ROBUST SMITH PREDICTOR

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หัวข้อวิทยานิพนธ์	Smith Predictor ที่มีความคงทน
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บทคัดย่อ

วิทยานิพนธ์นี้นำเสนอการเพิ่มความสามารถของตัวควบคุม PID ในการควบคุมกระบวนการที่มีปัญหาเรื่องเวลาไร้ผลตอบสนอง (Process Dead Time) ระบบควบคุมที่นำเสนอนี้ได้ถูกปรับปรุงมาจาก Smith Predictor ซึ่งเป็นอีกทางเลือกหนึ่งของกระบวนการที่มีปัญหาเรื่องเวลาไร้ผลตอบสนอง แต่สิ่งหนึ่งที่ Smith Predictor ต้องการก็คือ ค่าพารามิเตอร์ของกระบวนการ (Process Parameters) ที่ประกอบด้วย ค่าอัตราขยาย (Process Gain) ค่าเวลาคงตัว (Process Time Constant) และค่าเวลาไร้ผลตอบสนองของกระบวนการจริงต้องค่อนข้างใกล้เคียงกับค่าพารามิเตอร์ของกระบวนการในแบบจำลอง ซึ่งการได้มาของแบบจำลองที่ถูกต้องนั้นค่อนข้างที่จะทำได้ยากเนื่องจากอาจมีสิ่งรบกวนที่ไม่สามารถวัดค่าได้ (Unmeasured Disturbances) ระหว่างการหาแบบจำลองของกระบวนการ (Process Identification) ประกอบกับความไม่แน่นอนของค่าพารามิเตอร์ของกระบวนการต่างๆ ที่มีการเปลี่ยนแปลงตามสภาวะอากาศหรืออายุการใช้งานของอุปกรณ์ต่างๆ ของระบบ เป็นต้น ดังนั้น Smith Predictor ที่มีความคงทน (Robust Smith Predictor) จึงได้ถูกนำเสนอเพื่อเพิ่มประสิทธิภาพและความแน่นอนในการควบคุมในย่านที่กว้างขึ้นโดยไม่ต้องกลับไปปรับแต่ง (Tuning) หรือปรับเปลี่ยนแบบจำลองของกระบวนการ (Update Process Model) อยู่เสมอ

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ABSTRACT

This thesis presents the another methodology to apply PID controller to control the dominant process dead time. The model predictive control is the main idea behind for controlling the difficult loop by recording the process behavior as a first order process inside PID control configuration. One of the real problem that challenges all process control engineer is to get the accurate process model, which is generally not possible due to too many unmeasured disturbances from the process e.g., heavy rain, equipment's lifetime etc. The unmeasured disturbance can introduce the modeling errors and control performance will deteriorate significantly. The robustness of overall control loop can be improved while performance can be maintained by applying Robust Smith Predictor. Tuning for trade-offs will also be described in this paper.

In this study, the control performance of Smith Predictor and proposed Robust Smith Predictor will be described. The Simulink (MATLAB) is a tool to present the comparison.

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My thanks also to Rungnapa Buranatrivedhya, a Lead Technologist of Thaioil Refinery, who brought me to the real world of applying Smith Predictor and shared her experiences either advantages or disadvantages from this implementation in the plant [14].

My last thanks would like to dedicate to Mr. Pittaya Pannil, who aided me in formatting this thesis to be in line with the standard form.

The inspiration of this thesis is from once in my experience of losing five days for tuning a long dead time process until the book [1] that reveals the fact of using PID was found.

Finally, I would like to pay my respect to my beloved mother, Boonchuay Janchookiat, who has always been encouraging and keeping me stepping forward.

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CHAPTER 1
INTRODUCTION

1.1 Overview

A PID controller alone has the limitation and difficulty to deal with the dominant dead time process. In 1957, O.J.M. Smith introduced a well-known predictor, so-called Smith Predictor, in order to use PID and additional network to control the dominant dead time process more effectively. Smith Predictor is an approach of the model-based control (MBC) or model predictive control (MPC). For MBC (or MPC), the process model is a cornerstone. Performance and robustness of the overall control system depend on the accuracy of the process model. A disadvantage of the Smith Predictor is so-called process model sensitive [1,2,5,11,12,13]. Therefore, several control engineers have been attempting to develop this predictor to overcome this weak point. The investment cost for a Smith Predictor control loop is relatively low when compared to the other commercial MPC products. This is the reason why Smith Predictor is of interest by control engineers to study and research.

The Smith Predictor has still been developed even though there are a number of methodologies proposed since the last decades until now e.g. Flexible Smith Predictor by Vrancic, Vrecko, Juricic and Strmcnik in 1999, Adaptive Smith Predictor by Vogel and Edgar in 1980, etc. All of them are intended to increase the robustness in the presence of modeling error caused by unmeasured disturbances [2,5,7].

In this study, the proposed methodology is outstanding due to its low-cost, minimal efforts required for maintenance e.g. re-tuning, re-parameterized and less complexity in terms of control configuration and tuning technique.

At the end of the thesis, the experimentation results are illustrated by comparing the outcome of the Robust Smith Predictor to the original Smith Predictor. They show that the proposed methodology is able to overcome the weak point of the original Smith Predictor.

1.2 Objective

It is intended to study the way to maximize the capabilities of the PID controller to control the dominant dead time process in the economical way. The performance and robustness of PID controller are decreased significantly if apply it into the dominant dead time process and even worst during the presence of modeling error. In contrast, the performance and robustness of PID controller to a non-dominant dead time process is still acceptable because high controller gain is allowed.

The Smith Predictor is selected to study by modifying its control scheme in order to improve its weak point to be able to handle such process parameter variations. The PID tuning skill will also be described in section 4.3.3 particularly on the original Smith Predictor and the proposed Robust Smith Predictor.

Moreover, the thesis will present the another approach of model-based control in the difficult dynamic process (e.g. inverse response and open loop unstable process).

1.3 An Initiative Approach in this Thesis

The thesis presents some techniques by adding another PID controller to counter the modeling error signal between the process model and the actual process. The tuning technique for trade-offs is also studied and presented by based on ITAE-SP and ITAE-Disturbance [2].

1.3.1 Original Smith Predictor

Smith Predictor has one set of tuning parameters (one PID controller). The dead time compensator in the model can completely remove the actual process dead time only in the absence of modeling error otherwise nothing is done to counter the modeling error signal [5,6]. The modeling error can degrade the overall control performance significantly [3].

1.3.2 Proposed Robust Smith Predictor

Robust Smith Predictor offers 2 sets of tuning parameters (two PID controllers). Another PID controller, so-called PIDe, is designed for countering the modeling error signal and any unmeasured disturbances. These allow the Robust Smith Predictor to work in the wider operating range says +/- 2 or 3 times from the nominal process model.

1.4 Outline of the Thesis

Five chapters and the other two appendices (Appendix A and B) are arranged to describe the operational and drawbacks of a single PID controller until the generation of developed dead time compensators e.g. IMC (Internal Model Control), Smith Predictor, and the proposed Robust Smith Predictor to a dominant dead time process.

Chapter 1: An overview of the thesis, shortly identify the weak point of the original Smith Predictor and introduce the development of Smith Predictor since the last decades until now.

Chapter 2: Principle of Smith Predictor, this chapter will explain the effect of the process dead time to the performance and robustness of a single PID loop, the control function of Smith Predictor and introduce the causes that can deteriorate the performance of a PID controller and Smith Predictor e.g. ultimate gain and ultimate frequency limitation.

Chapter 3: This chapter is arranged in order to describe the control methodology of applying model-based concept in difficult dynamic processes.

Chapter 4: The Principle of Robust Smith Predictor, this topic will thoroughly explain its control methodology. Modeling error, measured disturbance and unmeasured disturbance will be discussed in this chapter. They are the sources of making process model mismatch and degrading the performance and robustness of the control system. The tuning techniques of Smith Predictor and Robust Smith Predictor will be described.

Experimentation Results, this will compare the outcome of Smith Predictor and Robust Smith Predictor both in the absence and presence of modeling error. This will show that the proposed Robust Smith Predictor is able to overcome the weak point of original Smith Predictor.

Chapter 5: Discussions and Conclusions, the last chapter of the thesis.

Appendix A: Smith Predictor in process industries, this will show how practitioners applied this concept to overcome the long dead time and non-linearity of the processes. The configuration in DCS (Distributed Control System) will also be presented.

Appendix B: Controller tuning rules for the approximate model, the various tuning guidelines e.g. Cohen-Coon, ITAE, etc., will be presented.

Appendix C: Published Journals declarations

CHAPTER 2

PRINCIPLE OF SMITH PREDICTOR AND EFFECT OF TIME DELAY

2.1 Overview

There are different techniques to cope with delays. The most popular is, perhaps, the Smith Predictor. Dominant dead time process is considered to be one of the three in the group of processes with difficult dynamics [1] besides the inverse response process and the open loop unstable process. Additionally, the two latter processes will discuss again in chapter 3.

The background of the time delay or dead time must be discussed prior to grasping the essence of the Smith Predictor and some other dead time compensation techniques. The following topics will intend to describe the difficulties of classical PID when controlling the dominant dead time process.

2.2 Effect of Time Delay (or dead time)

Time delays in the process industries are common and their presence complicates the implementation of process control techniques, exhibit input-output delays as shown in figure 2.1 and figure 2.2. The process output variable, $y(t)$, is just delayed by a dead time (D) while the process gain (G_p) and time constant (Tau) remain unchanged.

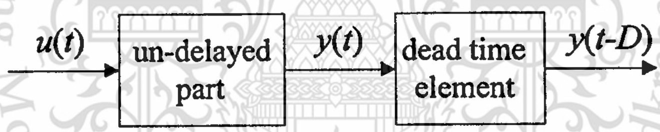


Fig. 2.1 Effect of dead time element

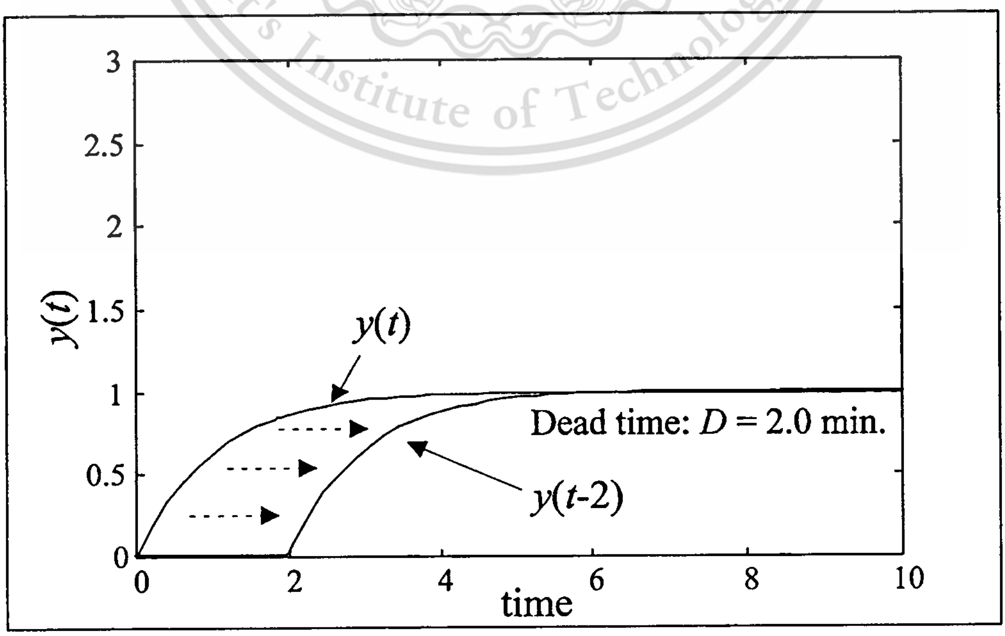


Fig. 2.2 Input-Output Delays

The reason for the prevalence of time delays is due to the nature of the process industries. That is, the effect of a change in the manipulated variable is not felt on the process until the dead time has elapsed. Transportation of fluids over long distances (or sometimes as the result of the processes with dynamics composed of multiple chain lags as shown in Fig. 2.4) is considered to be the most common cause of time delays. In addition, some measuring devices require long cycle times for sampling and analysis of process streams. A Product Quality Analyzer is a typical example of such a device. Time delays are sometimes introduced by final control elements that require some time to develop the actuating signal or by the controller's scanning time itself [6].

The net effect of time delays is the degradation of closed-loop response if a conventional PID feedback controller is used. This is due to disturbances going undetected for a significant period of time, control action being taken on a particular measurement, and control action not affecting the process output until some time in the future. The difficulties of controlling process with significant dead time are well known and are due to the fact that a stability margin of the closed-loop system is reduced (i.e., the crossover frequency and ultimate gain decrease) and a dead time also produces a phase lag that deteriorates the phase margin. Therefore, to maintain the stability of the closed-loop system, the gain of the controller must be reduced (which has to be added to the dead time of the process) in order to avoid high oscillations. This leads to have a sluggish closed-loop response [7].

2.2.1 Combination of Dead Time [10]

Figure 2.3 shows a block diagram of a cascade of dead time lags together with the signals resulting from an input step through a first order process.

The effect of the system is simply that one dead time lag with a magnitude equal to the sum of the values of the individual lags.

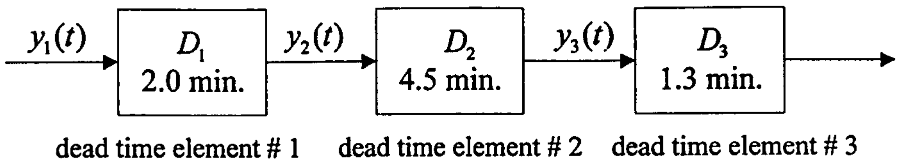
2.2.2 Combination of Exponential Lags (or time constant, *Tau*) [10]

Figure 2.4 shows a block diagram of a cascade of exponential lags together with the signals resulting from an input step.

The effect of this system is somewhat more difficult to ascertain than in the case of a cascade of dead time lags. This is due to the fact that process time constant chains increase the order of the system.

Figure 2.5 shows the step responses of equal exponential lags in cascade. The sum of the magnitudes of the lags is the same in all cases which means that the larger the number of elements the smaller each lag because some of them become a dead time.

The responses consist of an initial "dead" part, followed by an *S*-shaped part going towards the final value. The larger the number of lags, the predominant is the "dead part and the steeper is the *S*-shaped part. The limit case is a cascade of an infinite number of infinitely small exponential lags, which responds like a pure distance-velocity lag (i.e. dead time or delay time). In fact, a process pipeline can be considered to be such a system.



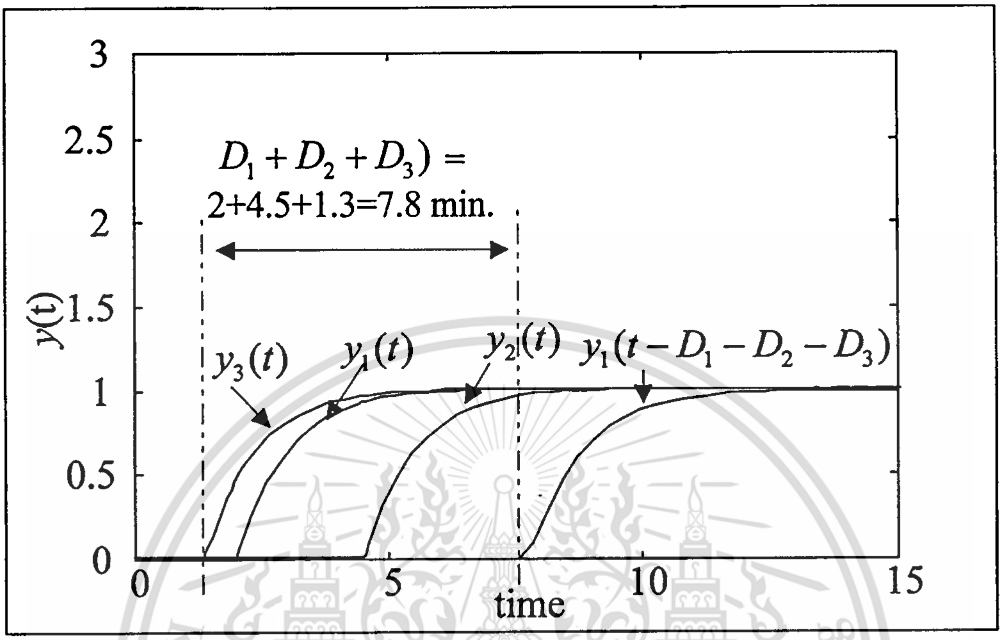


Fig. 2.3 Cascade of dead time lags

Even if the number of exponential in a cascade is finite and the lags have different magnitudes, an approximation to a dead time lag equals to the sum of the component exponential lags can still be used for a simplified process description. The only requirement is that the lags are of the same order of magnitude. This is valid when no one has a magnitude, which is larger than the sum of the others. If this is not the case, however, there will be one dominant lag, which has to be taken into separate account as a real exponential lag. The remaining exponential lags can then be approximated to a dead time lag with a magnitude equal to the sum of their magnitudes. In this case the approximated system becomes a cascade of one dead time lag and one exponential lag [8,10,13].

Consequently, in order to describe a cascade of exponential lags, one should first examine whether there is a dominant lag in the cascade. If this is the case the cascade can be approximated to one dead time lag and one exponential lag. If there is no dominant lag in the cascade, then approximated to one dead time lag can be made.

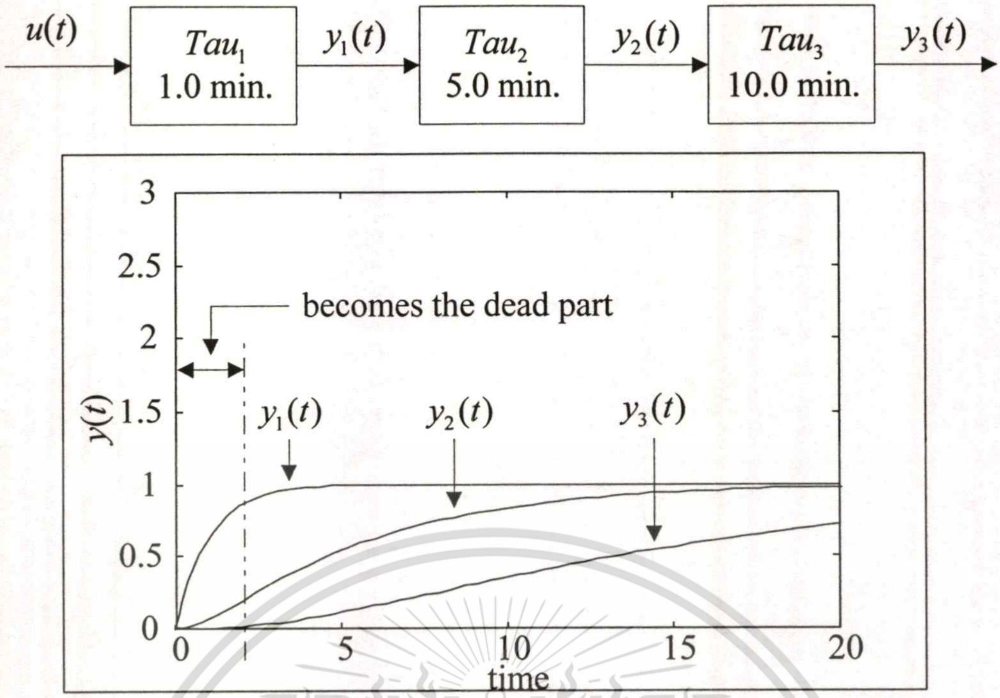


Fig. 2.4 Cascade of exponential lags

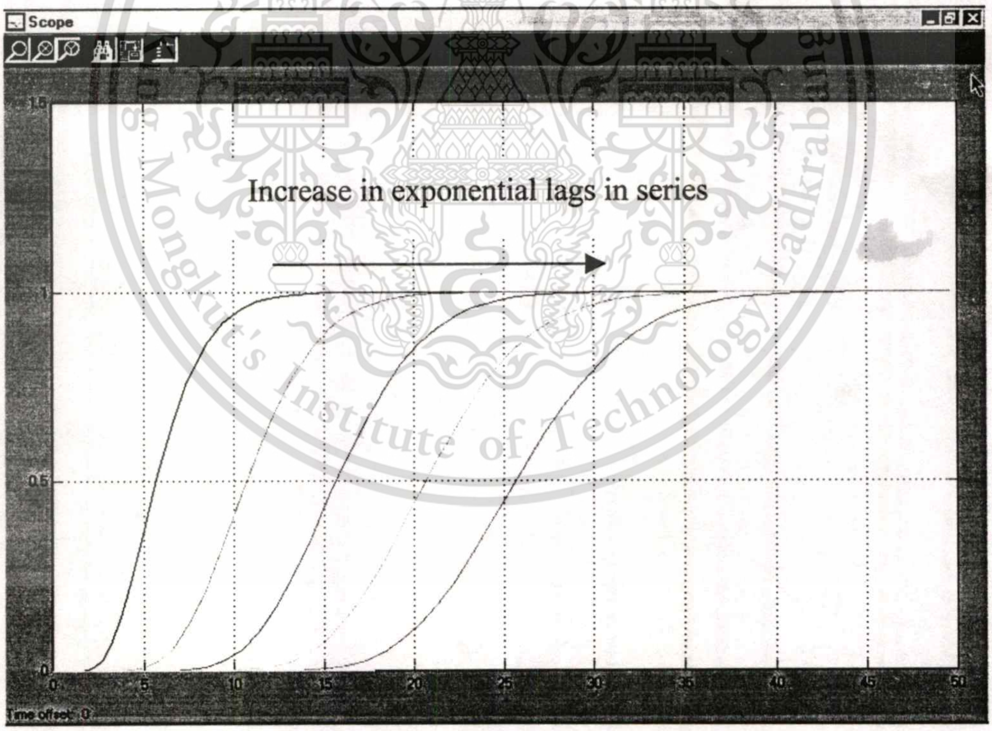


Fig. 2.5 Step response of exponential lags in series

As an example, refer to figure 2.4, if *Tau1, Tau2* and *Tau3* are 4 min., 2 min. and 6 min. respectively. *Tau3* is dominant and should be taken into separate account. The system can then be approximated to a dead time of 6 min. and a time constant of 6 min. in cascade. This is indicated in figure 2.6 and done by curve fitting tools so-called PCTP (Process Control Tools Package) from Shell Oil Company.

A 3^{rd} order process response generated from Control Station package to emulate the 3^{rd} order plant and use curve fitting package to estimate it to conventional 1^{st} order plus dead time process. It can be seen that the small time constants (*Tau1* and *Tau2*) can approximate to a dead part of the process and the largest time constant (*Tau3*) acts as an estimated process time constant.

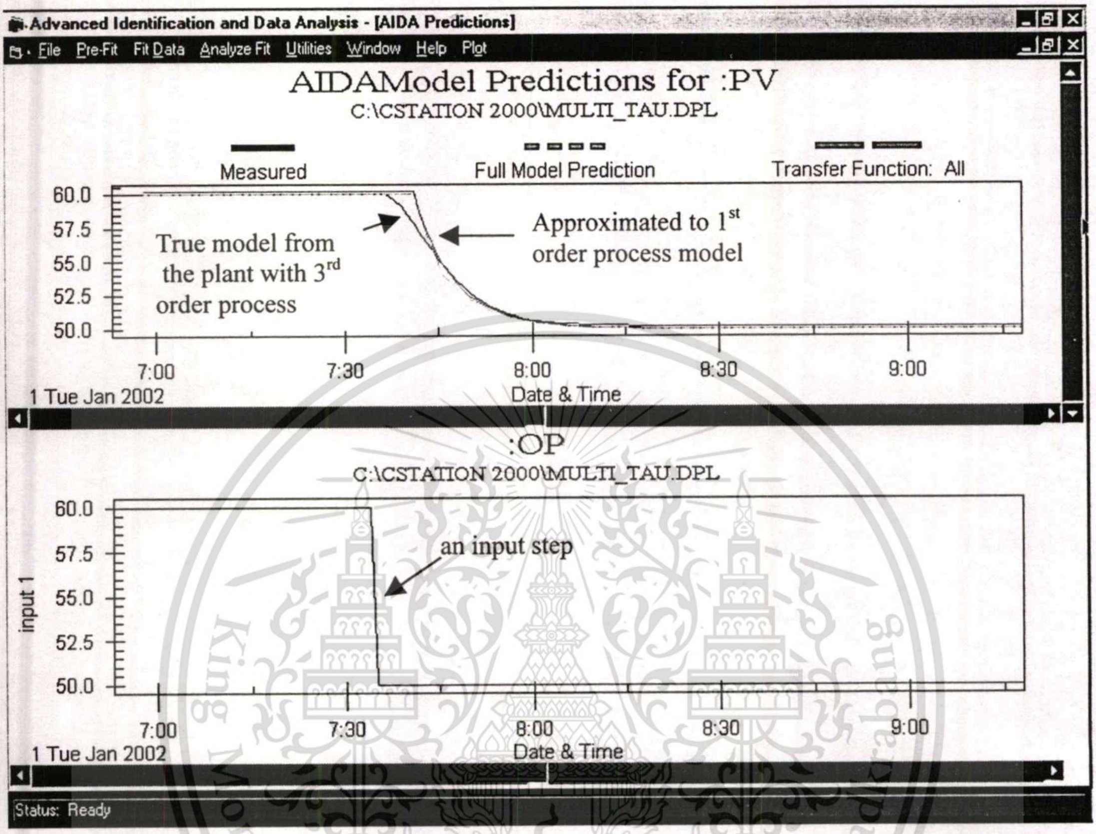


Fig. 2.6 Cascade of exponential lags (*Tau1, Tau2* and *Tau3*) with dominant lag (*Tau3*)

An example of a cascade of exponential lags is the propagation of liquid flow from tray to tray in a distillation column. Each tray behaves like an exponential lag, thus the response of the flow from the lowest tray to a change of the reflux can be represented approximately as a dead time lag [10,11,13].

2.3 Relation: Dead time, Ultimate Gain (K_{cu}) and Frequency

This section will describe the relation of the dead time to the ultimate gain and frequency. An increase in the dead time tends to reduce the ultimate loop gain very rapidly as depicted in figure 2.7. This effect is similar to the effect of increasing the dominant time constants of the loops in that it is relative to the magnitude of the time constant. The ultimate gain directly affects the controller gain. The ultimate gain decreases when dead time increases meaning that controller gain must be reduced to maintain the system stability.

An estimate of the ultimate gain (K_{cu}) and frequency of a loop with dead time may sometimes be obtained by using an approximation to the dead time transfer function. A popular approximation is the 1^{st} order Pade approximation, which is given by

$$e^{-Ds} = \frac{1-\frac{D}{2}s}{1+\frac{D}{2}s} \tag{2.1}$$

where D is the dead time.

2.3.1 An Analysis of the Impact of the Dead Time on Ultimate Gain and Frequency

This section will derive the relation of ultimate gain and frequency of a *1st* order plus dead time process. Let the process transfer function of the loop be

$$G_p(s) = \frac{K_p e^{-Ds}}{Tau(s+1)}$$

Assume a controller is a proportional controller: $G_c(s) = K_c$
The characteristic equation of the loop is

$$1 + G_c(s)G_p(s) = 0$$

and the transfer function will be as follow

$$1 + \frac{K_p K_c e^{-Ds}}{Tau(s+1)} = 0$$

Substitute the equation (2.1) and rearrange

$$\frac{D}{2}Tau\, s^2 + (Tau + \frac{D}{2} - K_p K_c \frac{D}{2})s + K_p K_c + 1 = 0$$

Substitute, $s = j\omega_u$ at $K_c = K_{cu}$, yields

$$\frac{D}{2}Tau(j\omega_u)^2 + (Tau + \frac{D}{2} - K_p K_{cu} \frac{D}{2})j\omega_u + K_p K_{cu} + 1 = 0$$

$$(-\frac{D}{2}Tau\, \omega_u{}^2 + K_p K_{cu} + 1) + j(Tau + \frac{D}{2} - K_p K_{cu} \frac{D}{2})\omega_u = 0$$

After setting the real part and imaginary parts equal to zero and solving the two equations simultaneously, we find that the solution is [11,13]

$$K_p K_{cu} = 1 + 2(\frac{Tau}{D})$$
$$\omega_u = \frac{2}{D}\sqrt{\frac{D}{Tau} + 1} \tag{2.2}$$

These formulas in equation (2.2) prove that the ultimate loop gain goes to infinity with no stability limit as the dead time approaches zero. However, any finite amount of dead time imposes a stability limit on the loop gain. The ultimate frequency increases with decreasing dead time and become very small as the dead time increases. This means that dead time slows the response of the loop. Both formulas are illustrated in figure 2.7.

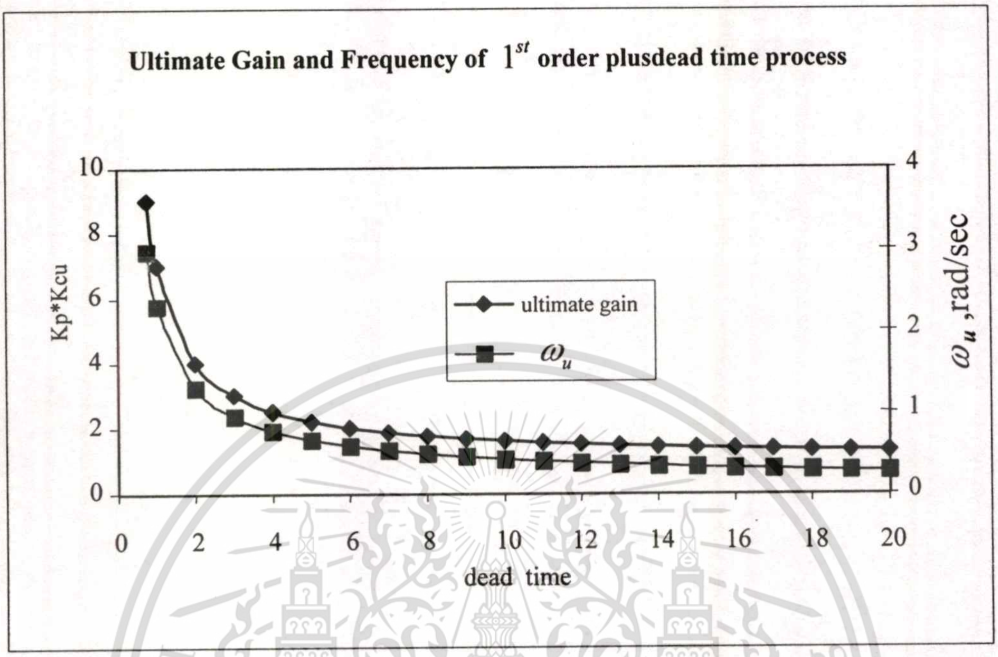


Fig. 2.7 Effect of the dead time to overall loop gain and frequency response

Figure 2.7 explains that the controller gain must be reduced due to the decrement of ultimate loop gain when dead time becomes larger. In conclusion, the smaller of controller gain causes by a significant process dead time will introduce a sluggish control loop response and deteriorates the control system performance significantly.

2.4 Principle of Smith Predictor

The Smith Predictor is model-based or a model predictive control approach. It was invented in order to speed up the control loop response in term of setpoint tracking and disturbance rejection particularly on the dominant dead time process. Also, a conventional PID controller gives unsatisfactory outcome for this kind of process as already proved in the previous section. The controller gain of a conventional PID controller is limited by the ultimate gain and will be more limited when the dead time become larger.

A conventional PI controller and some additional lead-lag blocks in DCS (Distributed Control System) are configured as shown in figure 2.8. The essence of model-based approach is to configure the process model running in parallel with the controller. This is to get the unnecessary dynamics (e.g. delay part) out of the closed loop by generating a prediction of the process output and designing a controller for the process minus the dead time. The error between process output and predictions is fed back to the controller to cope with plant and model mismatch [6]. But the original Smith Predictor is a prototype of the dead time compensation techniques so that it still lacks the capability to counter the practical model mismatch.

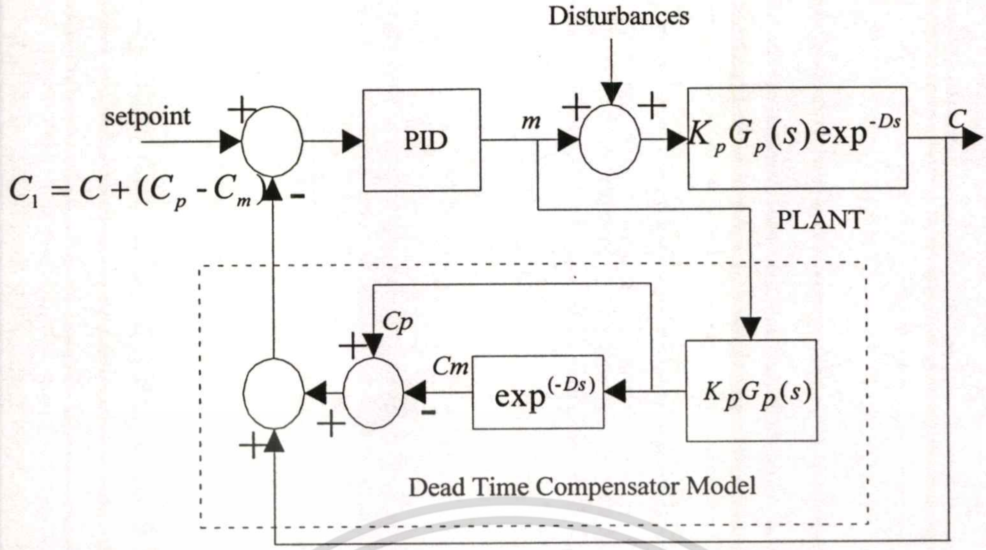


Fig. 2.8 Original Smith Predictor Scheme

2.4.1 Control Philosophy

Ideally, only the un-delayed part (C_p) of the process model will be an input of the controller in the absence of modeling error. The difference of the actual plant response, C, and the full model prediction output (i.e. process model), C_m, is also ideally zero ($C = C_m$). In other words, only C_p is the input to the controller so that the controller will be tuned to the process model (un-delayed part) not to the plant as if no dead time presented. This allows high controller gain because the controller itself sees no process dead time and ultimate gain is theoretically unlimited. Practically, all control systems will have at least one scanning time delay. Smith Predictor will give perfect outcome as long as the model is perfect [2,5,8,11,12].

2.4.2 Control Strategy of Smith Predictor

Figure 2.9 shown the response of conventional PID, which is optimally tuned to the *1st* order plus dead time process. The process equips with a process gain of 0.3, time constant of 3.0 minutes and dead time of 6.0 minutes [14]. The optimal PID controller tuning parameters ended up with a controller gain of 1.3, integral time of 3.5 and derivative time of 0.35. The ultimate gain is 6.67, which means the maximum controller gain should be lower than 6.67 but in the Matlab shown that the closed loop was started oscillating at the controller gain more than 6.0 onwards.

It was found that the conventional PID control was constrained by the ultimate gain, which is caused by the long process dead time while figure 2.10 shown the better result from Smith Predictor. The PID controller in Smith Predictor was not constrained by the ultimate gain because the dead time was removed and controller output, m, was well predicted by the perfect model and compensated signal, C_p-C_m (see figure 2.11).

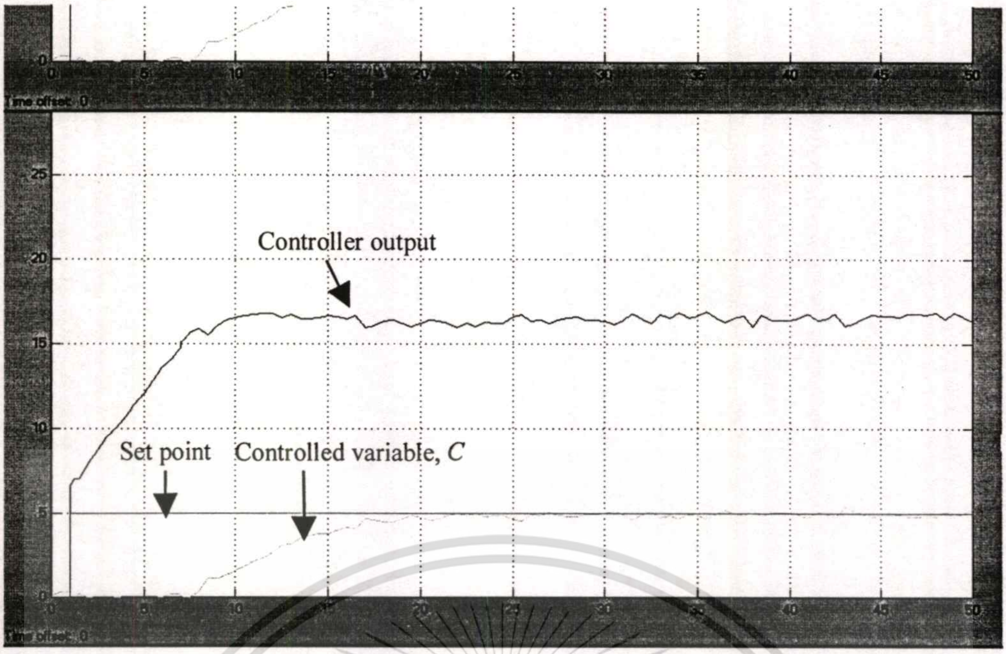


Fig. 2.9 Response from conventional PID to the dominant dead time process

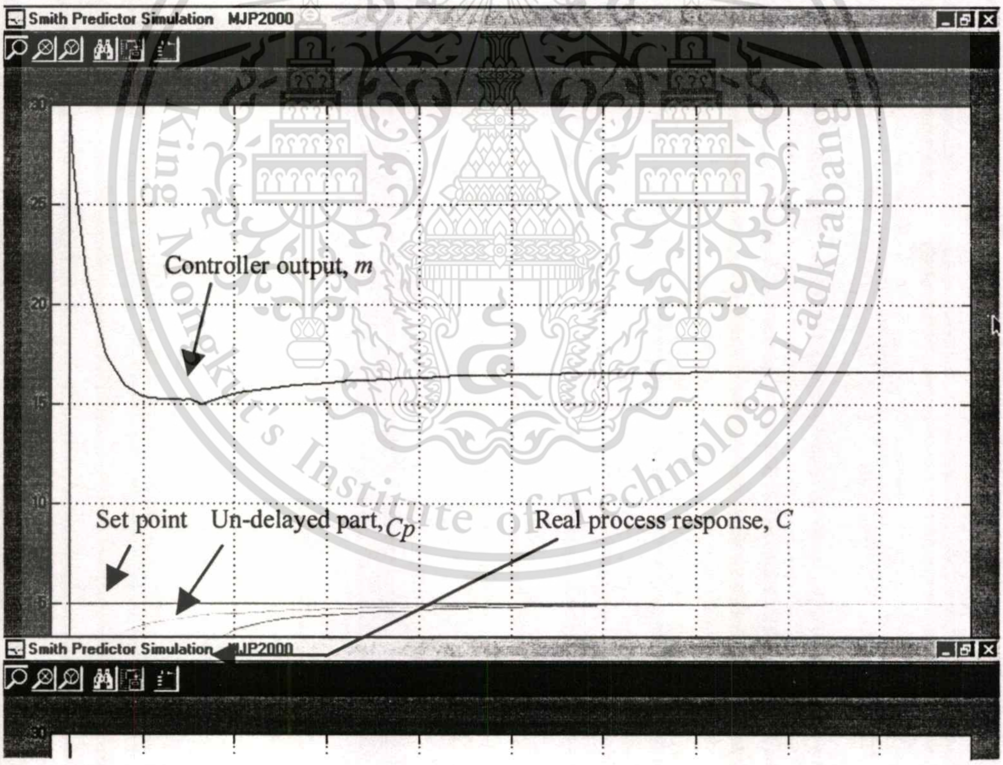


Fig. 2.10 Response from Smith Predictor in the absence of modeling error

The controlled variable in figure 2.10 was reached the setpoint much faster than the response of controlled variable shown in figure 2.9, which can be noticed from their controller outputs.

Figure 2.11 shown the compensated signal from the Smith Predictor, which is the difference of C_p and C_m. The compensated signal becomes zero by the time that the controller variable C reached its full response and the C_1 becomes equal to C as shown in figure 2.10 and 2.11 [3,11]. That is,

$$\begin{aligned} C_1(s) &= \overbrace{K_pG_p(s)e^{-Ds}m(s)}^{\text{Process}} + \overbrace{K_pG_p(s)(1-e^{-Ds})m(s)}^{\text{model}} \\ &= K_pG_p(s)m(s) \end{aligned} \tag{2.3}$$

The manipulated variable, $m(s)$, acts on the $K_pG_p(s)$ portion of the model and provides a low-order lag signal, which is added to the controlled variable signal (process part) and compared immediately with the setpoint. The closed loop control signal has no dead time. As the model $K_pG_p(s)$, C_m, output is acted upon by the dead time term. The compensated signal in figure 2.11 is added to the process output feedback signal, C_1, starts toward zero at the time when the dead time has elapsed.

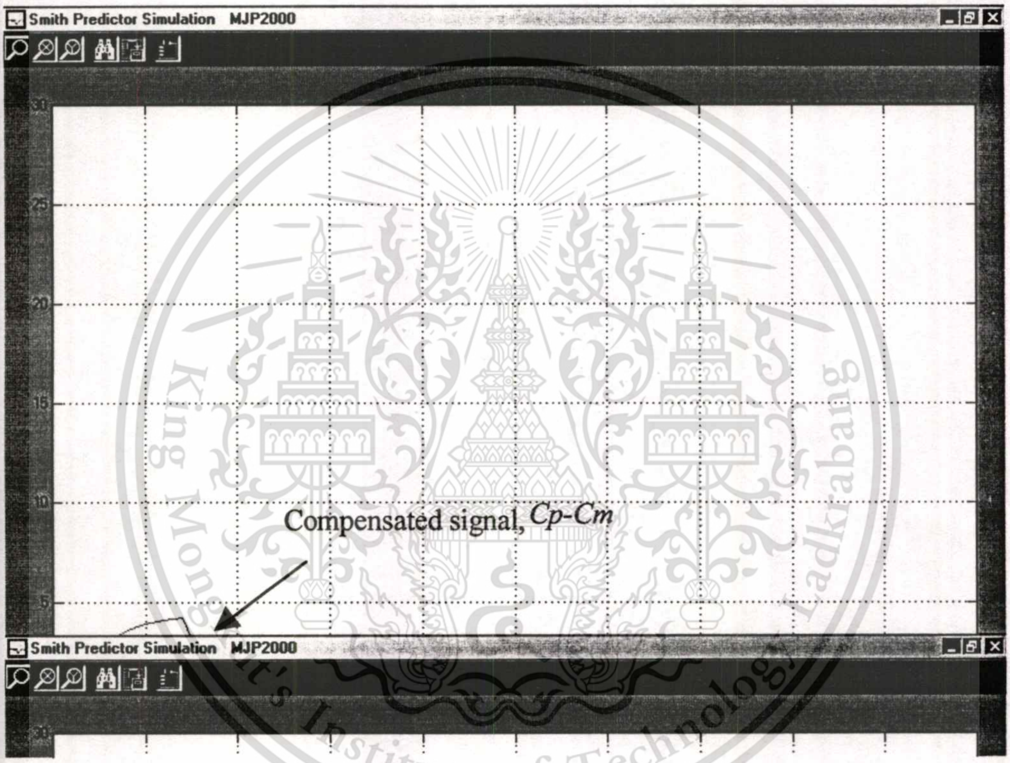


Fig. 2.11 Compensator Output from Smith Predictor

The equation (2.3) can be graphically shown in figure 2.12, which is an equivalent to the scheme shown in figure 2.8. The process part and the model part are the open loop response to a change in a manipulated variable $m(s)$ [3].

2.4.3 The Analysis of Time Delay Compensation Techniques in Smith Predictor

To implement time delay compensation, it should consider the control scheme in figure 2.12 to the new configuration of figure 2.13 where a minor feedback loop has been introduced around the conventional controller, as shown. The subscript *m* in figure 2.13 denotes a model, while un-subscripted elements are the real process.

Thus:

$$y_m(s) = G_m'(s)e^{-D_m s}m(s) \tag{2.4}$$

represents the model of the real process.

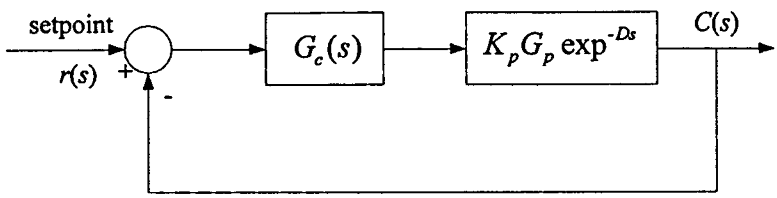


Fig. 2.12 Block diagram of a time delay system under conventional feedback control

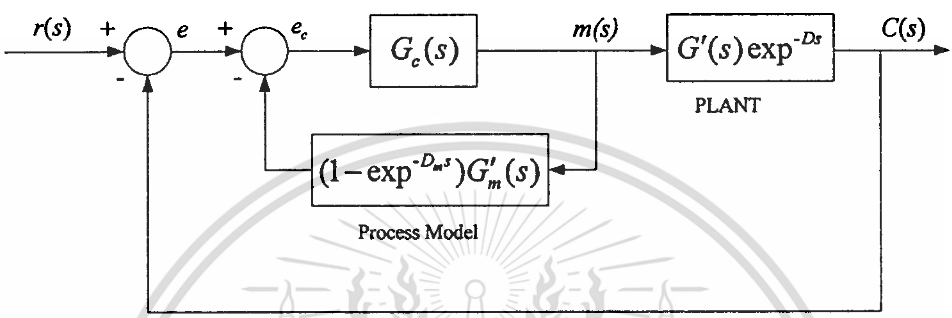


Fig. 2.13 Block diagram incorporating the Smith Predictor

Introduce new variables $C(s)$, $y_m(s)$ as follows:

$$\begin{aligned} C'(s) &= G'(s)m(s) \\ y_m'(s) &= G_m'(s)m(s) \end{aligned} \tag{2.5}$$

Since the actual process output C is given by:

$$C(s) = G'(s)e^{-Ds}m(s) \tag{2.6}$$

then $C'(s)$ is the output of the "un-delayed" version of the process output $C(s)$.

The analysis of the time delay compensator will now assume that are no model errors (so that $G_m(s) = G(s)$ and $D_m = D$). Observe that the signal reaching the controller, designated as e_c in the diagram, is a "corrected" error signal given by:

$$e_c = r(s) - C(s) - [C'(s) - C(s)] \tag{2.7}$$

or

$$e_c = r(s) - C'(s) \tag{2.8}$$

implying, as a result, that the block diagram of figure 2.13 is apparently equivalent to that shown in figure 2.14. If this is in the same manner, then the net result of the introduction of the minor loop is therefore to eliminate the time delay factor from the feedback loop where it causes stability problems and "move" it outsides of the loop, where it has no effect on closed loop system stability. The characteristic equation of the equivalent system in figure 2.14 is:

$$1 + G_c(s)G'(s) = 0 \tag{2.9}$$

which no longer contains the time delay element and therefore allows the use of higher controller gains without placing the closed loop stability in jeopardy.

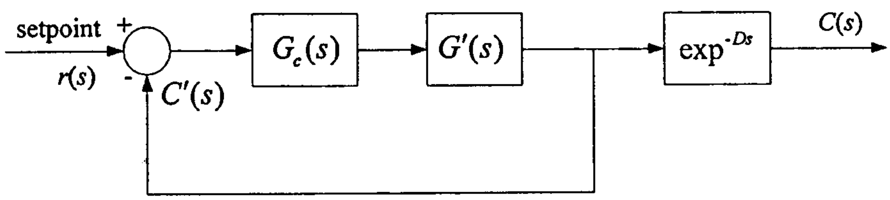


Fig. 2.14 Equivalent block diagram for system incorporating the Smith Predictor

It can be established directly from the block diagram in figure 2.13 that the closed loop characteristic equation is really as in equation (2.9). It is proposed to assume that there are no model errors, the minor loop can be consolidated around the controller to obtain the transfer function relationship between $e(s)$ and $m(s)$ as:

$$m(s) = G_c^{'}(s)e(s) \tag{2.10}$$

where,

$$G_c^{'}(s) = \frac{G_c(s)}{1 + G_c(s)G^{'}(s)(1 - e^{-Ds})} \tag{2.11}$$

The overall closed loop transfer function is now given by:

$$C(s) = [\frac{G^{'}(s)e^{-Ds}G_c^{'}(s)}{1 + G^{'}(s)e^{-Ds}G_c^{'}(s)}]r(s) \tag{2.12}$$

introduce equation (2.10) for $G_c^{'}(s)$, obtain: [7,8,11]

$$G'(s)e^{-Ds}G_c^{'}(s) = \frac{G^{'}(s)G_c(s)e^{-Ds}}{1 + G'(s)G_c(s) - G^{'}(s)G_c(s)e^{-Ds}} \tag{2.13}$$

so that:

$$1 + G'(s)e^{-Ds}G_c^{'}(s) = \frac{1 + G^{'}(s)G_c^{'}(s)}{1 + G'(s)G_c^{'}(s) - G^{'}(s)G_c^{'}(s)e^{-Ds}} \tag{2.14}$$

Simplifying the expression for the closed loop transfer function in equation (2.12) by combining equations (2.13) and (2.14) gives:

$$C(s) = [\frac{G'(s)G_c^{'}(s)}{1 + G'(s)G_c^{'}(s)}]e^{-Ds}r(s) \tag{2.15}$$

Establishing two things [11]:

1. The figure 2.12 block diagram is a real equivalent to that in figure 2.11, because equation (2.15) is the closed loop transfer function for the figure 2.12 system.
2. The characteristic equation for the system is as given in equation (2.9), by inspection of the denominator equation (2.15).

The specialized control scheme, which has just considered is known in general as time-delay compensation. The minor loop is therefore often referred to as a compensator.

The following points are of important for this time delay compensation scheme:

1. The effective action of the compensator is to feed the signal y_m' to the controller instead of the actual process output $C(s)$.
2. By the definition in equations (2.5) and (2.6), it can be observed that:

$$y_m'(s) = e^{-Ds}C(s)$$

so that:

$$y_m'(t) = C(t+D) \tag{2.16}$$

and it becomes perfectly clear that $y_m'(t)$ is a prediction of $C(t)$ exactly D time delay units ahead, hence the name "Smith Predictor" generally associated with the scheme. The most significant criticism of the Smith Predictor technique is its sensitivity to modeling errors.

3. The scheme will work perfectly as long as the process model is perfectly known; modeling errors will obviously affect its performance. The most significant criticism of the Smith Predictor technique is its sensitivity to modeling errors.
4. In those chemical processes for which the time delays are due to transport of material and/or energy through long pipes, the time delays observed for such processes will vary with the fluid flow rate; an increase in flow rate giving rise to lower time delays, and vice-versa. The Smith Predictor scheme is designed for constant time delays and may therefore not perform as well for systems with delays, which vary significantly over time.

2.4.4 Design Procedure [1]

The following is the design procedure for using Smith Predictor for time delay compensation:

1. Design the Smith Predictor (the minor loop)

With reference to the implication of the minor loop is to cause the controller to utilize a "corrected error" signal e_c instead of the actual error e; i.e., the control law is:

$$m(s) = G_c(s)e_c \tag{2.17}$$

where,

$$e_c = e - [y_m'(s) - C(s)] \tag{2.18}$$

The design of the minor loop involves setting up a means by which $y_m'(s)$ and $C(s)$ are produced from the process model, typically by simulation, using a digital computer; $C(s)$ is obtained directly from the process model, and $y_m'(s)$ is obtained from the un-delayed part of the process model.

2. Design $G_c(s)$

Since, according to the Smith Predictor scheme, the controller "thinks" it is controlling the process $G'(s)$ for which there is no time delay (see figure 2.12), the controller is designed by this basis, using any of the previously discussed technique; i.e., design $G_c(s)$ for the un-delayed part only. Observe that the absence of the time delay from the apparent process permits the use much higher controller gain than would otherwise be allowable. However, since, for perfect time delay compensation, the Smith Predictor requires a perfect model, and real models are never perfect, it must be cautions in choosing the controller parameter for $G_c(s)$. In practice, one would choose controller parameters large enough to achieve much better performance than using than a feedback control alone, but not so large as to cause serious deterioration in performance resulting from inevitable plant/model mismatch.

2.5 The Direct Synthesis Controller in the Smith Predictor form [1,9]

This section will describe together with the reference to the topic in chapter 3 because it is related to the model-based approach.

To implement the controller as given in equation (3.52), the control action $m(s)$ will be determined using $m(s) = G_c(s)e(s)$:

$$m(s) = (\frac{Tau \cdot s + 1}{K_p})(\frac{1}{Tau_r \cdot s + 1 - e^{-Ds}})e(s) \tag{2.19}$$

rearrange,

$$K_p(Tau_r \cdot s + 1 - e^{-Ds})m(s) = (Tau \pm \cdot s + 1)e(s)$$

or

$$\frac{K_p Tau_r \cdot s}{Tau \cdot s + 1} m(s) + \frac{K_p}{Tau \cdot s + 1} m(s) = (\frac{K_p e^{-Ds}}{Tau \cdot s + 1}) m(s) + e(s) \tag{2.20}$$

As discussed in section 2.4.4 that the *1st* order process with time delay can be described as:

$$C(s) = [\frac{K_p e^{-Ds}}{Tau \cdot s + 1}] m(s) \tag{2.21}$$

The output of the equivalent system without the delay can also be described as:

$$y_m'(s) = [\frac{K_p}{Tau \cdot s + 1}] m(s)$$

This is being the case when the desired reference trajectory of the closed loop response, Tau_r, is defined as shown in equation (3.46). Equation (2.20) then becomes:

$$[\frac{K_p Tau_r \cdot s}{Tau \cdot s+1}]m(s)+y_m'(s)=C(s)+e(s)$$

so that $m(s)$ is now given by:

$$m(s)=(\frac{Tau \cdot s+1}{K_p Tau_r \cdot s})\{e(s)-[y_m'(s)-C(s)]\}$$

or, finally:

$$m(s)=\frac{Tau}{K_p Tau_r}(1+\frac{1}{Tau \cdot s})\{e(s)-[y_m'-C(s)]\} \qquad (2.22)$$

Observe that this is a PI controller operating on a signal composed of $e(s)$, the regular feedback error signal, augmented by the signal $y_m'(s)-C(s)$, recognizable as the signal from the minor loop of the Smith Predictor strategy (see figures 2.8 and 2.13). With the direct synthesis controller however, the parameters required for the PI controller are provided. By contrast with the Smith Predictor strategy as presented in section 2.4.4, neither the controller type nor the controller parameters are specified; the main "conventional" controller must be designed separately. Thus the direct synthesis approach has some advantages.

2.6 Summary

The effect of dead time to a conventional feedback control system is obvious in term of degrading the control performance. The controller gain applied to the dominant dead time process is limited by the ultimate gain. The ultimate gain is decreased significantly when the process dead time is increasing. Chapter 2 explained thoroughly that a conventional PID controller would give a poor performance and not recommended. The Smith Predictor is more attractive than conventional PID because it is a prototype of model-based control. High controller gain is allowed in Smith Predictor because the effect of dead time to the closed loop control is removed.

The direct synthesis controller in the Smith Predictor yielded the PI controller is best suited. But several practitioners realized the modeling error effect that the error signal, e_c, to the controller may contain the dead time so that PID is frequently applied (see figure 2.8).

The modeling error is harmful to the control system using Smith Predictor because the very high control gain is allowed and, however, this effect will be discussed again in the next two chapters.

Many process industries apply Smith Predictor concept in the real world as described in Appendix A and at the end of chapter 4. Thaioil Refinery uses it for controlling the fuel gas distribution control system in order to over come the long dead time 6 minutes from LPG vaporizer to the fuel gas header [14]. In Shell Bukom Singapore, Smith Predictor is implemented to overcome the non-linearity of the system during reducing the DIPA and Gas flow ratio in ADIP Absorber plant [15].

But various practitioners still spend their time for re-parameterization during the model is mismatch such as fine-tuning or perform the process identification from time to time.

Chapter 4 will propose the methodology to give more flexibility to Smith Predictor during encountering the model mismatch. That is an essence of this thesis so-called "Robust Smith Predictor". Before going to chapter 4, it is very important to understand the concept of Model-based control, which will present in chapter 3.

CHAPTER 3

MODEL-BASED CONTROL FOR PROCESSES WITH DIFFICULT DYNAMICS

3.1 Overview

This chapter presents the special control system design based on model-based control approach for countering the processes that equip with dynamic constraints. The control problems created by these processes can be quite difficult. As a result, control design strategies that will produce effective controllers for such processes must necessarily take into consideration the unusual open loop dynamic behavior they exhibit. This chapter is thus concerned with controller design for processes having these difficult types of dynamics: time delays, inverse response, and open loop instability. The dominant dead time process (only presents in model based control part), the inverse response process and open loop instability process will be discussed in this chapter.

3.2 Difficult Process Dynamics [1]

These types of process require special attention because PID alone again cannot give satisfactory performance and robustness. Therefore, special tuning techniques generated by direct synthesis method and model-based approach are another way out of these process control problems.

For such a system, if the input variable was, for example, increased from an initial steady state value of m_1 to a new value of $m_1+\Delta m$,; the dynamic behavior is considered normal if the output variable responds qualitatively as one of the responses depicted in figures 3.1 (a) and (b); i.e., the output satisfies the following conditions:

1. It begins to respond quickly without significant delay.
2. It heads directly for a new steady state value without first taking an excursion in the opposite direction.
3. It finally settles to a new steady stage value.

The three control system structures discussed above are paradoxes of the dominant dead time process, inverse response process, and open loop instability respectively. They are the processes with normal dynamics and PID with classical feedback control can be well applied. By contrast to the three normal dynamic processes, conventional control systems are generally not applied. Therefore, it is proposed to analyze the key features of these difficult processes and provide new control system designs for improved closed loop performance of these processes.

3.2.1 Characteristics of Difficult Process Dynamics

The presence of any of these difficult characteristics in the dynamic behavior of a process will be identified in the process model as indicated below:

- Time delay	transfer function has the e^{-Ds} term
- Inverse response	transfer function has a RHP zero
- Open loop instability	transfer function has a RHP pole

Processes that exhibit "normal" behavior do not have any of these terms in their transfer function models. Time delay system was already discussed in chapter 2 and the following will describe only the rest of these three processes with difficult dynamics.

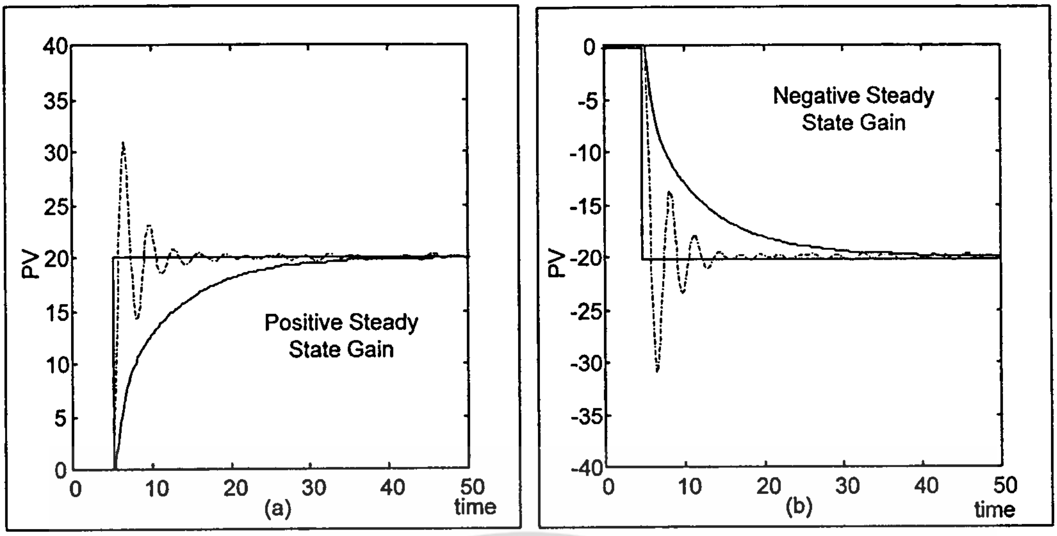


Fig. 3.1 Step response for process with "normal" open loop dynamics

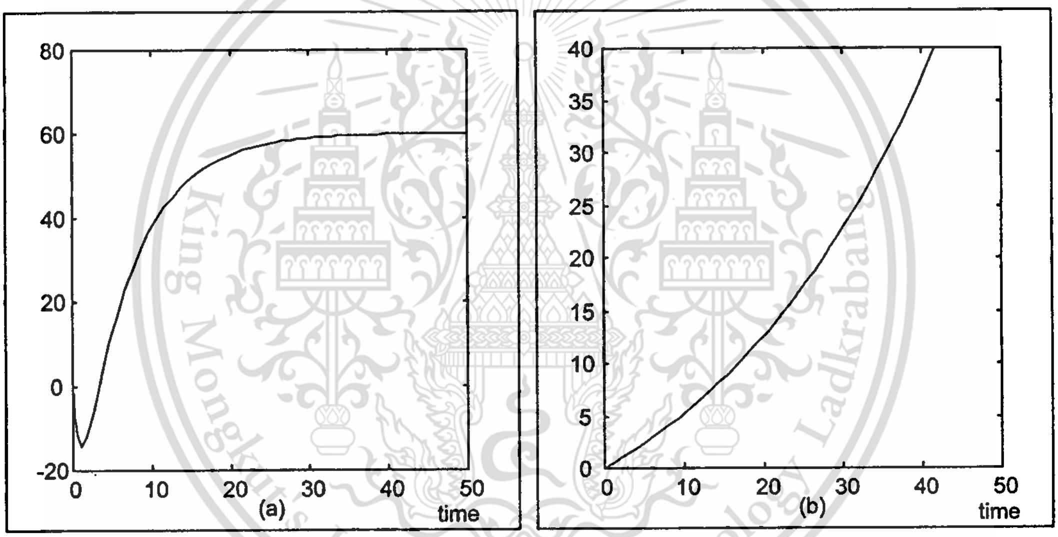


Fig. 3.2 Step responses for processes with difficult dynamics: (a) inverse response, (b) open loop unstable

3.2.2 Non-Minimum Phase (NMP) Systems

Processes with time delays and inverse response are sometimes collectively referred to as non-minimum phase (NMP) systems. The following will explain the meaning of this terminology.

A process with a general "normal" transfer function $g_1(s)$ has identical amplitude ratio (AR) characteristics as the process whose transfer function is $g_2(s) = g_1(s)e^{-Ds}$, but the phase angle characteristics are very different. If $g_1(s)$ has n poles and m zeros, its phase angle $\Phi_1(s)$, approaches $(n-m)(-90^\circ)$ asymptotically at high frequencies. The phase angle of $g_s(s)$, on the other hand, is given by:

$$\Phi_2(s) = \Phi_1(s) - D\omega \tag{3.1}$$

and decreases monotonically due to the influence of the delay term.

Hence, all possible transfer functions that show identical AR characteristics, the one possessing a time delay cannot be the one having the minimum possible phase characteristics.

In a similar way, the two processes having transfer functions:

$$g_1(s) = g^{\circ}(s)(1 + n \cdot s) \quad (3.2)$$

and

$$g_2(s) = g^{\circ}(s)(1 - n \cdot s) \quad (3.3)$$

show identical AR characteristics but the asymptotic limit of the phase angle for $g_2(s)$ is -180° in excess of the corresponding value for $g_1(s)$. Therefore, the process $g_2(s)$ does not have the smallest possible phase characteristics of all processes with which it shares identical AR characteristics. It is in this sense that such systems are referred to as non-minimum phase systems.

It has been customary to reserve the term non-minimum phase for time delay and inverse response systems only. What is not widely acknowledged, however, is the fact that open loop unstable systems also exhibit non-minimum phase characteristics [1,11].

Observe, for example, that the 1^{st} order process:

$$g_1(s) = \frac{K_p}{Tau \cdot s + 1} \quad (3.4)$$

has identical AR behavior as the open loop unstable process:

$$g_2(s) = \frac{K_p}{Tau \cdot s - 1} \quad (3.5)$$

(although the AR is meaningless since the unstable process does not have finite output amplitude); however, it can be shown that:

$$\Phi_2 = -180^{\circ} + \Phi_1 \quad (3.6)$$

so that the open loop unstable process is also non-minimum phase.

The presence of NMP elements in a process system's transfer function is thus identified as being responsible for its "difficult" dynamics behavior; it is also the source of a considerable amount of difficulty in control system design.

With reference to the process background as mentioned above, it is time to consider in more detail the special control problems presented by these systems, and the controller design techniques available for handling them.

3.3 Inverse Response Systems

3.3.1 Control Problems

The major problem created by the inverse response system is the confusing scenario it presents to the automatic controller: observe that having taken the proper action that will eventually yield the desired result, the controller is first given the impression that it, in fact, took the wrong action. The "uninformed" controller, in reacting to this illogical state of affairs, is liable to compound the problem further. It is therefore not difficult to see that such a system's closed loop stability stands in real jeopardy [1,11].

3.3.2 Conventional Feedback Controller Design

Because the derivative mode of the PID controller endows it with "anticipatory" character, the controller, of all the conventional controllers, is able to cope somewhat with controlling the inverse response system; it does this by anticipating the "wrong way behavior" and appropriately accommodating it.

It is not difficult to visualize how the PID controller achieves this: at the initial stage of the process response, rather than the error reducing in response to the correct controller action, it actually increases because of its inversion. However, the derivative of the error is also positive during this period, and when this information is incorporated into the controller equation (in this case for the PID controller), the result is a further increase in the magnitude of the control action.

On the other hand, immediately after the inversion is over, and the response begins heading in the right direction, the derivative of the error is negative and usually quite large, translating into a net decrease in control action.

Hence, at the initial stage, when the initial, temporary increase in the error would cause other conventional controllers to increase the control action slowly, the PID controller with its access to the derivative of the error, actually accelerates the applied control action. When the initial period of inversion is over, and it is now advantageous to reduce the magnitude of control action in order not to overshoot the objective, the PID controller is again able to do precisely this, because of the negative derivative of the error in this region [1].

3.3.3 Inverse Response Compensation

Iinoya and Altpeter [1] have extended the same principles behind the time delay compensation techniques discussed in chapter 2 to inverse response systems.

Consider the block diagram shown in figure 3.3 for the conventional feedback control of an inverse response system with transfer function representation $g(s) = g^{\circ}(s)(1 - n \cdot s)$; where $g^{\circ}(s)$ represents the portion of the transfer function left after factoring out the problematic RHP zero element [11].

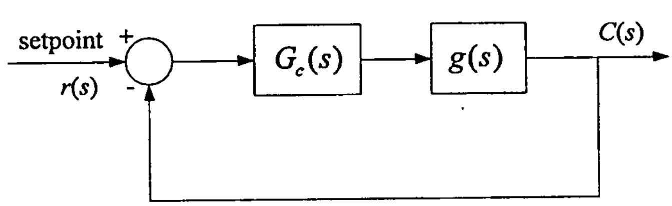


Fig. 3.3 Conventional feedback control of an inverse response system

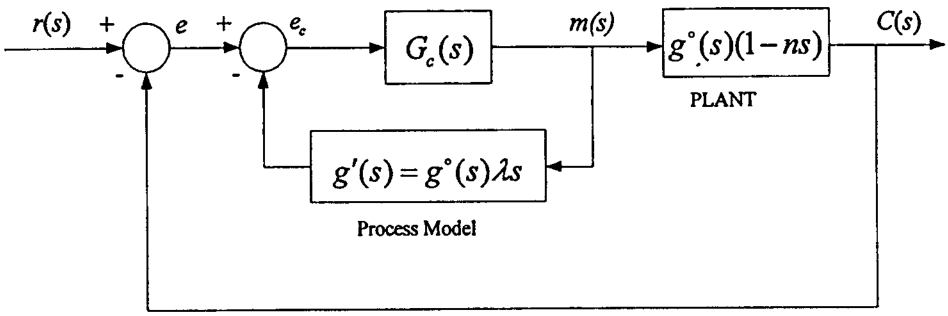


Fig. 3.4 Block diagram incorporating the inverse response compensator

Now consider the situation in figure 3.4 in which a minor loop is introduced as shown, with the transfer function $g'(s)$ given by:

$$g'(s) = g^{\circ}(s)\lambda \cdot s \tag{3.7}$$

The objective here is to choose the quantity λ such that the signal reaching the controller appears to be form a "normal" system; in the context, one which does not exhibit inverse response.

The variable $y_m'(s)$ is defined according to:

$$y_m'(s) = g'(s)m(s) \tag{3.8}$$

and observe that this is the signal generated by the minor loop. As a result of this minor loop, the signal reaching the controller, designated as e_c in the diagram, is given by:

$$e_c = r(s) - C(s) - y_m'(s) \tag{3.9a}$$

or

$$e_c = r(s) - [g(s) + g'(s)]m(s) \tag{3.9b}$$

Let,

$$g^{*}(s) = g(s) + g'(s) \tag{3.10}$$

and

$$y^{*}(s) = g^{*}(s)u(s) \tag{3.11}$$

then equation (3.9b) becomes:

$$e_c = r(s) - y^{*} \tag{3.12}$$

As a result of equation (3.12), observe that it now has a situation in which, as far as the controller, $g_c(s)$, is concerned, it thinks it is interfaced with the apparent process that generates the signal y^{*}, and whose transfer function, $g^{*}(s)$, is as given in equation (3.10).

Introducing the expression for g and g' into equation (3.10), obtain:

$$g^{*}(s) = g^{\circ}(s)(1 - n\cdot s) + g^{\circ}(s)\lambda \cdot s \qquad (3.13)$$

or

$$g^{*}(s) = g^{\circ}(s)[1 + (\lambda - n)s] \qquad (3.14)$$

Observe that if choose λ such that:

$$\lambda \geq n \qquad (3.15)$$

the transfer function of the apparent process generating y^{*} no longer contains a RHP zero. Hence, the minor loop provides a corrective signal that effectively eliminates the inverse response from the feedback loop. Owing to its similarity to the Smith Predictor, the inverse response compensator also suffers from the same sensitivity to the model inaccuracies.

There is some strategy in selecting the exact value of λ satisfying equation (3.15). Choosing $\lambda > n$ (as opposed to $\lambda = n$) has some advantage in case of plant model mismatch. However, one must be careful not to choose λ too large because then $g^{*}(s)$ will have a much faster response than $g^{\circ}(s)$ and the control loop will be sluggish. It can be shown that the choice:

$$\lambda = 2n \qquad (3.16)$$

is optimal, providing minimum mean square deviation of plant output from desired setpoint [1,11].

The following examples will demonstrate the design of the inverse response compensator and the influence on closed loop system stability.

Example 3.1 Design of an inverse response compensator

Given an inverse response system as follow:

$$g(s) = \frac{(1-3s)}{(2s+1)(5s+1)} \qquad (3.17)$$

Solution:

The design of the inverse response compensator boils down to obtaining the appropriate transfer function $g'(s)$ to use in the minor feedback loop in the block diagram shown in figure 3.4.

For the given process, $g^{\circ}(s)$ will be:

$$g^{\circ}(s) = \frac{1}{(2s+1)(5s+1)} \qquad (3.18)$$

and therefore:

$$g'(s) = \frac{\lambda \cdot s}{(2s+1)(5s+1)} \qquad (3.19)$$

For this system $n=3$; thus according to equation (3.16) a good value of λ to be used in equation (3.19) is $\lambda=6$ so that:

$$g'(s)=\frac{6s}{(2s+1)(5s+1)} \tag{3.20}$$

is the transfer function to use in the inverse response compensator loop.

Using this transfer function in the inverse response compensator loop produces the effect of interfacing the controller with the apparent process whose transfer function is given by:

$$g^*(s)=\frac{(3s+1)}{(2s+1)(5s+1)} \tag{3.21}$$

which does not have a RHP zero.

The influence that the inverse response compensator has on the closed loop system stability characteristics can be dramatic, as described in the following example.

Example 3.2 Closed loop stability of an inverse response system under conventional feedback control with and without the compensator

Investigate the closed loop stability properties of the inverse response system of equation (3.17) under proportional-only feedback control, first without any compensation, and then with the inverse response compensator designed in Example 3.1.

Solution:

Under conventional, proportional feedback control, the characteristic equation for the closed loop system is:

$$1+\frac{K_c(1-3s)}{(2s+1)(5s+1)}=0 \tag{3.22}$$

which rearranges to:

$$10s^2+(7-3K_c)s+(1+K_c)=0 \tag{3.23}$$

From here, it is observed that the condition for stability is:

$$K_c<7/3 \tag{3.24}$$

any value of K_c higher than this will make the system unstable.

With the inverse response compensator, it first obtained the overall closed loop transfer function from the block diagram of figure 3.4; it is then deduced the characteristic equation from here and uses it to investigate the stability properties.

Consolidating the block diagram, dealing first with the minor loop, gives:

$$m=g_c^*\cdot e \tag{3.25}$$

where

$$g_c^* = \frac{G_c}{1+G_c g'} \tag{3.26}$$

The overall closed loop transfer function is now given by:

$$C = \left(\frac{g \cdot g_c^*}{1+g \cdot g_c^*}\right) r \tag{3.27}$$

and the characteristic equation is:

$$1 + g \cdot g_c^* = 0 \tag{3.28}$$

Upon introducing into equation (3.28) all the appropriate expressions for the indicated transfer function elements, and rearranging, the characteristic equation becomes:

$$10s^2 + (7+3K_c)s + (1+K_c) = 0 \tag{3.29}$$

which is stable for all positive value of K_c; clearly denominating the restrictive effect of the RHP zero on closed loop system stability and the advantages of using the inverse response compensator.

Figure 3.5 illustrated the performance of the inverse response compensation compared to conventional PID control. The inverse response compensator produces the smallest negative deviation and a rapid response without overshoot.

3.3.4 Design Procedure [1]

1. Design the inverse response compensator loop

As demonstrated in Example 3.1, this simply involves obtaining the appropriate transfer function $g'(s)$ to use in the minor feedback loop in the block diagram shown in figure 3.4; it specifically entails finding λ, which satisfies the conditions in equation (3.16) and using this in the expression for $g'(s)$ in equation (3.7).

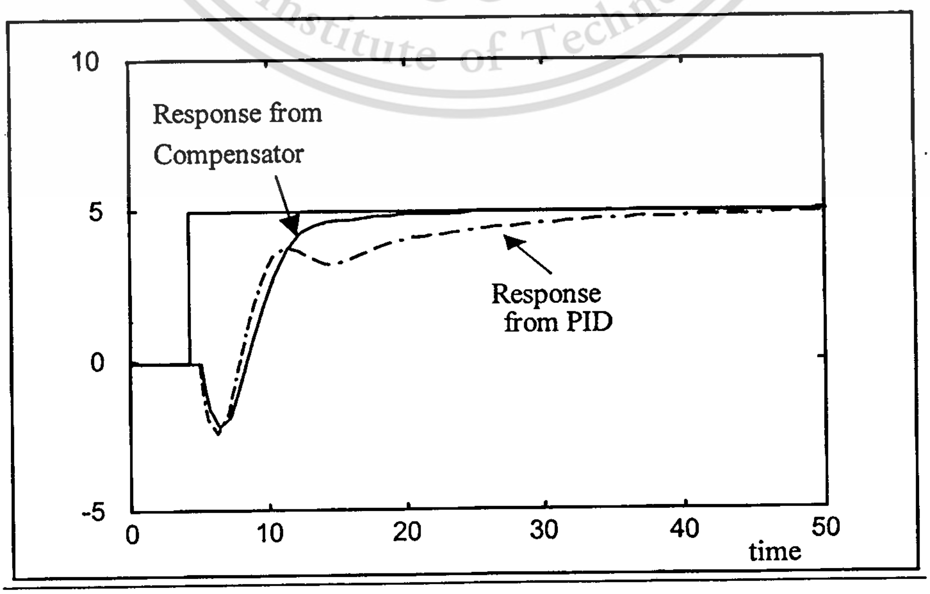


Fig. 3.5 Comparison of closed loop response of the inverse response system

2. Design G_c

Once the compensator has been designed, its effect is to make the controller "think" it is interfaced to the process $g^*(s)$, which has no RHP zero. Again, as with the time delay compensator, it simply designs the controller for $g^*(s)$; and the absence of the RHP zero permits the use of higher controller gains than would otherwise be possible. However, because of process/model mismatch, one must be careful not to increase the controller gain too aggressively.

3.4 Open Loop Unstable Systems [1,11]

The transfer function that describes the dynamic behavior of an open loop unstable has at least one RHP pole. The obvious problem with such a system is that, in its natural state, it is unstable, so that any upset in any direction will result in unstable response. This creates one of the most significant difficulties in control system design; i.e., one cannot use the standard process model identification procedures (such as step test), but must keep the process under control while carrying the model experiments. If one would like to obtain only the critical controller gains, it is recommended to use the "auto tuning relay controller" to determine the upper bound on controller gain and then decrease the gain in closed loop experiments until the lower bound is determined. Obtaining the explicit model can be done by identifying the model under feedback control with known controller parameters using a sequence of setpoint changes (i.e., step response) and disturbances. The open loop model can then be determined.

This difficult model identification problem is balanced by the fact that a process which is unstable in the open loop can usually be controlled quite well by conventional feedback control if the controllers are carefully chosen. The following examples are given to mathematically represent the explanation above.

Example 3.3 Stabilization of a *1st* order open loop unstable system by proportional feedback control

Obtain the range of K_c values required to ensure that the closed loop system involving the *1st* order system:

$$g(s) = \frac{K}{Tau \cdot s - 1} \tag{3.30}$$

and a proportional controller is stable.

Solution:

The characteristic equation for this closed loop system is:

$$1 + \frac{K \cdot K_c}{Tau \cdot s - 1} = 0 \tag{3.31}$$

which rearranges to give:

$$Tau \cdot s - 1 + K \cdot K_c = 0 \tag{3.32}$$

an equation with only one root located at:

$$s = \frac{1 - K \cdot K_c}{Tau} \tag{3.33}$$

Hence, observe that this root will be negative (and the closed loop system will be stable) as long as:

$$K_c > \frac{1}{K} \tag{3.34}$$

with the immediate implication that any K_c value which satisfies equation (3.34) will stabilize the otherwise open loop unstable system.

Beyond merely stabilizing the system, observe that one may go one step further and obtain the values of controller parameters that will not merely stabilizing the closed loop system, but which will place the closed loop system poles in pre-specified location in the LHP. The demonstration will be in the example 3.4.

Example 3.4 Stabilizing of an open loop unstable system by closed loop placement

Design a PI controller for the system of example 3.3 that will stabilize the closed loop system with the closed loop system poles located at s = -2, and at s = -4.

Solution:

The closed loop characteristic equation in this case becomes, upon some element rearrangement:

$$Tau \cdot Tau_1 \cdot s^2 + (K \cdot K_c - 1) \cdot Tau_1 \cdot s + K \cdot K_c = 0 \tag{3.35}$$

The rots of this quadratic are related to its coefficients by:

$$-(r_1 + r_2) = \frac{(K \cdot K_c - 1)}{Tau} \tag{3.36}$$

and

$$r_1 r_2 = \frac{K \cdot K_c}{Tau \cdot Tau_1} \tag{3.37}$$

Introducing the process parameters, K =2, Tau =5 and solving equations (3.36) and (3.37) simultaneously gives the required controller parameter values:

$$K_c = 15.5; Tau_1 = 0.775 \tag{3.38}$$

It should be mentioned that not all open loop unstable process can be stabilized by P control or PI control. To establish that, using P or PI controller, it is impossible to stabilize the process whose open loop transfer function is given as:

$$g(s) = \frac{2}{(2s-1)(5s+1)} \tag{3.39}$$

Here either a PD or a PID controller is required for stabilization. This illustrates the fact that open loop unstable systems can require special types of controllers to stabilize them.

Open loop unstable systems can also have conditioned closed loop stability, where there is only a range of controller gain, $K_{cl}<K_c<K_{cu}$, which stabilize the process. This occurs whenever there is an upper limit in controller gain (e.g., when the open loop phase angle is less than -180° for some frequency) combined with the lower threshold level of controller gain necessary for closed loop stability of the open loop unstable system. The below example will explain.

Example 3.5 Conditional closed loop stability of n open loop unstable system

Consider the open loop unstable process given by:

$$g(s)=\frac{2(-s+1)}{(4s-1)(2s+1)} \tag{3.40}$$

under proportional feedback control. Determine the range of controller gains for which the closed loop system is stable.

Solution:

The characteristic equation for the closed loop system is given by:

$$8s^2+2(1-K_c)s+(2K_c-1)=0 \tag{3.41}$$

and by inspection, the stable range of controller gain is $\frac{1}{2}<K_c<1$. Then the system exhibits conditional stability.

3.5 Model-Based Control

A feedback controller design has been approached from the classical viewpoint in which the controller structure choice is restricted to the PID form, and design guidelines are used merely to choose appropriate parameters for this pre-specified class of controllers.

There is an alternative approach in which is specified a priori is the dynamic behavior desired of the control system, not the controller structure; the design procedure is then invoked to derive the controller (the structure as well as the parameters) that will achieve the pre-specified desired objectives [9]. This completely different controller design paradigm involves the explicit use of a process model directly; it is therefore often referred to as model-based control.

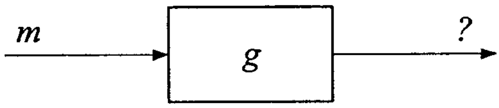
3.5.1 An introduction to Model-Based Control

- The three constituent elements of process analysis are the inputs to the process, the process model (as an abstraction of the process itself), and the outputs from the process. By specifying any two of these elements, and requiring that the unspecified third be determined from the supplied information. Three fundamental problems of systems analysis illustrated in figure 3.6:

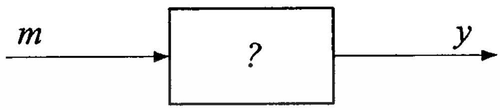
- The "Process Dynamics" problem: in which the input *m* is specified along with the model, say, in the form of a transfer function *g* and the resulting output is to be determined. It is the most straightforward problem. See figure 3.6 (a).

- The "Process Modeling/Identification" problem: in which the process input *u* and output *y* are provided, and it is required to determine the process model *g*. This is the most difficult problem. See figure 3.6 (b).

- The "Process Control" problem: in which the desired output y^* is specified along with the model g, and the input m required to produced such an output is to be determined. This is the major discussion in this chapter.



(a) The Process Dynamic Problem.



(b) The Process Modeling/Identification Problem.

(c) The Process Control Problem.

Fig. 3.6 The three fundamental problems of systems analysis

3.5.2 Model-Based Approaches

There are two approaches to model-based control system design [1]:

(1) The "Direct Synthesis: Approach: in which the desired output behavior is specified in the form of a trajectory, and the process model is used directly to synthesize the controller required to cause the process output to follow trajectory exactly. There are 3 particular techniques falling under this category:

- Direct Synthesis
- Internal Model Control
- Generic Model Control

But only Direct Synthesis method will be discussed in this section.

(2) The "Optimization" Approach: in which the desired output behavior is specified in the form of an objective function (which may or may not involve an output trajectory explicitly), and the process model is used to derived the controller required to minimize (or maximize) this objective. It is also possible to include some known operating constraints in the optimization objective. But this approach is out of scope in this thesis.

The model-based based control makes use of the process model explicitly in deriving the resulting controller; and without making the issue of the hardware required for implementation. This section will derive the controller parameters of inverse response process and open loop unstable (dominant dead time process already discussed in chapter 2).

3.5.2.1 The Controller Synthesis Problem [1,8,11,12,13]

Consider the block diagram of figure 3.7, where g represents the consolidated transfer function for the process model (including measurement device and final control element). In this case the closed loop transfer function is given by:

$$C(s) = \frac{g \cdot g_c}{1 + g \cdot g_c} r(s) \tag{3.42}$$

Suppose that the required closed loop behavior is:

$$C(s) = q(s)r(s) \tag{3.43}$$

where $q(s)$ is a specific, predetermined transfer function. The reference trajectory $q(s)$ depends on the type of closed loop response desired and on the possible response from the process. Some particular types of reference trajectory are shown in figure 3.8. Note that for systems with no time delay or inverse response, reference trajectories of type (a) or (b) would be appropriate. However, if the process has a significant time delay, then a reference trajectory of type (c) is required because no controller can overcome the initial delay in the closed loop response. Similarly, if the process has an inverse response, then the reference trajectory must allow inverse response.

Having defined an appropriate form for the reference trajectory, the controller synthesis problem is to obtain the form of controller g_c required to produce in the process the closed loop behavior represented by the reference trajectory $q(s)$. In other words, given q and g, find the g_c required to make the process closed loop transfer function exactly equal to q. Noting that the closed loop behavior (as represented in equation (3.42)) will be as expected it to be in equation (3.43) if, and only if:

$$q(s) = \frac{g \cdot g_c}{1 + g \cdot g_c} \tag{3.44}$$

then the controller synthesis problem reduces to solving equation (3.44) for g_c to yields:

$$g_c = \frac{1}{g}\left(\frac{q}{1-q}\right) \tag{3.45}$$

This is the controller synthesis formula from which, given the process model g, the required controller g_c can be derived to obtain any desired closed loop behavior represented by q.

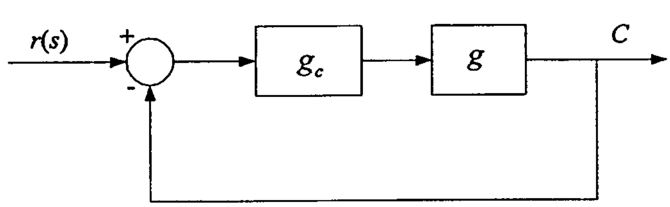


Fig. 3.7 Block diagram of a feedback control system

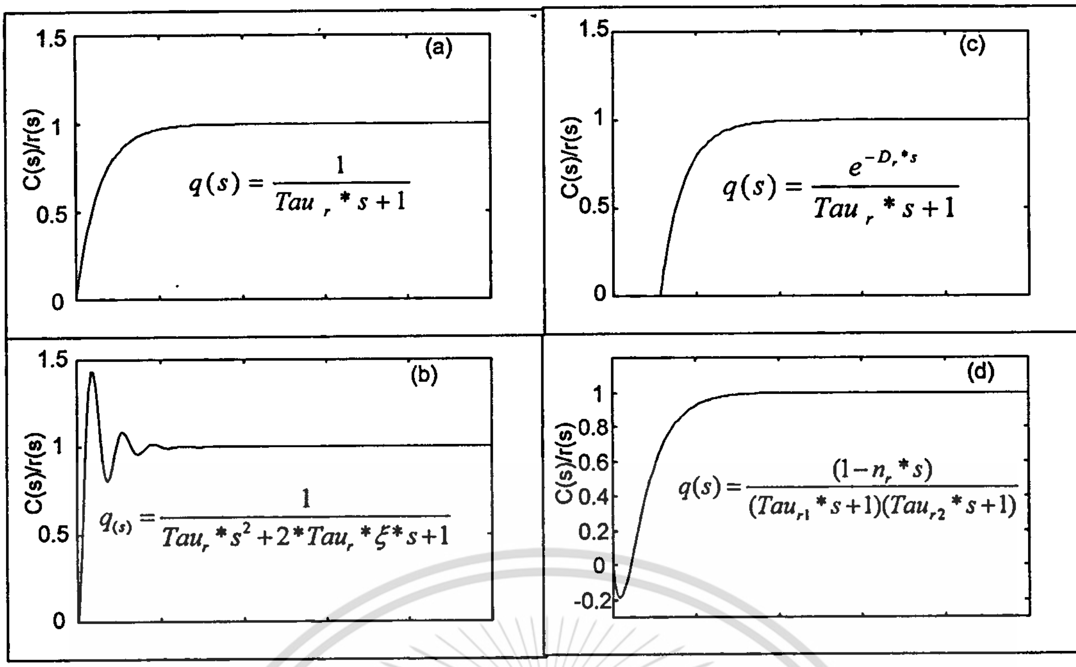


Fig. 3.8 Some possible reference trajectories for model-based control

Observe that there are no restrictions on the form this controller can take; for this reason, it is expected that there will be no guarantees that the controller will be able to implement in all cases. However, if q is chosen appropriately, the synthesized controller g_c will take on practical forms. In particular, the synthesized controller actually takes the familiar form of conventional PID controllers.

3.5.2.2 Specifying the Desired Closed Loop Behavior

The type of controller synthesized using equation (3.45) clearly depends on the nature of the transfer function form chosen q, the desired closed loop response. The guidance to the good value of q is summarized below [1]:

- No-steady offset,
- Quick, stable response, having little or no overshoot,
- A dynamic response which the process is capable of achieving, and
- A mathematical form which is as simple as possible.

Consider the 1^{st} order response, which is a simple form and adequate for many processes that leads to simple controller structures:

$$q(s) = \frac{1}{Tau_r\, s + 1} \tag{3.46}$$

For this choice of q, the controller synthesis formula (equation (3.45)) simplifies to:

$$g_c = \frac{1}{Tau_r\, s}\,\frac{1}{g} \tag{3.47}$$

It can be seen that the direct synthesis controller involves the inverse of the process model. This feature, common to all model-based controllers, will have significant implications for the issue of synthesis for non-minimum phase systems.

3.6 Synthesis for Processes with Difficult Dynamics [1,11]

The fact that the general controller synthesis formula in equation (3.45) involves the inverse of the process model. This should carefully consider in applying it for time delay as well as inverse response systems. The e^{-Ds} term in the time delay system's transfer function will become e^{+Ds} in the controller, thereby requiring prediction; and for the inverse response system, the relatively harmless right half plane zero translates to a right half plane pole for the controller, making it unstable. The primary reason for caution in applying equation (3.45) for open loop unstable systems is not as obvious, but it is equally critical, as it will soon show.

3.6.1 Synthesis for Time Delay Systems

Consider the time delay system below:

$$g(s) = \frac{Ke^{-Ds}}{Tau \cdot s + 1} \tag{3.48}$$

If the 1^{st} order reference trajectory given in equation (3.46) is still retained as the desired closed loop behavior, then the direct synthesis controller that will achieve this objective, as derived from equation (3.47), is:

$$g_c = \frac{(Tau \cdot s + 1)e^{+Ds}}{K \cdot Tau_r \cdot s} \tag{3.49}$$

which is unrealizable, since it requires a prediction. The problem of course is that the choice of reference trajectory in equation (3.46) fails to consider the most critical dynamic characteristic of time delay systems: their inherent inability to respond instantaneously. Therefore, one must choose a more realistic form of the reference trajectory:

$$q(s) = \frac{e^{-D_r s}}{Tau_r \cdot s + 1} \tag{3.50}$$

shown in figure 3.8. If the controller equation (q) in equation (3.50) is redefined in equation (3.45), obtain:

$$g_c = \frac{(Tau \cdot s + 1)}{K}\left[\frac{e^{-(D_r - D)s}}{(Tau_r \cdot s + 1) - e^{-D_r s}}\right] \tag{3.51}$$

which is realizable in practice so long as the delay in the reference trajectory is at least as long as the delay in the process, i.e., $D_r \geq D$. In case of $D_r = D$, the controller in equation (3.51) reduces to:

$$g_c = \frac{(Tau \cdot s + 1)}{K}\left(\frac{1}{Tau_r \cdot s + 1 - e^{-Ds}}\right) \tag{3.52}$$

which is identical to the Smith Predictor (Chapter 2), plus a PI controller.

3.6.2 Synthesis for Inverse Response Systems

Consider the inverse response system below:

$$g(s)=\frac{K(1-n\cdot s)}{(Tau_1\cdot s+1)(Tau_2\cdot s+1)} \tag{3.53}$$

The reference trajectory is proposed below:

$$q(s)=\frac{(1-n\cdot s)}{(Tau_{r1}\cdot s+1)}\frac{1}{(Tau_{r2}\cdot s+1)} \tag{3.54}$$

which is show shown in figure 3.8 (d) and recognizes the inevitability of inverse response behavior in the closed loop response. A good response for an inverse response system can be obtained when a closed loop pole is placed symmetric with the right half planes zero. Hence, if choose $n_r = n, Tau_{r1} = Tau_r, Tau_{r2} = n$ in equation (3.54), a direct synthesis controller will be obtained and could be rearranged in two forms:

$$g_c=\frac{Tau_1}{K(2n+Tau_r)}(1+\frac{1}{Tau_1\cdot s})(\frac{Tau_2\cdot s+1}{Tau\cdot s+1}) \tag{3.55}$$

i.e., the commercial PID controller form (with the parameters as indicated), or, alternatively:

$$g_c=\frac{(Tau_1+Tau_2)}{K(2n+Tau_r)}[1+\frac{1}{(Tau_1+Tau_2)s}+\frac{Tau_1Tau_2}{(Tau_1+Tau_2)}s](\frac{1}{Tau'\cdot s+1}) \tag{3.56}$$

the standard PID form with the additional *1st* order filter. In each case:

$$Tau'=\frac{n\cdot Tau_r}{2n+Tau_r} \tag{3.57}$$

It had indicated in the beginning of this chapter that the PID type is the only one that has been found useful in controlling inverse response systems; this direct synthesis controller provides another justification for this fact.

3.6.3 Synthesis for Open Loop Unstable Systems

Consider the *1st* order open loop unstable system whose transfer function model is given as:

$$g(s)=\frac{K}{Tau\cdot s-1} \tag{3.58}$$

with the indicated single RHP pole; equation (3.47) gives the direct synthesis controller required to provide the closed loop behavior indicated by q in equation (3.46) as:

$$g_c=\frac{Tau}{K\cdot Tau_r}(1-\frac{1}{Tau\cdot s}) \tag{3.59}$$

which looks like a PI controller with $K_c = \frac{Tau}{K \cdot Tau_r}$ but with the singular, and very important, difference that its integral time is negative; i.e., $Tau_1 = -Tau$.

The problem with this controller is that it will only function properly if all the process parameters are exactly equal to the model parameters; if this is not the case the overall closed loop system will be unstable. In other words, the controller in equation (3.59) will give rise to a stable closed loop system only under the obviously unrealistic situation that the model is an exact representation of the process; the controller therefore has a severe robust stability problem.

3.6.3.1 Robust Stability Problem

To have more idea about robust stability problem, consider the situation in which the actual open loop unstable process has the transfer function:

$$g_p = \frac{K_p}{Tau_p \cdot s - 1} \tag{3.60}$$

for which equation (3.58) is now only an approximate model. When the system is operating in the closed loop with the controller in equation (3.59) derived on the basis of the approximate model of equation (3.58), the closed loop characteristic equation:

$$1 + g_p g_c = 0 \tag{3.61}$$

becomes

$$K \cdot Tau_r \cdot Tau_p \cdot s^2 + (K_p \cdot Tau - K \cdot Tau_r)s - K_p = 0 \tag{3.62}$$

where $K_p \neq K$ and $Tau_p \neq Tau$.

Because of the negative coefficient of K_p, according to the Routh stability test, the system with this characteristic equation will always be unstable. (If the plant and model parameters had been identical, cancellation would have been possible in equation (3.61), and the characteristic equation would have indicated a single, closed loop pole located at $s = -1/Tau_r$.

The direct synthesis philosophy, as embodied in requiring the closed loop response to be as in equation (3.46), is responsible for this problem. According to equation (3.46), the single, closed loop system pole is to be located at $s = -1/Tau_r$; to achieve this requires a controller that will do two things simultaneously: cancel the RHP pole, and replace it with the desired LHP pole (the one located at $s = -1/Tau_r$). Such perfect pole cancellation is, of course, only possible when the location of the RHP pole is exactly known.

3.6.3.2 Robust Controller Synthesis

The indicated robustness problem may be solved by the following not so obvious modification to q:

$$q(s) = \frac{(n_r \cdot s + 1)}{(Tau_{r2} \cdot s + 1)} \frac{1}{(Tau_{r1} \cdot s + 1)} \tag{3.63}$$

With this modification:

$$\frac{q}{1-q}=\frac{n_r\cdot s+1}{(Tau_{r1}+Tau_{r2}-n_r)s\ [\frac{Tau_{r1}\cdot Tau_{r2}}{Tau_{r1}+Tau_{r2}-n_r}s+1]} \tag{3.64}$$

If choose the coefficient of s in the denominator term inside the large brackets to be equal to $-Tau$; i.e.:

$$\frac{Tau_{r1}Tau_{r2}}{Tau_{r1}+Tau_{r2}-n_r}=-Tau$$

rearrangement gives:

$$n_r=Tau_{r1}+Tau_{r2}+\frac{Tau_{r1}Tau_{r2}}{Tau} \tag{3.65}$$

so that equation (3.64) becomes:

$$\frac{q}{1-q}=\frac{n_r\cdot s+1}{\frac{Tau_{r1}Tau_{r2}}{Tau}s\ (Tau\cdot s-1)} \tag{3.66}$$

Using this result, the direct synthesis controller based on equations (3.66) and (3.45) is:

$$g_c=\frac{Tau\cdot n_r}{K\cdot Tau_{r1}Tau_{r2}}(1+\frac{1}{n_r\cdot s}) \tag{3.67}$$

recognizable as a normal PI controller with $K_c=Tau\cdot n_r/K\cdot Tau_{r1}Tau_{r2}$ and $Tau_I=n_r$.

It can be shown that the closed loop characteristic equation for this system, where there is plant/model mismatch, is given by:

$$K\cdot Tau_{r1}Tau_{r2}Tau_p s^2+(K_p\cdot Tau\cdot n_r-K\cdot Tau_{r1}Tau_{r2})s+K_p\cdot Tau=0 \tag{3.68}$$

Thus if the parameters Tau_{r1}, Tau_{r2} are chosen such that:

$$K\cdot Tau_{r1}\cdot Tau_{r2}<K_p\cdot Tau\cdot n_r \tag{3.69}$$

the closed loop system will be stable even though the parameters of the plant and its model are not exactly the same.

Note:

1) By examining the controller gain indicated in equation (3.67), it can be seen that the robust stability condition indicated in equation (3.69) is exactly equivalent to requiring that:

$$K_c > \frac{1}{K_p} \tag{3.70}$$

which is the same condition in section 3.4 for closed loop stabilization of the open loop unstable system by conventional feedback control.

2) The condition indicated in equation (3.69) is used to choose the parameters that characterize the desired closed loop response q. Only two of the three parameters can be chosen independently (equation (3.65) determines the dependence of n_r on Tau_{r1} and Tau_{r2}). Hence, equation (3.69) can be rearranged to give:

$$\frac{K_p}{K}\left(\frac{Tau}{Tau_{r1}}+\frac{Tau}{Tau_{r2}}+1\right) > 1 \tag{3.71}$$

and the two closed loop time constant Tau_{r1} and Tau_{r2} are now chosen such that equation (3.71) is satisfied.

For the *2nd* order open loop unstable system with a single RHP pole:

$$g(s) = \frac{K}{(\sigma \cdot s+1)(Tau \cdot s-1)} \tag{3.72}$$

the reference trajectory in equation (3.63), and with the aid of the same choice of parameters as indicated in equation (3.65), the direct synthesis controller is obtained as:

$$g_c = \frac{(\sigma+n_r)Tau}{K \cdot Tau_{r1} \cdot Tau_{r2}}\left[1+\frac{1}{(\sigma+n_r)s}+\frac{\sigma \cdot n_r}{(\sigma+n_r)}s\right] \tag{3.73}$$

which is a PID controller with the indicated parameters.

3.7 Summary

This chapter is intended to present the methodologies to handle the processes, which only PID controller cannot give the acceptable outcome. The model-based control concept is explained in such a way of being able to apply this concept into the processes that equip with dynamic constraints.

The model-based approaches allow the control system designer to specify the closed loop behavior desired of the process, and from this, to derive the controller required to obtain the specified closed loop behavior directly, using the process model. It can be seen that the model-based controller shares in common the concept of using the process model inverse in one form or another as part of the controller. This chapter also showed that even though philosophically different from conventional feedback control, model-based control strategies often give rise to controllers that may be rearranged to take on the familiar forms of PID controllers. The appropriated PID tuning parameters for each type of process are obtained as the result from the direct synthesis method.

The methodology of Smith Predictor is similar to the concept presented in this chapter. Also, the Robust Smith Predictor is developed by combining the concept of model-based control and Smith Predictor, which will be explained next.

CHAPTER 4
ROBUST SMITH PREDICTOR

4.1 Overview

The Smith Predictor is a dead time compensator and given the high control performance if process model and actual plant are identical or slightly mismatch. The sources of unmeasured disturbances are unknown and the control performance will deteriorate if these are introduced into the dominant dead time process (or non-minimum phase process).

To increase the capability of Smith Predictor [2], the Robust Smith Predictor is proposed in this thesis. Due to unmeasured disturbance are unavoidable no matter difficult control loops or other control loops. The objective of Robust Smith Predictor is to improve the control performance and robustness in order to handle as many unmeasured disturbances as possible while the control variable must be well controlled. In this study, it is intended to present the economical and easiest way to construct the control system for overcoming the modeling errors when dealing with the difficult loops as mentioned.

4.2 Principle of Robust Smith Predictor

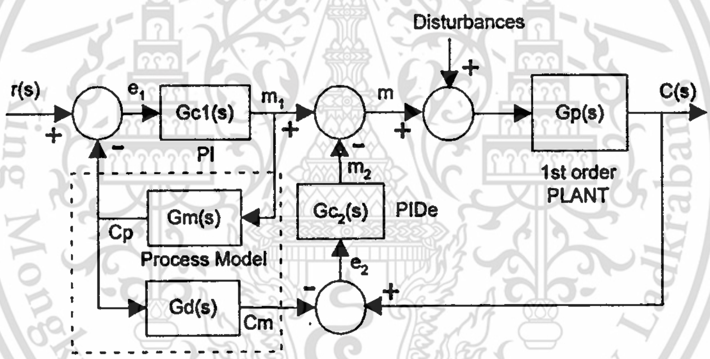


Fig. 4.1 Robust Smith Predictor

The control scheme is shown in figure 4.1. PIDe (same function as normal PID) is proposed to add into the control scheme to increase the robustness during model mismatch or whenever disturbances entering to the process. If the model is perfectly matched or slightly different, the Robust Smith Predictor gives the same outcome as Smith Predictor. But the model and actual plant are always mismatched so that PIDe is supposed to work at all time to reject the disturbances from the plant or modeling errors. The output from PIDe, m_2, is the compensated signal resulting from modeling error effect while the actual manipulated variable, m, to the final element (e.g. control valve) is:

$$m = m_1 - m_2 \tag{4.1}$$

where m_1 is an output from PI controller. $G_m(s)$ and $G_d(s)$ represent the un-delayed and delay portion of the actual plant respectively. During the presence of modeling error or disturbance (assume process has been in steady state), m_1 is inherent or being the bias to the process so that e_2 will be very small and PIDe will just move a small m_2 to bring the controlled variable to the setpoint smoothly. The overall closed loop transfer function will be similar to equation (2.12) when the model is perfect. The followings will explain more about the initiative methods used in this thesis.

4.2.1 Unmeasured Disturbance

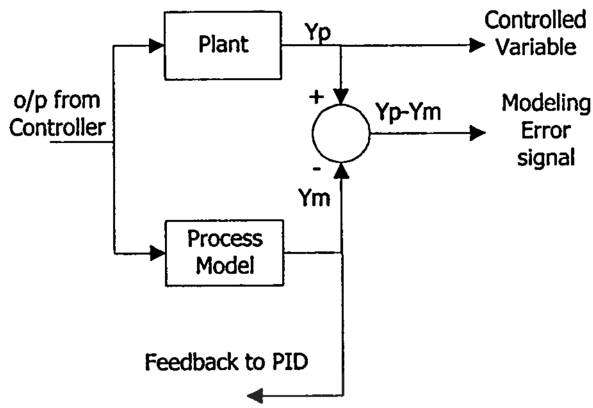


Fig. 4.2 Model Mismatch

Refer to figure 4.2, for the perfect process model, the difference of Y_p and Y_m is zero. But this cannot be true to get the perfect model meaning that the erroneous always appears and the real causes stay by definition unknown. If the disturbances can be measured the feedforward techniques can be applied. If nothing is done to counter the unmeasured disturbance effect, the offset and instability will be occurred [4].

It can be noticed that the modeling error signal is represented by the difference of Y_p and Y_m. Y_p is the actual process response and Y_m is the output prediction from the process model. With reference to the figure 4.1, e_2 is the modeling error signal, which is an only input to the PIDe.

4.2.2 Basic Idea for Countering Modeling Error Signal

The difference of Y_p and Y_m at each scanning time is behaved as a series of impulse train [4]. It is an erroneous occurring when the process parameters in the process model differ from the actual process. The magnitudes of the error may not be identical (as show in Fig. 4.3) and can be treated as same as an offset. Removing an offset can basically be done by adding an integrator. In this study, proportional, integral and derivative (PIDe) are proposed to counter the modeling error signal.

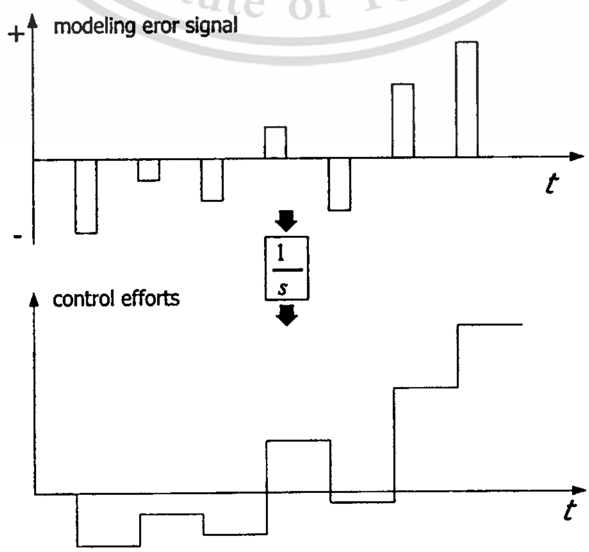


Fig. 4.3 Basic idea for countering modeling error signal

4.2.3 Model Mismatch

Process identification is the most important step for model predictive control. This is done by doing open loop response. Introducing a step change at the controller output (most likely control valve) and records the reaction curve from process is the popular way to find the process parameters e.g. process gain, time constant and dead time. The reaction curve is possible to be *1st* order until *n*-order system but most of the actual plant can be estimated to *1st* order system, which can present most of process behavior from the plant. The model mismatch is unavoidable but it can be minimized by making sure the process value has been in steady state and no disturbance entering to the process for a period of time. Once the process is steady, a step change can be made. The reaction curve must be clear and able to identify undoubtedly.

The step test is recommended to carry out during normal operation and avoid doing it during heavy rain (abnormal climate) or some of process conditions are out of range. Those lead to have the erroneous during process identification step. The most accurate model can increase the robustness and performance to the model predictive control e.g. Smith Predictor or Robust Smith Predictor.

In fact, the model mismatch is already introduced during curve fitting step as shown in figure 2.6. As mentioned, the true order of the process is higher than one but in control system design; the true model will likely be estimated to *1st* order to *2nd* order system. Hence, some actual process behaviors will be lost and unable to represent all process characteristics. Moreover, most of commercial process identification tools also limit the result to *2nd* order system.

4.2.4 Where to Apply Robust Smith Predictor

Only dominant dead time process is recommended. Because there is a limitation for using PID to control this kind of control loop. Most of PID tuning formulae is sensitive to the dead time/time constant ratio. The ratio must be in range of 0.1-1.0 otherwise PID is not suitable [1].

Nowadays, there are a lot more commercial products such as SMOC (Shell Multivariable Optimization and Control) invented by Shell group [4], RMPCT (Robust Multivariable Predictive Control Technology) from Honeywell, etc. that created to overcome the said problems and for multivariable control purpose. But they are of course expensive and worth having when there are numbers of multivariable process control. Most of refineries have those products to specifically control a number of distillation columns. However, the Robust Smith Predictor can be constructed by using the application blocks in DCS (Distributed Control System) and the outcome is satisfied with the low investment cost.

4.3 Experimental Results

The tests were carried out with many cases to prove the control performance and robustness. In this section, the results will show clearly how Smith Predictor and Robust Smith Predictor react to the setpoint changes, disturbances rejection during the presence and absence of modeling errors.

4.3.1 Configuration

Simulink in MATLAB is used as a tool for configuration, analysis and experimentation. PI is a reverse acting controller sending its output signal to a summing block. PIDe is a direct acting controller sending its output to a same summing block as PI. The summing block is configured the sign as shown in figure 4.4, its output is directly connected to the final element (control valve). Here is the simulation so its output is connected to the dead time and first order blocks represent actual plant model. PV is a process value or controlled variable and fed back to connect to a PV of PIDe. The setpoint of PIDe is a feed back signal from process model. Clearly, PIDe will try somehow to equalize the setpoint and PV. The output from PI is also connected to the input of first order block in the process model through dead time block until finished the loop at setpoint of PIDe.

The control mode of the PI controller is AUTOMATIC mode receiving the setpoint from operator while PIDe is requested to be on CASCADE mode at all time. Because the main control function of PIDe is to always reject any disturbances to the plant.

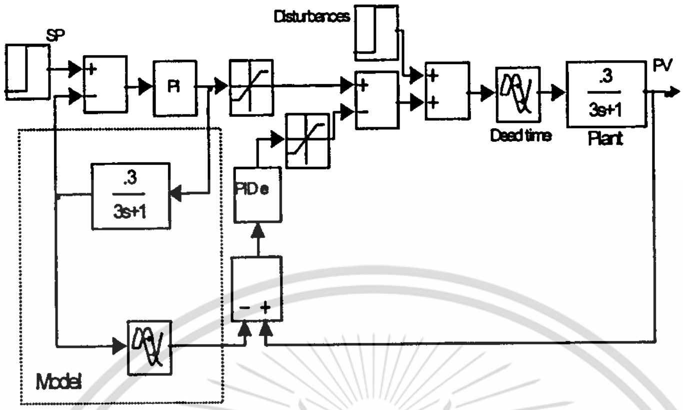


Fig. 4.4 Robust Smith Predictor configuration

4.3.2 Test Procedures

In this test, it is used the real process parameters from the plant. The plant is a fuel gas distribution control system. The main producer to the fuel gas header is LPG (Liquefied Petroleum Gas) and NG (Natural Gas). The distance between LPG vessel and fuel gas balance drum is 500 meter. The LPG pressure is 5.5 bar and has a very sluggish response to the fuel gas header pressure. The process model used in this study is LPG pressure to fuel gas header. The actual plant model is process gain = 0.3, time constant = 3.0 minutes, and dead time = 6.0 minutes [14]. That means the normal PID would give the poor control response for this kind of process particularly when the load changes (disturbances). For NG, it has a fast response to the fuel gas header but it is more expensive. The LPG is preferred to control the fuel gas header pressure so that its control response must be improved. However, this process, Fuel Gas Distribution Control System, will be described more in appendix 1. This is a case study. The Simulink in MATLAB is used to construct the Smith Predictor and Robust Smith Predictor (as shown in figures 2.17 and 4.1) respectively. The control performance and robustness of both schemes will be compared and explained case by case.

Moreover, the result from the Smith Predictor Scheme in the real processes, Fuel Gas Distribution Control System and ADIP Absorber Control System will be compared to the result from Robust Smith Predictor. It should be noted that the process parameters used in this experiment are belonged to the process from Fuel Gas Distribution Control System.

Base Case:
actual plant model: Gp = 0.3, time constant = 3.0 min. and dead time = 6.0 min.
Process model: Gp = 0.3, time Constant = 3.0 min, dead time = 6.0 min.
PID: Gc = 5.0, t1 (integral time) = 3.0 min, t2 (derivative) = 0 min.
PI: Gc = 5.0, t1 = 3.0 min, t2 = 0.0 min.
PIDe: Gc = 0.7, t1 = 6.0 min, t2 = 2.0 min.
Setpoint: changed from 0 to 5.0% at time = 5.0 min.
Disturbance: entered to the process as step in magnitude of –5.0% at time = 70.0 min.

- **Case 1:** No modeling errors. Figures 4.5 and 4.6 show the control behavior of Smith Predictor and Robust Smith Predictor respectively.

For Smith Predictor, PID sees no process dead time [3,5]. Therefore, C_p is an only input to PID because PV = Cm. PV is fast and smoothly reaches the setpoint and quickly reject the disturbance. The disturbance has small effect to the controlled variable. Smith Predictor gives perfect response.

For Robust Smith Predictor, the control response is almost identical to Smith Predictor particularly on the setpoint changed. No PIDe action before disturbance is entered. The disturbance in the magnitude of –5.0% has a little more impact on controlled variable than Smith Predictor. As mentioned, the main control function of PIDe is to reject any disturbances and give the robustness when process model and actual plant is mismatched. The output signal from PIDe is the response from PIDe to the disturbance (step down 5.0% at t =70 min.). Clearly, the control performance can be

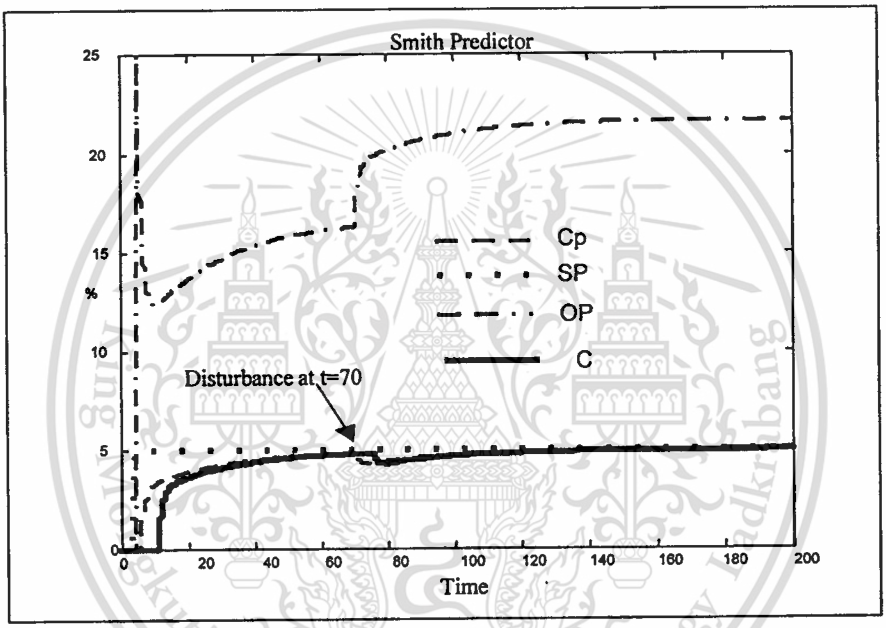


Fig. 4.5 Smith Predictor when no modeling errors

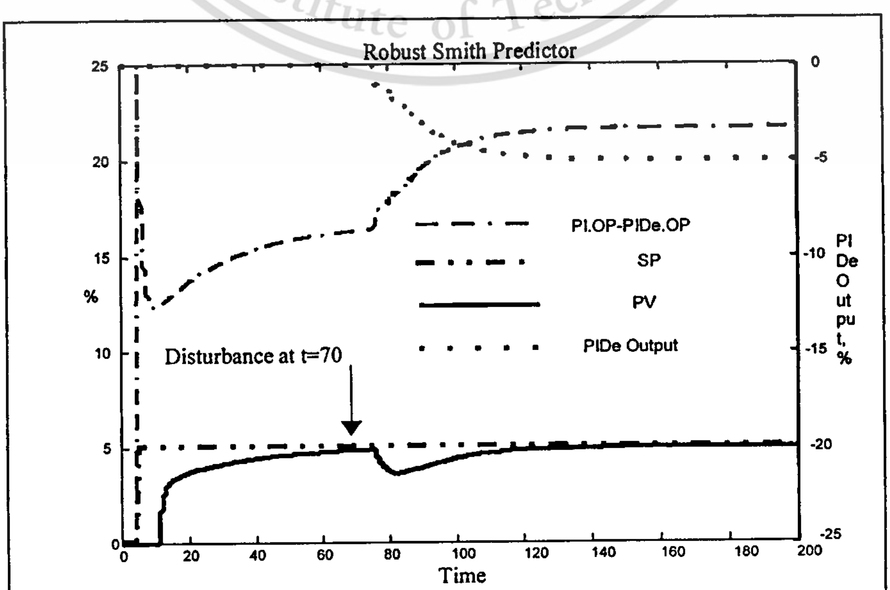


Fig. 4.6 Robust Smith Predictor when no modeling errors

improved with a set of tight tuning parameters on PIDe. The tuning techniques will be described later. Carefully consider the control action of Robust Smith Predictor in figure 4.6, PIDe decreased its output due to the disturbance made the controlled variable dropped below setpoint because it is a direct acting controller. But the actual output to the final element is then increased to recover the controlled variable to its setpoint (actual o/p = PI.OP - PIDe.OP, see also figures 4.4 and 4.6).

- **Case 2**: Modeling errors, actual process gain is 3 times higher than process gain in the model. This is an extreme case, assume all conditions in base case remain unchanged except actual process gain in the plant is changed from 0.3 to 1.0. Figure 4.7 will clearly present the robustness of Robust Smith Predictor (solid line). It is intended to not fine tune any controllers frequently because practically the actual process behavior can naturally change and vary. Therefore, controllers are supposed to perform satisfactory without paying much effort.

When applying a Smith Predictor, the process model requires updating regularly to maintain control performance and robustness. Similarly, fine-tuning on PID must also be done frequently to keep it well control.

As shown in figure 4.7 (dash line), Smith Predictor gave oscillations when an actual process gain is higher than a designed process gain in the model (higher process gain requires smaller control efforts) because the same tuning parameters of PID act on the higher actual process gain. It is worst to trade-offs between performance and robustness. If the PID is de-tuned, it will give a sluggish response in other cases. Smith Predictor has a limitation in handling the modeling errors while Robust Smith Predictor has PIDe to counter this effect.

It can be seen that the Robust Smith Predictor gives the difference outcome. The tuning parameters in PI and PIDe are kept the same as mentioned in base case. The controlled variable reaches the setpoint smoothly and response well for the disturbance rejection. Carefully attention to the control action of PI and PIDe in figure 4.8, PIDe reacts promptly to the erroneous of the model and suddenly gives the corrective action. PIDe increases its output because the controlled variable is getting higher. An overshoot happens because the same tuning parameters in PI reacts to the higher actual process gain. At the same time, the actual output signal to the final element is then decreased (see figure 4.8) to bring the controlled variable back from overshoot. Again, at time = 70 min. the controlled variable dropped below setpoint (5.0%) due to the disturbance (-5%) entered to the process. PIDe decreases its output because the controlled variable dropped thus makes the actual output increases to maintain process value at setpoint.

- **Case 3**: Recommendation. This case is quite practical and it could deteriorate the control system. When all three actual process parameters are mismatch in the direction of leading the control instability problem. For instances, higher process gain, smaller process time constant and longer dead time can make control system unstable. Assume the actual process parameters are changed to the worst: process gain changed from 0.3 to 0.6, process time constant changed from 3.0 to 1.0 minute and process dead time is changed from 6.0 to 10.0 minutes.

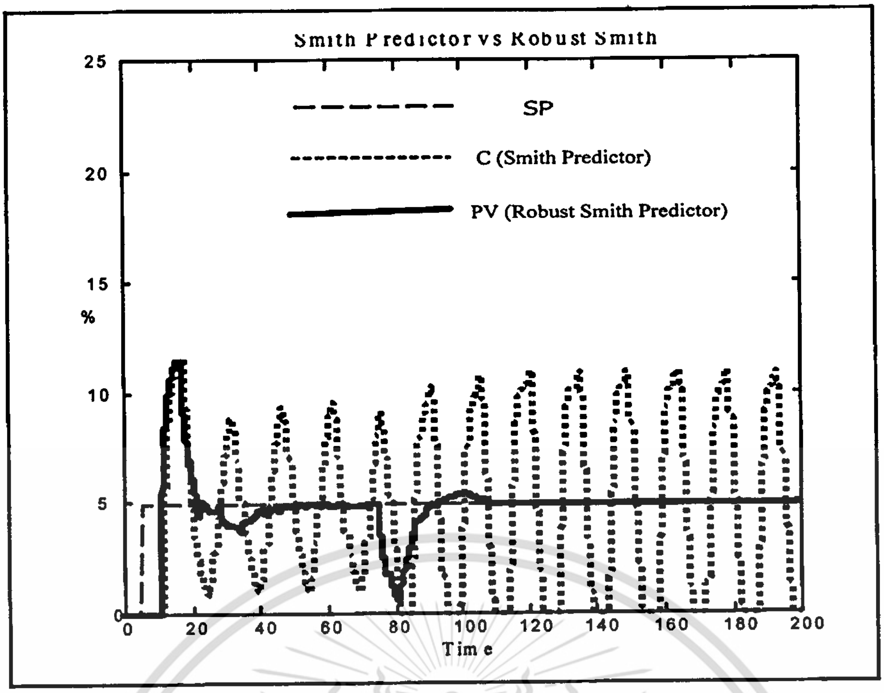


Fig. 4.7 Comparison when model mismatch

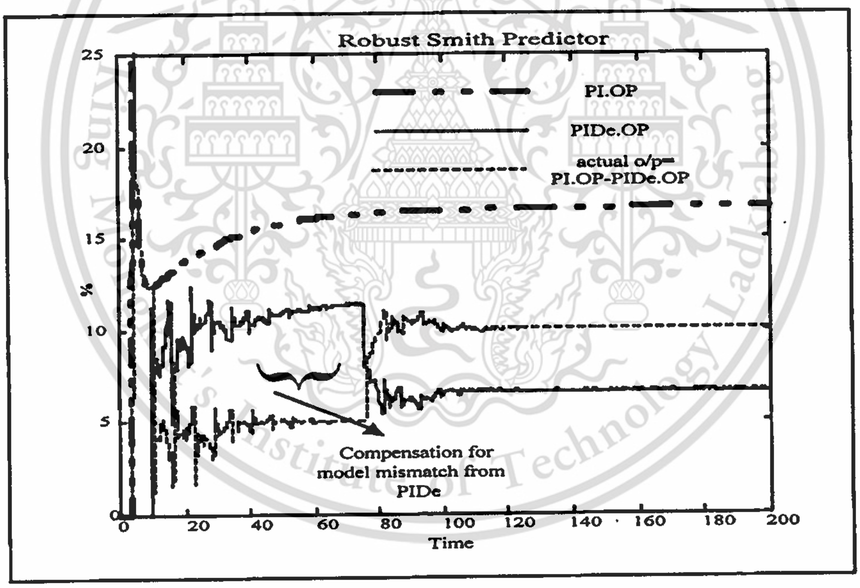


Fig. 4.8 Control action of Robust Smith Predictor

To make the control system more robust for all cases, it is recommended to set the derivative time (t_2) to the value in between zero to 10 percents of Integral Time (t_1). In this case, the tuning parameters in PID and PI are unchanged only PIDe is recommended to set derivative action (t_2) to 0.6 (10% of t_1) and the rest remain unchanged.

Figure 4.9 compares the control robustness and performance of both control schemes when all three of actual process parameters are mismatch to the process model. The controlled variable of Robust Smith Predictor is still controlled well and stable even the worst process scenario while the other control scheme is oscillating.

All lines in figure 4.10 are the controlled variable against setpoint changed 5.0% at different process conditions. Process parameters are varied from the based case in the magnitude of +/- 3 times for process gain and +/- 2 times for time constant and dead time of nominal values without fine tuning PI and PIDe.

4.3.3 Tuning Techniques

In this study, minimum ITAE for setpoint and disturbance case [1] is used as a guideline for PI and PIDe respectively. It gives more proper control response than others do such as Ziegler-Nichols and Cohen-Coon.

Refer to process model in base case, PI is tuned to the process model as if no dead time presented. But in the formulae, dead time is always set at least 1.0 minute. Dead time 1.0 minute comes from DCS (Distributed Control System) scanning time and database historian capability. Process gain = 0.3, time Constant = 3.0 minutes and dead time is set to 1.0 minute. With these settings, minimum ITAE-SP yields, K_c = 5.0, t_I = 3.0 minutes. They are the tuning parameters of PI.

For PIDe, control engineers must know and understand the process behavior. The assumption should be made to be a design case that how flexibility of Robust Smith Predictor can handle such process parameter variation, says 2 times or 3 times of nominal values. PIDe is then fine-tuned to the worst process parameters.

In this study, process gain is estimated to vary 3 times higher than the nominal value and time constant including dead time are varied within 2 times of nominal value. But from the test, the variation of process gain has more impact on the stability of the system than time constant and dead time. Therefore, PIDe is tuned to the process as follows:

Process gain = 1.0 (assume 3 times of nominal process gain), time constant = 3.0 minutes and dead time = 6 minutes. With the worst condition, minimum ITAE-disturbance yields, K_c = 0.7, t_I = 6.0 minutes and t_2 = 2.0 minutes. As mentioned in case 3, for robustness, t_2 must be set to the value in between zero to 10 percents of t_I. This is the fact found during the experimentation and Fig. 11 has proved that with these tuning parameters, the PIDe is able to cope with the wide operating range, says +/- 3 times from nominal values in base case.

Trade-offs between performance and robustness can be done at PIDe with tighter tuning (higher gain, shorter integral time and more derivative action) and de-tuning (lower gain, longer integral time and less derivative action) respectively. Trade-offs is recommended after monitoring its control action for a period of time. It is worth to first make Robust Smith Predictor robust to all cases. Thereafter, performance can be increased while robustness is still maintained

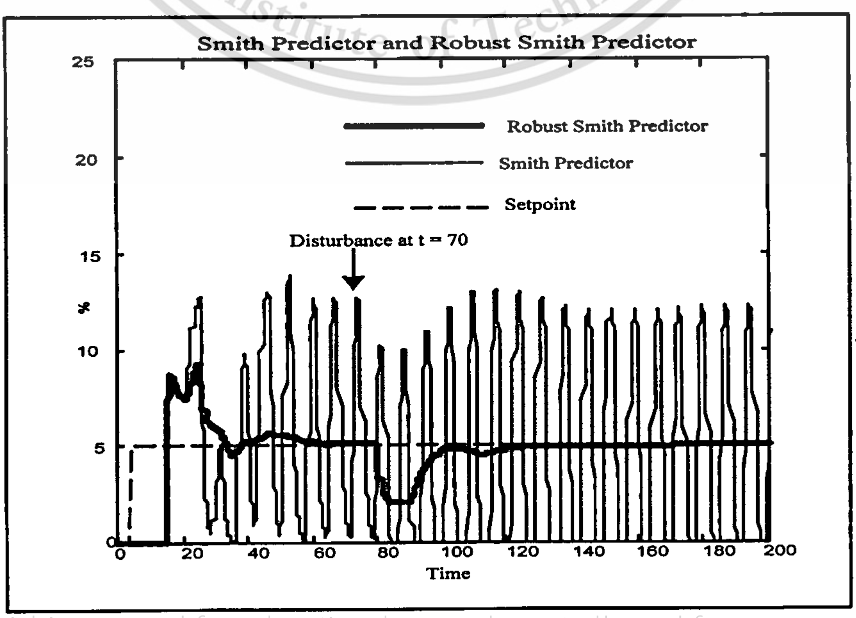


Fig. 4.9 Smith Predictor versus Robust Smith Predictor

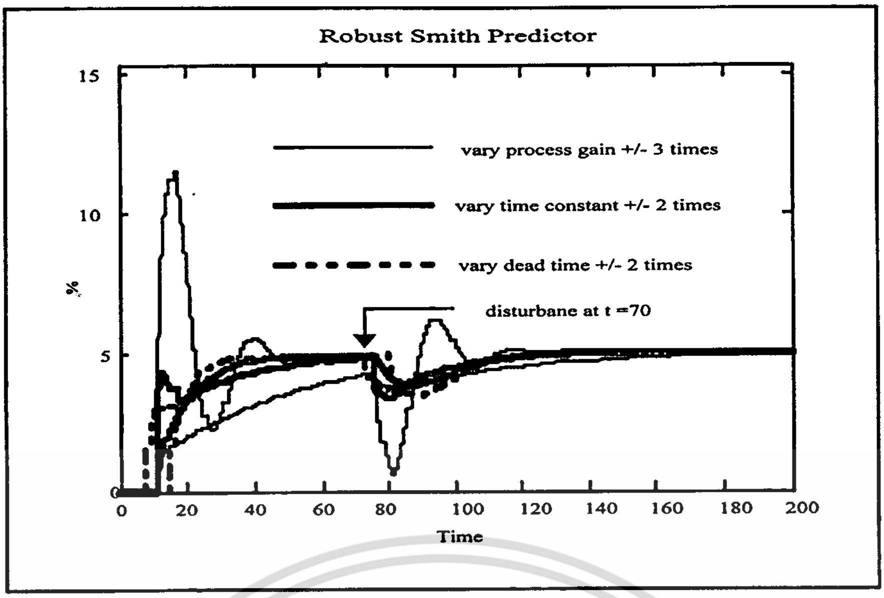


Fig. 4.10 Performance and robustness to all cases

4.4 Comparison Robust Smith Predictor to the Smith Predictor in Process Industries

This section will compare the result from the Smith Predictor in the Fuel Gas Distribution Control System [14] with the same process parameters. It should be noted that the disturbance in the real process is assumed to be sinusoidal and actual process gain is 2 times higher ($G_p = 0.6$).

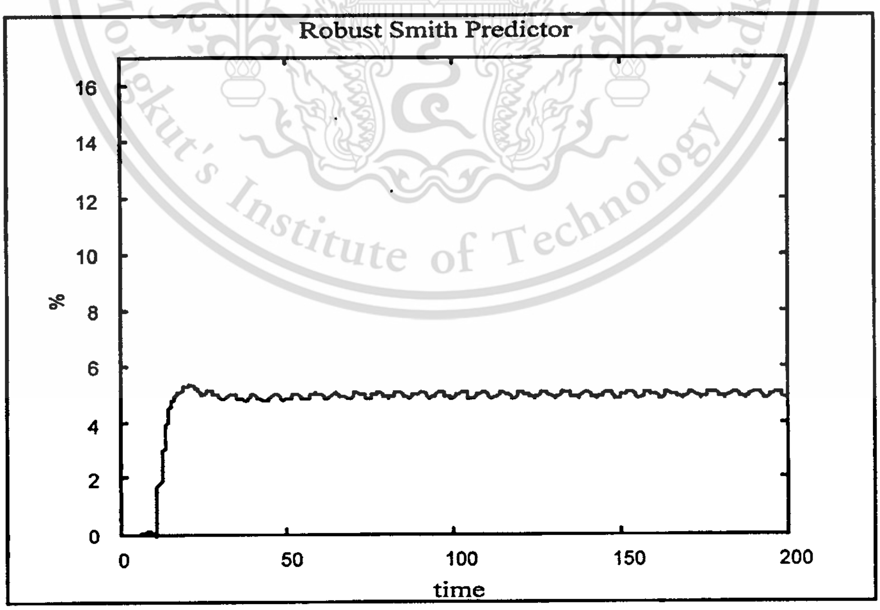


Fig. 4.11 Robust Smith Predictor with sinusoidal disturbances (1% amplitude and frequency 1 rad/sec)

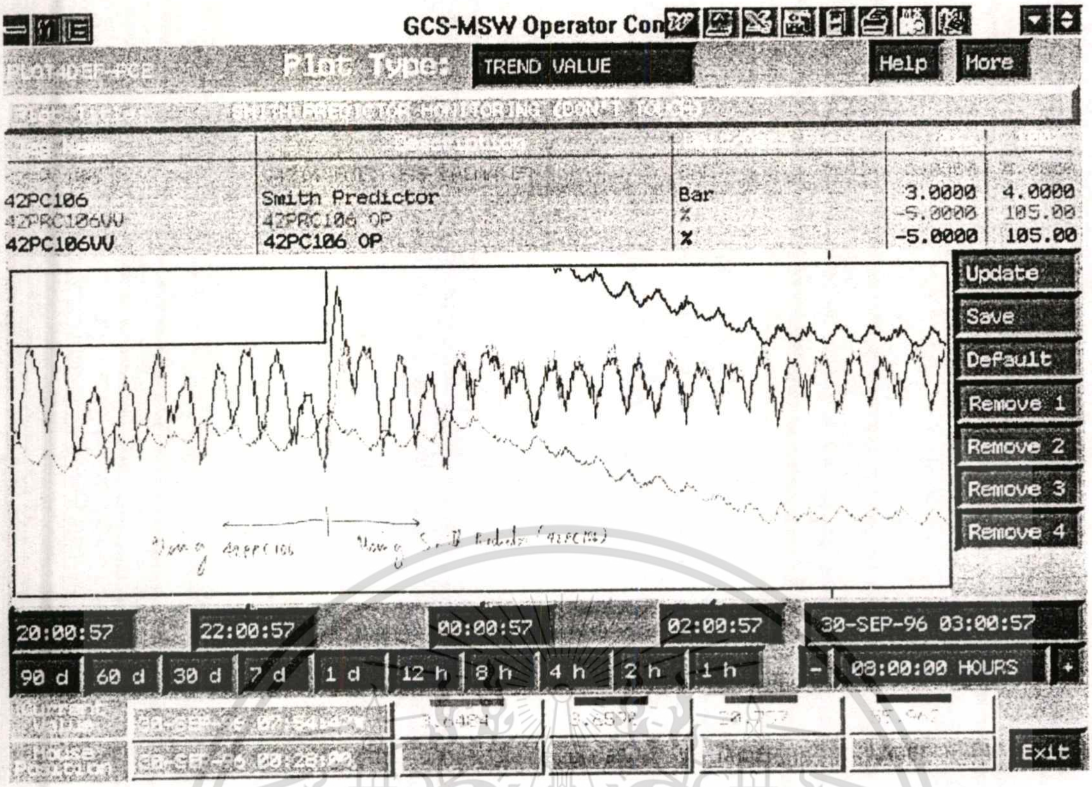


Fig. 4.12 Result from Smith Predictor in the Fuel Gas Distribution Control System

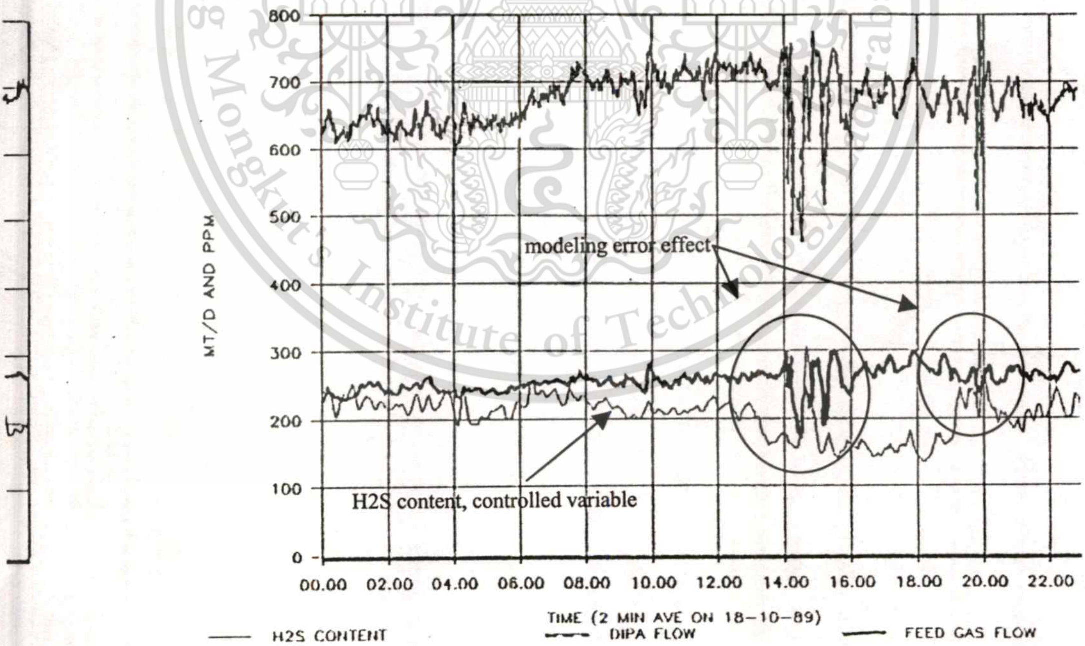


Fig. 4.13 Modeling error effect of Smith Predictor in ADIP Absorber Process

The scales in figures 4.11 and 4.12 are identical in term of percentage (the control range of 41PRC106 is in range of 0-6 bar) for comparison purpose. Figure 4.11 shown that the Robust Smith Predictor gives smaller fluctuation during the disturbance is presented. Additionally, figure 4.13 shown that the ADIP Absorber process [15] upset caused by the modeling error effect. If compare figure 4.13 to the results from Robust Smith Predictor in figures 4.7 and 4.9 during the presence of modeling error, the Robust Smith Predictor gives only one undershoot (or overshoot if disturbance is a positive value) and converge to the setpoint smoothly.

4.5 Summary

One of the issues that have always arisen in control system design is how sensitive the control system is to expect variations in the process parameters. For example, if PI controller has tuned to a particular loop, how will this control loop behave if process gain changes by 20% or the dead time changes by 30%? This is a question of process sensitivity and the robustness of the control system design. Robust Smith Predictor has developed to address this issue particularly on the dominant dead time process. This is because of inadequate modeling from a set of experimental data set such as step test or pulse test data. Modeling mismatch could be due to unmodeled nonlinearities, poor experimental design, or measurement noise problem that prevent the model from representing all features of the process. Robust Smith Predictor makes use the modeling error signal to input to PIDe. The main function of normal PID is to decrease its error to zero. PIDe makes control loop more robust to any model uncertainties. Performance and robustness will depend on tuning in PIDe.

It can be seen from the test that the Robust Smith Predictor is robust to the model uncertainty, which is able to work in wider operating range without spending much effort for re-tuning and re-parameterization.

CHAPTER 5

DISCUSSIONS AND SUGGESTIONS

5.1 Discussions

A PID controller is crucial in running a plant but it must be used with cautions. The dead time/time constant ratio of the process must be known prior to designing the control system. All types of dead time compensator are recommended to apply if the ratio is greater than one otherwise any modeling error effect will deteriorate the overall control system.

Some of the papers that related to the Smith Predictor focused on improving the control performance and robustness during the absence and presence of modeling error respectively. But some required complexity control configuration and tuning while some can be achieved the desired reference trajectory by only one tuning parameter e.g. λ, Tau_r, etc. The reference trajectory is similar to a 1^{st} order filter.

In this thesis, it is proposed to use all three tuning parameters in PIDe to counter the modeling error effect. Because the appropriated derivative value allows higher controller gain (see Appendix B) rather than using only 1^{st} order filter to bias the setpoint or integral time to just simply remove the offset from unmeasured disturbance (caused by modeling error or non-linearity of the process that was lost during process identification).

The test result in chapter 4 already shown that the Robust Smith Predictor can overcome the modeling error effect, which can be controlling with the same tuning parameters in PI and PIDe while all process parameters (actual plant) are varied +/- 3 times from the nominal model. It was compared also in figures 4.11 and 4.12, the fluctuation was suppressed significantly.

It can be seen that the operating range of Robust Smith Predictor is much wider than the original Smith Predictor as shown in figures 4.7, 4.9, and 4.10. That's the reason why it is called "Robust Smith Predictor" because it still gives the satisfactory outcome even the worst process scenario.

5.2 Suggestion for Further Development

As stated in chapter 3, the inverse response and open loop unstable process are considered to be a non-minimum phase system. They are also of interest to study further the new compensators to counter such a system. As mentioned in section 3.3 and 3.4, these compensators are also sensitive to the model mismatch.

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APPENDICES

APPENDIX A

SMITH PREDICTOR IN PROCESS INDUSTRIES

Since 1957, his scheme has still been interested. Various practitioners apply it in the real world even though the modeling error effect is still obvious. But it can still provide improvement over conventional feedback control if the modeling error is not too large (i.e., if the parameters in the process model are within about +/- 30% of the actual values). Smith Predictor is commonly used in the chemical plant, refinery, etc. The product quality analyzer control loop and the long transportation line process are most applied.

- Apply Smith Predictor into Fuel Gas Distribution Control System

In 1996, Rungnapa Buranatrivedhya a process control engineer from Thaioil Refinery had implemented the Smith Predictor into the Fuel Gas Distribution Control System. She found that the conventional PID gave poor response in term of disturbance rejection. An investigation took place to identify the root cause of poor disturbance rejection by doing some step tests to get the process parameters from the plant.

Briefly, the plant equips with a process gain of 0.3, time constant of 3.0 minutes and dead time of 6.0 minutes. It is considered to be a dominant dead time process. The fuel gas is utmost important in refinery because it is used for firing in the furnaces. There are 52 furnaces in refinery and good control stability will give stable temperature control to the distillation columns that directly related to the product qualities.

Refer to figure A.1, the main producer to the fuel gas header is LPG (Liquefied Petroleum Gas) and NG (Natural Gas). Before implementation, there was only PRC106 (conventional PID). Its function is to control the fuel gas header pressure by manipulating either LPG flow controller (FRC102) or NG flow controller (FRC114). Either LPG or NG flow controller is allowed to be in Cascade mode one at a time only to avoid interaction.

Due to the price of LPG and NG are always changing but a control problem happen when the price of NG is higher. In this case, NG flow make up (i.e., fixed setpoint in Automatic mode) is aimed to minimize and PRC106 should manipulate only LPG (FRC102) for fuel gas header pressure variation upon the disturbance and the demand of fuel gas producer (by product from distillation) and consumer (mostly furnace).

There are two dead parts in this process. Firstly, LPG vessel, it takes some to vaporize the LPG liquid to LPG vapor. Secondly, the distance between LPG vessel and fuel gas balance drum (V-4214) is 500 meter. The LPG pressure is 5.5 bar and approximately takes 6.0 minutes to the fuel gas header.

There are 2 penalties from the header pressure variation. Firstly, poor fuel gas firing in 52 furnaces. Secondly, even worst when the pressure is getting higher; the dead time 6 minutes will delay PRC106 in decreasing the LPG make up flow going to the header and PIC407 (High Pressure Protective Controller) will release the excess pressure to the flare.

Those penalties were the reasons to apply the Smith Predictor as shown in figure A.1 and A.2. Refer to figure A.1, PRC106 is a conventional PID and PC106 is a Smith Predictor, which allow operator to switch over from PID mode to Smith Predictor mode via 42HS109.

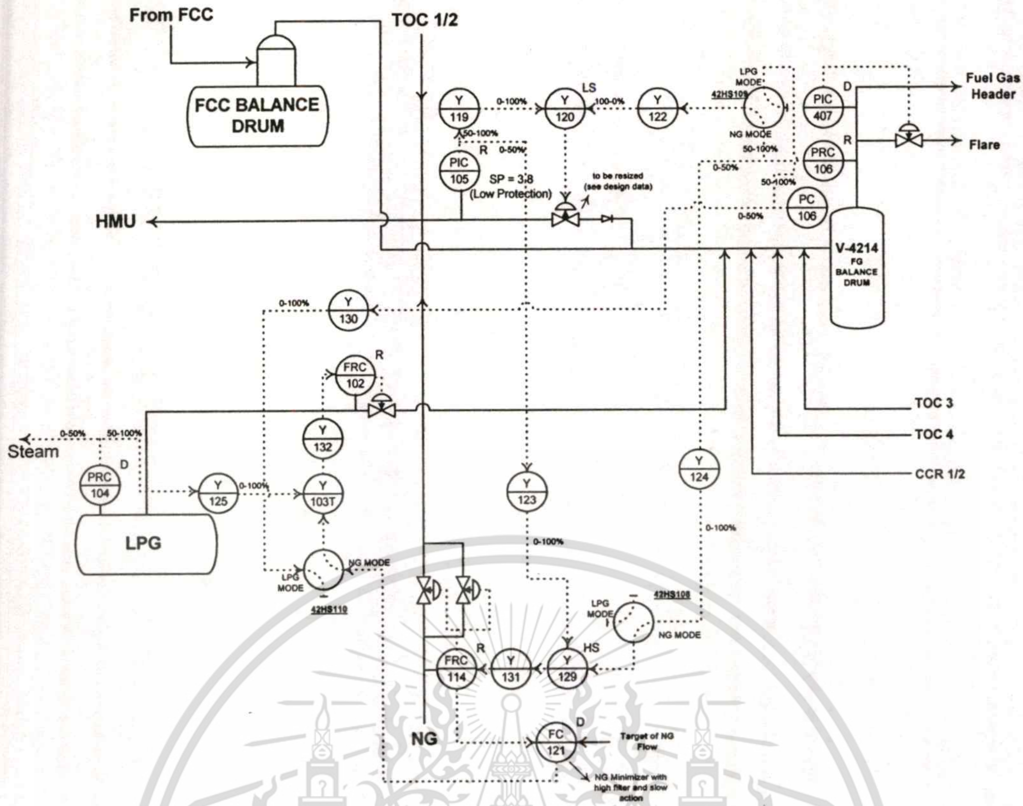

Fig. A.1 Fuel Gas Distribution Control System using Smith Predictor

Figure A.2 shown the configuration of Smith Predictor in the DCS (distributed control system) TDC3000 Honeywell. This control scheme has still been using even though it still lacks the robustness to the modeling error as its nature. The weak points of an original scheme are studied and about to migrate to Robust Smith Predictor.

Refer to figure A.3, the improvement of 42PC106 is clearly noticeable that Smith Predictor gives better control performance that a conventional PID (42PRC106). The standard reduction is 32.43% by comparing the trend of 42PC106 (or PRC106). The benefit from controlling header pressure more tightly is having less excess fuel gas pressure released to the flare, which waste energy or money. This can be observed from having less over shoot of a fuel gas head pressure.

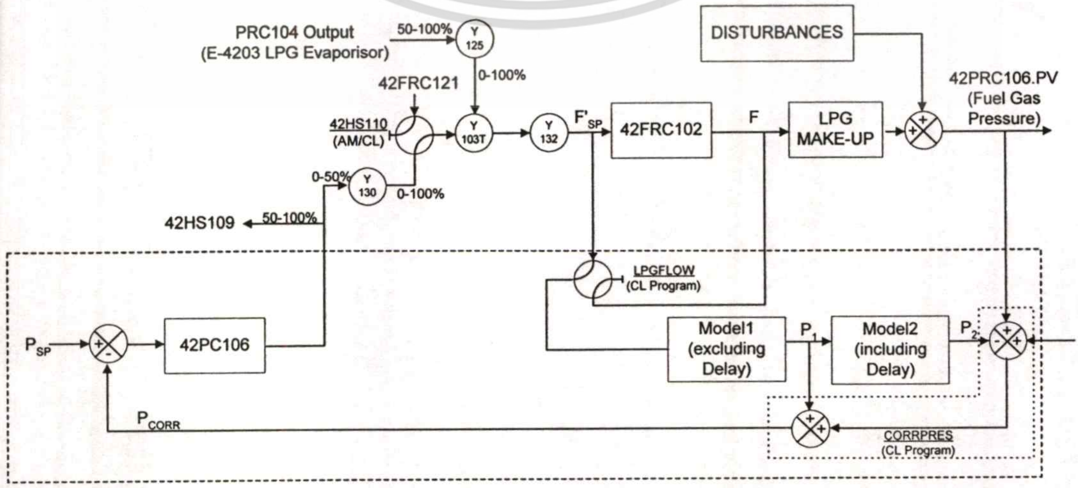

Fig. A.2 DCS Configuration of Smith Predictor invented by Rungnapa Buranatrivedhya

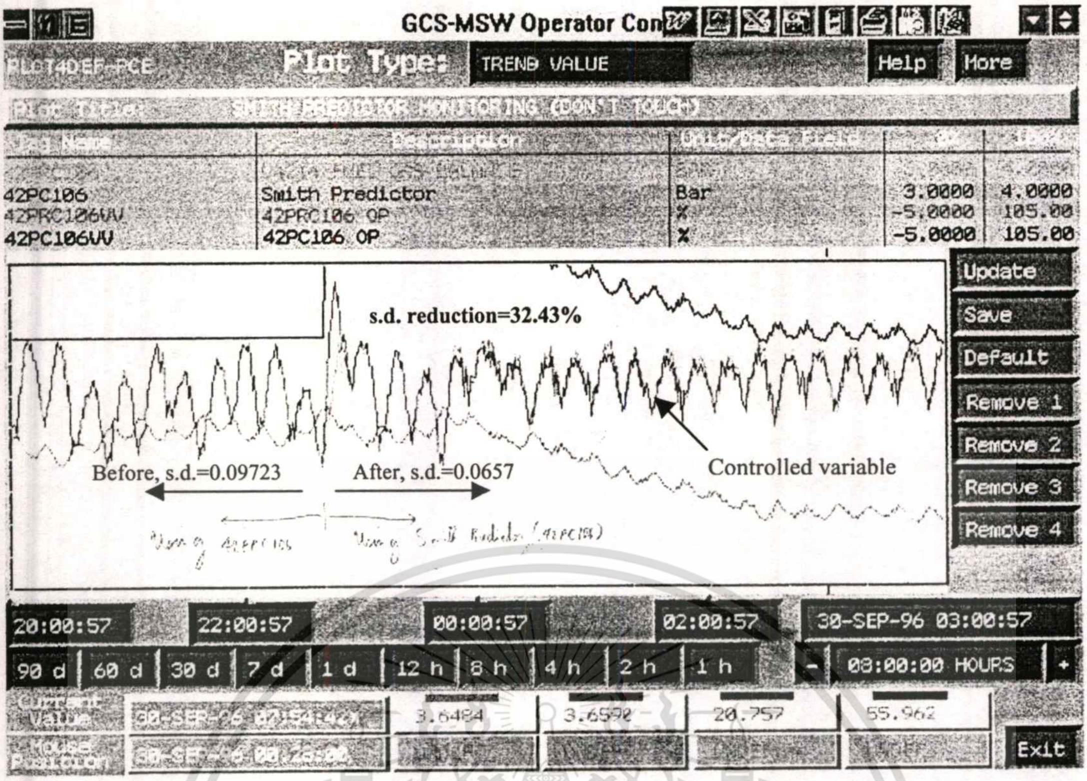

Fig. A.3 Improvement before and after applying Smith Predictor in Thaioil Refinery

- Closed loop control of H2S content in ADIP Absorber using Smith Predictor

In 1989, Lim Fung Suan a process control engineer in Shell Bukom Singapore had also applied the Smith Predictor in order to control H2S content more effectively. Analysis of H2S absorber revealed a non-linearity relationship between the DIPA flow and treated H2S gas content.

Hydrogen sulfide is a very toxic gas. At 1000 PPM, it can cause instantaneous death; at 700 to 900 PPM, it rapidly produces unconsciousness and death occurs a few minute later.

The purpose for controlling the H2S content in fuel gas within limits is to keep the H2S content well below the acceptable limit. This would incur a high-energy cost. Therefore, the strategy is to regulae the H2S content just below the allowed limit.

The process shown in figure A.4, consists of the absorber column C6801 and the "knock out" vessel V6801. Sour gas, rich in H2S, is fed at the bottom of the column. Regenerated (or lean) DIPA flows through the trays of the column to absorb the H2S from the sour gas. The H2S content of the treated gas is measure downstream of the knock out vessel by a Maihak H2S analyzer. The fat DIPA, at stage rich in H2S, is sent to the regenerator to be stripped-off of the H2S.

The Smith Predictor configuration is shown in figure A.5 and A.6 and applied to overcome the non-linearity of the system. Because the existing system at that time was a non-linear controller but the it still acted too slow when reducing the DIPA/Gas flow ratio and acted quickly when increasing the DIPA/Gas flow ratio. The process is modeled a *1st* order lag of 15 minutes and a deadtime of 5 minutes. The process is shown as Hp and a time delay e^{-sT_p}, and the model is shown as Hm and e^{-sT_m}.

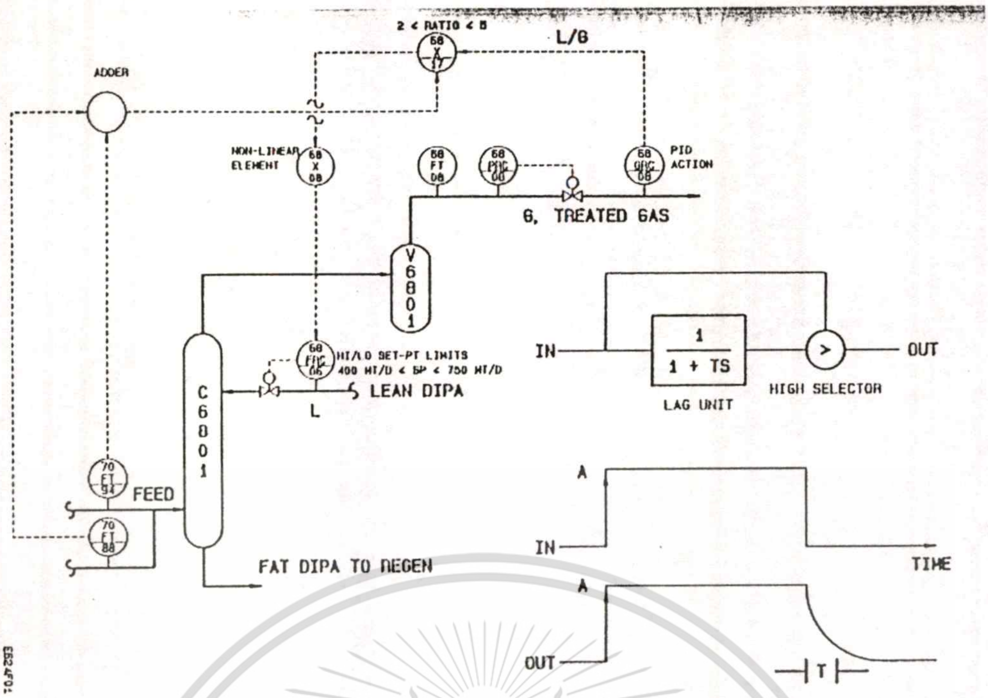

Fig. A.4 H2S Content in an ADIP Absorber Process

Refer to figure A.5, if the model is correct, and the disturbance is zero, then the process output (Q=H2S content) would equal the model output Q_m. Therefore, the modeling error Em=0. The predicted H2S content Q_p is used as the feedback signal, and the controller can be tuned with a faster response as though there is no deadtime in the system. In practice, the modeling error and the disturbances are not zero. Hence, these signals are also used in the feedback loop to correct for any deviations. Figure A.6 shows the configuration in the DCS (distributed control system).

The non-linearity of the process can be ignored if the control system is to operate as a regulator, keeping the H2S content near the setpoint.

Based on the Ziegler-Nichols tuning method, the controller gain and integral time for the PID controller are 0.18 and 20 minutes respectively. However, it is found that a gain of 0.15 and an integral time of 30 minutes provided a better response.

The control improvement is shown in figure A.6 for non-linear control techniques and figure A.7 for Smith Predictor. With the Smith Predictor, the control is tighter as the H2S content varies approximately +/- 50PPM about the setpoint. The variation in the DIPA flow is much reduced, which is more acceptable to operation.

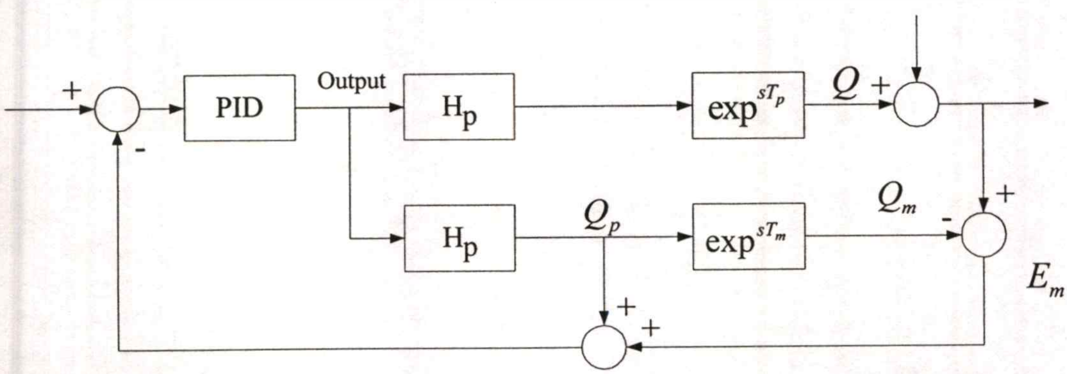

Fig. A.5 Canonical form of Smith Predictor in ADIP Absorber Process

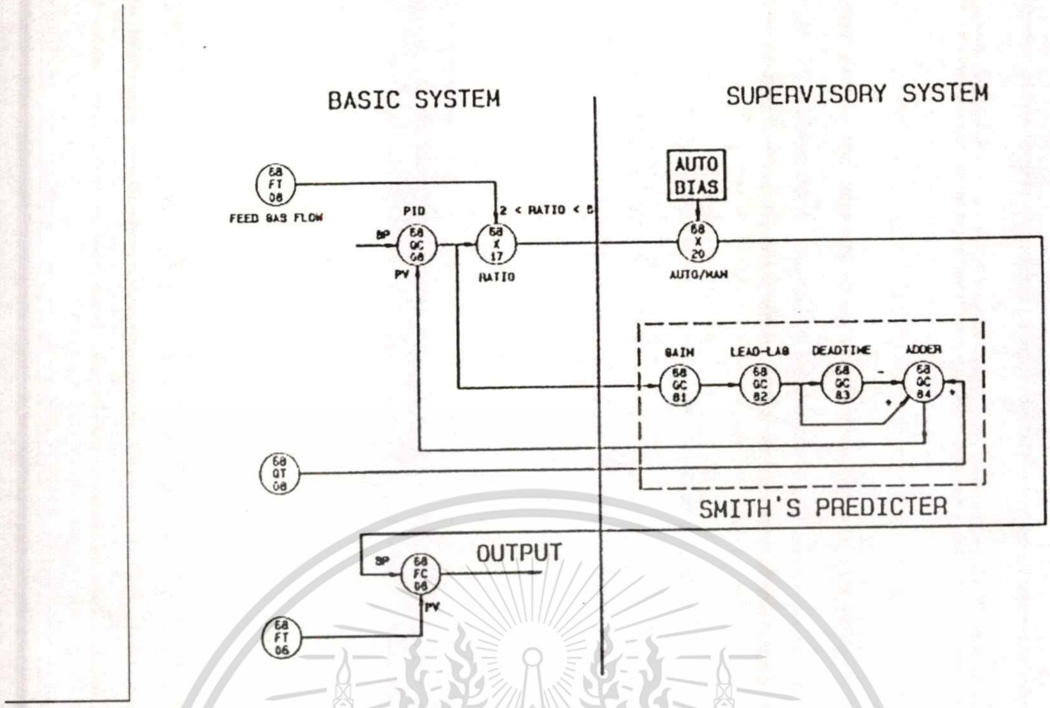

Fig. A.6 Configuration in DCS for ADIP Absorber Process

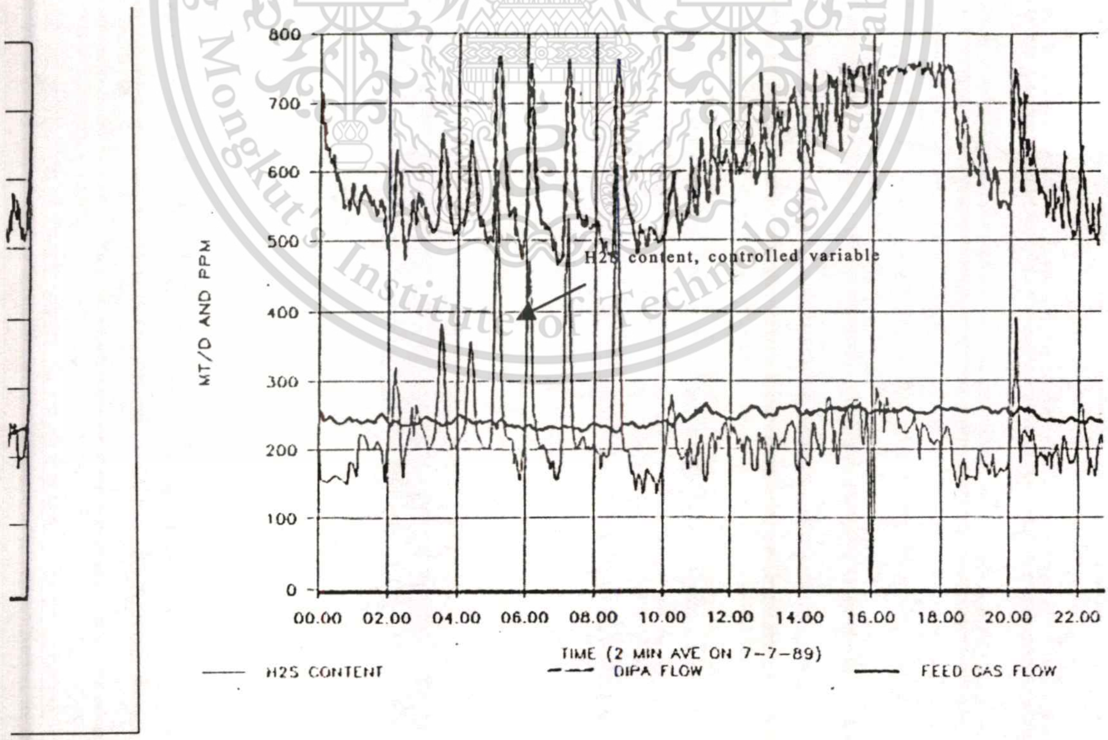

Fig. A.7 The result of non-linear control before Smith Predictor

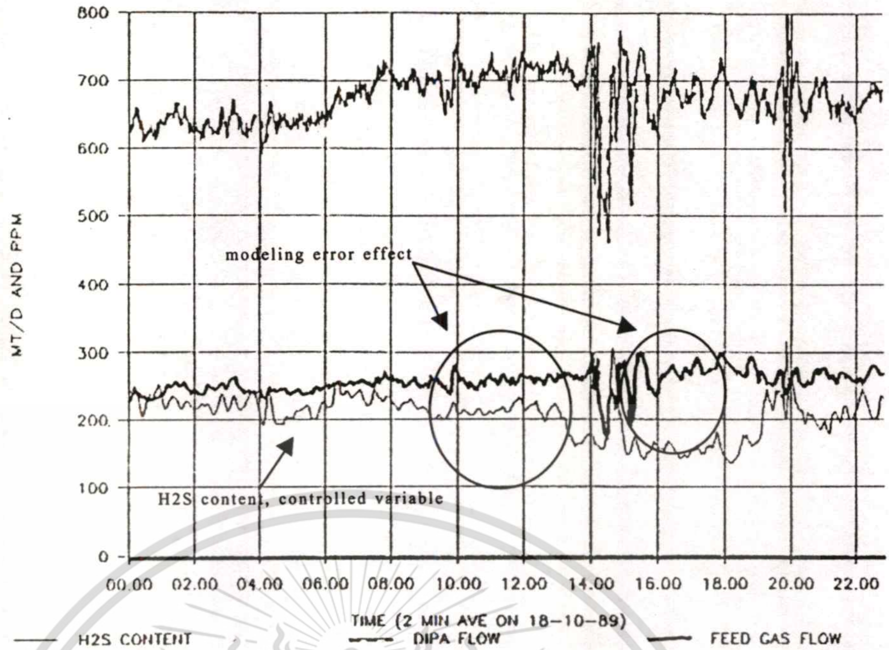

Fig. A.8 Better result from Smith Predictor in ADIP Absorber Process

APPENDIX B

CONTROLLER TUNING RULES FOR THE APPROXIMTE MODEL [1],[8],[13]

Having obtained an approximate model in the form of equation (3.48), Cohen and Coon (and later many others) have developed controller tuning rules based on the approximate model parameters *K*, *Tau*, *D*. Five tuning rules are presented.

A-1 Ziegler-Nichols Approximate Model Tuning Rules

In their classic paper, Ziegler and Nichols also proposed tuning rules designed to provide a quarter decay ratio when an approximate model of the form equation (3.48) is known. Table B.1 provides their guidelines. Smith and Corripio point out that these tuning rules are very sensitive to the time delay/time constant ratio; they recommend these rules be limited to models with $0.1 < (D/Tau) < 1.0$.

Table B.1 Ziegler-Nichols Approximate Model PID Tuning Rules (reinterpreted by Smith/Corripio)

Controller Type	K_c (Controller Gain)	t_1 (Integral Time)	t_2 (Derivative Time)
P	$\frac{1}{K}(\frac{Tau}{D})$	-	-
PI	$\frac{0.9}{K}(\frac{Tau}{D})$	$3.33D$	-
PID	$\frac{1.2}{K}(\frac{Tau}{D})$	$2.0D$	$0.5D$

Table B.2 Cohen-Coon Approximate Model PID Tuning Rules

Controller Type	K_c (Controller Gain)	t_1 (Integral Time)	t_2 (Derivative Time)
P	$\frac{1}{K}(\frac{Tau}{D})\left[1+\frac{1}{3}(\frac{D}{Tau})\right]$	-	-
PI	$\frac{1}{K}(\frac{Tau}{D})\left[0.9+\frac{1}{12}(\frac{D}{Tau})\right]$	$D\left[\frac{30+3(\frac{D}{Tau})}{9+20(\frac{D}{Tau})}\right]$	-
PID	$\frac{1}{K}(\frac{Tau}{D})[\frac{4}{3}+\frac{1}{3}(\frac{D}{Tau})]$	$D[\frac{32+6(\frac{D}{Tau})}{13+8(\frac{D}{Tau})}]$	$D[\frac{4}{11+2(\frac{D}{Tau})}]$

A-2 Cohen-Coon Tuning Rules

Cohen and Coon also developed tuning rules based on the concept of achieving a quarter decay ratio. However, because this criterion does not produce a unique set of tuning parameters, the Cohen-Coon rules given in table B.2 are somewhat different from those of Ziegler - Nichols. Again, these should be applied only for a limited range 0.1< (*D/Tau*) <1.0.

A-3 Time-Integral Tuning Rules

Smith, Murrill and coworkers have developed correlation for PID tuning parameters which minimize integral-time objective such as IAE, ISE, ITAE, and ITSE. Their correlation distinguish between setpoint changes and disturbance-rejection responses. This thesis will present only the ITAE as shown in tables B.3 and B.4 because these are often the best solution in a practical sense and also applied well in this thesis. Again, these shpuld only be applied in the approximate range 0.1< (*D/Tau*) <1.0.

It is particularly interesting to note how these different tuning rules based on somewhat different criteria all depend on the time-constant-to-time-delay ratio. It is therefore easy to say why many practical industrial control engineers consider this ratio to be a very crucial process parameter when it comes to tuning feedback controllers.

A-4 Direct Synthesis Approximate Model Tuning Rules

As shown in chapter 3, given an approximate model as in equation (3.48), it is possible to develop tuning rules for PID controllers based upon requiring a closed loop trajectory $q(s)$ which is 1^{st} order plus time delay with a time constant indicated by the parameter Tau_r. This determines the desired speed of the closed loop response, so that for small Tau_r, the controller will respond more quickly than for larger Tau_r. The tuning rules are given in table B.5

A-5 IMC Approximate Model Tuning Rules

Rivera and Morari et al. have proposed tuning rules for PID controllers based on the Internal Model Control (IMC) methodology. In addition to the model parameters, the designer must select a "filter parameter," λ, which amounts to the desired closed loop time constant for a 1^{st} order response. Hence for λ small, the controller will respond more quickly than if λ is larger. The tuning rules are given in table B.6

A number of other approximate model tuning rules are available, but ones presented here are certainly sufficient to provide a wide choice.

Table B.3 Minimum ITAE-Disturbance Rejection

Controller Type	K_c (Controller Gain)	t_1 (Integral Time)	t_2 (Derivative Time)
P	$\frac{0.49}{K}(\frac{Tau}{D})^{1.084}$	-	-
PI	$\frac{0.859}{K}(\frac{Tau}{D})^{0.977}$	$\frac{Tau}{0.674}(\frac{D}{Tau})^{0.68}$	-
PID	$\frac{1.357}{K}(\frac{Tau}{D})^{0.947}$	$\frac{Tau}{0.842}(\frac{D}{Tau})^{0.738}$	$0.381Tau(\frac{D}{Tau})^{0.995}$

Table B.4 Minimum ITAE-Setpoint Changes

Controller Type	K_c (Controller Gain)	t_1 (Integral time)	t_2 (Derivative time)
P	-	-	-
PI	$\frac{0.856}{K}(\frac{Tau}{D})^{0.916}$	$\frac{Tau}{\left[1.03-0.165(\frac{D}{Tau})\right]}$	-
PID	$\frac{0.965}{K}(\frac{Tau}{D})^{0.855}$	$\frac{Tau}{\left[0.796-0.147(\frac{D}{Tau})\right]}$	$0.308Tau(\frac{D}{Tau})^{0.929}$

Table B.5 Direct Synthesis Approximate Model Controller Tuning Rules

Controller type	K_c (Controller Gain)	t_1 (Integral time)	t_2 (Derivative time)	Additional 1^{st} order filter parameter
PI	$\frac{Tau}{K(Tau_r+D)}$	Tau	-	-
PID	$\frac{2Tau+D}{2K(Tau_r+D)}$	$Tau+\frac{D}{2}$	$\frac{DTau}{2Tau+D}$	$\frac{DTau_r}{2(Tau_r+D)}$

Table B.6 IMC Approximate Model Controller Tuning Rules

Controller Type	Kc (Controller Gain)	t_1 (Integral time)	t_2 (Derivative time)	Recommended Choice of λ ($\lambda > 0.2Tau$ always)
PI	$\frac{Tau}{\lambda K}$	Tau	-	$\frac{\lambda}{D}>1.7$
Improved PI	$\frac{2Tau+D}{2\lambda K}$	$Tau+\frac{D}{2}$	-	$\frac{\lambda}{D}>1.7$
PID	$\frac{2Tau+D}{2K(\lambda+D)}$	$Tau+\frac{D}{2}$	$\frac{DTau}{2Tau+D}$	$\frac{\lambda}{D}>0.25$

APPENDIX C

PUBLISHED JOURNALS

1. **Mongkol Janchookiat,** Prasit Julsereewong, and Kitti Tirasesth
   ***"Robust Smith Predictor"*,** LADKRABANG ENGINEERING JOURNAL, volume 18 number 4, December 2001, pp. 31-36.

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วิศวสาร ลาดกระบัง

คณะวิศวกรรมศาสตร์ สถาบันเทคโนโลยีพระจอมเกล้าเจ้าคุณทหารลาดกระบัง

LADKRABANG ENGINEERING JOURNAL

ปีที่ 18 ฉบับที่ 4 ธันวาคม 2544

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Robust Smith Predictor

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Abstract:

This paper presents an another methodology to apply PID controller to control a dominant dead time process. The model predictive control is a main idea behind for controlling the difficult loop by recording process behavior as a first order process inside PID control configuration. One of a real problem that challenges all process control engineer is to get the accurate process model, which is generally not possible due to too many unmeasured disturbances from the process e.g., heavy rain, equipment's lifetime etc. The unmeasured disturbance can introduce modeling errors and control performance will deteriorate. The robustness of overall control loop can be improved while performance can be maintained by applying Robust Smith Predictor. Tuning for trade-offs will also be described in this paper.

In this study, the control performance of Smith Predictor and proposed Robust Smith Predictor will be described. The Simulink (MATLAB) is a tool to present the comparison.

1. Introduction

The sources of unmeasured disturbances are unknown. The control performance of PID will clearly notice when applying PID to control the difficult loop. The difficult control loops are long process dead time (Dead time/Time constant > 1), inverse response and open loop unstable [1]. The long dead time the low controller's gain the low integral action (long integral time) introduce the low control performance. For other loops (0.1<dead time/time constant< 1.0), PID can fully handle the modeling errors by using feedback control techniques and PID can fast reject any unmeasured disturbances from control variable.

The Smith Predictor is a dead time compensator and given the high control performance if process model and actual plant are identical or slightly mismatch.

To increase the capability of Smith Predictor [2], the Robust Smith Predictor is proposed in this paper. Due to unmeasured disturbance are unavoidable no matter difficult control loops or other control loops. The objective of Robust Smith Predictor is to improve the control performance and robustness to handle as many unmeasured disturbances as possible while the control variable must be well controlled. In this study, it is intended to present the economical and easiest way to construct the control system for overcoming the modeling errors when dealing with the difficult loops as mentioned.

2. Principle of Smith Predictor

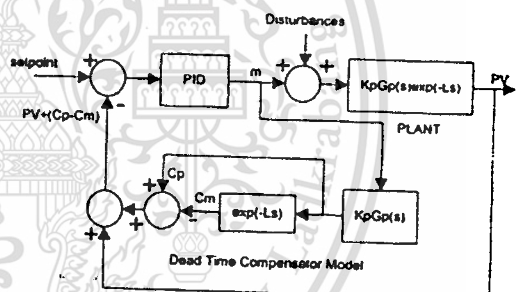

Fig. 1 Smith Predictor control scheme

The control scheme is shown in Fig. 1. PID controller sees no process dead time because the dead time compensator will remove the dead time for PID so that PID can tune fast as if no dead time presented. Technically speaking, PID is tuned to the process model (Cp) not for the plant by ignoring the dead time.

Ideally, only Cp is the input to PID while PV and Cm are perfectly matched if there is no modeling error [3]. If the process gain in model lower than the actual, the loop will start unstable. Also, if the process gain in the model is higher than the actual process, the loop is possible to generate the offset [4]. The robustness to the modeling errors is depended on the tuning parameters. If tight tunings are used the control loop will sensitive even small modeling errors occurs and vice versa.

3. Principle of Robust Smith Predictor

The control scheme is shown in Fig. 2. PIDe (same function as normal PID) is proposed to add into the control scheme to increase the robustness during model mismatch or whenever disturbances entering to the process. If the model is perfectly matched or slightly different, the Robust Smith Predictor gives the same outcome as Smith Predictor. Surely, the model and actual plant always mismatch and PIDe is supposed to work at all time to reject the disturbances from the plant or modeling errors. The output from PIDe is the compensated signal to the final element (e.g. control valve).

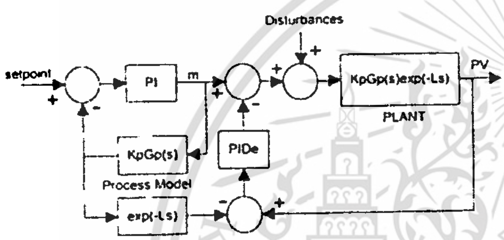

Fig. 2 Robust Smith Predictor

3.1 Unmeasured Disturbance

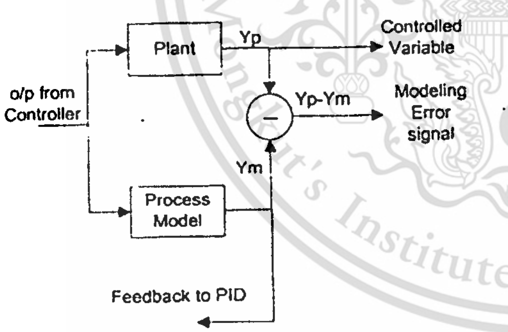

Fig. 3 Model Mismatch

Refer to Fig. 3, for the perfect process model, the difference of Yp and Ym must be zero. But this cannot be true to get the perfect model meaning that the erroneous always appears and the real causes stay by definition unknown.

If the disturbances can be measured the feedforward techniques can be applied. If nothing is done to counter the unmeasured disturbance effect, the offset and instability will be occurred [4].

3.2 Model Mismatch

Process identification is the most important step for model predictive control. It is done by doing open loop response. Introducing a step change at the controller output (most likely control valve) and records the reaction curve from process is the popular way to find the process parameter e.g. process gain, time constant and dead time. The reaction curve is possible to be first order until n-order system but most of the actual plant can be estimated to first order system, which can present most of process behavior from the plant. The model mismatch is unavoidable but it can be minimized by making sure the process value has been in steady state and no disturbance entering to the process for a period of time. Once the process is steady, a step change can be made. The reaction curve must be clear and able to identify undoubtedly.

The step test is recommended to do during normal operation and avoid doing it during heavy rain (abnormal climate) or some of process conditions are out of range. Those lead to have erroneous during process identification. The most accurate model can increase the robustness and performance to the model predictive control like Smith Predictor or Robust Smith Predictor.

3.3 Where to apply Robust Smith Predictor

Only dominant dead time process is recommended. Because there is a limitation for using PID to control this kind of control loop. Most of PID tuning formulae is sensitive to the dead time/time constant ratio. The ratio must be in range of 0.1-1.0 otherwise PID is not suitable [1].

Nowadays, there are a lot more commercial products such as SMOC (Shell Multivariable Optimization and Control) invented by Shell group [4], RMPCT (Robust Multivariable Predictive Control Technology) from Honeywell, etc. that created to overcome the said problems and for multivariable control purpose. But they are of course expensive and worth having when there are numbers of multivariable process control. Most of refineries have those products to specifically control a number of distillation columns. However, the Robust Smith Predictor can be constructed by using the application blocks in DCS (Distributed

Control System) and the outcome is satisfied with the low investment cost.

4. Experimental Results

The tests were carried out with many cases to prove the control performance and robustness. In this section, the results will show clearly how Smith Predictor and Robust Smith Predictor work or react to the setpoint changes, disturbances and modeling errors.

4.1 Configuration

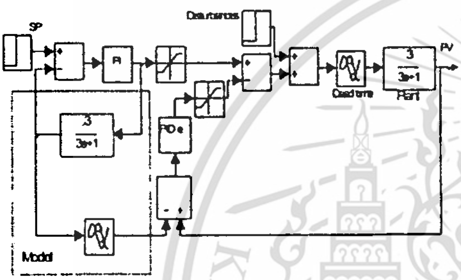

Fig. 4 Robust Smith Predictor configuration

Simulink in MATLAB is used as a tool for configuration, analysis and experimentation. PI is a reverse acting controller sending its output signal to a summing block. PIDe is a direct acting controller sending its output to a same summing block as PI. The summing block is configured the sign as shown in Fig. 4, its output is directly connected to the final element (control valve). Here is the simulation so its output is connected to the dead time and first order blocks represent actual plant model. PV is a process value or controlled variable and fed back to connect to a PV of PIDe. The setpoint of PIDe is a feed back signal from process model. Clearly, PIDe will try somehow to equalize the setpoint and PV. The output from PI is also connected to the input of first order block in the process model through dead time block until finished the loop at setpoint of PIDe.

The control mode of the PI controller is AUTOMATIC mode receiving the setpoint from operator while PIDe is requested to be on CASCADE mode at all time. Because the main control function of PIDe is to always reject any disturbances to the plant.

4.2 Test procedures

In this test, it is used the real process parameters from the plant. The plant is a fuel gas distribution control system. The main producer to the fuel gas header is LPG (Liquefied Petroleum Gas) and NG (Natural Gas). The distance between LPG vessel and fuel gas balance drum is 500 meter. The LPG pressure is 5.5 bar and has a very sluggish response to the fuel gas header pressure. The process model used in this study is LPG pressure to fuel gas header. The actual plant model is process gain = 0.3, time constant = 3.0 minutes, and dead time = 6.0 minutes. That means the normal PID would give the poor control response for this kind of process particularly when the load changes (disturbances). For NG, it has a fast response to the fuel gas header but it is more expensive. The LPG is preferred to control the fuel gas header pressure so that its control response must be improved. This is a case study. The Simulink in MATLAB is used to construct the Smith Predictor and Robust Smith Predictor (as shown in Fig. 1 and Fig. 2) respectively.

The control performance and robustness of both schemes will be compared and explained case by case.

Base Case:

actual plant model: Gp = 0.3, time constant = 3.0 min. and dead time = 6.0 min.
Process model: Gp = 0.3, time Constant = 3.0 min, dead time = 6.0 min.
PID: Gc = 5.0, t1 (integral time) = 3.0 min, t2 (derivative) = 0 min.
PI: Gc = 5.0, t1 = 3.0 min, t2 = 0.0 min.
PIDe: Gc = 0.7, t1 = 6.0 min, t2 = 2.0 min.
Setpoint: changed from 0 to 5.0% at time = 5.0 min.
Disturbance: entered to the process as step in magnitude of –5.0% at time = 70.0 min.

- **Case 1**: No modeling errors

Fig. 5 and Fig. 6 show the control behavior of Smith Predictor and Robust Smith Predictor respectively.

For Smith Predictor, PID sees no process dead time [3,5]. Therefore, Cp is an only input to PID because PV = Cm. PV is fast and smoothly reaches the setpoint and quickly reject the disturbance. The disturbance has small effect to the controlled variable. Smith Predictor gives perfect response.

For Robust Smith Predictor, the control response is almost identical to Smith Predictor particularly on the setpoint changed. No PIDe action before disturbance is entered. The disturbance in the magnitude of –5.0% has a little more impact on controlled variable than Smith Predictor. As mentioned, the main control function of PIDe is to reject any disturbances and give the robustness when process model and actual plant is mismatched. The output signal from PIDe is the response from PIDe to the disturbance (step down 5.0% at t =70 min.). Clearly, the control performance can be improved with a set of tight tuning parameters on PIDe. The tuning techniques will be described later. Carefully consider the control action of Robust Smith Predictor in Fig. 6. PIDe decreased its output due to the disturbance made the controlled variable dropped below setpoint because it is a direct acting controller. But the actual output to the final element is then increased to recover the controlled variable to its setpoint (actual o/p = PI.OP - PIDe.OP, see also Fig. 4 and Fig. 6).

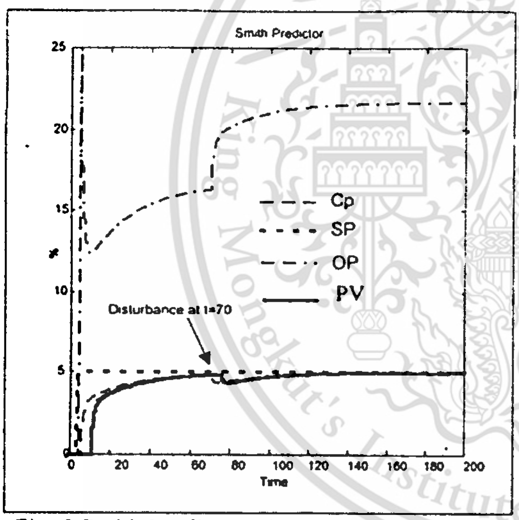

Fig. 5 Smith Predictor when no modeling errors

- **Case 2:** Modeling errors, actual process gain is 3 times higher than process gain in the model

This is an extreme case, assume all conditions in base case remain unchanged except actual process gain in the plant is changed from 0.3 to 1.0. Fig. 7 will clearly present the robustness of Robust Smith Predictor (solid line). It is intended to not fine tune any controllers frequently because practically the actual process behavior can naturally change and vary. Therefore, controllers are supposed to perform satisfactory without paying much effort.

When applying a Smith Predictor, the process model requires updating regularly to maintain control performance and robustness. Similarly, fine-tuning on PID must also be done frequently to keep it well control.

As shown in Fig. 7 (dash line), Smith Predictor gave oscillations when an actual process gain is higher than a designed process gain in the model (higher process gain requires smaller control efforts) because the same tuning parameters of PID act on the higher actual process gain. It is worst to trade-offs between performance and robustness. If the PID is de-tuned, it will give a sluggish response in other cases. Smith Predictor has a limitation in handling the modeling errors while Robust Smith Predictor has PIDe to counter this effect.

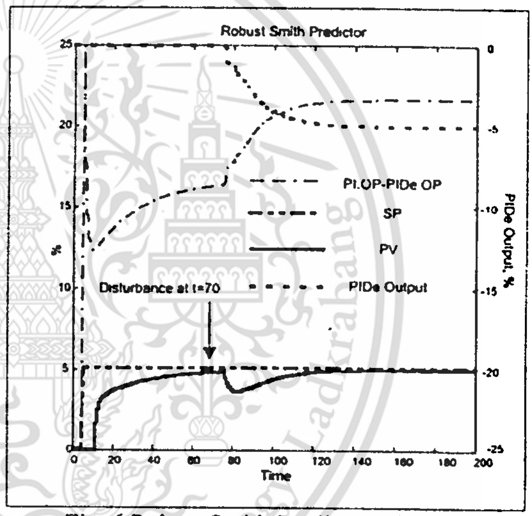

Fig. 6 Robust Smith Predictor when no modeling errors

Refer to Fig. 7, Robust Smith Predictor gives the difference outcome. The tuning parameters in PI and PIDe are kept the same as mentioned in base case. The controlled variable reaches the setpoint smoothly and response well for the disturbance rejection. Carefully attention to the control action of PI and PIDe in Fig. 8, PIDe reacts promptly to the erroneous of the model and suddenly gives the corrective action. PIDe increases its output because the controlled variable is getting higher. An overshoot happens because the same tuning parameters in PI reacts to the higher actual process gain. At the same time, the actual output signal to the final element is then decreased (see Fig. 8) to bring the controlled variable back from overshoot. Again, at time = 70 min. the controlled variable dropped below setpoint (5.0%) due to the disturbance (-5%) entered to the process. PIDe decreases its output because the controlled variable dropped thus makes the actual output increases to maintain process value at setpoint.

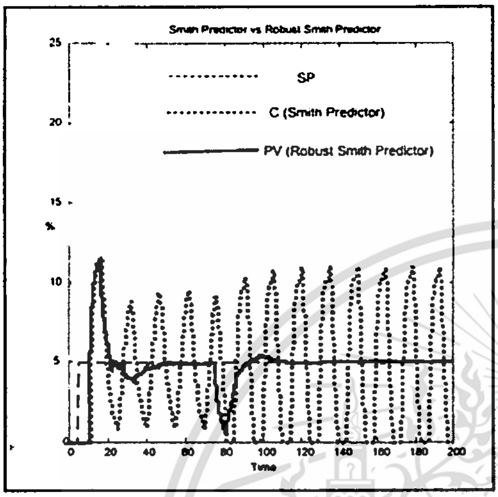

Fig. 7 Comparison when model mismatch

- **Case 3: Recommendation**

This case is quite practical and it could deteriorate the control system. When all three actual process parameters are mismatch in the direction of leading the control instability problem. For instances, higher process gain, smaller process time constant and longer dead time can make control system unstable. Assume the actual process parameters are changed to the worst: process gain changed from 0.3 to 0.6, process time constant changed from 3.0 to 1.0 minute and process dead time is changed from 6.0 to 10.0 minutes.

To make the control system more robust for all cases, it is recommended to set the derivative time (t2) to the value in between zero to 10 percents of Integral Time (t1). In this case, the tuning parameters in PID and PI are unchanged only PIDe is recommended to set derivative action (t2) to 0.6 (10% of t1) and the rest remain unchanged.

Fig. 9 compares the control robustness and performance of both control schemes when all three of actual process parameters are mismatch to the process model. The controlled variable of Robust Smith Predictor is still controlled well and stable even the worst process scenario while the other control scheme is oscillating.

All lines in Fig. 10 are the controlled variable against setpoint changed 5.0% at different process conditions. Process parameters are varied from the based case in the magnitude of +/- 3 times for process gain and +/- 2 times for time constant and dead time of nominal values without fine tuning PI and PIDe.

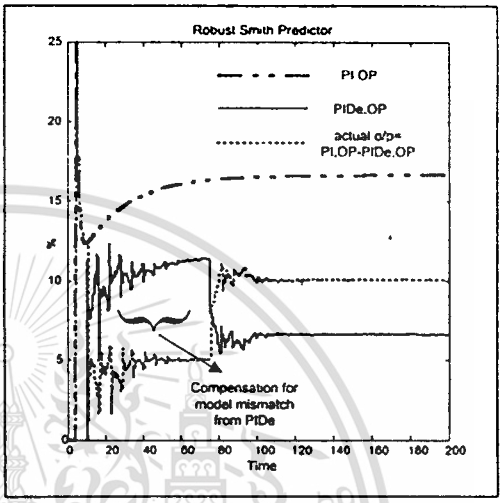

Fig. 8 Control action of Robust Smith Predictor

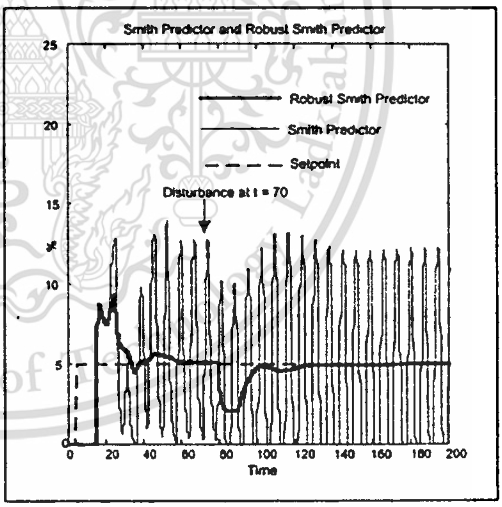

Fig. 9 Smith Predictor versus Robust Smith Predictor

4.3 Tuning Techniques

In this study, minimum ITAE for setpoint and disturbance case [1] is used as a guideline for PI and PIDe respectively. It gives more proper control response than others do such as Ziegler-Nichols and Cohen-Coon.

Refer to process model in base case, PI is tuned to the process model as if no dead time presented. But in the formulae, dead time is always set at least 1.0 minute. Dead time 1.0

minute comes from DCS (Distributed Control System) scanning time and database historian capability. Process gain = 0.3, time Constant = 3.0 minutes and dead time is set to 1.0 minute.

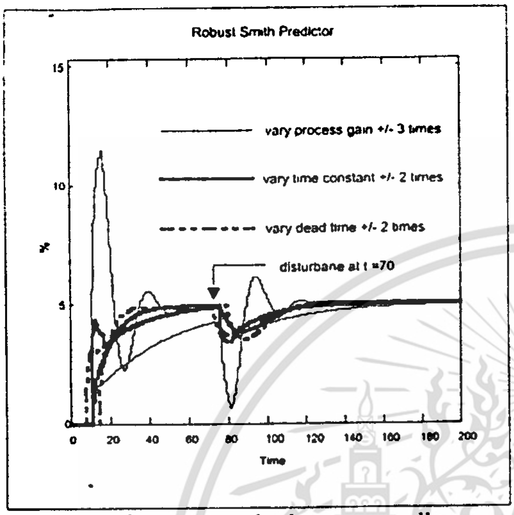

Fig. 10 Performance and robustness to all cases

With these settings, minimum ITAE-SP yields, Kc = 5.0, t1 = 3.0 minutes. They are the tuning parameters of PI.

For PIDe, control engineers must know and understand the process behavior. The assumption should be made to be a design case that how flexibility of Robust Smith Predictor can handle such process parameter variation, says 2 times or 3 times of nominal values. PIDe is then fine-tuned to the worst process parameters.

In this study, process gain is estimated to vary 3 times higher than the nominal value and time constant including dead time are varied within 2 times of nominal value. But from the test, the variation of process gain has more impact on the stability of the system than time constant and dead time. Therefore, PIDe is tuned to the process as follows:

Process gain = 1.0 (assume 3 times of nominal process gain), time constant = 3.0 minutes and dead time = 6 minutes. With the worst condition, minimum ITAE-disturbance yields, Kc = 0.7, t1 = 6.0 minutes and t2 = 2.0 minutes. As mentioned in case 3, for robustness, t2 must be set to the value in between zero to 10 percents of t1. This is the fact found during the experimentation and Fig.10 has proved that with these tuning parameters, the PIDe is able to cope with the wide operating range, says +/- 3 times from nominal values in base case.

Trade-offs between performance and robustness can be done at PIDe with tighter tuning (higher gain, shorter integral time and more derivative action) and de-tuning (lower gain, longer integral time and less derivative action) respectively. Trade-offs is recommended after monitoring its control action for a period of time. It is worth to first make Robust Smith Predictor robust to all cases. Thereafter, performance can be increased while robustness is still maintained.

5. Conclusion

One of the issues that have always arisen in control system design is how sensitive the control system is to expect variations in the process parameters. For example, if PI controller has tuned to a particular loop, how will this control loop behave if process gain changes by 20% or the dead time changes by 30%? This is a question of process sensitivity and the robustness of the control system design. Robust Smith Predictor has developed to address this issue particularly on the dominant dead time process. This is because of inadequate modeling from a set of experimental data set such as step test or pulse test data. Modeling mismatch could be due to unmodeled nonlinearities, poor experimental design, or measurement noise problem that prevent the model from representing all features of the process. Robust Smith Predictor makes use the modeling error signal to input to PIDe. The main function of normal PID is to decrease its error to zero. PIDe makes control loop more robust to any model uncertainties. Performance and robustness will depend on tuning in PIDe.

6. References

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2001	Advanced Process Control M262 Course at Shell Learning Center Netherlands (2 weeks).