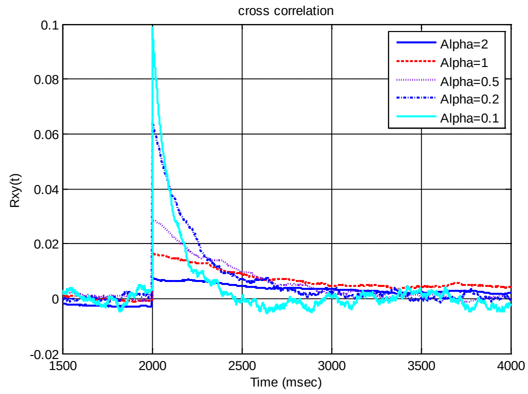


Fig. 12 Closed Loop cross correlation functions for various α values

TABLE II MEASURED DEAD TIME FOR CLOSED LOOP (BASED ON FIG.12)

Actual Dead Time	Measured Dead Time
1	1.002
2	2.002
3	3.002
4	4.002
5	5.002
6	6.002
7	7.001
8	8.002
9	9.001
10	10.002

TABLE III CALCULATED PLANT POLE AND ASSOCIATED ERRORS FOR CLOSED LOOP (BASED ON FIG.12)

Pole $(1/\alpha)$	α	Measured Mean $\alpha^{(*)}$	STD	MAD	MAPE	RMS
0,5	2	1,96877203	0,703677	0,585444	29,2722	0,668296
1	1	0,9960724	0,158167	0,141428	14,14279	0,150102
2	0,5	0,49988289	0,070788	0,053084	10,61674	0,067155
3	0,333333	0,32966703	0,037863	0,028759	8,62765	0,036107
4	0,25	0,25055228	0,019768	0,016251	6,500421	0,018761
5	0,2	0,19697561	0,017549	0,011685	5,842496	0,016921
6	0,166667	0,16911044	0,013155	0,010008	6,004929	0,012717
7	0,142857	0,14530929	0,011583	0,008457	5,919862	0,011259
8	0,125	0,12201161	0,008302	0,006623	5,298692	0,008424
9	0,111111	0,10991094	0,007415	0,006378	5,740305	0,007136
10	0,1	0,10252137	0,005119	0,003964	3,964042	0,005472

Unlike dead time measurement (Table2), plant pole measurement is subject to an error that increases as plant bandwidth decreases, i.e. larger value of α, as given in Table 3. When $\alpha = 2$ MAPE is 29.2722, while $\alpha = 10$ MAPE is noted as 3.9640, which is considerably smaller than that of $\alpha = 2$. This is a natural consequence of a bandwidth limitation, a smaller bandwidth will result in less data to be correlated. Hence a flatter cross correlation function will be obtained. It will therefore be more ambiguous to determine the rate of decay. Fig. 13 depicts the response of the closed loop to step response when actual $\alpha = 2$, as the worst mismatch is observed. From the Fig. 13, we read a 5% overshoot while no overshoot is observed in the fully matched system.

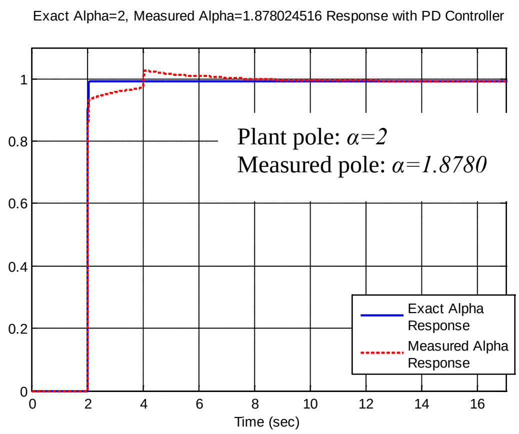


Fig. 13 Step response of closed loop

V. DISCUSSIONS AND CONCLUSIONS

The stability and performance of the SP or modified SP control scheme directly linked to the coupling between the plant being controlled and its mathematical model. It is important to maintain this coupling even if the plant parameters vary in time. This paper deals with the FOPDT processes with uncertain dead time and pole position, for which on-line correlation algorithms are presented to maintain the stability and performance of the control loop. A dither signal is injected on to the controlled variable input to generate the primary random signal to be used for correlation algorithms. The operation is split into two parts; first, the open loop operation, here the objective is to obtain the initial values of plant pole location and dead time by isolating plant from the rest of the system. And second, the closed loop operation aims to keep track of these parameters on-line with certain intervals, and tune the SP model building blocks accordingly. In both operations, as presented in the section 2, the dither source is required to have much higher bandwidth than plant bandwidth in order to act as a white noise. We have tuned dither source to 6283radsec^{-1}(1000Hz) while plant cutoff frequencies varies between 0.5 and 10radsec^{-1}, so that we guaranteed dither signal's role in the loop. Further a random distortion signal having 0.01Hz of bandwidth is attached to the closed loop operation.

A PD controller is placed for closed loop tuning. It could have been a different controller since no loop requirement is identified at the onset of loop tuning. The objective here is not to improve the loop performance or provide robustness but to sustain whatever the performance of the loop was under the plant and model match.

ACF and CCF are both facilitated to determine plant pole ($1/\alpha$) and dead time (L), respectively, in the open loop operation. Since the system is isolated from the rest, as per given in Table 1 and Fig. 8, the parameter estimation is found to be more accurate than in the closed loop case. These values are then used initial parameter assignment of the model so that blind initial values would be avoided. The open loop operation would, therefore, reduce the transients when switched to closed loop operation. The closed loop operation is the dominant operation and parameter estimation needs to be continuously updated to keep system fine tuned. The CCF provides both α and L from the resulting function, while rejecting low frequency distortion and other uncorrelated signals around the loop. Our simulation has been conducted under certain values as noted in the body of the text.

The results presented in the paper reveal that the correlation analysis can well be suited for determining the plant parameters so that control system stability and performance are secured. In this study, the correlation functions are executed using Matlab/Simulink pair where the execution period for determining plant parameters took 180 seconds under an assumed correlation window (e.g. $\tau=40sec$). Matlab and Simulink are multipurpose programs, so that the execution times are naturally longer than an embedded microcomputer system dedicated to correlation analysis. In the terms of microinstructions in the embedded systems, the discrete correlation function is composed of a series of multiplication, additions and shifting codes of which execution times are closely linked to the clock frequency, register and ALU structure of the microprocessor as well as to the correlation algorithms used. Today, commercially available embedded systems in the market are fast enough to execute these functions in the order of milliseconds. In addition, a priori knowledge of the range of system parameters may reduce the size of the correlation window (τ) so that no excessive calculation would be needed. However it should be noted that, regardless of how fast the process execution times, correlation analysis cannot be less than that of predetermined period of the correlation window.

The premise of the random dither signal injection was based on driving the actuator with large enough power just to stimulate the plant but small enough not to mask the actual manipulated signal. The applicability of this process depends on the plant under control. For example, it may be applicable for some industrial processes like temperature, flow or pressure controls while may not be applicable to servo control systems since no room exists even for the minor changes in the controlled variable.

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