STUDIES IN PERFORMANCE MONITORING OF SIMPLE FEEDBACK CONTROL LOOPS

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Summary

With the increasing emphasis on production geared towards a quality conscious market, chemical and related companies are relying more and more on their automatic control systems to maintain and improve product quality. This means that the control systems are expected to deliver high performance on a continuous basis. Even though a process control loop may function well at the time of commissioning, the performance is likely to degrade over time because of changes in the state of the equipment, feed conditions, plant throughput etc. This means that the *health* of the process controllers should be monitored on a frequent basis and corrective action such as controller tuning and hardware (e.g. control valve) checking must be initiated whenever necessary. Research work done in this thesis is motivated by the growing interest among control research community towards performance monitoring of control loops.

The minimum variance benchmark for control loop performance that was first proposed by Harris (1989) and developed further by other researchers (e.g. Desborough and Harris (1992), Stanfelj *et al.* (1993), Huang *et al.* (1997) and Vishnubhotla *et al.* (1997)) is highly suited for this purpose. With only the knowledge of the process time delay, this monitoring methodology can estimate the performance index of a control loop on a scale of 0 to 1. A performance index close to 1 indicates that there is no scope for control performance improvement by retuning the existing controller, while a value close to 0 indicates that retuning the parameters of the current controller will very likely enhance control performance.

In the chemical process industries, well over 95% of the control loops employ PID type controllers. This heavy usage of PID type controllers is expected to continue in the near foreseeable future. The achievable performance possible with a PID type controller is therefore a very important piece of information for the process control engineer. Knowledge of the PID achievable performance will help in knowing when to stop tuning a PID controller in a chemical facility – one should not persist with tuning the PID controller in an attempt to reach a performance index of 1 because that limit might never be reached with a PID type controller.

In this thesis, a method that can determine the PI achievable performance for control loops is proposed. No *a priori* knowledge of the open loop process model is assumed but experimental closed loop data (e.g. set point response data) are employed. It is shown that it is possible to estimate the PI achievable performance without having to determine the open loop process model. In addition to estimating the PI achievable performance, deterministic performance metrics and robustness margins for the "best" PID type controller are also provided. The PID settings obtained are then utilized for tuning the controller and various controller-tuning guidelines are proposed. While performing the optimization to determine the "best" controller parameters, chances of getting trapped in a local optimal solution are rather high. To handle this situation, we advocate the use of multi objective optimization using Genetic Algorithm in the final chapter of this work. Formulation of the objective function and various other issues related to optimization are also discussed.

Nomenclature

a_t : White noise sequence

d : Time delay

F : First (d-1) parameters of closed loop output sequence

G : Closed loop process transfer function

GM : Gain Margin

H : Closed loop disturbance transfer function

H_{approx} : Approximate close loop disturbance transfer function

IAE_d : Normalized integral absolute error

K_R : Process gain of recycle loop

L : Remaining parameters after F

N : Open loop disturbance transfer function

N_m : Approximate open loop disturbance model

PM : Phase margin

Q : Controller transfer function

R : Solution to Diophantine equation on open loop disturbance transfer function

T : Open loop process transfer function

$\tilde{T}$: Delay free process transfer function

T_m : Approximate open loop process model

T_R : Open loop recycle transfer function

y_t : Process output

σ_a^2 : White noise variance

σ_{mv}^2 : Minimum variance

σ_y^2 : Variance of process output

$\eta(d)$: Closed loop performance index

$\eta(d+h)$: Extended horizon closed loop performance index

θ_R : Time delay in recycle loop

τ_R : Time constant of recycle loop

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Agrawal, P., & Lakshminarayanan, S., (2002) Estimating PI Achievable Control Performance Through Analysis of Closed Loop Experimental Data, *Proceedings of International Symposium on Process Systems Engineering and Control (ISPSEC'03),* I.I.T. Bombay, India, Dec

Agrawal, P., & Lakshminarayanan, S., (2003) Tuning PID Controllers using Achievable Performance Indices, *Ind. and Eng. Chem. Research, 42 (22)*, pp. 5576-5582.

Agrawal, P., & Lakshminarayanan, S., (2002) PI / PID Achievable Control Loop Performance for Processes with Recycle, *Proc. of PSE Asia, Taipei, Taiwan, Dec 4-6*

Madhukar, G.M., Dharmesh, G.B., Agrawal, P. and Lakshminarayanan, S., (2003) Feedback Control of Processes with Recycle: A Control Loop Performance Perspective*, Submitted to Chemical Engineering Research and Design*

Chapter 1.

Introduction

The activity of process control is to take information from the process using sensors located in the plant and provide commands to the actuators with a view to maintain the plant at desirable performance levels. Various control algorithms implemented using different control configurations are utilized in achieving this. This whole task may involve various steps starting from the selection and location of sensors, control valves, process modeling, control structure selection (e.g. loop pairing), controller design (type of controller e.g. PID), implementation and tuning. In this already long list of tasks, control loop performance monitoring, troubleshooting and maintenance are to be included as well.

Various desirable performance specifications are provided for the control system. A few examples are:

- Load rejection: Load disturbances and noises acting on the system should have minimum effect on the controlled variables.
- Servo Response: Controller should closely follow the changes in output targets without undesirable levels of overshoot and oscillations.
- Constraints on actuator moves: valve movement should not be excessively wild and should remain within allowable operating limits.
- Robustness: Over the period, the process is susceptible to perturbations due to changes in operating conditions, equipment fouling, nonlinearities, sensor or

actuator failure etc. The control system must deliver satisfactory performance in any such eventuality.

Other controller specifications are possible. Unfortunately many of these performance targets are conflicting in nature. Arbitrarily selected performance targets may not provide a feasible solution. If the selected solution is feasible, there should be an analytical technique to reach the solution in efficient and reliable manner. Also, simply specifying performance targets does not mean that they will be achieved in practice. Problems such as model-plant mismatch, nature of disturbances, nonlinearities etc. may limit the achievable performance.

Coming to the issue of performance monitoring of control loops, it is easy to understand that a suitable benchmark is needed. The performance of a controller could be compared against the desired performance expected from it. Alternatively, its performance may be compared with a universal or theoretically “best” benchmark (like the Carnot engine in thermodynamics). Since the specifications are conflicting in nature, the benchmarks for each of the specifications are bound to contradict one another. Therefore a few questions need to be answered before developing the framework for performance monitoring of control loops.

1) What should be the suitable performance benchmark (selection of benchmarks)?
2) How to monitor performance with respect to benchmark (procedure)?
3) How to tune the controller to achieve the best possible performance?
4) How to formulate and solve the problem analytically for this purpose?
5) What are the main constraints to the performance improvements?

This work aims to provide partial answers to some of these questions. Chapter 2 deals with questions 1 and 5. Chapter 3 focuses on the performance monitoring issue of PID type controllers (related to question 2). Chapter 4 deals with answering question 3 for PID type controllers. Chapter 5 provides discussion on formulation and global optimization issues of the loop monitoring and performance enhancement problem using genetic algorithm, which is the answer to question 4.

Chapter 2.

Performance Monitoring of Control loops: a review

2.1 Introduction

Control loop performance monitoring (CLPM) has been a very active area in the last decade. The emergence of highly sophisticated data acquisition and control systems, development of various analysis tools and rapid growth in computational power has fuelled research and application activity in this area. It is well known that actual benefits from advanced process control (APC) implementations can be realized only if the base level control loops are performing well. Chemical industry's growing dependence on MPC has raised the demand for including CLPM as a part of APC package. The quantum of interest by both academia and industry was seen at the Chemical Process Control VI Conference (CPC VI) (Tucson, 2001) where an entire session was devoted to the topic of controller performance monitoring. More insights of this topic can be gained from review papers and monographs such as Qin (1998), Harris et al. (1999), Huang and Shah (1999) and Kozub (2002). The purpose of this chapter is to provide a discussion on the reasons for limitations to the controller's performance, overview of the CLPM area, presently available methods and future challenges. This chapter also addresses questions 1 and 5 that were listed in the earlier chapter.

2.2 Fundamental obstacles to the performance of controllers

Any controller design procedure must take into consideration the different types of process dynamics, disturbances, uncertainties, actuator limitations, critical nature of the process etc. The controller is expected to achieve desired performance targets in the presence of these issues and difficulties. The full control design problem is quiet complicated and is beyond the scope of this work. There are various methods to estimate the optimal performance of any given control structure. Boyd and Barratt (1991) provide a good discussion of this problem. The question is: "For a given type of process, is it possible to say what is the best possible control performance (irrespective of the controller type) that can be achieved?" While this question cannot be answered so easily, it is obvious that the answer to this question can provide a very good performance benchmark for any control structure.

The limitations to the control system performance can be factored into two components: limitations due to the inherent process structure and limitations due to the control structure. These two issues are discussed in turn below.

2.2.1 Performance limitations due to inherent process structure

Irrespective of the control structure, the process itself may pose formidable challenges to the performance of the controller. Generally, this issue is given very limited attention in the literature (e.g. Bode (1945), Freudenberg and Looze (1985), Meddleton (1991)). Aström (1995) provides a good review on these limitations and also discusses solution to several such problems, mainly based on the work by Bode. A few process inherent limitations are: non-minimum phase systems (system with zeros in right half plane or with dead time), system with poles in right half plane etc. These inherent limitations have always been a challenge for control engineer. Frequently, the best solution to the controller design desires the inverse of the process transfer function. Taking inverse of process transfer function might lead to causality problem if these inherent limitations are present in process. In other words, phase lag/lead offered by above-mentioned limitations gives upper or lower bounds to the achievable bandwidth.

2.2.2 Performance limitations due to controller structure

Different processes and performance specification require different controller structures and controller tuning parameters. Each control structure imposes limitations to performance e.g. a proportional only controller cannot remove offset, a PID controller cannot provide high performance control on significantly nonlinear processes (some nonlinear control scheme is required). For a given type of process and performance requirements, what is the suitable control structure? This problem can be called the *controller design problem* if one was to take a broader view of "process control". In practice, a very small number of processes require complicated control structures or control algorithms. Most often, linear time invariant (LTI) controllers such as the PID controller works fine (as long as they are properly tuned). Complicated control structures are not desired because while high performance is required, issues such as easy implementation, low maintenance requirements and high reliability are equally important. Discussion about controller structure design can be found in many standard control textbooks e.g. Marlin (1995) and Seborg et al. (1999). Various methods have been proposed to provide optimal solutions to the controller performance limitations e.g. Boyd and Barratt (1991), Newton et al. (1957).

Knowledge of the limits imposed by the control structure is very necessary while deciding the controller performance targets. It is important to know what set of specifications are achievable and what set of performance specifications are unrealistic while designing and assessing the performance of the controller. An analytical approach as opposed to the frequently employed trial-and-error approach should be preferred. Obtaining solution to full performance capabilities, tradeoff between various performance targets and the successful use of optimization methods are a major challenges. There is some classic work in this area: solutions to convex optimization problems are given by Boyd and Barratt (1991), integral theorem by Bode and further extension by Zames (1981), discussion on tradeoffs by Middleton (1991), optimal solution techniques by Skogestad (1996), etc. In this thesis, performance limitation of PID type controllers and algorithm to calculate PID achievable targets using closed loop data are the primary focus. Some of the issues related to performance tradeoffs and optimization techniques have also been investigated.

2.3 Selection of a suitable benchmark

Even though a process control loop may function well at the time of commissioning, its performance is likely to degrade over time because of changes in the state of the equipment, feed conditions, plant throughput etc. This means that the *health* of the process controllers should be monitored on a frequent basis and corrective action such as controller tuning and hardware (e.g. control valve) checking must be initiated whenever necessary. This is the area of control loop performance monitoring (CLPM). To initiate the CLPM, there is a need to have a suitable performance-monitoring framework. Various development stages and requirements for this framework are discussed below.

2.3.1 Historical development of the CLPM

Historically, for evaluating performance of control loops, analysis of qualitative trends in process data and human intuition have played a big role in the monitoring of control loops. This approach is no longer practical considering that a typical operator in the control room is responsible for about 200 (typical refinery) – 1000 (pulp and paper mills) control loops. Field check of control valve movement, step response of the control loop in closed and/or open loop condition are also used for monitoring control loop in question. These measures will be applied on demand to diagnose poorly performing controller, particularly when it pertains to a critical controlled variable. For regular CLPM, methods such as basic controller statistics are very frequently applied e.g.

a) On / off time of the controller commonly referred to as the “percentage up time” of the controller.
b) Percentage of time the control variable is inside or outside the constraints.
c) Number of times the controlled variable crosses the set point.
d) Mean and variance of the process output.

Quantitative analysis of process output variable is also considered. Aström (1970) employed the autocorrelation plot from closed loop process output data for loop performance monitoring. If the autocorrelation is significant even beyond the dead time of the process and decays very slowly, then it represents poor controller performance. If the controller is unstable, except for the presence of integrators in disturbance, then the observed closed loop may appear to be a moving average process of order less than dead time (Foley and Harris (1992)). Except in these rare cases, autocorrelation test works very efficiently to check if the SISO process is working at minimum variance performance. Devries and Wu (1978) used closed loop data to assess MIMO control performance. They used spectral analysis to diagnose the root cause of poor performance. They also estimated lower bound to the variance considering no delay in the process. Tyler and Morari (1995) proposed use of likelihood ratio to determine if control loop performance is acceptable or not. Kendra and Cinar (1997) discussed the use of frequency analysis approach for CLPM.

The information generated from above mentioned methods is important and provides a lot of insight to the control loop performance. However, they do not offer any suitable approach to *diagnose and improve* the health of the controller. These methods provide no idea of the capability of the control system, quantitative performance statistic of the controller nor do they diagnose the root cause of the problem. Overall, it can be said above-mentioned techniques do not use statistics to explore the full potential of the available process data. The obvious question then is "how should the performance monitoring be performed?"

2.3.2 CLPM Guidelines

There are several thousand loops in a typical refinery. It is well known that in a typical process plant several control loops may be performing sub-optimally at any given time. It is reported that as many as 60% of all the industrial controllers have some kind of problems. Please refer Bialkowski (1993), Ender (1993), Rinehart and Jury (1997) and most recently Van Overschee and De Moor (2000), Desborough and Miller (2001). Poor control performance directly transforms to reduced safety and profit and increased environmental losses. Manual monitoring of such control loops is virtually impossible considering the several ten thousand control loops in a typical chemical facility. It is necessary to have a quick, reliable and computationally effective method to provide the initial screening of these loops and isolate loops that are performing badly and need further attention. Very few control applications require sophisticated control schemes and hence more sophisticated scheme for performance monitoring. In most cases, process controllers are of PID type and a generally acceptable method for control loop performance monitoring can be implemented to handle most of the controllers in a typical plant.

Based on the work done by various researchers over the past decade (e.g. Kozub and Garcia (1993), Kozub (1997)), Harris (1999) provides guidelines for an effective plant wide control monitoring and performance assessment package.

1) Automated background operation, including scheduled remote collection of control loop data and data integrity checks.
2) Theoretically sound, efficient, and automated computational procedure.
3) Decision support (for example; problem reporting by exception)
4) Technical support
5) Suitable user interface.

Together, these properties form the basis of a comprehensive control performance monitoring and assessment system. The statistical tools chosen for performance monitoring should be compatible with the above guidelines. Methods that can provide control loop performance measure based on routine operating data alone are the most useful for this initial screening. The minimum variance benchmark for control loop performance that was first proposed by Harris (1989) is highly suited for this purpose. With only the knowledge of the process time delay, this monitoring scheme can estimate the performance index on a scale of 0 to 1. A performance index close to 1 indicates that there is no scope for control performance improvement by retuning the existing controller while a value close to 0 indicates that retuning the parameters of the current controller is very likely to enhance the control performance.

2.3.3 Minimum Variance Controller

An approach that has become very popular in the determination of the control loop performance measure (e.g. Harris (1989), Desborough and Harris (1992), Stanfelj *et al.* (1993), Huang *et al.* (1997) and Vishnubhotla *et al.* (1997)) will now be outlined. This method uses the performance of the linear Minimum Variance Controller (MVC) as the benchmark against which the performance of the current controller is evaluated. It is generally undesirable to install a MVC in practical applications as it may result in excessive or aggressive control actions that can damage or limit the life length of final control elements. It also has very poor robustness characteristics. Also, if the process has non-invertible zeros (zeros outside the unit circle), it is not possible to design a minimum variance controller (most of these shortcomings can be overcome by suitable modifications to the basic MV control law). Despite these drawbacks, one can exploit the property that the MVC provides a fundamental lower bound on the achievable process variance by linear feedback control alone. Armed only with the knowledge of the process delay, this minimum bound can be obtained in a non-intrusive way through the application of time series analysis techniques. The MVC benchmark method constitutes a quick yet powerful tool in the screening and analysis of poorly performing control loops.

- To begin with, let us consider a regulatory control system (see Figure 2.1)

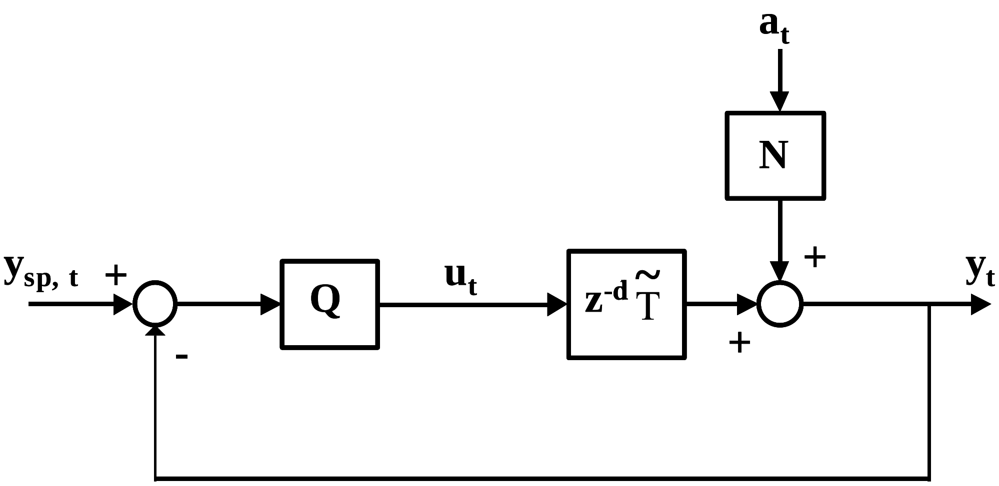

Figure 2.1 Block Diagram of a basic closed loop system

Under these circumstances the process output y_t can be expressed in terms of the transfer functions and the white noise signal a_t as:

$$y_t = \left\{ \frac{N}{1 + T\,Q} \right\} a_t = \left\{ \frac{N}{1 + z^{-d}\,\tilde{T}\,Q} \right\} a_t \qquad (2.1)$$

Let us factor the transfer function N as

$$N = F + z^{-d}\; R \qquad (2.2)$$

where $F = F_o + F_1 z^{-1} + \ldots\ldots + F_{d-1} z^{-(d-1)}$ and R is some appropriate transfer function. y_t may now be written as

$$y_t = \left\{ \frac{F\left(1 + z^{-d}\ \tilde{T}\ Q\right) + z^{-d}\ R - F\ z^{-d}\ \tilde{T}\ Q}{1 + z^{-d}\ \tilde{T}\ Q} \right\} a_t \qquad (2.3)$$

which can be collapsed into

$$y_t = \left\{ F + \frac{z^{-d}\ \left(R - F\ \ \tilde{T}\ Q\right)}{1 + z^{-d}\ \tilde{T}\ Q} \right\} a_t \qquad (2.4)$$

Consequently,

$$y_t = F\ a_t + \left\{ \frac{\left(R - F\ \ \tilde{T}\ Q\right)}{1 + z^{-d}\ \tilde{T}\ Q} \right\} a_{t-d} = F\ a_t + L\ a_{t-d} \qquad (2.5)$$

It is interesting to note that the polynomial F is independent of the controller Q and hence is termed as the *controller invariant part* of y_t. L, among other things, depends on Q. It is easy to note that if $Q = \frac{R}{\tilde{T}\ F}$ then L = 0 in which case y_t = F a_t. This choice of Q gives us the Minimum Variance Controller (MVC); the output variance under MVC is:

$$\sigma_{mv}^2 = \mathrm{var}\left(y_{t,MVC}\right) = \left(F_0^2 + F_1^2 + \cdots + F_{d-1}^2\right)\sigma_a^2 \qquad (2.6)$$

Notice that the variance of the signal a_t is denoted as σ_a^2.

For any other choice of Q, we have L ≠ 0 and

$$y_t = \left\{ \frac{F + z^{-d}\ R}{1 + z^{-d}\ \tilde{T}\ Q} \right\} a_t \qquad (2.7)$$

We then have

$$\sigma_y^2 = \mathrm{var}\left(y_t\right) = \left(F_0^2 + F_1^2 + \cdots + F_{d-1}^2 + L_0^2 + L_1^2 + \cdots\right)\sigma_a^2 \qquad (2.8)$$

If the closed loop system is stable, the above series converges to a finite value. However, this finite value will be larger than or equal to σ_{mv}^2. It is therefore understandable why $Q = \frac{R}{\tilde{T}\ F}$ is called the *minimum variance controller*. Any other controller will result in an output variance that exceeds this minimum variance. The minimum variance controller thus qualifies as a theoretically sound benchmark for the performance monitoring of linear time-invariant feedback controllers.

The closed loop performance index η using MVC as benchmark can be given as

$$\eta(d) = \frac{\sigma_{mv}^2}{\sigma_y^2} \tag{2.9}$$

where d represents the process delay (assumed to be known) and σ_y^2 represents the actual process output variance. σ_{mv}^2 can be computed from a time series model for y_t once the time delay d is known. The control loop performance index η(d) is therefore the ratio of the sum of squares of the first d closed loop disturbance impulse response coefficients to the sum of squares of the complete closed loop disturbance impulse response coefficients. Knowledge of the closed loop disturbance impulse response is all that is needed to compute the performance index.

2.3.4 Properties of CLP Index

If the actual process variance is close to the theoretical bound σ_{mv}^2, then one can conclude that the process output variance cannot be reduced by retuning the existing feedback controller. In such cases, improvement in process output variance can only be realized via process modifications, reduction of disturbances affecting the process etc. However, if the current performance is significantly poor compared to the MVC performance, this is a clear indication that the loop under question needs attention -

this may be due to poor tuning, hardware problem (e.g. sticking valve), process constraints, large time delays, presence of non-invertible zeros etc. These kind of control loops should be carefully examined by suitable identification experiment and if loop retuning cannot or does not result in improved performance one must investigate the necessity for feed forward controllers, cascade control, sensor and actuator relocation, maintenance of hardware or even a process revamp.

Huang and Shah (1997) and Harris (1999) reported various properties of the CLPI. Thornhill et al. (1999) provided discussion on issues such as selecting the data record length, sampling interval, model order, and an analysis of the effect of data compression on the computation and interpretation of CLPI. Desborough and Harris (1992) provided crude bounds for the confidence interval of CLPI. They showed that the choice of various parameters such as data length and model orders affect the confidence interval of the CLPI. They also provided sampling properties and spectral interpretation of CLPI estimates. Since the equation for minimum variance controller requires the inverse of the delay free part of the process model, it is impossible to implement a minimum variance controller if the process transfer function is non-invertible. For such cases, Bergh and MacGregor (1987), and Harris and MacGregor (1987) proposed a modified minimum variance controller using spectral factorization methods.

Stanfelj et al. (1993) extended the MV benchmark to feed forward *plus* feedback systems. They point out an important limitation in diagnosing poor controller performance. Poor feedback controller performance can be attributed to modeling error or poor controller tuning or inadequate control structure if measured external perturbations enter the feedback system. Normal operating data from a feedback system without any measured external perturbations cannot provide information for such a diagnosis. The issue of deterministic disturbances vs. stochastic disturbance still remains a challenge. Eriksson and Isaksson (1994) showed that it is possible to separately analyze the performance against stochastic and deterministic disturbance. This separate modeling can be done using intervention analysis (Box and Tiao (1975), Krishnamurthi et al. (1989)).

Besides the well known definition of CLPI ($\eta(d)$), an extended horizon performance index $\eta(d+h)$, was also used by Desborough and Harris (1992,1993), Kozub (1997) and Thornhill et al. (1999):

$$\eta(d+h) = 1 - \frac{1 + F_1^2 + ... + F_{d-1}^2 + ... + F_{d+h-1}^2}{1 + F_1^2 + ... + F_{d-1}^2 + F_d^2 + ...} \qquad (2.10)$$

The extended horizon performance index decreases monotonically with (increase in) the horizon h. Harris et al. (1996) provides a discussion on theoretical consequences of using positive values of h. It is shown by Thornhill et al. (1999) that calculation of the process dead time for each control loop may be time consuming and that the extended horizon performance index could instead serve as the engineering criteria. They also provide a discussion on interpretation of extended horizon performance index plots and show that these plots can help in solving many control performance problems.

2.3.5 Extension of SISO CLPI (η) to MIMO systems

While the derivation and concepts related to the SISO MVC is relatively straightforward, the multivariable extension of this problem is far more challenging from both theoretical and practical viewpoints. Several researchers have proposed methods for MIMO performance monitoring e.g. Harris et al. (1996), Huang et al. (1997), Huang and Shah (1999), Ko and Edgar (2001a) and Seppala et al. (2002). Huang and Shah (1999) have used weighted output error variance metric for MVC based benchmarking of MIMO loops. This is because such a strategy closely relates to the cost function employed in multivariate, unconstrained linear quadratic controller designs. This solution requires the computation of the unitary interactor polynomial matrix (the multivariate generalization of the univariate time delay) from the process transfer matrix (or from experimental closed loop data) and the solution of a polynomial, multivariable Diophantine equation. Ko and Edgar (2000) discussed CLPM for cascade control using multivariate time series modeling of primary and secondary measurements collected under normal operation. Theoretical developments as well as industrial applications of MIMO controller monitoring is still fairly limited and the tools are still under development. Recently, Kozub (2002) discussed the limitations of MIMO CLPM. This work highlighted the fact that MIMO controller monitoring is far more involved relative to the SISO case and hence the methods and applications will take more time to reach a state of maturity.

The performance monitoring of advanced process controllers is a very important problem for both academia and industry owing to the importance of model predictive control (MPC) implementation in the chemical industry. Unfortunately, there is very limited work in monitoring performance with hard constraints of MPC system. Ko and Edgar (2001) showed some studies of performance monitoring of constrained MPC. Kozub (2002) discussed issues related to CLPM of MPC system in a MVC framework. Clearly, this area is still wide open for research.

2.3.6 PID achievable performance as a benchmark for CLPM

The minimum variance benchmark provides a theoretical upper limit on control loop performance. However, a minimum variance controller is never implemented in practice owing to its poor robustness properties. In the chemical process industries, well over 95% of the control loops employ PID type controllers. This heavy usage of PID type controllers is expected to continue in the nearly foreseeable future – simplicity of the controller structure, vast amount of accumulated experience in using and tuning them, ability of the PID controller to provide a good quality of control in a majority of situations all make the PID the workhorse of the chemical industries. The achievable performance possible with a PID controller is therefore a very important piece of information for the process control engineer. Knowledge of the PID achievable performance will help in knowing when to stop tuning a PID controller in a chemical facility – one should not persist with tuning the PID controller in an attempt to reach a performance index of 1 because that limit can never be reached with a PID type controller. Eriksson and Isaksson (1994) discussed this point and recommended use of PID achievable performance as a benchmark. Their criticism of MVC was that if retuning were warranted in an industrial control loop, the control engineer would be reluctant to implement a PID controller knowing that its performance in presence of non-stationary disturbance would be very poor.

Ko and Edgar (1998) developed a method called “Approximate Stochastic Disturbance Realization (ASDR)” to determine the PI achievable performance using routine closed loop data. Because routine operating data is employed to determine the limit of performance, they need to assume complete knowledge of the open loop process model. Their method works well as indicated in the case studies considered in their paper. However, knowledge of the open loop process model is often unavailable and this restricts their use in an industrial setting. Agrawal & Lakshminarayanan (2002a) proposed a method to determine the PI achievable performance for control loops without knowledge of open loop process model. Considering the practical importance of PID achievable performance limits, it has been chosen as performance benchmark in this thesis. Methods have been proposed to determine the PI achievable performance for control loops with / without knowledge of open loop process model and also in presence of recycle dynamics.

2.4 Status of CLPM in industry

Today's industry slogan is "do more with less". Higher quality and low cost driven market is forcing the control engineer to look for poorly performing control loops and fix them quickly. This task eats up most of the resources available with smaller and "rightsized"[1] process control groups in plant. This situation emphasizes an immediate need for automated CLPM tools in the process industry. To fill this void, several business enterprises have come out with CLPM tools. MATRIKON Consulting Inc. developed and markets a tool called ProcessDoc (1997). Miller et al. (1998) described a comprehensive system for CLPM (LoopScout™) developed by Honeywell HI-Spec Solutions (Thousand Oaks, CA). Harris et al. (1999) discussed many industrial applications and outlined the challenges for large-scale CLPM relevant to the industries. It was shown that any performance measure chosen for CLPM should match with the objectives for which the control system was implemented. The invasiveness required for obtaining the measure (off-spec production during dynamic

[1] often employed as a euphemism for "downsized"

experimentation if the process model is required) and its complexity (computational effort and *a priori* process knowledge) are also very relevant issues to be considered.

The MVC based CLPI benchmark fits these requirements very well and many industrial case studies have been reported in literature based on this theory. Kozub (1997) shared his experiences through an industrial case study. Thornhill et al. (1999) discussed implementation of CLPM in a refinery setting. Haarsma and Nikolaou (2000) discussed their experiences of MIMO CLPM on an industrial (snack food) process. Paulonis and Cox (2003) discussed their experiences in indigenous development of a large scale (14000 PID loops in 40 plants at 9 sites) CLPM system in Eastman Chemical Company, USA. Besides user interfacing, networking, compatibility issues, the salient feature of their system are a) it ranks loops by performance b) it performs preliminary problem diagnosis for poorly performing loops. They reported that one Eastman site has been using CLPM system for over two years. In that site, over the last year, off-class production due to process control related causes has been reduced by 53%. The standard deviation of primary specification of main product has been reduced by 38%. That site has advanced from the 40^{th} percentile to 75^{th} percentile of all Eastman process plants worldwide in overall controller performance. This is indicative of the fact that a well thought out and well-implemented CLPM program will yield benefits consistent with six sigma practices.

2.5 Future directions

In the last decade, significant developments have happened in the area of control loop performance monitoring. With increasing number of publications from academia and industrial implementations being reported, future development in this area is bound to be very exciting. Process variability reduction has been identified as a main priority in evaluating performance at the base control layer level. Harris and Seppala (2002) have summarized recent developments in controller performance monitoring and assessment techniques. There are enormous number of challenges left in theory as well as application of these methods.

MIMO performance monitoring especially in the framework of MPC is still a major challenge. Many process plants have real time optimizer (RTO) and CLPM for RTO's have not been studied properly. Suitable performance benchmarking method for MPC and RTO's can be taken as active research area. How the active constraints affect the performance of MPC or RTO? How often does the optimization system shift the constraint set? Are the outputs of the optimization (typically set points) being adjusted in a timeframe that the control system can respond? Is there cycling in the outputs of the optimization? How can one tell if the optimization algorithm is in fact helping the process enterprise realize an economic objective?

Multi-loop PID controllers are most often used in practice. Their performance monitoring in MIMO environment needs to be done. Methods that can identify which loops should be tightly tuned and whether the controller structure is adequate or not may prove very useful. How much performance improvement will be there if one shifts to higher-level control scheme? (e.g. from multi-loop PID to MPC, simple feedback loop to cascade control etc.) would be some of the immediate questions that need to be answered.

Root cause analysis of the control loops needs to be explored in detail. When the controlled variability displays high variability it is important to know what is hurting the closed loop performance? Is it a tuning issue, the problem due to a sticking valve, control structure inadequacy or the impact of an external disturbance? Is it possible to locate the source of variability in process plant from routine data? It is of significant interest to know the common disturbances that impact the many control loops in a process unit. Is it possible to prioritize the control loops in the order of importance and shift the variability from the more critical to the less critical control loops? What is the effect of deterministic disturbances and how to resolve it from CLPI calculation without extensive modeling? What technique will work well for a regular deterministic disturbance - a feed forward controller or a cascade controller?

The extension of the MVC based benchmarking scheme to nonlinear systems needs to be studied. Pattern of nonlinearities can offer important clues for root cause analysis of control system. Statistics and qualitative shape analysis techniques (Rengaswamy et al. (2001)) for CLPM can be explored further. They might be utilized for proactive failure prediction in control loops.

Variability is not the only performance specification for controller design. Under special circumstances (e.g. if disturbance is stationary), the controller can have CLPI close to 1 but can exhibit poor deterministic performance (e.g. closed loop rise time or integral absolute error (IAE) etc.). There is a clear tradeoff between these performances and both (performance against stochastic and deterministic disturbances) are required properties. A method that can give performance measures for stochastic as well as deterministic settings will be valuable for CLPM. Also well known is the tradeoff that exists between robustness and performance. A balanced approach needs to be taken while doing control loop benchmarking. Studies that can consider performance tradeoffs between different performance objectives during CLPM are necessary.

There are practical challenges like development of a framework for automatic data collection, data filtering, suitable modeling, robust optimization, fault detection, reporting etc. Issues like operator acceptance, reliability of the results, maintenance, and system integrity etc. will remain to be resolved.

2.6 Conclusions

It is visible that the success stories of implementation of control loop performance monitoring have started to come from industry. The process industry is close to adapting CLPM as a standard feature for the control systems. Theoretical developments are coming from the academia at a rapid pace. Still there are many theoretical and practical challenges that need to be resolved. Minimum variance benchmark has been used extensively for CLPM in the existing commercial software but a more suitable benchmark like PID achievable targets should be used. This would be better and realistic in plants that are predominantly regulated using PID controllers.

Consideration for other performance tradeoffs e.g. robustness and performance should be given. Most of the problems are multivariable in nature and there is a lot of scope for developments in the MIMO domain. Automatic fault detection and PID tuning can reduce the load of process engineer considerably and proper framework including man machine interface MMI) should be developed.

Chapter 3.

PID achievable performance of simple feedback control loops

3.1 Introduction

More than 90% of controllers in the chemical industry are of PID type without time delay compensation. Due to inherent controller structure limitation (chapter 2.2.2) no matter how much tuning is applied on PID controller under some conditions (high process time delays and non-stationary disturbance dynamics) they cannot perform exactly as minimum variance controller. Using MVC benchmark for performance monitoring of PID type controller may provide wrong impression of the health of controller (The idea discussed in the section 2.3.6). Therefore problem of calculating PID achievable performance target is of practical importance. Simple, efficient and non-invasive technique is required to monitor the PID achievable performance (Chapter 2.3.2 CLPM guidelines).

Based on the information available from the process plant, we have divided this problem in to three parts a) When approximate information about open loop process model is known, b) when no information of open loop model is available (closed loop experiment is desired), and c) When known recycle dynamics is affecting the controller performance. Each of these sub-problems is discussed in this chapter and suitable technique to calculate PID achievable performance for each case is proposed. A stochastic performance criterion has been used as the basis. The second problem is of utmost importance because availability of open loop process model is very rare in practice. Using experimental closed loop data (i.e. data from a closed loop system excited by set point changes or dither signal), the second method is able to estimate the control loop performance achievable with PI or PID type controllers.

The organization of the chapter is as follows. Section 3.2 provides a brief overview of performance assessment of PID controllers. Section 3.3 describes how approximate information about open loop process model can be used to calculate PID achievable performance targets. Section 3.4 discusses a method to calculate PID achievable performance with out apriori information of open loop process model. Robustness issues and deterministic performance measures are dealt with subsequently. Section 3.5 discusses the effect of recycle dynamics on PID achievable performance targets. Several examples are considered in every section to show the efficacy of each technique and validate our theory. The paper concludes by highlighting the research work done in this chapter.

3.2 Overview of PID achievable performance assessment

Qin (1998) notes that only 20% of PID type controllers employed in a typical refinery can reach the minimum variance performance. For the rest of the controllers, minimum variance performance is not achievable because of significant dead times, non-stationary disturbances etc. In these cases, it would be of interest to know the maximum performance that is achievable with a PID type controller. Åström (1991) employed measures such as bandwidth, normalized peak error, etc. to characterize the performance of the PID type controllers. Swanda and Seborg (1999) used set point response data to assess the performance of PI controllers. They used two normalized performance indices namely the normalized settling time (actual settling time divided by the apparent time delay) and the normalized integral absolute error (integral absolute error divided by the product of the apparent time delay and size of the set point change). Through exhaustive simulations they were able to show that the optimal value of the normalized settling time (T_s) was 2.3 and the optimal value of the normalized integral absolute error (IAE_d) was 2.0 for a PI controller. This lower bound was found to be independent of both model type and model order. With PID controllers these optimal values are slightly lower. Swanda and Seborg (1999) also considered the important issue of robustness-performance tradeoff by relating the T_s, IAE_d, gain margin and phase margin to the specified closed loop time constant for the IMC-PI controller and showed that the high performance controllers can indeed have acceptable gain and phase margins.

Ko and Edgar (1998) estimated the achievable performance for PI controllers using a stochastic framework by utilizing routine closed loop data. Their results indicate that the PI controllers can deliver a performance greater than or equal to 60% of the minimum variance performance in most practical situations. These results indicate that we may not lose much in terms of control performance by restricting the controller to be of PI / PID type for controllers in the regulatory layer. The Approximate Stochastic Disturbance Realization (ASDR) technique developed by Ko and Edgar (1998) for estimating the PI / PID achievable performance assumes that the process model is known. This assumption is needed owing to the fact that routine operating data were employed to determine the limits of performance.

Assuming that the open loop model (including time delay) is known, Ko and Edgar (1998) used routine closed loop operating data (no set point change is made to excite the process) to estimate the PI achievable performance. Using an ARIMA(p,1,1) model with $2 \le p \le 5$, they approximate the disturbance (noise) model N by matching the first few coefficients of the estimated closed loop disturbance impulse response model. Once, the process and noise models are known, Ko and Edgar (1998) employ a numerical optimization procedure to estimate the highest performance index reachable by restricting the feedback controller Q to a PI or PID structure. Their results indicate that for a first-order-plus-dead-time (FOPDT) process, a PID type controller can provide minimum variance performance as long as the noise (Na_t) is stationary. Qin (1998) showed that for a FOPDT process, the PID controllers are able to achieve close to minimum variance performance when the process time delay is very small or very large.

3.3 Computation of PID achievable performance with knowledge of open loop process model

The Approximate Stochastic Disturbance Realization (ASDR) technique developed by Ko and Edgar (1998) for estimating the PI / PID achievable performance assumes that the process model is known. If the open loop process model (including the delay) is not known, then an obvious procedure to calculate the PI achievable performance is to first obtain the open loop process model using closed loop experimental data. This experiment can involve a sequence of acceptable set point changes. Any of the closed loop identification methods can be used to obtain the open loop process model. In the second step, the identified process model can be employed in the ASDR method of Ko and Edgar (1998) to calculate the PI achievable performance.

Calculating a very good open loop process model is a very involved procedure. Even if open loop model are identified and employed in performance assessment framework chances are model parameters will change with time and may lead to unreliable results. There is a need for a method, which requires most approximate information about open loop process model but still provides reliable predictions. In other words, PID achievable performance targets calculation should be robust to process parameter changes.

In this section, a technique is proposed to calculate PID achievable performance if approximate open loop process is known. Consider a performance monitoring system shown in Figure 3.1. Dotted lines are the part of CLPM framework. T_m and N_m are approximate process and noise model respectively.

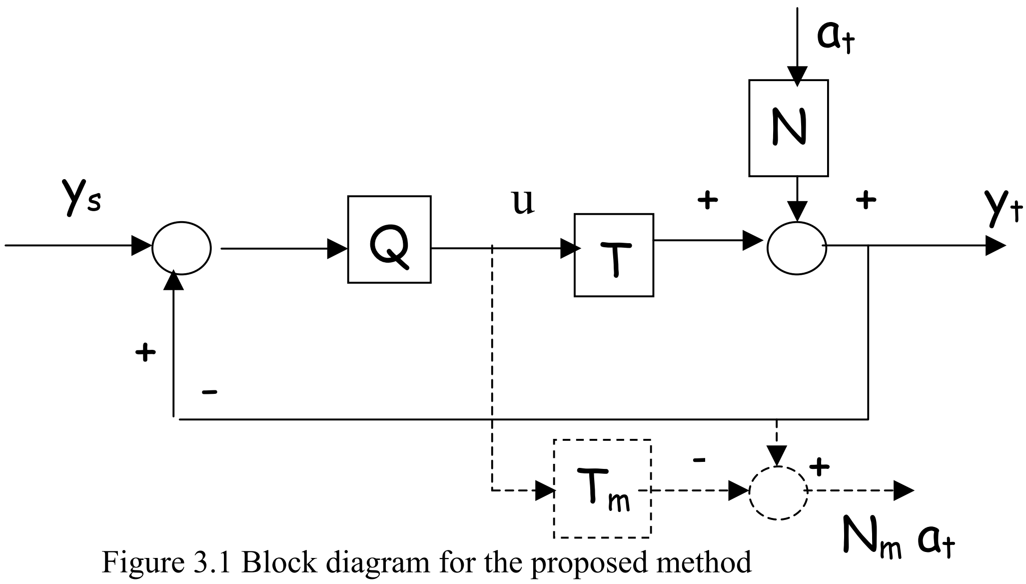

Figure 3.1 Block diagram for the proposed method

It can be shown that

$$N_m a_t = y_t - T_m u_t \tag{3.1}$$

If T_m is specified then left hand side of equation 3.1 is a time series. N_m can be calculated as suitable time series estimates e.g. ARIMA with a_t as filtered white noise sequence. N_m can be called model filtered disturbance transfer function. If there is no model-plant mismatch i.e. T_m = T then it can be shown easily N_m = N. It means if available plant model is very good match with process model then noise transfer function can be calculated very efficiently. For notation simplicity suffix t will not be used for now on.

For a given controller Q, the relationship between the controlled variable and the set point under closed loop is:

$$y = \frac{Q\,T}{1 + Q\,T}\,y_{sp} + \frac{N}{1 + Q\,T}\,a = G\;y_{sp} + H\;a \tag{3.2}$$

In case of no set point change y_{sp}=0, it can be shown using equations 3.1 and 3.2

$$Ha = \frac{N}{1 + Q\,T}\,a = \frac{N_m}{1 + QT_m}\,a \tag{3.3}$$

For proof of equation 3.3 please see appendix A. If N_m is calculated, for some controller setting Q then this value can be used to calculate the close loop disturbance transfer function using T_m. Equation 3.3 is exact and provides correct estimates of CLPI. To calculate PID achievable targets, for any given controller Q^* closed loop transfer function H^* can be shown as

$$H^* = \frac{N}{1 + TQ^*} = \frac{\dfrac{(1+TQ)}{(1+T_mQ)}N_m}{(1+TQ^*)}$$

thus

$$H^* = \left(\frac{1+TQ}{1+T_mQ}\right)\left(\frac{1+T_mQ^*}{1+TQ^*}\right)\left(\frac{N_m}{1+T_mQ^*}\right) \tag{3.4}$$

If the first two terms in equation 3.4 are ignored then approximate closed loop transfer function will be

$$H^*_{approx} = \left(\frac{N_m}{1+T_mQ^*}\right) \tag{3.5}$$

Thus N_m calculated from one controller is being used for any other controller as if it is the actual noise dynamics.

If T_m = T or Q^*=Q then

$$\left(\frac{1+TQ}{1+T_mQ}\right)\left(\frac{1+T_mQ^*}{1+TQ^*}\right)=1 \qquad (3.6)$$

This is a very useful result for estimating closed loop process transfer function approximately with help from closed loop data. Given that the process delay d remains constant, it is possible to determine the optimal PID type controller Q^* that "shapes" H^*_{approx} in a manner that maximizes the performance index. There will be error in the results depending two factors a) how much away optimum PID predictions (Q^*) are from current controller values (Q), and b) how accurate is process model (T_m vs. T). Fortunately, if any of these factors are close to each other then prediction will be very close to the true value.

3.3.1 Case studies

To show the efficacy of the method proposed, several case studies were considered. Optimization was performed over several thousand combinations of process transfer functions, approximate open loop process models and disturbance transfer functions. Typical example:

$$T(z^{-1}) = \frac{0.1\, z^{-4}}{1-cz^{-1}}\,;\, N(z^{-1}) = \frac{(1-0.3z^{-1})z^{-3}}{(1-z^{-1})(1-0.4z^{-1})(1-0.6z^{-1})(1+0.8z^{-1})};$$

$$Q(z^{-1}) = \frac{1.2-2.4\, z^{-1}}{1-z^{-1}}\,;\; T_m(z^{-1}) = \frac{b\frac{(1-a)}{(1-c)}z^{-4}}{1-az^{-1}}\,;$$

Here the value of c represents various true process models in consideration. For each true process model (c value) various model approximations T_m are checked by varying values of a and b corresponding to time constant and process gain respectively. For example: a=0.4, b=0.2 and c=0.8 means process gain is overestimated (b/a) by 100% and process time constant is underestimated. Ratio by which time constant is underestimated can be checked using continuous time true and approximate process model. See Figure 3.2 for results.

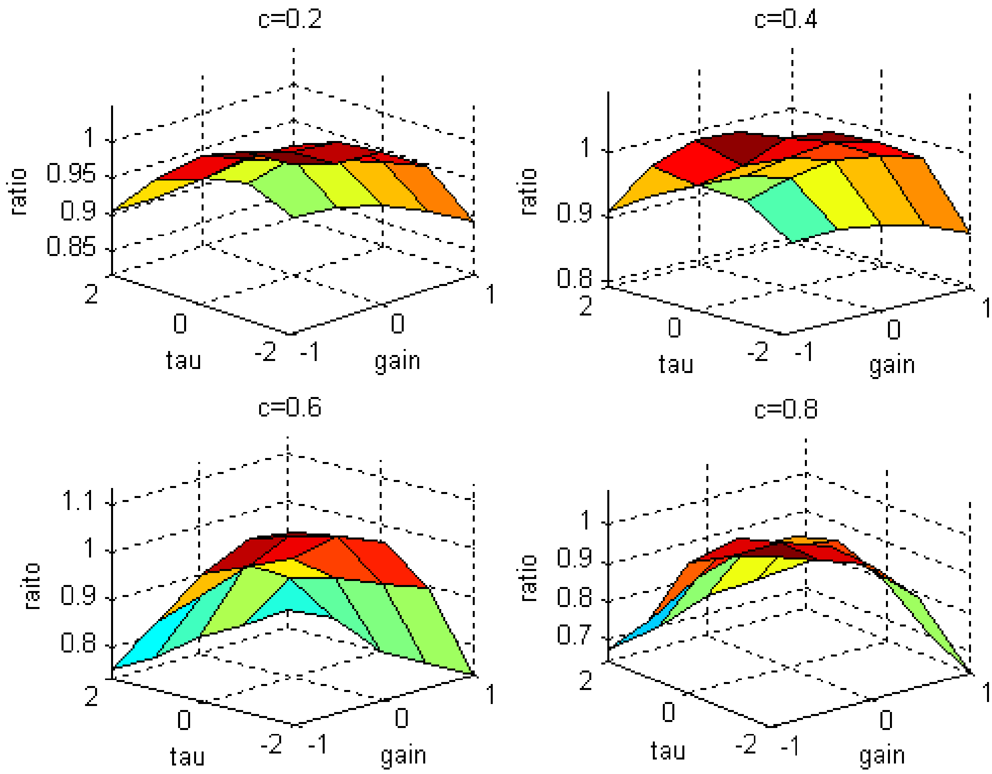

Figure 3.2 Effect of model-plant mismatch on calculated CLPI for Example 1

Ratio of calculated optimal CLPI with true optimal CLPI is shown in z-axis. X-axis represents how many times gain is away from true process gain. The true process gain is 0.1 and gain vector [-1 -0.5 0 0.5 1] in Figures 3.2 & 3.3 means approximate gain used is [0.05 0.07 0.1 0.14 0.2] respectively. Y-axis represents how many times time constant is away from true process time constant. If true process time constant is 0.6 then tau vector [-2 -1 0 1 2] in Figures 3.2 & 3.3 means approximate tau used is [0.14 0.37 0.60 0.78 0.88] respectively. Similarly if true process time constant is 0.8 then tau vector [-2 -1 0 1 2] in Figures 3.2 & 3.3 means approximate tau used is [0.41 0.64 0.80 0.89 0.95] respectively. Figure 3.3 shows similar case study with time delay 10 and rest of the transfer functions same as before.

Both of these Figures 3.2 and 3.3 show that exact estimate of optimal CLPI target can be obtained if knowledge of accurate open loop process model is provided. In case of approximate open loop process model, calculated optimal CLPI is very close to true optimal CLPI over a significant range. In most cases even if process gain is known with up to 2 times error and time constant is known up to 3 times error, optimum CLPI value can be calculated within +/-10% of true optimal CLPI. For many practical applications this range is satisfactory and can provide useful information about process.

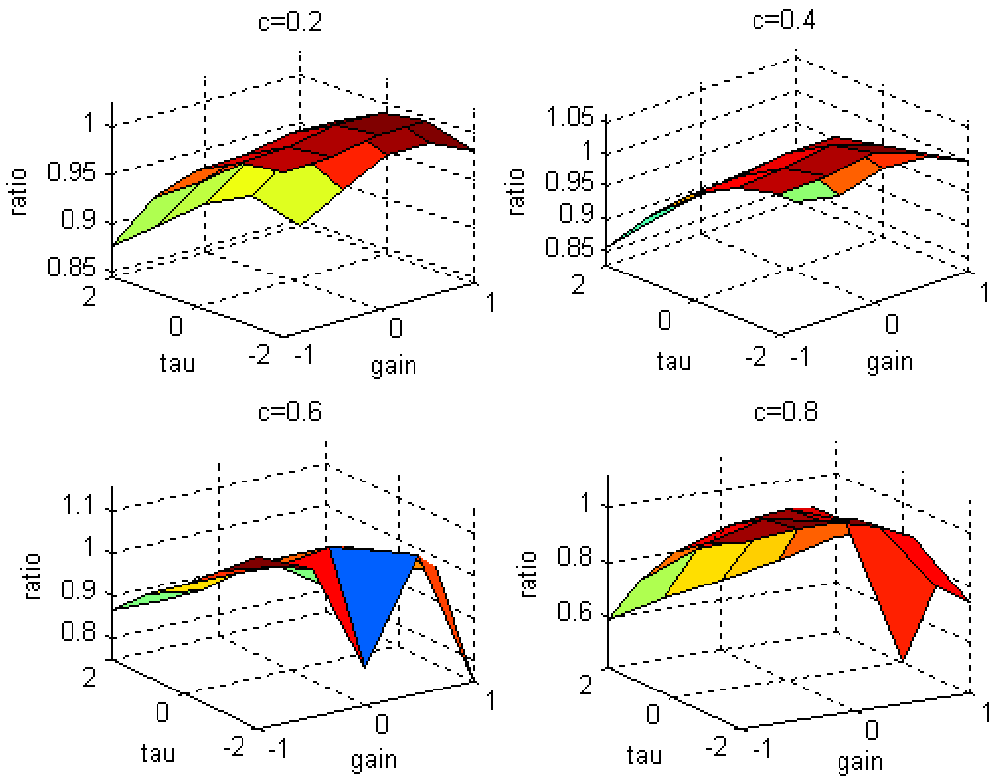

Figure 3.3 Effect of model-plant mismatch on calculated CLPI for Example 2

3.4 Direct assessment of PID achievable performance using experimental closed loop data

In this section, an alternate way of determining the PI achievable performance from closed loop experimental data is presented. Such an assumption warrants the use of experimental closed loop data (e.g. set point response data) if one wants to determine the 'best' closed loop performance possible with a PID type controller. In this method, the identification of the open loop models for the process and disturbance are not needed. The relationship between the controlled variable and the set point under closed loop is:

$$y = \frac{Q\,T}{1 + Q\,T}\, y_{sp} + \frac{N}{1 + Q\,T}\, a = G\, y_{sp} + H\, a \qquad (3.2)$$

Any closed loop identification method can be employed to determine the closed loop servo transfer function – the ARMAX (autoregressive moving average model with exogenous input) model serves the purpose very well. Using Equation (3.2), we may write $T = \frac{G}{(1-G)\,Q}$ and $N = \frac{H}{(1-G)}$. Assuming time invariant process (T) and noise dynamics (N), we have for a new controller Q^* the closed loop impulse response H^* given as

$$H^* = \frac{N}{1 + Q^*\,T} = \frac{\dfrac{H}{(1-G)}}{1 + Q^*\dfrac{G}{(1-G)\,Q}} = \frac{H}{1 + G\left(\dfrac{Q^*}{Q} - 1\right)} \qquad (3.7)$$

It was seen earlier that an estimate of the closed loop impulse response (H) and process delay d are enough to compute the control loop performance index. Equation (3.7) implies that with the knowledge of the current closed loop impulse response (H), closed loop servo transfer function (G) and the controller Q, it is possible to estimate the closed loop impulse response H^* for any given controller Q^*. Given that the process delay d remains constant, it is possible to determine the optimal PID type controller Q^* that "shapes" H^* in a manner that maximizes the performance index. In summary, the maximum PID achievable control loop performance index can be computed from the knowledge of the current controller and current closed loop servo and disturbance transfer functions.

3.4.1 Case Studies

The computational results for Examples 1 through 5 are tabulated in Tables 3.1. The data employed in the studies are shown in Figures 3.4 through 3.8. In these Figures, the top left and top right plots, show the closed loop experimental data with the current controller and the bottom row plots show the set point (y_{sp}), y and u trajectories with the estimated optimal controller controlling the true process. The results obtained for Example 1 will be described in detail; for Examples 2 through 5, only the salient features will be pointed out.

Example 1. The first example is a simulation of the closed loop system for a first order plus time delay process regulated by a PI controller. In particular, the process, noise and controller transfer functions are given by $T(z^{-1}) = \dfrac{0.2\, z^{-3}}{1 - 0.8\, z^{-1}}$,

$N(z^{-1}) = \dfrac{1}{1 - 0.95\, z^{-1}}$ and $Q(z^{-1}) = \dfrac{0.14 - 0.12\, z^{-1}}{1 - z^{-1}}$ respectively.

If the closed loop system is simulated without any set point change and the resulting "routine operating data" is analyzed using the method described in Chapter 2 (minimum variance benchmark) the performance index is calculated to be 0.4329. Assuming perfect knowledge of the process and the noise model, the PI achievable performance index is estimated to be 0.7896 using optimization routines in

MATLAB/SIMULINK. Thus, there is enough scope for improvement in control performance using the PI controller itself. The optimal PI controller Q* is determined to be $Q^*(z^{-1}) = \dfrac{1.41 - 1.06\, z^{-1}}{1 - z^{-1}}$. If we were to use Ko and Edgar's method (which assumes perfect knowledge of the process alone), the PI achievable performance would be estimated to be very near the value calculated above.

For the method proposed in this thesis, no *a priori* process knowledge is assumed. Therefore, the closed loop system needs to be excited by a dither signal which in most practical cases would be limited to a set point change of reasonable magnitude.

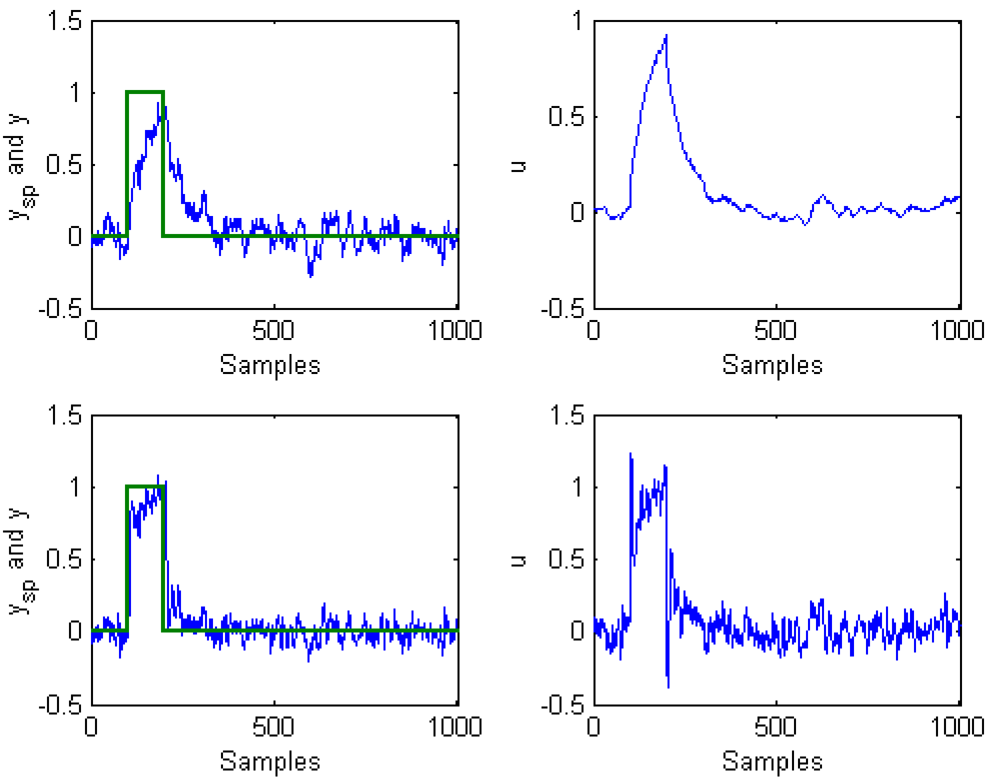

Figure 3.4 Closed loop data and results for Example 1

The top left plot in Figure 3.4 shows the set point profile and the process response while the plot shown on top right displays the manipulated variable trajectory. It is obvious that the controller is fairly detuned. Secondly, we have used a significant amount of noise in our simulation. This would render the direct application of the methods based on deterministic performance criteria e.g. settling time and IAE somewhat difficult.

With the experimental closed loop data, we evaluate the performance index based on minimum variance benchmark to be 0.4354. Then the closed loop data is used to identify the controller (Q), closed loop servo transfer function (G) and the closed loop noise model (H). Standard tools from the MATLAB identification Toolbox are employed for this purpose. An ARMAX(3,4,4,3) model (the last index stands for the process delay) was found to be adequate (confirmed by diagnostic tests on residuals) to model the data. These identified models are used in Equation (3.7) to determine the "optimal" PI (or PID) controller Q^* that maximizes the control loop performance (which is a function of the first d coefficients of H^*). Using this approach, we obtain the achievable performance using PI controller to be 0.7810. This is very close to that calculated from a complete knowledge of the open loop process and noise models or via Ko and Edgar's method.

While complete knowledge of the open loop process and noise models and the controller yields the optimal PI controller as $Q^*(z^{-1}) = \dfrac{1.41 - 1.06\, z^{-1}}{1 - z^{-1}}$; our method predicts the optimal controller to be $Q^*(z^{-1}) = \dfrac{1.24 - 1.18\, z^{-1}}{1 - z^{-1}}$ (see row corresponding to Example 1 in Table 3.1). Compared to the current controller, the optimal controller is seen to have a significantly higher proportional action.

Table 3.1: Summary of results for Examples 1 to 5

Example No.	Theoretical Values			Proposed Method			ARMAX order
	$\eta_{present}$	$\eta_{PI,achievable}$	Optimal PI Controller	$\eta_{present}$	$\eta_{PI,achievable}$	Optimal PI Controller	
1	0.4329	0.7896	1.41 1.06	0.4354	0.7810	1.24 1.18	[3 4 4 3]
2	0.4106	0.6741	1.24 1.00	0.4085	0.6892	1.19 1.13	[3 4 4 3]
3	0.9375	0.7896	1.41 1.06	0.9704	0.8036	1.38 1.27	[3 4 5 3]
4	0.1543	0.5748	2.57 1.12	0.2407	0.6272	2.64 2.35	[3 4 7 5]
5	0.0340	0.2431	3.99 1.03	0.0323	0.2274	3.99 3.90	[3 4 4 3]

These results confirm that our estimates of the optimal controller PI achievable performance using the estimated models are accurate enough for practical applications. With a more persistent set point perturbation, the accuracy of our estimates can be improved considerably. However, the type of set point perturbation we have employed is suitable in an industrial setting and we chose to work with it.

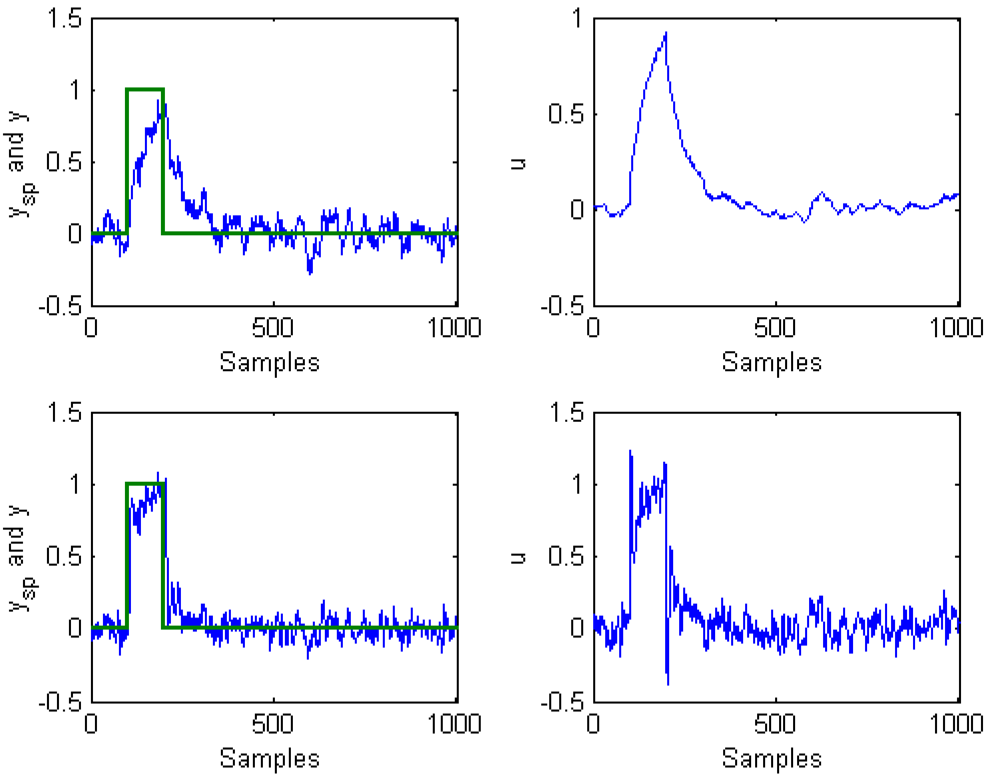

Figure 3.5 Closed loop data and results for Example 2

Example 2. To investigate the effect of having more complicated process transfer functions, we now choose a third order model for the process. The transfer functions for the noise and the controller remain as given in Example 1. Thus, $T(z^{-1}) = \dfrac{0.0429\, z^{-3}}{1-1.95\, z^{-1} + 1.2675\, z^{-2} - 0.2746\, z^{-3}}$, $N(z^{-1}) = \dfrac{1}{1-0.95\, z^{-1}}$ and $Q(z^{-1}) = \dfrac{0.14-0.12\, z^{-1}}{1-z^{-1}}$ for this example. Identification experiment is shown in Figure 3.5 and the results shown in Table 3.1 indicate that considerable increase in controller performance is possible with a PI controller.

Example 3. This example is chosen particularly to illustrate the effect of controller tuning. All of the previous examples employed moderately tuned PI controllers. Here, we choose a highly tuned controller (actually a minimum variance controller) but retain the process and noise models used in Example 1. We therefore consider

$$T(z^{-1}) = \frac{0.2\, z^{-3}}{1 - 0.8\, z^{-1}}; \quad N(z^{-1}) = \frac{1}{1 - 0.95\, z^{-1}} \quad \text{and} \quad Q(z^{-1}) = \frac{4.287 - 3.429\, z^{-1}}{1 - 0.857\, z^{-3}}$$ for this

example. The current performance index turns out to be very high as expected (if offset is not taken into account). However, even with a very tight controller in place, we are still able to compute the PI achievable performance and the "optimal" PI controller fairly accurately. This is a case where the minimum variance controller is optimal for stochastic disturbances but not good enough to handle deterministic external inputs such as the set point change (please see the offset in Figure 3.6 top-left curve). A PI controller with slightly inferior performance is more suitable.

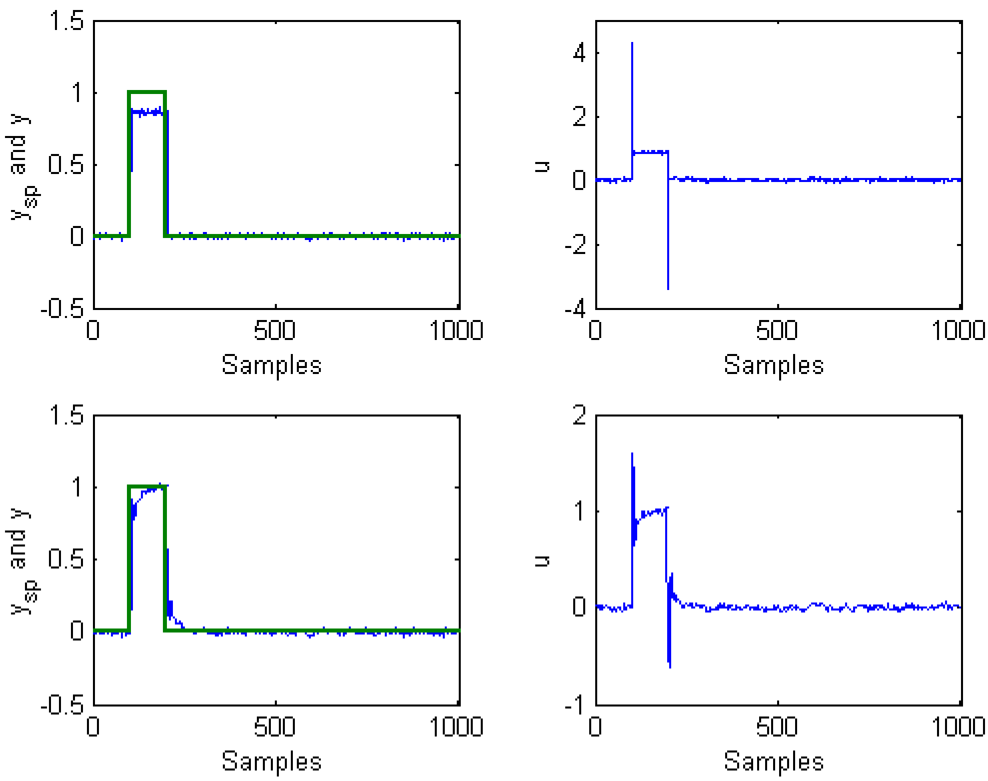

Figure 3.6 Closed loop data and results for Example 3

Example 4. As pointed out earlier, PI controllers cannot reach minimum variance performance when the disturbance Na_t is non-stationary. In this example, we will consider the following transfer functions for the process, noise and controller:

$$T(z^{-1}) = \frac{0.1\, z^{-5}}{1 - 0.8\, z^{-1}}, N(z^{-1}) = \frac{1}{\left(1 - z^{-1}\right)\left(1 - 0.3\, z^{-1}\right)\left(1 - 0.6\, z^{-1}\right)}$$

$$\& \, Q(z^{-1}) = \frac{1.6 - z^{-1}}{1 - z^{-1}}.$$

It is obvious from the top row of Figure 3.7 and from the values reported in Table 3.1 that the performance of the current controller is poor. Also, the performance index achievable with a PI controller is not as high as those achieved in the earlier examples. The proposed method provides good estimates of the PI achievable performance. The results shown in the bottom row of Figure 3.7 indicates the improvement in performance obtained with the optimal PI controller Q^*.

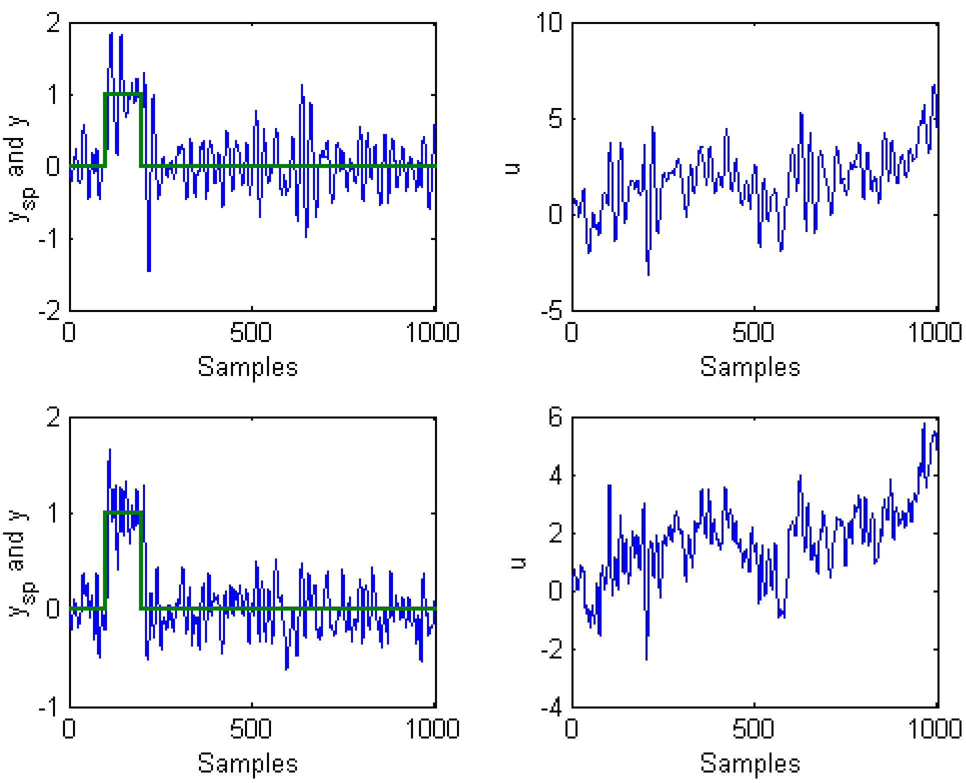

Figure 3.7 Closed loop data and results for Example 4

Example 5. As a final example, we consider the control of an open loop unstable process. In this example the process, noise and controller transfer functions are given by

$$T(z^{-1}) = \frac{0.1\, z^{-3}}{1 - 1.1\, z^{-1}}, N(z^{-1}) = \frac{1}{\left(1 - z^{-1}\right)\left(1 - 0.3\, z^{-1}\right)\left(1 - 0.6\, z^{-1}\right)}$$

$$\& \, Q(z^{-1}) = \frac{1.6 - 1.5\, z^{-1}}{1 - z^{-1}}.$$

The unstable open loop process and the integrating noise model pose no new challenges since our method does not involve the determination of open loop models. The results obtained (Figure 3.8) are similar to those obtained with Example 4. Significant improvement in control loop performance is obtained by using the optimal controller but a final performance index of about 0.23 may motivate us to use a controller of higher complexity than a PI controller.

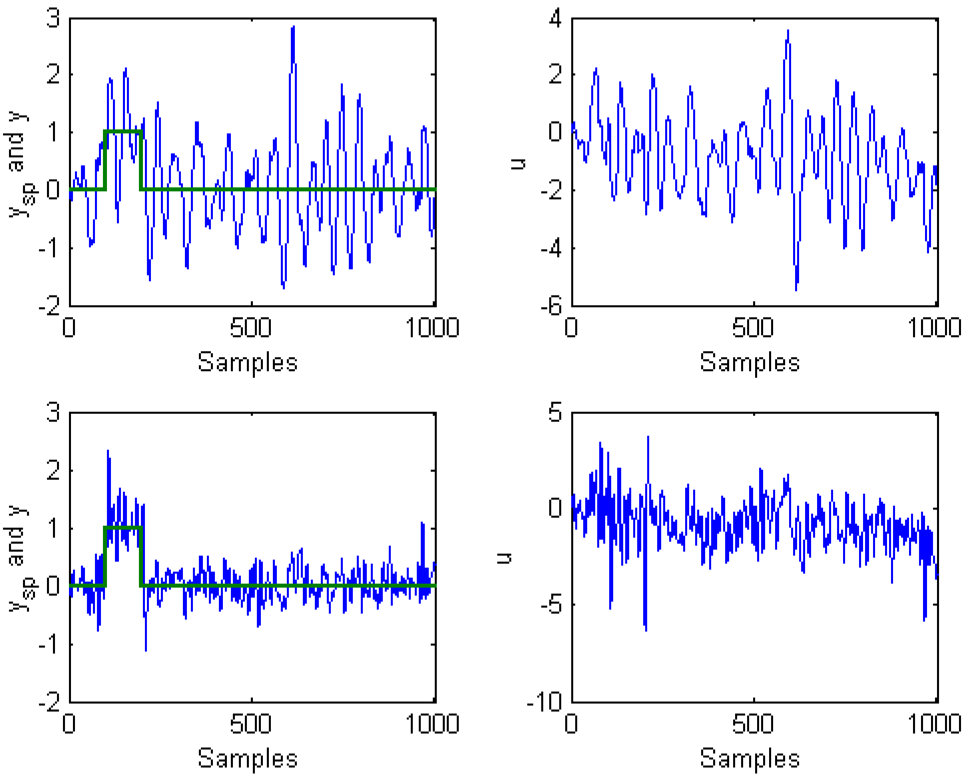

Figure 3.8 Closed loop data and results for Example 5

3.5 PI / PID Achievable Control Loop Performance for Processes with Recycle

3.5.1 Introduction

Processes with material and energy recycles are very common in the chemical industry. The design of control schemes for processes with recycle of material and/or energy streams is presently an active research area. Controller design and tuning for such processes must be done carefully. Chodavarapu and Zheng (2001) provide some guidelines about the type of tuning (aggressive vs. conservative) that are appropriate for processes with recycles. Emoto and Lakshminarayanan (2002) developed guidelines to estimate the loss in control loop performance if the recycle dynamics is neglected in the design of the feedback controller. Another possible technique in the design of control systems for recycle processes involves the use of recycle compensators in addition to the traditional feedback controller. Scali and Ferrari (1999) demonstrated simulation based case studies using Taiwo's (1986) recycle compensation technique.

In the current work, we focus on the following questions:

(1) Given that a process with recycles is to be regulated via feedback control, what is the control loop performance achievable with a PI controller?

(2) If the performance achievable is low then how to improve it?

To answer these questions, we make use of the stochastic performance monitoring criteria (CLPI). PID achievable performance idea is extended to processes with recycle. Several examples are considered with a view to discuss the effect of recycle dynamics. Certain performance improvement guidelines are provided.

3.5.2 PI achievable performance for processes with recycle

The idea of PI achievable performance can be similarly extended to the processes with recycle dynamics as well. The block diagram for this scheme is given in Figure 3.9.

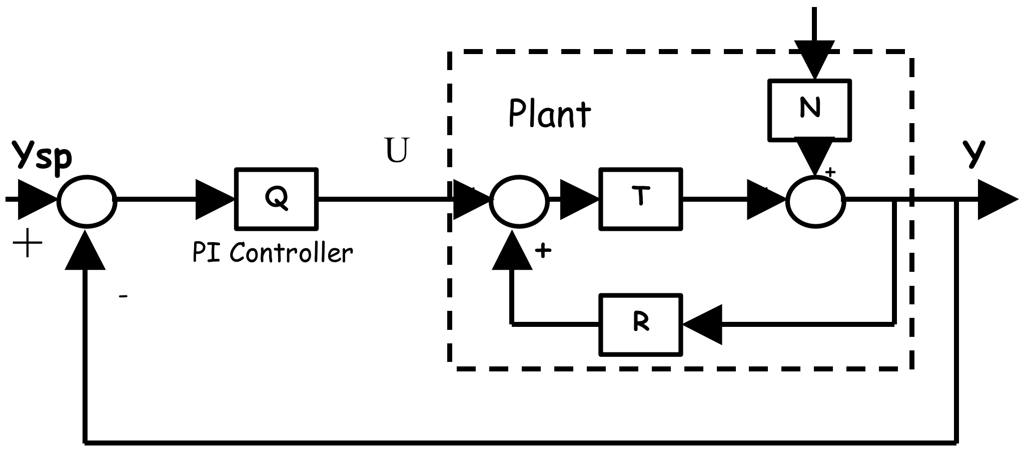

Figure 3.9 A Process with Recycle

Here, Q denotes the feedback controller (PI), $T = z^{-d}\,\tilde{T}$ denotes the transfer function of the forward path (where d is the time delay of the forward path), T_R denotes the transfer function of the recycle path and N denotes the disturbance dynamics.

Under these circumstances the process output y_t can be expressed in terms of the transfer functions and the white noise signal a_t as:

$$y_t = \left\{ \frac{N}{1 + TQ - TT_R} \right\} a_t = \left\{ \frac{N}{1 + z^{-d}\tilde{T}Q - z^{-d}\tilde{T}T_R} \right\} a_t \qquad (3.8)$$

Using the long division as done in equation (2.5), output variance σ_y^2 and σ_{mv}^2 can be calculated with equations (2.6) and (2.8). This information can be used to calculate the present CLPI (closed loop performance index) with equation (2.9).

To calculate the PI achievable targets, choosing Q in the form of a PI controller can optimize the CLPI. The controller parameters K_c and τ_I serve as decision variables.

Thus

$$\text{CLPI}_{\text{achievable}} = \max_{K_c,\, \tau_I} \left(\frac{\sigma_{mv}^2}{\sigma_y^2} \right) \tag{3.9}$$

The resulting value provides the achievable performance for process with recycle dynamics. If this value is close to 1 we may conclude that the PI controller can provide superior control performance on a process with recycle if tuned optimally. A value of $\text{CLPI}_{\text{achievable}}$ close to 0 will indicate that the PI controller cannot provide good control performance on the recycle process and a more complicated controller (more complicated than a PI controller) or control structure (more complicated than a simple feedback control strategy) will be needed for performance enhancement.

3.5.3 Case Studies

In Figure 3.10, we show some representative results for a process with $T = \dfrac{e^{-10\,s}}{10\,s+1}$ and $R = \dfrac{K_R\, e^{-\theta_R\, s}}{\tau_R\; s+1}$ and disturbance model represented in discrete domain as

$$N = \frac{(1+0.6z^{-1})}{(1-0.5z^{-1})(1-0.6z^{-1})(1+0.7z^{-1})\,(1-z^{-1})}$$

The noise model has an integrator and would therefore corrupt the "noise-free" process output with a non-stationary signal. In Figure 3.11, we show similar results for a process with the same T and R but with different disturbance dynamics i.e.

$$N = \frac{(1+0.6z^{-1})}{(1-0.5z^{-1})(1-0.6z^{-1})(1+0.7z^{-1})}$$

The results obtained from these two examples will provide information about the effect of noise dynamics on the PI achievable performance for a process with recycle.

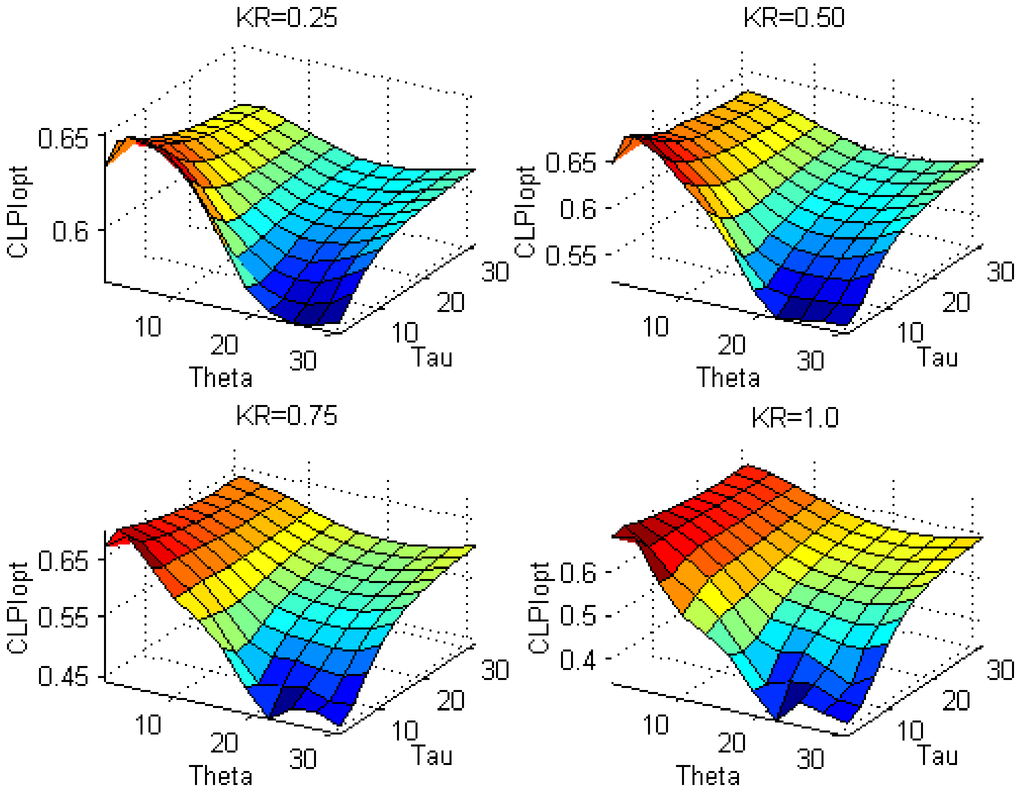

Figure 3.10 PI achievable performance for different values of K_R, θ_R & τ_R, Example 1

From Figure 3.10, it can be interpreted that the

(a) PI achievable performance can range between 0.35 and 0.7 depending on the values of K_R, τ_R and θ_R.

(b) As the recycle loop gain K_R increases the PI achievable performance tends to decrease in general (particularly at low values of τ_R and high values of θ_R)

(c) PI achievable performance tends to decrease with increase in τ_R at low values of θ_R and the trend becomes reverse at the higher values of θ_R where it decrease monotonically.

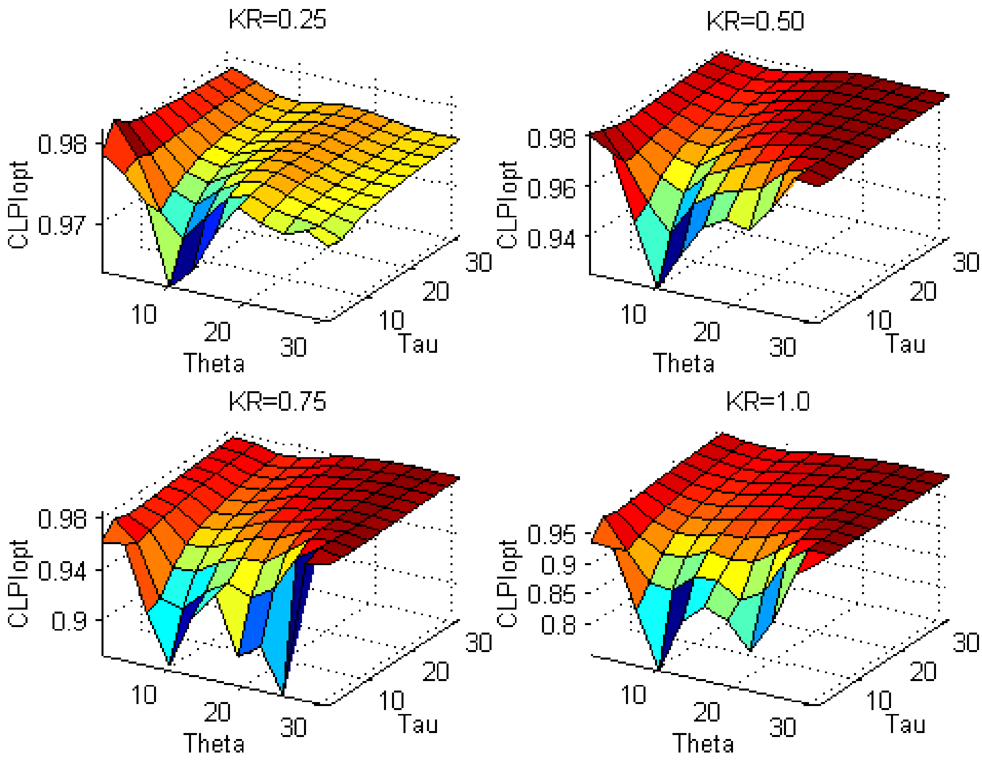

Figure 3.11 PI achievable performance for different values of K_R, θ_R & τ_R, Example 2

PI achievable performance depends on the disturbance model but the trends observed above still hold. Similar results can be shown for performance with PID controller. Compared to a PI controller, improved performance is achieved with the PID controller. The trends, however, remain the same.

From Figure 3.11 it is clear that, with a stationary noise dynamics, a much superior control loop performance is obtained. This means that with a stationary noise affecting the process, a process with recycle can be effectively controlled with a well-tuned PI feedback controller. With a non-stationary disturbance, even an optimally tuned feedback PI controller may not be able to provide good control performance and more complex controllers or control structures may be needed.

3.5.4 Performance improvement guidelines

We now present a scheme to monitor and improve the Control loop performance for processes with recycle.

1) Estimate the process time delay (Lynch and Dumont, 1996).

2) Collect the closed loop process output data and calculate the CLPI for existing controller settings (Harris, 1989).

3) If CLPI is not satisfactory: Obtain the open loop transfer function for process and recycle dynamics. If disturbance model is available calculate PI/PID achievable performance for process with recycle with the method proposed. Otherwise use the method proposed in section 3.3 with modification for recycle system.

4) If the PI/PID achievable performance is high enough, retune the controller and go to step 2.

5) Otherwise, design a suitable recycle compensator for the process and check the CLPI.

6) If performance improvement is still not achieved then it is a clear indication that the loop under question needs attention. Such loops, if critical, must be examined carefully by identification experiments, hardware inspection and so on. Poor performance may be due to hardware problem (e.g. sticking valve), process constraints, big time delays, presence of non-invertible zeros etc. or due to measurable disturbances (that can be handled through feedforward controllers) or due to unmeasured disturbances (that can be handled by cascade control if appropriate secondary measurements are available).

3.6. Conclusions

Methods are provided to calculate the PID achievable performance of control loops. A method that uses information of approximate open loop process model is shown to be very effective in calculating PID achievable performance. It calculates exact PID achievable performance if true open loop process model is known otherwise also very good estimate of PID achievable performance can be calculated. This method can be useful when open loop process model is approximately known and stable.

In many situations open loop process model may not be available e.g. process is time varying, complex, open loop unstable etc. A method that uses closed loop experimental data to determine the maximum control loop performance achievable with a PID type controller has also been described. Though all the examples involved consider PI controllers, this method is equally valid for PID controllers. While some set point excitation is required, the method does not need the open loop process or noise models. This is a positive aspect of the proposed method. Furthermore, optimal PI settings are also obtained. The method enables the calculation of the values of the deterministic performance measures (T_s, IAE_d) thereby leading to the estimation of robustness margins (GM and PM) for the current and the estimated optimal PI controller. Five examples using realistic data sets were employed to illustrate the workability of this strategy.

It is shown that the recycle dynamics can lower the control performance particularly when the product of the gains of the forward and recycle paths approach the value of 1. The noise dynamics play a crucial role – a process affected by non-stationary noise can be controlled adequately using a well-tuned PI controller. Certain combinations of the parameters of the recycle dynamics (low value of the recycle time constant and high values of recycle time delay) can limit the quality of control obtainable from PI controllers. The effect of recycle dynamics needs to be identified in process plants and should be compensated properly to attain desired control targets. A method to calculate the PI achievable targets for the process with recycle is described. A scheme is presented to systematically improve the control performance for processes with recycles.

Chapter 4. Tuning PID controllers using achievable performance indices

4.1 Introduction

PID type controllers continue to be the workhorse for process control in the chemical and related industries despite big advances such as MPC (Model Predictive Control) and its nonlinear variant i.e. NMPC (Nonlinear MPC). Desborough and Miller (2001) surveyed the status of industrial process controllers and estimate that 98% of the controllers in a "median" chemical plant were PID controllers. This situation is not likely to change in the foreseeable future because successful advanced control implementation requires well-tuned PID controllers in the lower control layer. A recent survey by O'Dwyer (2000) indicates that there are more than 200 tuning methods for PID controllers including procedures such as gain scheduling, adaptive control, relay-based auto-tuning etc. Not withstanding the plethora of tuning rules, the current state of controller performance in the process industry appears to be far from adequate. Van Overschee and De Moor (2000) report that 80% of PID type controllers in the industry are poorly / less optimally tuned. They state that 30% of the PID loops operate in the manual mode and 25% of PID loops actually operate under default factory settings. More tragically, 30% of PID controllers actually increase the variability of the process variable being controlled thereby causing more harm than good. This has been attributed to excessive integral action in the controllers. These reported Figures mirror those provided by Ender (1993) and Desborough and Miller (2001). Very often, the performance of an "optimally" tuned controller may deteriorate due to changes in process dynamics and/or disturbance characteristics. It is therefore important to monitor the performance of a feedback controller on a continuous basis and adapt its parameters if the performance deteriorates significantly.

Åström *et al.* (1993) survey the different approaches for the automatic tuning of PID controllers. They indicate the scenarios under which different procedures such as gain scheduling and adaptive control should be used. Also described are the procedures used for automatic tuning in a few commercial controllers. In Foxboro's EXACT controller, the controller starts adaptation when the error signal exceeds the user defined noise band by a factor of 2. In the Honeywell UDC 6000 controller, the adaptation is activated when the value of the controlled variable changes more than 0.3% from the set point or if the set point changes more than a prescribed value (±5% to ±15%). In Yokogawa's SLPC-181, 281, the performance of the system is monitored by computing the ratio of the variances of the actual process output and the output from a model (of the process). This ratio is expected to be close to 1; if this ratio happens to be lower than 0.5 or higher than 2 (indicative of model plant mismatch), the retuning of the controller is initiated. This ensures that the model-based PID controller continues to perform "optimally" on the process. In these approaches, the open loop model of the process is obtained using an open loop step test or from a relay feedback experiment.

In this work, we aim to exploit the significant developments made in the area of control loop performance assessment to determine the optimal tuning of PID type controllers (Agrawal & Lakshminarayanan 2002b). Using routine and experimental closed loop data from a process controlled by a PID type controller, we determine the current controller performance, the maximum achievable performance that can be obtained with a PID type controller as well as the "optimal" PID tuning parameters. Any significant difference between these current and maximum achievable performance will indicate the need for retuning of the controller. The salient features of the proposed method are:

a) Experiments are performed in closed loop and no external equipment is required. This may make the procedure more acceptable for industrial application.
b) The signal to noise ratio can be low since graphical procedures are not employed.
c) Robustness and achievable performance issues are dealt with explicitly. The engineer or operator will have an idea of what best to expect with respect to controller performance as well as the robustness margins.
d) There is no attempt to determine the open loop model of the process. All the computations are based on the closed loop servo and disturbance transfer functions.

The material of this chapter is organized in the following manner. In Section 4.2, an overview of the performance assessment literature for simple feedback loops as well as methods for computing the maximum performance achievable with a PID type controller is provided. A novel method that is capable of estimating the "optimal" PID parameter settings will be described in Section 4.3. We will also quantify the robustness and deterministic performance for the current controller and the "optimal" controller. Several examples are considered in Section 4.4 with a view to discuss, test and validate our methodology. We also include an example where we highlight the need to balance between the stochastic and deterministic performance measures. The chapter concludes by summarizing the key features of this study.

4.2 PID parameter calculations and guidelines

From the previous chapter (section 3.4 Direct assessment of PID achievable performance using experimental closed loop data), it is known that for time invariant process (T) and noise dynamics (N), we have for a new controller Q^* the closed loop disturbance impulse response H^* given as

$$H^* = \frac{N}{1+Q^* T} = \frac{\dfrac{H}{(1-G)}}{1+Q^* \dfrac{G}{(1-G)Q}} = \frac{H}{1+G\left(\dfrac{Q^*}{Q}-1\right)} \qquad (3.7)$$

It was seen earlier that an estimate of the closed loop disturbance impulse response (H) and process delay d are enough to compute the control loop performance index. Equation (3.7) implies that with the knowledge of the current closed loop disturbance impulse response (H), closed loop servo transfer function (G) and the controller Q, it is possible to estimate the closed loop disturbance impulse response H^* for any given controller Q^*. Specifically, in order to determine the optimal PI controller Q* (parameters K_c^* and τ_I^*), the objective function used is:

$$\min_{Q^* = K_c^*,\, \tau_I^*} \phi = (1-\eta)^2 = (1-CLPI)^2 \qquad (4.1)$$

One can change the decision parameters K_c^* and τ_I^* to get H* from equation 3.7. Using H* and the process delay 'd', the control loop performance index η can be obtained. The "fmincon" function available in the Optimization Toolbox (Matlab Version 6.5 Release 13) is employed to minimize $\phi = [1-\eta]^2$. The "fmincon" function implements a local optimization method, which performs constrained optimization using sequential quadratic programming. Constraint optimization method was employed because K_c^* and τ_I^* are greater than zero We have crosschecked the optimization results with various initial guesses and the method was seen to work very well.

It is important to note that, with the proposed method, the "optimal" PID parameters can be computed without estimating the open loop process or noise models and using only one set of closed loop experimental data. The optimal controller settings will obviously depend on the data set used to determine the closed loop transfer functions. We therefore recommend using plant data that contains the disturbances that the controller is expected to negotiate. The "optimal" controller settings will ensure that these "typical" disturbances are regulated in the most effective manner by the control system.

It is imperative that the controller not only provides exemplary performance in dealing with stochastic disturbances but also remains robust to process changes and model plant-mismatch. Also, the performance measures for stochastic and deterministic disturbances are different. Traditional deterministic performance assessment literature deals with measures such as settling time, overshoot, decay ratio, integral of absolute errors (IAE) etc. It has been well understood that achieving the best disturbance response does not guarantee good set point response with standard (one degree of freedom) PID controllers. When we try and tune the PI controller for maximizing its performance in handling stochastic disturbances, we must also consider its robustness and measures of deterministic performance. Under such circumstances, the objective function for the optimization problem should be suitably modified. A modified objective function that considers the tradeoff between stochastic and deterministic performance measures is shown in Example 3; the consideration of sufficient robustness margins is a more involved issue that requires posing the problem as a constrained multi-objective optimization problem that may be solved using heuristic optimization procedures such as genetic algorithms.

Swanda and Seborg (1999) categorize a loop performance based on its 90% normalized settling time. The normalized settling time (T_s) is equal to the actual 90% settling time divided by the apparent time delay. They characterize the closed loop performance to be high if $T_s \leq 4.6$, excessively sluggish if $T_s > 13.3$ and overshoot $\leq$ 10% and poorly tuned if $T_s > 13.3$ and overshoot > 10%. They also showed that for a FOPDT process regulated by an IMC-PI feedback controller the following approximate relationship holds between T_s and the normalized integral absolute error, (IAE_d):

$$IAE_d = \frac{T_s}{2.43} + 0.878 \tag{4.2}$$

The normalized integral absolute error is equal to the integral absolute error divided by the product of the apparent time delay and size of the set point change.

They also relate the gain and phase margins to IAE_d as follows:

$$\text{Gain Margin: } GM = \frac{\pi}{2} * IAE_d \tag{4.3}$$

$$\text{Phase Margin: } PM = \frac{\pi}{2} - \frac{1}{IAE_d} \tag{4.4}$$

Equations (4.2), (4.3) and (4.4) hold only if $T_s \geq 3.3$. They are very accurate for overdamped, underdamped and critically damped closed loop servo responses; furthermore, these relationships work well with open loop process models such as FOPDT, higher order overdamped systems with time delays and RHP zeros. These equations are therefore of great practical utility in the sense that the knowledge of T_s

alone can throw light on the performance and robustness. Equations (4.2), (4.3) and (4.4) clearly indicate that if T_s is large, the gain and phase margins are large leading to better robustness at the cost of poor performance.

To summarize our approach to determining the "optimal" PID tuning parameters, we follow the procedure outlined below:

a) Use routine closed loop experimental data with the current controller (Q) to determine the control loop performance index relative to the minimum variance controller.

b) If the performance index computed in (a) turns out to be low, we will then estimate the closed loop servo and disturbance transfer functions (i.e. G and H) using experimental closed loop data. A set point change is required for this purpose.

c) Using the estimated 'G', we obtain the estimates for T_s and IAE_d obtained with the current controller. The current robustness margins (GM and PM) are then obtained by using this IAE_d value in Equations (4.3) and (4.4). If the current control loop performance index is high and if the deterministic performance measures & robustness margins are satisfactory, we leave the loop alone. If the control loop performance index is high but if the robustness margins are not satisfactory, we may consider detuning the current controller. This scenario is pursued in Example 3 later.

d) If the current loop performance index is low, then with the knowledge of the current controller Q, the estimated models G and H, Equations (4.3) and (4.4) are used to obtain the parameters of the "optimal" PI / PID controller Q* that will maximize the loop performance index. This involves using the parameters of the "optimal" PI / PID controller Q^* as decision variables to get H* (from Equation 3.7) and consequently the PI / PID achievable performance index using the method discussed earlier in Section 3.

e) With Q*, the expected (new) closed loop servo transfer function (G*) is determined from:

$$G^* = \frac{G}{G + \frac{Q}{Q^*}(1 - G)} \tag{4.5}$$

f) The expected T_s and IAE_d values (for the "optimal" controller) are computed using G^*. The expected robustness margins can be obtained by using Equations (4.3) and (4.4).

g) The achieved T_s and IAE_d values can be obtained by implementing Q^* on the true process and making a set point change. These values will in general be different from the expected values because of model-plant mismatch. The achieved robustness measures can be obtained by using Equations (4.3) and (4.4).

The above steps may have to be repeated a few times in order to reach the "optimal" performance. Our experience with simulated data (shown later) indicates that it is possible to achieve the "best" performance in one or two iterations.

4.3 Illustrative Examples

<u>Example 1: Linear open-loop stable system</u>

This example is a simulation of the closed loop system for a first order plus time delay process regulated by a PI controller. The process, noise and controller transfer functions are given by $T(z^{-1}) = \dfrac{0.2\, z^{-5}}{1 - 0.8\, z^{-1}}$, $N(z^{-1}) = \dfrac{1}{(1 + 0.4\, z^{-1})(1 - z^{-1})}$ & $Q(z^{-1}) = \dfrac{0.14 - 0.12\, z^{-1}}{1 - z^{-1}}$ respectively.

With help of routine closed loop data, the current control loop performance index is calculated to be 0.33 relative to the minimum variance benchmark. This low value implies we can improve the loop performance via controller retuning. A set point change was made in order to generate experimental data and apply the method proposed here. This experimental data is shown in the top plots of Figure 4.1. Notice that we have added significant amount of noise in our simulation. An ARMAX (2, 3, 2) model with 5 samples of delay was found to capture the essence of this experimental data. From the estimated closed loop servo response, it was determined that the current controller provided a T_s value of 12.4 and a IAE_d value of 6.1. The gain margins were estimated to be 9.6 and 81^o respectively. All these measures are indicative of a sluggish controller with more than necessary robustness margins.

The proposed method was then used to determine the optimal control settings with a view to maximizing the performance index. This exercise revealed that a performance index of 0.91 is achievable with the PI controller $Q^*(z^{-1}) = \dfrac{0.97 - 0.86\, z^{-1}}{1 - z^{-1}}$ and also predicted that, with the "optimal" controller, the T_s value would be 1.4. Since the T_s value is less than 3.3, equations (4.2), (4.3) and (4.4) are not applicable. When the controller Q* was implemented on the true process, the closed loop performance is as shown in the bottom plots of Figure 4.1. The performance is very tight as expected. With the routine closed loop data obtained with the new controller Q*, the control loop performance index achieved was 0.89. This is very close to the predicted value of 0.91. Noise free simulation (not shown here) revealed that the normalized settling time with Q* was 2.2 which is somewhat higher than the predicted value of 1.4. This example indicates that the proposed method can provide reliable information for retuning the controller.

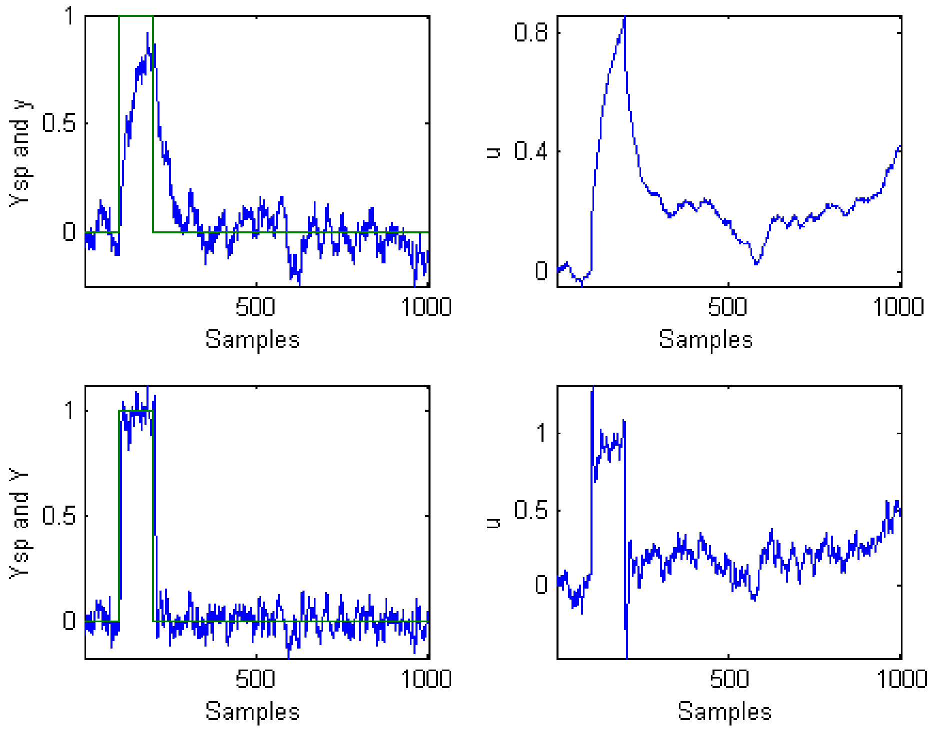

Figure 4.1 Closed loop data and results for Example 1

<u>Example 2: Nonlinear level control system</u>

In the second example, we consider the control of level in a spherical tank. A schematic of the tank is shown in Figure 4.2. The dynamics of the level 'y' in the tank is described by the differential equation

$$Q_i(t-d) - Q_0 = \pi R^2\left[1 - \frac{(R-y)^2}{R^2}\right]\frac{dy}{dt}$$

where R is the radius of the spherical tank, Q_i is the inlet volumetric flow rate and Q_o is the outlet flow rate. The delay from the manipulated input Q_i to the controlled output 'y' is indicated by 'd'. The outlet flow rate Q_o is related to the level 'y' via the Bernouli equation:

$$Q_0 = \sqrt{2g(y - y_0)}$$

where 'g' represents the gravitation constant, y_0 represents the height of the outlet pipe as measured from the base of the column.

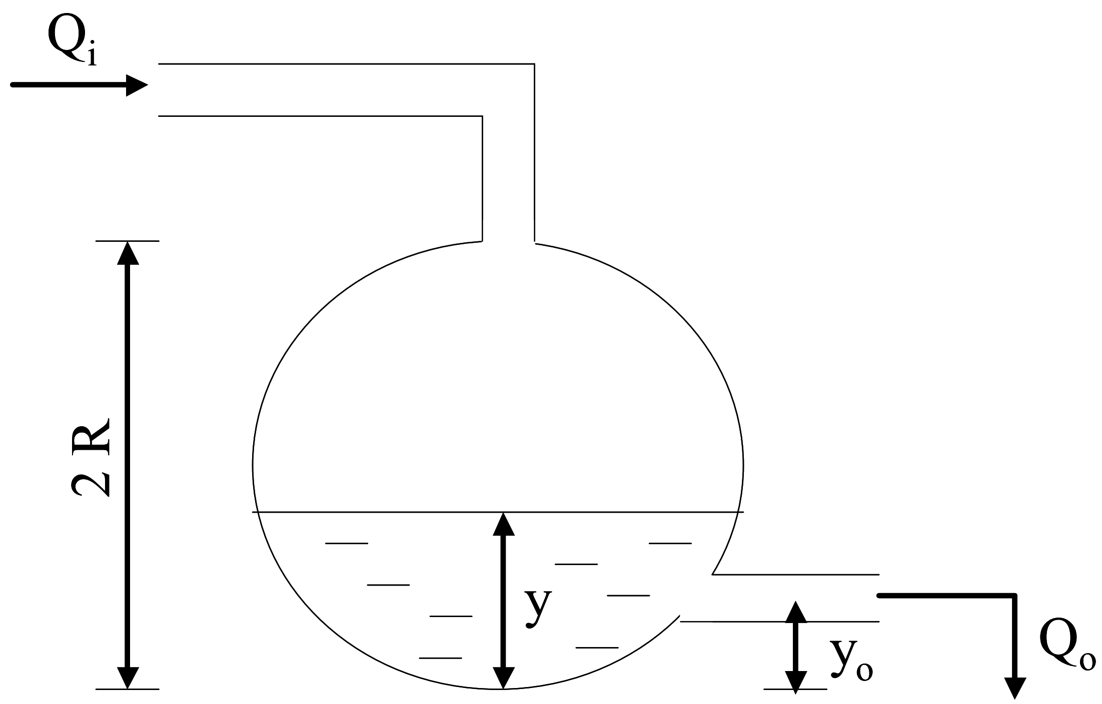

Figure 4.2 Schematic of the Spherical Tank system

We will use R = 1 m, d = 3 seconds and y_0 = 0.1 m in our simulations. The nominal operating value of y is 0.5 m. The output y will respond faster at this nominal operating value than at situations when y is close to 1 (i.e. a half-filled tank). The noise dynamics and the current PI controller settings are given by $N(z^{-1}) = \dfrac{1}{(1+0.4\,z^{-1})(1-z^{-1})}$ and $Q(z^{-1}) = \dfrac{0.3 - 0.1\,z^{-1}}{1 - z^{-1}}$ respectively. The current control loop performance index is calculated to be 0.37. To enable the calculation of the optimum controller parameters that will deliver the optimum performance, a set point change in level from 0.5 to 0.55 was made. The analysis revealed that with the controller $Q_1^*(z^{-1}) = \frac{2.12 - 1.42\, z^{-1}}{1 - z^{-1}}$, a performance index of 0.81 is obtainable. To see the effect of nonlinearity, another set of closed loop data was collected by changing the set point from 0.5 to 0.45. This data set predicted that a maximum performance of 0.75 was obtainable using the controller $Q_2^*(z^{-1}) = \frac{1.8 - 1.2\, z^{-1}}{1 - z^{-1}}$. We see that the "optimum" controller settings are different with the two different data sets. In addition, the achievable performances with the PI controllers are also slightly different. In any case, it seems possible to improve the loop performance index significantly higher than the current value of 0.37. When the "optimum" controller $Q_1^*(z^{-1})$ is implemented on the true process, a performance index of 0.76 with T_s = 3.6, IAE_d = 1.9, GM = 3 and PM = 60^o was obtained. With the "optimum" controller $Q_2^*(z^{-1})$ implemented on the true process, a performance index of 0.70 with T_s = 3 and IAE_d = 1.9 was obtained. These results indicate that significant improvement in control loop performance index is possible irrespective of the direction of the set point change for this system. With $Q_1^*(z^{-1})$ in place, the set point was changed from 0.5 to 1; this represents a significant change in the process characteristics. For this set point change, the closed loop servo response had high overshoot and was quite oscillatory. At this operating point, the control loop performance index dropped to 0.57. If better control loop performance is required at this operating point, the data from the set point change could be employed immediately in order to determine the optimal controller setting.

Example 3: Coupled FEHE/Furnace/Reactor Process

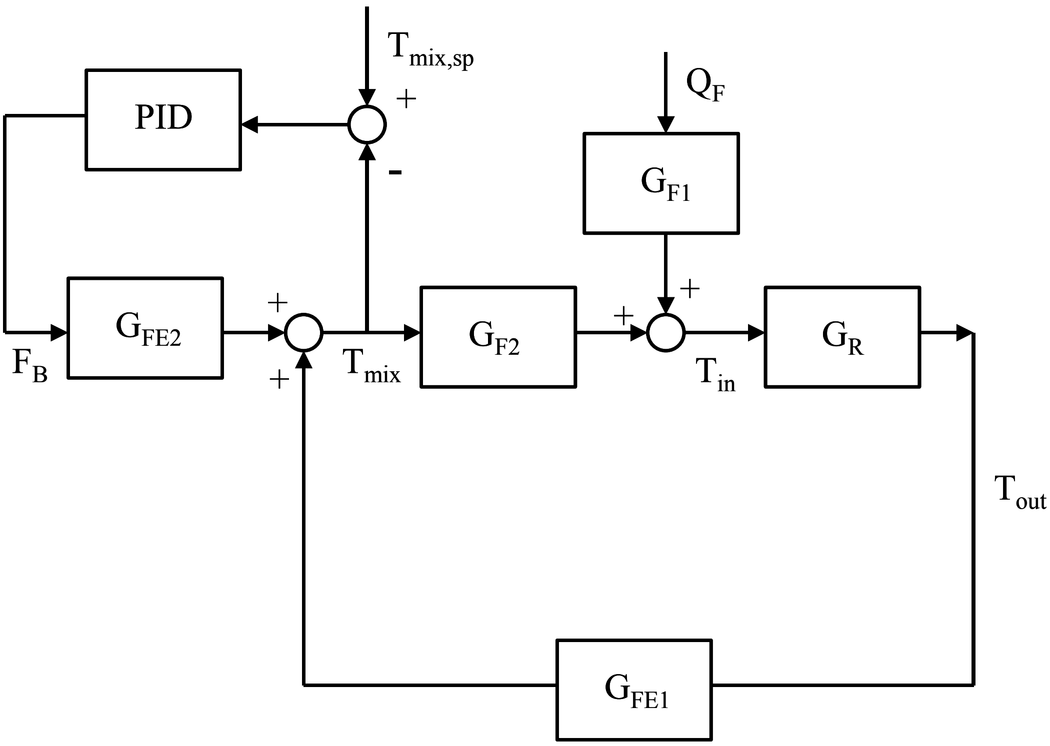

Figure 4.3 Block Diagram of Feed Effluent Heat Exchanger system

Figure 4.3 shows a block diagram schematic of a typical chemical process in which a feed-effluent heat exchanger (FEHE) and a furnace are used to preheat the feed for an adiabatic exothermic reactor. Reyes and Luyben (2000) have used this process to examine the steady state and dynamic effects of alternative process designs. A portion of the fresh feed plus recycled material is preheated in the FEHE by the reactor exit stream (temperature T_{out}; transfer function G_{FE1}) while the remaining bypasses the FEHE (flow rate F_B; transfer function G_{FE2}). A temperature controller manipulates the bypass flow to regulate the temperature of the mixed stream (the feed coming through the FEHE + the feed bypassing the FEHE) at T_{mix}. This stream is further heated in the furnace to a temperature T_{in}. The transfer function relating T_{mix} to T_{in} is denoted as G_{F2}. The fuel flow to the furnace is denoted as Q_F and the transfer function relating the fuel flow rate to T_{in} is denoted as G_{F1}. For purposes of this study, Q_F is considered to be a disturbance. In practice, a feedback controller manipulates the fuel flow in the furnace to maintain constant T_{in}. This loop is not included in the present study. Here, we will demonstrate the tuning of the feedback controller that manipulates the bypass flow F_B. The transfer functions for the different blocks in this study are:

$$G_{FE1} = \frac{0.005\, e^{-2s}}{0.25\, s + 1}; \quad G_{FE2} = \frac{-0.005\, e^{-2s}}{0.25\, s + 1}; \quad G_{F1} = \frac{1}{(s+10)^3\ (s+1)}; \quad G_{F2} = \frac{0.05}{0.125\, s + 1}$$

and $G_R = \dfrac{8\, e^{-6s}}{s+1}$.

Initially, the PID controller settings are K_c = 15, τ_I = 1.5 and τ_D = 0 (i.e. a PI controller). From routine closed loop data, the control loop performance index is determined to be 0.88. When a set point change is implemented, we find the following deterministic performance measures: T_s = 15.33, IAE_d = 6.7, GM = 10.5 and PM = 81.4^o. The large T_s value indicates sluggish performance. We use the experimental data in conjunction with the proposed method to determine the “optimal” PI controller that maximizes CLPI. This results in a PI controller that provides a CLPI of 0.956 but results in a IAE_d measure of 26.78. While the performance of the control loop has improved with respect to the regulation of stochastic disturbances, the deterministic performance measure for a set point change has worsened considerably. If we were to determine the “optimal” PI controller that minimizes the IAE_d measure, we get the lowest possible IAE_d to be 1.45; however the CLPI has decreased to about 0.63. The tradeoff between deterministic performance index measures and stochastic performance measure is clearly evident.

To resolve this conflict, we propose a modification to the objective function introduced in equation (4.1). The new objective function provides a tradeoff between the stochastic and deterministic performance measures as follows:

$$\min_{K_c,\, \tau_I} \left[w \frac{IAE_d}{IAE_{d,0}} + (1-w)\,(1-CLPI) \right]^2 \qquad (4.6)$$

In Equation (4.6), 'w' represents the weight given to the deterministic performance measure ($0 \le w \le 0$). Notice also that the IAE_d values are scaled down by a value of $IAE_{d,0}$ (the value of IAE_d obtained if one were to optimize based on CLPI alone i.e. with w = 0) – this would make the two terms in equation (4.6) to be of comparable magnitude. For this example, $IAE_{d,0}$ equals 26.78. The optimal controller will depend on the value of 'w' selected in equation (4.6). Figure 4.4 shows the values of CLPI and IAE_d generated from the optimization of the objective function shown in equation (4.6). Note that these curves can be generated using just one set of experimental data. As expected, both the CLPI and IAE_d decrease with increasing 'w'. Choosing a value of w = 0.7 provides an acceptable tradeoff between stochastic and deterministic performance measures – the 'optimal' PI controller is determined to be $K_c = 50$ and $\tau_I = 1.83$. This PI controller is expected to provide: CLPI = 0.8, $T_s = 5.67$, $IAE_d = 2.44$, GM = 3.84 and PM = 66.54°. Indeed when the "optimal" PI settings were implemented, the achieved performance indices and robustness measures were very close to the predicted values. Figure 4.5 illustrates the set point tracking performance with: (a) the initial controller settings (b) the "optimal" controller settings obtained by optimizing CLPI alone and (c) the "optimal" controller settings obtained by optimizing a weighted combination of CLPI and IAE_d (equation 4.6). It is evident that significant improvement can be obtained in deterministic performance with only a slight (yet acceptable) drop in stochastic performance.

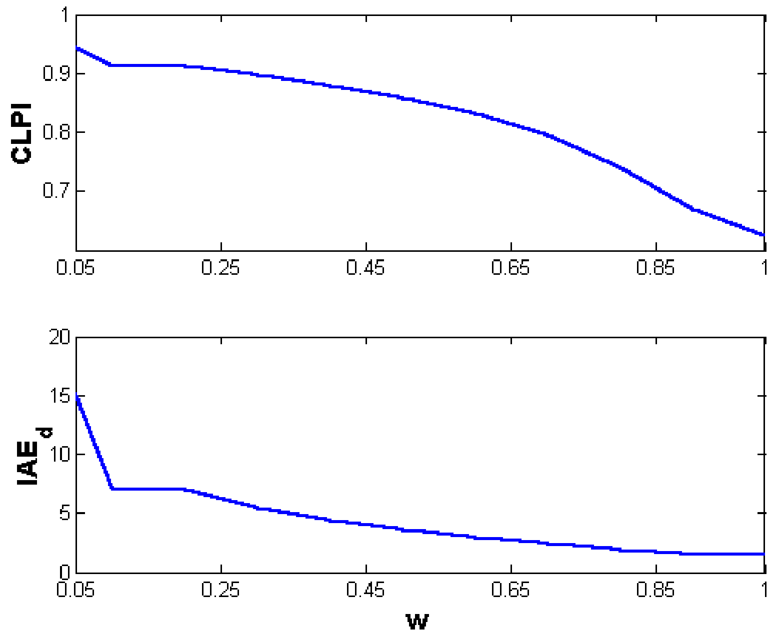

Figure 4.4 Tradeoff curve in CLPI and IAE_d values for Example 3

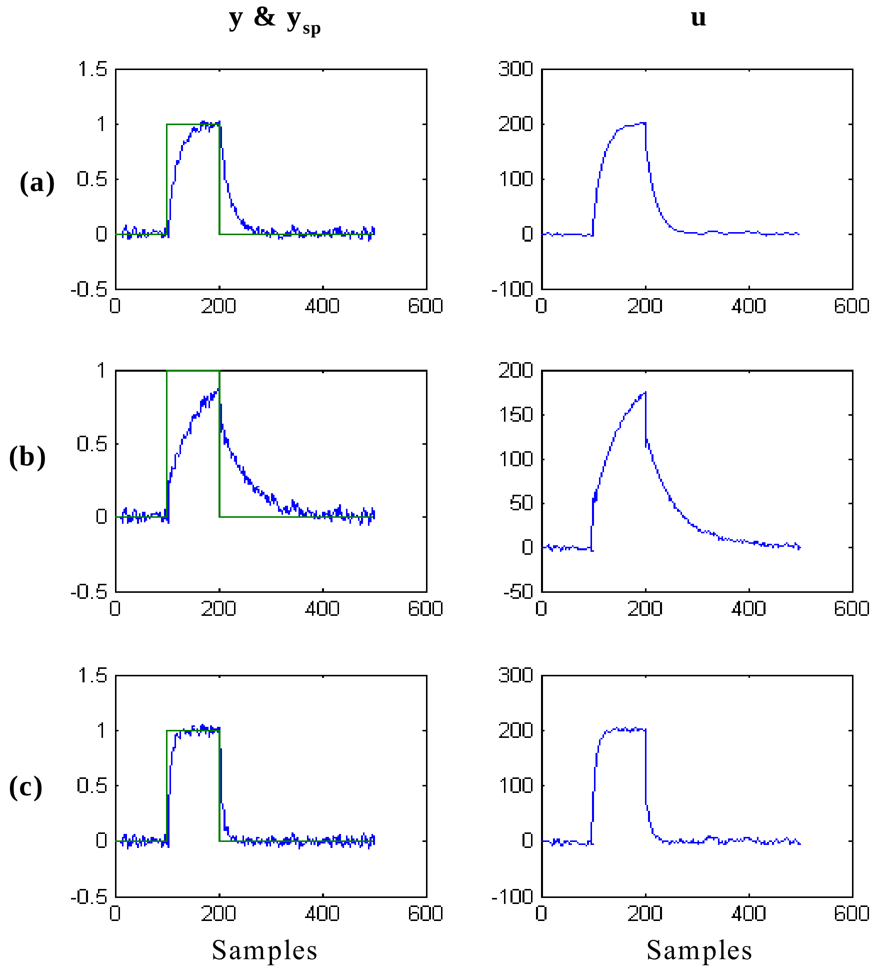

Figure 4.5 Closed loop data and results for Example 3

4.4 Conclusions

In the present chapter, a systematic way for tuning PID type controllers has been described. This method uses closed loop experimental data to determine the optimum controller settings for a PID type controller. Closed loop experimental data is used to determine the closed loop models for servo and disturbance transfer functions via time series modeling. These estimated transfer functions and knowledge of the current controller are then used to optimize a composite performance measure that takes into account both the deterministic and stochastic performance aspects. Tradeoff curves and robustness measures (gain and phase margins) can also be obtained. The results from the three case studies included here indicate that the proposed method can be used to tune PID type controllers in order to realize their "optimum" potential for set point tracking and stochastic disturbance rejection.

Chapter 5.

Multi-objective optimization of performance targets using Evolutionary Algorithm: A Study

5.1 Introduction

In the previous chapters estimation of stochastic and deterministic performance was presented. Both of these performance criteria are important for good performance of control loops. The tradeoff between different performances is clearly observed from Example 3 of the previous chapter. In this situation, the control engineer has to tune the controller so as to ensure the “best” stochastic and deterministic performance of the control loops. This is an example of decision making under conflicting objectives. In real world, multi-criteria decision-making forms an extensive field, where the best possible compromise should be found by evaluating several conflicting objectives. These optimization problems are very broad in character e.g. linear to nonlinear, convex to non-convex, continuous variable to discrete variable etc. These conflicting goals naturally yield a set of possible good solutions and human decision-making is often required to choose the solution for implementation. Before making any decision, all the possible good solutions should be available to decision maker. Classically, conflicting objective functions are combined to generate a scalar objective function and then optimized. Convex approximation of some of the control problems using linear matrix inequalities (LMIs) was proposed by Boyd et al (1994) but these solutions are limited to certain problems and do not provide true multi-objective solutions. Moreover, convexity is lost if the control structure is fixed as is the case in most industrial controllers.

The multi-objective optimization problem has drawn a lot of research attention in recent years. There have been numerous efforts on solving the multi-objective problem in a deterministic way. The interested reader can refer to the monographs of Chankong and Haimes (1983), Hwang and Masud (1979), Keeney and Rai (1976), Steuer (1986), Vincke (1992) and in more detail from Miettinen (1999) to learn more about the deterministic approach to solve the multi-objective optimization problem. The potential of evolutionary algorithms to solve such problems has been only recently recognized by the researchers. An overview of the developments and applications of multi-objective evolutionary algorithm (MOEA) especially in context of process control applications will be presented in next section. Subsequently, a methodology (including problem formulation) for multi-objective optimization for controller tuning is proposed. The use of this methodology and the efficacy of MOEA in making decisions related to process control will be shown by case studies in the section prior to conclusions section of this chapter.

5.2 Multi-objective Optimization for process control: An overview

There is a very vast literature and related software available on multi-objective genetic algorithm owing to the fact that multi-objective optimization is a very hot research topic for both scientists and engineers. This is not only due to the multi-objective nature of most real world problems but also because there are still many open research questions in this area. In operations research, more than 20 techniques (Coello et al., 2002) have been developed over the years to try to deal with functions that have multiple objectives, and many approaches have been suggested going all the way from a naïve combination of objectives into a single one to the use of game theory to coordinate the relative importance of each objective. However, the challenge in this area lies on the fact that there is no accepted definition of optimum as in single objective optimization and it is therefore difficult to even compare results of one method to another. Only a human decision maker can pick the “best answer”.

Evolutionary algorithms have their roots in the principles of natural selection and population genetics (Darwin, 1859; Fisher, 1930). Rosenberg (1967) hinted the potential of evolutionary algorithms for solving multi-objective problems. For almost 25 years not much progress was made in this area. Advancement of computational power fueled the surge in research publications and monographs in the area of evolutionary algorithms. The key strengths of evolutionary algorithms are their robust search methodology, which is able to work on problems that are multimodal, discontinuous & time variant and data that are random and noisy.

Genetic algorithm developed by Holland (1975) and co-workers was the seminal work in using the genetic algorithm as search technique. Genetic algorithm is the most frequently used method to search the solution space and find the global optimal solution using stochastic selection operators on a population of parameter values. The population is evolved, over generations, to produce better results by improving the fitness. The fitness value probabilistically determines how successful the individual will be at propagating its genes to subsequent generations. Better solutions are assigned higher values of fitness than worse performing solutions. Various operators are used to diversify the population in the search space before selecting the new generation. Genetic algorithm search technique combined with Pareto based ranking methods forms the very established convergence characteristics. The interested reader is refered to selected recent monographs on multi-objective optimization using evolutionary algorithms - Deb (2001), Bagchi (1999), Collette and Siarry (2003), Coello et al (2002), Matthias and Xavier (2002), Masatoshi (2002), Osyczka (2002), Sarker et al. (2002), Vincent and Billaut (2002).

MOEA have been applied to a wide range of design problems in many different fields. Zhang et al. (2003) used the GA for multi-objective optimization of SMB and Varicol process for chiral separation. Rajesh et al. (2001) studied multi-objective optimization of industrial hydrogen plants. Bhaskar et al. (2000) reviewed multi-objective optimization on typical chemical engineering problems. Due to the availability of vast literature on this topic, this thesis does not intend to present the details and working principles of multi-objective optimization that employ genetic algorithms.

Like various other applications, the use of multi-objective optimization for process control is not a new concept. Fleming and Purshouse (2002) provided a recent survey on use of evolutionary algorithm in control system applications. They comprehensively review the published literature on the use evolutionary algorithms (EA) in areas such as controller design, model identification, robust stability analysis, and fault diagnosis. They pointed out that online applications of EA tend to be quite rare because of the difficulty associated with using EA in real time to directly influence the operation of any system. Definition, uncertainty and human factors hinder the use of automatic decision-making using MOEA techniques and continue to be the open challenge for the researcher. The following quote by Goel (1997) relating to creative design captures these aspects:

"…problem formulation and reformulation are integral parts of creative design. Designers' understanding of a problem typically evolves during creative design processing. This evolution of problem understanding may lead to (possibly radical) changes in the problem and solution representations. [….] in creative design, knowledge needed to address a problem typically is not available in a form directly applicable to the problem. Instead, at least some of the needed knowledge has to be acquired from other knowledge sources, by analogical transfer from a different problem for example. […] creativity in design may occur in degrees, where the degree of creativity may depend upon the extent of problem and solution reformulation and the transfer of knowledge from different knowledge sources to the design problem."

Offline applications in process control are proving to be the most popular and successful. The monograph by Liu et al. (2002) covers the central concepts of multi-objective optimization and control techniques. It explains the fundamental theory along with a number of design methods and algorithms. In addition, applications of multi-objective optimization and control are presented by reporting on leading recent research work on this subject. Their monograph also includes a chapter dedicated to multi-objective PID Controller design. The strength of EA's in robust search and optimization has made them especially useful for the control engineers. Fleming and Purshouse (2002) described the main features of EA's that are beneficial to control systems engineering, together with the challenges that may limit their applications.

The main advantages of EA in process control advocated were its suitability to operate on ill-behaved landscapes with diverse types of variables. For example, the decision vector can be {sensor_type_A, 18.3^{o}, blue, 2π). This does not pose any problem whatsoever to EA. The main disadvantages cited by Fleming and Purshouse (2002) were, 1) for problems that are well understood, that are approximately linear, and for which trusted solution exists, the EA is unlikely to produce competitive results. This is true for problems where analytical solutions exist with an acceptable set of assumptions. 2) mission-critical and safety-critical applications do not appear, initially to be favorable towards EA usage due to the stochastic nature of evolutionary algorithm. No guarantee is provided that the results will be of sufficient quality for on-line use. When EAs are evaluated on benchmark problems, they are commonly tested many (typically 20–30) times due to the stochastic nature of the algorithms. There is also the matter of how individuals will be evaluated if no process model is available (as may well be the case). Some supporting theory exists for evolutionary algorithms, but this is unlikely to prove sufficient to win the approval of standards and certification agencies. Much care would clearly be needed for critical systems. Real-time performance is of particular interest to the engineer. However, EAs are very computationally intensive, often requiring massively parallel implementations in order to produce results within an acceptable timeframe. Hence, on-line application to real-time control is largely infeasible at present. Processes with long time-constants represent the most feasible application opportunities in the near future.

Offline design application of the MOEA is finding successful applications in the field of process control. MOGA (multi-objective genetic algorithms) and genetic programming are being applied to design controllers. Various possible designs can be generated with MOEA with the standard tradeoff (complexity vs performance) and the best design can be selected. Most control engineering problems are subject to constraints. For example, actuators have finite limits on their operation and control loops are required to be stable. EAs can handle constraints in a number of ways. The most efficient and direct method is to embed these constraints in the coding of the individuals. Where this is not possible, penalty functions may be used to ensure that invalid individuals have fitness that indicates they are low performers. However, appropriate penalty functions are not always easy to design for a given problem and may affect the efficiency of the search (Richardson et al., 1989). An alternative approach is to consider constraints as design objectives and recast the problem as a multi-objective one.

Use of MOEA for generating best tuning coefficients is the most obvious problem (Vroemen and Jager, 1997), as control engineering very seldom requires the optimization of a single objective function. Instead, there are usually a number of competing design objectives that are required to be satisfied simultaneously. Conventionally, members of the Pareto-optimal solution set are sought through solution of an appropriately formulated nonlinear programming problem. With development of more robust and fast algorithms, MOEAs are finding numerous applications in control engineering. Patton et al. (1997), Kowalszuk et al. (1999) used the MOEA for fault diagnosis. Marrison and Stengel (1997), Schroder et al. (2001) used the MOEA in robust control.

It is clearly observed that MOEA applications are finding tremendous potential to solve process control problems. MOEA is finding good use in generating controller parameters and searching for alternative structures. The control engineer in the process industry normally has to deal with conflicting performance criteria. MOEA could be of immense help in such situations by providing a Pareto of best results for difficult problems. As research work in this area gets more mature, MOEA can make a significant impact in the way optimization is done for process control problems.

5.3 Pareto construction for controller tuning problem

Problems in control engineering very seldom require the optimization of a single objective function. Instead, there are usually a number of competing design objectives that are required to be satisfied simultaneously. In order to tune controllers by parameter optimization using multi-objective functions, the knowledge about the set of compromises forms the basis of decision. Developing methods and tools for finding the entire set of compromises, the Pareto set, is the aim of the study. One must look closely at the contradictory properties of set of performance in the Pareto set before making any decision.

Conventionally, members of the Pareto-optimal solution set are sought through the solution of an appropriately formulated nonlinear programming problem. A number of approaches are currently employed including the e-constraint, weighted sum (presented in chapter 4) and goal attainment methods (Hwang and Masud, 1979). However, such approaches require precise expression of a (usually not well understood) set of weights and goals. If the trade-off surface between the design objectives is to be better understood, repeated application of such methods will be necessary. In addition, nonlinear programming methods cannot handle multimodality and discontinuities in function space well and can thus only be expected to produce local solutions.

MOEA (Fonseca and Fleming, 1994) evolve a population of solution estimates thereby conferring an immediate benefit over conventional MO methods. Using rank-based selection and niching techniques, it is feasible to generate populations of non-dominated solution estimates without combining objectives in some way. This is advantageous because the combination of non- commensurate objectives requires precise understanding of the interplay between those objectives if the optimization is to be meaningful. The use of rank-based fitness assignment permits different non-dominated individuals to be sampled at the same rate thereby according the same preference to all Pareto-optimal solutions. EAs have the potential to become a powerful method for multi-objective optimization. Including the control engineer in the optimization process as a decision maker, the EA can be guided, through the progressive articulation of preferences, to particular areas of interest. The trade-offs between design criteria and their interactions can be examined closely and the engineer's knowledge and experience can be employed to make informed decision on the basis of design requirements rather than the properties of the objective functions. Guiding EA to particular tradeoff will be shown in the case study at the end of this chapter.

In any typical chemical process industry, 95 % of the controllers are of PID type controller. We will therefore limit our treatment to the PID type structure and more specifically to the PI controller. There are various applications published in tuning PID parameters using genetic algorithms. Examples include Grefenstette (1986), Porter and Jones (1992), Vlachos et al. (2002) etc. The selection of a suitable MOEA technique for PID tuning is not well established. Very few applications can be found in literature that uses MOEA for tuning PID controllers. A good example for such an application is Herreros et al. (2000). Comparing different MOEA methods for generating PID optimal parameters is beyond the scope of this work and we leave to reader to try and select best suited technique for generating Pareto solutions.

Process control loop performance can be measured by minimum variance control performance (Harris, 1989). However, it is not advisable to tune the controller just for minimum variance performance and not to consider other important performance benchmarks like deterministic performance criteria and robustness. Tradeoff exist between 1) deterministic and stochastic performance, 2) robustness and stochastic performance. The control engineer cannot ignore the effect of these tradeoffs as was shown in Example 4.3.

There is no previous work available on use of MOEA on Pareto decision-making on stochastic performance and deterministic performance criteria. Finding the tradeoff between these competing objectives is of great interest. Keeping the consistency from the previous chapters we have chosen normalized integral absolute error (IAE_d) (Swanda and Seborg, 1999) as performance criteria to measure good set point tracking of process control loops. Thus, two conflicting performance criteria chosen for control loop tuning are control loop performance index (CLPI) and IAE_d. The aim of the controller will be to give good performance on set point tracking as well as stochastic disturbance regulation. Prediction of optimal CLPI tuning parameters from experimental closed loop process data was presented in the previous chapter. Closed loop transfer function models G and H were used to predict the closed loop transfer function for any other controller settings using equations 3.7 and 4.5. These equations are reproduced below for the reader's convenience.

$$H^* = \frac{N}{1 + Q^* T} = \frac{\dfrac{H}{(1-G)}}{1 + Q^* \dfrac{G}{(1-G)Q}} = \frac{H}{1 + G\left(\dfrac{Q^*}{Q} - 1\right)} \tag{3.7}$$

$$G^* = \frac{G}{G + \dfrac{Q}{Q^*}(1-G)} \tag{4.5}$$

Equation 3.7 can be used to predict the CLPI value following the discussion in chapter 3 and equation 4.5 can be use to prediction IAE_d value following the discussion in chapter 4. This implies that a set of CLPI and IAE_d values can be generated from a given set of PID parameters.

The multi-objective objective function can be written as

$$\min_{Q^* = K_c^*,\, \tau_I^*} \phi = \{IAE_d, 1/CLPI\} \tag{5.1}$$

The second objective is written as 1/CLPI owing to the fact that a high CLPI value represents good stochastic performance; thus, 1/CLPI should be minimized (originally proposed definition for performance index by Harris (1989) was of the form of 1/CLPI and later it was inverted by Huang and Shah (1997) to make it between 0 to 1). This multi-objective optimization problem can be given user defined constraints like robustness (gain margin, phase margins) or weightings on control valve movements etc. Once the objective functions and constraints are defined, they can be optimized using suitable MOEA technique in literature Coello (1998).

In summary, the process of finding controller-tuning decision Pareto can be summarized as

1) Select the control performance criteria's (CLPI and IAE_d are good choices for most industrial applications).
2) Select any constraints required (e.g. gain margin or phase margin are readily interpretable parameters for robustness and qualify as constraints).
3) Carry out system identification and calculate the closed loop process and disturbance transfer function (as per chapter 3).
4) Select a MOEA strategy to find Pareto between IAE_d and CLPI calculated using equations 3.7, 4.5 and 5.1 (This process may require few trials in tuning MOEA parameters).
5) Make decision for best tuning parameters from Pareto optimal solutions.

5.4 Case Studies

The multi-objective optimization is applied to one typical test problem of industrial relevance. The basic idea is to show the applicability and efficacy of methodology proposed on a problem of this kind. The MultiObjective Evolutionary Algorithm Toolbox developed by Tan et al. (2001a) was used. Information on this toolbox can be obtained from http://vlab.ee.nus.edu.sg/~kctan/. This toolbox allows design trade-offs for multi-objective scenarios to be examined aiding decision-making for a global solution that best meets specifications. In addition, the toolbox is capable of handling problems with hard and soft constraints. Features include various graphical displays for problem and result analysis. The settings for the simulation are done through Graphical User Interfaces (GUIs). The toolbox also comes with comprehensive help files and demonstrations in HTM format. The main strength of the toolbox is the utilization of novel incrementing multi-objective evolutionary algorithm (IMOEA) with dynamic population size that is computed adaptively according to the online discovered tradeoff surface and its desired population distribution density (Tan et al., 2001b). It incorporates the method of fuzzy boundary local perturbation with interactive local fine-tuning for broader neighborhood exploration. Armed with strong theoretical MOEA tools, friendly GUI and the power of MATLAB/SIMULINK codes, this toolbox is ideal for testing MOEA on control applications. The example presented below demonstrates tuning the PID controller using MOEA generated Pareto decision curve.

Example 1

In Example 3 of Chapter 4 tradeoffs between CLPI and IAEd was clearly observed. This problem was tested on MOEA. Keeping the initial PI settings and problem parameters same, a set point change is implemented on the system to capture the system dynamics. Using system identification, the closed loop process and disturbance transfer functions (G and H respectively) are identified. These transfer functions were used to generate a multi-objective optimization problem as proposed in equation 5.1.

The problem was solved real coded in MOEA toolbox with parameter constraints on K_c and τ_I as [0 100], cross over probability 0.7, number of crossover points 2, mutation probability 0.01, selection process tournament selection, population size 150, number of generations 25, no constraints or preference on objectives, niching distance static 0.02 and sharing distance scale 1 for both objectives. Most of the values are taken from default values in toolbox and were found to be suitable when optimized.

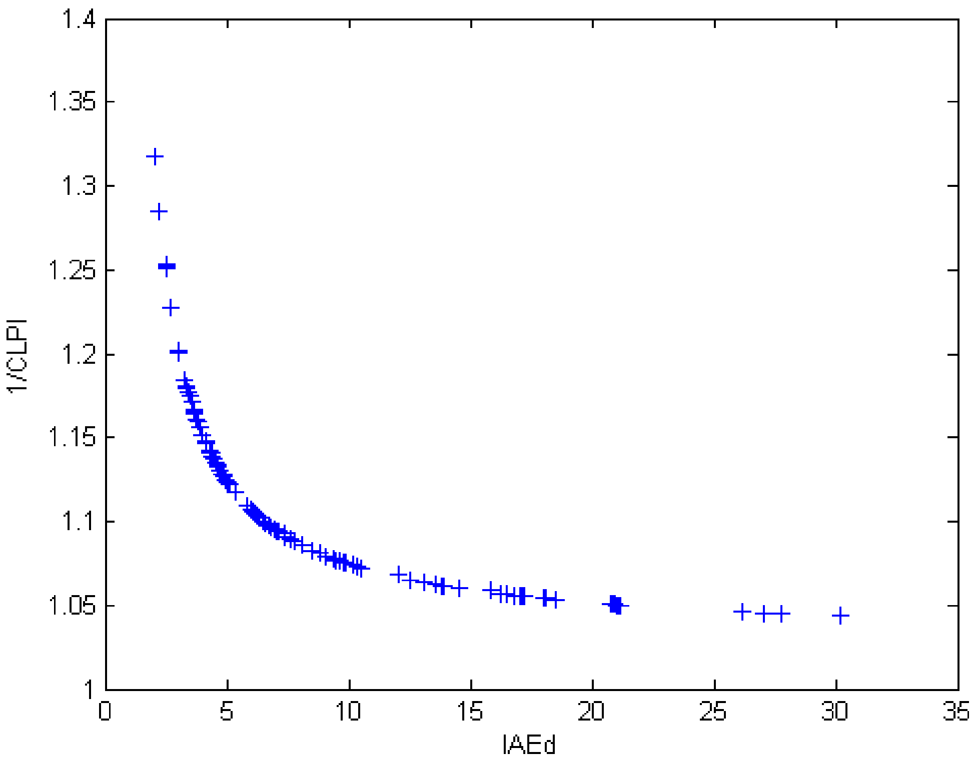

Figure 5.1 Pareto optimal curve for Example 1, with sharing distance scale 1:1 and sharing distance static 0.02

Figure 5.1 shows the Pareto curve generated. It is observed that more optimal points are close to higher values of IAE_d. This is clear indication of preference of population towards high IAE_d compared to going towards high 1/CLPI values. To better spread the Pareto, the sharing distance scale on the first objective was adjusted to 22 = 30/1.35 (maximum optimal value from the first objective/ maximum optimal value from the second objective). Pareto optimal curve for adjusted sharing distance scale 22:1 is shown in Figure 5.2. There is clear improvement in the spread of population in terms of covering the corners of Pareto. Despite this improvement, the Pareto is still not well dispersed and population still tends drift to certain areas of Pareto. This was further improved by increasing the niche sharing distance from static 0.02 value to dynamic (phenotype/cost, refer to Tan et al 2001b) and keeping rest of the parameters at their previous values. The resulting Pareto curve is shown in Figure 5.3. There is a clear improvement in spread as well as diversity of population on Pareto curve. This fine-tuning can be continued for some more trials but we reckon this Pareto to be satisfactory for practical use.

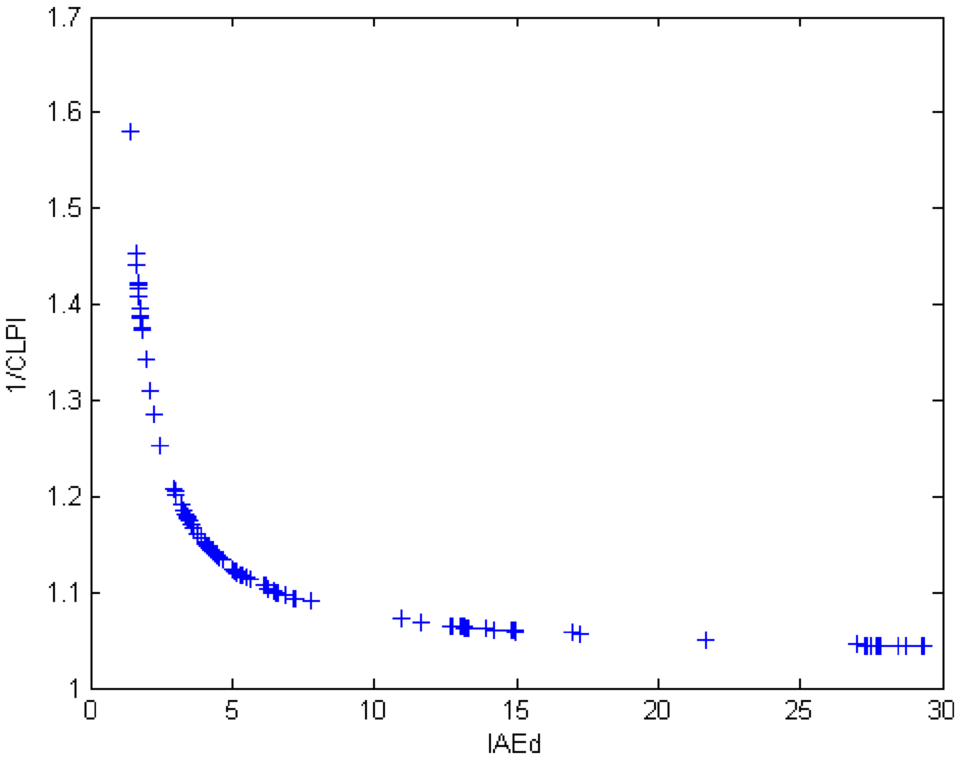

Figure 5.2 Pareto optimal curve for Example 1, with sharing distance scale 22:1 and sharing distance static 0.02

Four Pareto optimal solutions curves between K_c vs. IAE_d, K_c vs. 1/CLPI, τ_I vs. IAE_d and τ_I vs. 1/CLPI are shown in Figure 5.4. It is obvious from Figure 5.4 that CLPI and IAE_d are more sensitive to the reset time and relatively insensitive to changes in controller gain. The optimal pattern of input variables on optimal parameters can be used to develop correlation between them to fine-tune the controller for optimal performance. For example, with the help of Figure 5.4, the optimal controller gain can be fixed at about 50 and one-knob tuning by varying only integral action can be performed. The 'optimal' PI controller can be determined to be $K_c = 50$ and $\tau_I = 1.83$. This PI controller is expected to provide: CLPI = 0.8, $T_s = 5.67$, $IAE_d = 2.44$, GM = 3.84 and PM = 66.54^o. This is a very interesting finding and can be described as a strong advantage of MOEA compared to traditional optimization techniques in control applications. Population of the entire optimal parameters can be obtained at a time and can be used to understand more about the effects of inputs on optimization objectives.

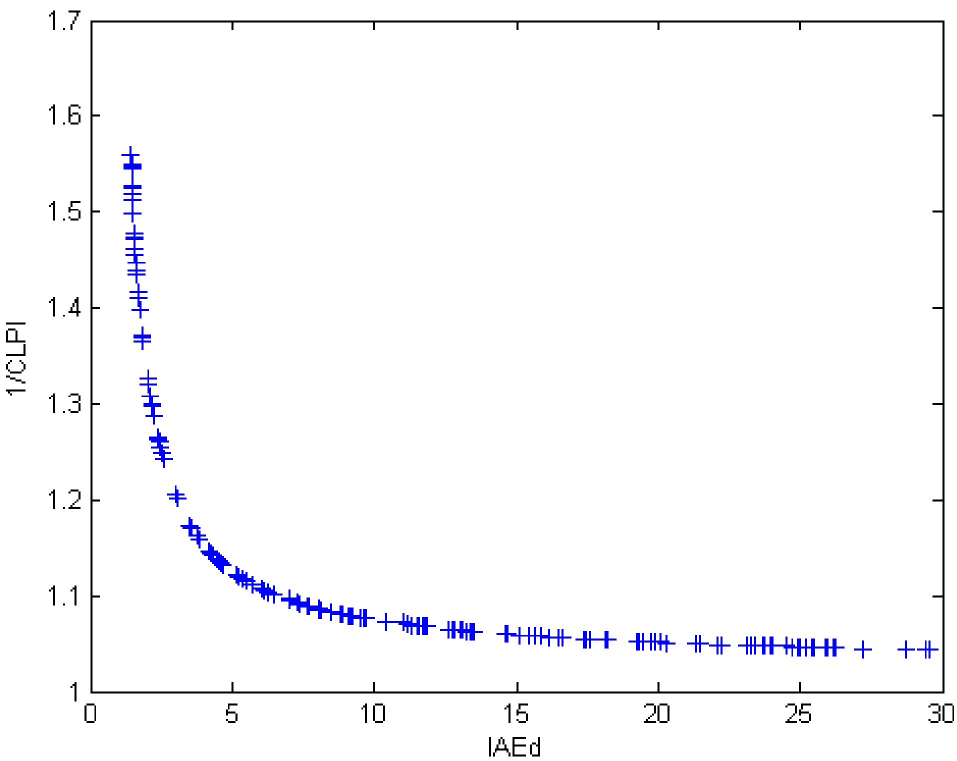

Figure 5.3 Pareto optimal curve for Example 1, with sharing distance scale 22:1 and sharing distance dynamic (phenotype/cost)

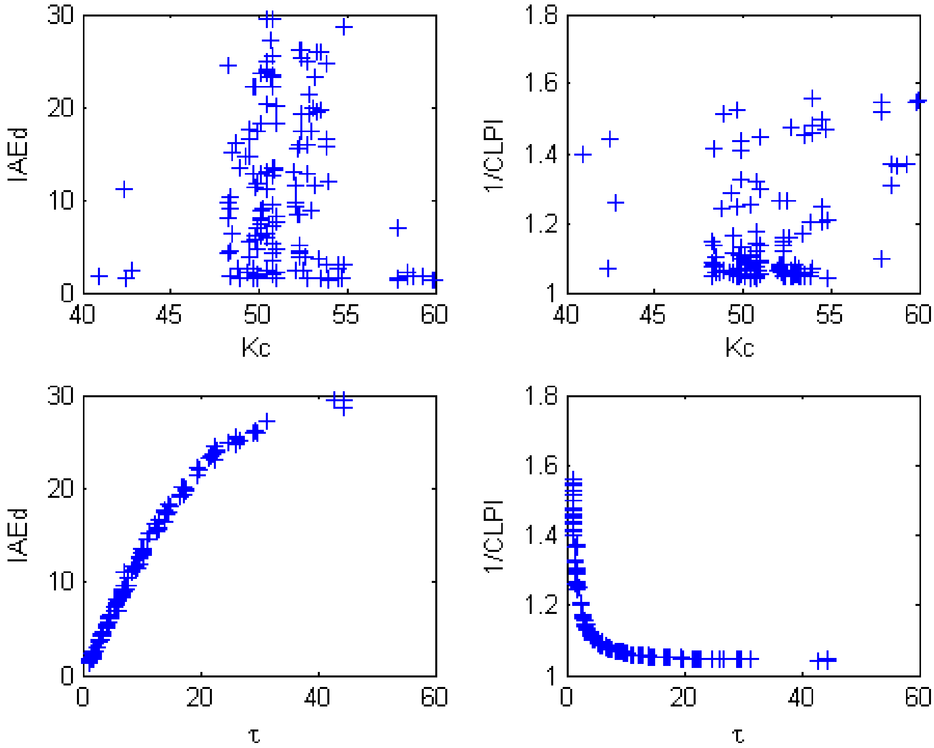

Figure 5.4: Effect of inputs on optimal parameters

5.5 Conclusions

An application of multi-objective evolutionary algorithm on generation of optimal Pareto decision curve was presented. MOEA methodology from the work of Tan et al (2001a) was adopted and was used for generating various optimal PID tunings. Despite the advances in research on MOEA, tuning of various parameters of MOEA to produce robust results is still a trial and error approach. An example for tuning few parameters for MOEA was presented. It was shown that the relationship between input parameters and Pareto optimal solutions can be very interesting. These relationships can be very informative in understanding the nature of control system and behavior of optimal control parameters for tuning purposes. It is clear from the discussion and the case study that MOEA is a very strong tool for generating optimal solutions to process control problems.

Chapter 6. Conclusions and Future Directions

In this research, methods are provided to calculate the PID achievable performance of control loops. A method that uses information of approximate open loop process model is shown to be very effective in calculating PID achievable performance. It calculates exact PID achievable performance if true open loop process model is known otherwise also very good estimate of PID achievable performance can be calculated. This method can be useful when open loop process model is approximately known and stable.

In many situations open loop process model may not be available e.g. process is time varying, complex, open loop unstable etc. A method that uses closed loop experimental data to determine the maximum control loop performance achievable with a PID type controller has also been described. Though all the examples involved consider PI controllers, this method is equally valid for PID controllers. While some set point excitation is required, the method does not need the open loop process or noise models. This is a positive aspect of the proposed method. Furthermore, optimal PI settings are also obtained. The method enables the calculation of the values of the deterministic performance measures (T_s, IAE_d) thereby leading to the estimation of robustness margins (GM and PM) for the current and the estimated optimal PI controller. Five examples using realistic data sets were employed to illustrate the workability of this strategy.

It is shown that the recycle dynamics can lower the control performance particularly when the product of the gains of the forward and recycle paths approach the value of

1. The noise dynamics play a crucial role – a process affected by non-stationary noise can be controlled adequately using a well-tuned PI controller. Certain combinations of the parameters of the recycle dynamics (low value of the recycle time constant and high values of recycle time delay) can limit the quality of control obtainable from PI controllers. The effect of recycle dynamics needs to be identified in process plants and should be compensated properly to attain desired control targets. A method to calculate the PI achievable targets for the process with recycle is described. A scheme is presented to systematically improve the control performance for process with recycles.

In the chapter 4, a systematic way for tuning PID type controllers has been described. This method uses closed loop experimental data to determine the optimum controller settings for a PID type controller. Closed loop experimental data is used to determine the closed loop models for servo and disturbance transfer functions via time series modeling. These estimated transfer functions and knowledge of the current controller are then used to optimize a composite performance measure that takes into account both the deterministic and stochastic performance aspects. Tradeoff curves and robustness measures (gain and phase margins) can also be obtained. The results from the three case studies included here indicate that the proposed method can be used to tune PID type controllers in order to realize their "optimum" potential for set point tracking and stochastic disturbance rejection.

An application of multi-objective evolutionary algorithm on generation of optimal Pareto decision curve was presented. MOEA methodology from the work of Tan et al (2001a) was adopted and was used for generating various optimal PID tunings.

Despite the advances in research on MOEA, tuning of various parameters of MOEA to produce robust results is still a trial and error approach. An example for tuning few parameters for MOEA was presented. It was shown that relationship between input parameters and Pareto optimal solutions can be very interesting. These relationships can be very informative in understanding the nature of control system and behavior of optimal of control parameters for tuning purposes. It is clear from the discussion and the case study that MOEA is a very strong tool for generating optimal solutions to process control problems. Still there are challenges left in this area especially in making online application of these methods. Development of robust and fast algorithms will continue to be the key focus in process control related research. Issues of automatic decision making from optimal Pareto set will be another interesting challenge to the control engineer.

It is visible that the success stories of implementation of control loop performance monitoring have started to come from industry. The process industry is close to adapting CLPM as a standard feature for their control systems. Theoretical developments are coming from the academia at a rapid pace. Still there are many theoretical and practical challenges that need to be resolved. Minimum variance benchmark has been used extensively for CLPM in the existing commercial software but a more suitable benchmark like PID achievable targets should be used. This would be better and realistic in plants that are predominantly regulated using PID controllers. Consideration for other performance tradeoffs e.g. robustness and performance should be given. Most of the problems are multivariable in nature and there is a lot of scope for developments in the MIMO domain. Automatic fault detection and PID tuning can reduce the load of process engineer considerably and proper framework including man machine interface (MMI) should be developed.

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Appendix A

Proof of theorem from Section 3.3

If $y_{sp} = 0$ then from equations 3.1 and 3.2;

$$N_m a + T_m u = y = \frac{N}{1 + Q\,T}\,a$$

Also, from closed loop relation: $u = -\frac{QN}{1 + Q\,T}\,a$

Therefore,

$$N_m a + T_m\left(-\frac{QN}{1 + Q\,T}\,a\right) = \frac{N}{1 + Q\,T}\,a$$

Multiplying by (1+QT):

$$N_m(1 + QT) + T_m(-QN) = N$$

Taking terms with N one side and with N_m other side

$$N_m(1 + QT) = N(1 + QT_m)$$

Hence

$$Ha = \frac{N}{1 + Q\,T}\,a = \frac{N_m}{1 + QT_m}\,a$$

Proved