A CONTROL PERFORMANCE MONITOR AND
A MODEL PERFORMANCE MONITOR
FOR PROCESS CONTROLLERS

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CHAPTER 1

INTRODUCTION

History

This work was sponsored by the Measurement and Control Engineering Center (MCEC). The title of this MCEC project is "Automatic Initiation of Model Adjustment." The original objective is to automatically suggest model adjustment for process model-based applications after the process model becomes outdated due to process changes. As the investigation developed, it became obvious to focus on model-based control applications only, and to evaluate the model goodness not on the model accuracy but on its functional performance measures of the model-based control applications. Two approaches, the control performance monitor and the model performance monitor, evolved. The control performance monitor does not argue the original question, but appears to have great utility for calling attention to poorly performing loops. The model performance monitor solves the original problem, but undesirably requires process excitation.

Control Performance Monitor

Chemical plants are controlled by a large number of process controllers to maintain safe and economic operation. The good performance of a controller is important not only for people's safety, environmental protection, and equipment protection, but also for smooth plant operation, high product quality, low operating costs, and high profit.

Control loop performance will change during plant operation due to many reasons, such as changes in operating conditions (feed conditions, catalyst conditions, or equipment conditions), changes in plant characteristics (gain, time constant, or delay), changes in control or measurement device conditions (valve stiction), hitting constraints, etc. Since these changes happen gradually, the poor control performance caused by these changes may not be easy to detect without close watching by an experienced operator or engineer. However, since an operator or engineer in a typical plant is usually responsible for a large number of control loops, among many other responsibilities, he or she usually does not have enough time to watch each control loop very closely, or give timely, accurate evaluation of each control loop's performance. Even if a poor control performance is detected, it often has existed for a quite long time before an operator noticed it. Furthermore, human evaluation of the control loop performance not only is tedious and time-consuming, but also is subjective and requires expertise and experience.

There is a need in the process industry for control performance monitoring techniques for automatic, prompt, objective, and accurate detection of poor control performance. The desired characteristics of a control performance monitoring technique include:

(1) Require minimum *a priori* knowledge about the process or control system. Since the characteristics of a plant process or control system devices will change during plant operation, a monitoring technique dependent on the characteristics of the plant or control system may become unreliable after any changes in these characteristics.

(2) Do not disturb the routine plant operation. No plant tests are required.

(3) Use the routine plant operation data only. No new sensors or special measurements are required, and just use whatever measurements already available during plant operation.

This work proposes a control performance monitor to automatically detect poor control performance. The proposed technique has the above three characteristics.

Model Performance Monitor

For a process model-based controller, the quality of the process model directly affects the controller's performance. Since the characteristics of an industrial process often change with time, the process model may become outdated after these process changes. The outdated process model needs adjustment for the model-based controller to continue to achieve good performance. For example, the activity of a catalyst will decrease gradually, so in order for a controller based on the reactor model to maintain good performance, the reactor model may need to be adjusted to reflect the change in catalyst activity.

Adjusting a process model usually means to re-estimate or rebuild the process model, and therefore it is often very costly in process industry. Process model estimation often induces upsets to the plant. Even the simple step tests are not only disruptive to the process, but also very time-consuming due to the fact that many chemical processes have very large time constants. For example, it may take hours to perform a single step test on an industrial distillation column. Furthermore, since a chemical process usually has multiple inputs and multiple outputs, and these inputs and outputs often interact with each other, re-estimate or rebuild a chemical process model is a very demanding task.

Therefore, we usually do not want to adjust a process model through re-estimating or rebuilding the model unless the benefit is significant.

The benefit of adjusting a process model is in the improvement in the performance of the model-based controller, i.e., the benefit is in the function of the model, not in accuracy of the model prediction or accuracy of the model parameter values, as normally considered by modelers or statisticians. Therefore, we do not want to suggest model adjustment unless a significant improvement in control performance of the model-based controller can be achieved by the model adjustment.

The measure of the benefit of model adjustment is uncertain because there is uncertainty in model parameters, and there are noise and disturbances on process outputs. Therefore statistical techniques must be used to anticipate when the benefit of model adjustment is significant.

This work proposes a model performance monitor to automatically suggest model adjustment. It suggests model adjustment only when a statistical test indicates that the function of the model, i.e., the control performance of the model-based controller, can be improved significantly by model adjustment. The model performance monitor uses the routine plant operation data only to make decisions after it is properly setup. However, the initial setup of the model performance monitor undesirably requires process excitations or upsets.

CHAPTER 2

CONTROL PERFORMANCE MONITOR

Good control performance is important to process safety, product quality, and manufacturing costs. But, once a controller is tuned, changes in the process can make a controller undesirably sluggish or aggressive. These changes include process gain and dynamics, valve stiction, constraints and many others. Evaluating control loop performance is important and becomes a routine, but time consuming, human effort. It would be nice to develop an automatable procedure to flag poorly performing control loops.

2.1 Literature Review on Control Performance Monitoring

Currently most control loop performance monitoring techniques are concerned with the evaluation of the controlled variable variance due to unmeasured, stochastic disturbances. Most of these techniques are based on the work of Harris (Harris, 1989), who proposed the use of closed-loop data to evaluate control loop performance using minimum variance control as a benchmark. Theoretically, a minimum variance controller is the controller that can completely remove all effects of disturbances after process delay leaving only white noise. Therefore, for any disturbance sequence, no controller can do a better job to reduce process output variance than the minimum variance controller.

The controlled variable variance under minimum variance control is used as a lower bound to evaluate the performance of single-loop controllers (Harris, 1989). The ratio of the minimum variance to the variance of the controlled variable is defined as normalized performance index (Desborough and Harris, 1992; Desborough and Harris, 1993a; Desborough and Harris, 1993b). Other similar measures have also been proposed, such as the closed loop potential index (Kozub and Garcia, 1993; Kozub, 1996), and the relative variance index that compares actual control to both minimum-variance control and open-loop control (Bezergianni and Georgakis, 2000).

Many applications of these performance assessment schemes in pulp and paper processes were reported (Perrier and Roche, 1992; Desborough and Harris, 1994; Jofriet et al., 1995; Harris et al., 1996b; Jofriet and Bialkowski, 1996; Jofriet et al., 1996; Lynch and Dumont, 1996; Owen et al., 1996). The applications of performance assessment techniques in refineries were also reported (Thornhill et al., 1996; Thornhill and Hagglund, 1997; Thornhill et al., 1999).

Extension of Harris' performance assessment concept to MIMO feedback controllers has been studied (Harris et al., 1995; Huang et al., 1995; Ettaleb et al., 1996; Harris et al., 1996a; Huang et al., 1996; Huang et al., 1997a; Huang et al., 1997b; Kesavan and Lee, 1997; Huang and Shah, 1998; Ettaleb, 1999; Huang and Shah, 1999). And the extensions to unstable and non-minimum phase processes (Tyler and Morari, 1995a; Tyler and Morari, 1995b; Tyler and Morari, 1996) and cascade control (Ko and Edgar, 2000) have also been reported.

Minimum variance control (MVC) based techniques greatly reduce the amount of process knowledge required for control performance evaluation. If the process delay is known or can be estimated effectively online, these MVC-based techniques can evaluate the control performance by using only routine plant operation data. However, the delay for many processes will change during routine operation, and estimating the delay online is not an easy task. Also a useful MVC based monitor is computationally complex and burdensome.

Another limitation on MVC based performance monitoring is that the minimum variance is not achievable unless the perfect process model and disturbance model are perfectly known. But these are not available in practice. In addition, to achieve minimum variance control often requires large moves of manipulated variables, which is usually unacceptable in practice. A more realistic lower bound of controlled variable variance for PID controllers was studied (Ko and Edgar, 1998). And a modified performance index, which is based on the desired pole locations and MVC, was also proposed for a larger range of processes (Horch and Isaksson, 1999; Horch, 2000).

The major problem for the above minimum variance based techniques is that for processes with a changing time delay, the minimum-variance based techniques are not applicable unless online estimation of process delay is performed. Therefore, a control performance monitoring technique not dependent on a process model or process delay is desired, and this paper proposes a control performance monitor, which does not depend on a process model or the process delay and uses only the routine plant operation data.

There are approaches other than minimum variance based control performance monitoring, such as frequency analysis (Kendra and Cinar, 1997), likelihood ratio (Tyler and Morari, 1995a), setpoint response data (Swanda and Seborg, 1997; Swanda and Seborg, 1999), and the control structure constraints (Eriksson and Isaksson, 1994). A performance index, called idle index, was proposed to detect sluggish control loops (Hagglund, 1999). Many methods to detect oscillations in control loops were reported

(Ettaleb et al., 1996; Taha et al., 1996; Ettaleb, 1999; Miao and Seborg, 1999). Methods to detect oscillations in control loops based on the integral of absolute error (IAE) between zero crossings (IAEZC) to detect oscillations in control loops were also reported (Hagglund, 1995; Thornhill et al., 1996; Thornhill and Hagglund, 1997; Thornhill et al., 1999). The IAEZC is compared to a threshold value, which is the IAEZC value of a sinusoidal oscillation. Choices of oscillation amplitude and frequency were proposed. For example, a good choice for oscillation frequency is $2\pi/\tau_I$, where τ_I is the controller integral time, and a good choice for oscillation amplitude is one percent of the controller range over a supervision time of 50 times the presumed oscillation period (Hagglund, 1995). This method provides a quantitative measure of oscillation sizes, but it has disadvantages: First, it is difficult to decide how large of an IAEZC value is large enough to indicate oscillations. The threshold value is affected by the amplitude of noise and disturbance, which may change during plant operation. Secondly, the oscillation period is assumed to have a specific value, which may not be true. Detection of multiple oscillations in control loops was reported (Thornhill et al., 2002). Performance diagnostics of model-based controllers were discussed (Patwardhan and Shah, 2002).

An automated on-line goodness of control performance monitor was developed by Rhinehart (Rhinehart, 1995; Venkataramanan et al., 1997; Narayanaswamy, 1998). The method uses a computationally simple, robust statistic, called the r-statistic, which is defined as the ratio of the expected variance of the deviation of the controlled variable from the setpoint to one half of the expected variance of the deviation of two consecutive process measurements. It compares the current r-statistic values with some critical values to indicate performance changes. The critical values are determined from the distribution of the r-statistic values obtained during a period judged "good" by engineers and operators, usually being set at the values of the r-statistic with 15% and 85% cumulative probabilities. The goodness-of-control monitor can indicate periods when a controller becomes too sluggish or aggressive, or when a constraint or other poor performance is reached. It is computationally efficient and is easy to understand and implement. The benchmark is built from the data during 'good' operation periods, and is able to adapt itself, and therefore is easy to obtain and adjust by the operators or engineers.

The above goodness of control monitor and most other performance monitoring techniques compare a single index value (or a single average index value) to a trigger value to judge the performance, and do not consider the distributions of the index values. If a performance index has large variation ranges, a single or average value of the performance index is not a good representation of control performance, and the variance of the performance index or, more informatively, the distribution of the index values should also be used to determine control performance. One author (Rhinehart) reports that some oscillatory controlled variable patterns from a too aggressive controller resulted in r-statistic values which remained within the critical values.

Our objective here has been to develop a conceptually simple, computationally simple, robust and comprehensive automated goodness of control monitor.

This work proposes a control performance index, called run length (RL), and proposes to compare the RL distribution of a current control system to a reference RL distribution, which is obtained from the data collected during a period with good control performance. The proposed technique does not require a process model or process delay, and therefore is suitable for monitoring time-varying and nonlinear processes. It only needs a window of the controlled variable data collected during a representative period defined as having good control by the user. It can detect and flag poor control performances, such as too sluggish control, too aggressive control and oscillations.

The control performance monitor flags when statistical tests indicate that there is a sustained period with significant changes in the RL distribution compared to the reference RL distribution obtained from a good control period. The control performance monitor uses only routine plant operation data: plant controlled variable (CV) and setpoint (SP).

2.2 Run Length (RL) Performance Index

The values of the error signal (i.e., setpoint minus controlled variable) usually fluctuate around a value of zero. When the error signal changes its sign from + to -, or vice versa, it is called a zero crossing. *Run length*, RL, is defined as the time period between two consecutive zero crossings. In the special case where the error signal is exactly zero, we choose to let this zero value form a new run because as far as control performance is concerned, situation of a zero value is closer to that of a zero crossing than that without sign change. In practice, measurements are rarely exact zero, so how to treat a zero value does not have a big effect. Since we are dealing with sampled data, we choose to use number of samplings rather than a time unit (seconds or minutes) as the unit for time and for RL.

Figure 2.1 illustrates the zero crossing and run length concepts. A vertical bar represents a zero crossing, and the time period between two consecutive zero crossings is the run length.

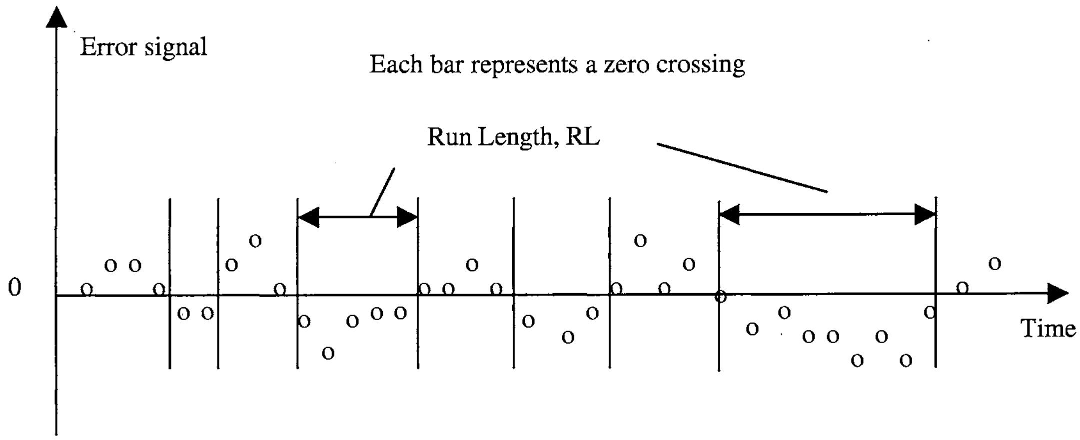

Figure 2.1 Zero Crossing and Run Length

As a monitoring index, RL offers several practical advantages. First, the RL distribution can indicate whether oscillations exist in the controlled variable. When there exist oscillations, the probability of having an RL index value equal to or close to half of the oscillation period will increase compared to a reference case with good control and no oscillations. Second, the RL distribution can indicate slow elimination of offsets and sustained offsets. When there are offsets, the probability of having large run length values increases compared to the reference case with good control. Third, the RL distribution under good control is not sensitive to changes in noise magnitude. Theoretically, when the CV is at the SP, the noise magnitude has no effect on the RL distribution at all. Therefore, during plant operation with good control, even if the noise magnitude has changed, the RL distribution will not change much.

The RL index also has several theoretical advantages. First, the RL distribution of a white noise random process can be quantified theoretically, and is derived in Section

2.4. A white noise random process, or white noise for short, is a sequence of independent, identically distributed random variables with certain probability density function. A white noise with a Gaussian probability density function is called a Gaussian noise. In the perfect control case, where the true value of the controlled variable is exactly at the setpoint all the time, the actuating error signal, e = SP – CV, is equal to the measurement noise, which usually can be described well by a Gaussian noise. Therefore, the RL distribution in the perfect control case can be quantified theoretically. Second, the derived theoretical RL distribution in the perfect control case not only applies to a Gaussian noise case, but also applies to any other noise with a probability density function symmetrically distributed around zero value, such as a noise with a uniform or a triangle probability density function. Third, as long as the noise probability density function is symmetrically distributed, the derived theoretical RL distribution of the error signal will not change even if other parameters of the noise have changed. For example, Gaussian noises with different variance values will have the same RL distribution as long as the mean values of the noises are equal to zero. Similarly, changes in the shape of a uniform or triangle probability density function of the noise will not affect the theoretical RL distribution in the perfect control case, as long as the noise is symmetrically distributed around zero value. Therefore, the changes in noise variance will not affect the theoretical RL distribution in the perfect control case, which makes the RL performance index very attractive because the noise variance does change in practice and is difficult to estimate.

The RL performance index was chosen after simulation exploration with several other performance indices. Simulation exploration shows that the RL performance index gives the best results.

The following performance indices are investigated using simulation.

(1) Error: $e(k) = SP(k) - CV(k)$, where, k is discrete sample time, SP is setpoint, and CV is controlled variable measurements.

(2) Normalized error: $NE(k) = e(k)/\sigma_e$, where σ_e^2 is the estimated noise variance, and is estimated recursively by

$$\sigma_e^2(k) = (1-\lambda)\sigma_e^2(k-1) + \frac{\lambda}{2}(e(k) - e(k-1))^2$$

where λ is a filter constant, usually between 0.001 and 0.100.

(3) r-statistic (Rhinehart, 1995): $r(k) = S_1(k)/S_2(k)$, where

$S_1^2(k) = (1-\lambda)S_1^2(k-1) + \lambda e^2(k)$

$S_2^2(k) = (1-\lambda)\, S_2^2(k-1) + (\lambda/2)(e(k)-e(k-1))^2$ (same as $\sigma_e^2(k)$ above)

λ is also a filter constant, and e(k) is the error.

(4) g-statistic: $g(k) = 2 - 1/r(k)$, where r(k) is the r-statistic. This is a re-arrangement of the r-statistic, such that $0<g(k)<1$. $g(k) = 1$ means perfect control, and $g(k) = 0$ means the error signal changes sign at each sample (high frequency oscillations).

(5) Zero crossing rate: ZCR(k)

$$ZCR(k) = \frac{\text{(number of zero-crossings within a window of samples e(k))}}{\text{(number of e(k) samples within the window)}}$$

ZCR is the average frequency (or probability) of zero crossings among sampled values of e(k). For any sample sequences: $0 \le ZCR \le (N-1)/N$. For a zero-mean random number sequence, ZCR = 0.5. A ZCR value close to zero indicates existence of long-time offsets or low frequency oscillations. A ZCR value close to1.0 indicates high frequency oscillations.

2.3 Overall Structure of Proposed Control Performance Monitor

Figure 2.2 shows the flow chart of the proposed control performance monitor. At each sampling time, measure the process controlled variable (CV) and setpoint (SP), and calculate the error (SP – CV). Calculate the RL distribution from a window of the past N error values. The partial run length at each of the two ends of the window is counted as a complete RL with the data within the window, which makes use of all data within the window, and helps early detection of long run lengths caused by sluggish control or hitting a constraint. The choice of the window length N will be discussed in detail later. Apply the statistical chi-square test to compare the current RL distribution to a reference RL distribution, which had previously been built from data collected during a good control period. If the chi-square test indicates that the two RL distributions are significantly different, increment a counter, called a violation counter VC, which records the length of the continuous time period during which the chi-square test continuously indicates significant differences in the RL distribution. Otherwise, if the chi-square test does not indicate significant differences, reset the violation counter to zero. Compare the violation counter with the pre-selected grace period, which is the time period allowed for a good controller to handle changes in setpoint or non-random disturbances plus the time period needed for a window length of data used to build the current RL distribution. If the violation counter becomes greater than the grace period, then the control performance monitor flags poor control performance. Otherwise, it does not flag. At the next sampling time, repeat the whole procedure.

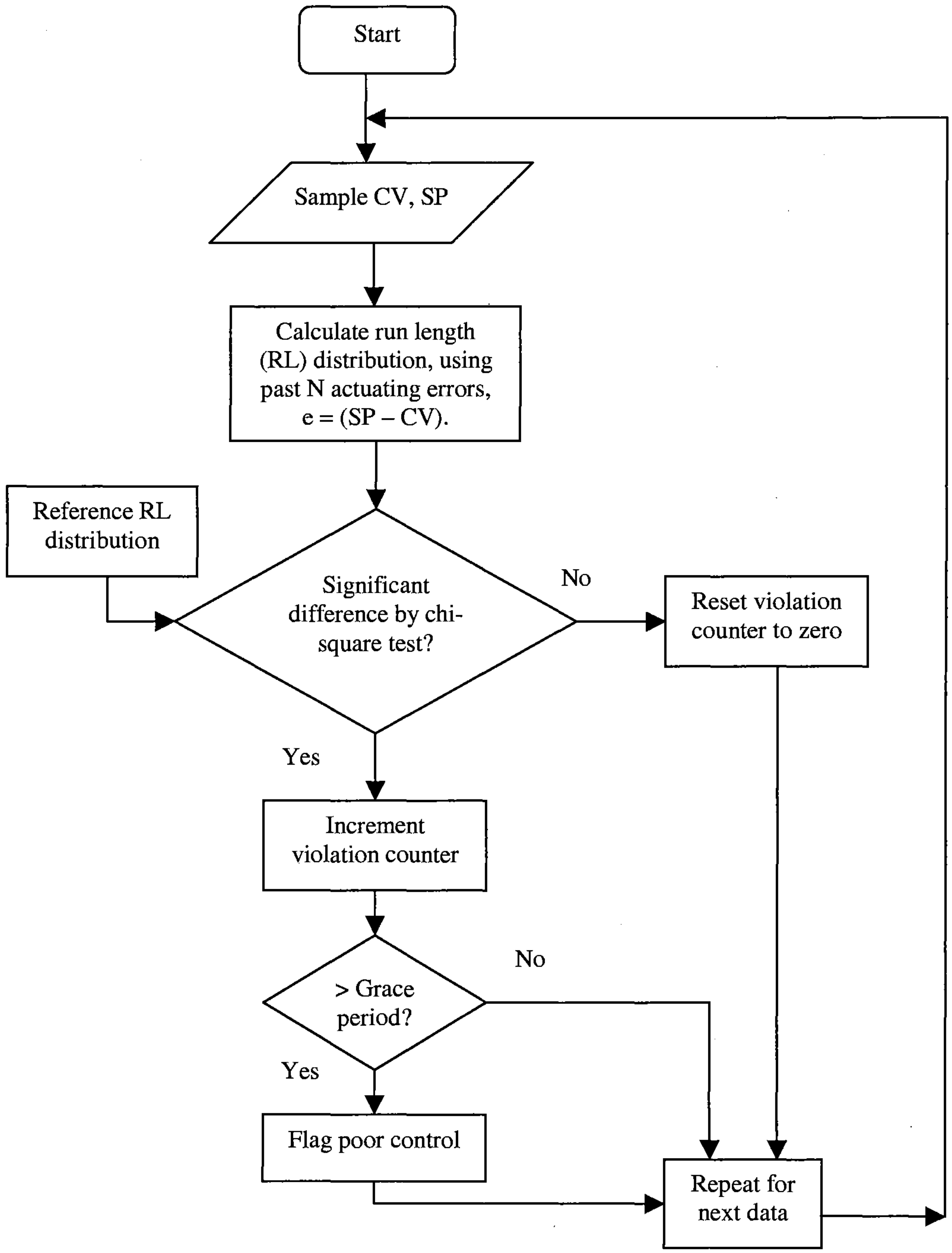

Figure 2.2 Flow Chart of the Control Performance Monitor

2.4 RL Distribution of a Random Signal

2.4.1 RL Distribution of White Noise

Consider a time series of samples of actuating errors (e = SP – CV), which are assumed to be a white noise with certain independent and identical distribution function, such as the Gaussian (normal) distribution function.

A run length may consist of either all positive data values or all negative data values. We call a run length consisting of all positive data a positive side run length, and a run length consisting of all negative data a negative side run length. All positive side run lengths start with a sign pattern -+. Among all positive side RLs, the probability for RL = 1 with a sign pattern -+- is (1 – p), where p is the probability for a positive data value at each sampling and (1 – p) is the probability for a negative data value at each sampling. Therefore the probability for RL = 2 with a sign pattern -++- is p(1 – p). The probability mass function for positive side RL distribution, f_{PRL}, is

$$f_{PRL}(RL; p) = p^{RL-1}(1 - p), \qquad RL = 1, 2, \ldots$$

where the distribution parameter p is the probability of having a positive data value at each sample.

The probability mass function for negative side RL distribution, f_{NRL}, can also be obtained as

$$f_{NRL}(RL; p) = (1 - p)^{RL-1}p, \qquad RL = 1, 2, \ldots$$

Since the positive side RLs and negative RLs appear alternately, one following the other, each of the two types of run lengths has an equal probability of 0.5 to appear. Therefore, the probability mass function for the distribution of all RLs regardless of its type, f_{RL}, is the average of f_{PRL} and f_{NRL}, i.e.,

$$f_{RL}(RL; p) = (p^{RL-1}(1-p) + (1-p)^{RL-1}p)/2, \quad RL = 1, 2, \ldots \quad (2.1)$$

Under ideal perfect control condition, the CV is equal to the SP at all times, and therefore the error signal (e = SP – CV) is just the measurement noise, which can be assumed to be a white noise with zero mean. Each error sample has an equal opportunity to be positive and negative, so the probability of having a positive value at each sampling, p = 1/2. From Equation (2.1), the RL probability mass function when the error signal is a white noise with zero mean, i.e., under the ideal perfect control condition, is

$$f_{RL}(RL) = (1/2)^{RL}, \qquad RL = 1, 2, \ldots \qquad (2.2)$$

When a constant offset is added to the a zero mean white noise, the RL distribution can also be determined from Equation (2.1) after specifying the value of p, the probability of having a positive error value at each sampling, which can be determined from the probability density function $f_X(x)$ of the white noise:

$$p = p(x>0) = \int_0^{\infty} f_X(x)dx \qquad (2.3)$$

For a Guassian white noise $N(\mu, \sigma^2)$, where μ is its mean, and σ^2 is its variance, the probability density function is

$$f_X(x;\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \qquad -\infty < x < \infty$$

Therefore, when the error signal is a Gaussian noise with a constant offset (mean) μ and variance σ^2, the probability of having a positive value at each sampling, $P_{N(\mu,\sigma^2)}$, is

$$p = P_{N(\mu,\sigma^2)} = \frac{1}{\sqrt{2\pi}\sigma} \int_0^{\infty} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx$$

$$= \frac{1}{\sqrt{\pi}} \int_{\frac{-\mu}{\sqrt{2}\sigma}}^{\infty} e^{-z^2} dz$$

where $z = \frac{x-\mu}{\sqrt{2}\sigma}$. The integration can be represented using the error function erf(x) or the complementary error function erfc(x). The error function erf(x) is defined as:

$$\text{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-z^2} dz$$

and the complementary error function erfc(x) is defined as

$$\text{erfc}(x) = \frac{2}{\sqrt{\pi}} \int_x^\infty e^{-z^2} dz = 1 - \text{erf}(x)$$

Then, the probability of having a positive value at each sampling when the signal is a Gaussian noise $N(\mu, \sigma^2)$ with a mean (constant offset) μ and variance σ^2 is

$$p = P_{N(\mu, \sigma^2)} = \frac{1}{2} erfc(\frac{-\mu}{\sqrt{2}\sigma}) \tag{2.4}$$

For example, when the mean (offset) is equal to the standard deviation of the noise, i.e., $\mu = \sigma$, then $p = \frac{1}{2} erfc(\frac{-1}{\sqrt{2}}) = 0.8413$. Another way to find p in this case is that since 68.27% of data will be between (μ - σ) and ($\mu + \sigma$), then the probability of having a positive value is 0.5 + 0.6827/2 = 0.84135.

Therefore, the RL distribution of a Gaussian white noise with one standard deviation offset is

$$f_{RL}(RL) = (0.84^{RL-1}*0.16 + 0.16^{RL-1}*0.84)/2, \tag{2.5}$$

Figure 3 shows the RL distribution with simulated Gaussian noise with $N(\sigma, \sigma^2)$, i.e., the offset equal to one standard deviation σ of the noise, the theoretical RL distribution calculated from Equation (2.5), and the theoretical RL distribution calculated from Equation (2.2) for no offset case for comparison. We can see that simulated RL distribution agrees with the theoretical RL distribution calculated from Equation (2.5).

Comparing the RL distribution with a non-zero offset to that with a zero offset, we can see that the two RL distributions are different in that the bins with large RL values have much larger probabilities when there is a non-zero offset than when there is zero offset.

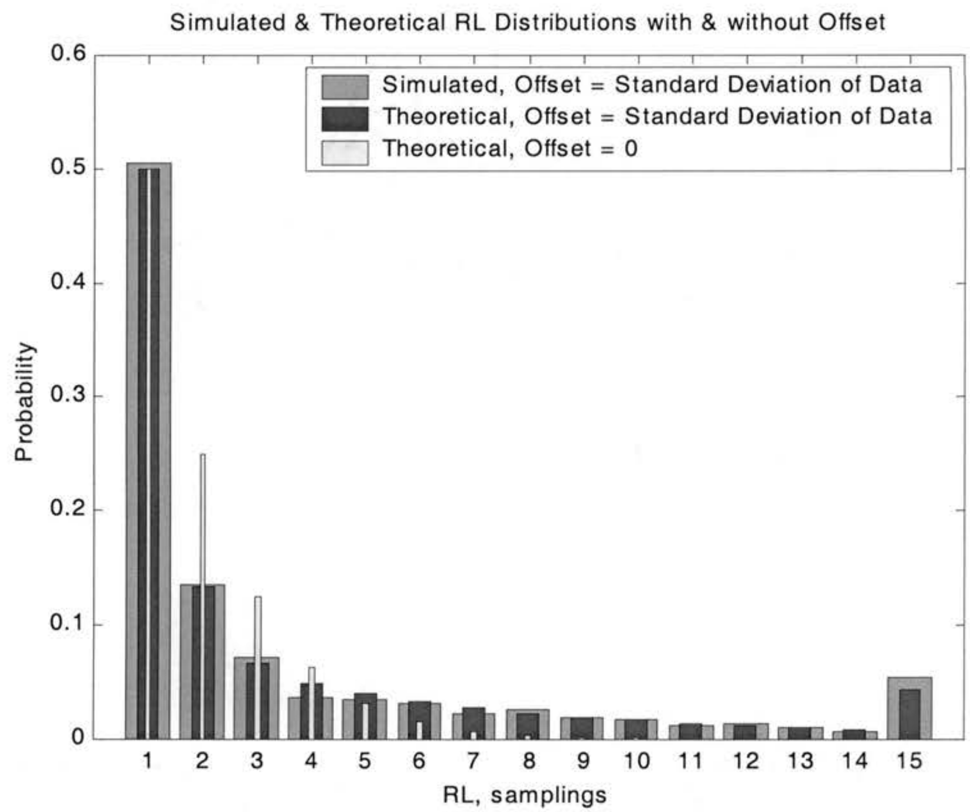

Figure 2.3 Simulated and Theoretical RL Distributions with and without Offset. The simulated RL distribution is generated using 3858 Data (1000 RLs) with a Gaussian distribution $N(\sigma, \sigma^2)$ with an offset (mean) equal to the data's standard deviation σ. The theoretical RL distributions for non-zero offset $d = \sigma$ and zero offset $d = 0$ are calculated from Equation (2.5) and Equation (2.2), respectively. All RL observations with RL > 15 samplings are put into the bin with RL = 15 samplings.

When the white noise is uniformly distributed between (-L+d, L+d) with a mean (offset) of d and range of 2L, its probability density function is

$$f_x(x, L) = 1/(2L) \qquad -L+d < x < L+d$$

Then by using Equation (2.3), the probability of having a positive value at each sampling is

$$p = \int_0^{L+d} \frac{1}{2L} dx = \left(\frac{1}{2} + \frac{d}{L}\right)$$

Therefore, we can get the theoretical RL distribution of a white noise uniformly distributed between (-L+d, L+d) with a mean (offset) of d and range of 2L as follows:

$$f_{RL}(RL; d, L) = \frac{\left(\frac{1}{2}+\frac{d}{L}\right)^{RL-1}\left(\frac{1}{2}-\frac{d}{L}\right) + \left(\frac{1}{2}-\frac{d}{L}\right)^{RL-1}\left(\frac{1}{2}+\frac{d}{L}\right)}{2}, \quad RL = 1, 2, \ldots$$

2.4.2 RL Distribution of a Deterministic Signal Added with White Noise

Let the (error) signal be

$$y(k) = x(k) + w(k)$$

where w(k) is a zero mean white noise, and x(k) is a deterministic function of (discrete) time k. At sample k, the mean (offset) of y(k) is equal to x(k), so using Equation (2.4), we obtain the probability of having a positive value at sample k is

$$p(k) = \frac{1}{2} erfc\left(\frac{-x(k)}{\sqrt{2}\sigma}\right) \tag{2.6}$$

Consider first only the positive side RLs. Since a positive side RL with RL = 1 has a sign pattern -+-, the probability of RL = 1 is (1-p)p(1-p), where (1-p) represents probability of having a negative value. Therefore the probability of a run with length RL is $(1-p)p^{RL}(1-p)$.

Note from Equation (2.6) that p(k) is a function of x(k), which is a function of time k, so the probabilities of RLs will also be a function of time k.

We can obtain the expected RL distribution over a time range, say [k_1, k_2], as follows. The probability of having a sign pattern -+- is p(-+-) = $(1-P_0)P_1(1-P_2)$, where P_0, P_1, and P_2 is the probability of having a positive value at sampling 0, 1, and 2. Therefore, the probability of the sign pattern $-(+)^{RL}-$ is $p(-+^{RL}-) = (1-P_0)P_1P_2P_3\ldots P_{RL}(1-P_{RL+1})$. Since all positive side RLs start with a sign pattern -+ and the probability of a positive RL is p(-+) = $(1-P_0)P_1$, then among all positive side RLs starting with a sign pattern of -+ at samples 0 and 1, the probability of RL = 1 starting at k = 0 is

$$p(RL{=}1, k{=}0) = p(-+-)/p(-+) = (1-P_2),$$

and the probability of RL = RL starting at k = 0 is

$$p(RL, k{=}0) = p(-+^{RL}-)/\ p(-+) = P_2P_3\ldots P_{RL}(1-P_{RL+1}).$$

Then the expected probability mass function for RL variable among all positive side RLs over the time range of interest, [k_1, k_2], is

$$f_{PRL}(RL) = \frac{\sum_{k_1}^{k_2}\left((1-p(i))\left(\prod_{j=1}^{RL} p(i+j)\right)(1-p(i+RL+1))\right)}{\sum_{k_1}^{k_2}(1-p(i))p(i+1)}$$

And among all negative side RLs, the expected probability mass function for RL variable can also be obtained as

$$f_{NRL}(RL) = \frac{\sum_{k_1}^{k_2}\left(p(i)\left(\prod_{j=1}^{RL}(1-p(i+j))\right)p(i+RL+1)\right)}{\sum_{k_1}^{k_2}p(i)(1-p(i+1))}$$

Since positive side RLs and negative side RLs appear alternately in any signal, one following the other, each has a probability of 1/2 to appear. Therefore combining both positive side RLs and negative RLs, the expected probability mass function for RL variable over the time range $[k_1, k_2]$ is equal to $f_{PRL}(RL)/2 + f_{NRL}(RL)/2$.

The expected probability mass function of the RL variable for a deterministic signal x(k) over the time range $[k_1, k_2]$ added with a zero mean Gaussian noise $N(0, \sigma^2)$ is

$$f_{RL}(RL) = \frac{\sum_{k_1}^{k_2}\left((1-p(i))\left(\prod_{j=1}^{RL} p(i+j)\right)(1-p(i+RL+1))\right)}{2\sum_{k_1}^{k_2}(1-p(i))p(i+1)} + \frac{\sum_{k_1}^{k_2}\left(p(i)\left(\prod_{j=1}^{RL}(1-p(i+j))\right)p(i+RL+1)\right)}{2\sum_{k_1}^{k_2}p(i)(1-p(i+1))} \tag{2.7}$$

$$p(k) = \frac{1}{2}erfc\left(\frac{-x(k)}{\sqrt{2}\sigma}\right) \qquad k = k_1+1, k_1+2, \ldots, k_2$$

where x(k) is a deterministic function of time k.

For a periodic deterministic function x(k), we only need to do summation over one period. Let x(k) be a periodic deterministic function with a period of K, i.e.,

$$x(i+nK) = x(i), \quad i = 0, 1, \ldots, K-1, \qquad \text{for any integer n.}$$

Then the expected probability mass function of the RL variable for a periodic deterministic signal x(k) with a period of K added with a zero mean Gaussian noise $N(0, \sigma^2)$ is

$$f_{RL}(RL) = \frac{\sum_{i=0}^{K-1}\left((1-p(i))\left(\prod_{j=1}^{RL} p(i+j)\right)(1-p(i+RL+1))\right)}{2\sum_{i=0}^{K-1}(1-p(i))p(i+1)} + \frac{\sum_{i=0}^{K-1}\left(p(i)\left(\prod_{j=1}^{RL}(1-p(i+j))\right)p(i+RL+1)\right)}{2\sum_{i=0}^{K-1}p(i)(1-p(i+1))} \quad (2.8)$$

$$p(i) = \frac{1}{2} erfc\left(\frac{-x(i)}{\sqrt{2}\sigma}\right) \qquad i = 0, 1, 2, \ldots, K-1 \quad (2.9)$$

$$x(i+nK) = x(i), \qquad \text{for any integer n. } i = 0, 1, 2, \ldots, K-1, \quad (2.10)$$

When a sinusoidal oscillation signal with amplitude A and period K is added with a Gaussian noise $N(0, \sigma^2)$, we have

$$x(k) = A\sin(2\pi k/K) \quad (2.11)$$

$$p(i) = \frac{1}{2} erfc\left(\frac{-A\sin(\frac{2\pi i}{K})}{\sqrt{2}\sigma}\right) \quad (2.12)$$

Since for a sinusoidal signal, we can verify that the positive side RLs and the negative side RLs have the same distribution, i.e., the two terms in Equation (2.8) are equal, so we have,

$$f_{RL}(RL) = \frac{\sum_{i=0}^{K-1}\left(p(i)\left(\prod_{j=1}^{RL}(1-p(i+j))\right)p(i+RL+1)\right)}{\sum_{i=0}^{K-1}p(i)(1-p(i+1))} \quad (2.13)$$

Using Equations (2.12) and (2.13), we can obtain the theoretical RL distribution of a sinusoidal signal as in Equation (2.11) added with a Gaussian noise $N(0, \sigma^2)$.

For example, when the deterministic signal x(k) is a sine wave with a period of K = 10 and an amplitude A = σ, the standard deviation of the Gaussian noise, i.e.,

$$x(k) = \sigma\sin(2\pi k/10) \tag{2.14}$$

Or the measurement y(k) is

$$y(k) = x(k) + w(k) = \sigma\sin(2\pi k/10) + w(k)$$

Then the probability of having a positive side RL at time i is

$$p(i) = \frac{1}{2}erfc\left(\frac{-\sin(\frac{2\pi i}{10})}{\sqrt{2}}\right)$$

Then the RL probability mass function is

$$f_{RL}(RL) = \frac{\sum_{i=0}^{9}\left(erfc\left(\frac{-\sin(\frac{2\pi i}{10})}{\sqrt{2}}\right)\left(\prod_{j=1}^{RL}\left(1-\frac{1}{2}erfc\left(\frac{-\sin(\frac{2\pi(i+j)}{10})}{\sqrt{2}}\right)\right)\right)erfc\left(\frac{-\sin(\frac{2\pi(i+RL+1)}{10})}{\sqrt{2}}\right)\right)}{2\sum_{i=0}^{9}erfc\left(\frac{-\sin(\frac{2\pi i}{10})}{\sqrt{2}}\right)\left(1-\frac{1}{2}erfc\left(\frac{-\sin(\frac{2\pi(i+1)}{10})}{\sqrt{2}}\right)\right)} \tag{2.15}$$

We can use Equation (2.15) to calculate the theoretical RL distribution for the sinusoidal signal in Equation (2.14) added with a Gaussian noise $N(0, \sigma^2)$.

Table 2.1 lists the theoretical RL mass function values for RL = 1 to 10 and compares with those obtained through 100,000 simulated data with 39936 RLs. We can see that the theoretical calculation agrees with the simulation.

Table 2.1 Theoretical and Simulated RL Distributions of a Deterministic Sinusoidal Signal Added with a Gaussian Noise (The deterministic signal is $x(k) = \sigma\sin(2\pi k/10)$ with a period of 10 samplings and an amplitude of σ, the standard deviation of the Gaussian noise $N(0, \sigma^2)$. Simulation results are obtained using 100,000 sample data with 39936 RLs.)

Probability	RL=1	2	3	4	5	6	7	8	9	10
Theoretical	0.4209	0.1824	0.1291	0.1104	0.0834	0.0473	0.0190	0.0056	0.0013	0.0003
Simulation	0.4222	0.1818	0.1286	0.1108	0.0850	0.0466	0.0184	0.0053	0.0011	0.0003

Figure 2.4 shows the RL distribution of a Gaussian noise signal with $N(0, \sigma^2)$, added with a sinusoidal oscillation signal, $\sigma\sin(2\pi k/10)$, i.e., with an oscillation amplitude equal to the standard deviation of the noise signal and an oscillation period equal to 10 samplings. We can see that the probabilities in the bins with RL equal to 4, 5 and 6 samplings, which are about half of the oscillation period, are significantly higher than those without oscillations.

Compared with the RL distribution of the white noise with zero mean (no offset), we can see that the RL distribution are different in that the probabilities at the bins with RL close to half of the oscillation period becomes much higher than those without oscillations.

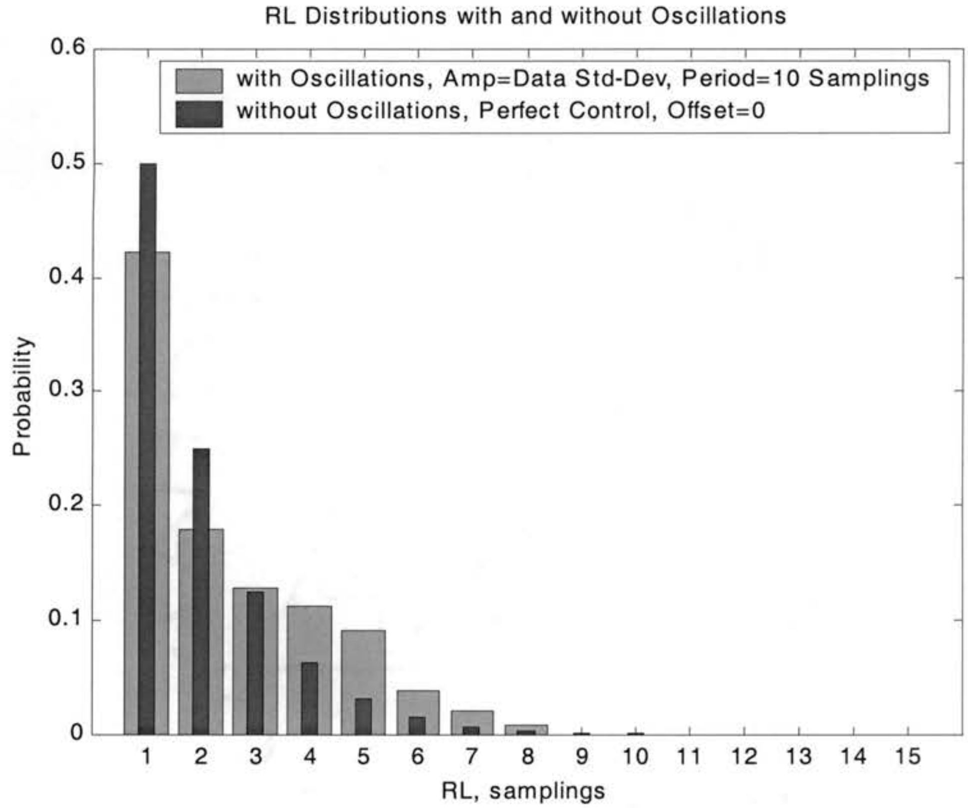

Figure 2.4 RL Distributions with and without Oscillations. The RL distribution with oscillations is calculated using 2628 error data (1000 RLs) generated from $e = e_0 + \sigma\sin(2\pi k/10)$, where e_0 is a random variable with a Gaussian distribution $N(0, \sigma^2)$, and the sinusoidal oscillations have an amplitude equal to e_0's standard deviation σ and an oscillation period of 10 samplings. The theoretical RL distribution of the errors e_0 without oscillations or offsets is also shown for comparison.

The most common poor control performance includes two cases: sluggish control and oscillations. In sluggish control, the CV takes long time to reach the SP. Extreme sluggish control is close to no control. In this case, the CV mostly drifts with disturbances, and may stay on one side of the SP for a long time, which is similar to the case of an offset. Hitting an upper or lower constraint of the controller output has similar results. Like the cases with a Gaussian noise signal discussed above, an offset will cause the RL distribution shifts to high RL values compared to no offset case. Under oscillation conditions, the bins with RL close to half of the oscillation period will have much larger probabilities than those without oscillations. Therefore, situations with undesirably sluggish control and oscillations will have very different RL distributions from those under good control, and these differences in RL distributions are used to detect poor control performance in this work.

2.5 Chi-Square Test on Differences in Distributions

To compare a current distribution with a reference distribution, the standard chi-square goodness of fit test method is used (Bethea and Rhinehart, 1991; Montgomery and Runger, 1994). The test procedure requires a random sample of size n RL observations from the population whose probability density distribution is unknown. These n RL observations are arranged in a frequency histogram, having k class intervals. Let O_i be the observed frequency (i.e., the actual number of observations) in the i^{th} class interval. From the reference probability distribution, we compute the expected frequency (i.e., the expected number of observations) in the i^{th} class interval, denoted E_i. The test statistic is

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \tag{2.16}$$

It can be shown that if the population follows the reference RL distribution, χ^2 has, approximately, a chi-square distribution (Montgomery and Runger, 1994) with k-p-1 degrees of freedom, where k is number of class intervals, and p is the number of parameters of the reference distribution estimated by sample statistics. In this work, p = 0 since the reference distribution is pre-determined and is not affected by the samples used for the chi-square test. The chi-square distribution approximation improves as n increases. We would reject the null hypothesis (that the observed RL distribution is identical to the reference RL distribution) if the calculated value of test statistic $\chi^2 > \chi^2_{\alpha,k-p-1}$, the critical chi-square value with α level of significance (or $1 - \alpha$ confidence coefficient) and $(k - p - 1)$ degree of freedom. In order to have a low rate of false flaggings, we recommend choosing a small value of α. We choose $\alpha = 0.003$ because about 99.7% of samples of a random variable with a Gaussian distribution $N(\mu, \sigma^2)$ will have a value within the region $\pm 3\sigma$ around μ. A sample value outside this $\pm 3\sigma$ region occurs at a probability 0.003, and is considered highly unlikely to happen unless this variable's distribution has changed.

Although a chi-square random variable is defined as sum of square of k standard Gaussian random variables, the above chi-square goodness of fit test does not require the reference distribution to be Gaussian. The reference distribution to be tested can be any distribution. When two underlying distributions are the same, the differences between expected and observed frequencies at each bin should be close to be Gaussian.

In the application of this chi-square test, the expected number of observations in each class should not be too small. There is no general agreement regarding the minimum number of expected observations in each class, but values of 3, 4, and 5 are widely used as a minimum. Classes with small number of expected observations can be combined with an adjacent class. Class intervals are not required to be of equal width.

Before doing a chi-square test, the following steps must be done: (1) build the reference RL distribution, (2) divide the RL range of the reference distribution into several class intervals, and (3) choose a sampling window length N to build the current RL distribution.

Each step will follow a specific choice-free procedure and can be fully automated.

Step1: Build the Reference RL Distribution

The reference RL distribution is built from the data that is a representative of good control periods. The user must choose an operating period that is judged "good" and is long enough to include all data nuances. The period should be at least several times the closed loop settling time, but a longer period is desired to construct the true distribution under good control.

A representative period of good control with 1000 experimental data from a water flow control loop is shown in Figure 2.5. The closed loop settling time is about 50 samples. (The sampling period is 0.1 second.)

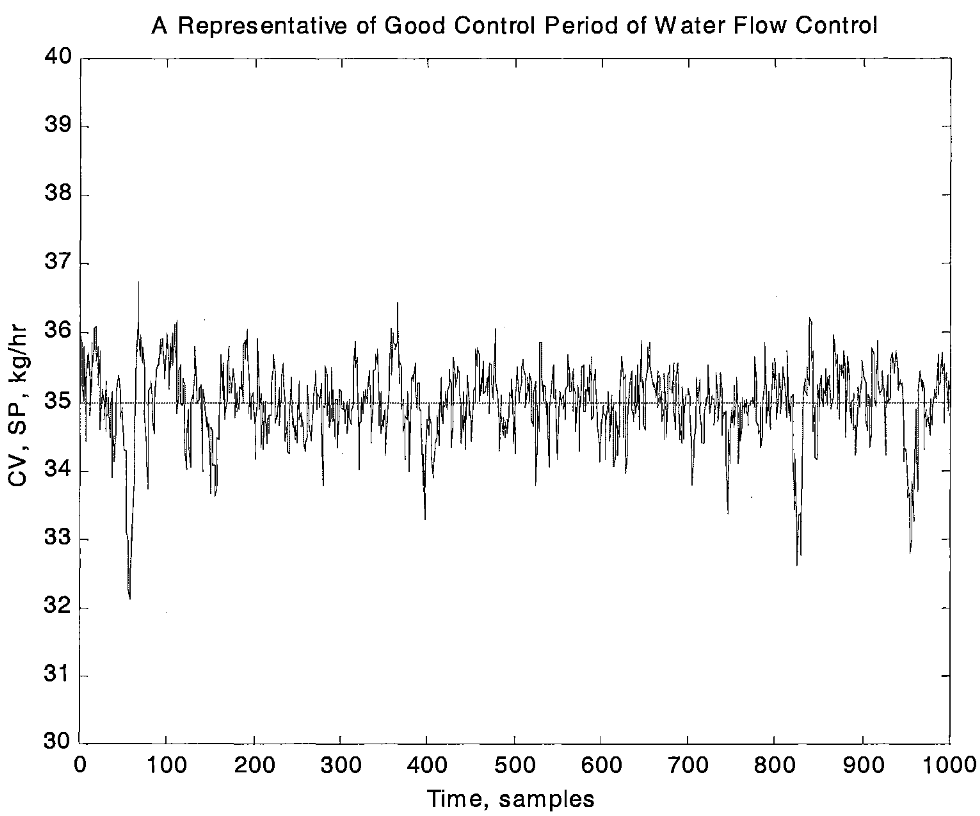

Figure 2.5 A Representative Period with Good Control for Water Flow Control (Sampling period Ts = 0.1 second)

There are 295 run length observations in these 1000 sampled data. The reference RL distribution built from these 1000 samples with 295 RL observations is shown in Figure 2.6.

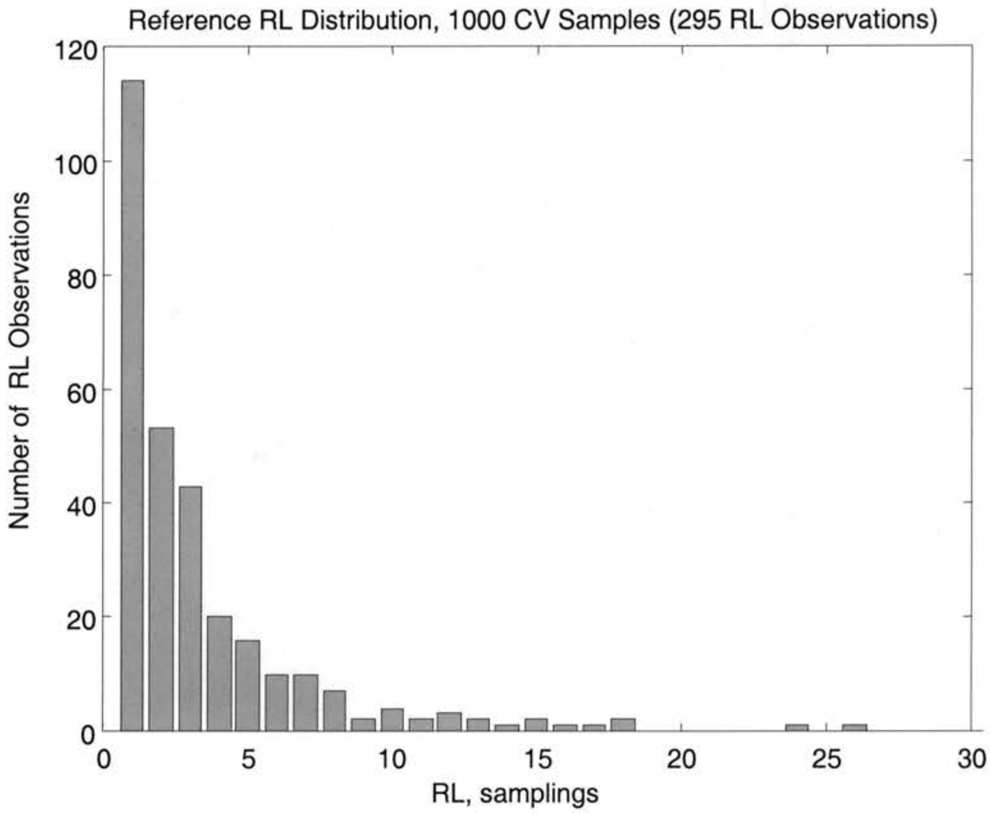

Figure 2.6 Reference RL Distribution for Water Flow Control Loop. Use 1000 data samples with 295 RL observations. (Sampling period Ts = 0.1 second)

Step 2: Divide the RL Range of Reference Distribution into Class Intervals

The general principle is to divide the RL range of the reference distribution into about 5 classes such that all classes have as even as possible probability values. The probability for a class is calculated as the ratio of number of RL observations that fall into this class to the total number of RL observations. If a single bin has a very high probability value and can form a class by itself, the remaining probability should be divided as evenly as possible among the remaining classes.

Figure 2.7 shows how to divide the reference RL distribution shown in Figure 2.6 into 5 classes with as even as possible probabilities. The first bin with RL = 1 forms a class by itself because its probability (0.386) is greater than 1/5, the even probability among 5 classes. Similarly, the second bin with RL = 2 forms another class by itself because its probability (0.180) is greater than (1 – 0.386)/4 = 0.154, the even probability among the remaining 4 classes. The third bin with RL = 3 forms class 3 by itself for the same reason. Finally, class 4 (with RL = 4, 5 and 6) and class 5 (with RL ≥ 7) are determined such that both classes have as even as possible probabilities, 0.156 for class 4 and 0.132 for class 5. Table 2.2 shows the RL values for each class and the probabilities for each class.

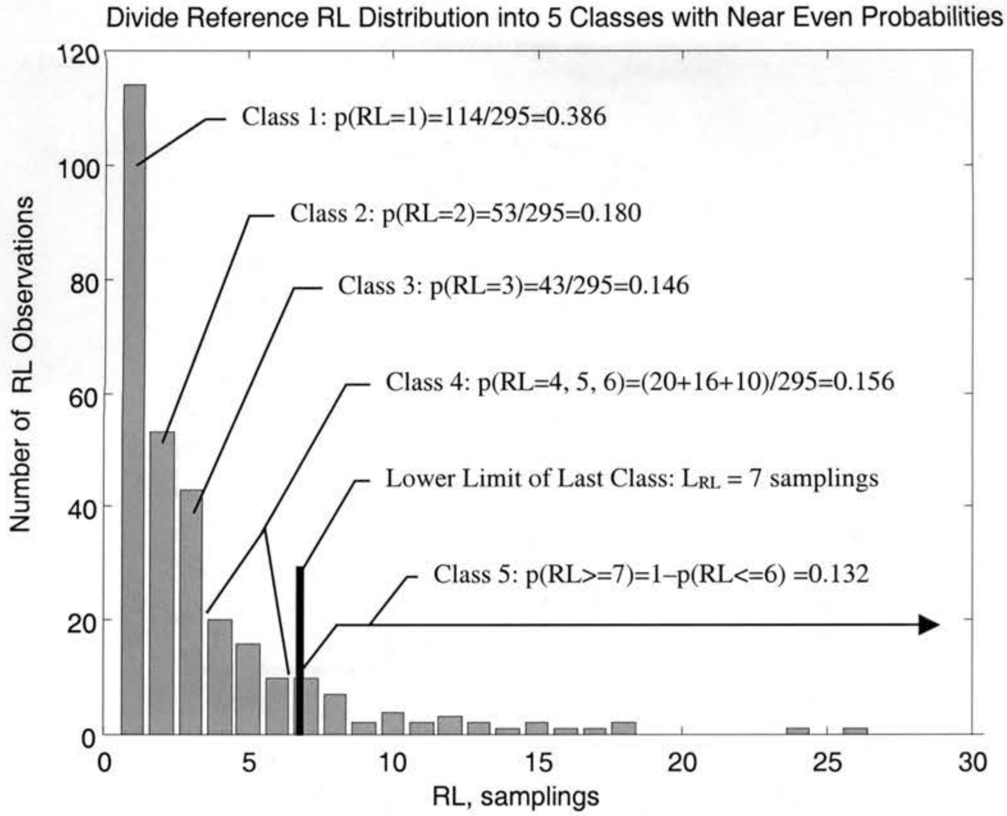

Figure 2.7 Divide Reference RL Distribution into 5 Class Intervals with as Even as Possible Probabilities. The lower limit RL value of the last class, L_{RL} = 7 samplings.

Table 2.2 Divide Reference RL Distribution into Classes, Water Flow Control

Class #	1	2	3	4	5
RL, samplings	1	2	3	4, 5, 6	7, 8, …
Probability	0.386	0.180	0.146	0.156	0.132

Note that any run length with RL $\geq L_{RL}$, the lower limit of the last class interval, will belong to the last class interval, which has an infinite width $[L_{RL}, \infty)$. For example, the run lengths with RL = L_{RL}, $2L_{RL}$, $10L_{RL}$, or even more will all belong to the last class interval, and each will be counted as one RL observation in the last class interval and be treated equally by the chi-square test. Very long run lengths, such as those with $RL \geq 2L_{RL}$ usually indicate long time offsets, which are very poor performances caused by too sluggish controllers or hitting constraints.

In order for the chi-square test to be able to differentiate and penalize very long run lengths and therefore to be more sensitive to changes in the RL distribution, we will count a RL observation with $RL \geq 2L_{RL}$ as m RL observations with $RL = L_{RL}$, and

$$m = \text{int}(RL/L_{RL}), \qquad (2.7)$$

Here "int" means to take integer part of the ratio RL/L_{RL}. After doing this, the last class interval becomes $[L_{RL}, 2L_{RL} - 1]$ with a finite width, and a very long run length with $RL \geq 2L_{RL}$ will be counted as multiple (m) RL observations in the last class interval, and therefore will contribute more to the chi-square test than other run lengths with $RL < 2L_{RL}$ and be penalized.

In the reference RL distribution shown in Figure 2.7, $L_{RL} = 7$ samplings. So, we count each RL observation with $14 \leq RL \leq 20$ as 2 observations in class 5, the one with $21 \leq RL \leq 27$ as 3 observations in class 5, and so on.

This RL counting method enables the performance monitor to consider the differences within the last class interval when comparing two distributions, and therefore makes the monitor more sensitive to distribution changes than the original counting method that treats each RL observation equally in the last class interval. And since the differences in distributions caused by sluggish controller or hitting constraints mostly occur in the last class interval, such as the case with one σ offset shown in Figure 2.3, this method of penalizing long run lengths significantly increases the performance monitor's ability to detect poor control performances caused by sluggish controllers or hitting constraints. Note both reference and current distributions use this same method to count number of RL observations.

Step 3: Choose a Sampling Window Length N to Build Current RL Distribution

The current RL distribution is built from a window of sampled CV and SP data. During performance monitoring, after each sampling, the window moves one sampling ahead to include the new sample data and discard the oldest data. The window length N, i.e., the number of samplings of CV and SP data, is fixed during performance monitoring.

The minimum sampling window length can be determined through the chi-square test's requirement that each class have a minimum number of expected RL observations, or called events, using 5 RL Observations as the minimum. We have,

$$N_{RL} * p_{cmin} \geq 5 \qquad \text{(RL observations)}$$

where N_{RL} is the number of total RL observations within the data window length N, and p_{cmin} is the lowest among the expected probabilities that the RL observations will fall into each class. Since the window length $N = N_{RL} * \mu_{RL}$, where μ_{RL} is the mean of RL values (samplings per RL observation) during good control period, therefore, to satisfy the chi-square test requirement, the window length N should be,

$$N \geq \frac{5\mu_{RL}}{p_{c\min}} \tag{2.8}$$

The simplest way to determine the window length is to use the minimum window length calculated from Equation (2.8) above as the chosen window length N. The only required information for this method is a representative data collected during good control period, or equivalently, the reference RL distribution built from the data. Values of μ_{RL} and p_{cmin} can be obtained either from the representative data collected during good control period or from the reference RL distribution. Our experience indicates that using Equation (2.8) to determine window length gives good results.

From Figure 2.7 or Table 2.2, we can see that class 5 has the minimum probability of 0.132 among all 5 classes, so $p_{cmin} = 0.132$. And there are 295 RL observations among these 1000 data, so the average run length, $\mu_{RL} = 1000/295 = 3.4$ samplings per RL observation. Therefore, using Equation (2.8), we can determine the window length to build the current RL distribution as $N = 5*3.4/0.132 = 129$ samplings.

The sampling window length N will affect the probability of making type II errors when doing the chi-square test. A type II error is made when two distribution samples are actually from two different populations, and the chi-square test does not indicate they are significantly different, i.e., the test does not reject the null hypothesis. A type I error is made when two distribution samples are actually from the same underlying population, and the chi-square test indicates they are significantly different, i.e., the test rejects the null hypothesis. We choose type I error rate α directly, e.g., $\alpha = 0.003$. But, the type II error rate β will be affected by the window length N. In general, the longer the window length N, the smaller is the type II error rate. From our experience, using a window length N calculated from Equation (2.8) usually detects poor control when it is also visually obvious, i.e., usually gives a satisfactory type II error rate. The relationship between the window length N and type II error rate tells us that we can reduce type II error rates by increasing the window length N. However, the longer the window length, the longer the time to either detect distribution changes, or return to the reference distribution after good control is recovered, so a too long window length is undesirable.

Usually, it is not recommended to determine the window length N from type II error rate in practice because a specific poor control performance must be maintained for a period long enough for us to collect enough data to calculate its type II error rate, which is usually not acceptable in practice.

Step 4: Choose a Grace Period

In addition to random disturbances in a control loop, there are non-random events, such as setpoint changes or relative infrequent, special cause disturbances. These non-random events produce RL distributions, which are not equivalent to the good, at setpoint, period, but may not be an indication of poor control.

The grace period is the time allowed for the controller to overcome a change in setpoint or non-random disturbance, plus the time needed for the data window to pass the transient period caused by this change in setpoint or disturbances, before flagging poor control performance. The monitor does not flag poor control until chi-square tests rejects the null hypothesis continuously for a period longer than the grace period, and once the monitor starts flagging, the immediate previous period within the grace period is also flagged retroactively. The length of grace period depends on how fast we expect the controller to reject the changes in setpoint or disturbance and the data window length. Usually we can choose the closed-loop settling time (CLST) when the controller is well-tuned as the expected performance, and add to this the window length N to obtain the grace period. The addition of window length to the closed loop settling time ensures that the remnants of the upset have passed out of the distribution.

A modification on de-flagging rule by choosing another chi-square critical value for de-flagging can make the control monitor have a more steady flagging during poor control performance. The current monitor de-flags whenever the current chi-square statistic $\chi^2 < \chi^2_{\alpha,k-1}$, which is the critical value with significance level α and degrees of freedom k-1 and is used to indicate significant changes. We usually choose a very small number for the significance level α, such as 0.003, because we want a small type I error. However, this $\chi^2_{\alpha,k-1}$ usually is too large for indicating that the control becomes good again such that the monitor will de-flag for a moment then flag again during poor control. To avoid frequent alternates between flagging and de-flagging during poor control and to have a more steady flagging, we can choose a second chi-square critical value $\chi^2_{\alpha 2,k-1}$, which is smaller than $\chi^2_{\alpha,k-1}$ by choosing a $\alpha_2 > \alpha$. For example, if $\alpha_2 = 0.5$, $\alpha = 0.003$, and k=4, then $\chi^2_{\alpha 2,k-1} = 3.36$ and $\chi^2_{\alpha,k-1} = 16.17$. By adopting this modification on de-flagging rule, once the monitor flags, it will not de-flag until $\chi^2 < \chi^2_{\alpha 2,k-1} = 3.36$ instead of $\chi^2 < \chi^2_{\alpha,k-1}$ as before. Plots of flagging with and without this modification on de-flagging rule are shown and compared in Section 2.6.1.2.

2.6 Evaluation of Control Performance Monitor

Both experiments and computer simulations are used to evaluate the control performance monitor. The experiments are conducted on a water flow control loop and an air flow control loop. The processes on both loops exhibit first-order plus time delay dynamics, valve stiction, and nonlinear characteristics, and are controlled by two independent PI controllers. Simulations with a model predictive controller (MPC) and a wide variety of second-order plus time delay (SOPTD) processes with inverse response are also used to evaluate the control performance monitor.

2.6.1 Experimental Evaluation

2.6.1.1 Description of Experimental Unit

The experimental unit is shown in Figure 2.8. Two air streams (large and small) and one water stream are mixed and then enter the column, where water phase and air phase interact and flow through. The three streams are controlled independently by three PI controllers.

The unit is equipped with CamileTG 2000 hardware and software (version 4.0) for data acquisition and process control. It is fully automated for data acquisition and process control.

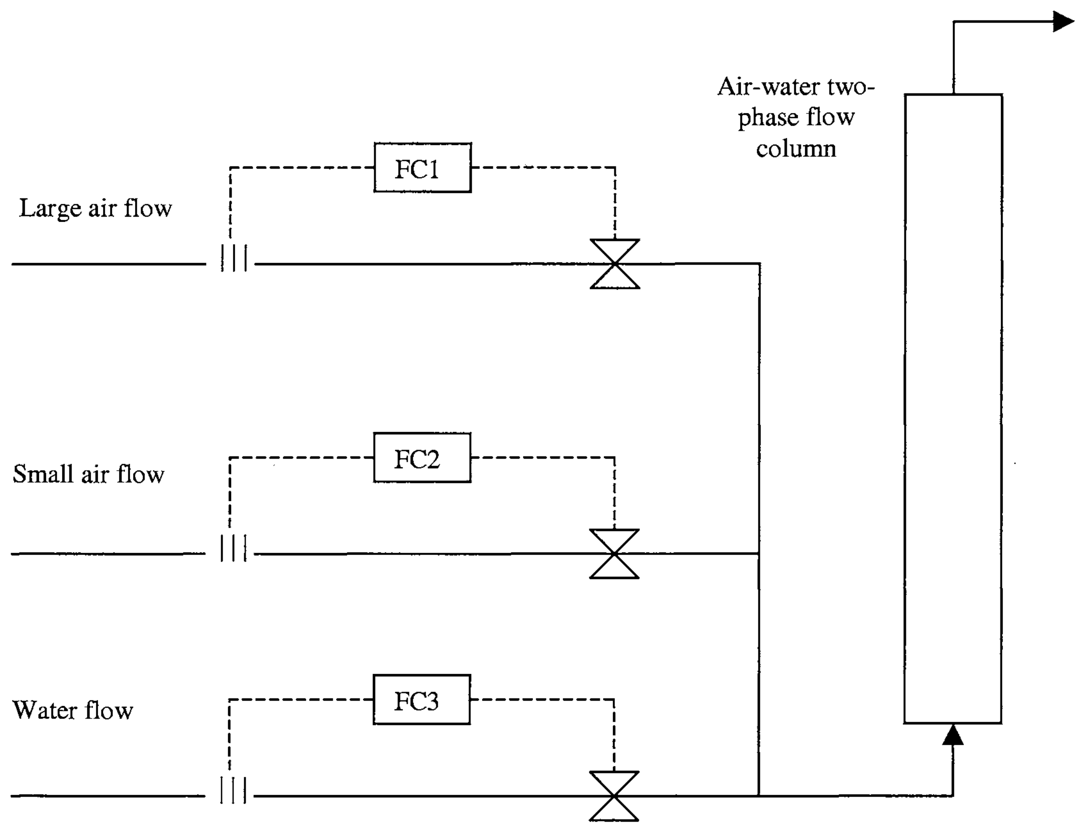

Figure 2.8 Two-Phase Flow Experimental Unit with One Water Flow Control Loop and Two Air Flow Control Loops.

Experimental Protocol

Tune the PI controller at the nominal operating point. After tuning, observe the closed-loop settling time from a step setpoint change. Choose a representative period of good control, and build the reference RL distribution. Divide the RL range into 5 class intervals. Choose a sampling window length N to build current RL distribution. Specify the level of significance or confidence coefficient for the chi-square test. Set the grace period equal to closed-loop settling time plus the data window length. Make a series of setpoint changes within the possible range, and monitor control performance using the control performance monitor.

2.6.1.2 Water Flow Control Experimental Results and Discussion

The nominal operating point of the water flow rate was 35 kg/hr. Through a step change in the setpoint, the closed-loop settling time was obtained to be 50 samples, the sampling period is 0.1 second. We have already shown the representative period of good control with 1000 data samples in Figure 2.5, the reference RL distribution built from these 1000 data with 295 RL observations in Figure 2.6, and the division of the reference RL distributions into 5 class intervals in Figure 2.7. We have determined in Section 2.5 (step 3) the window length N = 129 samplings using Equation (2.8). Select the chi-square test significance level (one-sided) of $\alpha = 0.003$. Since there are k = 5 classes of RL values and no distribution parameters are estimated from the data samples, therefore the chi-square statistic degree of freedom is 5 – 1 = 4. The critical value $\chi^2_{\alpha,k-1}$ is 16.17. Choose the grace period equal to the closed-loop settling time plus the window length, or 50 + 129 = 179 samplings.

The water flow control experimental data and control performance monitor output are shown in Figure 2.9.

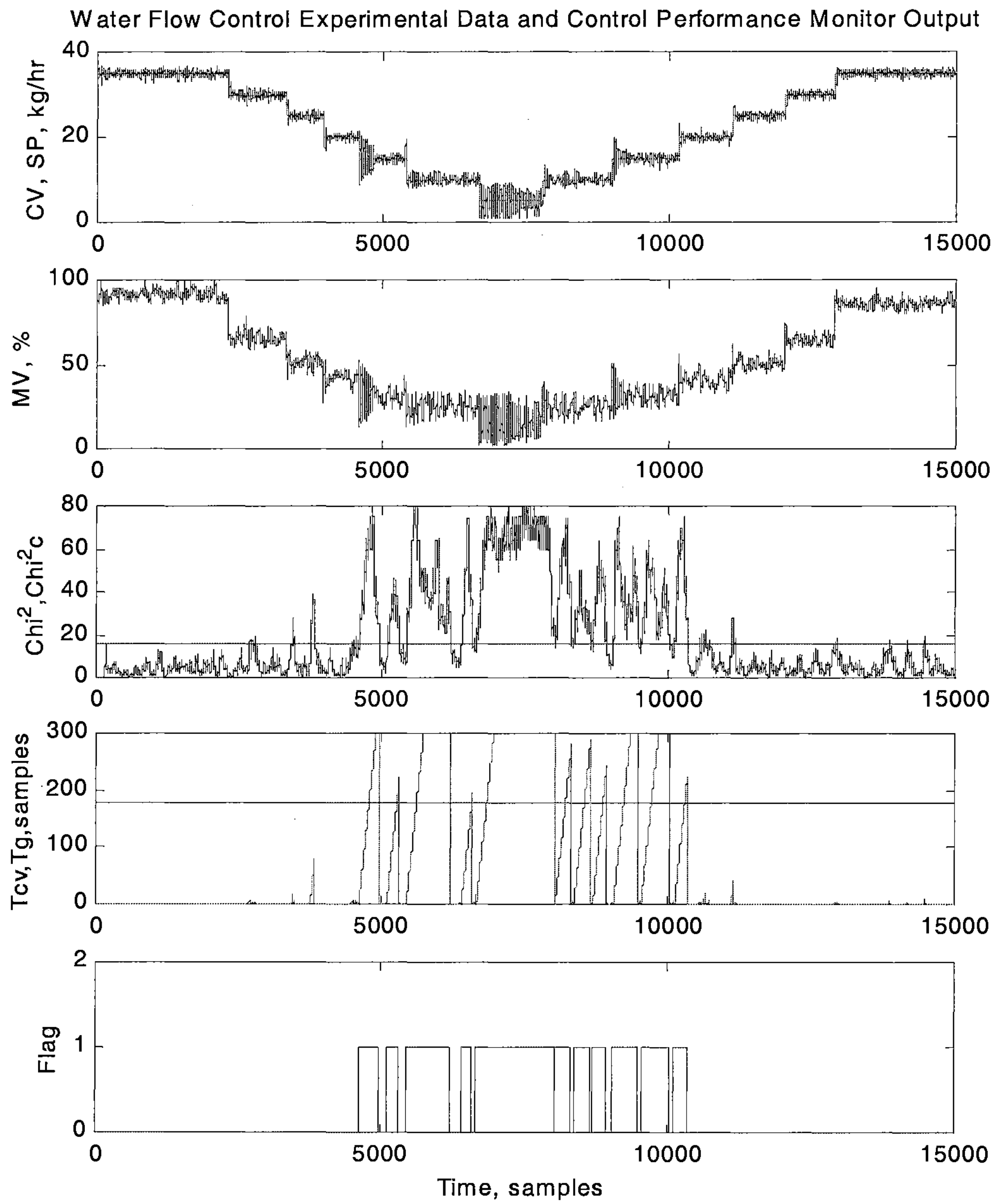

Figure 2.9 Water Flow Control Experimental Data and Control Performance Monitor Output (Sampling period Ts = 0.1 second. Window length N = 129 samplings. Grace period Tg = 179 samplings. Tcv is the time period counter in samplings for continuous violations of chi-square test critical value chi^2c.)

From Figure 2.9, we can see that when the plant operates near the nominal operating point with a water flow rate of 35 kg/hr, where the controller was tuned, the monitor does not flag even though there are setpoint changes. As the water flow rate decreases and moves away from the nominal operating point, the control performance deteriorates. The monitor starts flagging when the flow rate setpoint is reduced to 15 kg/hr from 20 kg/hr and the poor control performance with excessive oscillations occurs. We can see that the monitor flags most of the time when the water flow rate is less than 15 kg/hr and the controller performs poorly. After the flow rate moves back to the region near the nominal operating point, the control performance improves and becomes good again, and the monitor stops flagging.

The control performance monitor does not flag when the controller can reject setpoint changes and unmeasured disturbances within the grace period. Note the setpoint change from 25 to 20 kg/hr near sampling 4000 causes the chi-square test to indicate distribution changes for a period that is shorter than the grace period, so the monitor does not flag. Also, note near sampling 14000, due to unmeasured disturbances, the chi-square test also indicates distribution changes for a very short period, much shorter than the grace period, and the monitor does not flag. However, the control performance monitor does flag when the controller is not able to reject changes in setpoint and disturbance within the grace period, as in most of the time between sampling 4500 and sampling 10500.

After adopting the modification on the de-flagging rule, i.e., using a new critical value for de-flagging, the control performance monitor will keep flagging once it flags, until $\chi^2 < \chi^2_{\alpha 2,k-1}$ with $\alpha_2 = 0.5$ ($\chi^2_{0.5,4,} = 3.36$). The water flow control experimental data and control performance monitor output with the new critical value for de-flagging are shown in Figure 2.10.

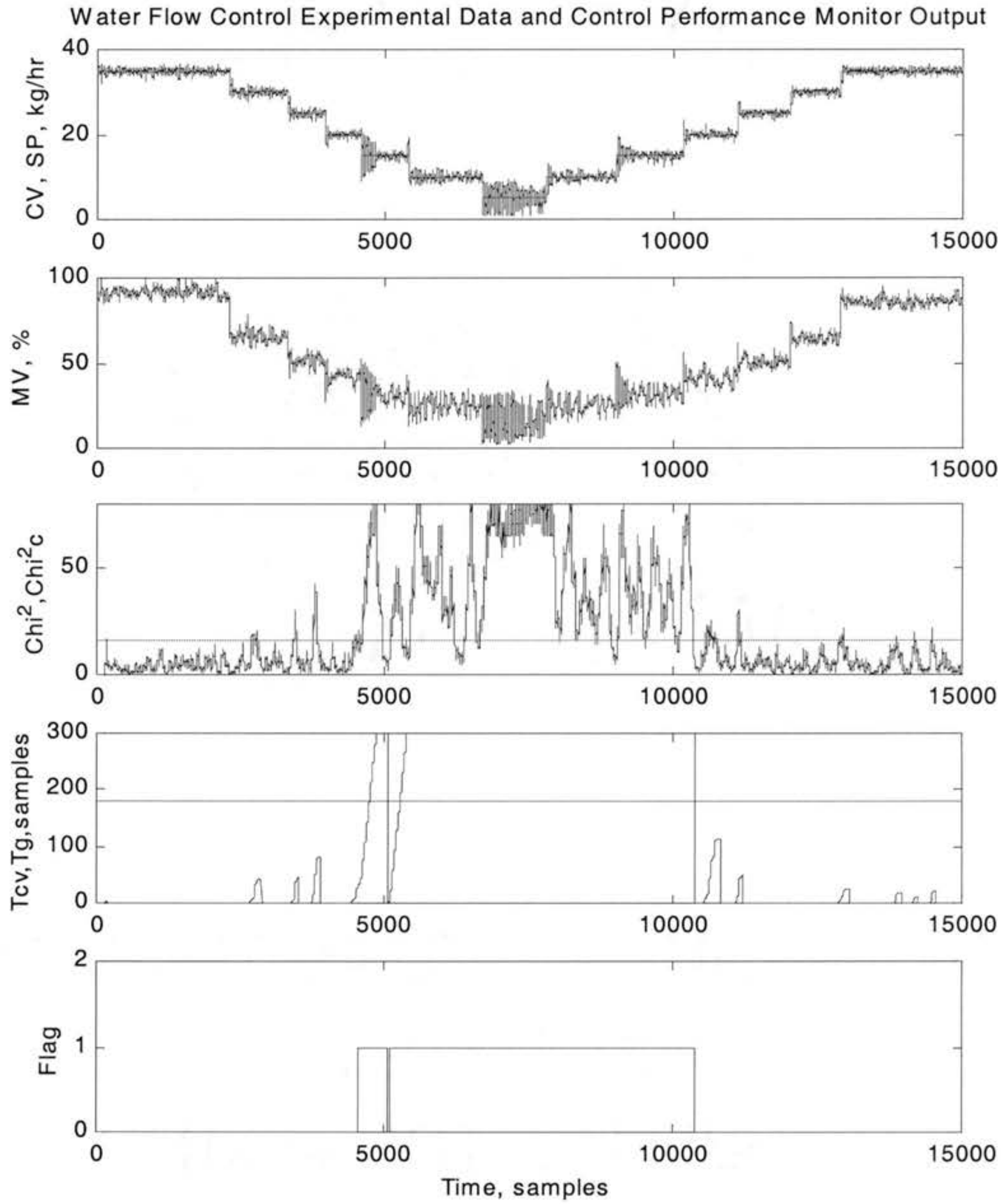

Figure 2.10 Water Flow Control Experimental Data and Control Performance Monitor Output Using a New Critical Value for De-flagging ($\chi^2_{\alpha 2,k-1}$ = 3.36 with α_2 = 0.5 and k = 5. Sampling period Ts = 0.1 second. Window length N = 129 samplings. Grace period Tg = 179 samplings. Tcv is the time period counter in samplings for continuous violations of chi-square test critical value chi^{2}c.)

We can see that the monitor has a steadier flagging during poor control when the new critical value for de-flagging is used.

2.6.1.3 Air Flow Control Experimental Results and Discussion

The nominal operating point of the air flow rate is 0.15 m^3/hr. Through a step change in the setpoint, we obtained the closed-loop settling time to be 50 samplings. (Again, the sampling period is 0.1 second.) A representative period of good control with 1000 sampled data and 357 RL observations are shown in Figure 2.11. The average RL, μ_{RL}, is 2.8 samplings per RL observation. The reference RL distribution is shown in Figure 2.12. The RL range of the reference distribution is divided into 5 class intervals as shown in Table 2.3. Class 3 has the minimum probability of 0.095, or $p_{cmin} = 0.095$. Using Equation (2.8), the window length to build current RL distribution is obtained: N = 147 samplings. The closed loop sampling time plus the window length, i.e., 50 + 147 = 197 samplings, is the grace period. Choose a significance level $\alpha = 0.003$ for the chi-square test. With k = 5 classes of RL values and 4 degrees of freedom, the critical value $\chi^2_{\alpha,k-1}$ is 16.17.

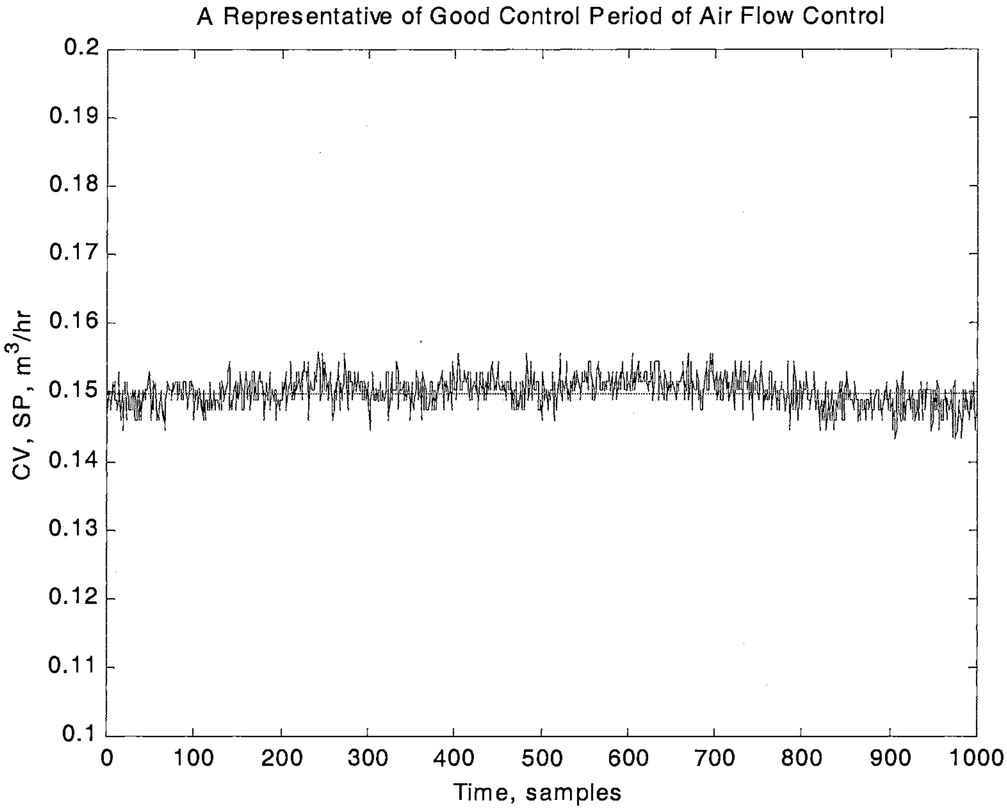

Figure 2.11 A Representative Period with Good Control for Air Flow Control
(Sampling period Ts = 0.1 second)

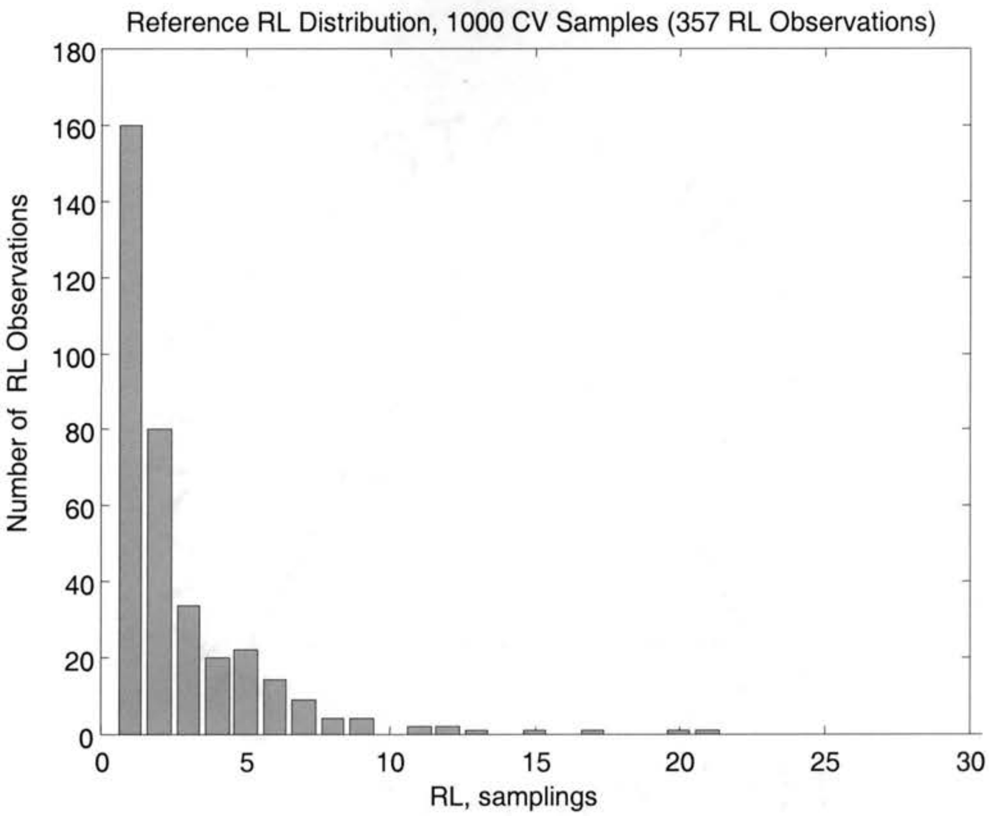

Figure 2.12 Reference RL Distribution for Air Flow Control Loop. Use 1000 data samples with 367 RL observations. (Sampling period Ts = 0.1 second)

Table 2.3 Divide Reference RL Distribution into Classes, Air Flow Control

Class #	1	2	3	4	5
RL, samplings	1	2	3	4, 5	6, 7, …
Probability	0.448	0.224	0.095	0.118	0.115

The air flow control experimental data and control performance monitor output are shown in Figure 2.13. From Figure 2.13, we can see that when the air flow rate is above 0.3 m^3/hr, far away from the nominal operating point at 0.15 m^3/hr, the setpoint changes cause excessive oscillations and the monitor catches these poor performance periods and flags, as near samplings 3000, 3700, 4400, 5300 and 5700. After the first setpoint change of air flow rate from 0.15 to 0.25 m^3/hr at sampling 1900, the controller is very slow in eliminating small errors and therefore causes long RL values. The monitor catches this poor control performance and flags it near sampling 2000. When the air flow rate is changed to 0.05 m^3/hr, there are high frequency fluctuations in CV and MV, and these poor control performance is also caught and flagged by the monitor near sampling 7400.

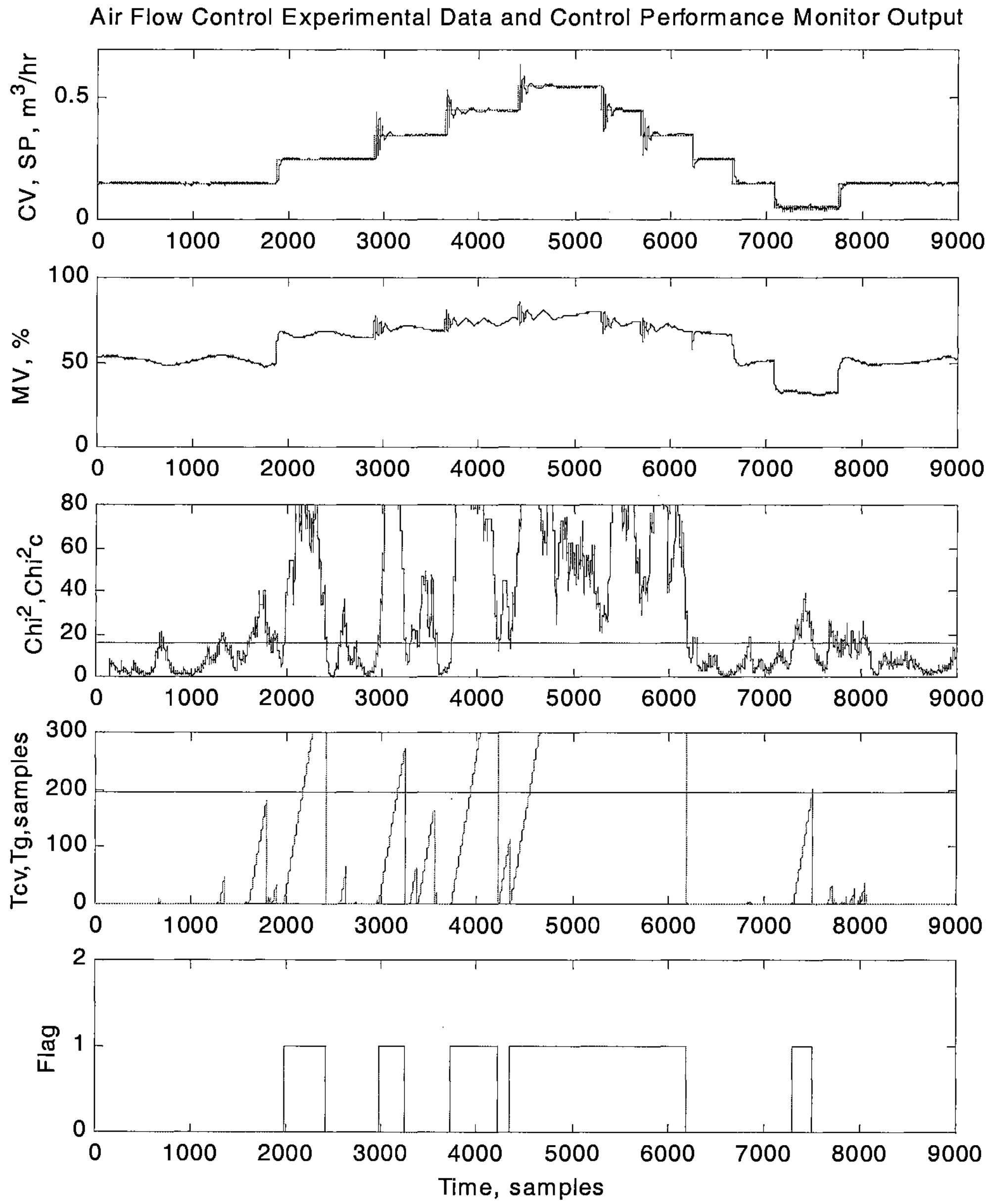

Figure 2.13 Air Flow Control Experimental Data and Control Performance Monitor Output (Sampling period Ts = 0.1 second. Window length N = 147 samplings. Grace period Tg = 197 samplings. Tcv is the time period counter in sampling period for continuous violations of chi-square test critical value chi^2c.)

2.6.2 Simulation Evaluation

The control performance monitor is also evaluated with simulations of a model predictive controller (MPC) on a second-order-plus-time-delay (SOPTD) process with inverse response, and is tested for good control, too aggressive control, too sluggish control due to changes in plant characteristics, constraints, changes in noise variance (or magnitude), and step changes in setpoint and disturbances.

2.6.2.1 Description of the Simulator

Matlab and Simulink are used to simulate the plant, controller and disturbances. The simulator block diagram is show in Figure 2.14.

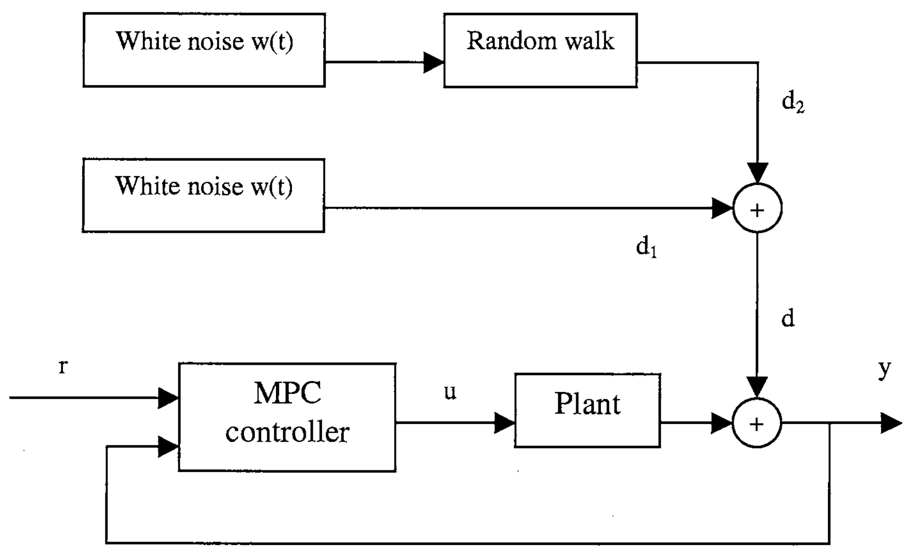

Figure 2.14 Simulator Block Diagram

PLANT

The plant is simulated using the following SOPTD Process with inverse response model:

$$10\frac{d^2y(t)}{dt^2}+7\frac{dy(t)}{dt}+y(t)=-3\frac{du(t-2)}{dt}+u(t-2)$$

where u(t) is process output, and u(t) is process input. In Laplace domain, we have

$$\frac{y(s)}{u(s)}=\frac{(-3s+1)e^{-2s}}{(2s+1)(5s+1)}=-0.3\frac{(s-\frac{1}{3})e^{-2s}}{(s+\frac{1}{2})(s+\frac{1}{5})} \tag{2.9}$$

The plant process has two poles, -1/2 and –1/5, one zero, 1/3, and a delay of 2. Its response to a unit step input is shown in Figure 2.15.

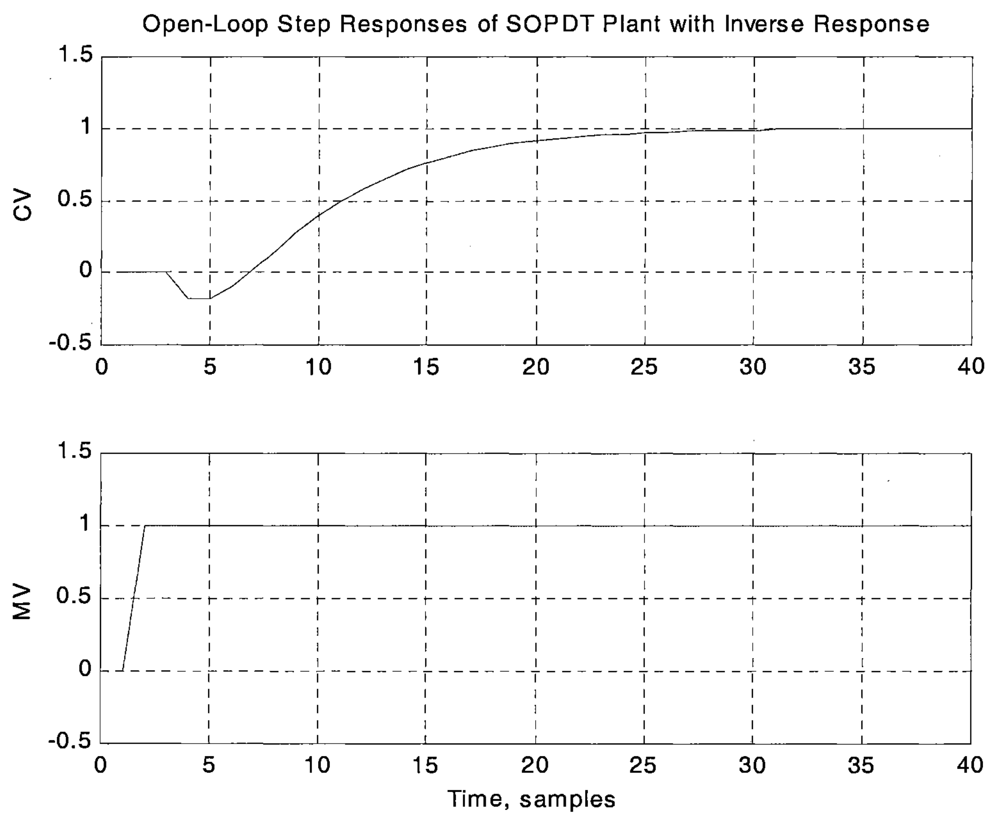

Figure 2.15 Step Response of a SOPTD Process with Inverse Response

DISTURBANCES

The disturbance of the simulator is the sum of two random processes: (1) the measurement noise process d_1, which is represented using a zero mean Gaussian white noise sequence with a variance $\sigma_1^2 = 0.1$, and (2) the plant disturbance process, which is represented using a "random walk" process d_2, i.e., the integration of another zero mean Gaussian white noise sequence with a variance $\sigma_2^2 = 0.1$, which, in discrete time, can be described as

$$d_2(k) = d_2(k-1) + w_2(k)$$

The random walk process d_2 is a non-stationary process, and it simulates time varying stochastic disturbances.

MPC CONTROLLER

The MPC controller is simulated using the Model Predictive Control Toolbox of Matlab/Simulink. The MV damping MPC controller has the following parameters: (1) Process model: the step response model, obtained after introducing a step change in setpoint, (2) Prediction horizon: p = 20 samples, (3) Sampling period: Ts = 1 second. (4) Control horizon: m = 5 control moves, (5) Control action period: Ts = 1 second, (6) Noise filter time constant = 5 seconds, (7) Control objective (MV damping) is to minimize the objective function: $\sum_{i=k}^{k+p} w_y (y_i - r_i)^2 + \sum_{l=k}^{k+m} w_u (u_l - u_{l-1})^2$, where equal weights are used: $w_y = w_u = 1$, and r is setpoint.

2.6.2.2 Simulation with a Well Tuned MPC Controller

Figure 2.16 shows the step response of the well-tuned MPC controller to a setpoint change. The closed loop settling time is about 29 samplings.

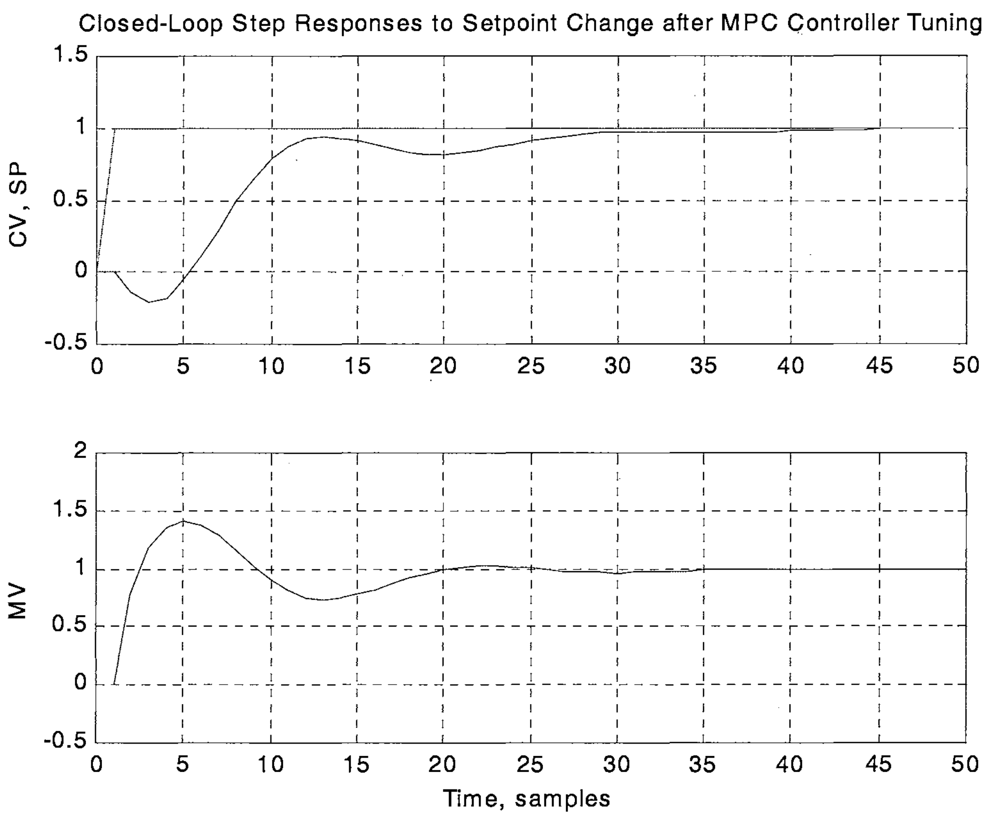

Figure 2.16 Closed-Loop Step Response to a Setpoint Change Using a Well-Tuned MPC Controller

A representative period of good control with 1000 sampled data and 320 RL observations is shown in Figure 2.17. The average RL, μ_{RL}, is 3.13 samplings per RL observation. The reference RL distribution is shown in Figure 2.18. The RL range of the reference distribution is divided into 5 class intervals as shown in Table 2.4. Class 4 has the minimum probability of 0.094, or $p_{cmin} = 0.094$. Using Equation (2.8), the window length to build the current RL distribution is obtained: N = 167 samplings. The closed loop sampling time plus the window length, i.e., 29 + 167 = 196 samplings, is the grace period. Choose a significance level $\alpha = 0.003$ for the chi-square test. With $k = 5$ classes of RL values and 4 degrees of freedom, the critical value $\chi^2_{\alpha,k-1}$ is 16.17.

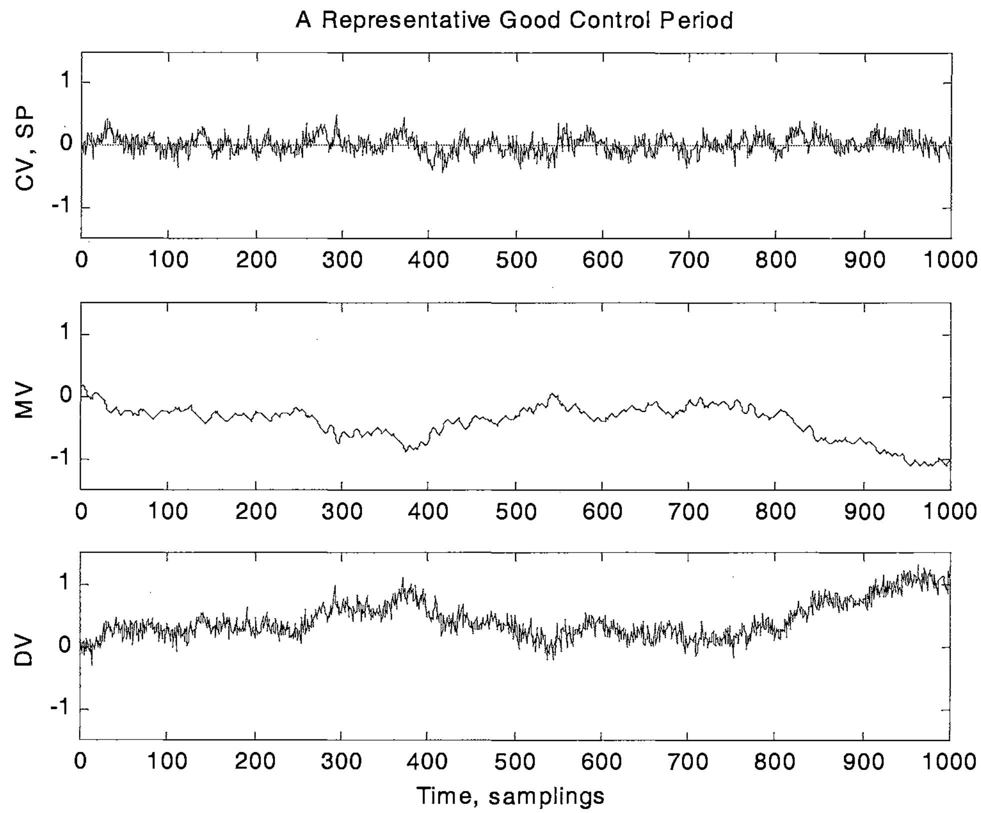

Figure 2.17 CV, MV and DV Data during Good Control Period of MPC Controller

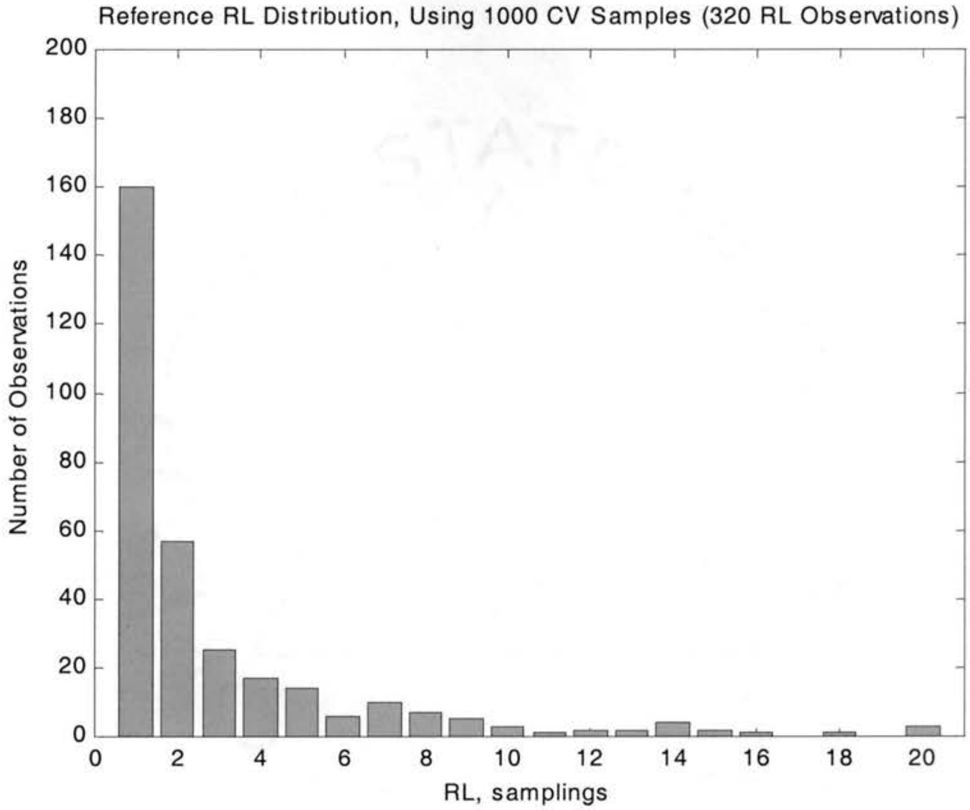

Figure 2.18 Reference RL Distribution Using 1000 Samples with 320 RLs

Table 2.4 Divide Reference RL Distribution into Classes, MPC Controller

Class #	1	2	3	4	5
RL, samplings	1	2	3, 4	5, 6, 7	8, 9, …
Probability	0.5000	0.1781	0.1313	0.0938	0.0969

The simulation data using the well-tuned MPC controller and the control performance monitor output are shown in Figure 2.19. We can see that the MPC controller is doing well, and the control performance monitor does not flag even during setpoint step changes at samplings 1500, 1700 and 2000, or during disturbance step changes at samplings 2300, 2500, and 2800.

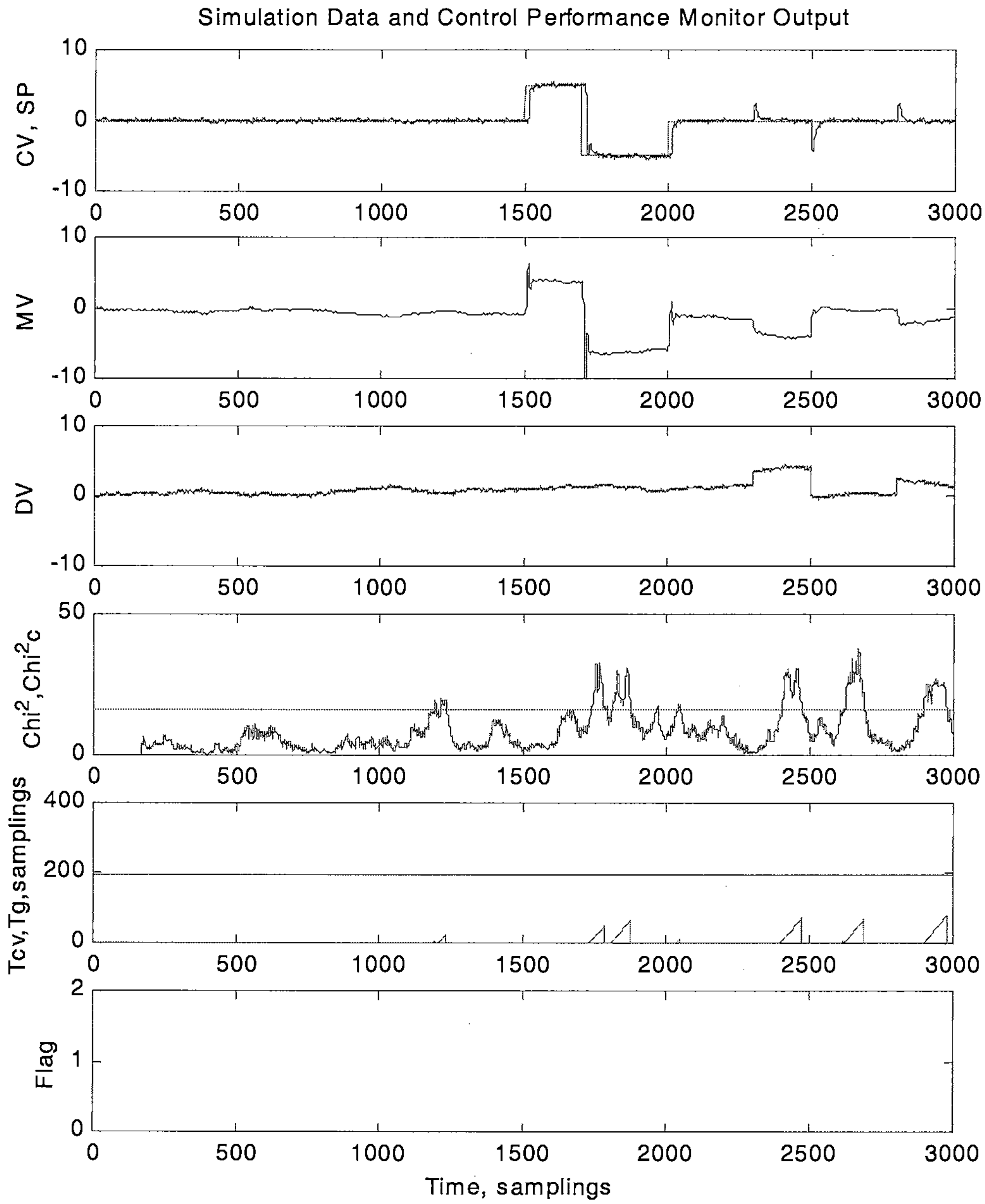

Figure 2.19 Simulation Data and Control Performance Monitor Output Using a Well-Tuned MPC Controller (Sampling period = 0.1 second. Window length N = 167 samplings. Grace period Tg = 196 samplings. Tcv is the time period counter in sampling period for continuous violations of chi-square test critical value chi^2c.)

2.6.2.3 Simulation with a Too Aggressive MPC Controller

The MPC controller becomes too aggressive when we change one pole of the plant from –1/2 to –1/6. The new plant's transfer function is below, and its step response is shown in Figure 2.20 along with the initial plant. Figure 2.20 shows that the steady state gain of the changed plant is increased from 1 to 3, and the settling time is almost doubled.

$$\frac{y(s)}{u(s)} = -0.3\frac{(s-\frac{1}{3})e^{-2s}}{(s+\frac{1}{2})(s+\frac{1}{5})} \rightarrow \frac{y(s)}{u(s)} = -0.3\frac{(s-\frac{1}{3})e^{-2s}}{(s+\frac{1}{6})(s+\frac{1}{5})}$$

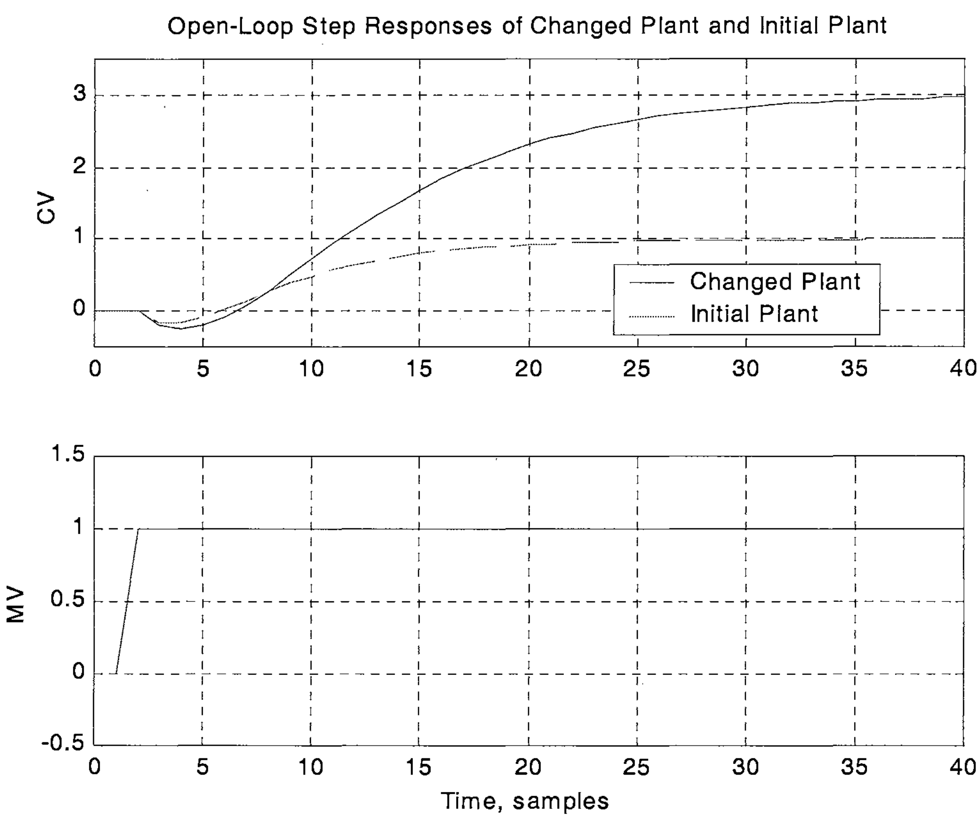

Figure 2.20 Open-Loop Step Responses of the Initial Plant and the Changed Plant, Plant Pole: -1/2 → -1/6 (The plant steady state gain is increased 3 times from 1 to 3. And the settling time is almost doubled)

After the plant is changed, re-run the simulation using the same MPC controller. The simulation data and the control performance monitor output are shown in Figure 2.21. We can see that the MPC controller becomes too aggressive due to the plant changes, and changes in setpoint or disturbance cause oscillations. The control performance monitor flags the poor control performance with oscillations. It flags even before the step changes in setpoint or disturbances are introduced. Figure 2.22 is an enlargement of the first 1000 CV, MV and DV data, and shows the poor performance of the aggressive controller before step changes in setpoint or disturbance are introduced.

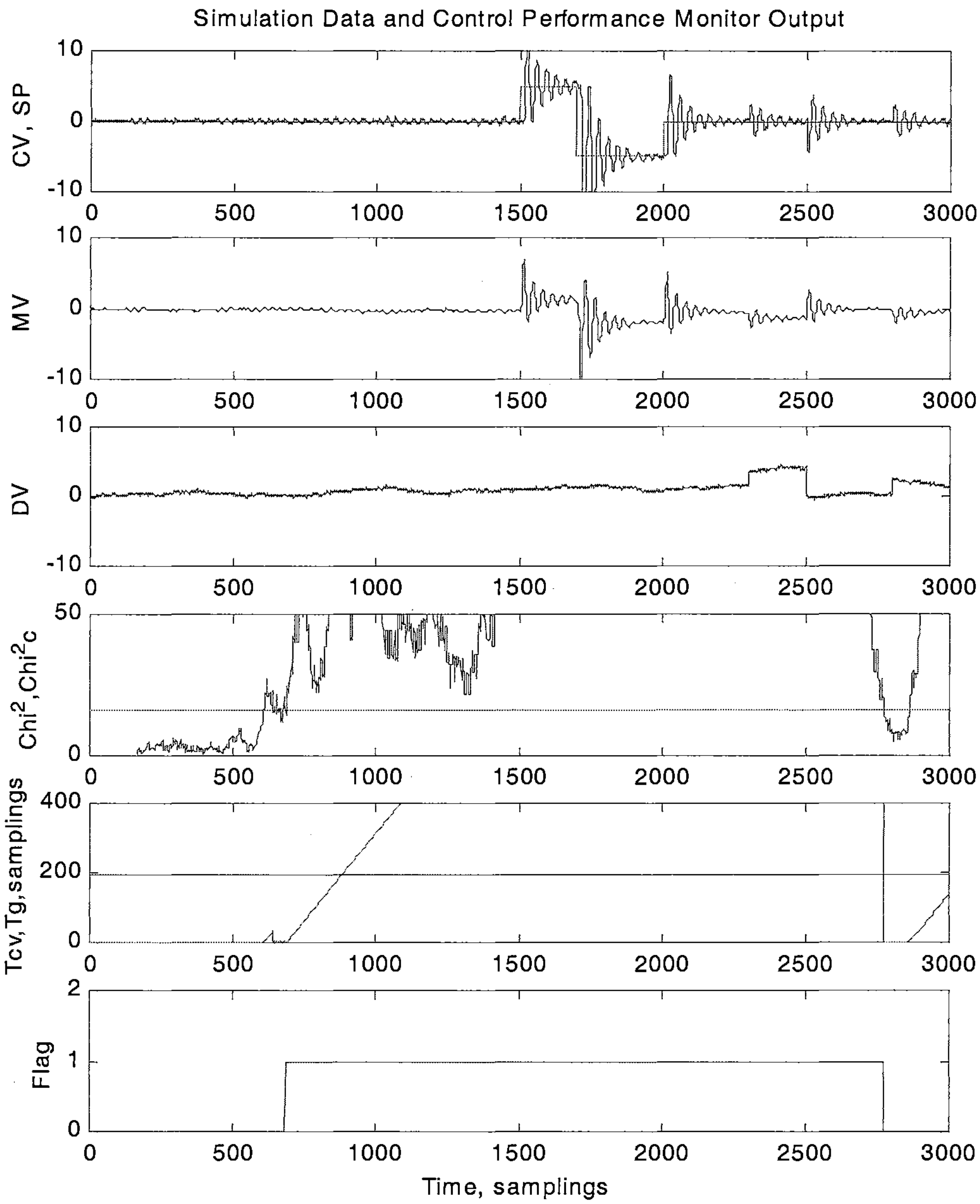

Figure 2.21 Simulation Data and Control Performance Monitor Output When Plant Gain is Increased and the MPC Controller Becomes Too Aggressive. (One pole of the plant is changed from –1/2 to –1/6. Window length N = 167 samplings. Sampling period = 0.1 second. Grace period Tg = 196 samplings. Tcv is the time period counter in sampling period for continuous violations of chi-square test critical value chi^2c.)

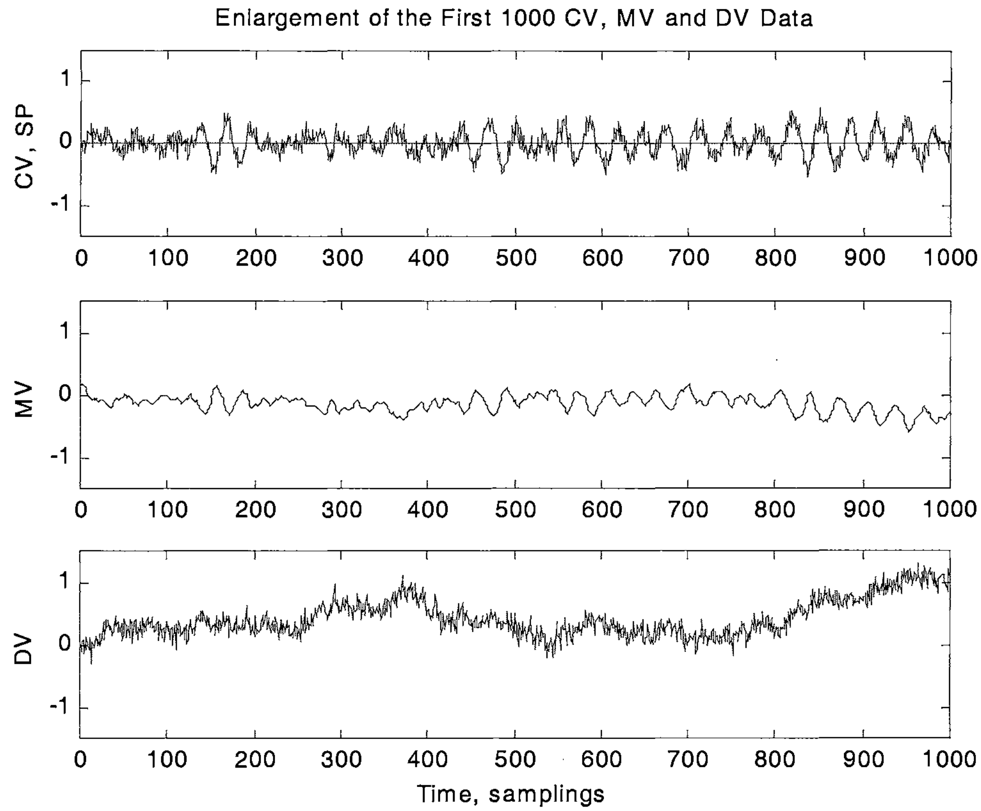

Figure 2.22 Enlargement of the First 1000 CV, MV and DV Simulation Data When the Plant Gain is Increased and the MPC Controller Becomes Too Aggressive. (One pole of the plant is changed from –1/2 to –1/6).

2.6.2.4 Simulation with a Too Sluggish MPC Controller

The MPC controller becomes too sluggish when we change the plant delay from 2 to 4 samplings, and the plant zero from 1/3 to 1/12. The new plant's transfer function is shown below, and its step response is shown in Figure 2.23 along with the initial plant. Figure 2.23 shows that the steady state gain of the changed plant is decreased from 1 to 0.25, and the delay is increased from 2 to 4 samplings.

$$\frac{y(s)}{u(s)} = -0.3\frac{(s-\frac{1}{3})e^{-2s}}{(s+\frac{1}{2})(s+\frac{1}{5})} \rightarrow \frac{y(s)}{u(s)} = -0.3\frac{(s-\frac{1}{12})e^{-2s}}{(s+\frac{1}{2})(s+\frac{1}{5})}$$

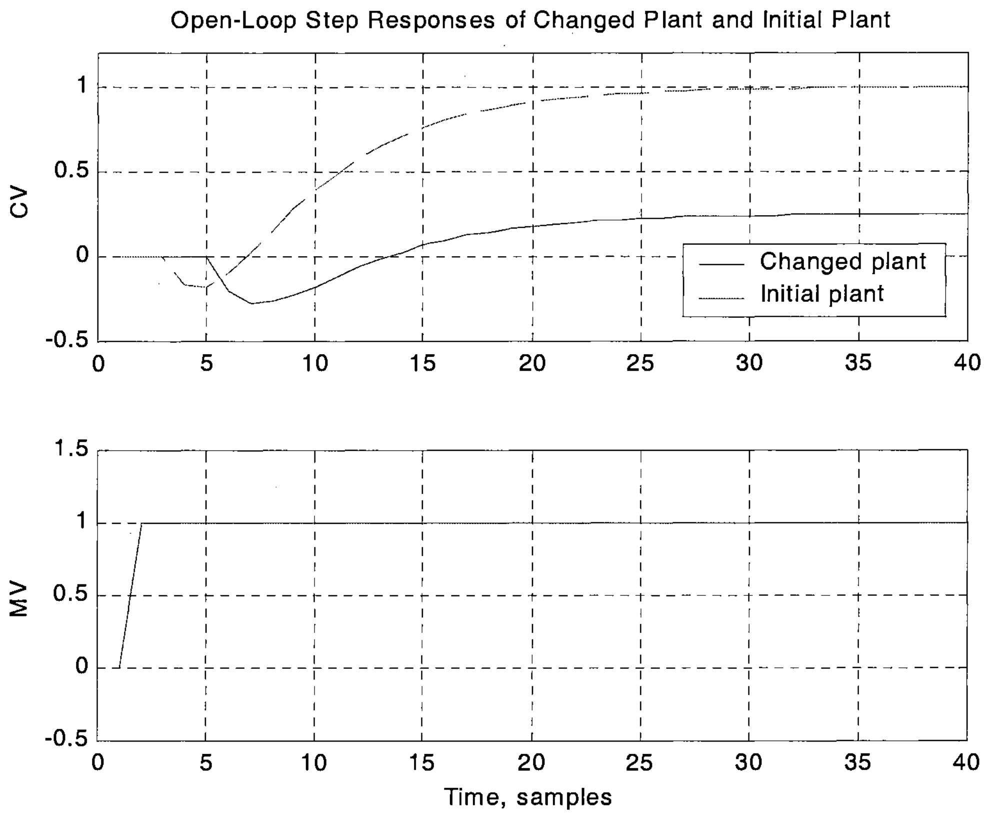

Figure 2.23 Open-Loop Step Responses of the Initial Plant and the Changed Plant, Plant Delay: 2 → 4, Plant Zero: 1/3 → 1/12 (Plant steady state gain is decreased from 1 to 0.25)

After the plant change, re-run the simulation using the same, initial MPC controller. The simulation data and the control performance monitor output are shown in Figure 2.24. We can see that the MPC controller becomes too sluggish due to the plant changes, and the controller is slow in overcoming setpoint changes and disturbances. The control performance monitor can detect and flag this sluggish poor control performance, even before the step changes in setpoint or disturbance are introduced.

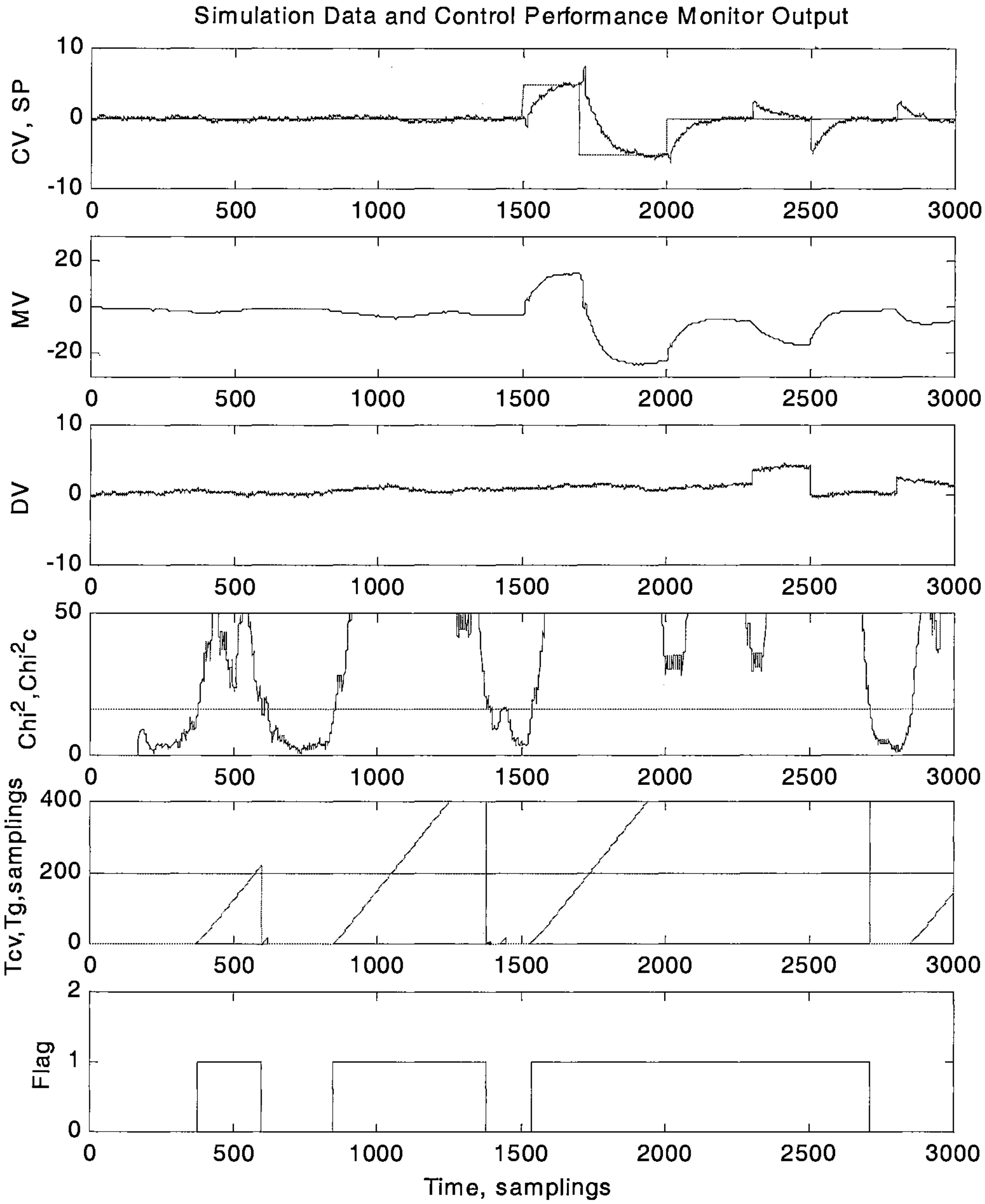

Figure 2.24 Simulation Data and Control Performance Monitor Output When the MPC Controller Becomes Too Sluggish due to Plant Changes. (The plant delay is increased from 2 to 4, and the plant zero is changed from 1/3 to 1/12. The plant steady state gain is decreased from 1 to 0.25. Window length N = 167 samplings. Sampling period = 0.1 second. Grace period Tg = 196 samplings. Tcv is the time period counter in sampling period for continuous violations of chi-square test critical value chi^{2}c.)

Figure 2.25 is an enlargement of the first 1000 CV, MV and DV data, and shows the poor performance of the sluggish controller before the step changes are introduced.

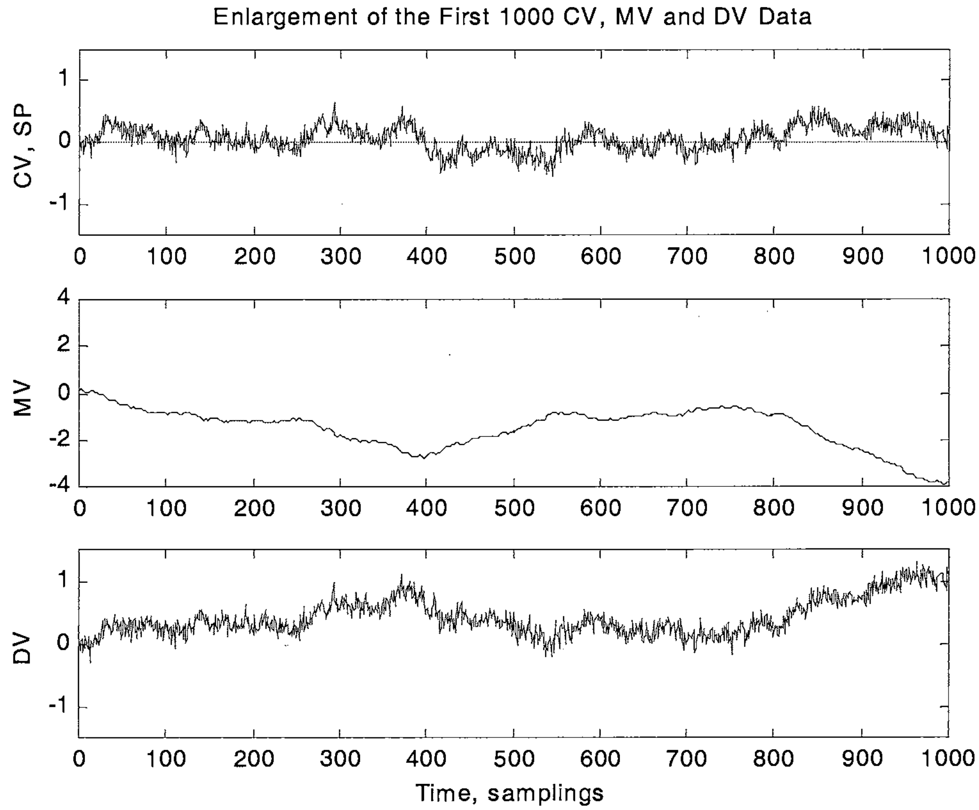

Figure 2.25 Enlargement of the First 1000 CV, MV and DV Simulation Data When the MPC Controller Becomes Too Sluggish due to Plant Changes. (The plant delay is increased from 2 to 4. The zero of the plant is changed from 1/3 to 1/12. The plant steady state gain is decreased from 1 to 0.25.)

2.6.2.5 Simulation of Hitting a Constraint

Add an upper limit constraint u_{max} on the manipulated variable of the initial MPC controller, i.e., $u_{max} = 1.2$. Re-run the simulation with everything else the same as the initial unconstrained, well-tuned control case as shown in Figure 2.19. The simulation results are shown in Figure 2.26, where the MV's upper limit constraint of 1.2 is hit during the setpoint change from 0 to 5, and the CV is not able to reach the new setpoint, leaving an offset. The control performance monitor flags this poor performance with offset. After the setpoint changes back to the initial value 0, the MPC controller brings the CV quickly to the new setpoint without reset windup, and the control performance monitor stops flagging.

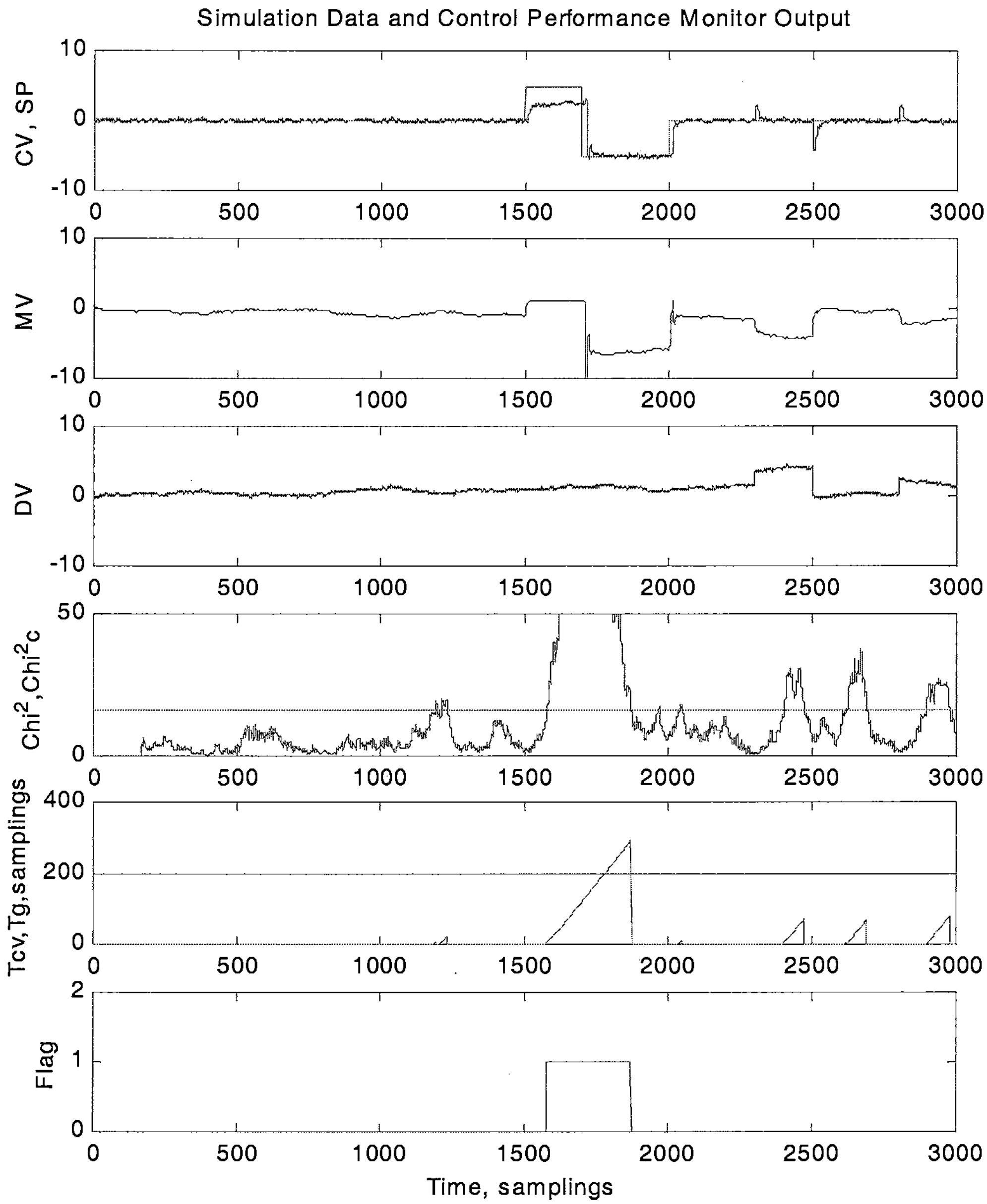

Figure 2.26 Simulation Data and Control Performance Monitor Output When the MPC Controller Hits a Constraint. (An upper limit constraint of 1.2 is imposed on the MV of the MPC controller. This constraint is hit after the setpoint change from 0 to 5. Data window length N = 167 samplings. Sampling period = 0.1 second. Grace period Tg = 196 samplings. Tcv is the time period counter in sampling period for continuous violations of chi-square test critical value chi^2c.)

2.6.2.6 Simulation with Changed Noise Variance

Double the noise variance from 0.1 to 0.2, and re-run the simulation with everything else the same as the initial case as in Figure 2.19. The simulation results are shown in Figure 2.27, and Figure 2.28 is the enlargement of the first 1000 CV, MV and DV data. We can see that the control performance monitor does not flag even though the noise variance has been doubled.

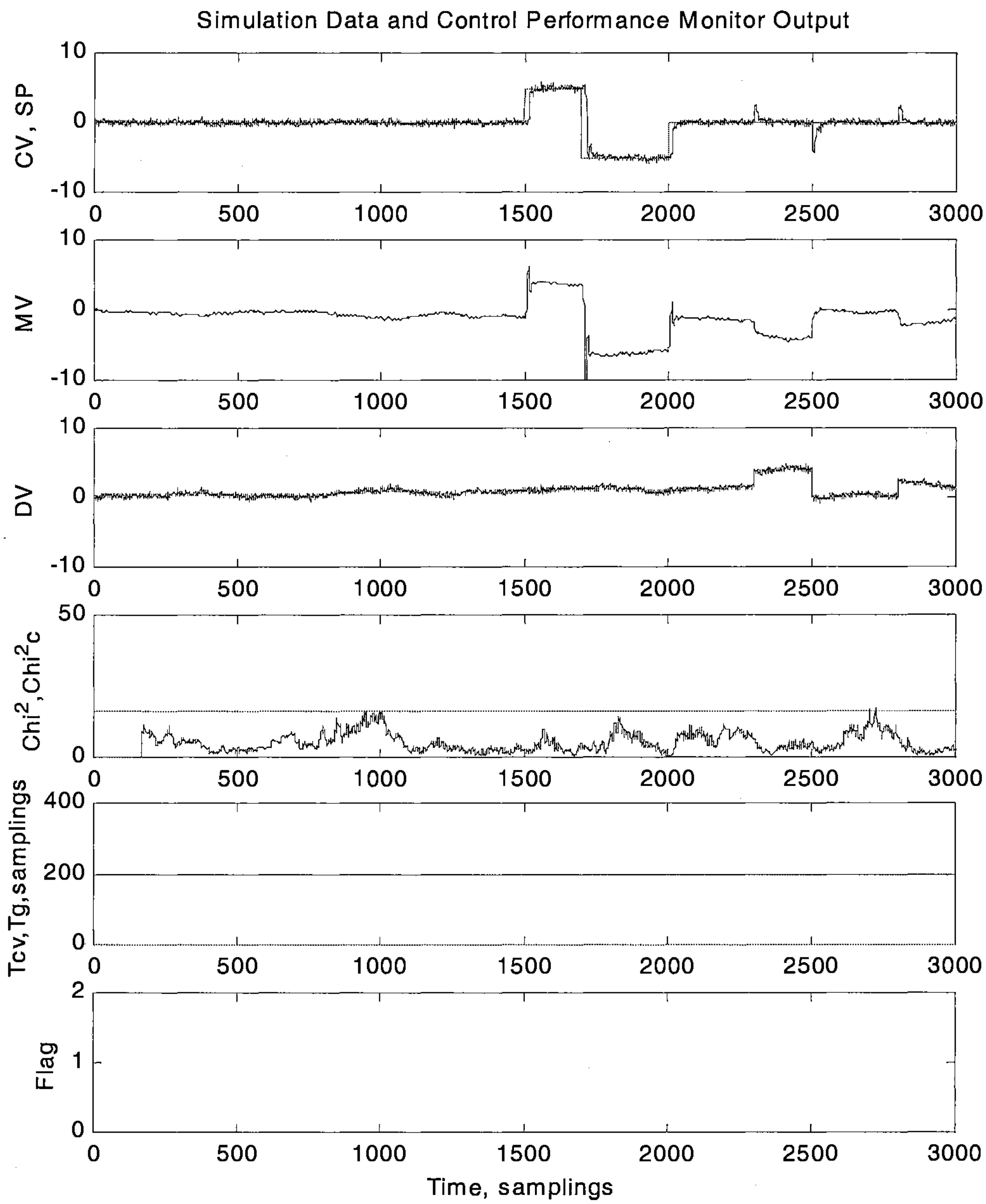

Figure 2.27 Simulation Data and Control Performance Monitor Output When the Noise Variance Has Been Changed. (The noise variance is doubled from 0.1 to 0.2. Data window length N = 167 samplings. Sampling period = 0.1 second. Grace period Tg = 196 samplings. Tcv is the time period counter in sampling period for continuous violations of chi-square test critical value chi^2c.)

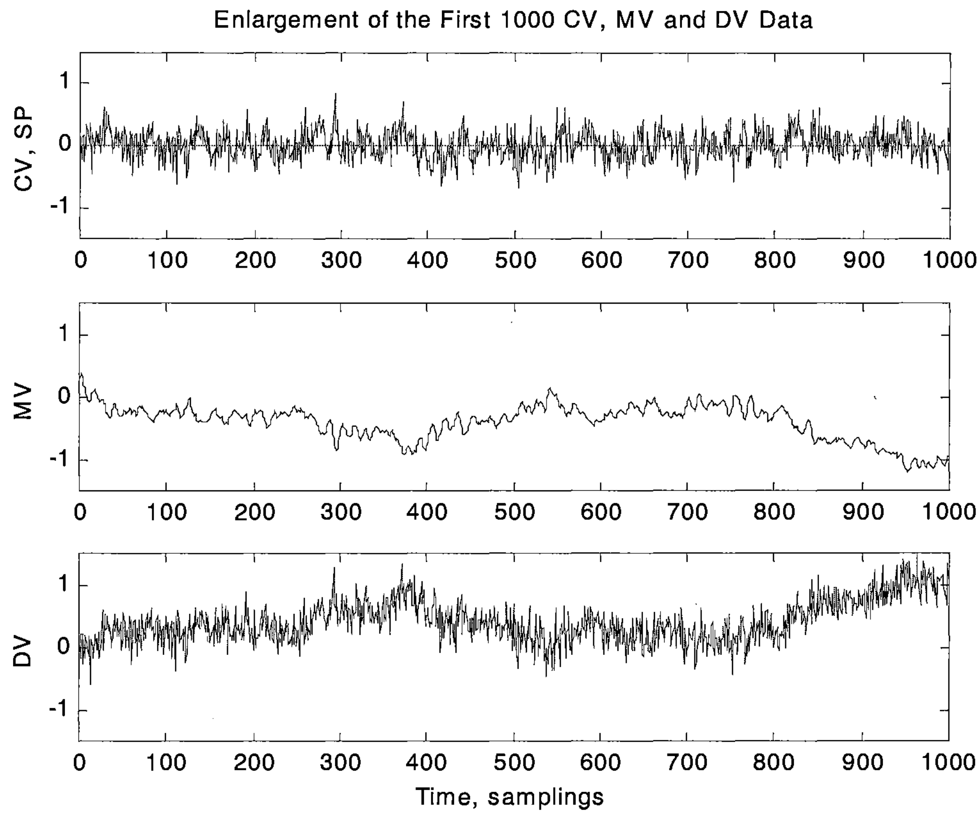

Figure 2.28 Enlargement of the First 1000 CV, MV and DV Simulation Data When the Noise Variance Has Been Changed. (The noise variance is doubled from 0.1 to 0.2).

2.7 Summary

A control performance monitoring technique is proposed to automatically detect and flag poor control performance. It compares the distribution of a performance index, called run length RL, to a reference distribution built from a representative data collected from a good control period. It detects poor control performance by a statistical chi-square test on the differences of the two RL distributions. The technique uses only routine plant operation data. It does not require *a priori* knowledge about the process (such as plant model or delay) or the controller except for a representative data of the controlled variable and setpoint collected during good control period, so it is applicable even when the process characteristics change during plant operation. The technique is simple to implement and is verified with experiments on a water flow control loop and an air flow control loop as well as simulations with a second-order-plus-time-delay (SOPTD) process with inverse response and a model predictive controller (MPC). The test cases include: a too aggressive controller, a too sluggish controller, hitting a constraint, and a change in noise variance. Experiments and simulations show that when the control performance is poor, the control performance monitor flags during most of the period although not 100% of the entire poor control period. This small percentage of non-flagging periods during poor control should not interpreted as good control, and it only indicates that evidence is not strong enough to indicate poor control during this short period. Any flagging is a strong indication of poor control although flagging is not continuous. When the control performance is good, the control performance monitor never flags.

CHAPTER 3

MODEL PERFORMANCE MONITOR

The performance of a model-based controller relies on the quality of the process model it uses. An initially good process model may become outdated because the characteristics of an industrial process often change during operation. Since most industrial processes are nonlinear and time-varying, a change in operating point may outdate a linear model or even a nonlinear model that is not sophisticated enough, and a change in other operating conditions, such as feed composition, catalyst activity, or equipment conditions, may also cause a process model to function poorly if the model parameters are not adjusted.

An outdated model will degrade the performance of a model-based controller, and therefore needs to be adjusted to maintain good control performance. However, re-developing a new process model or even re-estimating new model parameters usually is very time-consuming and costly in process industry, so, before actually adjusting a process model, a technique is desired to automatically detect a poor process model in a model-based controller, and to justify that there is sufficient advantage to warrant adjusting this model to maintain good control performance.

We choose to judge a process model by its function, i.e., the performance of the model-based controller, not by the accuracy of the model prediction. It is difficult to associate a particular model attribute to control performance. Many model-based controllers do not require an accurate model, and can function adequately well using a process model with quite large model errors. Therefore, we do not want to say a process model is poor as long as the controller based on this model functions well, even if this model has large errors. We say a process model is poor only when it causes the model-based controller to function poorly, and therefore, adjusting it can significantly improve the controller performance. The traditional measure of model goodness is the closeness of model prediction, and our measure is the function of the model, i.e., the performance of the model-based controller, which is what we really care about.

This work provides a model performance monitor, which automatically detects a poor process model in a model-based controller and suggests adjusting the process model only when a statistical test indicates that the control performance can be improved significantly by model adjustment. It provides a practical justification for model adjustment before actually doing model adjustment.

3.1 Literature Review on Model Performance Monitoring

To deal with the increase of process model mismatch during operation due to changes in plant characteristics, techniques to adjust a process model online are proposed. A model adjustment technique, the IMPOL (Incremental Model Parameterization On-Line) technique, was developed (Rhinehart and Riggs, 1991). The IMPOL technique is a one-step application of Newton's method, to update a model parameter using the actual process-model mismatch and the sensitivity of the modeled output to the parameter. Values of model parameters are adjusted such that the model mismatch is eliminated. To avoid the inappropriately large changes in the adjusted parameter because of ill-behaved or noise data, a relaxation coefficient (or damping factor) is used to smoothen the sudden change in the model parameter. A slow model adjustment is permissible because the controller's sampling frequency is much higher than the rate of change in parameter values. The adjustment is done at each sampling time in a one-step mode. The IMPOL method is easy to implement. Several applications of IMPOL have been simulated as well as demonstrated on laboratory equipment including: demonstration of IMPOL in fluid flow and heat exchanger pilot plant (Joshi et al., 1997), simulation of IMPOL to adjust model parameters in batch polymerization control and optimization (Choi and Rhinehart, 1997), demonstration of IMPOL to adjust model parameters in distillation and plasma reactor control (Subawalla et al., 1996), and demonstration of IMPOL to adjust model parameters in dynamic re-optimization of a fed-batch fermentor (Iyer et al., 1999).

One problem with IMPOL is that it continuously adjusts the model at each sampling time, and there is no justification procedure before adjusting the model, so it may make improper adjustments because the noise and disturbances are not considered and may cause inaccurate model parameter estimates and unreasonable changes in model parameters. A statistical technique for continuous on-line model adaptation for pH control was also reported (Mahuli et al., 1993).

Many adaptive control schemes (Narendra and Monopoli, 1980; Astrom, 1995; Landau, 1998) adjust models using online estimated model parameters. An adaptive system is one that continually monitors the changes in time-varying unknown parameters in a process model and adjusts its control parameters automatically to maintain good performance. Most adaptive control schemes use a recursive parameter estimator to update the model parameters. Model-reference adaptive control and self-tuning control (Soroush, 1999) are two important classes of adaptive control methods. There are many applications in chemical processes (Kosanovich et al., 1995; Youssef and Dahhou, 1996;

Henson and Seborg, 1997; Narayanan et al., 1997; Rho et al., 1998; Meleiro and Filho, 2000).

While the adaptive control approach can have a fast adaptation to a changing process, it has disadvantages. The major one is that the continuous adjustments of model parameters without sufficient justification is risky and may degrade performance in practice. If the process data which is used to estimate model parameters contains large noise or disturbances, or if the data are not well-conditioned, or the process is not fully excited, then the estimated model parameters will have large errors, and lead to a bad model adjustment. The success of continuous model adjustments as in adaptive control highly depends on the accuracy of estimated model parameters, which are difficult to obtain online during the routine plant operation, where exciting the plant is not desired, and noise and unmeasured disturbances are common.

Although there are methods for model validation in system identification procedure (Ljung, 1999), these model validation methods do not provide enough information about whether it is really necessary to adjust the model for practical purpose. The model validation methods focus on how close the estimated model prediction is to process data, i.e., how well the estimated model can predict the process output, not on how well a model-based application performs, which is more important in practice. Even though a newly estimated model is validated, it may be still unnecessary to adjust the model practically if the adjustment brings no, or little improvement on control performance of the model-based controller.

Currently in the process industry, most decisions on when to adjust a process model are usually made by personal judgments of engineers or operators based on their process knowledge and experiences, which may be qualitative, subjective and time-delayed. We want to automate the decision process.

3.2 Basic Idea of Proposed Model Performance Monitor

The basic idea of the proposed model performance monitor is to compare the process output (controlled variable CV) of the actual, current control system under monitoring to that of a reference control performance system to determine whether the current controller parameters and the process model that the current controller is based upon should be adjusted. Figure 3.1 shows this basic idea.

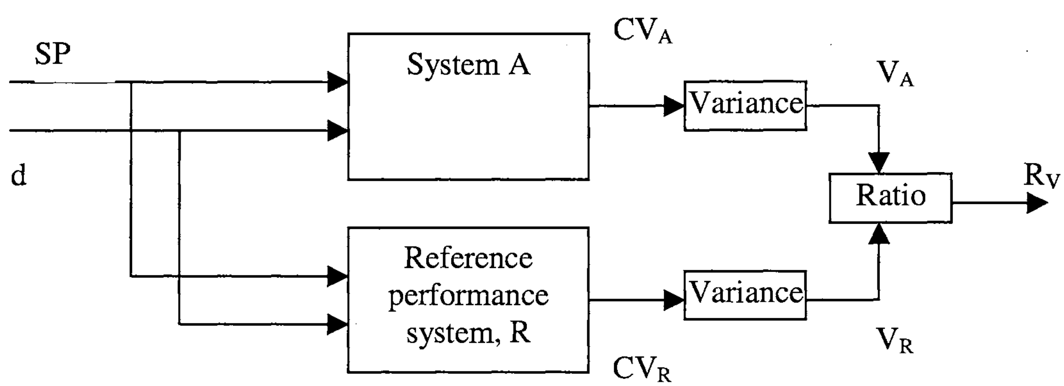

Figure 3.1 Basic Idea of Proposed Model Performance Monitor. System A represents the actual, current control system under monitoring, and its block diagram is shown in Figure 3.2. Reference Performance System R represents a simulated control system that has the desired control performance. V_A is the variance of the controlled variable CV_A of system A, and V_R is the variance of the controlled variable CV_R of system R. The performance index $R_V = V_A/V_R$. SP is the setpoint, and d is the disturbance variable.

System A in Figure 3.1 represents the actual, current control system under monitoring, and a typical one with feedback control is shown in Figure 3.2, where P_A represents the actual plant to be controlled, C_A represents the actual controller, CV, SP and MV represent the controlled variable, setpoint and manipulated variable, respectively, and d represents the effects of disturbances and noise that are added to the controlled variable CV. Note that for system A to have good control performance, the controller C_A should match the characteristics or the model M_A of the actual plant P_A. Generally speaking, the closer the model M_A matches the actual plant P_A, the better the controller performs. However, during plant operations, the actual plant P_A may change and therefore the mismatch between the actual plant P_A and the plant model M_A may increase. The increasing mismatch between the plant and model will deteriorate the controller's performance. Most model-based controllers, such as IMC and MPC controllers, explicitly include the model M_A of the plant within the control algorithm. A PID controller can also be thought of as a model-based controller because its tuning parameters can be seen as being determined from a simple first-order-plus-time-delay model, whose parameters represent the key plant characteristics: gain, time constant, and delay.

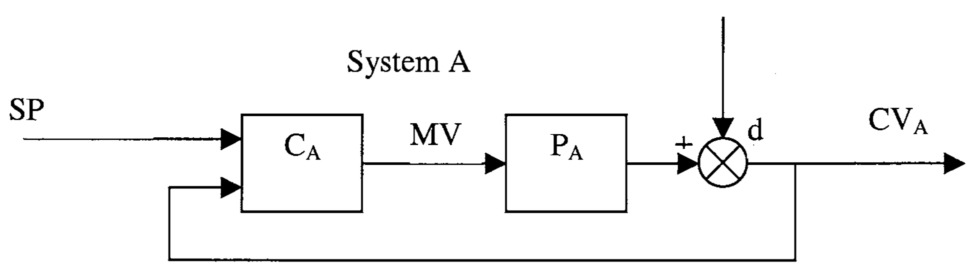

Figure 3.2 Block Diagram for a Typical Feedback Control System (System A)

The reference performance system R in Figure 3.1 represents a simulated control system that has the desired control performance. There are many different ways to define a reference performance system RPS, and the ideal RPS is shown in Figure 3.3. In this ideal RPS, the controller C_R is a perfect adaptive controller, i.e., whenever the actual plant P_A changes, the controller C_R always updates itself to match the changing plant such that the RPS always maintains good control performance. The adaptive controller has the capability of identifying online the model parameters of the changing plant and adjusting automatically the controller parameters according to the newly estimated model parameters. The plant P_R in the ideal RPS uses the online estimated plant model. More practical RPSs will be discussed in the next section.

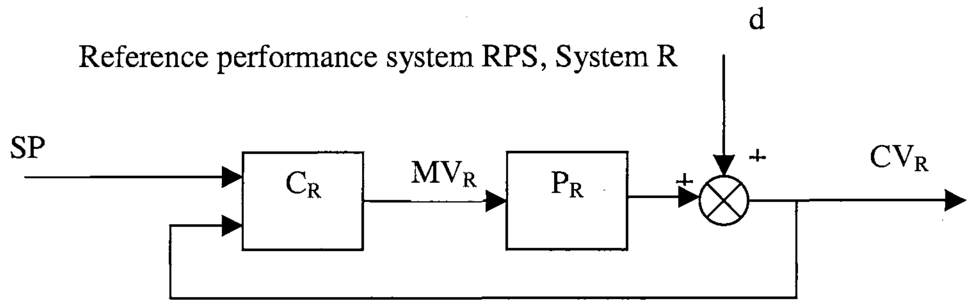

Figure 3.3 Block Diagram for the Ideal Reference Performance System

3.3 Performance Index R_V

To compare the performance of the actual system, system A, and the simulated reference performance system (RPS), system R, as shown in Figure 3.1, we define a performance index R_V of system A as the ratio of the variance V_A of the controlled variable CV_A of system A and the variance V_R of the controlled variable CV_R of the RPS, system R.

$$R_V = \frac{V_A}{V_R}$$

Variances V_A and V_R are calculated from the error signal e = (SP – CV). Both system A and system R should have the same input sequences, i.e., same SP and disturbance sequences.

Note that in the ideal RPS, the plant P_R is constantly updated using the online estimation of the actual, changing P_A, so, the major difference between system A and system R is in the two controllers. The controller C_R in system R constantly updates its process model parameters and its controller parameters according to the changing plant P_A, while the controller C_A in system A does not change as the plant C_A changes. Since the variance is commonly used to present the control performance, the difference in V_A and V_R represents the control performance difference of the actual controller C_A and ideal adaptive controller C_R in the RPS, and therefore the variance ratio R_V indicates how much control variance reduction can be achieved if the actual controller C_A is also updated or adjusted just like the controller C_R does. For example, $R_V = 3$ means the variance of the CV_A of the actual system A is 3 times the variance of the CV of the RPS, and can be reduced by 2/3 (= $1 - 1/R_V$) if the actual controller C_A is adjusted using the same parameters of the adaptive controller C_R. In other words, R_V indicates the improvement potential of the control performance (variance) if the actual controller C_A is adjusted.

An R_V value close to 1.0 indicates no significant control performance improvement can be achieved, and $R_V >> 1.0$ indicates significant control performance improvement can be achieved by adjusting the actual controller. Here we assume, at the beginning of monitoring, the actual controller C_A is well tuned, and has almost the same control performance as the RPS, i.e., $R_V \approx 1$.

When the system A and system R have the same control performance, the two variances, V_A and V_R, should be close to each other. A statistical test for equal variances, such as F test (will be discussed in detail later), can be performed to indicate whether the two variances V_A and V_R are significantly different. If the two variances are significantly different, the monitor suggests adjusting the current controller C_A.

A suggestion to adjust the initially well-tuned controller C_A indicates that the plant has changed, and therefore means a need to adjust the process model M_A of the model-based controller. An R_V value >> 1 indicates the actual plant P_A has changed a lot, and the initial plant model M_A, upon which the controller C_A is based, becomes outdated. So we call the index R_V as the model performance index, and the monitor as a model performance monitor.

Note the goodness of a process model in a model-based controller is judged by the control performance of the model-based controller, not by its mismatch from the true plant. As long as the process model in a controller can make the controller work adequately well for the specific purposes, and no significant improvement on control performance can be achieved by adjusting the model, we do not want to say it is a poor model even it has large plant-model mismatch. R_V is used to decide whether a process model in the controller is poor.

R_V can be thought of as an index for measuring the goodness of a process model in a model-based controller in terms of the controller's performance. It evaluates a process model, which the controller is based upon, in terms of how much improvement in controller's performance can be achieved by adjusting the model, rather than how accurate the process model is to the actual plant output. This evaluation standard is consistent to our purpose, which can be stated as suggesting model adjustment only when doing so can significantly improve the performance of the model-based controller.

3.4 Reference Performance System RPS

For practical purpose, the ideal reference performance system in Figure 3.3 can be simplified. Since the purpose of the RPS is to provide good control performance (in terms of the variance of the CV) under the same setpoint and disturbance sequences as in the actual plant, what we care about the RPS is its closed-loop response, i.e., how the controlled variable CV_R of the RPS responds to setpoint and disturbance changes, not its manipulated variable MV_R or its internal components: the controller C_R and plant P_R. Therefore, we can use a simple, linear model M_{SP} to relate the RPS's closed-loop responses to setpoint changes and another linear model M_d to relate the RPS's closed-loop response to disturbance changes.

Under the assumption that the RPS is a linear system, the RPS can be represented using the following linear closed-loop response model, i.e., the output CV_R of the RPS can be represented, in Laplace transfer function format, as

$$CV_R(s) = M_{SP}(s)SP(s) + M_d(s)d_e(s) \qquad (3.1)$$

where $M_{SP}(s)$ is the Laplace transfer function of the finite impulse responses (FIR) of the RPS to a setpoint SP(s), and $M_d(s)$ is Laplace transfer function of the FIR to disturbance d(s).

Figure 3.4 shows the proposed reference performance system R in the dashed-line box, the actual plant P_A, the controller C_A, and the blocks for calculation of controlled variable variances and the performance index R_V.

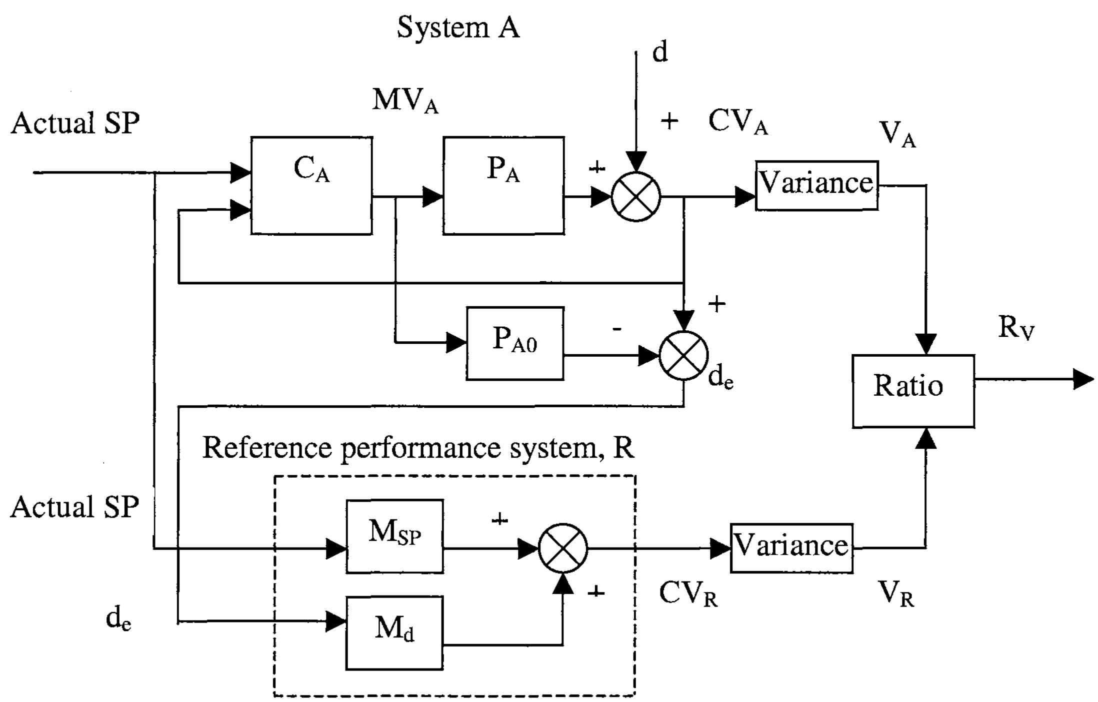

Figure 3.4 The Proposed Reference Performance System RPS, the Actual Control System (Plant P_A and Controller C_A), and the Performance Index R_V. The RPS in dashed-line box is represented using the closed-loop response models M_{SP} for setpoint input and M_d for disturbance input. The setpoint input to the actual system is known and is fed into the RPS, and the disturbance input is estimated using the model prediction error sequence: $d_e(k) = (CV_A(k) - P_{A0}(q)MV_A(k))$, where $P_{A0}(q)$ is the initial plant model and q is the forward shift operator.

The linear models M_{SP} and M_d should be specified such that its input-output relation is almost equivalent to a well-tuned control system with desired good control performance.

Actually, only the model M_{SP} needs to be specified because once M_{SP} is determined, M_d is also fixed. Consider the reference performance system R in Figure 3.3, and let the controller transfer function be $C_R(s)$ and plant transfer function $P_R(s)$, the transfer function for disturbances d_e is

$$M_d(s) = \frac{CV_R(s)}{d_e(s)} = \frac{1}{1+P_R(s)C_R(s)}$$

$$M_d(s) = 1 - \frac{P_R(s)C_R(s)}{1+P_R(s)C_R(s)} = 1 - \frac{CV_R(s)}{SP(s)} = 1 - M_{SP}(s)$$

$$M_d(s) = 1 - M_{SP}(s) \qquad (3.2)$$

So we only need to obtain the closed-loop response model M_{SP} of the RPS to setpoint change, and M_d can be determined from Equation (3.2).

The simplest way to obtain M_{SP} is to record the CV response when a step change Δ_{SP} in setpoint is introduced to the actual control system after the controller is well tuned. Record all CV response samples, $s_0, s_1, s_2, \ldots, s_n$, until the CV reaches the new steady state (at sample n). Then the RPS can be represented by a finite impulse response (FIR) model as

$$CV_R(k) = \sum_{i=0}^{n} (h_i SP(k-i) + (1-h_i) d_e(k-i)) \qquad (3.3)$$

where k is the sampling time, and the FIR model parameters h_i are

$$h_i = (s_i - s_{i-1})/\Delta_{SP}, \qquad i = 1, 2, \ldots, n, \text{ and } h_0 = 0 \qquad (3.4)$$

The advantage of using a step or impulse response model form is that both are easy to obtain, and can represent the closed-loop responses of any stable linear control system with any order or complex dynamics.

Here we use the control performance of the initial, well-tuned control system represented by Equation (3.3) as the benchmark to determine the potential for control performance improvement. Note this benchmark control performance represented by Equation (3.3) does not represent the best possible control performance for a changed process because a changed process could have a better control performance than the initial, well-tuned control system. However, to represent the best possible control performance for a changed process requires the accurate model of the changed process, which is very difficult to obtain online using routine plant operation data. So, to simplify the calculation of the potential for control performance improvement, we use the initial, well-tuned control system represented by Equation (3.3) as the benchmark to determine whether the control performance can be improved significantly by model adjustment. Note we assume that the control performance of the initial, well-tuned control system represented by Equation (3.3) is achievable by adjusting the controller even after the plant has changed. So, the performance index R_V, the ratio of the variance V_A of the actual system and the variance V_R of the RPS, indicates the improvement potential in control performance by adjusting the process model and the controller. We suggest model adjustment if $R_V >> 1$.

Since CV_A and MV_A are available, the block diagram of the performance monitor can be simplified as shown in Figure 3.5.

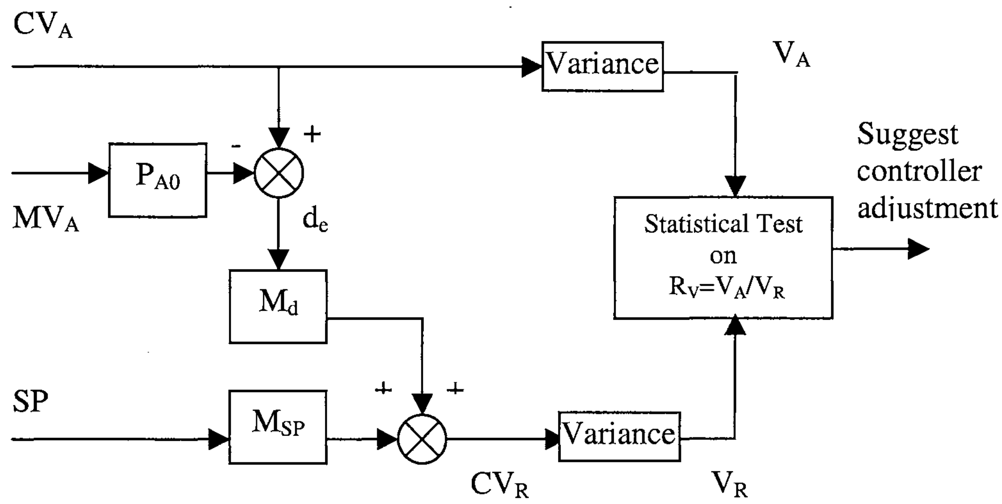

Figure 3.5 Block Diagram of the Model Performance Monitor

If the disturbance effect is negligible, the performance monitor does not need the initial plant model P_{A0}, and it only needs the well-tuned closed-loop response model M_{SP} to a setpoint change. The model performance monitor when the disturbance is small and negligible is then shown in Figure 3.6.

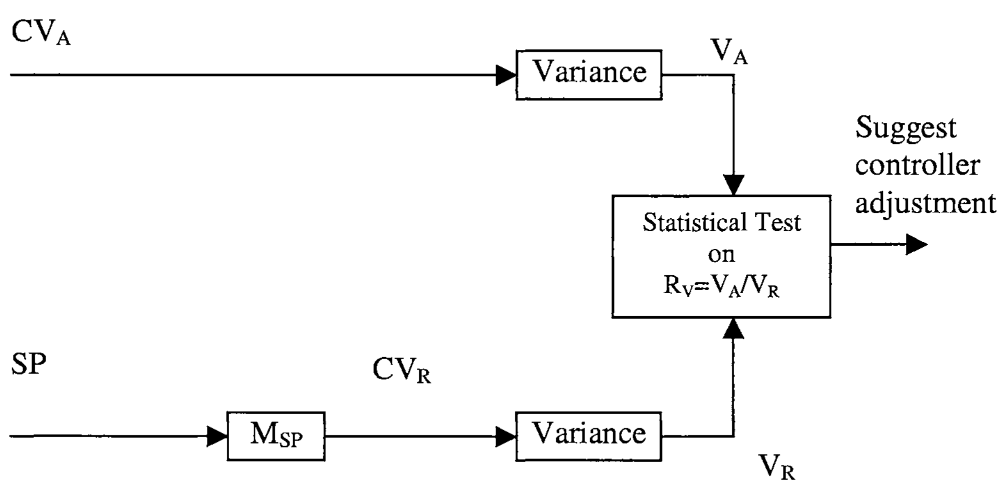

Figure 3.6 Model Performance Monitor When the Disturbance Effect is Negligible

3.5 Disturbance Estimation

To compare the variance V_A of the current system to the variance V_R of the reference system, both systems should have the same inputs (i.e., setpoints and disturbances). We know exactly the setpoint input sequence to the current system, but we do not know the disturbance sequence, and therefore we have to estimate it.

The model prediction error sequence obtained from the initial plant model P_{A0} is used as an estimate for the disturbance sequence:

$$d_e(k) = CV_A(k) - P_{A0}(q)MV_A(k) \tag{3.6}$$

where $P_{A0}(q)$ is the initial plant model in the form of the forward shift operator q. If we make a step change Δ_{MV} in MV in the open loop mode, and s_0, s_1, s_2, …, and s_n are the samples of the plant CV responses until the new steady state is reached (at sample n), then we have

$$P_{A0}(q)MV_A(k) = \sum_{i=0}^{n} g_i MV_A(k-i) \tag{3.7}$$

where k is the sampling time, and the FIR parameters g_i of the model P_{A0} are

$$g_i = (s_i - s_{i-1})/\Delta_{MV}\,, \quad i = 1, 2, \ldots, n, \text{ and } g_0 = 0 \tag{3.8}$$

So, the disturbance estimation of Equation (3.6) becomes

$$d_e(k) = CV_A(k) - \sum_{i=0}^{n} g_i MV_A(k-i) \tag{3.9}$$

The estimated disturbance sequence $d_e(k)$ and the known setpoint sequence SP(k) are fed into the reference system as input. If the model parameters g_i are perfect, Equation (3.9) should give perfect estimation of disturbance sequence. Note $CV_A(k)$ and $MV_A(k)$ are known.

If the actual (true) disturbance $d_a(k)$ can be represented as

$$d_a(k) = CV_A(k) - \sum_{i=0}^{n} g_{ai} MV_A(k-i)$$

where g_{ai} is the perfect model parameters, we have the following relation from Equation (3.9),

$$d_e(k) = d_a(k) + \sum_{i=0}^{n} (g_{ai} - g_i) MV_A(k-i) \qquad (3.10)$$

We can see that if the second term (the model error term) in Equation (3.10) is small relative to the first term (the true disturbance), then the estimated disturbance d_e is very close to the true disturbance $d_a(k)$, i.e., $d_e(k) = d_a(k)$

There are two cases where the second term (the model error term) in Equation (3.10) is small and thus Equation (3.9) gives good estimate of disturbances. The first case is when the plant does not change much, i.e., the model P_{A0} (or g_i) matches the current plant P_A, i.e., $P_A \sim= P_{A0}$, then $g_{ai} - g_i \sim= 0$, and the above d_e estimation is close to the true disturbance d_a. The second case is when the CV is at steady state, where MV(k) does not change much, i.e., $\Delta MV_A(k) \sim= 0$.

Therefore when the plant is at steady state, or when plant model matches the true plant, Equation (3.9) should give good estimate of disturbance.

So during setpoint changes, the estimated disturbances using Equation (3.9) should not be used. In stead, the previously estimated disturbance sequence before setpoint changes can serve as the substitute for the disturbance estimation during setpoint changes.

When there are significant disturbances, the true disturbance d_a usually is much larger than the model error term (the second term in Equation (3.10)), Equation (3.9) can still give reasonable disturbance estimate.

If we assume the true disturbance and the model error term in Equation (3.10) which includes measurement noise are independent, which is valid in practice, the variance of the estimated disturbance will be a larger than that of the true disturbance:

$$\mathrm{var}(d_e) > \mathrm{var}(d_a)$$

So we can see that the estimated disturbance, which will be fed into the reference performance system (system R), has a larger variance than the true disturbance, which is fed into the current control system (system A). And this estimated disturbance with an over-estimated variance will inflate the variance V_R of system R, and therefore deflate (underestimate) the performance index, R_V, the ratio of variances V_A and V_R. Since only a value of $R_V >> 1$ will cause the monitor to flag, the underestimated value of R_V makes the monitor more conservative, i.e., when the disturbance estimates have large errors, R_V will become smaller and it will become more difficult for the monitor to flag, which is not too bad for our purpose in most cases.

The major advantage of using the initial plant model to estimate the disturbance is to avoid the online plant model estimation. The major disadvantage is that good estimation for disturbance can not be obtained during setpoint change periods. We have to use the previously estimated disturbance sequence during a period without setpoint change as the substitute of the disturbance estimation for the setpoint change period.

3.6 Statistical Tests on Performance Index R_V

To determine whether the current control system and the reference performance system have the same performance, we compare the variances of the two systems' controlled variables, and perform a statistical F test for the equality of two variances.

F test is commonly used to test for equal variances. Assume the two error signals, $e_A = (SP - CV_A)$ and $e_R = (SP - CV_R)$, are two independent random variables with Gaussian probability distribution function, with unknown population variances σ_A^2 and σ_R^2. The null hypothesis H_0 and the alternative hypothesis H_1 are as follows:

$$H_0: \sigma_A^2 = \sigma_R^2$$

$$H_1: \sigma_A^2 > \sigma_R^2$$

One-sided test is used because we only want to detect whether the current system's performance is worse than the reference performance system.

Take na samples of e_A, and nr samples of e_R, and calculate the sample variances S_A^2 and S_R^2, as follows:

$$S_A^2 = \frac{\sum_{i=1}^{na} (e_{Ai} - \bar{e}_A)^2}{na - 1}$$

$$S_R^2 = \frac{\sum_{i=1}^{nr} (e_{Ri} - \bar{e}_R)^2}{nr - 1}$$

where

$$\bar{e}_A = \frac{\sum_{i=1}^{na} e_{Ai}}{na}$$

$$\bar{e}_R = \frac{\sum_{i=1}^{nr} e_{Ri}}{nr}$$

The test statistic F is the ratio of the two sample variances, i.e., the performance index R_V,

$$F = R_V = S_A^2 / S_R^2$$

If the null hypothesis H_0: $\sigma_A^2 = \sigma_R^2$ is true, the test statistic F, or the performance index R_V, should have an F-distribution with degrees of freedom of (na – 1, nr – 1). Therefore if $R_V > F_{\alpha, na-1, nr-1}$, the critical value of the F distribution with a significance level α and degrees of freedom (na – 1) and (nr – 1), we reject H_0, and accept H_1, i.e., we conclude that the current control system's variance is larger than the reference performance system's variance, and the current control performance can be improved by adjusting the process model and controller.

The choice of sample sizes na and nr can be determined from our choice of the type II error probability β. A type II error is made when the null hypothesis is accepted when it is not true. A lower value of β requires a larger sample size. The relationship between β and the sample sizes at various variance differences are plotted as the so-called operating characteristic curves, and can be found in most statistics books. For one-sided F test with a significance level of $\alpha = 0.01$, if $\sigma_A/\sigma_R = 2$ and we want $\beta < 0.1$, then we should choose a sample size > 30, i.e., na = nr > 30 samples. A practical choice of sample size is twice the closed-loop settling time.

3.7 Evaluation of Model Performance Monitor

Both experiments and computer simulations are used to evaluate the model performance monitor. The experiments are conducted on a water flow control loop and an air flow control loop, which are described in Section 2.6.1.1. The processes on both control loops exhibit first-order plus time delay dynamics and nonlinear characteristics, and are controlled by two independent PI controllers. Simulations with a model predictive controller (MPC) and a second-order plus time delay (SOPTD) processes with inverse response are also used to evaluate the model performance monitor.

3.7.1 Experimental Evaluation

Experimental Protocol

At a chosen nominal operating point, make a step change in the MV when the controller is off-line, and observe the open-loop CV responses. Calculate the FIR model parameters g_i of the initial plant P_{A0} using Equation (3.8). Tune the PI controller at the nominal operating point. After tuning, make a step change in the SP, and observe the closed-loop CV response. Calculate the FIR model parameters h_i of the closed-loop responses M_{SP} of the initial well-tuned control system to a setpoint change using Equation (3.4). Use Equation (3.9) to calculate $d_e(k)$, and Equation (3.3) to calculate $CV_R(k)$, the output of the RPS. Choose a sample size $n_A = n_R = 2*$(closed-loop settling time) for the F-test. Specify the level of significance for the F test. Make a series of setpoint changes within the possible range, and monitor performance using the model performance monitor.

3.7.1.1 Water Flow Control Experimental Results and Discussion

The nominal operating point of the water flow rate was 35 kg/hr. Put the controller in manual mode, make a step change in MV, and record the open-loop CV response. The experimental data and the estimated plant step response model parameters are shown in Figure 3.7. Put the controller in automatic mode after tuning the controller, make a step change in the setpoint, and record the closed-loop response. The experimental data and the estimated closed-loop response model parameters are shown in Figure 3.8. Choose the sample size na = nr = 100 (twice the closed-loop settling time). Select the F test significance level (one-sided) of $\alpha = 0.01$. The critical value $F_{\alpha,na-1,nr-1}$ is 1.6, i.e., the critical value for the variance ratio performance index is Rvc = 1.6. Run the water flow control experiments at different operating regions, collect CV, SP and MV samples, and feed the data into the model performance monitor.

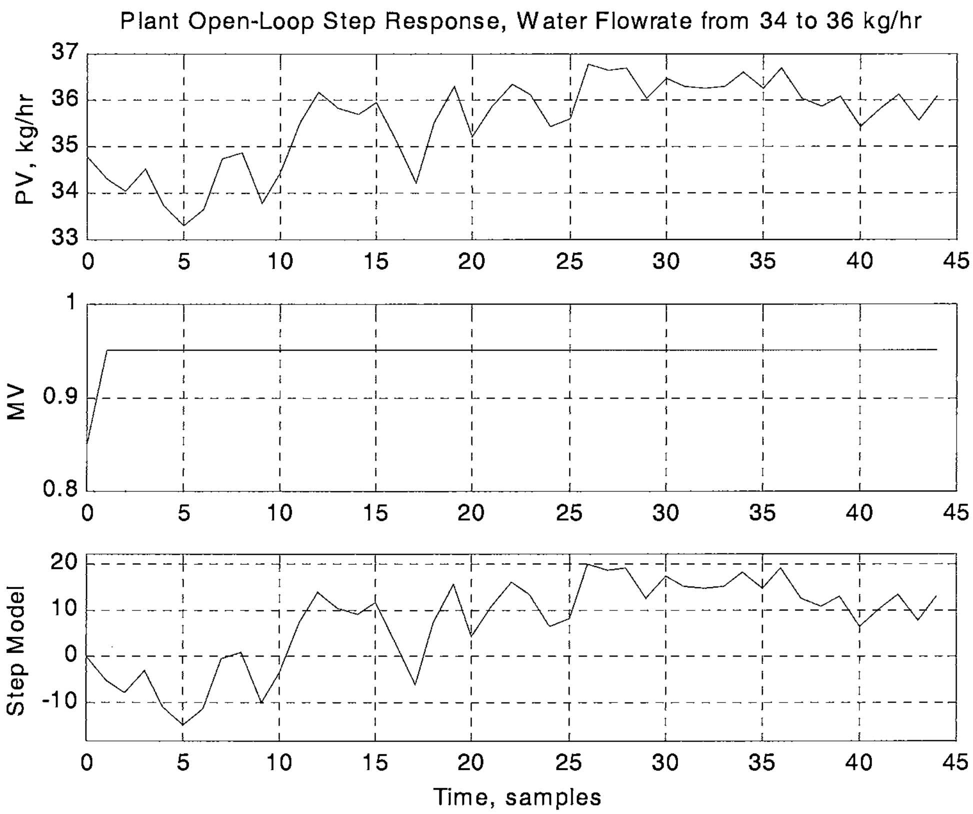

Figure 3.7 Experimental Open-Loop Step Response Data and the Estimated Plant Step Model Parameters for Water Flow Control Loop Near the Nominal Operating Point 35 kg/hr. Water flow controller input is changed from 0.85 to 0.95, and the water flowrate is changed from approximately 34 to 36 kg/hr. The steady state gain is about 10 kg/hr. Sampling Period = 0.1 Second.

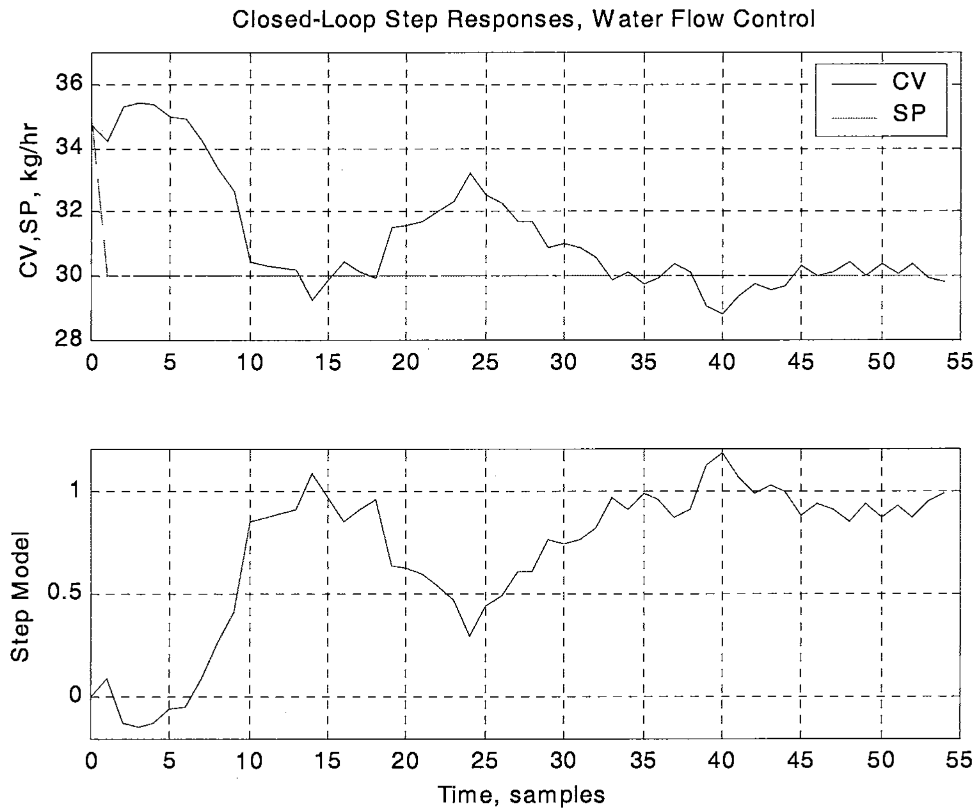

Figure 3.8 Experimental Closed-Loop Step Response Data and the Estimated Step Model Parameters When the Water Flow Controller is Well Tuned. Sampling Period = 0.1 Second.

The water flow control experimental data and the model performance monitor output are shown in Figure 3.9. From Figure 3.9, we can see that when the plant operates near the nominal operating point with a water flow rate of 35 kg/hr, where the process model is obtained and the controller is tuned, the monitor does not flag even though there are setpoint changes. As the water flow rate decreases and moves away from the nominal operating point, the plant characteristics change, and therefore, the process model mismatch increases. Figure 3.10 shows the open-loop step response experimental data and the estimated step response model parameters near the operating point with a water flowrate of 20 kg/hr, and Figure 3.11 shows those near the operating point with a 5 kg/hr water flowrate, and both are far away from the nominal operating point 35 kg/hr.

Comparing the estimated plant step response models near the three different operating points, as shown in Figures 3.7, 3.10, and 3.11, we can see that the plant has changed a lot. For example, the steady state gain is approximately 10 kg/hr near the nominal operating point 35 kg/hr, but it becomes 50 kg/hr near the operating point 20 kg/hr, and 90 kg/hr near the operating point 5 kg/hr.

As the plant changes, the initial process model obtained near the nominal operating point and is used to tune the controller becomes more and more inaccurate, and causes the control performance to deteriorate. The model performance monitor flags for a quite long time when the flowrate setpoint is below 20 kg/hr, where the plant steady state gain is at least 5 times that of the initial model obtained at the nominal operating point, and the poor control performance with excessive oscillations occurs. After the flow rate moves back to the region near the nominal operating point, the process model mismatch decreases, and the model performance monitor stops flagging.

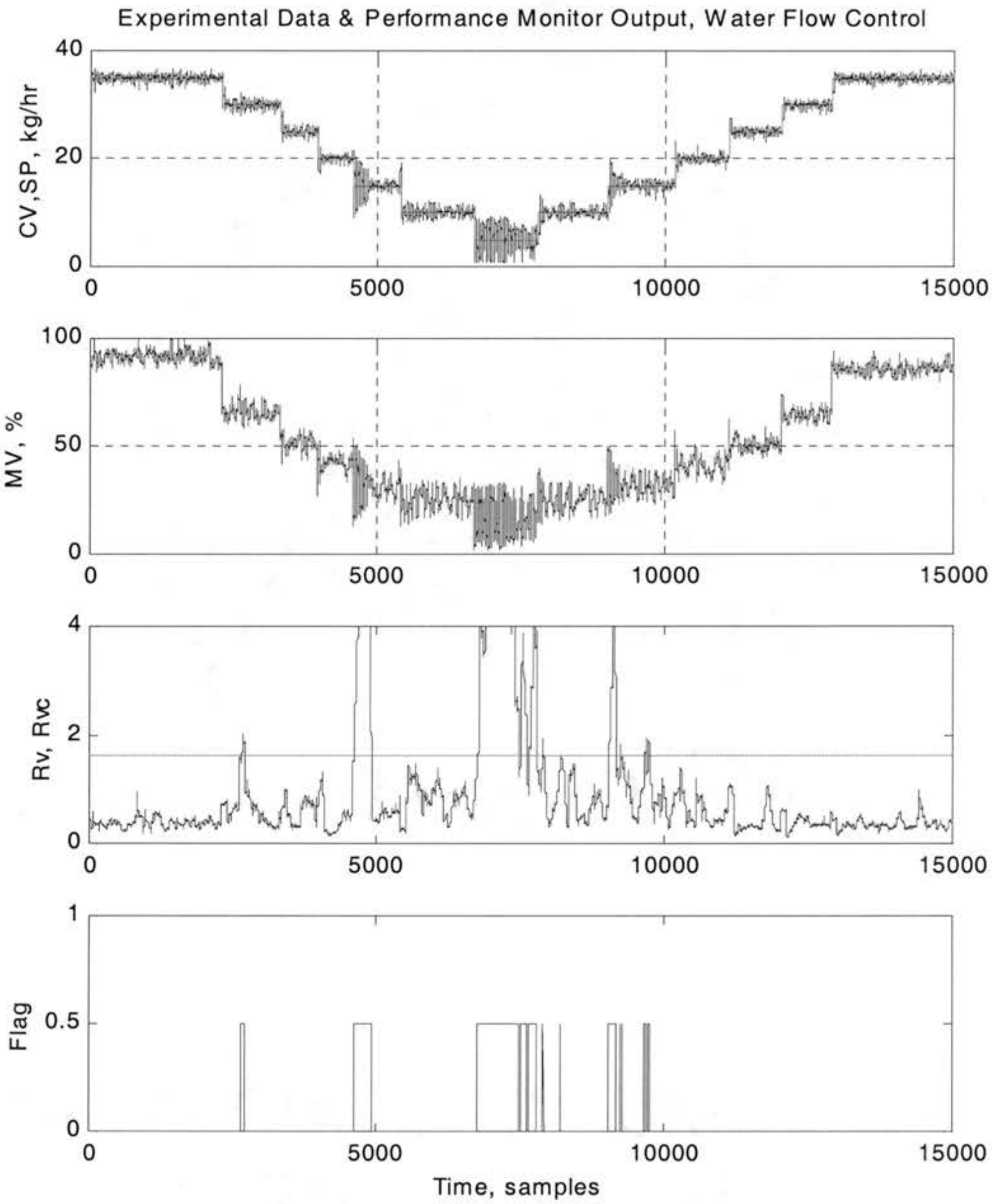

Figure 3.9 Water Flow Control Experimental Data and the Model Performance Monitor Output. R_V is the variance ratio performance index, and Rvc is the critical value for F distribution.

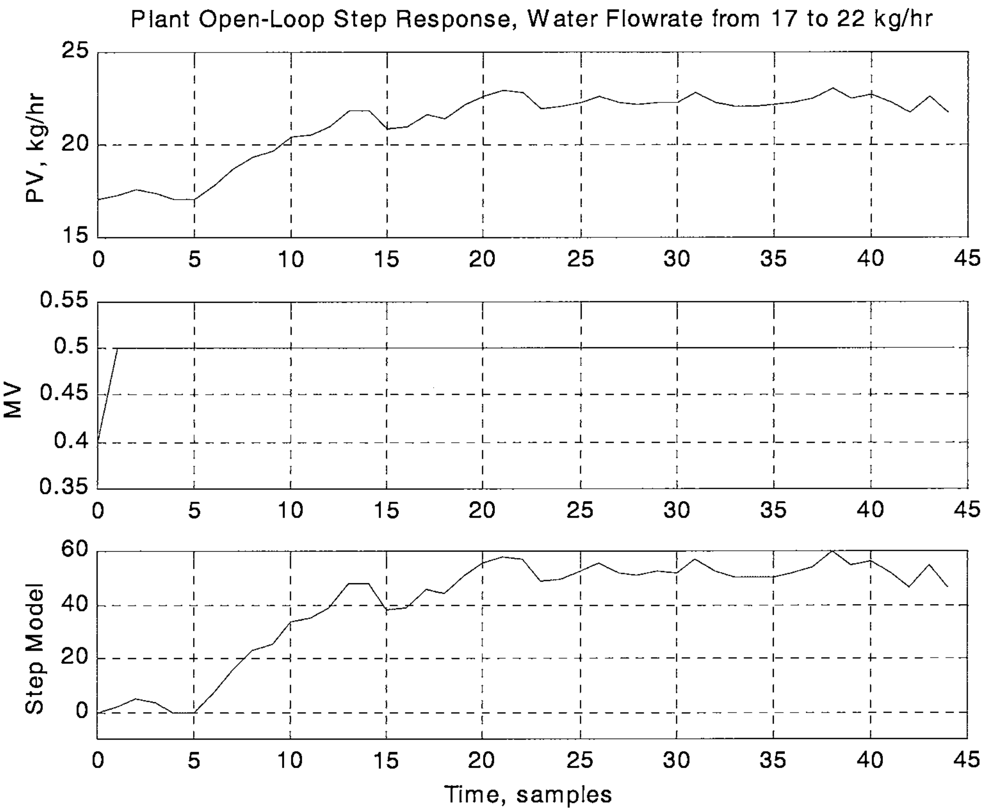

Figure 3.10 Experimental Open-Loop Step Response Data and the Estimated Plant Step Model Parameters for Water Flow Control Loop Near the Operating Point 20 kg/hr. Water flow controller input is changed from 0.4 to 0.5, and the water flowrate is changed from approximately 17 to 22 kg/hr. The steady state gain is about 50 kg/hr. Sampling Period = 0.1 Second.

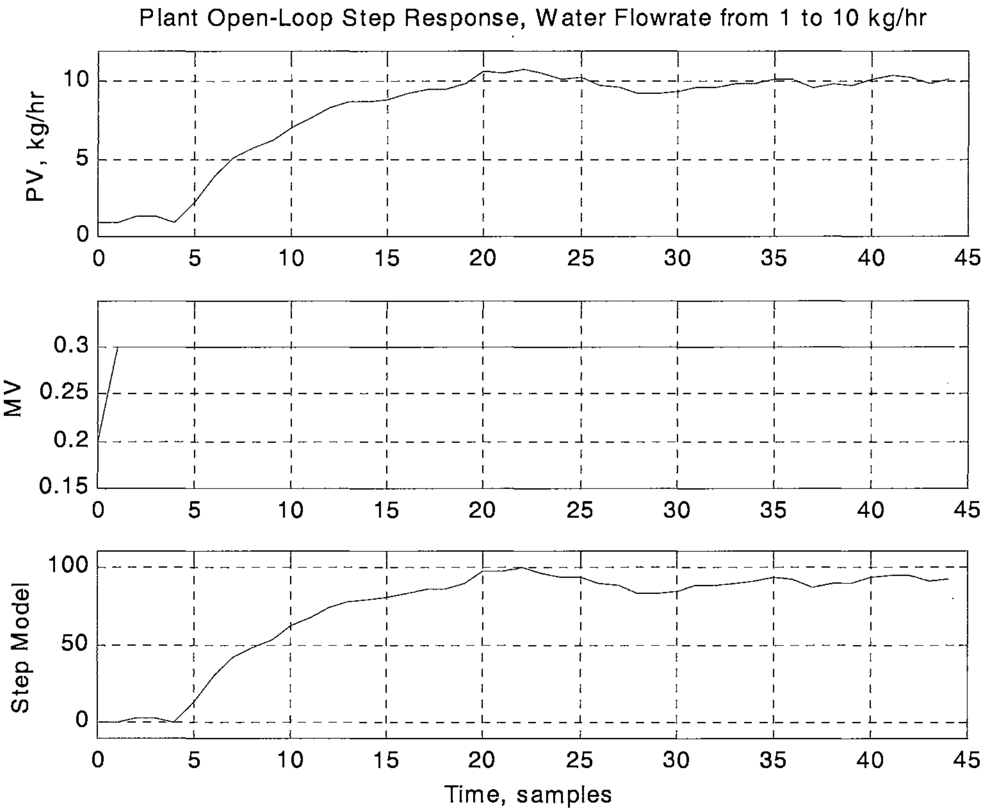

Figure 3.11 Experimental Open-Loop Step Response Data and the Estimated Plant Step Model Parameters for Water Flow Control Loop Near the Operating Point 5 kg/hr. Water flow controller input is changed from 0.2 to 0.3, and the water flowrate is changed from approximately 1 to 10 kg/hr. The steady state gain is about 90 kg/hr. Sampling Period = 0.1 Second.

3.7.1.2 Air Flow Control Experimental Results and Discussion

The nominal operating point of the air flow rate was $F_2 = 0.15\ m^3/hr$. Put the controller in manual mode, make a step change in MV, and obtain the open-loop CV responses. Figure 3.12 shows the open-loop experimental data and the estimated plant open-loop step response model parameters. Put the controller in automatic mode after tuning the controller, through a step change in the setpoint, the closed-loop responses were obtained. Figure 3.13 shows the closed-loop experimental data and the estimated closed-loop step response model parameters. Choose the sample size na = nr = 100 (about twice the closed-loop settling time). Select the F test significance level (one-sided) of $\alpha = 0.01$. The critical value $F_{\alpha,na-1,nr-1}$ is 1.6, or Rvc = 1.6. Run the air flow control experiments at different operating regions, collect CV, SP and MV samples, and feed the data into the performance monitor.

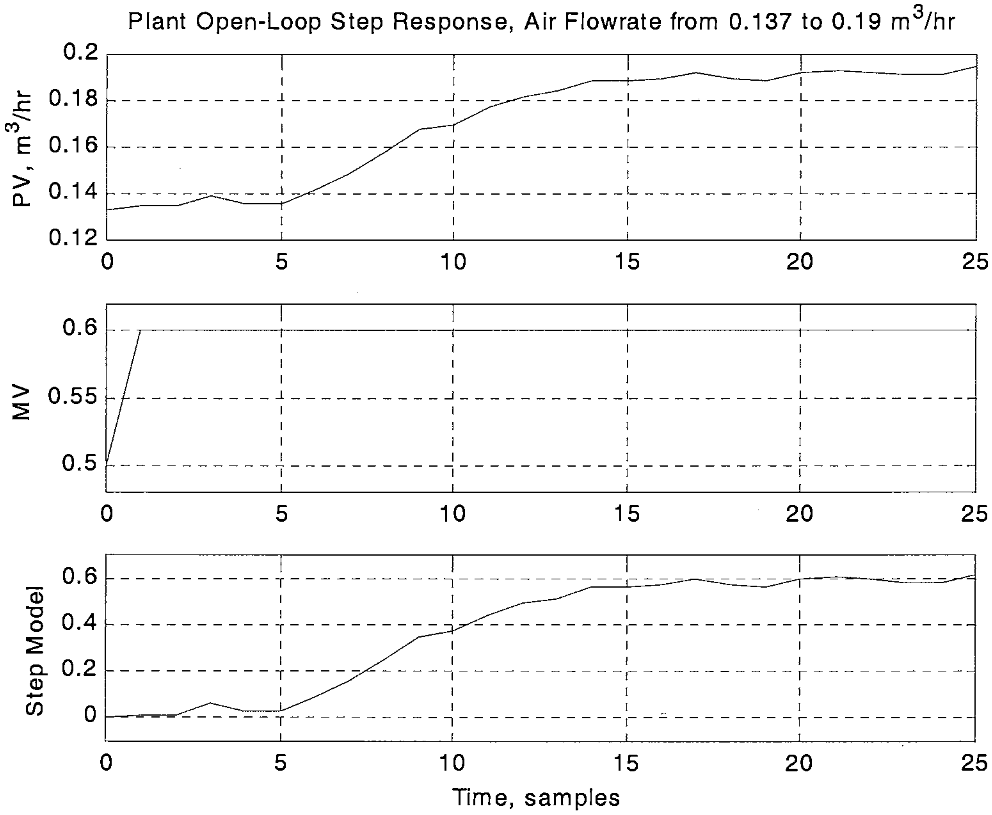

Figure 3.12 Experimental Open-Loop Step Response Data and the Estimated Plant Step Model Parameters for Air Flow Control Loop Near the Nominal Operating Point 0.15 m^3/hr. Air flow controller input is changed from 0.5 to 0.6, and the air flowrate is changed from approximately 0.137 to 0.19 m^3/hr. The steady state gain is about 0.6 m^3/hr. Sampling Period = 0.1 Second.

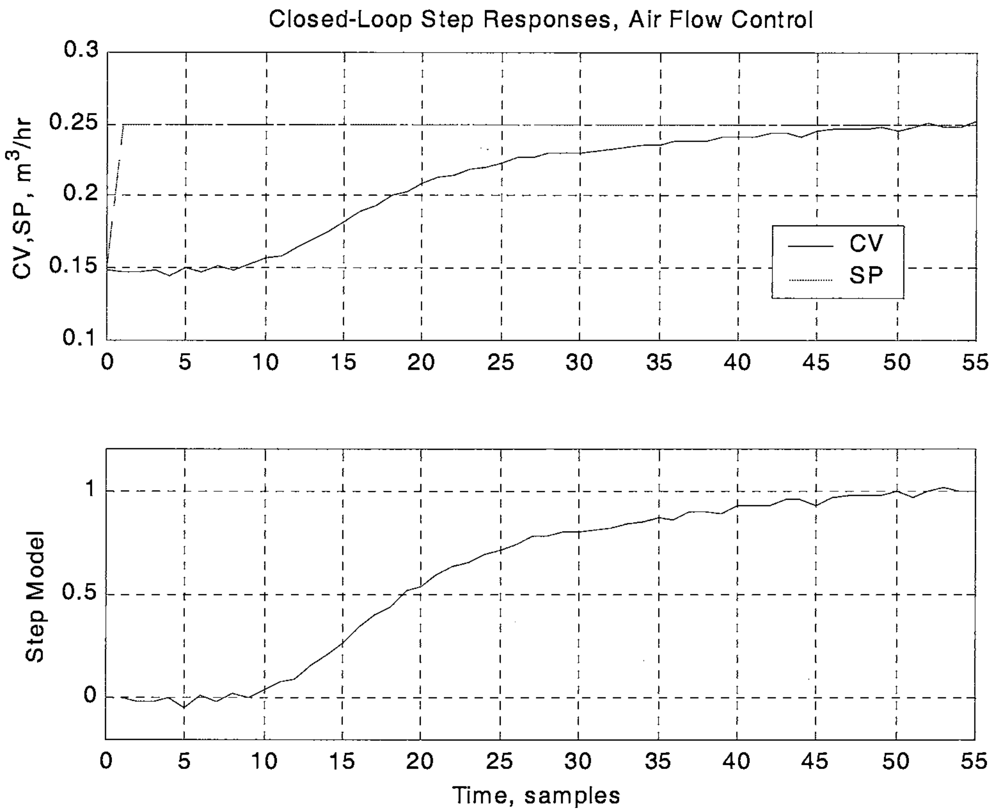

Figure 3.13 Experimental Closed-Loop Step Response Data and the Estimated Step Model Parameters When the Air Flow Controller is Well Tuned. Sampling Period = 0.1 Second.

The air flow control experimental data and the model performance monitor output are shown in Figure 3.14. When the air flow rate is near the nominal operating point 0.15 m^3/hr, where the plant model is obtained and the controller is tuned, the model performance monitor does not flag. When the plant operating point moves away from the nominal point, the plant characteristics change, and the model obtained near the nominal operating point becomes more and more inaccurate. Figure 3.15 shows the open-loop step response experimental data and the estimated open-loop step response model parameters near the operating point with an air flow rate of 0.25 m^3/hr, and Figure 3.16 shows those near the operating point 0.45 m^3/hr. Comparing the estimated plant step response models near the three different operating points, as shown in Figures 3.12, 3.15, and 3.16, we can see that the plant steady state gain has changed from 0.6 m^3/hr near the nominal operating point 0.15 m^3/hr, to 1.1 m^3/hr near the operating point 0.25 m^3/hr, and to 2.5 m^3/hr near the operating point 0.45 m^3/hr.

As the plant steady state gain changes, the process model obtained near the nominal operating point and used to tune the controller becomes outdated, and causes the control performance to deteriorate. The model performance monitor flags when the air flow rate is larger than 0.3 m^3/hr, (where the steady state gain is 1.1 m^3/hr, about twice the model gain 0.6 m^3/hr obtained near the nominal operating point 0.15 m^3/hr), and there are step changes. The more than doubled steady state gains and the step changes near samplings 2900, 3700, 4400, 5300, and 5700 cause the model performance monitor to flag. Also note that the monitor flags when the plant is operating near 0.05 m^3/hr, which is also away from the nominal operating point 0.15 m^3/hr, and has a different plant gain. When the plant is back to its nominal operating point, the model performance monitor stops flagging.

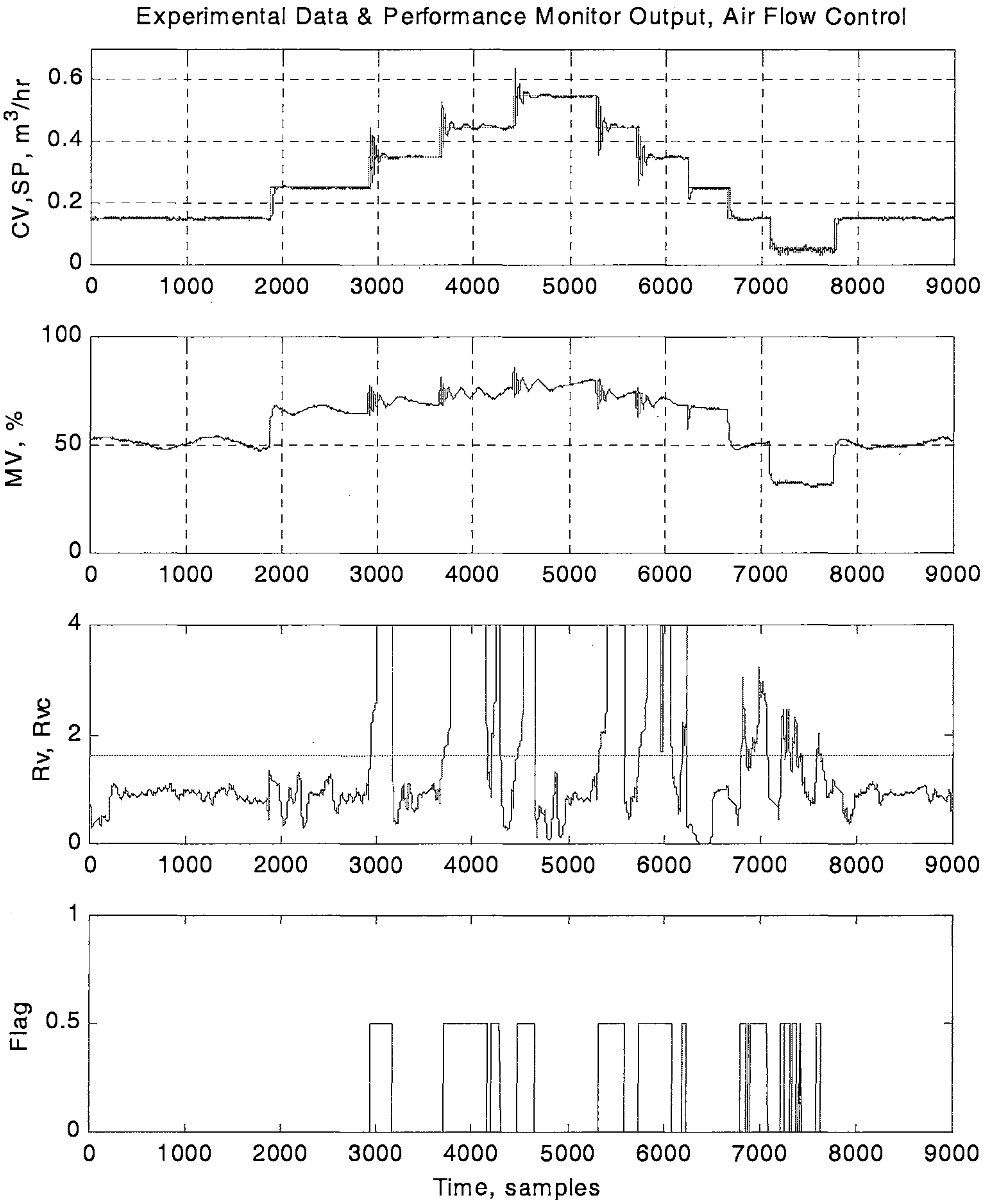

Figure 3.14 Air Flow Control Experimental Data and the Model Performance Monitor Output. R_V is the variance ratio performance index, and Rvc is the critical value for F distribution.

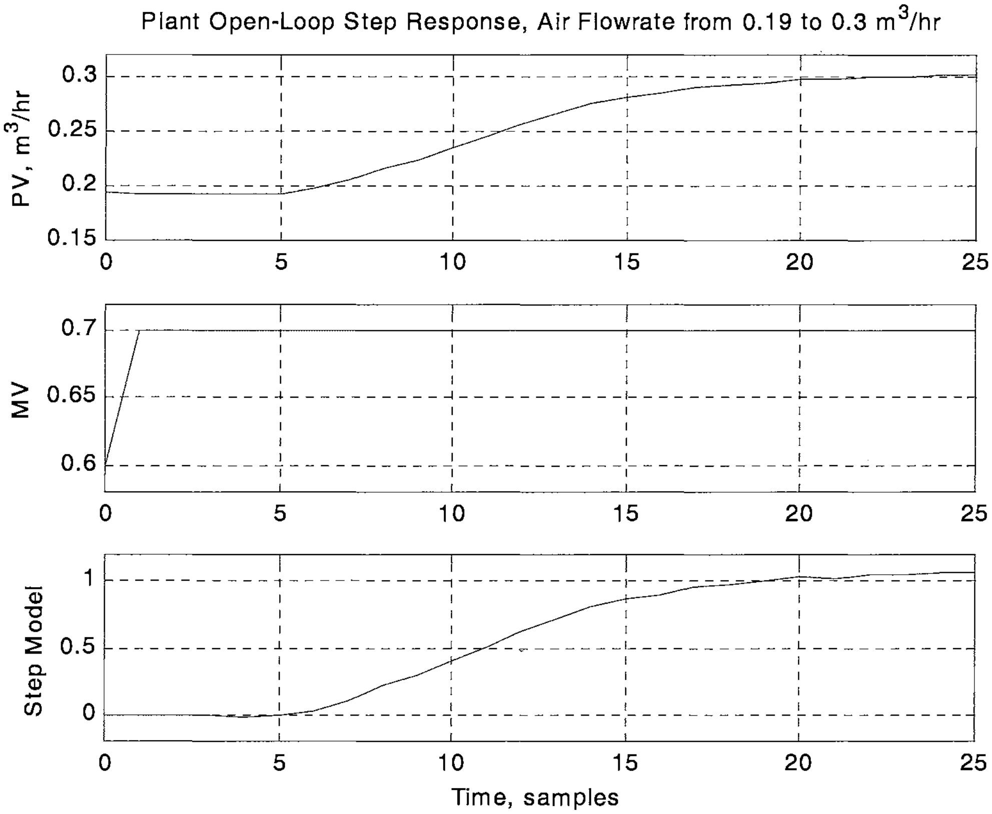

Figure 3.15 Experimental Open-Loop Step Response Data and the Estimated Plant Step Model Parameters for Air Flow Control Loop Near the Operating Point 0.25 m^3/hr. Air flow controller input is changed from 0.6 to 0.7, and the air flowrate is changed from approximately 0.19 to 0.3 m^3/hr. The steady state gain is about 1.1 m^3/hr. Sampling Period = 0.1 Second.

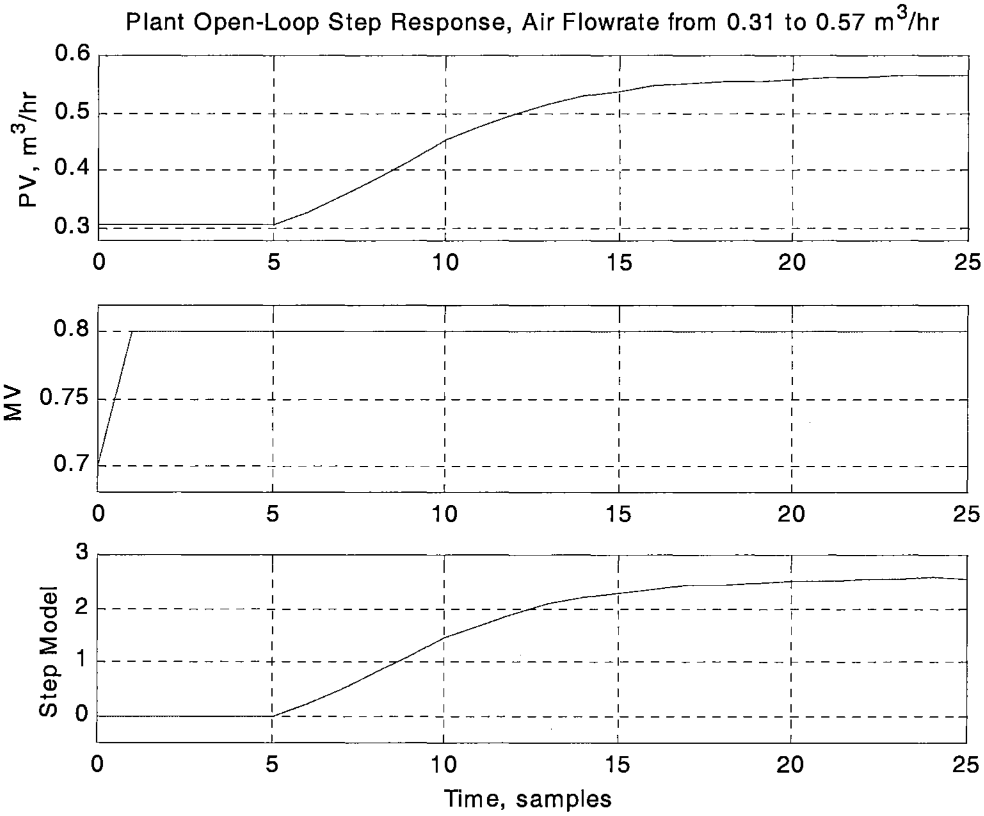

Figure 3.16 Experimental Open-Loop Step Response Data and the Estimated Plant Step Model Parameters for Air Flow Control Loop Near the Operating Point 0.45 m^3/hr. Air flow controller input is changed from 0.7 to 0.8, and the air flowrate is changed from approximately 0.31 to 0.57 m^3/hr. The steady state gain is about 2.5 m^3/hr. Sampling Period = 0.1 Second.

3.7.2 Simulation Evaluation

The control performance monitor is also evaluated with simulations of a model predictive controller (MPC) and a second-order-plus-time-delay (SOPTD) process with inverse response, and is tested for changes in plant characteristics, disturbances, and setpoint.

The descriptions of the MPC controller and the SOPTD plant with inverse response characteristic have been presented in Section 3.6.2.1.

3.7.2.1 Simulation with a Well Tuned MPC Controller with a Good Model

The open-loop plant step response is obtained and is shown in Figure 3.17. Use the well-tuned MPC controller with the good step response model as shown in Figure 3.17 to control the SOPTD process with inverse response, make a step change in setpoint, and obtain the CV response of this well-tuned control system. The closed-loop response to the step setpoint change is shown in Figure 3.18.

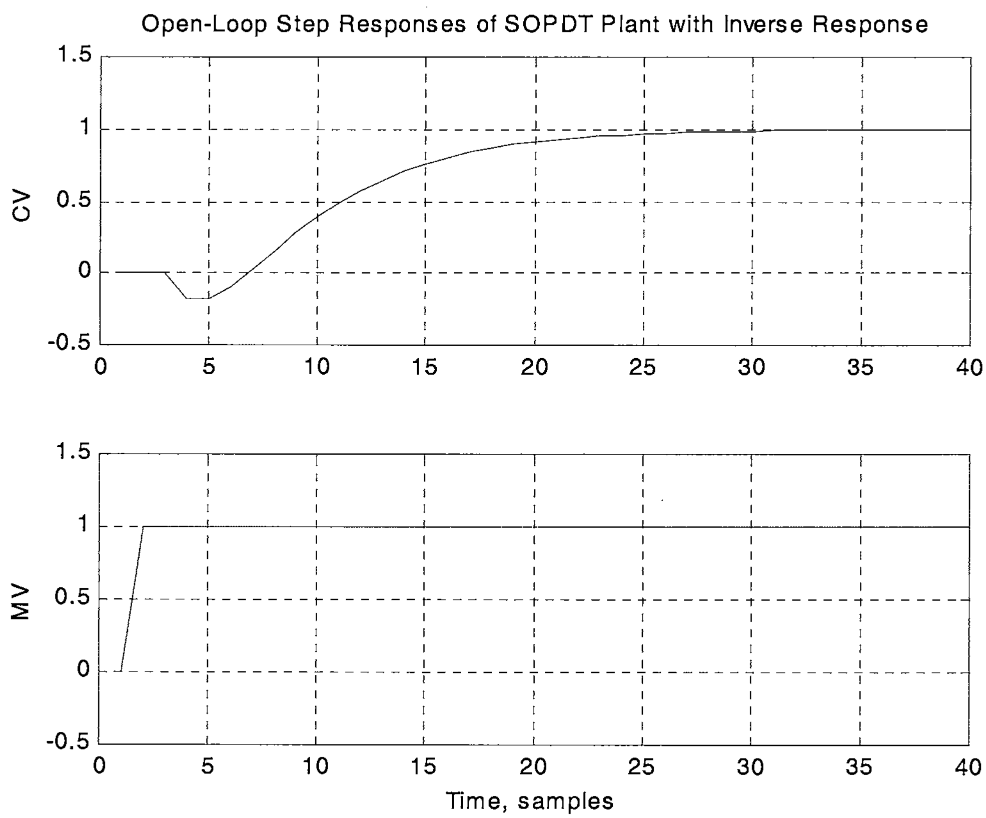

Figure 3.17 Open-Loop Step Response of a SOPDT Plant with Inverse Response

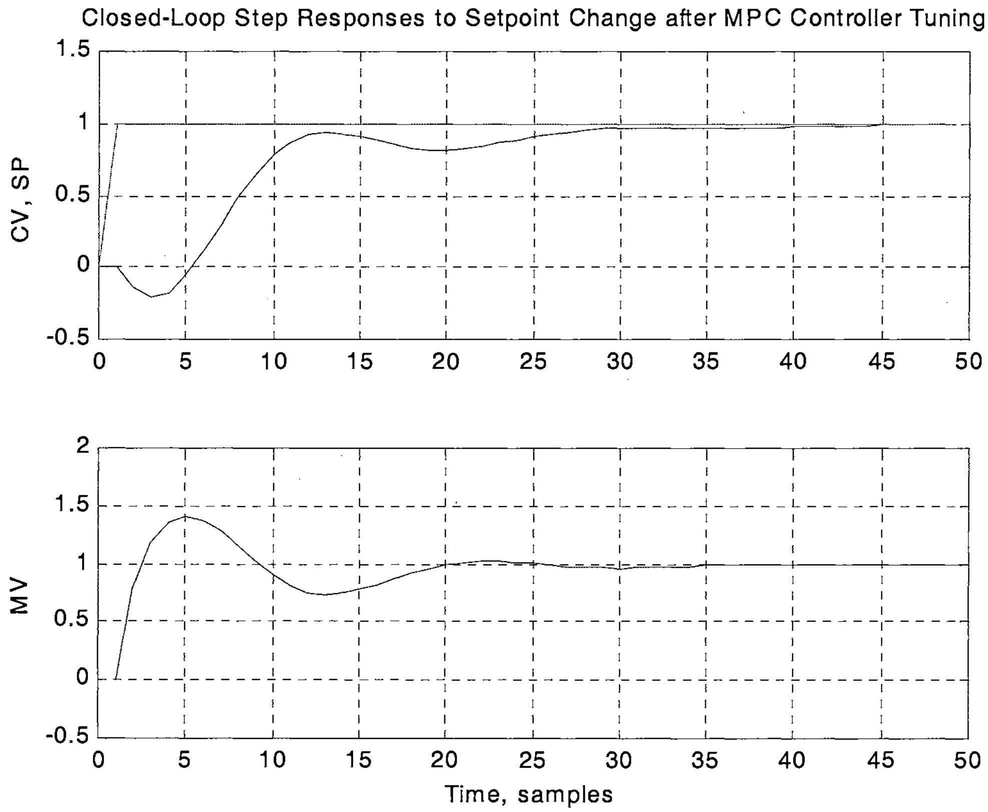

Figure 3.18 Closed-Loop Step Setpoint Response When the Process Model Used by the MPC Controller is Good.

Use the sample size na = nr = 60 (about twice the closed-loop settling time). Choose the significance level α of 0.01 for F-test. $F_{\alpha,na-1,nr-1} = 1.84$. Run simulations using the initial well-tuned MPC controller with good model, and the initial plant as described by the transfer function below,

Plant: $$\frac{y(s)}{u(s)} = -0.3\frac{(s-\frac{1}{3})e^{-2s}}{(s+\frac{1}{2})(s+\frac{1}{5})}$$

The CV, SP, MV and DV data and the output of the model performance monitor are shown in Figure 3.19. Figure 3.19 shows that the model performance monitor does not flag when the MPC controller uses a good process model and is well tuned. Note that step changes in both setpoint and disturbance are introduced into the process during this simulation.

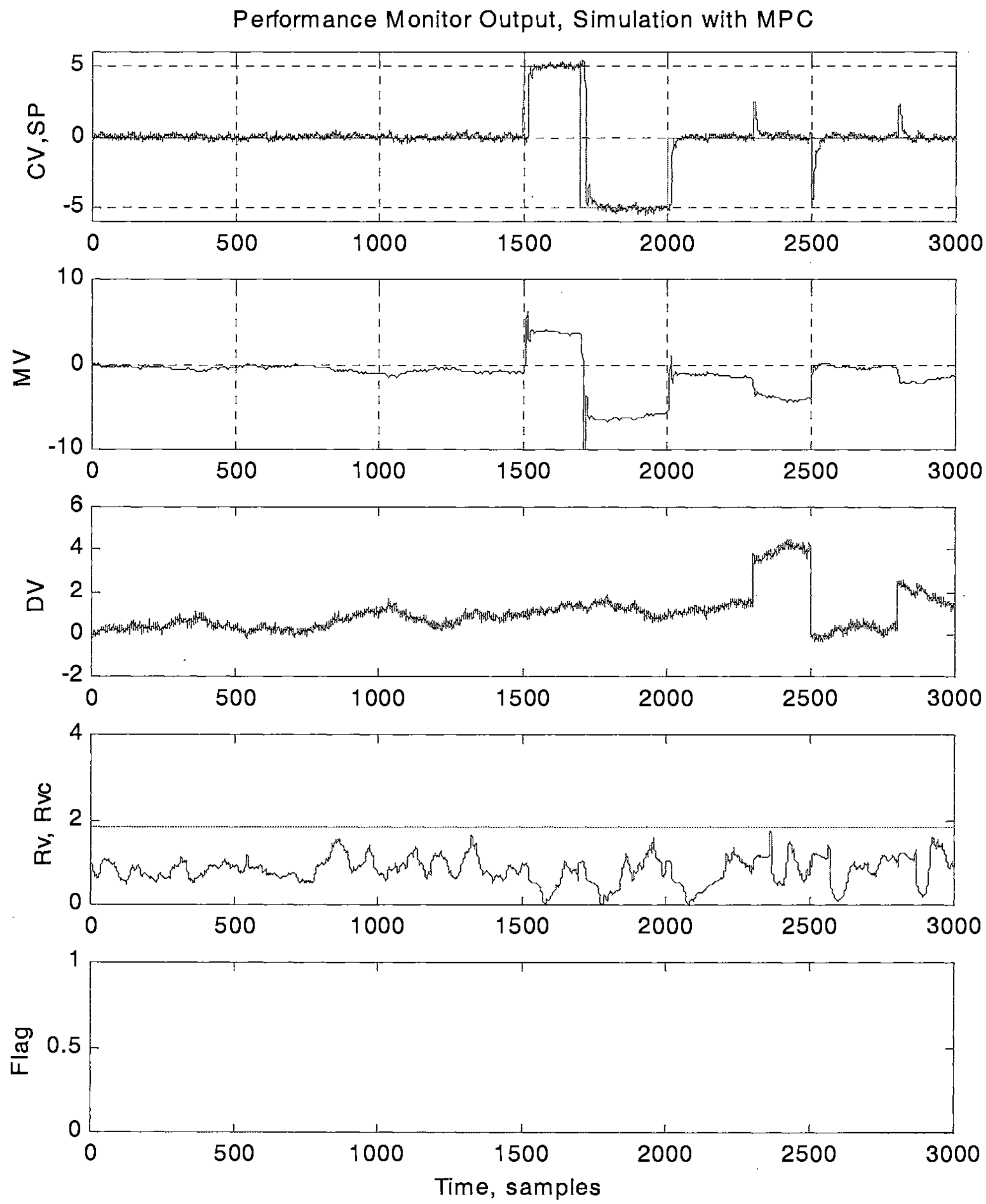

Figure 3.19 Model Performance Monitor Outputs When the Process Model Used by the MPC Controller is Good. The SOPTD with inverse response process is controlled by an MPC controller.

3.7.2.2 Simulation with a Too Aggressive Controller with a Poor Model

When one pole of the plant process is changed from –1/2 to –1/6, the process model in the MPC controller becomes poor, and the controller becomes too aggressive. The new process transfer function is shown below, and its step response is shown in Figure 3.20 along with the initial plant. Figure 3.20 shows that the steady state gain of the changed plant is increased from 1 to 3, and the settling time is almost doubled from 20 to 40.

$$\frac{y(s)}{u(s)} = -0.3\frac{(s-\frac{1}{3})e^{-2s}}{(s+\frac{1}{2})(s+\frac{1}{5})} \rightarrow \frac{y(s)}{u(s)} = -0.3\frac{(s-\frac{1}{3})e^{-2s}}{(s+\frac{1}{6})(s+\frac{1}{5})}$$

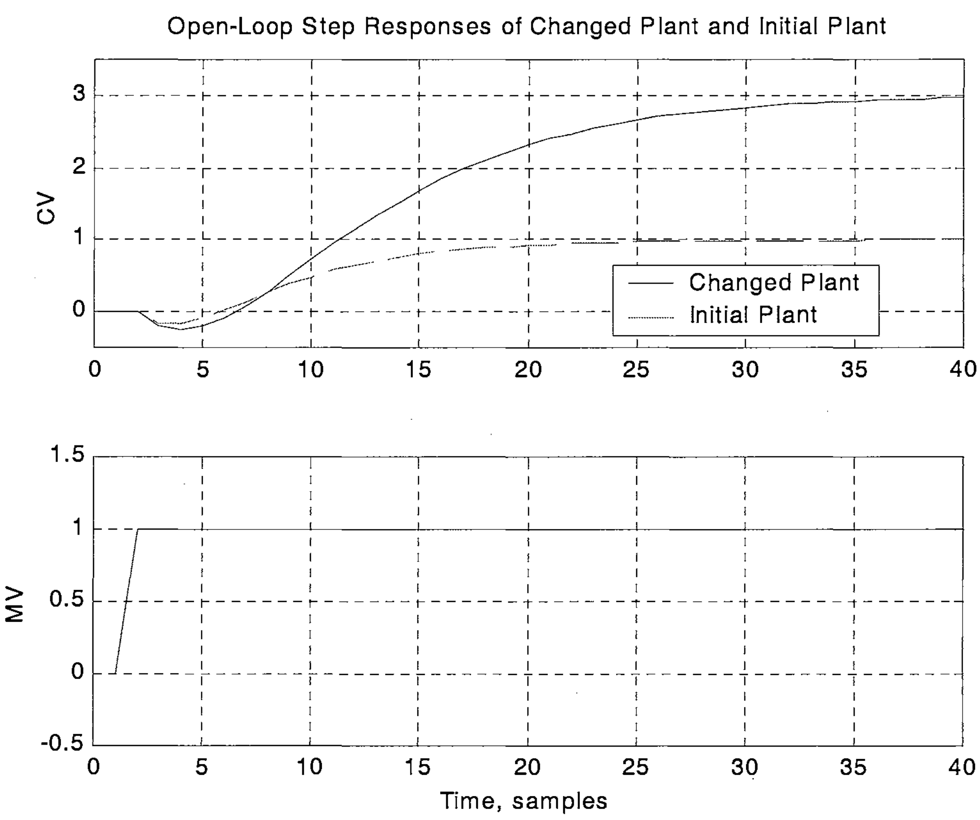

Figure 3.20 Open-Loop Step Responses of the Initial Plant and the Changed Plant, Plant Pole: –1/2 → -1/6 (The plant steady state gain is increased 3 times, from 1 to 3, and the plant time constant also changed)

With the changed plant and the initial MPC controller, re-run the simulation using the same setpoint and disturbance sequences as the initial case in Figure 3.19. The data and output of the model performance monitor are shown in Figure 3.21. We can see that the model performance monitor can detect and flag the poor process model when there are sufficient excitations, such as setpoint changes. When the process is close to steady state, the model performance monitor is not able to detect the poor process model. It is because at steady state, the differences in control performance (indicated by the controlled variable variance) between the current control system and the reference performance system are not large enough to be indicated as significant by the statistical test.

When the model performance monitor flags, it means the process model in the controller is poor, and the control performance can be improved significantly by model adjustment. However, when the model performance monitor does not flag, it does not mean the process model is good. It only means that there is no sufficient evidence to indicate that the process model used by the control is poor. When the plant is operating at steady state, and there are no significant disturbances and no setpoint changes, the model performance monitor will not flag even if the process model in the model-based controller is poor. In other words, non-flagging of the model performance monitor means there is no enough evidence to determine the process model is poor, and it does not mean the process model is good. However, when the model performance monitor does flag, it indicates that the process model is poor.

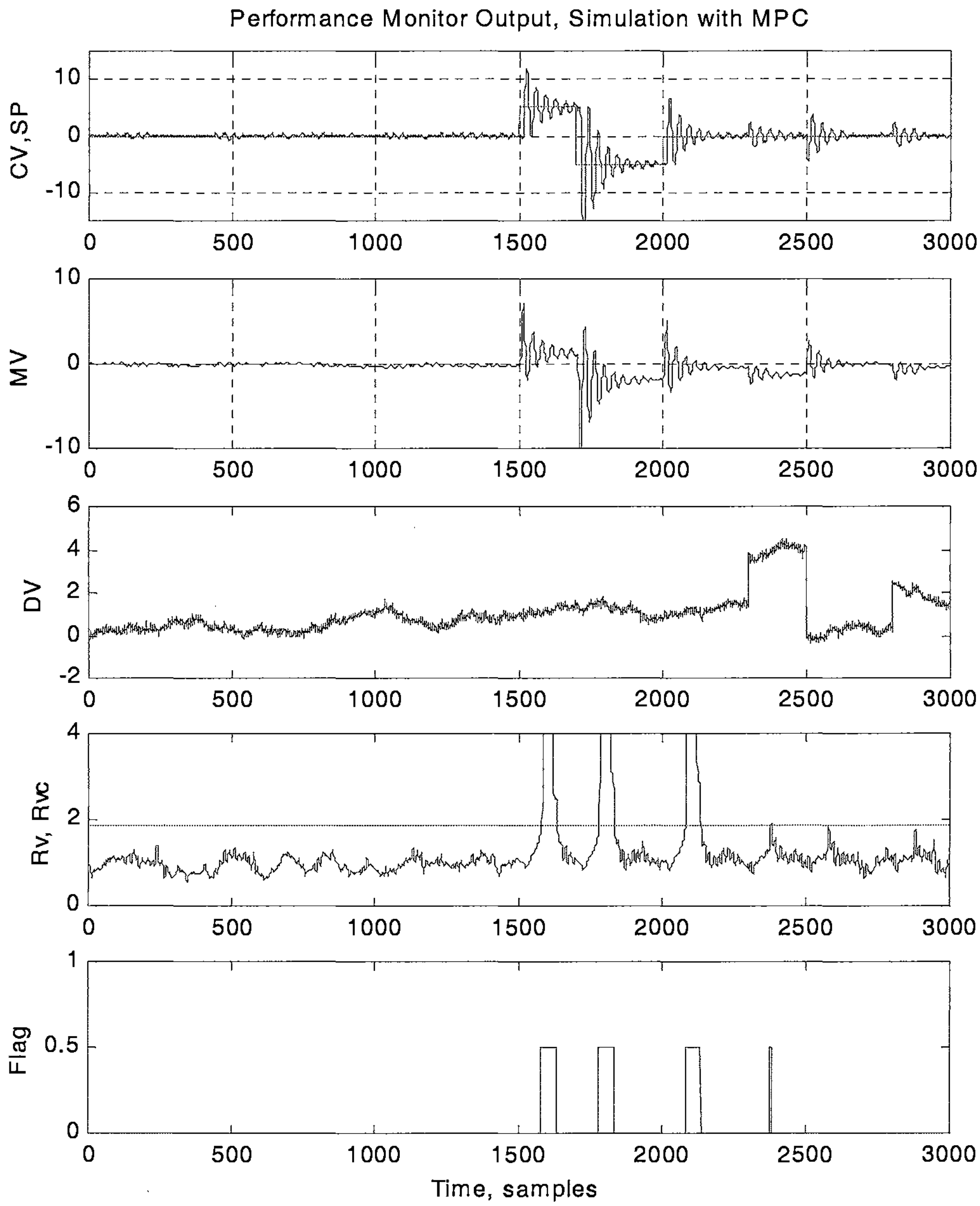

Figure 3.21 Model Performance Monitor Output When the Process Model Used by the MPC Controller Becomes Poor and the Controller Becomes Too Aggressive due to the Plant Change, Plant Pole: -1/2 → -1/6.

3.7.2.3 Simulation with a Too Sluggish MPC Controller with a Poor Model

When the plant delay is changed from 2 to 4, and the plant zero is changed from 1/3 to 1/12, the process model used by the MPC controller becomes poor, and the controller becomes too sluggish. The new plant's transfer is shown below, and its step response is shown in Figure 3.22 along with the initial plant. Figure 3.22 shows that the steady state gain of the changed plant is decreased from 1 to 0.25, and the delay is increased from 2 to 4.

$$\frac{y(s)}{u(s)} = -0.3\frac{(s-\frac{1}{3})e^{-2s}}{(s+\frac{1}{2})(s+\frac{1}{5})} \rightarrow \frac{y(s)}{u(s)} = -0.3\frac{(s-\frac{1}{12})e^{-2s}}{(s+\frac{1}{2})(s+\frac{1}{5})}$$

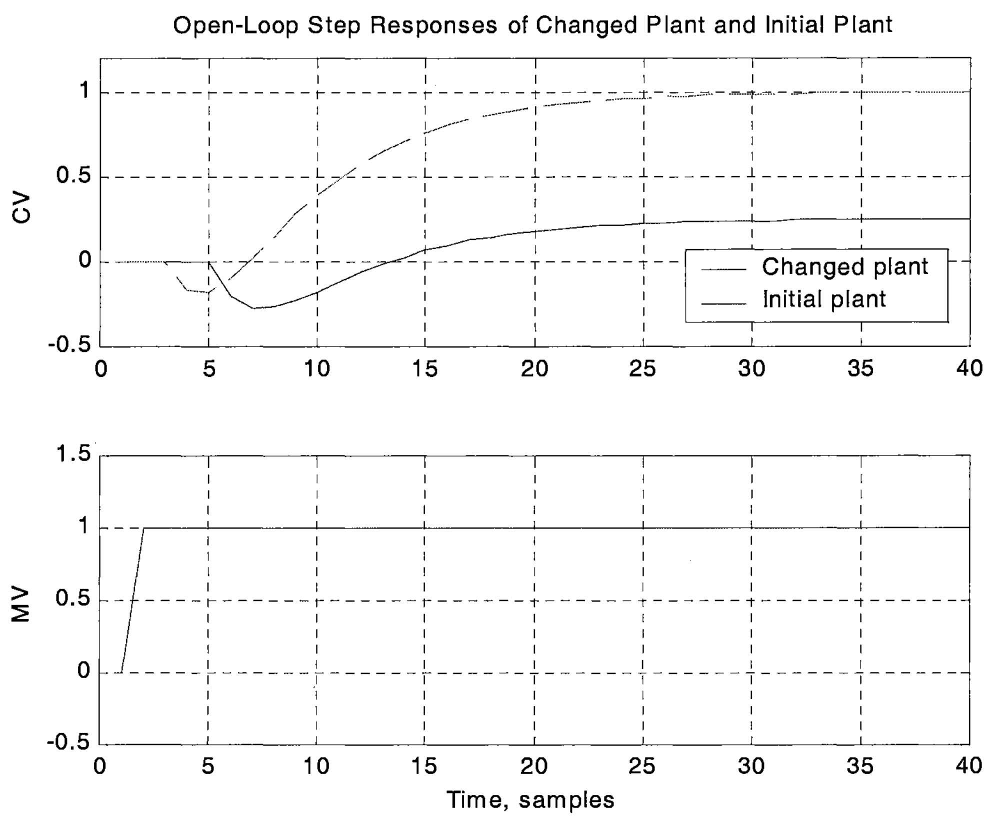

Figure 3.22 Open-Loop Step Responses of the Initial Plant and the Changed Plant, Plant Delay: 2 → 4, Plant Zero: 1/3 → 1/12 (Plant steady state gain is decreased from 1 to 0.25).

After the plant change, re-run the simulation using the same, initial MPC controller. Simulation data and the performance monitor output are shown in Figure 3.23.

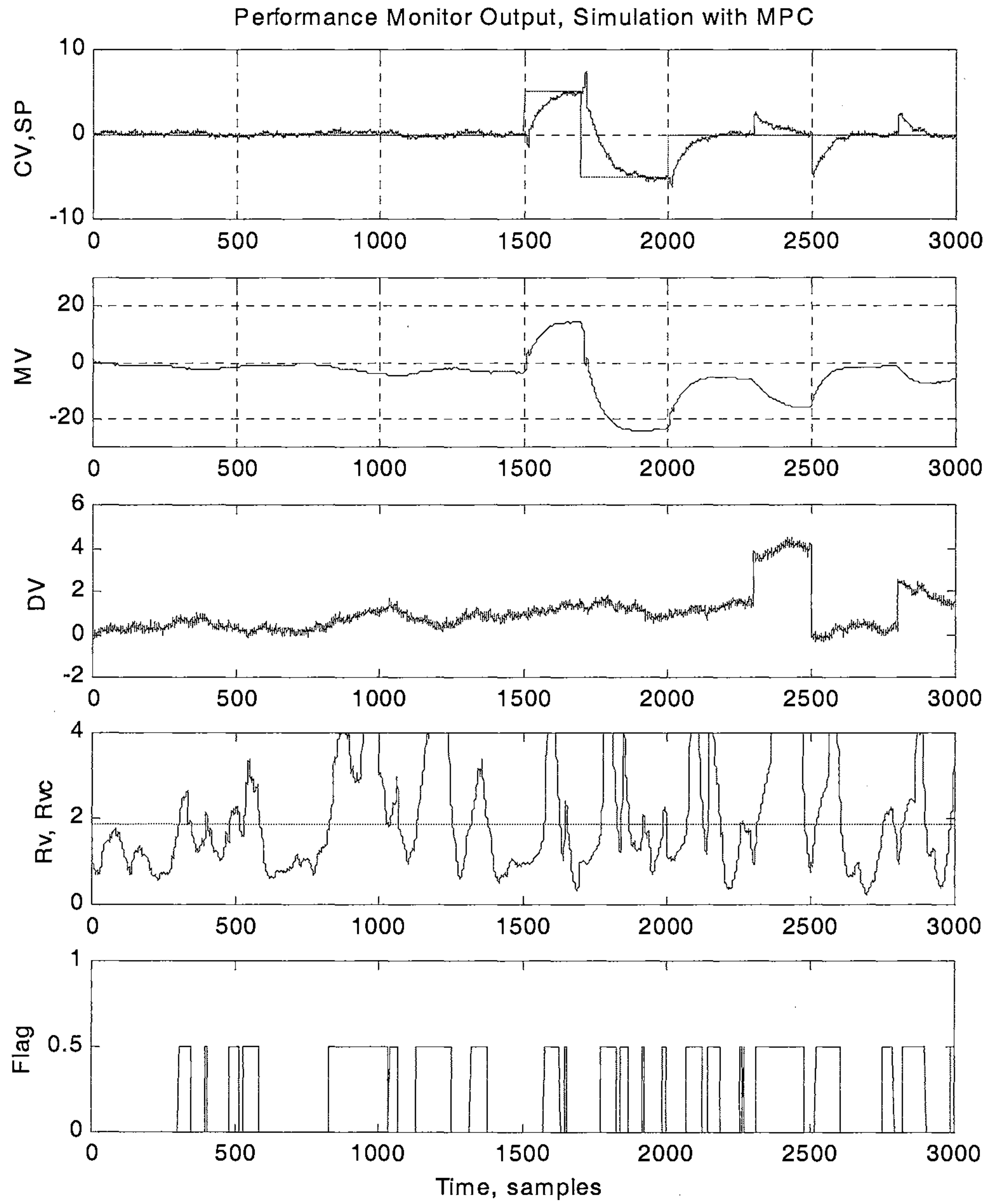

Figure 3.23 Model Performance Monitor Output When the Process Model Used by the MPC Controller Becomes Poor and the Controller Becomes Too Sluggish due to the Plant Changes. The plant delay is increased from 2 to 4, and the plant zero is decreased from 1/3 to 1/12. The steady state gain is reduced from 1 to 0.25.

From Figure 3.23, we can see that the poor process model due to the plant changes makes the MPC controller too sluggish, and the model performance monitor can detect and flag the poor model, even before step changes in setpoint or disturbances are introduced.

3.8 Summary

A model performance monitoring technique is developed to automatically detect a poor process model in a process model-based controller. The process model is judged by its function, i.e., the performance of the model-based controller, not by the accuracy of the model prediction, which is the traditional measure of model goodness. The model performance monitor suggests model adjustment only when a statistical F test indicates that the benefit of model adjustment, i.e., the improvement in performance of the model-based controller, is significant. The model performance monitor uses the initial well-tuned control system as a reference performance system, and uses the control performance of the reference performance system as the benchmark to determine whether the current control performance can be improved by model adjustment. A performance index, R_V, the variance ratio of the controlled variables of the current control system and the reference performance system, is proposed. The initial setup of the model performance monitor requires process upsets. However, after the initial setup, the model performance monitor uses the routine plant operation data only, and no more process upsets are required during model monitoring. The model performance monitor is evaluated using experiments on a water flow control loop and an air flow control loop as well as simulations with a SOPTD process with inverse response and an MPC controller.

The results show that when the process model becomes poor, the model performance monitor flags if there are enough excitations in the process, and does not flag if the process is at steady state. When the process model is good, the model performance monitor never flags.

CHAPTER 4

CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusions

Two process monitoring techniques, a control performance monitor and a model performance monitor, are developed in this work. The conclusions on these two monitors are listed in two separate sections below.

4.1.1 Conclusions on Control Performance Monitor

(1) The proposed control performance monitor provides an automatic tool to help a plant operator or a control engineer monitor the performance of a control loop more efficiently and more objectively. Currently, a plant operator or a control engineer in most plants in process industry monitors control loop performance by watching the process variable measurements and visually judging the performance based on his or her experience or knowledge about the process.

(2) The proposed monitor detects poor control performance automatically and promptly, and therefore helps ensure high product quality, low operation costs, and safe plant operations. In many plants, poor control performance often exists unnoticed for a long time before the operator or engineer has the time and expertise to detect it.

(3) This work introduced a new methodology into the area of control performance monitoring and statistical process control. The proposed method to detect performance changes, that is, comparing the distribution of a performance index, called run length (time period between two consecutive zero crossings), to a reference

distribution, is a novel approach in the area of control performance monitoring, and it has a sound theoretical basis. The theoretical RL distribution function under ideal perfect control condition is derived in this work, and can be used as a theoretical benchmark. The theoretical RL distribution function of a deterministic signal (such as a constant, a sinusoid, or other periodic or non-periodic signal) added by a white noise is also derived.

(4) The proposed control performance monitor can automatically detect and flag the common poor control performances in control loops in process industry, such as oscillations, too aggressive control, too sluggish control, and hitting a constraint.

(5) The proposed control performance monitoring technique is easy to understand, and simple to implement. The relationship between the RL distributions and poor control performances, such as oscillations, too aggressive and too sluggish control, is intuitive to the user. And the user-specified parameters are limited. The user only needs to choose a representative data with good control and the desired closed-loop settling time. All other settings of the monitor are determined automatically. Also no additional measurement devices or plant upsets are needed to implement or run the control performance monitor because it uses routine plant operation data only, which are usually already available in the plants.

(6) The proposed technique offers a model-free approach to monitor control performance. It does not require *a priori* knowledge about the process or the controller, and therefore is applicable even when the plant characteristics change during operation. The minimum variance control-based control performance monitoring technique requires the process delay to be known, or to be estimated, but in many plants, the process delay usually changes during operation and is difficult to estimate accurately.

(7) The control performance monitor flags most of the time during a poor control period although not 100% of the entire poor control period, and any flagging is a strong indication of poor control. When the control performance is good, the control performance monitor never flags.

4.1.2 Conclusions on Model Performance Monitor

(1) The proposed model performance monitor provides an automatic decision tool for a control engineer to timely and objectively decide when a process model used by a process model-based controller needs to be adjusted. Currently, this decision on the need for model adjustment for a model-based controller is based on his or her personal observation and judgment, which may be subjective, and time-delayed.

(2) A unique approach to evaluate a process model used by a model-based controller is proposed. The proposed method judges a process model by its function, that is, the performance of the model-based controller, not by the accuracy of the model prediction, which is the traditional measure of model goodness.

(3) The proposed reference performance system, which is constructed from the closed-loop response of a well-tuned control system, offers a simple, realistic way to determine whether the performance of current control system can be improved by model adjustment, without using complex, upsets-inducing process identification procedures.

(4) The proposed model performance monitor can help reduce operating costs in two ways. The first way is through the early detection of a poor process model used by a model-based controller, since a poor process model will cause poor performance of the model-based controller, and therefore cause high operation costs. The second way is

through avoiding unnecessary model adjustments, which are often very costly and time-consuming to perform in process industry. The model performance monitor suggests model adjustment only when the benefit of the model adjustment is statistically significant, i.e., only when a statistical test indicates that the performance of the model-based controller can be improved significantly by adjusting the process model.

(3) The model performance monitor can detect a poor process model that causes poor performance of a model-based controller, and its suggestion for model adjustment is based on a statistically justified indication that the performance of the model-based controller can be significantly improved by model adjustment.

(4) The initial setup of the model performance monitor requires process upsets, but, after the initial setup, the model performance monitor uses the routine plant operation data only, and therefore does not require process upsets during monitoring.

(5) When the model is poor, the model performance monitor flags when there are sufficient excitations and will not flag when the process is at steady state. When the model is good, the model performance monitor never flags.

4.2 Recommendations

Recommendations for future work on the control performance monitor and the model performance monitor are listed in the following two sections.

4.2.1 Recommendations for Control Performance Monitor

(1) More experimental data from different kinds of control loops, especially those from industrial scale plants, are desired to further test the control performance monitor.

(2) The corresponding control performance monitor for multiple-input-multiple-output control systems should be developed.

(3) The theoretical derivation and proof of the RL distribution under the conditions other than the ideal perfect control case should be sought. The effect of autocorrelation of the error signal on the RL distribution, and the relationship between the RL distribution and the power spectrum are worth investigation.

(4) It is helpful to have a generalized reference RL distribution, which applies to different kinds of control loops, and can be used as a default reference distribution before a representative data with good control is available. A generalized reference RL distribution is possible because during good control periods, the RL distribution is determined by the "randomness" of the error signal, not by the magnitudes or variances of the error signal. While the magnitudes or variances of the error signals for different processes are different, the "randomness" of the error signals from different processes during good control periods should be similar.

(5) The idea of using the minimum variance control condition to derive theoretical reference RL distribution is worth exploring.

4.2.2 Recommendations for Model Performance Monitor

(1) Other disturbance estimation techniques, such as Kalman filters, or closed-loop system identification methods, may be tried because they may provide better disturbance estimation at the cost of more complexities and computations.

(2) To reduce the requirement of process upsets during the initial setup of the model performance monitor, a closed-loop method to determine the reference performance system is needed.

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