# EVALUATION OF PERFORMANCE OF A CONTROL SYSTEM

by

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# CHAPTER I

# INTRODUCTION

Statistical Process Control techniques (SPC) are used to minimize product variation in process plants. The concept of SPC is simple and straightforward. It consists of measuring key process and product qualities, running SPC techniques on them and informing the operator as to when the process is "statistically" out of control. When the process is out of control, the operator takes corrective action. There are also real-time computer systems to analyze *SPC alarms*, issue operator advisories and in some cases, even make closed-loop control changes to the process. This on-line SPC technique is a form of process control. Process control is a method through which actual process performance is measured, compared with the desired performance and action is taken on the difference [7].

Generally, there are three common situations that indicate ineffective control. The first is an extended period of oscillations at the set-point. This can be due to the response of a controller that is too aggressive or due to a large amplitude of noise on the measured variable. If the controller is too aggressive, then simple re-tuning will fix the problem. If past data values have considerable effect on the present, then action such as changing the control system model or increasing the sampling interval is appropriate. The

second situation is an extended period of steady state error. In this case, re-tuning the controller is an appropriate action. The third situation is a persistent succession of disturbances or load changes, which cannot be handled by the existing control strategy. In this case either ratio, feed-forward, cascade, or multi-variable strategies should be considered.

The goal of achieving reliable automated control requires controller performance monitoring and diagnostic techniques. A large number of different methods for designing and implementing control systems exist. However, as described in the next chapter, there are comparatively few techniques that are independent of noise, require small amounts of data storage and are insensitive to similarity between successively measured data. This thesis describes the theory and development of an automated, on-line, monitoring (alarm) system that assesses the performance of control loops. This alarm system is termed a 'watchdog' system in this study. The watchdog system is implemented on the controlled variable. This technique is insensitive to noise amplitude and to the effect of past data on the present. The watchdog system will trigger an alarm when the controller is working sluggishly and/or when the controller is not able to bring the process to its set-point due to a change in the process. The controller can be retuned either manually or by adaptive control techniques. In this thesis, a Fuzzy Logic Controller is used as a means to obtain adaptive control. A computer expert

system described in this study switches between a conventional PID controller and a Fuzzy Logic Controller, to control the process.

# CHAPTER II

# AUTOMATIC MONITORING AND CONTROL TECHNIQUES

## 2.1 Introduction

There have been many studies on automated controller performance monitoring and diagnostic techniques. Due to the many assumptions and compromises made during the design process and the many changes that occur in the process itself, controllers seldom work as desired. Statistically based performance monitoring of a controller is a way of guiding engineers or operators to make corrections in real time. This chapter presents a review of significant research done in this area.

## 2.2 Existing Monitoring Techniques

One of the present methods for assessing the performance of control loops is the F-test type statistic [3]. The F-test type statistic is a ratio of variances as measured on the same set of data by two different methods. The first variance is calculated as the mean-square-deviation from the averaged value of the data set in the most recent data window. The second variance is calculated from the mean of the squared differences of successive data points in the most recent data window. If the process is at steady state then, ideally,

the ratio of the two variances described above will be unity. However, due to random noise, the actual ratio of the variances will not be exactly unity but near unity. However if the process is not at steady state, the ratio will be unusually large. This method has many undesirable features. First, it requires user expertise. Second, a large amount of data must be stored and manipulated at each sampling. Third, the effect of past values on present values of the measured signal will affect the statistic. An alternate method is to perform a linear regression over a data window and then perform a t-test on the regression slope [4]. If the slope is significantly different from zero, the process is almost certainly not at steady state. This is usually an off-line technique. On-line versions require considerable data storage since at each time interval, the whole data window must be updated and linear regression must be performed. For a long data window, there will be considerable computational effort. Moreover user expertise is required to select the window length that would reduce the effect of noise amplitude on the analysis. Hence both methods have considerable drawbacks.

Recently, industry has responded with three techniques to automatically identify the performance of control loops [6]. One technique uses a moving average chart, common to statistical process control. The technique plots a moving average and the upper and lower '$3\sigma$' control limits. When the moving average violates the control limits, an alarm

indicates that a significant event has occurred. However, when the noise level is reduced, the effect of past data values may create a false alarm. Moreover this method is computationally expensive since it requires both updating and averaging a data window. Another method compares the average calculated from a recent set of data to a 'standard' based on an earlier set of data. The t-statistic [7] is used to test whether the average is unchanged or not. In this method the traditional root-mean-square (rms.) technique for calculating process variance produces a biased value when the process model changes and the controller is not able to keep the process at its set-point. Moreover, the storage and processing of all the data is a computational burden. Finally, the third method calculates the process measurement standard deviation over a moving window of recent data history [8]. This method relies on the ability to determine the key unit variables, the process variables' time period, and the standard deviation. Again, the storage of data and computation is a burden.

## 2.3 The Watchdog System

The techniques described in the previous section have major drawbacks of storage and computation of large amounts of data. Moreover some of the techniques are affected by large noise amplitude and require user expertise. The watchdog system is a technique insensitive to noise, and does

not require storage of data [refer Chapter 3, section 3.1]. Hence, the technique reduces the computational burden. The watchdog automatically identifies when the controller model does not match the system model. The watchdog system is explained in detail in Chapter 3.

## 2.4 Control Techniques

If the process changes, the controller may need to be retuned. This can be done by means of manual tuning or by adaptive control. Manual tuning is an artful science, in that it requires skills and creative imagination combined with study and practice on the part of the process supervisor [10]. However, this technique suffers from some drawbacks. First, manual tuning requires a large amount of time to tune a controller optimally. Second, it is driven by human biases. Another way to respond to the alarm is by means of adaptive control. In adaptive tuning software performs continuous tuning of the controller parameters, taking into account process changes, such as equipment's aging.

- Adaptive tuning algorithms use either process identification or heuristic methods to automatically tune controllers. The tuning algorithm, using the process identification method, continuously monitors the process input and output signals, and then builds a mathematical model of the process. After determining the process transfer function, the

tuning parameters are calculated. This technique involves a lot of computation and storage of data to determine the process model and controller parameters. As compared to the process identification method, the heuristic method requires an understanding of the process and setting up of heuristic rules that would determine the controller performance. The process response to startup, set-point changes and load disturbances is monitored [29]. The oscillation frequency, peak percent overshoot, damping ratio, etc., are measured and recorded. Heuristic rules are developed using this data. The heuristic methods include:

- Dead Zone Modification [22], where adaptation to the new process conditions takes place only when the process crosses from one zone to another.
- Pattern Recognition [22], where the tuning parameters of the controller are adjusted when a set point change or a load disturbance occurs. In this case, the process is characterized by its closed loop process response. The error signal between the process set point and the process output is always monitored and compared with a noise band that accounts for the noise present in the process output.
- Adaptive Law Modification, where the adaptation comes into operation only when the norm of the estimated controller parameters exceeds a certain value.

- Fuzzy Logic, where a set of conditions are implemented in a computer program, based on the knowledge of the process.

The issues for design of adaptive automatic systems have been examined from the standpoint of realizing the algorithms on microprocessors [12]. Fuzzy Logic Control is easy to implement on a microprocessor. It consists of a set of 'if then' statements and makes decisions based on the present process values, without the need of previous process conditions. This reduces the amount of stored data required and also reduces computational work. Most of the adaptive controllers are always in operation and take action even for sporadic noise spikes. This places an unnecessary load on the controllers. In the following study of adaptive control by Fuzzy Logic, adaptive control action is taken only when the watchdog system triggers an alarm. This reduces tampering with the controller and decreases much of the computational load. Fuzzy Logic Theory and the Fuzzy Logic Controller are explained in Chapter 5 and Chapter 6, respectively.

# CHAPTER III

# AUTOMATED ON-LINE MONITORING SYSTEM

A watchdog system, as described before, is developed in this chapter. This alarm system, which is insensitive to the past amplitude of process noise and also to changes in noise amplitude, indicates when controller re-tuning, a new control strategy or process changes are justified. This chapter explains the theory behind the development of this technique and also lists the steps to be followed to implement this method as an on-line monitoring technique.

## 3.1 Watchdog System

### 3.1.1 Basic Theory

A watchdog system is a statistical technique based on an analysis of variance concept. Many signals that occur in processes are noisy. Noise sometimes causes the process to vary from its set point. In Figure 3.1, there are two types of deviations.

$d_{1,i}$ = deviation of the process variable from its set point.

$d_{2,i}$ = deviation between successive process measurements.

When the process is at its set point and is subjected to normally distributed noise with zero mean and unit variance, the process variance can be estimated as

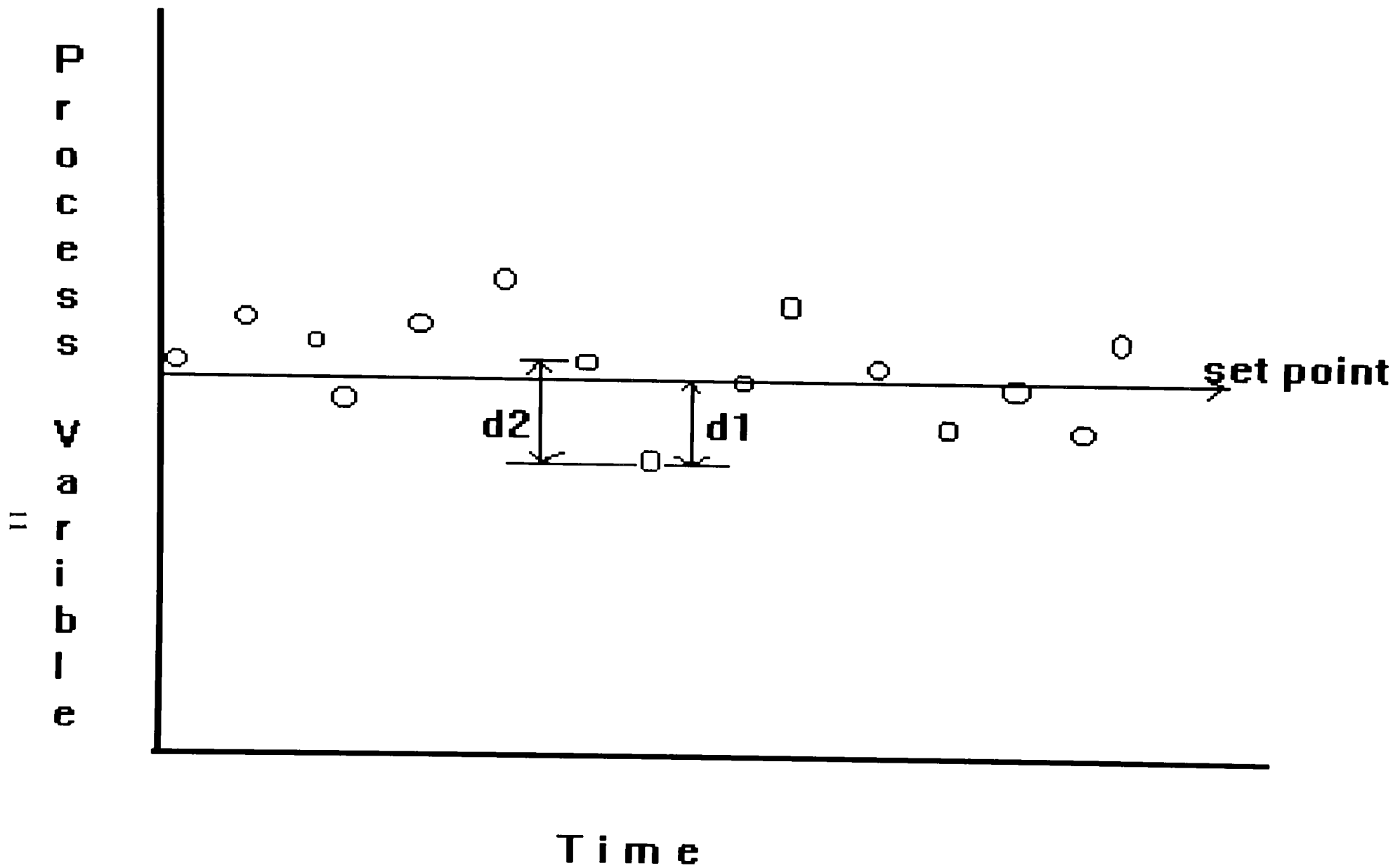


Figure 3.1 Deviations from set-point

$$S_1^2 = \frac{1}{N-1}\sum_{i=1}^{N}(d_{1,i})^2 \qquad \text{----------} \qquad (3.1)$$

If N is very large, the process variance can also be estimated by

$$S_2^2 = \frac{1}{2}\frac{1}{N-1}\sum_{i=1}^{N}(d_{2,i})^2 \qquad \text{----------} \qquad (3.2)$$

If the process is at its set point, and only subjected to noise then the expected values of $S_1^2$ and $S_2^2$ are identical, and the ratio

$$r = \frac{S_1^2}{S_2^2} \qquad \text{----------} \qquad (3.3)$$

will be nearly unity, regardless of the noise amplitude [9]. Alternately, if the process is not at its set point, then $d_{1,i}$ will be large with respect to $d_{2,i}$ and ratio 'r' will be larger than unity. Basically, a test of whether or not the controlled variable is at its set point is a test of whether 'r' is near to, or larger than unity.

Equations (3.1) and (3.2) require storing, updating and manipulating the past N data. To reduce the computational burden, a straight forward averaging of $d_1^2$ and $d_2^2$ can be replaced by a first-order filtering operation [9], which is basically an Exponentially Weighted Moving Average (EWMA).

$$S_{1f,i}^2 = \lambda\left(d_{1,i}\right)^2 + (1-\lambda)S_{1f,i-1}^2 \qquad \text{----------} \qquad (3.4)$$

$$S_{2f,i}^2 = 0.5\lambda\left(d_{2,i}\right)^2 + (1-\lambda)S_{2f,i-1}^2 \qquad \text{----------} \qquad (3.5)$$

where

$S_{1f,i}^2$ = variance due to deviation of process from its set-point

$S_{2f,i}^2$ = variance due to difference in successive data

$\lambda$ = filter factor (or weighting factor) ; $0 < \lambda \leq 1$.

The past deviation of data from its set-point has an effect on the present value of the variance. As can be seen from equations (3.4) and (3.5) the weight of past values of deviation could be represented by a filter factor $\lambda$ as shown

$$S_{f,i}^2 = \lambda d_i^2 + (1-\lambda)S_{f,i-1}^2 = \lambda d_i^2 + (1-\lambda)\lambda d_{i-1}^2 + (1-\lambda)^2 S_{f,i-2}^2$$

$$= \lambda\left[d_i^2 + (1-\lambda)d_{i-1}^2 + (1-\lambda)^2 d_{i-2}^2 + (1-\lambda)^2 d_{i-3}^2 + \ldots\right]$$

$$= \lambda \sum_{k=1}^{i} (1-\lambda)^k d_{i-k}^2$$

In all processes, the influence of past data values on the present data remains for a long time. This influence could possibly be minimized by using a correct value of $\lambda$.

From Equations (3.4) and (3.5), 'r' is calculated as

$$r_i = \frac{S_{1f,i}^2}{S_{2f,i}^2} \qquad \text{----------} \qquad (3.6)$$

The filtered variance estimates ($S_1$ and $S_2$) are updated at each sampling by the latest noise-influenced values of $d_1$ and $d_2$ (Equations (3.4)

and (3.5)). Consequently, even when process conditions do not change, the filtered variance estimates vary somewhat from sample to sample. Therefore, 'r' will have a distribution of values about unity, even if the process is at its set point.

The three possible process behaviors which affect the value of 'r' can be summarized as follows:

1. If the process data is at steady state (process mean is constant, additive noise is independent and identically distributed), then 'r' will be near 1.
2. If the process data mean shifts, or if the process is affected by white noise, then 'r' will be greater than 1. When there is a shift in the mean, both calculations of variance will be influenced temporarily. The first variance $S_1^2$ (Equation (4)) will increase more and persist longer. So 'r' will be greater than 1 for a long period of time, and that is the way that the change in process can be identified.
3. If sequentially sampled process data alternate between high and low extremes, then 'r' will be less than 1. This is very uncommon due to the persistence of past data in practical processes.

Critical values for 'r' can be calculated from the Probability Distribution Function (PDF) of 'r'. The variable 'r' exceeding some threshold value indicates, within a certain confidence level, that the process is not at

steady state. In practice, when there is no noise in the process, the value of $S^2_{2f,i}$ will go to zero. In order to prevent the possibility of a divide by zero situation, it is preferable to compare $S^2_{2f,i}$ * $R_{crit}$ ($R_{crit}$ is threshold value of 'r') to $S^2_{1f,i}$ instead of the relationship in Equation (3.6).

## 3.2 Development of Watchdog System

### 3.2.1 Selection of λ value

The weighting factor λ as mentioned in the previous section determines the influence of the past variance of the process on the present variance. The probability distribution of 'r', for λ = 0.01, as shown in Figure 3.2 was generated from a steady-state process with a normal, independently distributed noise with zero mean and unity standard deviation.

However, the persistence of "noise" signals due to process and controller auto-correlation shifts the distribution towards higher values of 'r'. For processes, which are at the set point, with little effect between past and present data maintain the distribution of 'r' around 1. The value of λ (Equation (4) &(5)) has a great effect on the distribution of 'r'. The probability distribution function of 'r', for λ = 0.1, 0.05 and 0.01 for normally distributed noise with unit variance, on a process simulated using a tenth order differential equation, is shown in Figures 3.3, 3.4 and 3.5. As can be seen

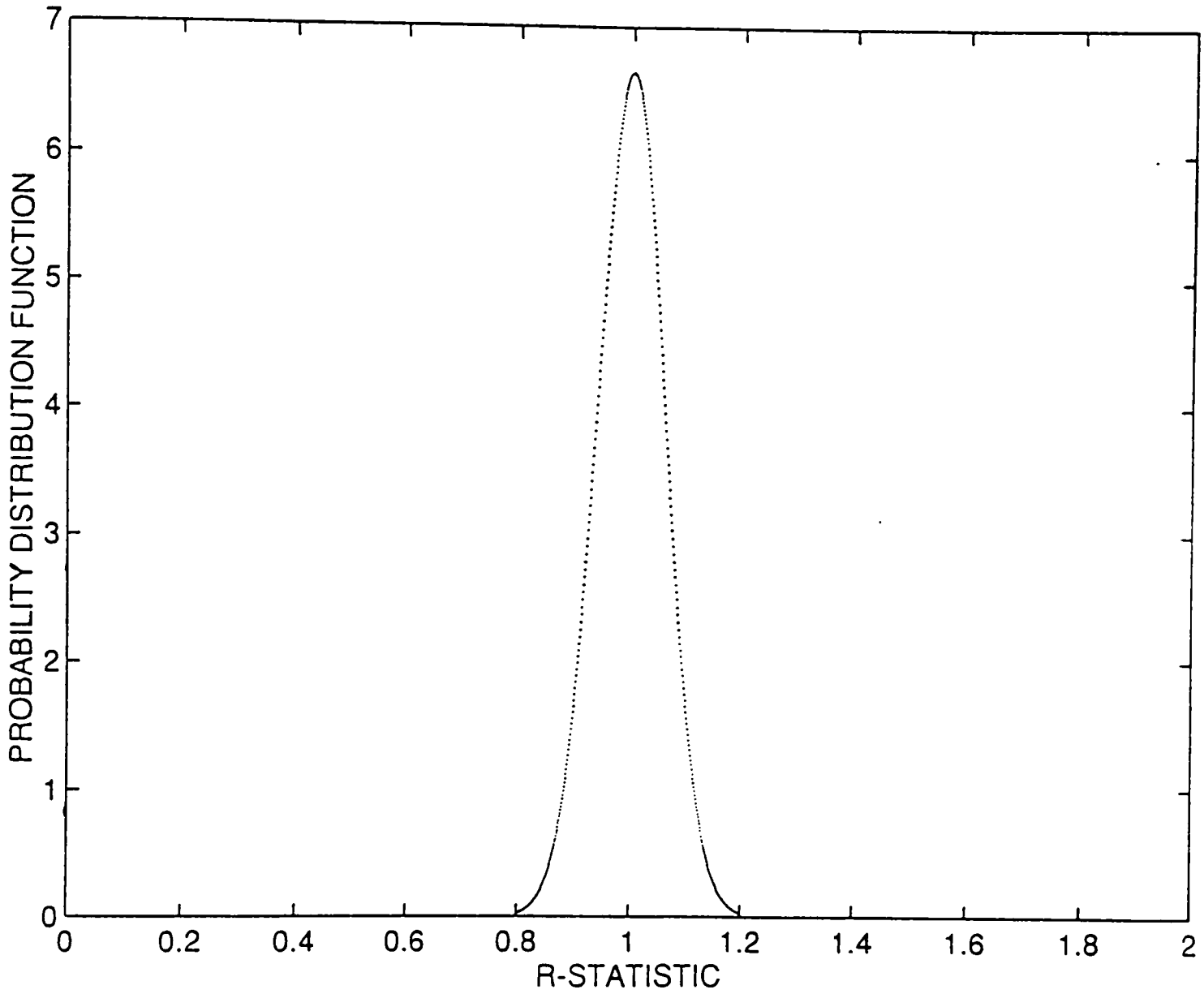


Figure 3.2 Probability Distribution Function

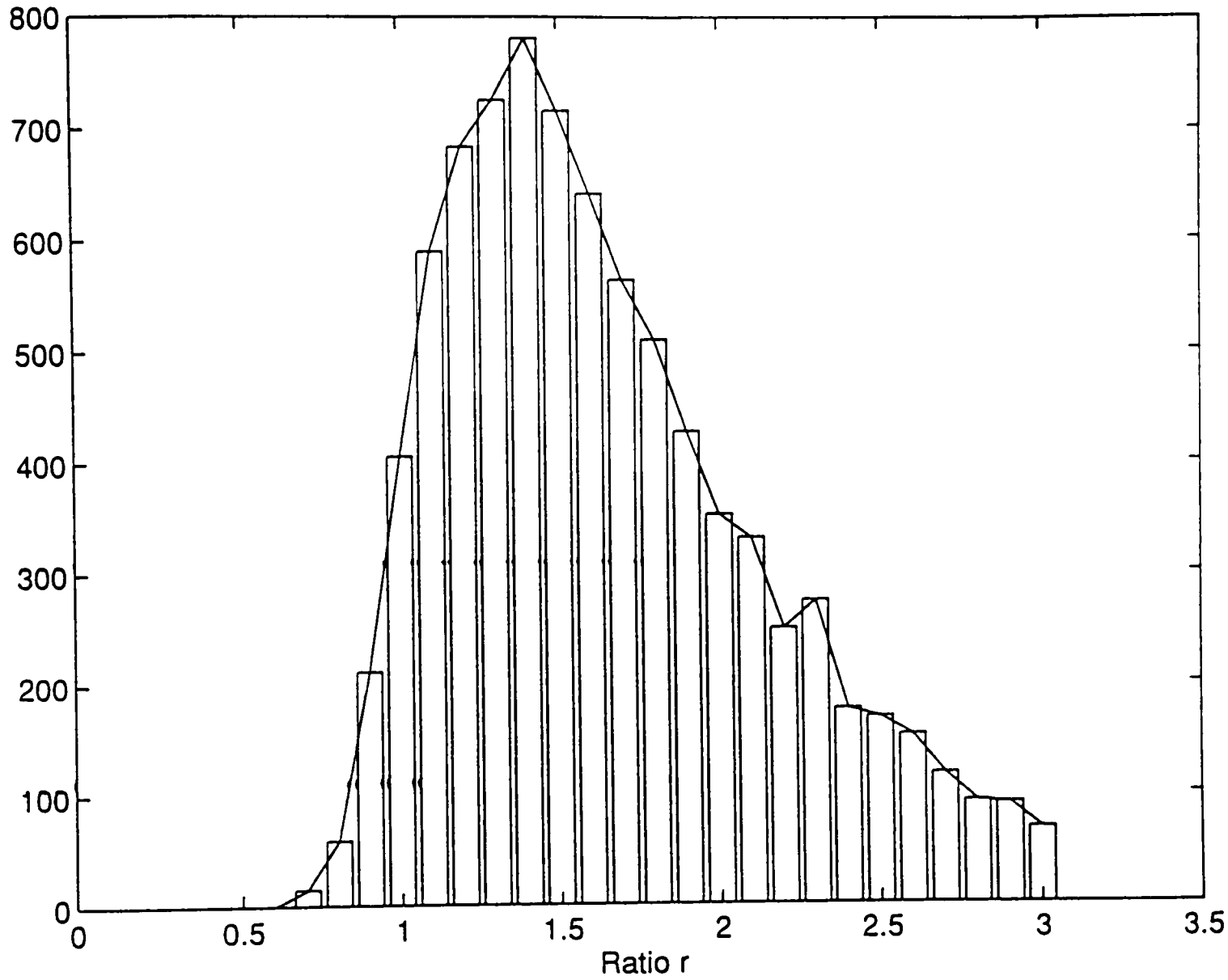


Figure 3.3 Probability Distribution Function for $\lambda = 0.1$

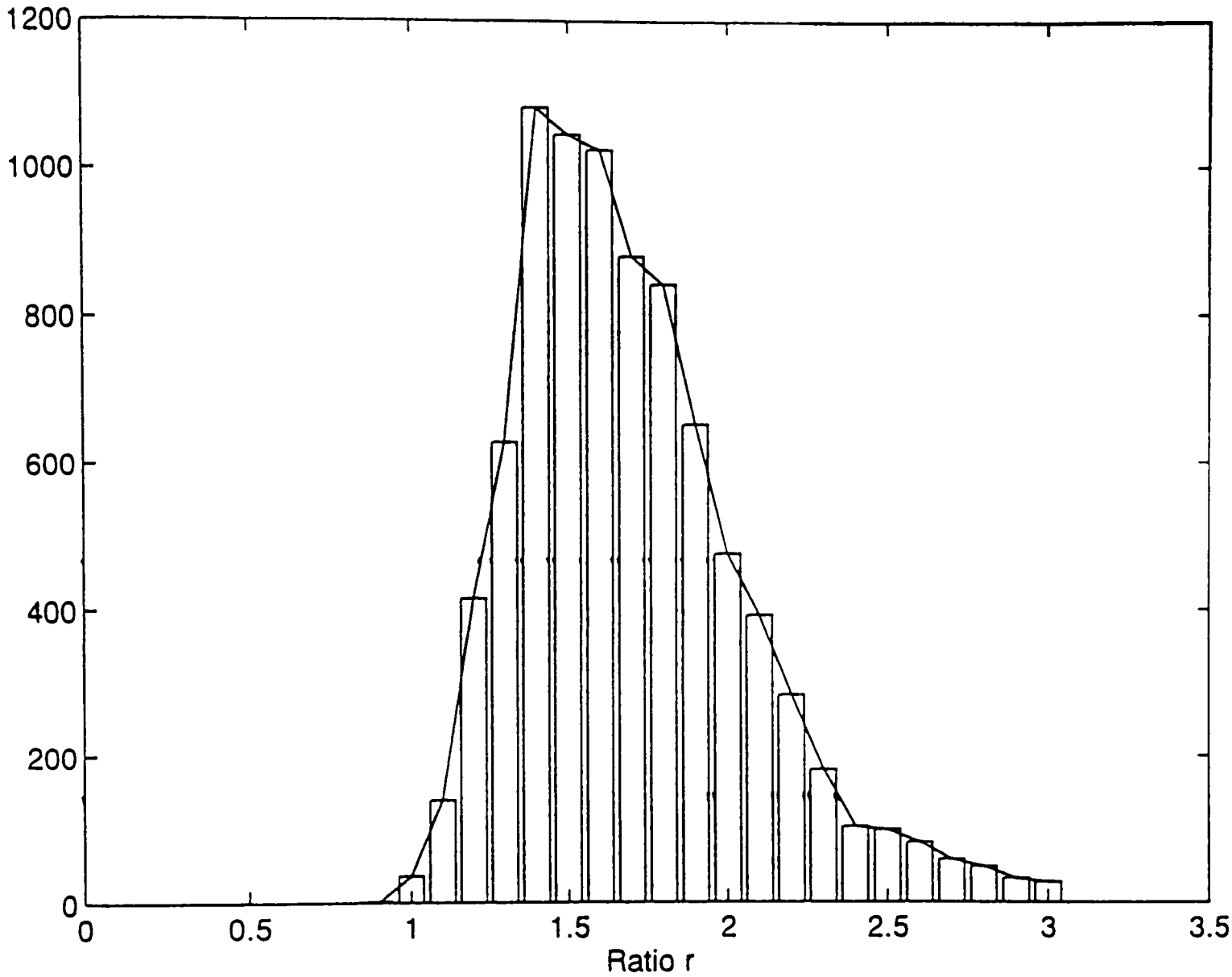


Figure 3.4 Probability Distribution Function for $\lambda = 0.05$

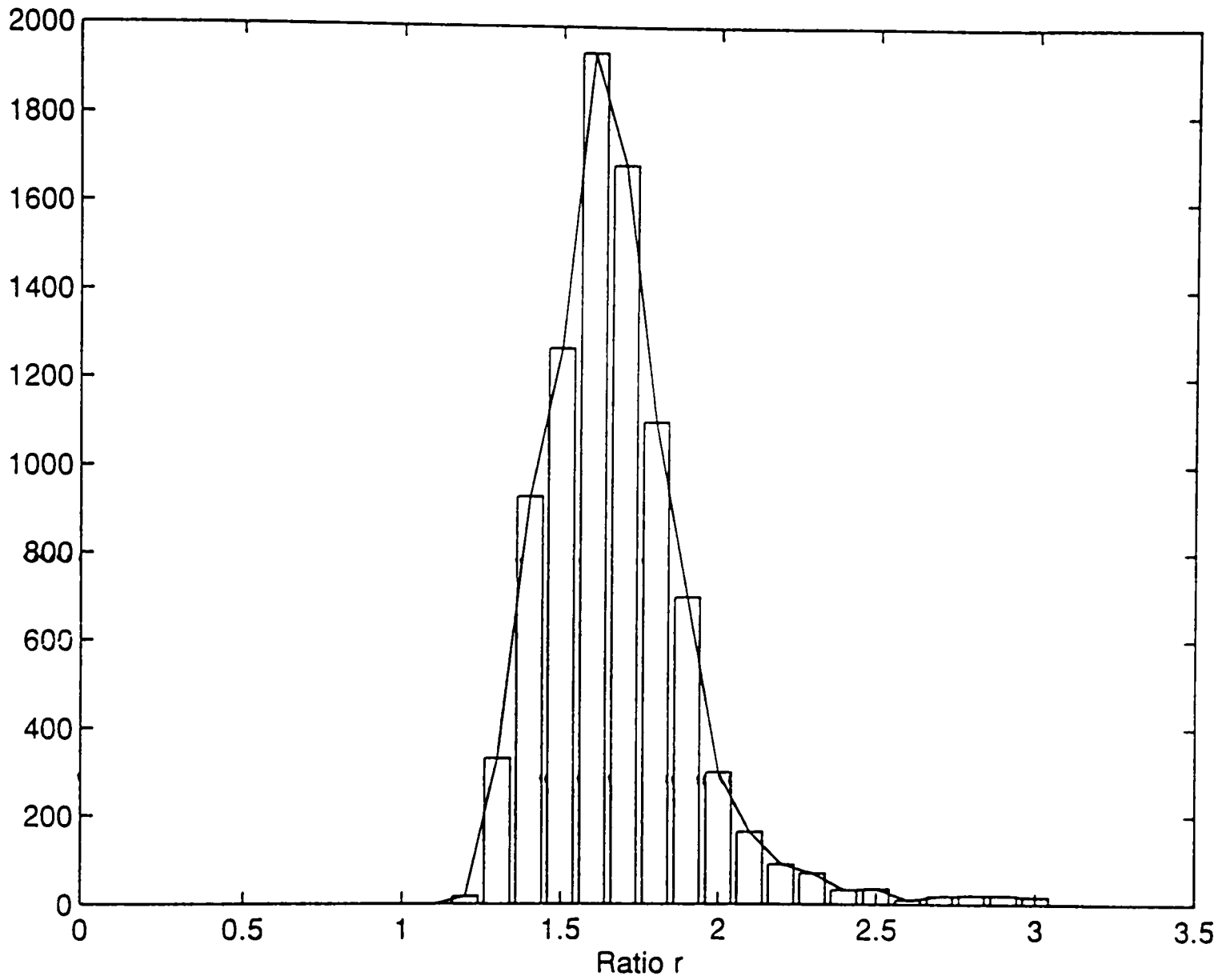


Figure 3.5 Probability Distribution Function for $\lambda = 0.01$

from these three figures, the spread in the distribution of 'r' with $\lambda$ =0.01, is the least compared to that with $\lambda$=0.05 and 0.1. The distribution of 'r' for $\lambda$=0.01 is more evenly distributed as compared to the distribution of 'r' for $\lambda$ = 0.05 and 0.1. In this case, the value of $\lambda$ = 0.01 seems best as it imitates the ideal PDF. In practice, a value of $\lambda$ = 0.01 makes the watchdog system response very sluggish to a process change. However, with $\lambda$ = 0.1, the response is found quickly and at the same time the watchdog system reduces the influence of past data on the present values.

### 3.2.2 Selection of $R_{crit}$ Values

During an upset (like a high amplitude noise spike, an unwanted input disturbance, etc.), even when the controller is functioning correctly and recovering control, the value of 'r' is certainly greater than 1. In this case, 'r', returns to its near unity value when the control to the process set point is recovered. However, if control cannot be recovered, then the high value of 'r' persists. If it persists for a long period, then the watchdog alarms.

Figure 3.3 shows the distribution of 'r' for a simulated process with no drifts and disturbances. The major part of 'r' distribution in the figure is below 2.5. If the value of 'r' goes above 2.5, then a problem with control is indicated. A value of 'r' less than 1.5 is less than about fifty percent of the 'r' distribution. Hence if the value of 'r' goes below 1.5, it indicates that the

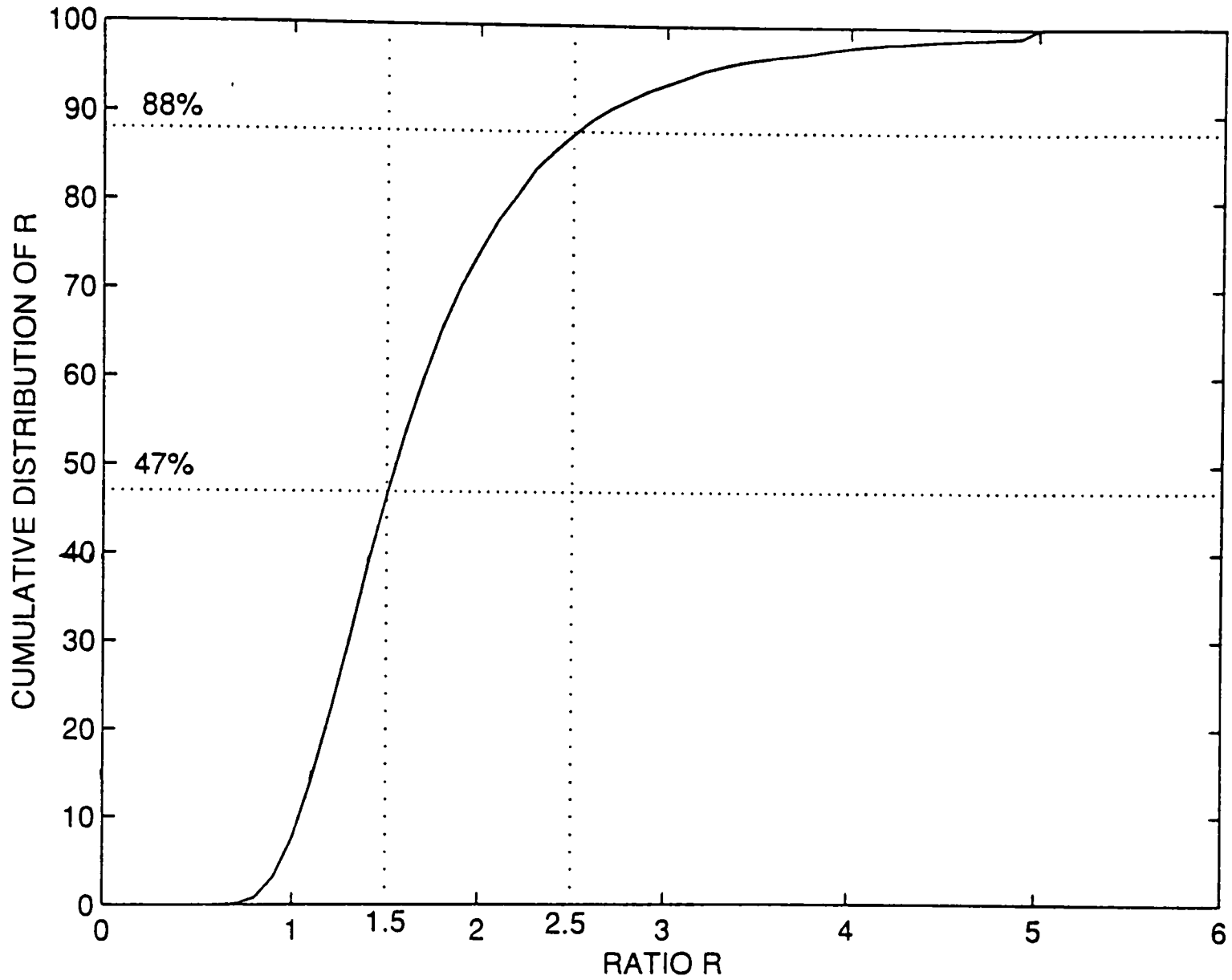


Figure 3.6 Cumulative Distribution Function

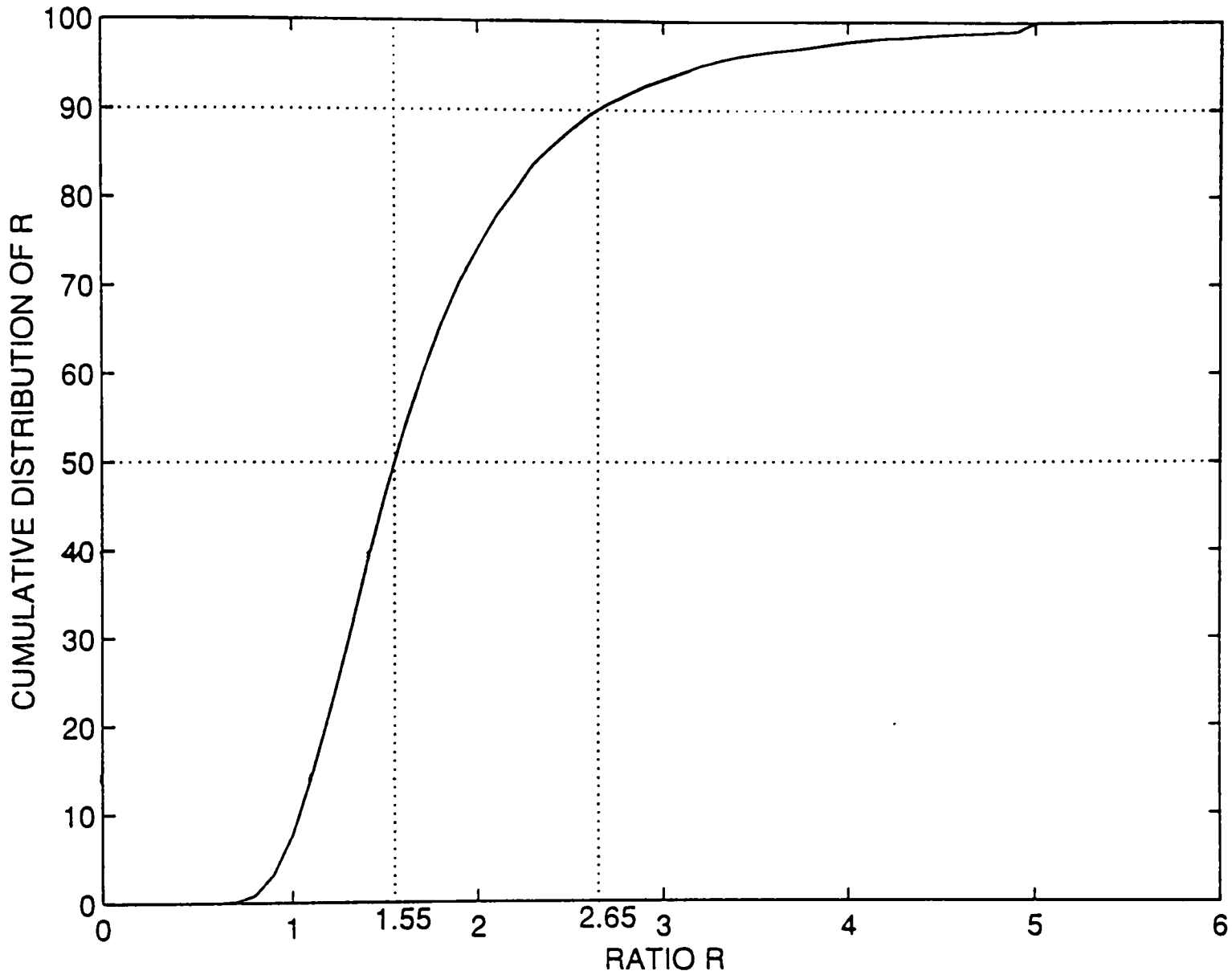


Figure 3.7 Cumulative Distribution Function

process is probably operating at its set-point. So the upper limit to trigger counting is 2.5 and the lower limit to stop the counting, indicating that control over the process has been achieved, is 1.5. These *triggering values* for the alarm system will again vary from one process to another, depending on the probability distribution plot of the ratio (Equation 3.6) calculated from process data.

Two techniques can be used to reduce the dependence amongst data values. The first approach is to execute the watchdog system at a lower frequency compared to the controller. This technique achieves the purpose of reducing the persistence of past data value on the present data value. The major drawback of this method is that if the sampling period is kept large then there might be periods between two samples where the changes in the process would go unnoticed. Also it makes the watchdog system sluggish as 'r' takes a longer time to fall below the lower triggering limit. Hence this method is not a very efficient way of reducing the effect of persistence of past data.

The second technique is to determine the triggering values by plotting a Cumulative Distribution Function (CDF) plot. In this technique a set of 'r' values are collected from the process window where no disturbance and/or drift has affected the process. A CDF is then plotted on these values.

The values of 'r' from Figure 3.3 are used to plot the CDF as shown in Figure 3.6. The triggering values of 'r' that were decided heuristically correspond to 47% ('r' = 1.5) and 88% ('r' = 2.5) on the CDF plot. These could be rounded off to 50% as the lower limit, and 90% as the upper limit. The corresponding values of 'r' are 1.55 and 2.65 (Figure 3.7), which hardly differ from the heuristically decided values of 'r' = 1.5 and 'r' =2.5, respectively. Even if the persistence of past data varies from one process to another, the 90% and 50% limits are perhaps a good way of determining the triggering limits of the watchdog alarm system.

### 3.2.3 Ceiling of 'r'

When the value of $S_{2\,f,i}^{2}$ becomes very small, the ratio 'r' in Equation (3.3) becomes very large. It takes a long time for 'r' to fall below the lower triggering limit. This is a frequently encountered problem. To overcome this, a ceiling is put on the value of 'r' at three times the upper triggering limit by making $S_{1\,f,i}^{2}$ equal to three times the product of the upper triggering limit ('r' = 2.65 in case of the simulated process discussed before) of the watchdog system and $S_{2\,f,i}^{2}$.

### 3.2.4 Selection of Continuous 'Badrun' Value

The next limit is the *threshold* value for the number of consecutive readings for which the process is almost certainly not at its set point (i.e., 'r' > 2.65). A process knowledgeable person can set the limits depending upon the settling time of the process. Keeping the threshold at 1 to 1.5 times the open loop settling time of the process gives sufficient time to the controller to bring the process to its set-point after a set-point change, disturbance etc. has occurred.

The watchdog system can be put on any process as an on-line alarm system. The following steps are to be followed to implement the system:

1. Collect a set of data from the process window, where control is judged to be "good".
2. Plot the Cumulative Distribution Function and use the 90 and 50 percentiles to find the upper and lower triggering limits of 'r'.
3. Set the threshold for the consecutive badruns of the process, by keeping it around 1.5 times the open loop settling time of the process.
4. Fix a ceiling on the value of 'r' ($3 * r_{90}$).

Using the above mentioned design rules, the watchdog system was implemented on a simulated linear process. The results of the watchdog system are explained in the following section.

## 3.3 Simulation Results

Figure 3.8 shows the data window of a simulated tenth order process. A set point change is made at sample 310. The controller brings the process to its new set point within the threshold value of badruns (1.5 times the settling time, which is 600). Similarly another process set-point change is introduced at sample 1130. Again the controller is able to bring the process back to the set point within the specified threshold value of badruns. The watchdog system does not trigger an alarm for both the situations. From instant 1990 to 3000 the controller gain is made large. The controller acts aggressively, which makes the process oscillate about its set-point. As the controller is not able to bring the process back to its set point within the threshold value of badruns, the system triggers an alarm. At sample 3400 a disturbance is introduced and the process recovers to its set point within the specified threshold value of badruns. Therefore the watchdog system does not trigger an alarm.

This technique was also tested on two experimental setups. They were:

1. Flow control of heat exchanger feed water using a Neural Network Controller.
2. pH control of an acid-base reactor using a Fuzzy Logic Controller.

A detailed description of the experimental setup and results for the above two processes is given in Chapter 6.

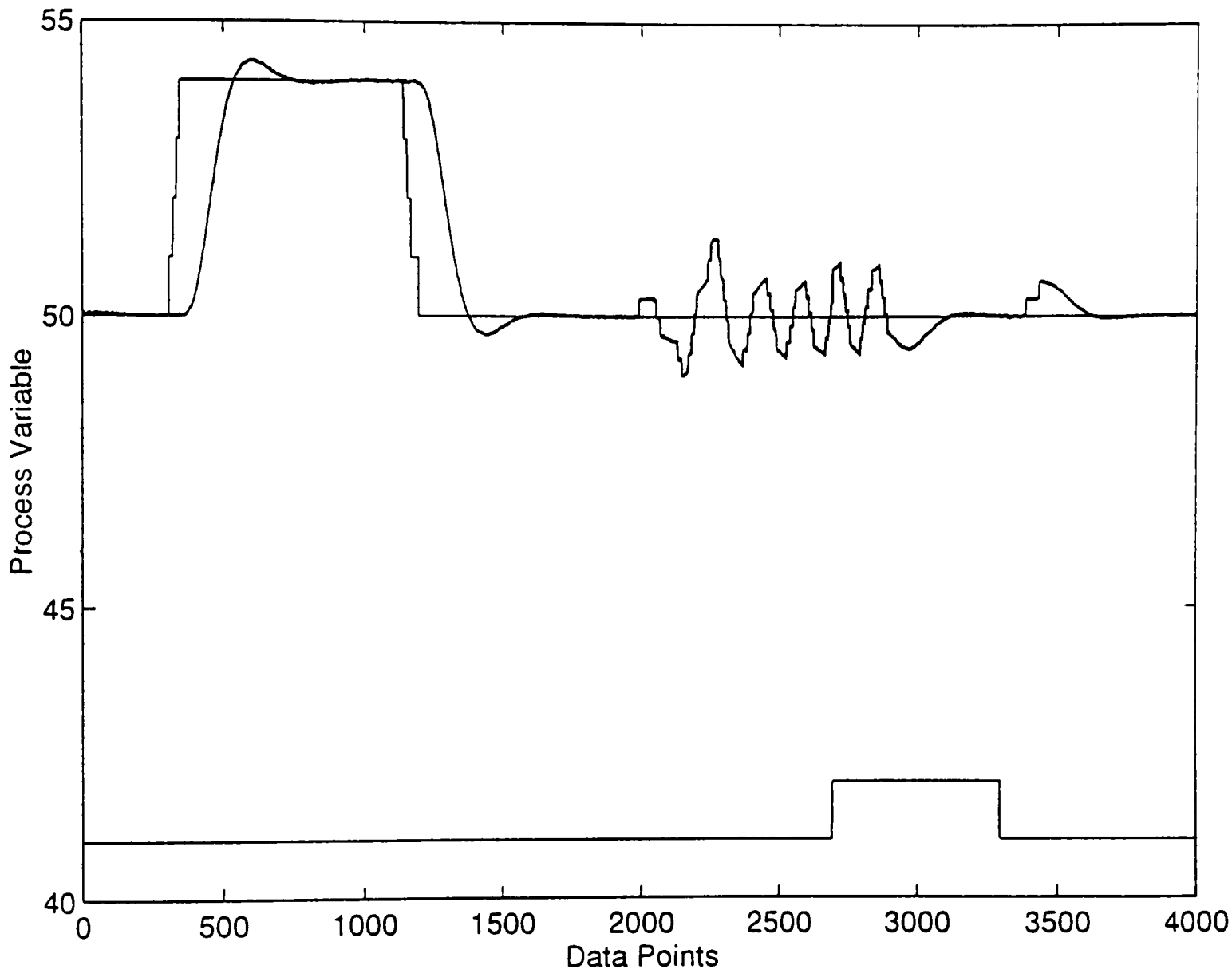


Figure 3.8 Watchdog System Alarm on a Simulated System

# CHAPTER IV

# ADAPTIVE CONTROL

The term Adaptive Control System has a variety of meanings, but it usually implies that the system is capable of accommodating unpredictable *environmental changes* (like changes in operating conditions, large amplitude disturbances, constraints, etc.), whether these changes arise within the system or external to it. This concept has a great deal of appeal to the systems designer. An adaptive control system, besides accommodating environmental changes, would accommodate moderate engineering design errors or uncertainties. It would also compensate for the failure of minor system components, thereby increasing system reliability [22]. This chapter introduces adaptive control theory and discusses in section 4.2 how the method has been implemented on a nonlinear fast acting process.

## 4.1 Introduction

In most feedback control systems, small deviations in parameter values from their design values will not cause any problem in the normal operation of the system. If the process parameters vary considerably, then the control system may exhibit satisfactory response for one process environmental condition but may fail to provide satisfactory performance under other conditions [15]. An adaptive control system works well for

different conditions. A satisfactory system performance is achieved by automatically varying the tuning parameters of the controller. The following section gives the definition and a brief description of the adaptive control system.

### 4.1.1 Definition

An adaptive control system is one which continuously and automatically measures the dynamic characteristics of the process, compares them with the desired dynamic characteristics, and uses the difference to vary the controller characteristics so as to keep the process under control. An adaptive controller generates actuating signals so that the performance can be maintained regardless of environmental changes. An adaptive control system continuously measures its own performance according to a given performance index and modifies, if necessary, its own parameters to maintain optimal performance regardless of environmental changes.

### 4.1.2 Theory

An adaptive controller consists of the following three functions:

1. Identification of the dynamic characteristics of the process.
2. Decision making based on the identification of the process.
3. Modification or actuation based on the decision made.

If the process is known, then the initial identification, decision and modification procedures will be sufficient to minimize (or maximize) the performance index. The Performance Index is a measure of "goodness" for control systems of any type [15]. The performance index for an adaptive control system defines optimal performance of the system. If the process is not known perfectly, it becomes necessary to carry out initial identification and modification procedures continuously or at certain intervals of time, depending upon how fast the process parameters are changing. This constant self-redesign or self-organization of the control system to compensate for unpredictable changes in the process is the aspect of performance that is considered in defining an adaptive control system.

A block diagram representation of an adaptive control system is shown in Figure 4.1. The dynamic characteristics of the process are measured and identified continuously. This is accomplished without affecting the operation of the control system in normal operating regions of the process. Identification must not take too long since if it does, further variations in the process may occur. Since the identification time is short compared to the rate of environmental changes, it is usually impossible to identify the process completely. A realistic calculation of tuning parameters (controller characteristics) will depend upon how much information about the process is acquired and upon the amount of prior knowledge of the process. The control signal is modified based on the results of the identification and decision.

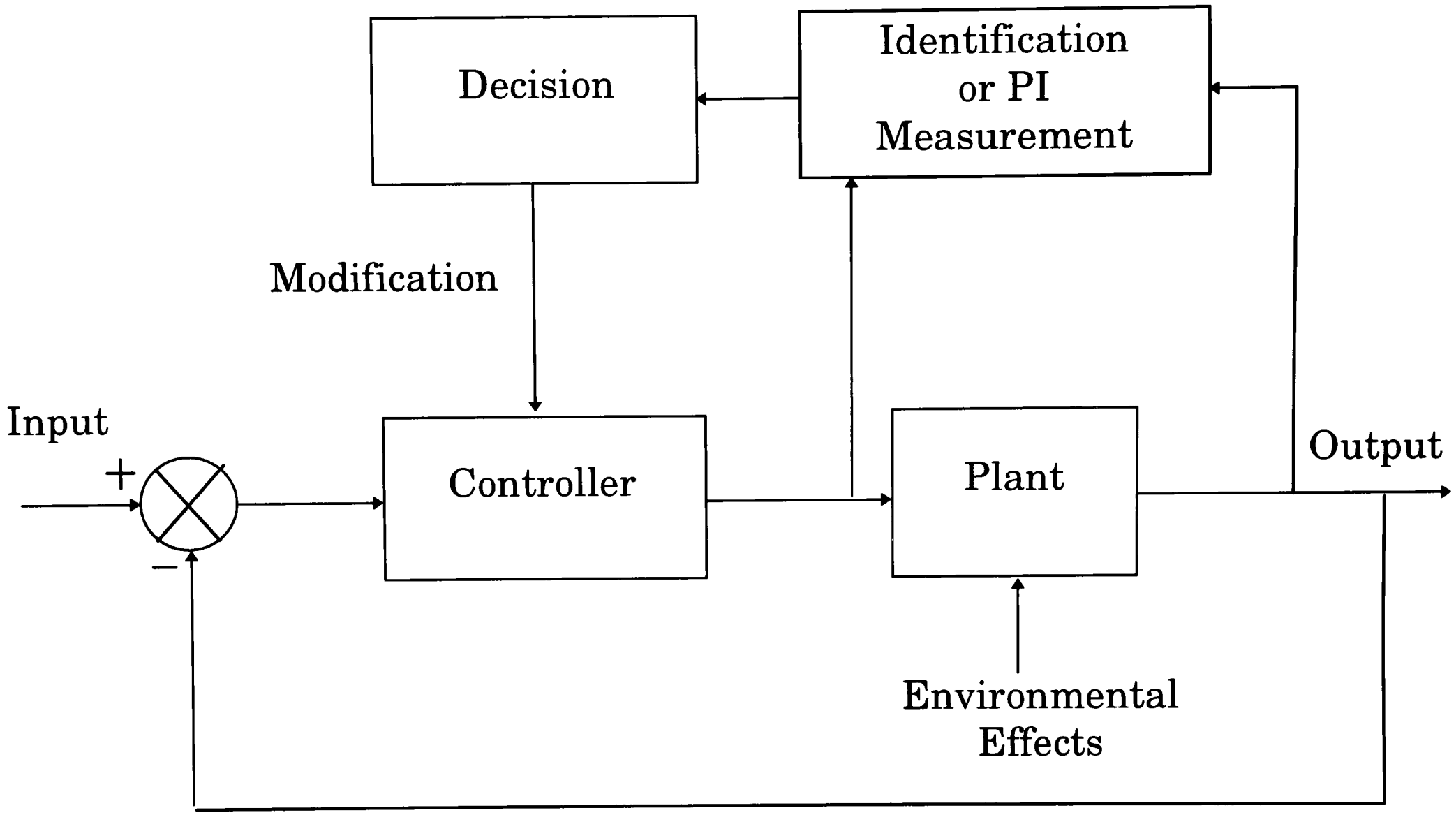


Figure 4.1 Block Diagram representation of an adaptive control system

There are basically two ways to modify the control signal. The first approach is to adjust the controller parameters in order to compensate for changes in the plant dynamics. This is called *controller parameter modification*. The second approach is to synthesize the optimal control signal, based on the plant transfer function, performance index, and desired transient response. This is called *control-signal synthesis*.

The choice between controller parameter modification and control-signal synthesis is primarily a hardware decision since the two approaches are conceptually equivalent. Where reliability is very important, the use of parameter change adaptation is often favored because the system can operate even after the failure of the adaptive loop [22].

## 4.2 Application

Most of the adaptive controllers are always in operation and take action even for sporadic noise spikes. To overcome this problem, the watchdog system is implemented on a system that is controlled by a conventional controller or a Model Based Controller. The watchdog triggers an alarm when the process goes outside the controlling range of the controller. Based on the alarm, the adaptive controller takes over as the control system for the process. Once the process is brought under control, the watchdog system clears the alarm, and the control is shifted back to the previous control system. This method prevents unnecessary tampering with

the controller, reduces computational time and data storage. In this study adaptive control is modeled by a Fuzzy Logic Controller, as explained in the Chapter V, and a Flash Tank dynamic simulator is used to imitate a real process.

# CHAPTER V

# FUZZY LOGIC CONTROL

During the past several years, fuzzy control has emerged as one of the most important areas for research. Fuzzy logic is much closer in spirit to human thinking and natural language than traditional systems. It provides an inexpensive solution for controlling complex or ill-defined systems that are difficult to control by conventional methods because of a lack of quantitative data regarding the input-output relations [31]. This chapter introduces fuzzy logic theory and the application of fuzzy logic control to control a flash tank dynamic simulator (Chapter VI).

## 5.1 Introduction to Fuzzy Logic Theory

As conceived by Lofti Zadeh [30], fuzzy logic provides a method of reducing as well as explaining system complexity. Zadeh formalized the case that humans reason, not in terms of discrete symbols and numbers, but in numbers of fuzzy sets. These fuzzy terms define general categories, but not rigid, fixed collections. Fuzzy set theory is the backbone of fuzzy logic. The following section describes classical set theory and compares it to fuzzy set theory.

### 5.1.1 Crisp Sets

Classical set theory is based on Boolean logic. Classical sets consist of objects that either belong to a given set or they do not. These types of constructs are called *crisp sets*. The objects belonging to a crisp set have a membership of 1, while other objects that do not belong to the set have a membership of 0. Consider the set FAST that is defined, on the basis of speed of a vehicle in miles per hour, such that

$\mu_{FAST} = 1$ if speed $\geq$ 60 miles/hour,

$\mu_{FAST} = 0$ if speed $<$ 60 miles/hour.

Thus anyone who drives above 60 miles/hours is driving fast. The membership graph for the set appears as shown in Figure 5.1.

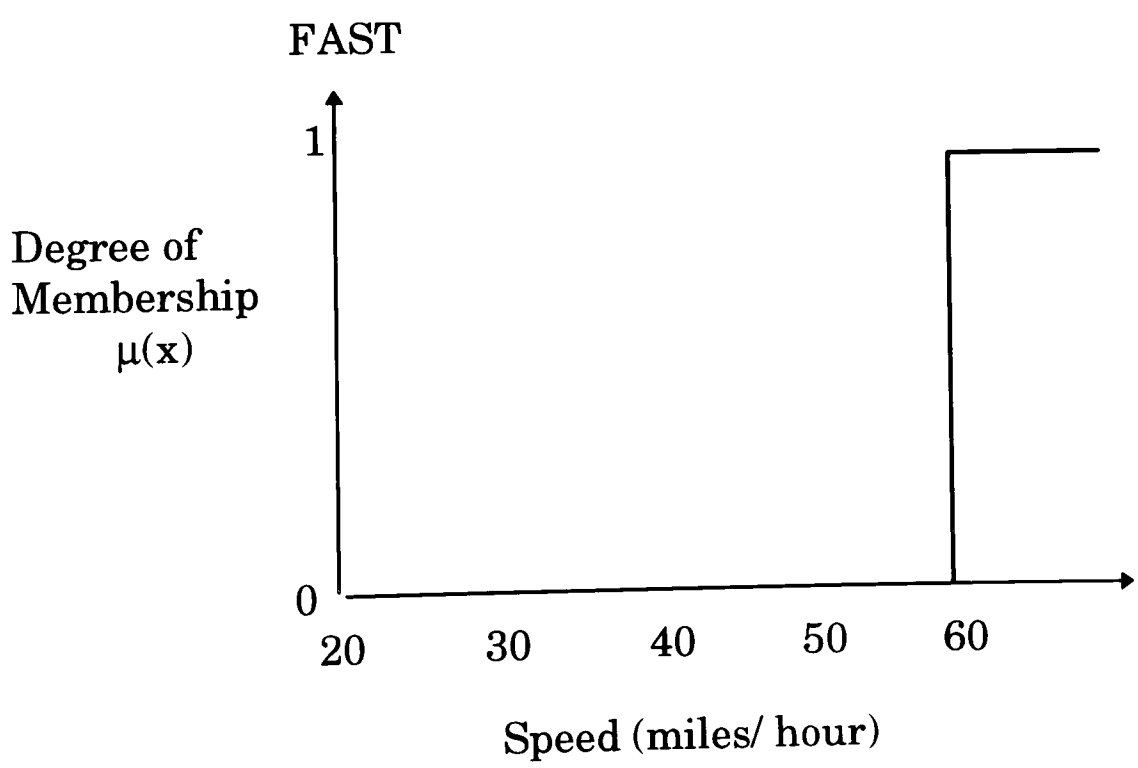


Figure 5.1 Crisp Set for the concept FAST

The characteristic function for this set reflects its Boolean nature. As we move along the domain (allowable values for the set), the membership of speed in the set Fast remains 0 (false) until we reach exactly 60 miles/hour, when it jumps to one (true). All classical or crisp sets have this kind of membership function.

### 5.1.2 Fuzzy Sets

Fuzzy set theory, on the other hand, is a multi-valued logic. Fuzzy sets are actually functions that map a value that might be a member of the set to a number between zero and one indicating its actual degree of membership. Under fuzzy logic the linguistic variable FAST may be defined as

$$\mu_{FAST} = 0 \qquad \text{if speed} < 20 \text{ miles/hour},$$

$$\mu_{FAST} = \frac{(speed - 20)}{40} \qquad \text{if } 20 \text{ miles/hour} \leq \text{speed} \leq 60 \text{ miles/hour},$$

$$\mu_{FAST} = 1 \qquad \text{if speed} > 60 \text{ miles/hour}.$$

The idea of speed is illustrated in Figure 5.2 . The membership function and domain are connected, in this case, by a simple piecewise linear curve (fastness is directly proportional to speed). Now, given a value for the speed, we can determine its degree of membership in the fuzzy set.

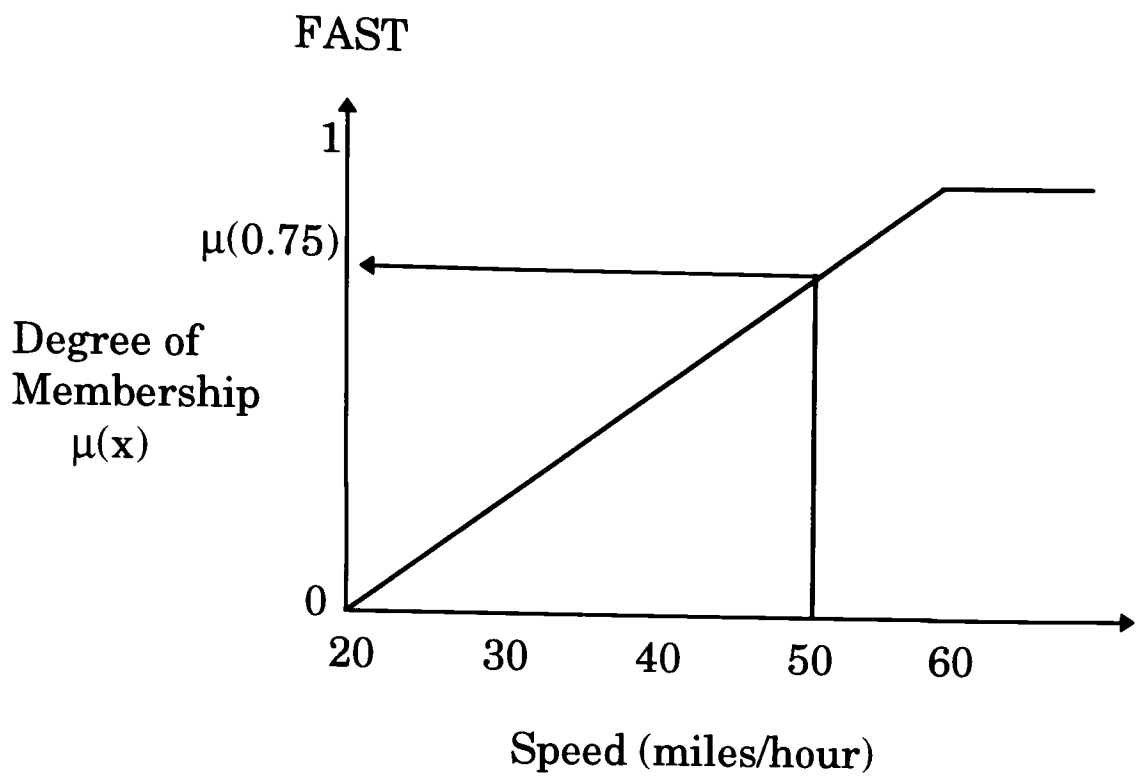


Figure 5.2 Fuzzy Set for the concept FAST

Thus a speed of 50 miles/hour has a 0.75 degree of membership. If the value for speed is less than 20, its membership is zero. If the speed is greater than or equal to 60 miles/hour, then its membership value is 1. In the case of 50 miles/hour, the membership of [0.75] means that it is strongly but not totally compatible with the fuzzy set FAST. The variable Speed may have many fuzzy sets associated with it (example, Slow, Medium and Fast), and the domains of all the fuzzy sets associated with a variable constitute its range and is referred to as its Universe of Discourse [12]. The fuzzy sets Slow, Medium and Fast, associated with the variable Speed, may be defined as shown in Figure 5.3.

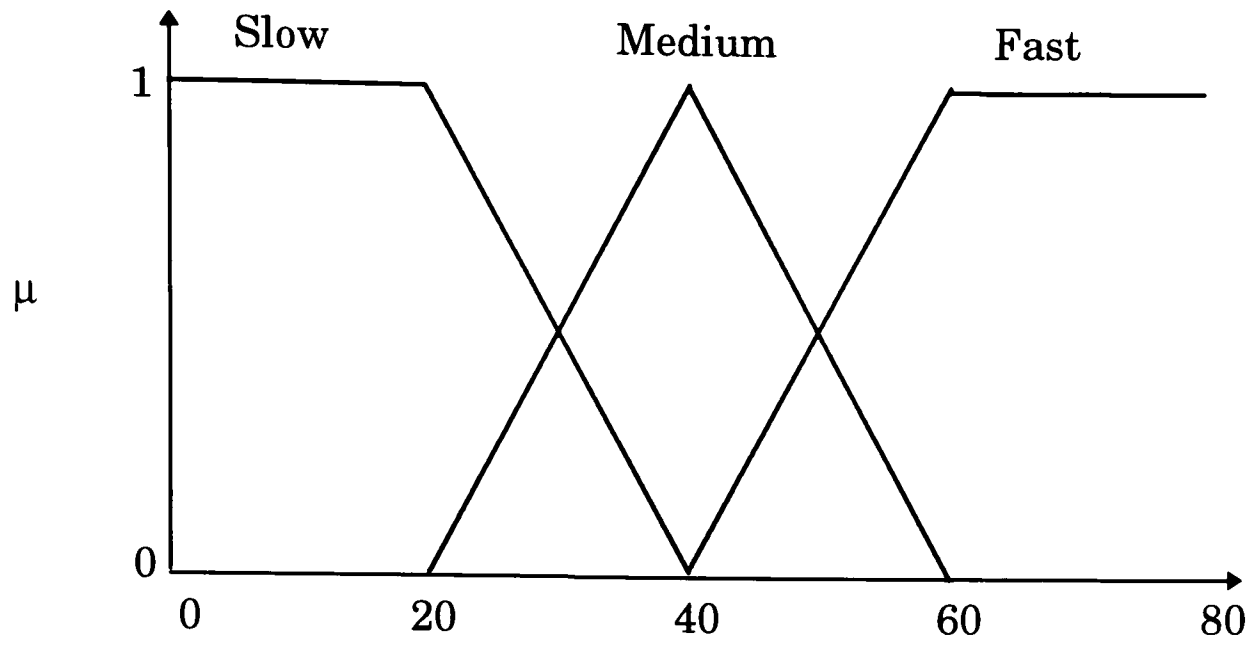


Figure 5.3 Speed (miles/hour)

The universe of discourse of Speed is the range of values from 0 to 80 miles/hour, while the domain for the fuzzy set Medium is 20 to 60 miles/hour. The fuzzy sets describing the universe of discourse need not be symmetric, but they always overlap to some degree indicating that their boundaries are fuzzy or imprecise. So a speed of 45 miles/hour belongs to the set Fast to a degree of 0.25, belongs to a degree of 0.75 to the set Medium, and belongs to the set Slow to a degree of 0.

## 5.2 Fuzzy Logic Control

The fuzzy logic control based on fuzzy logic set theory provides a means that can convert the linguistic control strategy based on expert

knowledge into an automatic control strategy. With fuzzy logic, manufacturers can significantly reduce development time, model highly complex nonlinear systems, deploy advanced systems using control engineers rather than control scientists, and implement controls using less expensive sensors [13.].

### 5.2.1 Fuzzy Logic Control Model

This section talks about the fundamental ideas underlying a Fuzzy Logic Controller (FLC). The basic configuration of an FLC is shown in Figure 5.4. The *fuzzification interface* measures the values of input variables of the FLC and scales them into fuzzy sets in the normalized universe of discourse, based on pre-defined membership functions. The typical input variables of FLC are controlled or state variables, and other process measurements that affect the process. In a flow controller, the error (E) between the process fluid flow and its set-point is an input variable, and is partitioned into fuzzy sets: Negative-Large (NL), Negative-Small (NS), Zero (Z), Positive-Small (PS), and Positive-Large (PL) as shown in Figure 5.5. Typically, the overlapping triangular fuzzy sets are used for process control applications.

The *Decision Making Logic* is the kernel of FLC. It has the capability of simulating human decision-making based on fuzzy concepts, employing rules of inference in Fuzzy logic. Every fuzzy control rule in the *Knowledge*

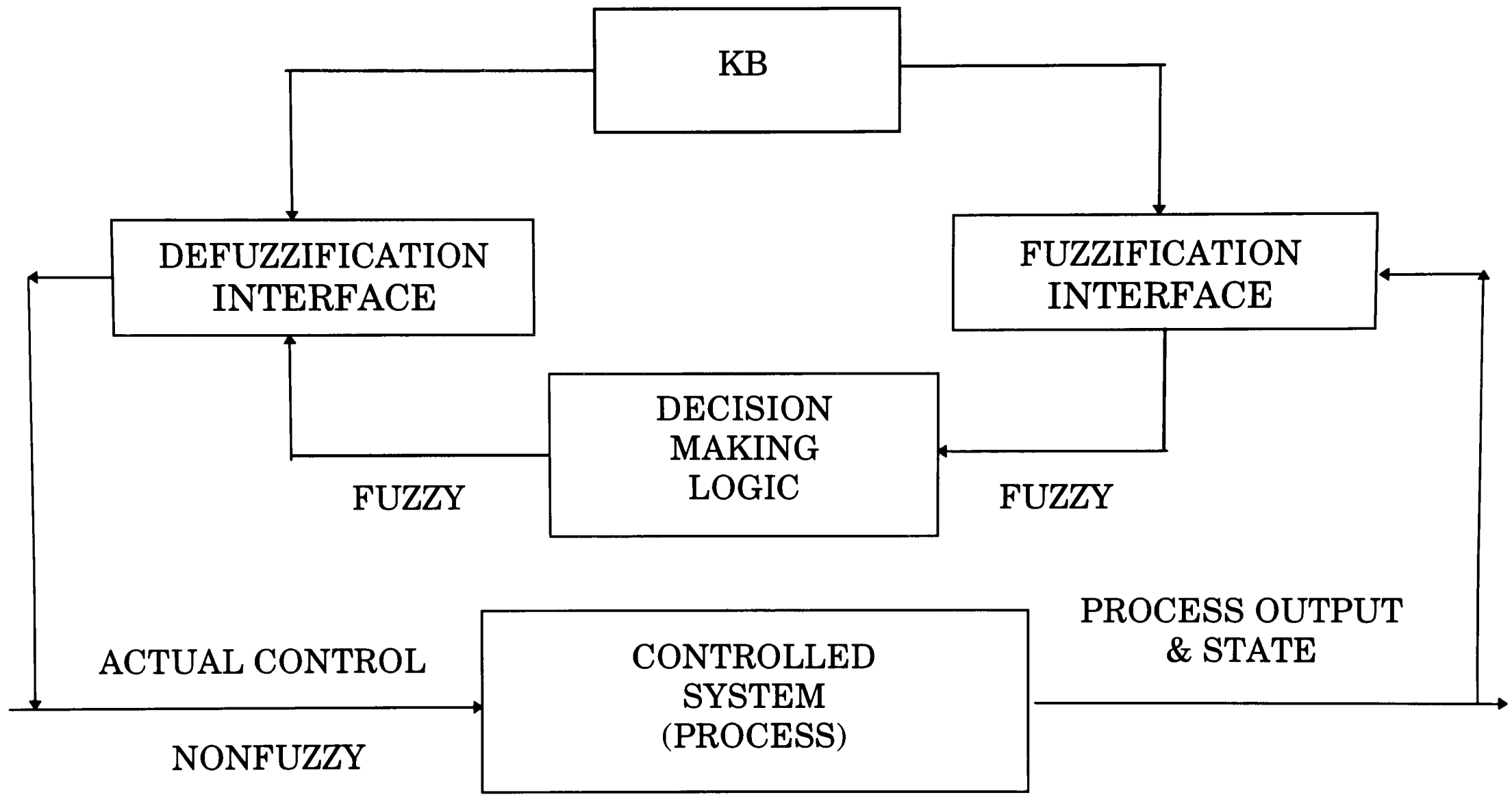


Figure 5.4 Basic Configuration of Fuzzy Logic Controller (FLC)

*Base* (KB) is a relationship between the input variables membership functions and an output action or command. A fuzzy control rule is a fuzzy conditional statement in a form such as

"IF {error (E) is PL and change in error (CE) is PS} THEN valve action is PL."

The collection of all such rules is known as the Knowledge Base (KB). All fuzzy rules may be executed with different strengths and the rules that are fired strongly will contribute more to the final conclusion. The rules are designed to mimic human thinking and they also incorporate information about process disturbances, constraints, process set-point changes, non-linearities, etc.

Since the input variables belong to several fuzzy sets, they produce non-zero membership values with reference to different rules. For example, the fuzzy sets for input variables error (E) and change in error (CE), and the output variable valve action (VA) are given by Figures 5.5, 5.6, and 5.7 respectively. The rule base that results in feed back control action is shown in Figure 5.8. The rule base builds this functional relationship into the controller. Hence the controller rule base has twenty-five rules in all. A trial and error procedure is used to classify the various variables in the fuzzy sets.

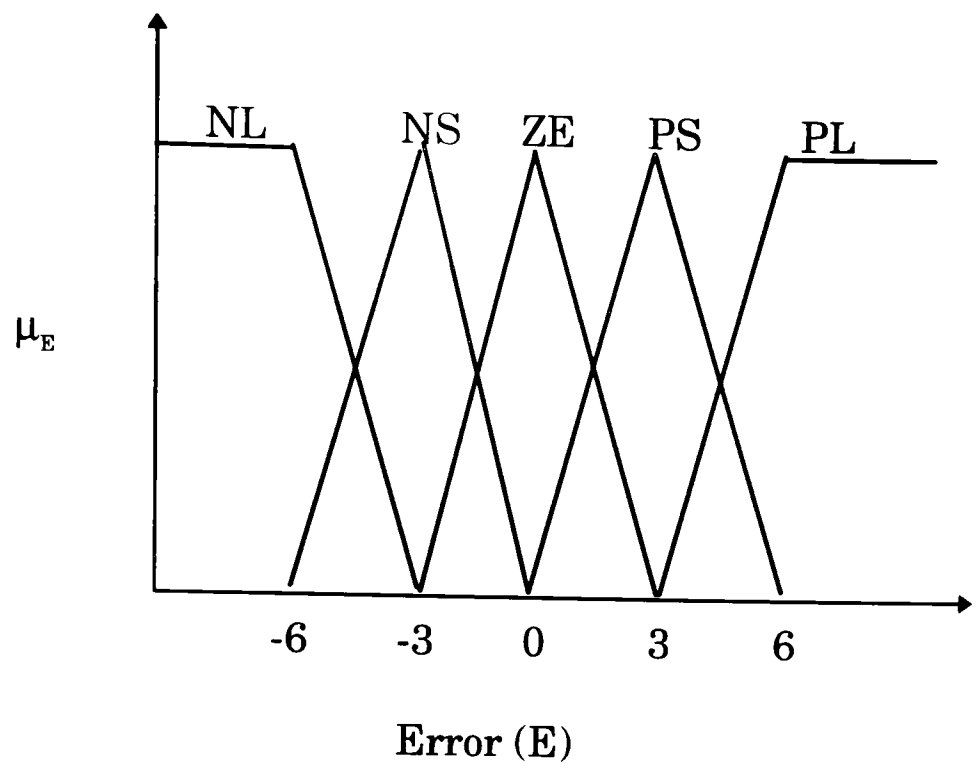


Figure 5.5 Fuzzy Set Definitions for the Variable Error

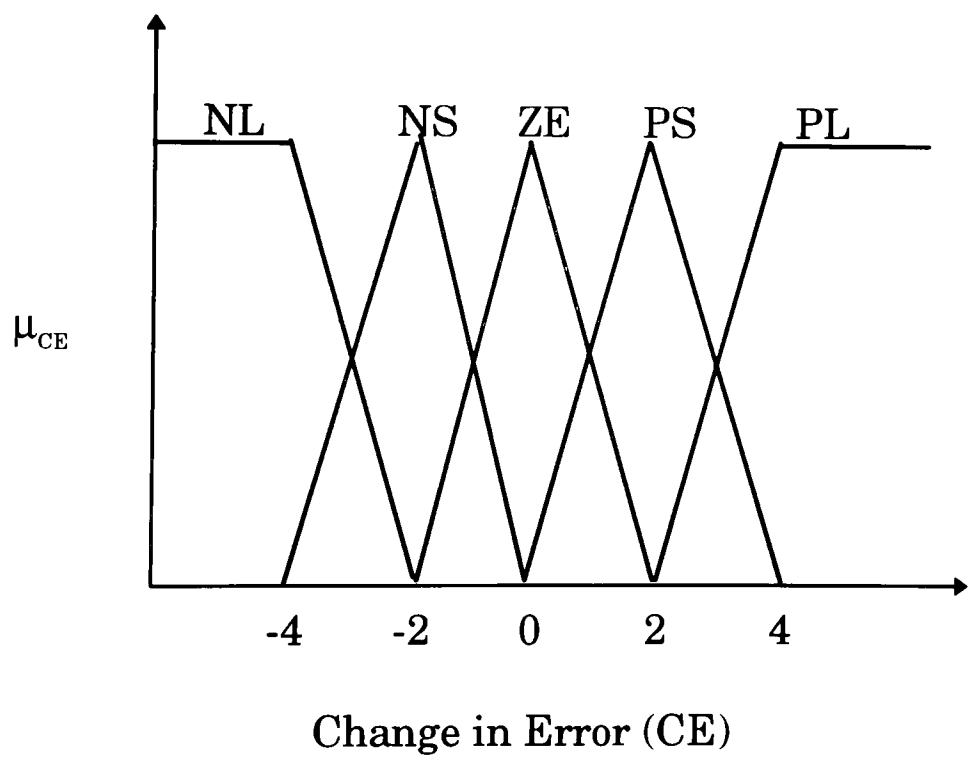


Figure 5.6 Fuzzy Set Definitions for the Variable Change in Error

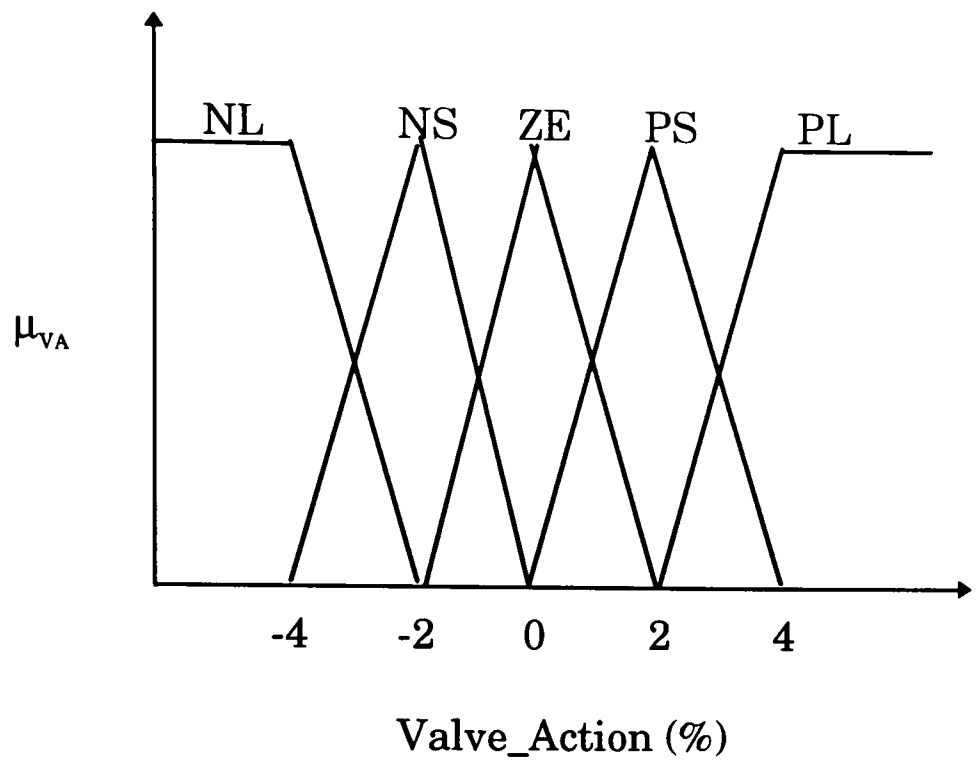


Figure 5.7 Fuzzy Set Definitions for the Output Variable Valve_Action

Error

Change in Error

| | **NL** | **NS** | **ZE** | **PS** | **PL** |
|---|---|---|---|---|---|
| **NL** | NS | ZE | PL | PL | PL |
| **NS** | NM | NS | PM | PM | PL |
| **ZE** | NM | NS | ZE | PS | PM |
| **PS** | NL | NM | NM | PS | PM |
| **PL** | NL | NL | NL | ZE | PS |

Figure 5.8 Rule Base for Fuzzy Controller

If E is 5 lb./min and CE is 0 lb./min/s, then

$\mu_{E,PS} = 0.33$, $\mu_{E,PL} = 0.67$, $\mu_{CE,ZE} = 1.0$.

The min equal to max method is then used for inference. The consequent fuzzy region is restricted to the minimum of the predicate truth. The output fuzzy region is updated by taking the maximum of these minimized fuzzy sets [29]. Accordingly, the following rules are activated since their antecedent or predicate membership values are non-zero.

[Rule 1]: IF { E is PS and CE is ZE } THEN VA is ZE.

[Rule 2]: IF { E is PL and CE is ZE } THEN VA is PS.

The *defuzzification interface* performs a scale mapping, which combines the output values and converts them into discrete values needed for driving certain control mechanisms. For this example,

$\text{Rule } 1_{\text{OUTPUT VALUE}} = \min(0.33, 1.0) = 0.33$

$\text{Rule } 2_{\text{OUTPUT VALUE}} = \min(0.67, 1.0) = 0.67$

The most commonly used defuzzification method is the center-of-area (COA) or center-of-gravity method given by equation 5.1

$$Y = \frac{\sum_{j=1}^{n} f_A(w_j) \bullet w_j}{\sum_{j=1}^{n} f_A(w_j)} \tag{5.1}$$

where n is the number of the contributed "if A then B" rules, $w_j$ is the grade value at which the membership function $f_A(w_j)$ reaches the maximum value, and Y is the defuzzified output. The defuzzification for this example is illustrated in Figures 5.9, 5.10 and 5.11.

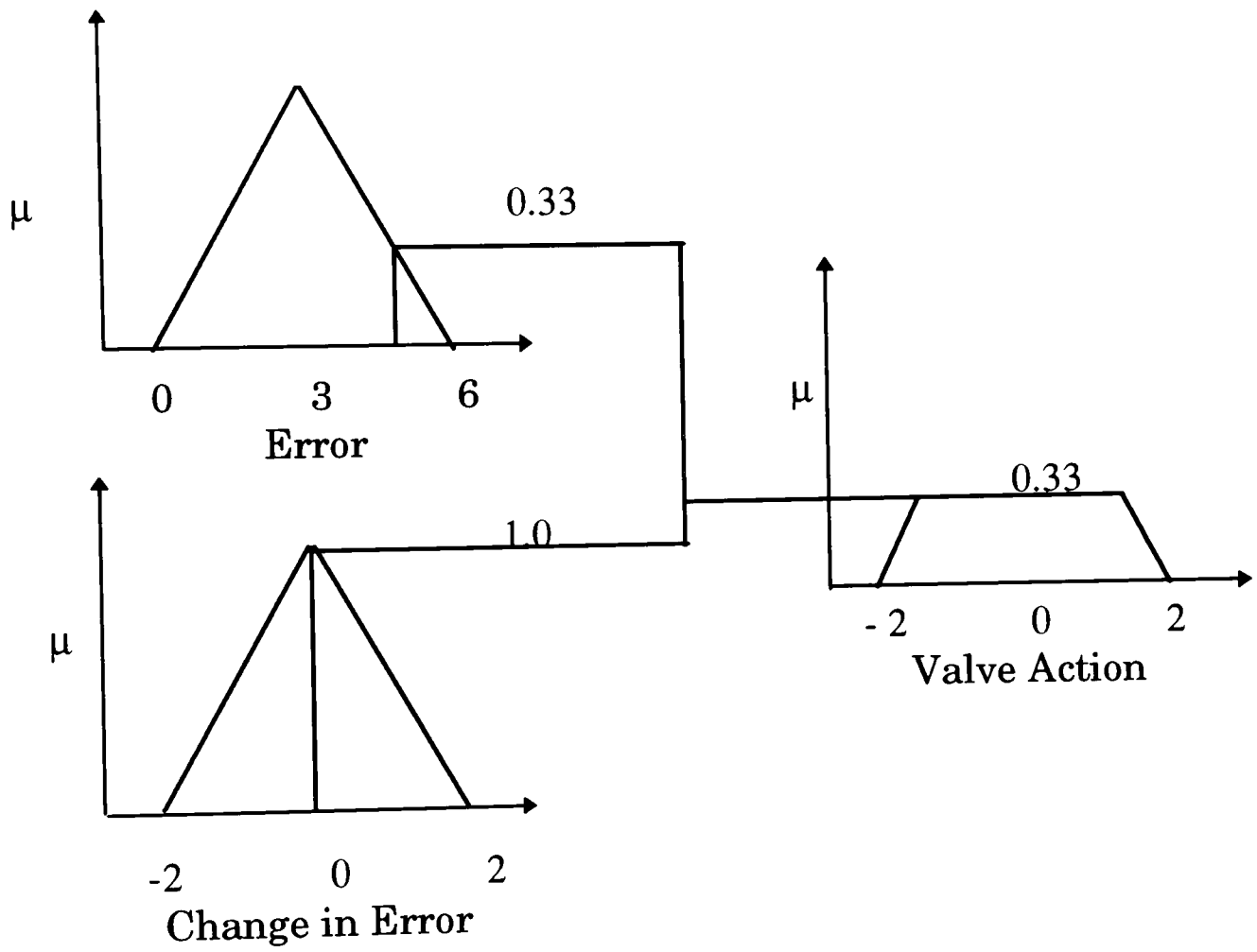


Figure 5.9 Valve Action for Rule 1

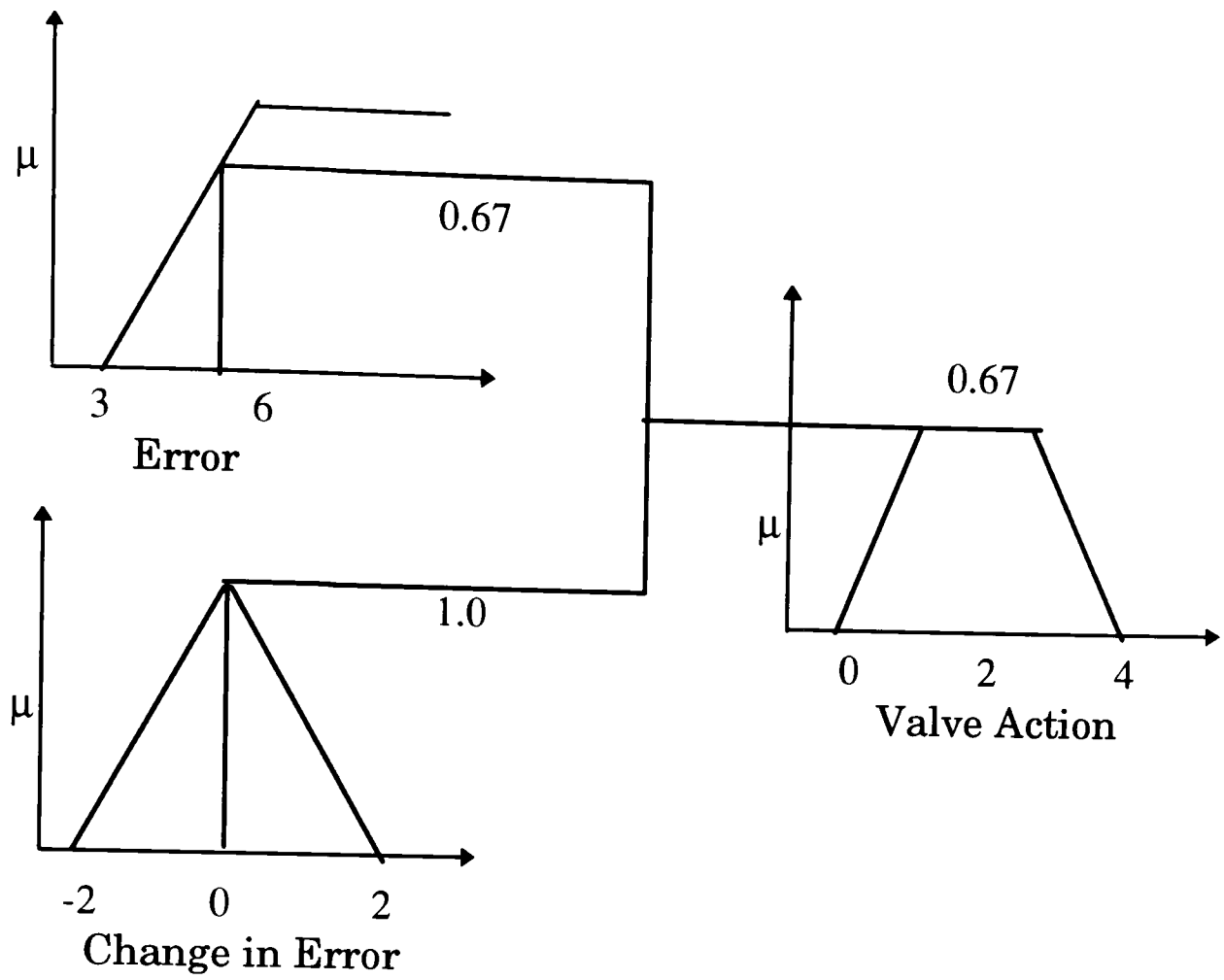


Figure 5.10 Valve Action for Rule 2

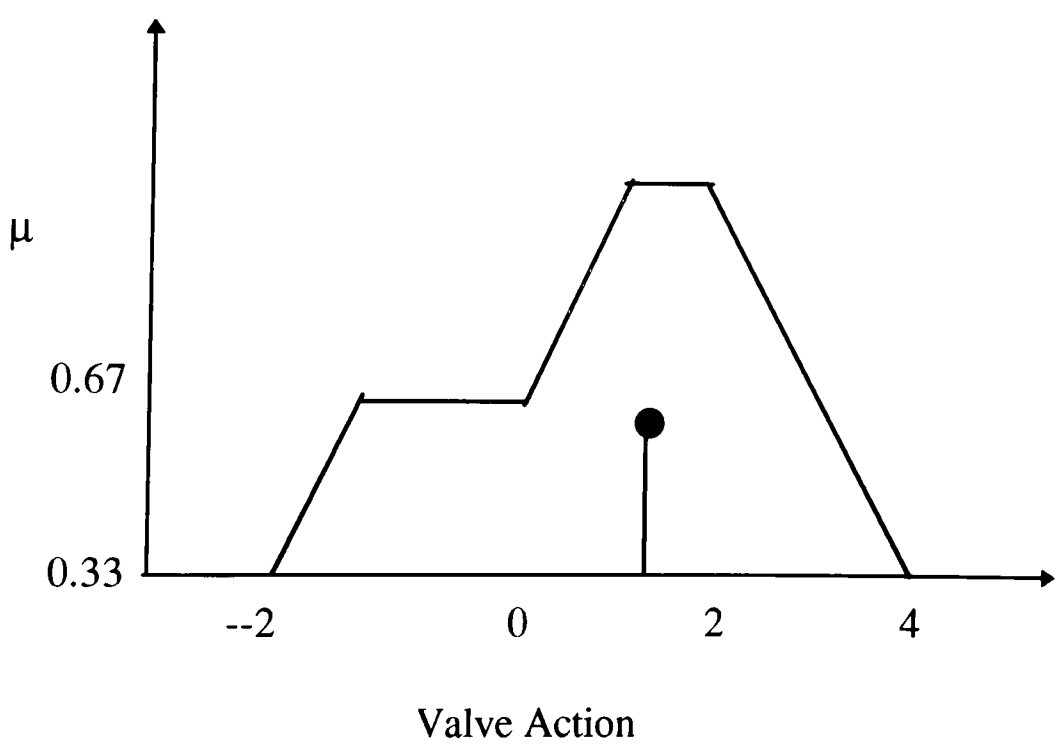


Figure 5.11 Net Valve Action by the COA method of Defuzzification

# CHAPTER VI

# EXPERIMENTAL SETUP AND RESULTS

This chapter illustrates the application of the on-line monitoring system on two pilot scale plants. It also discusses the set up of a Flash Tank Dynamic simulator and its control by means of a Fuzzy Logic Controller.

## 6.1 pH Control Using a Heuristic Model

### 6.1.1 Experimental Setup

The pH control experiment is related to the wastewater effluent discharged from a chemical plant. The experimental set up used for this system is a laboratory scale, on-line, control scheme. This unit is designed to be compact and portable so that the technology can be tested at an industrial site. The pH control is based on the dual reagent injection approach, which involves splitting of the reagent stream and its sequential addition to the process influent in two separate portions [32]. The concept of dual reagent injection has been patented by Riggs and Rhinehart (US Patent #4,940,551, July 1990). In this strategy the total base flow rate is split into two streams and injected sequentially into the acidic process line. Figure 6.1 shows the acidic stream flowing from left to right, its flow rate is controlled by a metering pump and its pH after mixer 2 (pH3) is monitored. After each base

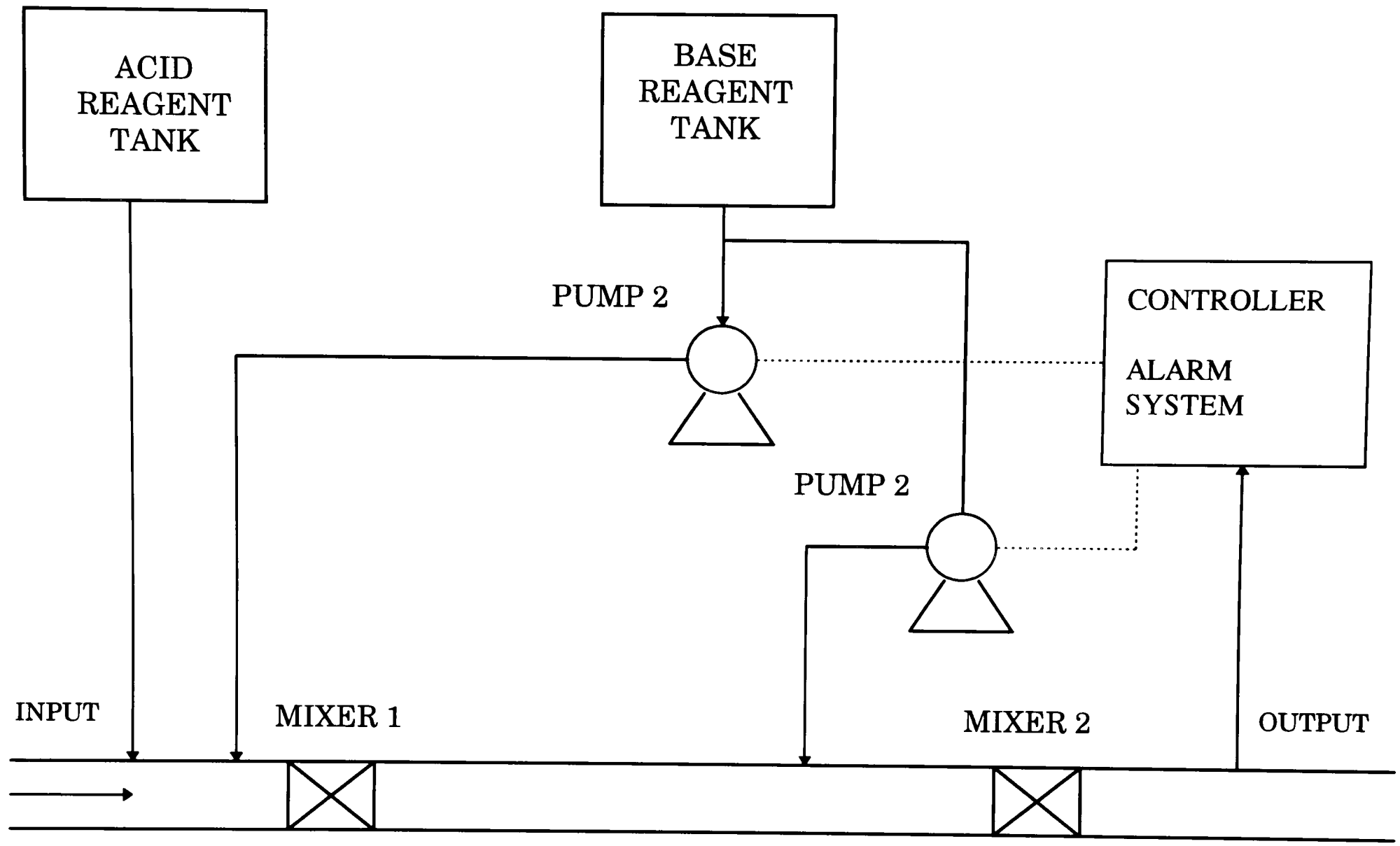


Figure 6.1 Block Diagram of pH Control Set-up

injection, the acid and the base streams are mixed using in-line static mixers and the resulting pH of these streams is monitored.

The influents used in this work are mixtures which were designed to express a wide range of titration curve behavior from highly buffered to strong acid to multiple intermediate dissociation. They are based on acetic, sulfuric and phosphoric acids, common-ion salts and weak bases. The titrant was aqueous sodium hydroxide. Mahuli et al. (1992) records the titration curves as well as the approximations generated by the reduced models.

For this experiment the base was 0.02 N NaOH prepared with reverse osmosis water and the acidic mixtures were prepared in city water. The sampling period was approximately 0.5s. The process response was used to calculate the various watchdog triggering parameters. The pH control was a good test for the watchdog, since pH control is a difficult process problem. The titration curve is a highly nonlinear classic 'S' shaped curve and the process gain changes drastically over the range. Moreover the wastewater composition is constantly changing, typically being an unpredictable mixture of substances with widely differing properties. Owing to this, an advanced prediction of the titration curve is not possible. In addition, the process is extremely sensitive to small changes and disturbances in the neutralization and equivalence regions. Hence, even if the controller is tuned relatively

well, the process wiggles about the set point. In this case, the watchdog is a good approach to determine if the process is at set point.

### 6.1.2 Results

Figure 6.2 shows an experimental run with a couple of disturbances in the influent stream. At sample number 950, the influent was switched from multprotic strong acid (phosphoric acid) to a buffered weak acid (acetic acid + sodium acetate). At sample number 1700 the influent was switched back to strong acid (phosphoric acid). This experimental run was used to determine the triggering values for the watchdog system.

A process window (data points after sample number 1900) not affected by drifts or disturbances was identified, to calculate the upper and lower triggering limits of the alarm system. A probability distribution and cumulative distribution curve (Figure 6.3) were generated using this data. The upper and lower triggering limits were identified to be 5.88 and 2.1, respectively. The threshold of consecutive badruns was determined to be equal to 1.5 times (475 in this case) the normal settling time of the process for a step change in the set-point of the process. The maximum value of r was clamped at 18, which is about 3 times the upper triggering limit (i.e., 5.88).

Using these triggering and clamping values the whole experimental run was analyzed for "bad" periods of control. Figure 6.2 shows that there

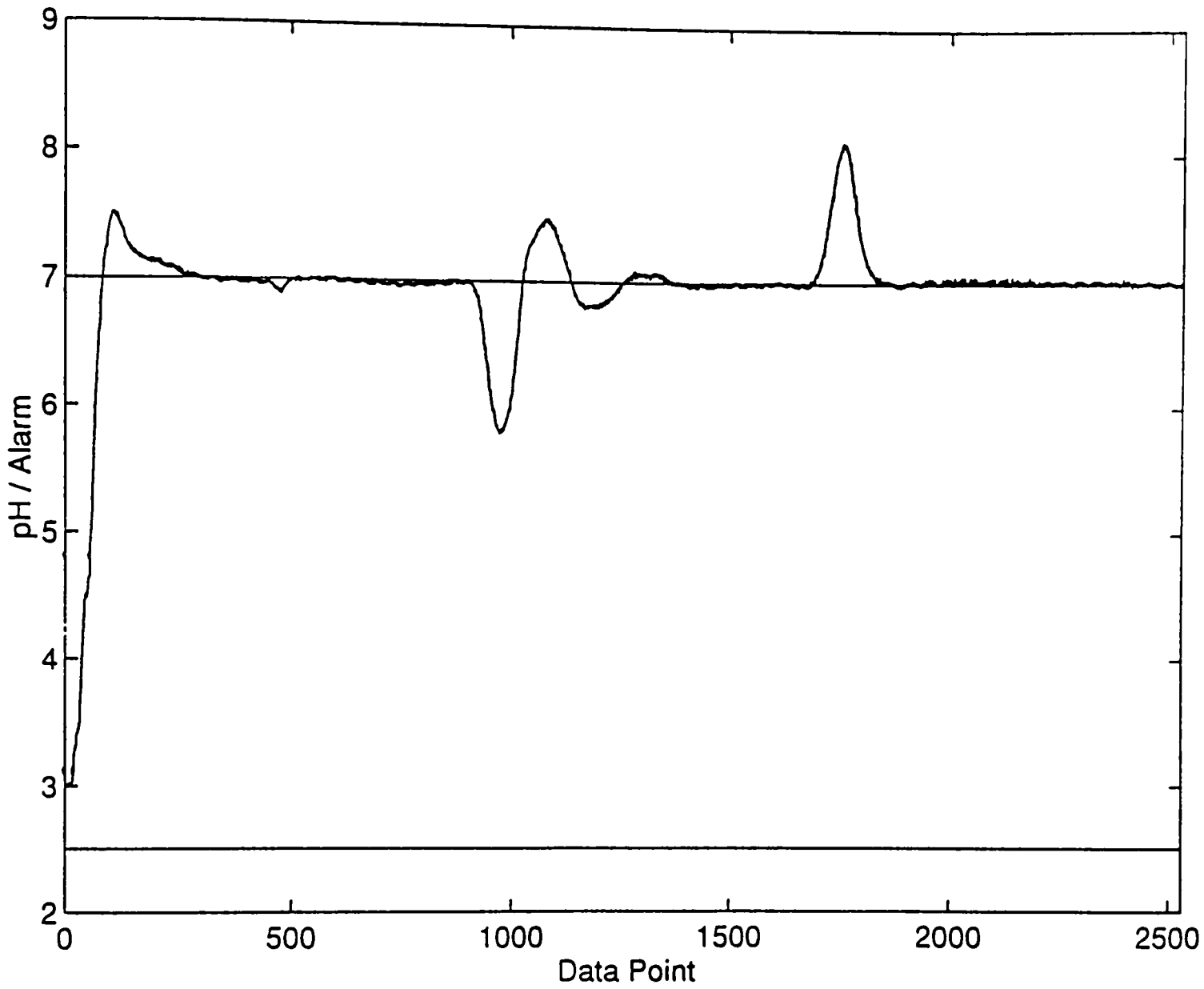


Figure 6.2 Experimental run on pH with Watchdog System

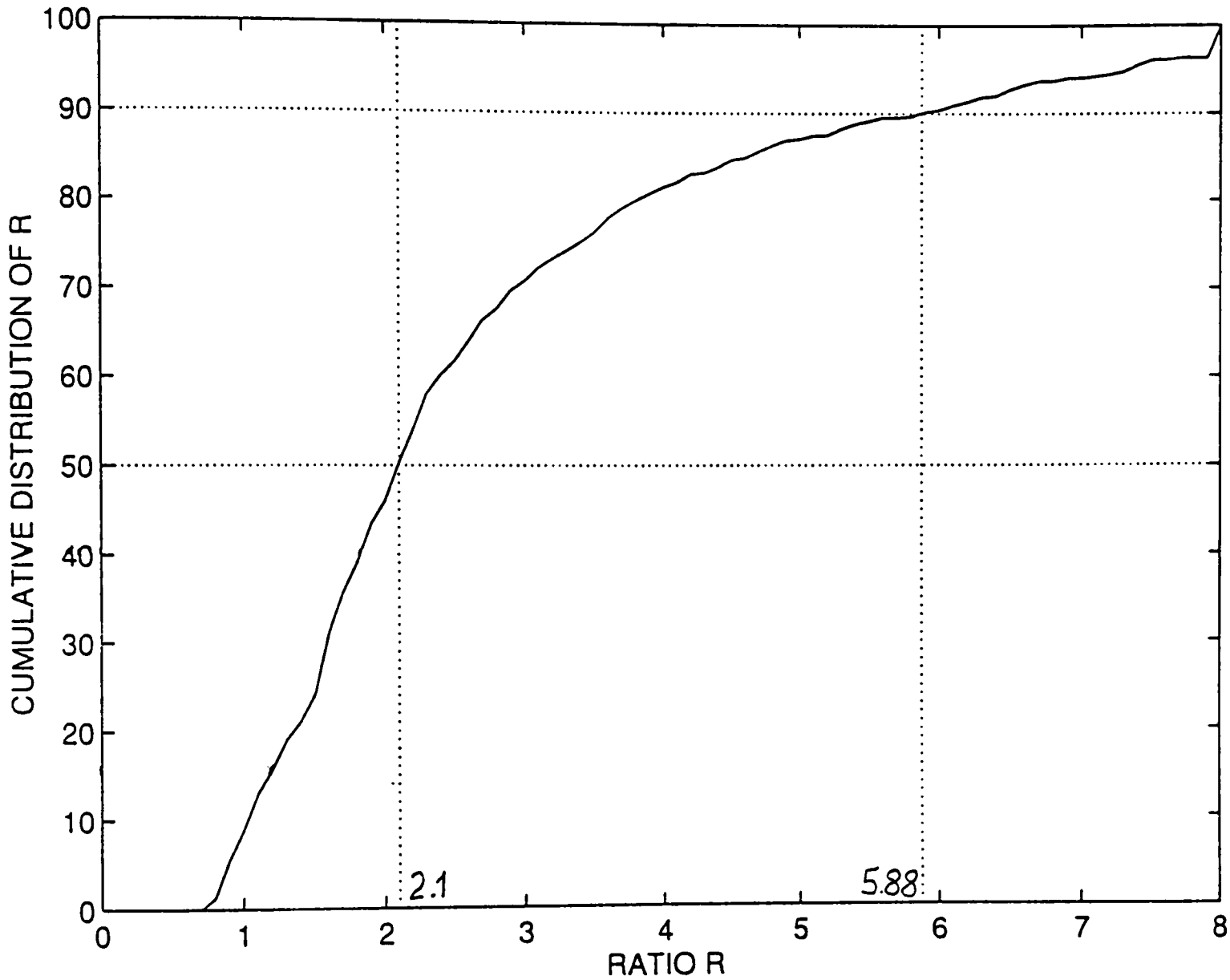


Figure 6.3 Cumulative Distribution Function Plot for pH Control

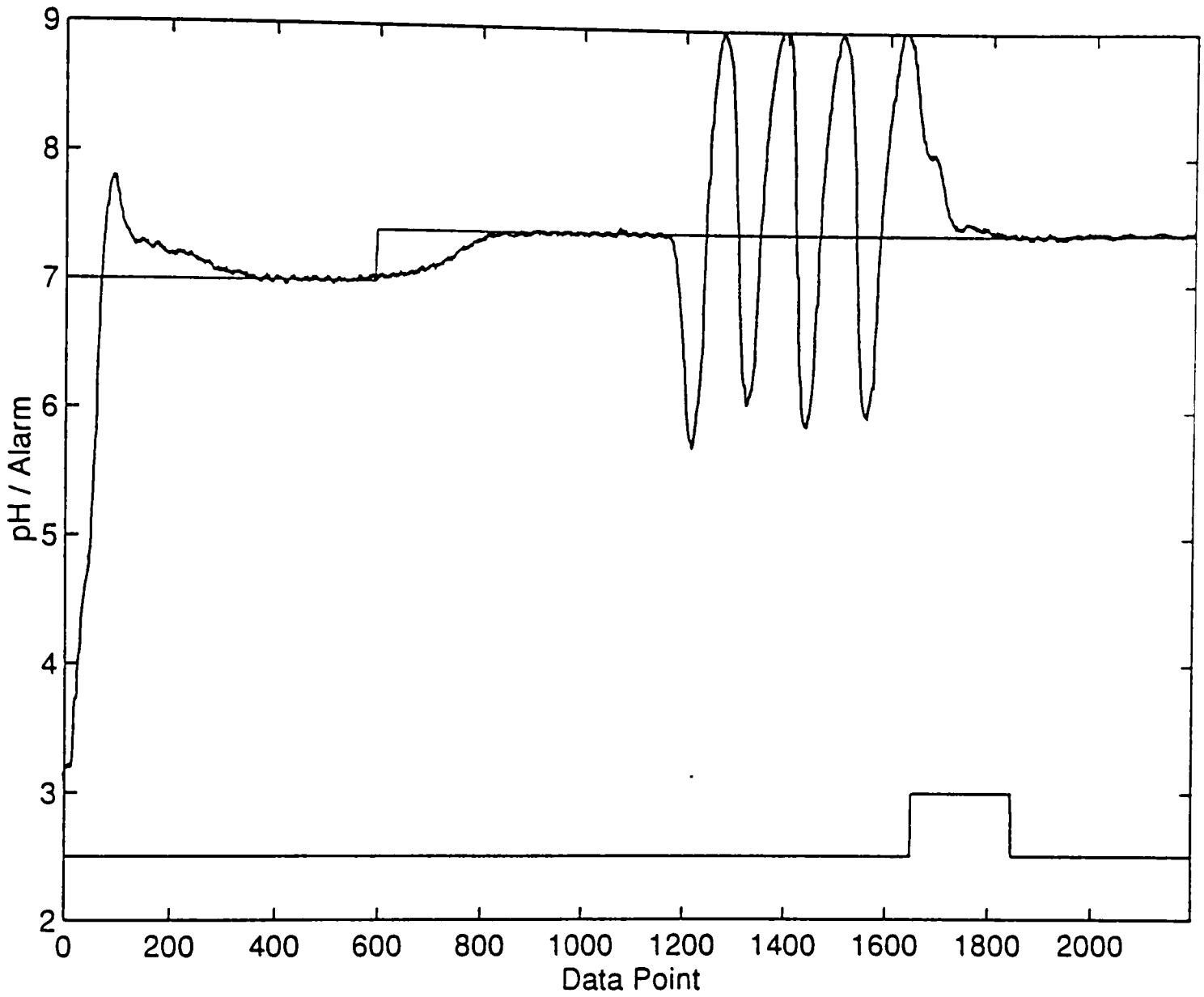


Figure 6.4 Experimental run on pH set-up with Watchdog System

never was a controller problem. Figure 6.4 shows another experimental run with the on-line alarm system. The influent initially was a strong acid (phosphoric acid). At sample number 600, the pH level of the mixture was changed from 7.0 to 7.4. Since the process reached and settled at the set point before 475 consecutive samplings, after the process set-point was changed, the alarm did not trigger. At sample number 1150 the influent was alternately switched between an acetic acid and the phosphoric acid mixture. This continuous disturbance did not allow the process to settle down to a steady state. As we can see from the Figure 6.4 the alarm triggers after the number of badruns exceeded the threshold value. Later on, after the disturbance in the flow rate was stopped, the process settled down to a steady state value (i.e., at pH = 7.4). The alarm also stopped, indicating that the process was under control.

## 6.2 Heat Exchanger (Flow Control)

### 6.2.1 Experimental Setup

A schematic flow diagram of the fluid flow and the heat exchanger experimental system is shown in Figure 6.5. The control valve is a modified equal-percentage air to open valve. The experimental system is equipped with a shell-and-tube heat exchanger. The heat exchanger has a single tube on the shell side and four passes (of four parallel tubes each) on the tube

side. The heat exchanger fluid could be either hot water or steam through the shell side and warm or cold water through the tube side. The condensate from the heat exchanger passes through a steam trap and a small double pipe heat exchanger for sub-cooling.

The process is interfaced to a Zenith 386/25 PC by a Camile 2000 data acquisition and control system. The flow rate is measured by a Foxboro integral flow orifice assembly. The control system sends an output signal of 4-20 mADC to an I/P converter which converts it to a 3-15 psig signal to operate the control valve. The sampling interval of the data acquisition system is one second. The desired objective is to control the temperature of the fluid at the outlet of the tube. This can be done either by controlling flow of steam or feed fluid. The controller used is a neural network based controller, with a feed forward network. The neural network controller controls the steam flow and fluid flow valves. A simple dynamic process is obtained by assuming that the fluid is an incompressible Newtonian fluid flowing with a flat profile [25]. The mass flow of fluid is the parameter that is sent to the controller and the controller takes action.

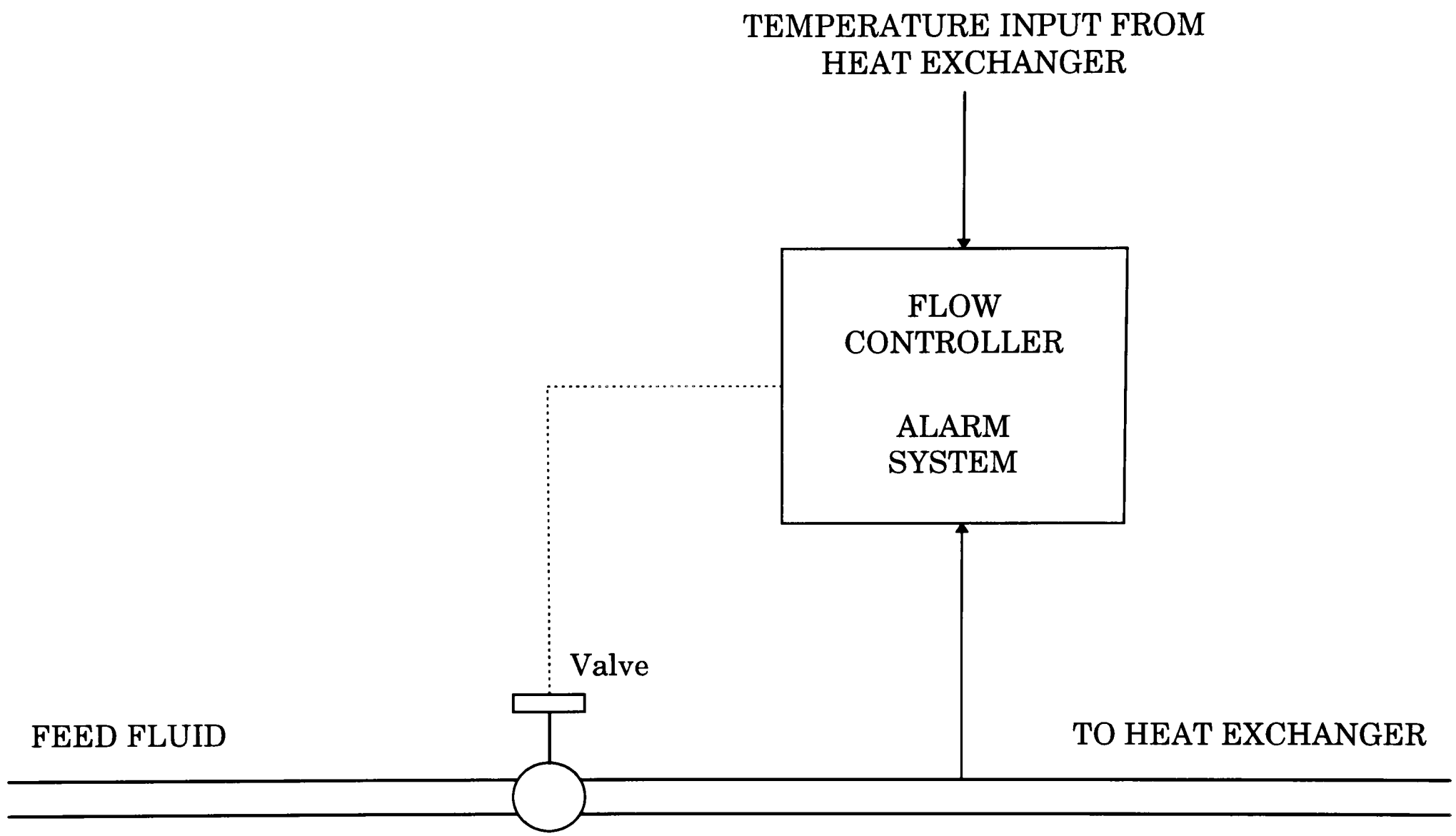


Figure 6.5 Block Diagram of Heat Exchanger Set-up

### 6.1.2 Results

Figure 6.6 shows an experimental run with a change in the set-point of the feed fluid, a controller with high gain (aggressive) and a controller with low gain (sluggish). At instant 400 the feed flow is changed from 70 lb./min to 20 lb./min, and at instant 700, the feed flow is changed from 20 lb./min to 70 lb./min. Since the flow reached and settled at its new set-point within the threshold value of badruns the watchdog did not trigger an alarm. At instant 1100 the fluid set-point is changed to 90 lb./min. The controller hits a constraint and so the fluid flow does not reach its new set-point. This condition triggers an alarm as shown in Figure 6.6. Now when the set-point is changed to 70 lb./min the fluid flow comes and settles at this value and so the alarm triggered by the monitoring system goes away. At instant 1900 the controller gain is increased, and so the watchdog alarm system triggers an alarm. The alarm remains on till the gain is reduced at instant 2150. At instant 2450 the flow set point is changed to 20 lb./min and the controller is made sluggish . A set point change is again made at instant 2750 with the sluggish controller.

In both the situations the watchdog triggers an alarm till the fluid flow finally settles at its set-point.

This experiment demonstrated that the watchdog can indicate when the controller is aggressive and /or when the controller is sluggish. Apart

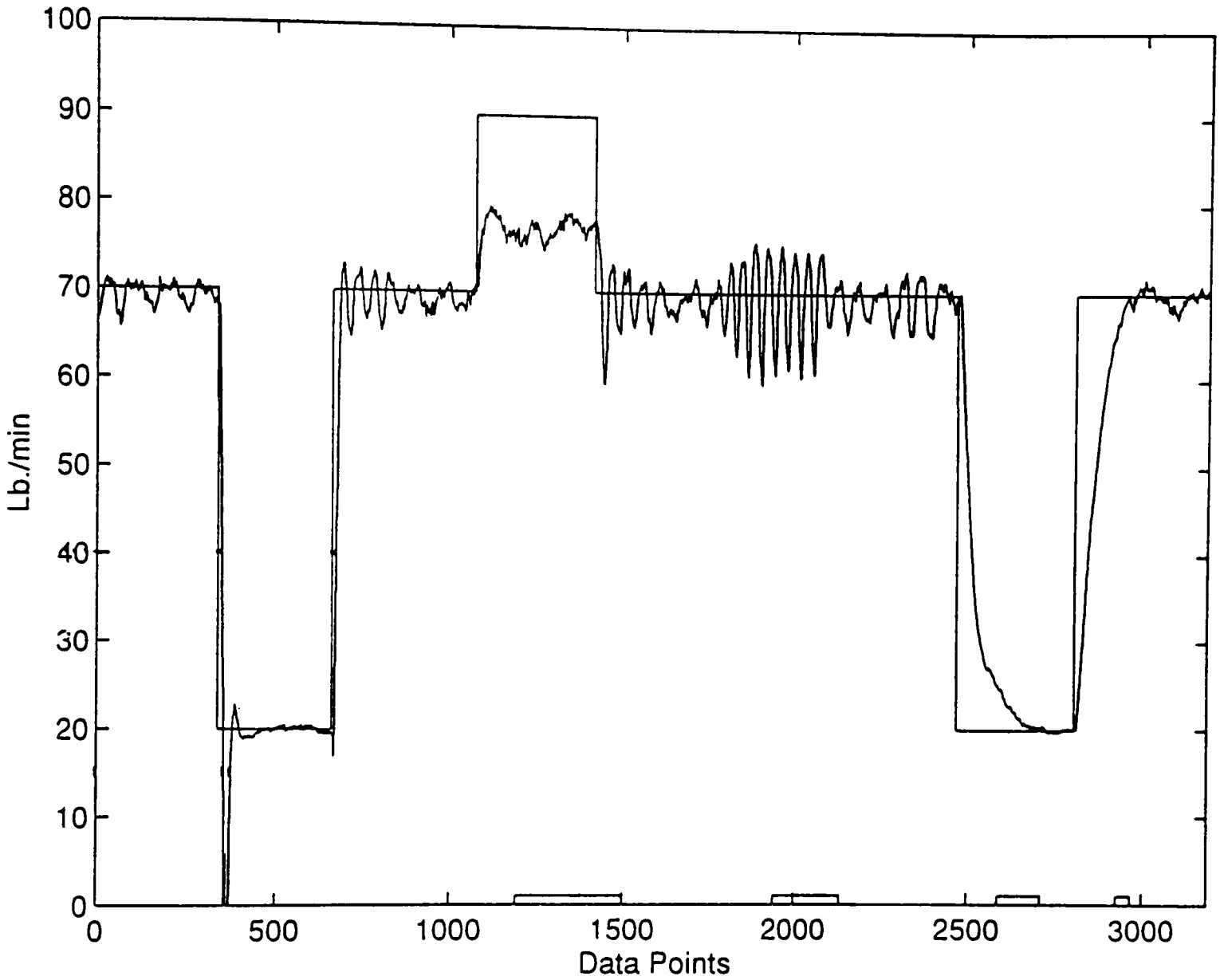


Figure 6.6 Experimental run on Heat Exchanger Flow Control

from this the watchdog is also effective when the controller hits a constraint and is not able to pull the process to its new set-point.

## 6.3 Flash Tank Dynamic Simulator

### 6.3.1 Simulator Description

The flash tank (Figure 6.7) involves a very fast and highly non-linear process, due its small dimensions. The feed is a liquid which consists of components A and B. The feed enters at a fixed flow rate and very high pressure. The pressure is low on the tank side of the flash valve. As liquid crosses into the low pressure region it flashes, boils, and fizzes. Component B preferentially flashes while Component A stays as a liquid. But some part of component A vaporizes, while some of B remains as a liquid.

The two flow control valves are FCV01 and FCV02 as shown in Figure 6.7. If FCV01 opens, more gas flows out, the tank pressure drops and component B vaporizes more. This makes the liquid that exists at the bottom purer. The reverse occurs if FCV01 closes. If FCV02 opens, liquid runs out of the tank faster and the liquid level drops, and the reverse occurs if FCV02 closes. Since the process is interactive, FCV01 also affects the level of the flash tank. If FCV01 opens, the pressure is reduced and the liquid isn't pushed out as fast. To prevent liquid A from accumulating, FCV02 opens simultaneously.

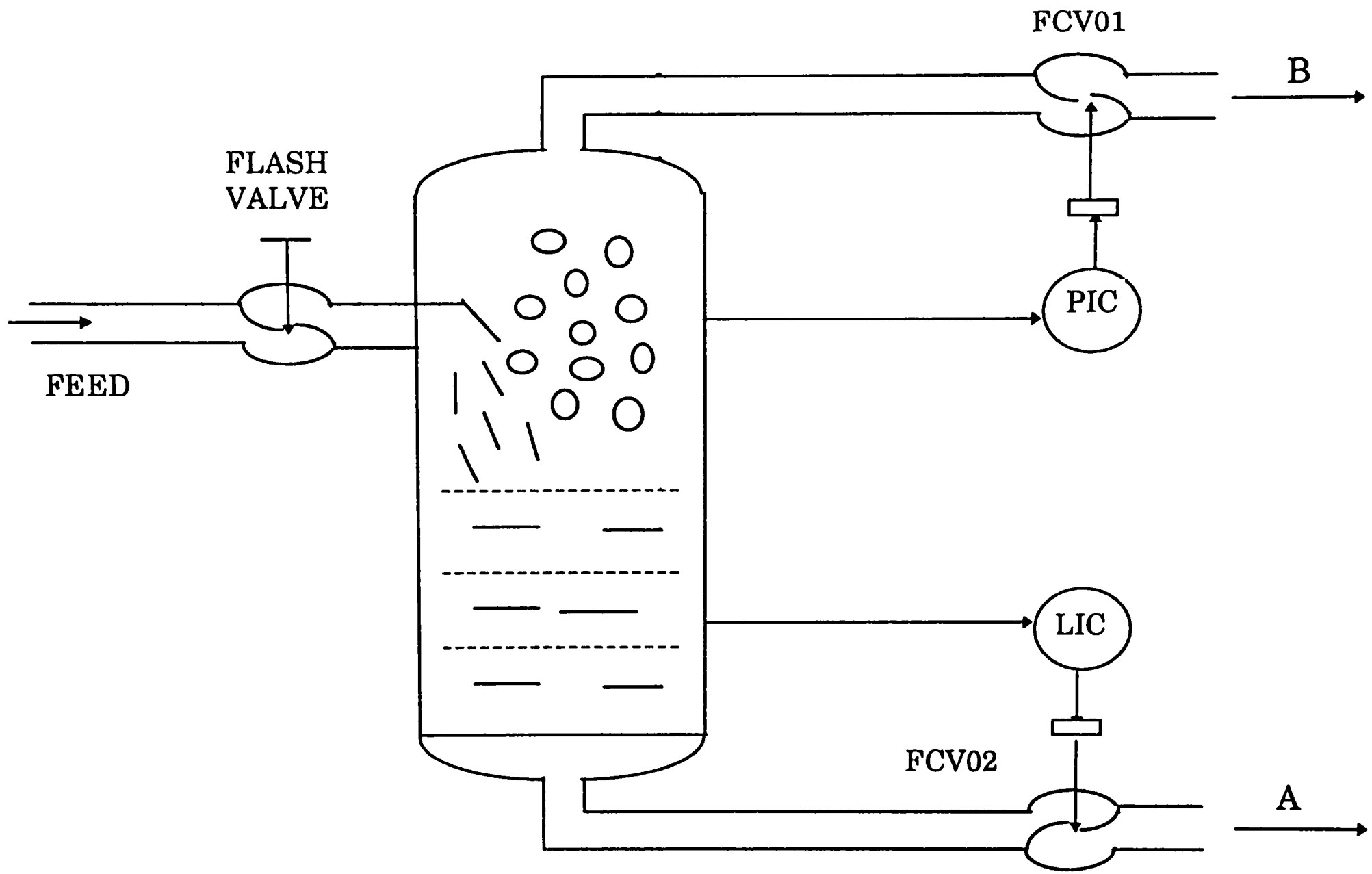


Figure 6.7 Flash Tank Dynamic Simulator

The main objective of the flash tank is to separate component B from A and keep the composition of A at 0.91. The level is maintained at 0.2m. The valves of the flash tank are controlled in such a way that the liquid level never rises above 0.8m and never falls below 0.075 m and also the pressure never goes above 350 kpa.

### 6.3.2 Fuzzy Control of Flash Tank

A Fuzzy logic controller is applied to valve FCV01 and FCV02 (Figure 6.7) of the flash tank dynamic simulator. The derivation of membership values for fuzzy rules to control the composition of component A is discussed in this section.

The two input variables to the fuzzy logic controller are the error in composition of component A as compared to its set-point and the rate of change of this error. The output variable is the change in stem-position. The fuzzy set definitions of these variables are shown in Figures 6.8, 6.9, and 6.10. The scale for the rate of change of error in Figure 6.9 is 10:1. The composition of component A also depends upon the percentage opening of valve FCV02. The fuzzy set definition of change in stem position of valve FCV02 is shown in Figure 6.11. The input variables to the fuzzy logic controller are the error in level of component A as compared to its set point and the rate of change of this error. This definition has been derived in the

same way as that of valve FCV01. A trial and error procedure is used to classify the various variables in the fuzzy sets.

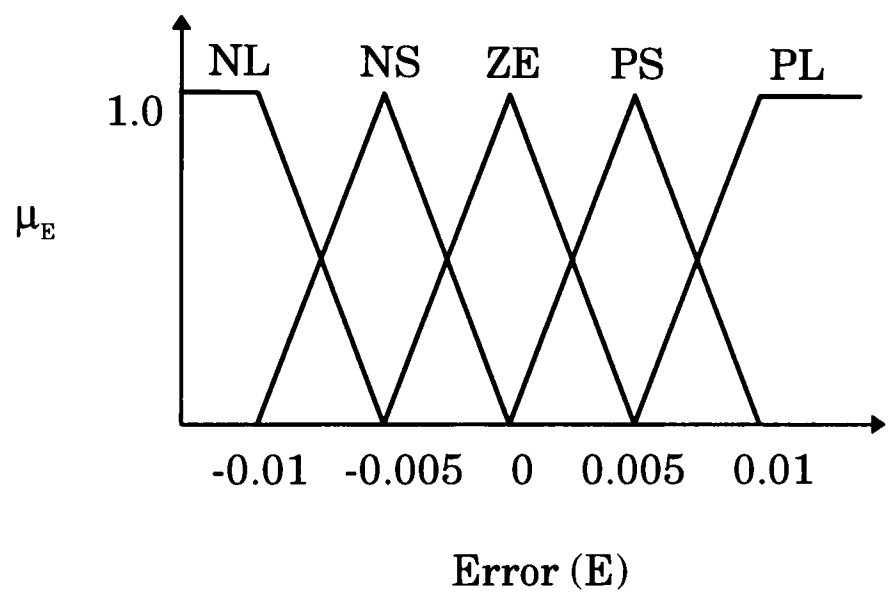


Figure 6.8 Fuzzy Set Definitions for Error in Composition

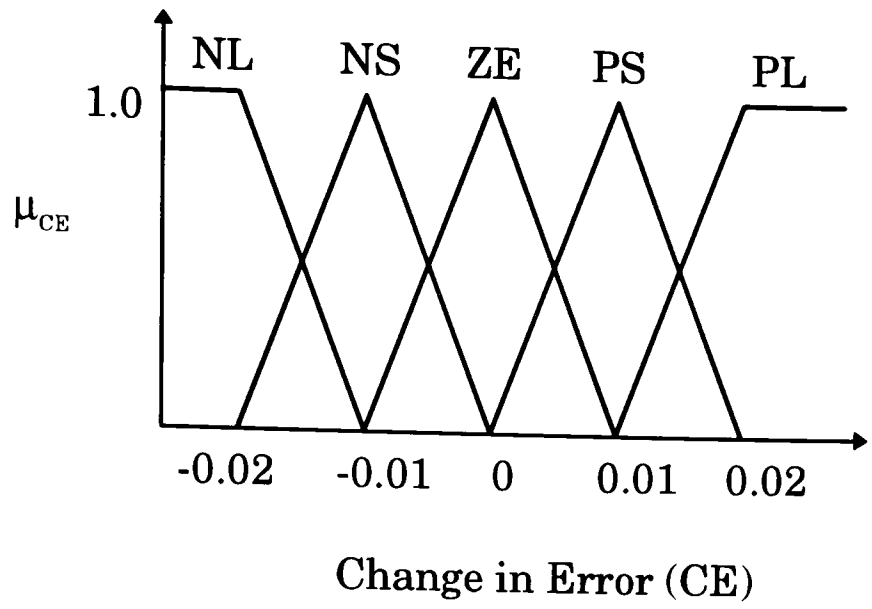


Figure 6.9 Fuzzy Set Definitions for Change in Composition Error

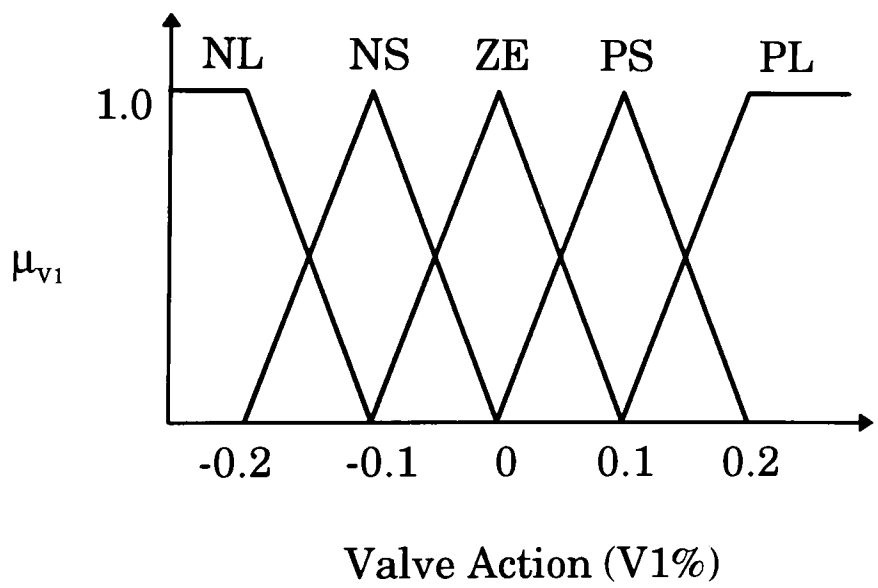


Figure 6.10 Fuzzy Set Definitions for Valve FCV01

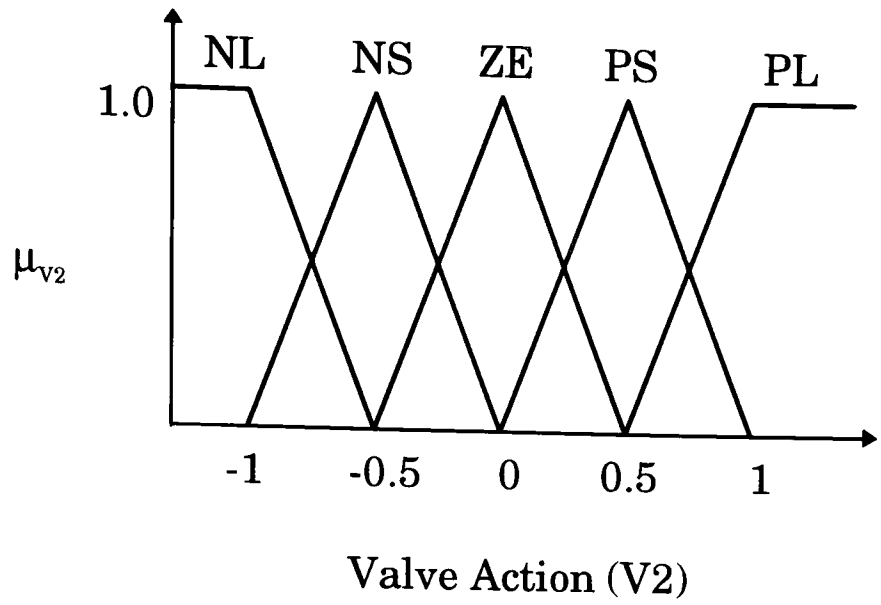


Figure 6.11 Fuzzy Set Definitions for Valve FCV02

### 6.3.3 Results

The results of adaptive control using the Fuzzy Logic Control strategy and on-line automatic evaluation of performance of a control loop are discussed in this section.

The triggering limits for the on-line monitoring system were calculated as per the steps listed in Chapter III (section 3.2, pg. 9). The fuzzy logic controller was implemented to control valves FCV01 and FCV02 of the Flash Tank Dynamic Simulator and its results are compared to those of the conventional PI controller. The control of the composition of component A is highly non-linear. When the composition goes from one operating region to another, a PI controller becomes sluggish or hits a constraint. To overcome

this problem, the fuzzy logic controller takes action based on the decision of the alarm system.

The performance of the PI controller is shown in Figure 6.12. The figure shows the plot of the composition of liquid component A. The controller is tuned optimally for a composition of 0.91. As can be seen in Figure 6.12 there is a negative spike in the beginning due to initial setup. The controller is able to bring the composition of component A to its set-point within a short interval of time and maintains the process at its set-point. At instant 140 the composition of component A is changed to 0.945. The controller pulls the process to its new set-point. Since the control of composition is nonlinear, the PI controller that was tuned optimally for the operating region around 0.91 behaves sluggishly in the operating region around 0.945. This makes for a long rise time. The watchdog triggers an alarm at instant 215 indicating that the controller is behaving sluggishly. The alarm remains on for a time period of 200 counts, after which the composition reaches the desired value of 0.945, as shown in Figure 6.12, and then the alarm goes away.

The performance of the fuzzy logic controller alone, is shown in Figure 6.13. The fuzzy logic controller maintains the composition at 0.91. A set point change in the composition is made at instant 135. The controller responds faster than the PI controller and pulls the composition towards 0.945. The watchdog triggers an alarm at instant 205. The fuzzy logic controller is able

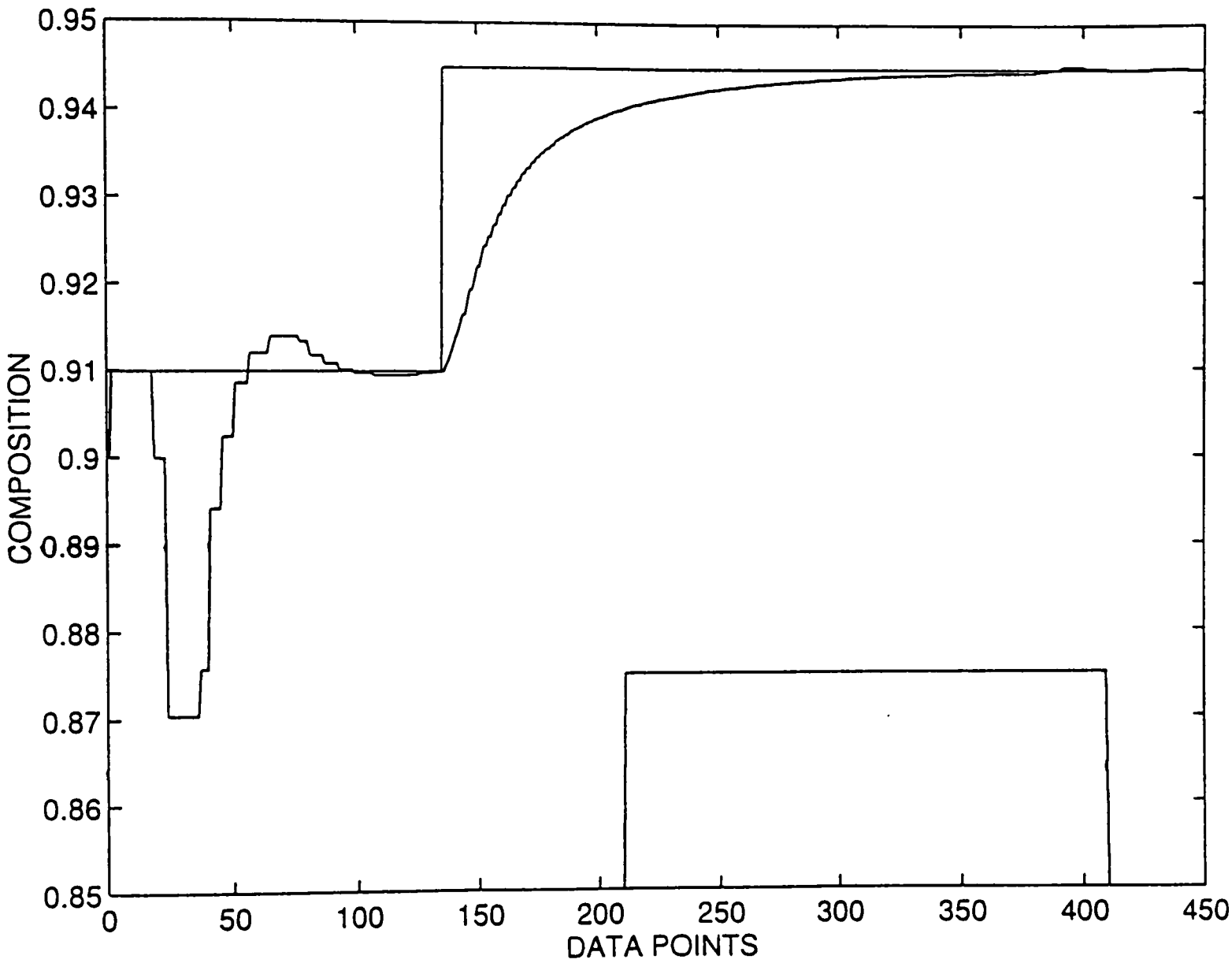


Figure 6.12 Composition of Liquid A controlled by PI Controller

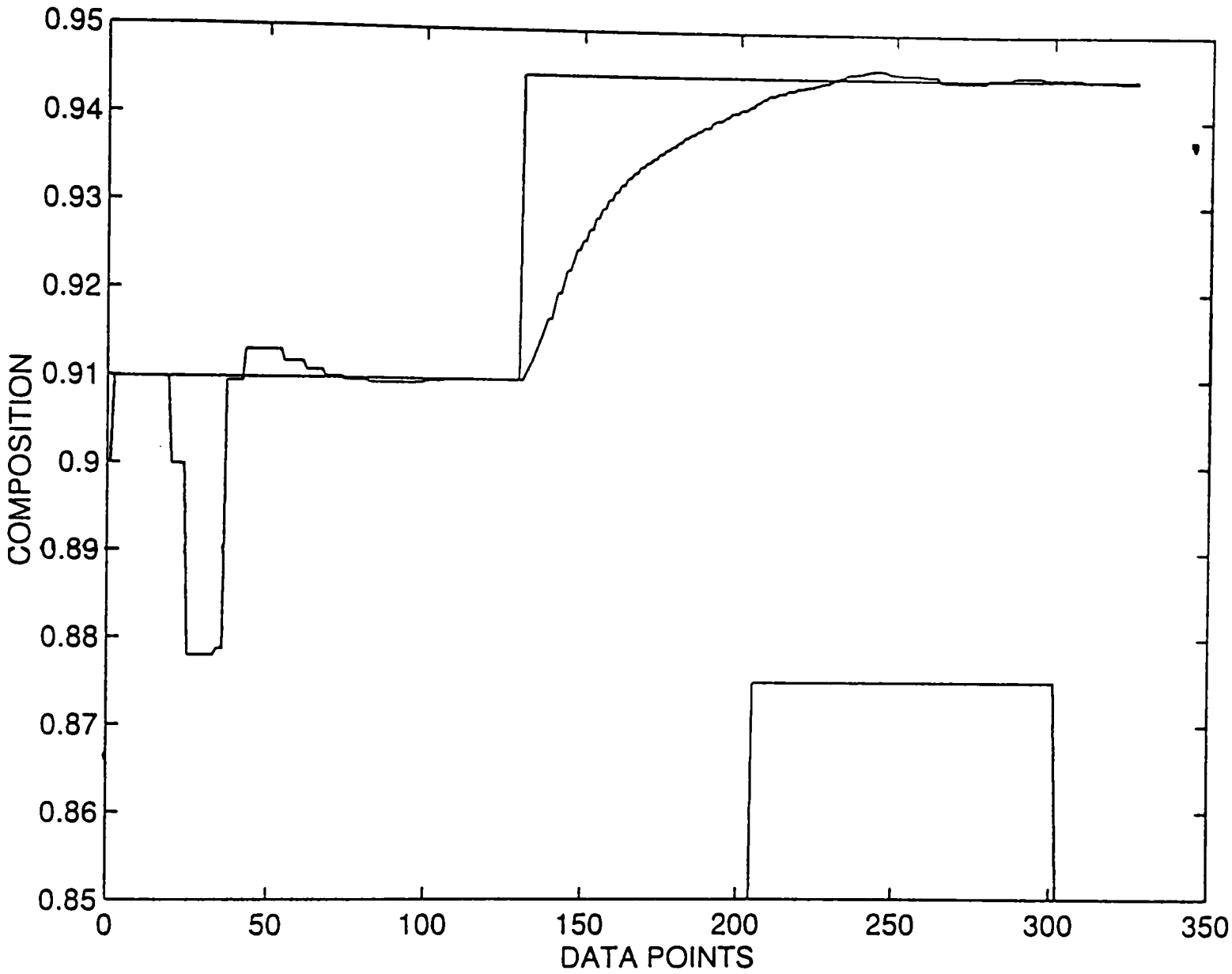


Figure 6.13 Composition of Liquid A controlled by FLC

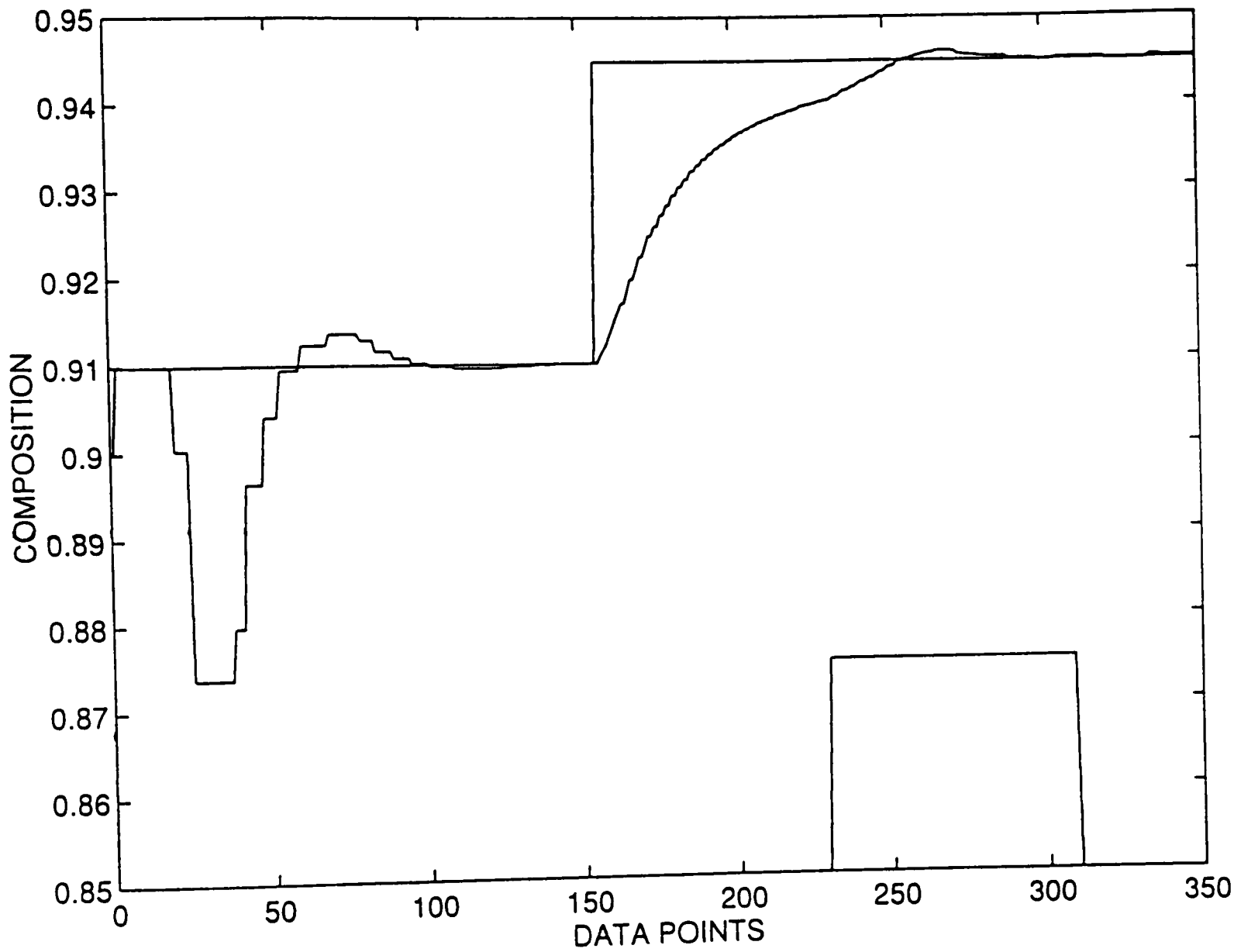


Figure 6.14 Composition of Liquid A controlled by FLC & PI Controller

to get the composition of A to its new set-point in a time period of 101 counts which is much shorter than the time taken by only PI controller on the system.

The performance of the fuzzy logic controller along with the PI controller is shown in Figure 6.14. The PI controller maintains the composition at 0.91. A set point change in the composition is made at instant 150. The controller behaves sluggishly and takes a long time to pull the composition to 0.945. The watchdog triggers an alarm at instant 230. Based on the alarm the system transfers control to the fuzzy logic controller. The fuzzy logic controller is able to get the composition of A to its new set-point in a time period of 81 counts which is much shorter than the time taken by only PI controller (and fuzzy logic controller only) on the system. The fuzzy logic controller demonstrated here exhibits good performance and results in a shorter settling time due to the combination of the watchdog alarm system.

# CHAPTER VII

# CONCLUSIONS

A new technique to monitor the performance of a controller system has been developed and experimentally demonstrated here. The technique uses a computationally simple, robust statistic; and compares it to the distribution of that statistic from a control period previously judged "good" by the user.

The statistically based technique is computationally inexpensive when compared to conventional techniques. The R-Statistic is dimensionless and independent of the past data values. Since it is a ratio of variances, it is also independent of process variance. Data from simulations and experimental process (pH Control and Heat Exchanger) show that for the recommended values of weighting factor, badrun threshold and $R_{crit}$, are effectively independent of the magnitude and distribution of the noise and the persistence of past data values. The combination of the monitoring technique with Fuzzy Logic Controller has also been show to be effective. The Fuzzy Logic Controller (FLC) is easy to build with practical knowledge. It is very flexible and the rules are easy to understand. The FLC gives better performance than conventional PI controller. This advanced control strategy accounts for nonlinearity of a process. If very little information is available about the actual process model, then a fuzzy logic controller, based on experimental knowledge, could be used. With the watchdog monitoring

system integrated to FLC system, the overall performance of the control system improves. The combination reduces the computational effort and tampering with the controller.

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