CONTROL SYSTEM BASED LOOP AND PROCESS MONITORING

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Due to about 10,000 km far away from China, I must thank my brother for everything he has done for me and my parents.

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I must place my gratitude and love for my parents and grandparents, whom I miss very much, on record.

To my wife and my parents

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ABSTRACT

For the sake of both economy and safety, the ability to diagnose a fault or disturbance is of great interest for an operator/engineer in process industries. To be practicable an on-line system with this capability must contain a suite of methods because no single method is likely to diagnose all possible faults. This thesis aims to contribute one novel component to this suite.

This thesis envisages the situation where the detection and diagnosis of faults and disturbances would be distributed to separate modules, each associated with the individual control systems located throughout a plant. In particular the thesis addresses those plants whose control systems inherently eliminate steady state error. Thus it seeks to address the large proportion of process plants that have proportional plus integral action as standard. By reasoning about changes in steady state an approach is proposed that requires very little process specific information and therefore should be attractive to control systems implementers who seek economies of scale. Because the approach can be implemented as modules that are largely based on standard control systems, the implementation can be configured and commissioned using various generic programmes and hence has the potential to be commercialised.

The approach is applicable to virtually all types of process plant, whether they are open loop stable or not, have a type number of zero or not and so on. It is founded on the application of both signed directed graph (SDG) and control systems theory to single and cascade control systems with integral action. This results in the derivation of cause-effect knowledge and fault isolation procedures that take into account factors like interactions between control systems, and the availability of non-control-loop-based measurements.

Following on from a survey of the more relevant methods published in the literature, a theoretical analysis is carried out of what happens to control systems when they are

subjected to various faults and disturbances. The main purpose is to derive equations to describe how control systems respond in the steady state to these occurrences. Although providing a foundation, these equations are unlikely to be suitable for direct use and a cause-effect analysis of the faults/disturbances involving signed-directed-graph (SDG) representation is then pursued. This leads to a search and test strategy for fault isolation involving interacting control systems, minimal knowledge acquisition and knowledge evolution. Since the approach is based on steady state deviations, a steady state change detection algorithm is proposed. The approach is tested by applying it to a continuous stirred tank reactor (CSTR) and to the Tennessee Eastman (T-E) process benchmark. Some recommendations are made for integrating the approach into a commercial software tool.

In principle, the approach can form the basis for the diagnosis of faults/disturbances in both control systems and in the process itself. One of the key features is that the approach can work at different levels of detail. Diagnosis is based on knowledge of the signs of steady state interactions (gains) between individual control loops, non-control-system-related measurements and on the steady state effects of disturbances. Both faults and disturbances (e.g. a load change) can be diagnosed, although diagnostic detail, i.e. degree of isolation, is clearly dependent on the measurements and knowledge that is available.

The concept of a distributed, control system based approach to the diagnosis of faults and disturbances, its development and application to various processes are all original, as are the integration aspects.

CHAPTER 1

INTRODUCTION

1.1 Background

The demand for real time diagnostic systems that enable the timely detection and isolation of abnormal operation is well-known. For instance, industrial statistics estimate the economic impact due to abnormal situations in the petrochemical industries in the US alone to be about US$20 billion per year (Nimmo, 1995). In addition "economic pressures are dispersing machine intelligence away from centralized computers toward distributed (Fieldbus) devices " (Clarke, 1995) to exploit economics of scale. If one looks at the measurements collected from a process plant, a large proportion relate to the control loops, the rest are largely collected to ensure that operation is within allowable constraints. Since these control loops are distributed throughout the plant, it seems sensible to examine the possibility of distributing fault detection and diagnosis tasks with them. Economies of scale would then be achieved by making use of common software which would be configured at the same time as individual loops were *tuned*. Clearly these economies of scale would be diminished if the algorithms were too plant specific and required knowledge not readily available from the plant.

1.2 The Overall Objective

This thesis describes a distributed process control system based, steady state approach for isolating incipient faults and disturbances in plants with control loops that inherently eliminate steady state error (Chen & Howell, 1998a, 1998b, 1998c, 1998d, 1998e, 1999a, 1999b). It is argued that this is the first step towards the long-term aim of providing distributed control systems with their own diagnostic capability so that they are not only self-validating, but are also able to isolate in-process faults.

In particular, the approach should be appropriate for the large number of process plants that adopt distributed proportional plus integral control strategies under supervisory control (Figure 1-1) (Chen & Howell, 1998d). Note the emphasis is on the steady state. Although the diagnosis of fault induced transients is clearly an issue and worthy of investigation, steady state analysis is equally important because it is quite possible that the 'faulty' plant would achieve a revised steady state. Clearly, in certain situations a new steady state would not be obtained and in others, the time to reach it might be too long. It is therefore envisaged that firstly other approaches would also be adopted and secondly a 'loose' definition of steady state would be required.

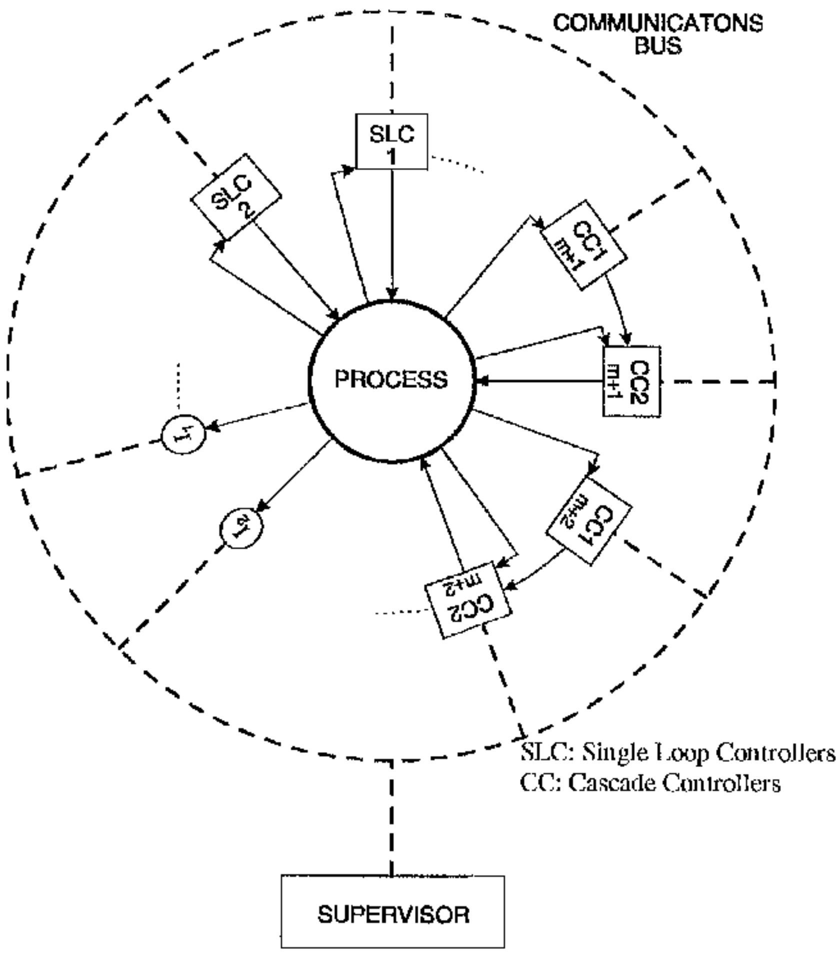


Figure 1-1: A distributed control system structure

Traditionally, a diagnostic engineer's view of feedback control is that it complicates, rather than aids, diagnostic reasoning. Feedback control adds to the complexity of fault detection in process plants by masking measurement deviations that might indicate a fault, and by making it difficult to distinguish between a sensor, actuator, or plant failure (Henry & Clarke, 1993). Wilcox & Himmelblau (1994a) have pointed out that control systems offer little decision-making assistance to an operator during the occurrence of process faults or abnormal disturbances, and in many cases, the actions of the control system can mask manifestations of the fault that would aid the operator in determining the cause of the process fault. In contrast to these opinions, this thesis attempts to show that some benefit can be obtained from individual controllers.

1.3 The Premise

Nowadays, feedback control loop components can be smart and have self-computational capabilities linked by a high-speed bi-directional data communication bus, which allows the central supervisory system to interrogate devices for status and other information. A natural extension to this structure would be to distribute fault detection and diagnosis (FDD) tasks in a similar way by associating a separate FDD module with each control system. The role of each of these modules would not be confined to the validation of the performance of the closed loops associated with it, each module would also monitor the performance of the process located in the proximity of these loops. The aim of monitoring performance is to detect and diagnose both faults and disturbances. The acronym FDD is then assumed to encompass both faults and disturbances. The boundaries specified for individual FDD module responsibilities would overlap one another and their union would encompass the entire plant. This overlapping would mean that devolution would not be complete necessitating some form of high level supervision and evaluation.

This thesis envisages a distributed FDD system which

- is modular in design;
- can be installed with minimal additional design costs;
- has low maintenance costs and
- can improve with operational experience.

This would be of considerable benefit for a large industrial process where scalability is a major issue. To be practicable such an FDD system would have to contain a suite of methods because no single method is likely to suit the diagnosis of all possible faults. This thesis aims to contribute one novel component to this suite, distributed steady state or pseudo steady state FDD.

It seeks to achieve these goals by

- making use of functional decomposition to produce novel simple signed directed graph (SDG) representations of a plant;
- basing these representations on a minimum amount of knowledge so that design costs and implementation effort are minimised;
- enabling these representations to evolve when additional knowledge becomes available after the FDD system is installed and is running;
- enabling individual control system FDD modules to reason about steady state deviations;
- knowing when a plant is in steady state and whether it has changed/deviated or not;
- gaining an understanding of control systems' steady state responses to various faults and disturbances and thereby
- developing a search and test strategy for inferring sets of likely fault/disturbance candidates from changes in steady state;
- making use of known interactions between control systems to improve this strategy;
- making use of a Supervisor to co-ordinate and to reach a final conclusion.

The approach (Figure 1-2) assumes that the plant meets the following fairly general criteria:

(1) controllers themselves perform to specification and all control loops are able to guarantee zero steady state error e.g. they have integral actions;

(2) controller outputs, together with measurements of the controlled variables are available as *observations*;

(3) the process is operated continuously.

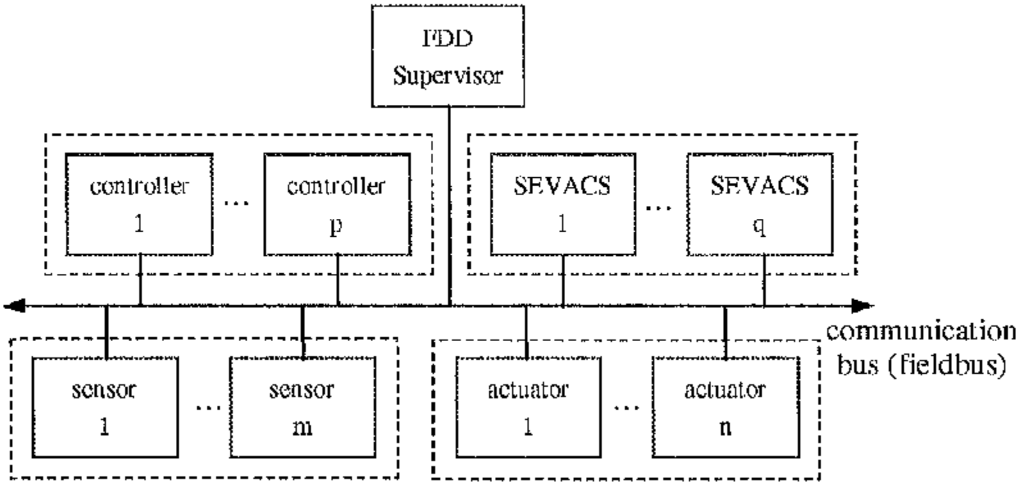


Figure 1-2: Plant-wide distributed self-validating control systems architecture

Note in Figure 1-2 that the term *self-validating control system* (SEVACS) has been adopted. Although not strictly correct, because the intention is that process faults as well as control system faults would be detected, SEVACS was chosen to acknowledge a certain similarity to SEVA components as described by Henry & Clarke (1993) and Clarke (1995).

The systems are designed in two stages, an offline design stage followed by an online design stage. The following steps are performed at the offline stage:

1) the plant is decomposed into compartments that broadly relate to individual process units;
2) for each compartment, each control system is examined in turn, and various characteristics of each control system are identified;
3) appropriate SEVACS configurations are then specified:
   - standard forms are adopted where appropriate ;
   - if not appropriate, the representation is analysed to generate one;
4) the FDD supervisor is specified. In particular an approach must be specified for integrating the various components of the FDD suite.

The various standard forms that are available are categorised by the types of control system installed:

- the process Type Number (Dorf, 1995);
- open loop stability.

The following steps are performed at the online stage:

1) the SEVACS is configured;
2) procedures are configured to detect changes in steady state;
3) the FDD supervisor is configured.

In addition, steady state gains between interacting loops need to be identified at either of the offline or online stages.

Finally it is envisaged that the suite of methods found in any FDD system that is installed on a process plant, might consist of 4 strategies:

1) a strategy using heuristic rules,
2) where available sensor and actuator validation (Clarke *et al.*, 1995),
3) a SEVACS approach and
4) a strategy based on governing equations and SEVACS.

The first strategy is well established (Kramer, 1987a; Becraft *et al.*, 1991,1993; Ayoubi & Isermann, 1996; Leonhardt *et al.*, 1997; Alonso *et al.*, 1998). It is essentially suitable for 'filtering out' the obvious faults or disturbances that are easy to diagnose. The second makes use of 'intelligent' or 'smart' hardware to generate device-specific diagnostic messages so that each individual sensor or actuator can have its own diagnostic capability. The third is the focus of this thesis. Like sensor and actuator validation, SEVACS can provide each control system with its own diagnostic capability. However, individual SEVACS do not have a global view so a Supervisor is needed to perform overall isolation. The fourth is an extension to an approach published by Kramer (1987a), which can be viewed as a verifier in the Supervisor.

Figure 1-3 summarises the overall procedure (Chen & Howell, 1998c). It is intended that the SEVACS would be configured using a number of generic computer programs.

The overall procedure can be described by the following action list.

- Decompose the plant functionally into compartments that broadly relate to individual control systems.

- Construct a simple representation of each compartment.
- Consider the design of the individual SEVACS within each compartment.
- Reason about deviations in measured variables by referring to these individual SEVACS: each SEVACS has 2 distinct features, cause-effect knowledge relating the deviations to likely faults and a choice of reasoning processes that are based on a search and test strategy.
- Configure, test and implement these SEVACS using a number of generic computer programs.
- Configure the Supervisor to co-ordinate the decision-making process.

Although the approach proposed here has the potential to be commercialised, more research is still needed on the generic programs, which should be considered from the viewpoint of software engineering and on the Supervisor where artificial intelligence techniques might be appropriate.

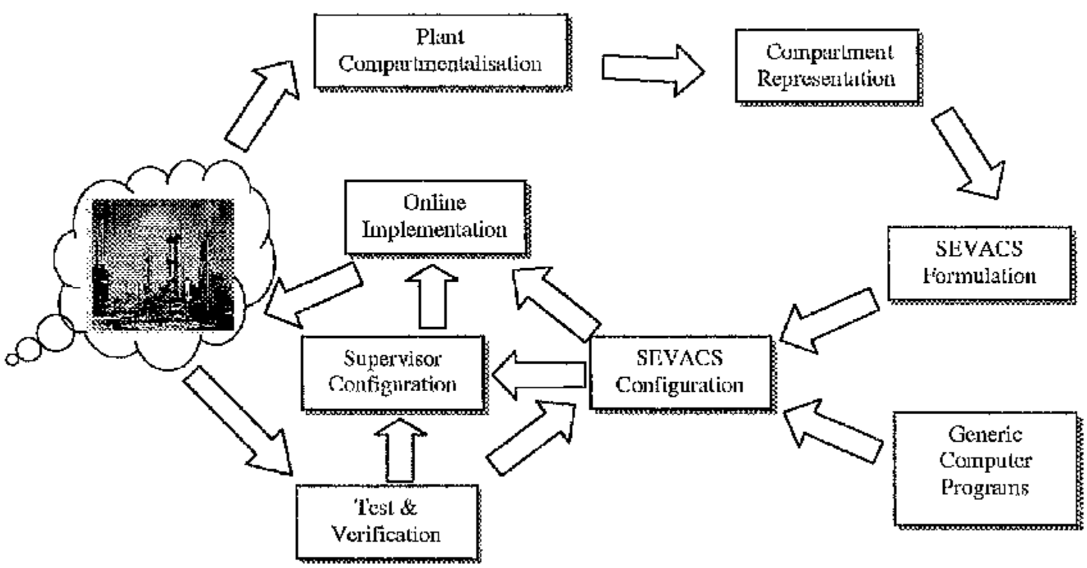


Figure 1-3: Development of the plant-wide diagnostic scheme

1.4 Outline of The Thesis

Chapter 2 contains a survey of those aspects of process monitoring and fault diagnosis that are important to this thesis. Thus there is an emphasis on functional decomposition, statistical approaches, model-based methods and the self-validating concept. Statistical approaches are included because they might be viewed as a competitor to the proposed approach. Although model-based methods have rarely been applied in process industries, they have attracted much academic interest because the principle of model-based methods is general and structurally attractive, and hence are discussed here. The self-validating concept is obviously relevant to this thesis and hence self-validating sensors, self-validating actuators and loop performance assessment are discussed.

To gain an understanding of the steady state performance of a control system when subjected to various faults/disturbances, a theoretical analysis is carried out in Chapter 3 for different processes, such as open-loop stable processes, open-loop unstable processes and capacitive processes. Various interactions between control systems as well as single loop control systems and cascade control systems will be discussed intensively for the purpose of fault detection and diagnosis.

It is a good philosophy to design systems that fit into the way people think when they perform a diagnosis, rather than to try to adapt people to fit them (Mjaavatten, 1994). In practice, people are accustomed to taking advantage of cause-effect knowledge to do fault diagnosis, so a more 'people-based' approach to understanding control system steady state response is to reason on the basis of simple SDGs. This is described in Chapter 4.

Various fault isolation issues, including the search and test strategy, will then be investigated in Chapter 5. A fault isolation principle and general procedure are suggested and by considering control system interactions, two alternative fault isolation improvements are introduced. One is to make use of different knowledge for different processes, the other is to make use of modified SDGs and to reason about them.

By now it should be clear that minimal amount of knowledge would be required to implement the proposed strategy on a plant. If this information is not available at the design stage, Chapter 6 introduces a method to acquire this by applying step tests. In addition the continued acquisition of knowledge is examined by proposing a framework and some guidelines for knowledge evolution so that the SEVACS based approach can have a learning and updating capability. A CSTR process is used as an application for illustrating the method and the framework.

Because the approach relies on knowing when a plant is in steady state and whether it has changed/deviated or not, a practical and useful steady state identification and change detection procedure is given in Chapter 7.

Chapter 8 will give two applications of self-validating control systems: one is to a simulated CSTR (Continuous Stirred Tank Reactor) (Appendix 1), the other is to a larger and more complicated chemical process benchmark, the Tennessee Eastman (T-E) process benchmark (Downs & Vogel, 1993) (Appendix 4). These two applications will show the potential use of self-validating control systems in process industries.

The conclusions of the work will be made and some future directions will be advised in the final chapter, Chapter 9.

1.5 Originality

The concept of a SEVACS, its development and application to various processes are all original, as are the integration aspects.

CHAPTER 2

SOME BACKGROUND TO PROCESS MONITORING AND FAULT DIAGNOSIS

This chapter reviews those general methods for process monitoring and fault diagnosis that had an influence on the development of the SEVACS approach. It is generally accepted that no single diagnostic method adequately addresses all the challenges of complex, industrial-scale diagnostic problems. As Venkatasubramanian (Harrold, 1998) says, *"One or two doctors are unable to diagnose the illness. It takes a team of specialists each looking at the symptoms, each developing an opinion, performing additional tests, and then conferring with team members to reach a final conclusion."*. And referring to chemical plants, *"Getting four or five methods looking at the same problem, each in its own unique way, yet each reaching the same conclusion is very challenging."*.

Although now 20 years old the comprehensive survey of Himmelblau (1978) still provides a basic introduction to fault detection and diagnosis methods that are available to the chemical process industry. Since the publication of that monograph, vigorous activity has resulted in many new approaches (see for instance, Watanabe & Himmelblau, 1982; Isermann, 1984, 1993, 1997; Frank, 1987; de Kleer & Williams, 1987; Milne, 1987; Peng & Reggia, 1987a, 1987b; Gertler, 1988, 1992, 1993, 1998; Patton *et al.*, 1989; Watanabe *et al.*, 1989; Chang *et al.*, 1990; Becraft *et al.*, 1991; Patton 1991; Basseville *et al.*, 1993; Blanke *et al.*, 1993, 1997; Mjaavatten, 1994; Chen, 1995; Blanke, 1996; Dorr, 1997; Isermann & Ballé, 1997; Leonhardt *et al.*, 1997; Mo *et al.*, 1997; Patton & Chen, 1997; Dragoni *et al.*, 1998; Gertler *et al.*, 1999). These various approaches can be classified in a number of different ways, for example, is the method quantitative or qualitative? signal-based, knowledge-based or model-based? artificial intelligence based or not? Is it based on neural networks, expert systems or fuzzy logic? (Kramer, 1987a, 1987b; Reiter, 1987; Rich & Venkatasubramanian, 1987; Finch *et al.*, 1990; Petti *et al.*, 1990;

Venkatasubramanian *et al.*, 1990; de Kleer *et al.*, 1992; Becraft & Lee, 1993; Kavuri, 1993; Kavuri & Venkatasubramanian, 1993a, 1993b, 1994; Lee, 1994; Rangaswamy 1995; Rangaswamy & Venkatasubramanian, 1995; Ayoubi & Isermann, 1996; Alonso *et al.*, 1998; Xiao *et al.*, 1998). The main advantage of using neural networks is that they only need the input-output data of the process, no detailed process models or other knowledge are necessary. However they need plenty of training data, face not only the problem of efficiency, but also the problem of the ability to detect and diagnose novel faults, and lack the physical explanation and understanding that can be useful to the operators. The expert system approach is a knowledge based heuristic solution that is simple and understandable. It has proved to be widely successful, provided the bottle-neck of knowledge acquisition, especially deep knowledge acquisition, can be overcome. Because vague information often exists in an engineering system, the approaches often recourse to fuzzy logic theory as provided by Zadeh (1973).

These are too many to be considered here in any detail, so this chapter will concentrate on the most relevant: knowledge-based hierarchical diagnosis using functional decomposition, statistical approaches, model-based methods, a self-validating concept and a control system performance index.

2.1 Hierarchical Diagnosis Using Functional Decomposition

In comparison to those nonhierarchical approaches that require process models and diagnostic algorithms sufficiently detailed to resolve individual faults at the unit level, the knowledge-based, multitiered and hierarchical diagnostic approach suggested by Finch and Kramer (1987) is arguably a more efficient and suitable approach to monitoring and improving large and complex processes. Based on functional decomposition, the approach has similarities to that proposed in this thesis. As such, some basics about their approach will be reviewed in this section.

Their approach is based on a two-stage diagnostic procedure. In the first stage, the potentially faulty systems of the plant are located. Based on the states of systems adjacent to the faulty system, the second stage involves the application of rules that narrow the fault candidate space further. This procedure is common and general to a lot of FDD systems.

For a large-scale plant, a proper decomposition or abstraction of the plant into a set of subsystems can reduce the perceived complexity of the plant in question. When a fault occurs, the fault diagnosis task can be quickly narrowed by identifying those affected control systems or other measurements in one or more of these sub-systems.

Rasmussen (1985) & Scarl *et al.* (1987) have observed abstraction in two dimensions: a structural dimension corresponding to physical groupings of components, and a functional dimension related to the purpose and behaviour of the equipment. Theoretically functional information should be discernible from structural descriptions, but in complex devices this transition is difficult (Davis, 1984). Finch and Kramer's functional decomposition (1988) deliberately masks details of system structure that are irrelevant at the early stages of the diagnostic task. This avoids the approach seeking all units that are causally connected to all fault symptoms via flows of mass, energy or information and hence requiring complete measurement of stream variables for complete effectiveness. Thus recycle streams and control feedback loops can be accommodated.

Finch and Kramer's functional decomposition idea is not only beneficial to whole plant compartmentalisation, but also to the identification and investigation of interactions between SEVACS. In their approach, the plant is represented as a set of abstract functional subsystems, each responsible for controlling certain aspects of the overall process. Any abnormal measurements would mean one or more of these subsystems is malfunctioning. Then by identifying the process units or control system components responsible, either directly or indirectly, for the regulation of the measurements that are abnormal, the focus of the diagnosis can quickly be narrowed to those components. The objective of their work is to identify the malfunctioning subsystems, not the actual faults within them. The latter is part of the work in this thesis.

However, having emphasised decomposition, Finch and Kramer fail to decompose the reasoning processes as well by focusing on process performance as a whole. In many ways, the focus of this thesis attempts to address this failure.

Another aspect of their work is that they classify three system types:

- control systems are characterised by an ability to actively regulate the process through manipulation of various process variables and parameters;
- passive systems or open-loop systems can be identified as those systems that produce measured outputs not directly involved in process regulation;
- external systems are systems on the periphery of the process being analysed, they can be either control systems or passive systems.

Control systems are deemed to have four states (Table 2-1), all of which depend on the deviation of control error e and the deviation of manipulated variable x from their nominal values. If both deviations are within their tolerances, the system is functional. If a fault/disturbance occurs but can be compensated by a control action, the system is said to be stressed. If the system is unable to compensate for a fault/disturbance, it is saturated. If the regulatory mechanism of the system fails to work, the system is uncontrolled.

Table 2-1: Four control system states (Finch and Kramer, 1988)

Observation	States
$\lvert e \rvert > 0$ & $\lvert x \rvert > 0$	Functional
$\lvert e \rvert > 0$ & $\lvert x \rvert \pi 0$	Stressed
$\lvert e \rvert \pi 0$ & $\lvert x \rvert > 0$	Uncontrolled
$\lvert e \rvert \pi 0$ & $\lvert x \rvert \pi 0$	Saturated

Passive systems have two states: functional and malfunctional. If the measured outputs of the passive systems deviate from their desired values, the systems are malfunctioning; otherwise, the systems are functioning.

In this thesis, the focus of the SEVACS approach is on diagnosing those sensor biases, valve biases and process disturbances that cause control systems to be stressed. However those faults or disturbances that cause control systems to be uncontrolled or saturated can still be diagnosed by that part of the hybrid approach that consists of a strategy using heuristic rules.

2.2 Statistical Approaches

Statistical approaches are prevalent in process industries, particularly in the detection of faults. Their main role in this thesis is in the detection of a change in steady state (Chapter 7). As will be discussed here, they are of little use for fault isolation. To explain why this is the case, univariate statistical process control (SPC) and multivariable SPC, which is one of hot topics in process monitoring, will be introduced briefly.

2.2.1 Univariate Statistical Process Control (USPC)

Univariate statistical process control (USPC) is a traditional method of monitoring, controlling and, ideally, improving a process through statistical analysis. There are seven major tools for USPC, they are often called "the magnificent seven" (Montgomery,1990):

- histogram;
- check sheet;
- Pareto chart;
- cause and effect diagram;
- defect concentration diagram;
- scatter diagram;
- control chart.

Among these magnificent seven, the control chart is the simplest type of on-line USPC procedure for process monitoring and fault diagnosis. The typical control chart given in Figure 2-1, shows a graphical display of sample measurements versus time. The chart contains a centre line (CL), which represents that value expected when the characteristic variable is in its in-control state, and two other horizontal lines, called the upper control limit (UCL) and the lower control limit (LCL).

When the process variable is subject only to tolerable random fluctuations, all of the sample points will fall between the control limits (UCL and LCL) and scatter above or below the CL randomly; it is said that the process variable is in statistical control (or in control) and no action is necessary. However, a point that plots outside of the control limits is an indication that the process is out of statistical control (or out of control), and investigation and corrective action is required to find and eliminate the assignable cause or causes responsible for this behaviour.

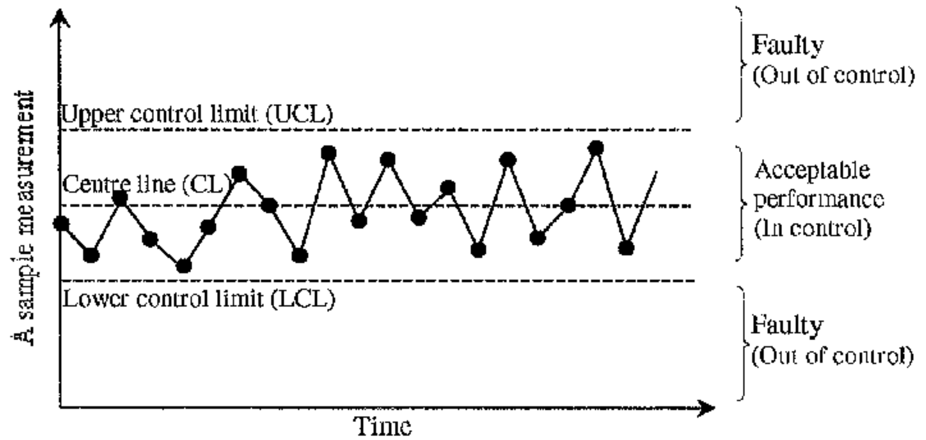


Figure 2-1: A typical control chart

The control limits can be determined from probability confidence intervals. Regardless of the distribution of the characteristic variable, it is standard practice in the United States to specify the control limits as a multiple of the standard deviation of the statistic plotted on the chart. The multiple usually chosen is 3; hence, 3-sigma limits are customarily employed on control charts, regardless of the type of chart employed.

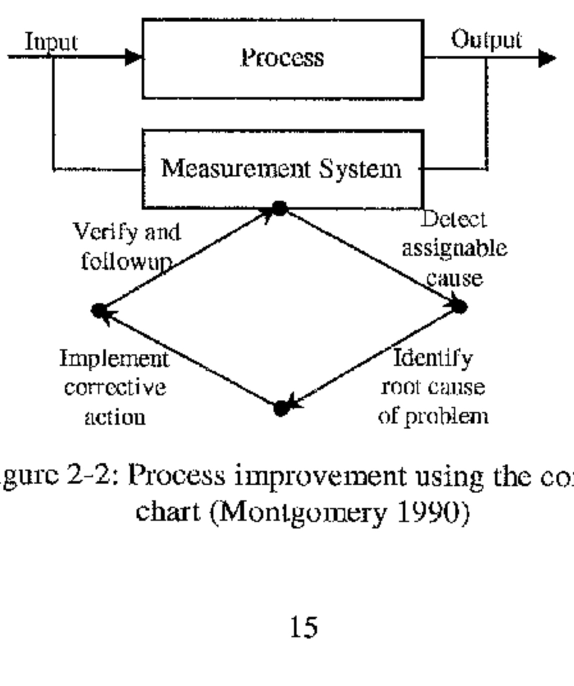


Figure 2-2: Process improvement using the control chart (Montgomery 1990)

Figure 2-2 illustrates a procedure for using a control chart to detect a fault and improve the process. The control chart will only detect assignable causes; management, operator and engineering action will usually be necessary to identify then eliminate the cause.

USPC can only be used as an indicator for faulty conditions. To diagnose and identify these faulty conditions remains a heavy duty for the operator. The operator might make use of either his/her own knowledge or some other tools such as expert systems to perform fault diagnosis further. However this task is beyond the ability of USPC.

2.2.2 Multivariate Statistical Process Control (MSPC)

Although the above conventional USPC methods are widely used in the field of process monitoring and fault detection, they are fraught with problems, notably (Wilson *et al.*, 1996):

- alarms are not raised until the fault is actually manifesting itself at the outputs, by which stage it may be too late to prevent product quality from being adversely affected;
- noise on the outputs will often be large enough to mask incipient faults until they have become quite serious; implementing a control loop on an output variable will also tend to "cover up" problems;
- many large plants have so many measured variables that it would be extremely cumbersome to attempt to monitor all of them separately.

MSPC aims to solve the above problems by treating a large number of data simultaneously, extracting more confirmatory information from observations on many variables and reducing the noise levels through averaging. Extensive research into the application of MSPC to process monitoring and fault detection has been done in recent years with considerable effort being put into implementation in real process industries.

Although, like USPC, there are multivariate versions of the Shewhart chart, the CUSUM chart and the EWMA chart, the most practical approaches to MSPC appear to be those based on multivariate statistical projection methods among which principal component analysis (PCA) and partial least squares (PLS) are the two most widely used. PCA and PLS methods are ideal for handling the large number of highly correlated and noisy process variable measurements that are collected by process computers on a routine basis; they can also handle missing data arising from sensor failure while multivariate control charts can't (MacGregor *et al.*, 1995) .

2.2.2.1 PCA and PLS Models

A PCA model decomposes an $m \times 1$ normalised vector into two portions,

$$\mathbf{x} = \hat{\mathbf{x}} + \tilde{\mathbf{x}}$$

$\hat{\mathbf{x}}$ and $\tilde{\mathbf{x}}$ are the modelled and residual portions of $\mathbf{x}$, respectively. Vector $\hat{\mathbf{x}}$ is the projection of $\mathbf{x}$ on its principal component subspace(PCS):

$$\hat{\mathbf{x}} = \mathbf{P}\,\mathbf{t} = \mathbf{P}\mathbf{P}^{\mathrm{T}}\mathbf{x} = \mathbf{C}\,\mathbf{x}$$

where $\mathbf{P}$ is the $m \times l$ PCA loading matrix, $\mathbf{t}$ is the $l \times 1$ score vector, $l \leq m$ is the number of principal components(PC) and $\mathbf{C}$ is an $m \times m$ projection matrix on the l dimension PCS. Vector $\tilde{\mathbf{x}}$ can be viewed as the projection of $\mathbf{x}$ on its residual subspace(RS):

$$\tilde{\mathbf{x}} = (\mathbf{I}-\mathbf{C})\,\mathbf{x} = \tilde{\mathbf{C}}\,\mathbf{x}$$

where $\tilde{\mathbf{C}}$ is an $m \times m$ projection matrix on the m-l dimension RS.

In the above, the loading matrix $\mathbf{P}$ can be determined by l eigenvectors, $[\mathbf{p}_1\ \mathbf{p}_2\ \dots\ \mathbf{p}_l]$, of the covariance matrix $\mathbf{\Sigma}_{m \times m}$ of the reference matrix $\mathbf{X}_{n \times m}$ which includes n rows of fault-free measurements of m variables, where $\mathbf{\Sigma}$ can be estimated by $\mathbf{X}^{\mathrm{T}}\mathbf{X}/(n\text{-}1)$, $\mathbf{p}_1$ is the eigenvector with the largest corresponding eigenvalue λ_1, $\mathbf{p}_2$ is the eigenvector with the second largest corresponding eigenvalue λ_2, ..., and $\mathbf{p}_l$ is the eigenvector with the l largest corresponding eigenvalue λ_l.

PCA can be viewed as the special case of PLS and PLS can be viewed as an extension of PCA. The difference is that the reference data of PLS includes not only the measurement matrix $\mathbf{X}$, but also the process quality data matrix $\mathbf{Y}_{n \times q}$ which consists of n rows of analytical values of q process quality variables.

Information is extracted that explains not only the variation in the process data $\mathbf{X}$, but also the variation in the product quality data $\mathbf{Y}$. Thus PLS may detect an out-of-control situation online before lab data on product quality becomes available. PLS can accomplish this by working on the reference covariance matrix of $(\mathbf{X}^T\mathbf{Y})(\mathbf{Y}^T\mathbf{X})$ instead of $\mathbf{X}^T\mathbf{X}$ as with PCA.

PCA or PLS model can be illustrated geometrically by Figure 2-3. In a well defined model, $\hat{\mathbf{x}}$ can be very close to $\mathbf{x}$ and can capture the intrinsic correlation among variables; the magnitude of $\tilde{\mathbf{x}}$ should be very small.

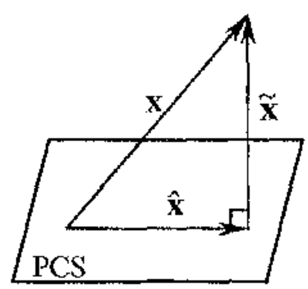


Figure 2-3: Geometrical explanation of PCA or PLS model

2.2.2.2 Fault Detection Using PCA or PLS Models

From the viewpoint of process monitoring, a change in variable correlation indicates an unusual situation because the variables do not conserve their normal relations. Under this situation the sample $\mathbf{x}$ increases its projection $\tilde{\mathbf{x}}$ on the residual subspace (RS). As a result, the magnitude of $\tilde{\mathbf{x}}$ reaches unusual values compared to those obtained during normal conditions.

Typically there are two methods using PCA or PLS to detect abnormal conditions in a process. One is based on the score distance and another is based on the model residual.

(1) The score distance based method

Testing if an observation is within the control envelop can be performed on a modified Hotelling's T^2-*statistic* s_i (MacGregor *et al.*, 1995):

$$s_l < s_\alpha$$

$$\text{with } s_l = \sum_{i=1}^{l} \frac{t_i^2}{\lambda_i^2} \text{ and } s_\alpha = \frac{m(n-1)}{(n-m)} F_{m,n-m,\alpha},$$

where t_i is the ith element in the score vector $\mathbf{t}$ and $F_{m,n\text{-}m,\alpha}$ is the *F-statistic* at confidence level α.

(2) The model residual based method

Another statistic for detecting abnormal conditions is the Square Prediction Error (SPE) on the residual subspace(RS):

$$\text{SPE} = \|\tilde{\mathbf{x}}\|^2 = \mathbf{x}^T \tilde{\mathbf{C}} \mathbf{x}$$

Jackson and Mudholkar (1979) developed a confidence limit expression for the SPE when $\mathbf{x}$ follows a normal distribution, which is known as the *Q-statistic*: the process is considered normal if $\text{SPE} \le \delta_\alpha^2$ and there exists an abnormal condition when $\text{SPE} > \delta_\alpha^2$,

where

$$\delta_\alpha^2 = \theta_1 \left[\frac{c_\alpha \sqrt{2\theta_2 h_0^2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2} \right]^{1/h_0}$$

and

$$\theta_i = \sum_{j=l+1}^{m} \lambda_j^i \qquad \text{for } i=1,2,3;$$

$$h_0 = 1 - \frac{2\theta_1\theta_3}{3\theta_2^2},$$

where c_α is the confidence limit for the 1-α percentile in a normal distribution; λ_1, $\lambda_2, \ldots, \lambda_l, \lambda_{l+1}, \ldots, \lambda_m$ are eigenvalues, in descending order, of the covariance matrix $\mathbf{X}^T\mathbf{X}$.

The result is derived under the following assumptions:

- the sample vector $\mathbf{x}$ follows a multivariate normal distribution;

- the result holds regardless of how many principal components are retained in the model;
- an approximation for the distribution is made when deriving the confidence limit.

To reduce unnecessary false alarms in cases where the data are not normally distributed, exponentially weighted moving average (EWMA) filters can be applied to the residuals. Since an EWMA filter is roughly equivalent to a windowed approach to a group of data samples, the filtered residuals are closer to normal distribution than the unfiltered residuals. The general EWMA expression for residuals is :

$$\bar{\mathbf{e}}_k = (\mathbf{I} - \Gamma)\bar{\mathbf{e}}_{k-1} + \Gamma\tilde{\mathbf{x}}_k ,$$

$$\overline{\mathrm{SPE}}_k = \|\bar{\mathbf{e}}_k\|^2 .$$

Although the $\overline{\mathrm{SPE}}$ is designed to reduce false alarms and provide more flexibility in detecting different types of faults, the original *Q-statistic* developed by Jackson *et al.* is not applicable any more. Qin *et al.*(1997) have extended the *Q-statistic* for the $\overline{\mathrm{SPE}}$ under the simplicity assumption $\Gamma = \gamma\mathbf{I}$ and defined a tighter confidence limit $\bar{\delta}_\alpha^2$ for the $\overline{\mathrm{SPE}}$:

$$\bar{\delta}_\alpha^2 = \frac{\gamma}{2-\gamma}\delta_\alpha^2 .$$

As a consequence , the *Q-statistic* for the $\overline{\mathrm{SPE}}$ is as the following: the process is considered normal if $\overline{\mathrm{SPE}} \le \bar{\delta}_\alpha^2$ and there exists an abnormal condition when $\overline{\mathrm{SPE}} > \bar{\delta}_\alpha^2$.

2.2.2.3 Fault Diagnosis Using PCA or PLS Models

Multivariate control charts based on PCA or PLS can help to diagnose assignable causes. By interrogating the underlying PLS or PCA model at the point where an event has been detected, one can extract diagnostic or so-called contribution plots which reveal the group of process variables making the greatest contributions to the deviations in the SPE or the scores. Although these plots will not unequivocally diagnose the cause, they will provide much greater insight into possible causes and thereby greatly narrow the search (MacGregor *et al.*, 1995). An alternative means of fault diagnosis would be to analyse the path of the score vector after the fault has been detected. However the abstract nature of the scores means that such diagnosis would depend on knowing which faults tend to cause the scores vector to move in a given direction, which, of course, requires a large database of past "faulty" plant behaviour, not to mention a good pattern recognition system (Wilson *et al.*, 1996).

In short, PCA or PLS models have great potential for use in fault detection systems in process industries as long as the variables are highly correlated. However they are unlikely to detect a fault in a controlled variable because these don't correlate to other variables. Of most significance to this thesis is that rarely can they be used for fault diagnosis.

2.3 Analytical Redundancy Based Methods (Model-Based Methods)

Model-based methods using analytical redundancy are still very attractive for researchers because of their elegant mathematical structures and explanations. Unfortunately they have limited applications in the process industries because of their need for complicated models. Mainly for theoretical completeness, these methods will be introduced in this sub-section briefly.

In order to perform the task of fault detection and fault diagnosis, it is necessary to access redundant information of the process. Three redundancy techniques are available theoretically and practically (Clarke, 1995; Rengaswamy, 1995):

(1) physical redundancy: multiple sensors are installed to measure a particular variable, normally this is restricted by cost and physical conditions although it is often necessary in safety critical processes such as in the nuclear and aerospace industries; data fusion theory can be used to analyse multiple data from various sensors;

(2) data redundancy: this makes use of history data and *a prior* knowledge; for example, the signal data required for control is often of low bandwidth, higher

frequency components in the raw data can often indicate fault modes; statistical analysis is a kind of data redundancy technique;

(3) analytical redundancy: the philosophy is to use mathematical models of the fault-free process to determine how different measurements should relate. If the relations don't hold, something is wrong. The pattern of the deviations between the predicted relations and the normal relations can then be used to distinguish the fault.

2.3.1 Introduction to The Analytical Redundancy Technique

Analytical redundancy based methods generally fall into one of three categories (Chow & Willsky, 1984; Isermann *et al.*, 1984, 1993, 1997b; Frank, 1987; Gertler, 1988, 1998; Patton *et al.*, 1989, 1991, 1997; Leonhardt & Ayoubi, 1997):

(1) parity space based methods;

(2) observer based methods;

(3) parameter estimation based methods.

All three suffer from the following complications:

- unmeasured disturbances and normal measurement noise;
- modelling errors;
- the mapping from deviation patterns to causes.

The different approaches share a common methodology which can be summarised by the two steps shown in Figure 2-4:

(1) residual generation: mathematical models are used to generate residuals, which are variables sensitive to faults; the residuals are designed to be zero or close to zero under normal (non-faulty) conditions and deviate significantly from zero if a fault occurs;

(2) residual analysis and decision making: this aims at detecting and, if possible, isolating the faults. While a single residual may be sufficient to detect a fault, a set of residuals is needed for the isolation of the fault. For ease of solution, one of two approaches is generally chosen. One is to use residuals that are said to be structured when each residual is designed to be sensitive to a given subset of faults, while remaining insensitive to other faults. The other way is to use

directional residuals which are designed to lie in a fixed fault-specific direction in the residual space in response to a particular fault.

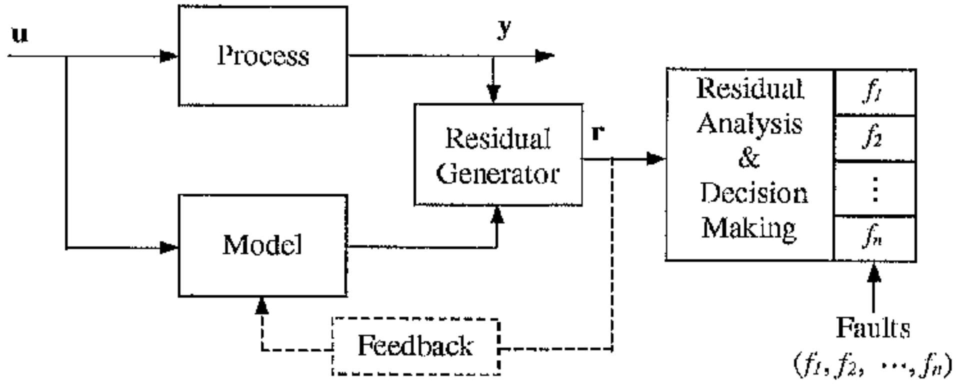


Figure 2-4: The general structure of model-based FDD schemes

The different approaches are closely related because all of them evaluate the same signals, namely the inputs and outputs of the actual process of interest. Hence only the parity space approach will be explained in detail, with a very brief introduction given for the others. Depending on the situation, each of the methods might be more or less efficient and hence the approaches are often used in combination.

2.3.2 Fault Detection Using Parity Space

The term *parity* is inspired by the use of parity bits for error checking in digital data transmission: an extra parity bit is added to a group of bits so that the coincidence of the binary sum of the digits before and after the transmission can be checked, any contradiction indicates a transmission error. By analogy, in the FDD area, the parity vector is a function of the measured and manipulated variables defined in such a way that a non-zero value indicates a fault while it is zero in normal conditions.

2.3.2.1 The Static Parity Space

The parity space approach is most clearly explained using an algebraic system having an unknown state vector $\mathbf{x}$ of dimension n, and a measurement vector $\mathbf{y}$ of dimension q. It is assumed $\mathbf{y}$ is related to $\mathbf{x}$ by the algebraic equation:

$$\mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{f} + \boldsymbol{\eta},$$

where **C** represents the $q \times n$ observation matrix, $q \times 1$ vector **f** contains instrument faults and is zero when there is no fault, $q \times 1$ vector $\boldsymbol{\eta}$ contains zero-mean measurement noises. Since **x** is unknown, the idea is to eliminate it in the previous equation in the following way: one defines the subspace called parity space, spanned by the row vectors of a $(q-n) \times q$ matrix **V** so that:

$$\mathbf{V}=\{\mathbf{v} \text{ independent} \mid \mathbf{v}^{\mathrm{T}}\mathbf{C}=\mathbf{0}\}.$$

By projection of the initial equation in the parity space, $q-n$ independent analytical redundancy relations are obtained given by:

$$\begin{aligned}\mathbf{p}&=\mathbf{V}\mathbf{y}\\ &=\mathbf{V}\mathbf{f}+\mathbf{V}\boldsymbol{\eta}.\end{aligned}$$

The columns of **V** define q distinct fault directions associated with each measurement. The $(q-n) \times 1$ vector **p** is called the parity vector. The components of **p** are used as residuals. Under non-faulty conditions, since **Vf**=0, **p** is almost null. The distribution of **p** is related to the distribution of the noise so that a non-vanishing parity vector indicates measurement error. Fault detection might be achieved by monitoring the norm of **p**.

2.3.2.2 The Dynamic Parity Space

The above static parity space approach can be extended to a dynamic system and temporal redundancy relations of the system can be obtained. Suppose the system is modelled by the discrete linear state space equations:

$$\begin{cases}\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) \\ \mathbf{y}(k) = \mathbf{C}\mathbf{x}(k)\end{cases},$$

where $n \times 1$ vector $\mathbf{x}(k)$ is the unknown state at the kth instance, $\mathbf{y}(k)$ is the $q \times 1$ measurement vector and $\mathbf{u}(k)$ is the $p \times 1$ input vector, $\mathbf{A}_{n \times n}$, $\mathbf{B}_{n \times p}$ and $\mathbf{C}_{q \times n}$ are model coefficient matrices. If the model is written in observation form with time window of size s:

$$\begin{bmatrix}\mathbf{y}(k-s) \\ \vdots \\ \mathbf{y}(k)\end{bmatrix} = \mathbf{H}_0\mathbf{x}(k-s) + \mathbf{H}_1\begin{bmatrix}\mathbf{u}(k-s) \\ \vdots \\ \mathbf{u}(k)\end{bmatrix},$$

where

$$\mathbf{H}_0 = \begin{bmatrix} \mathbf{C} \\ \mathbf{CA} \\ \vdots \\ \mathbf{CA}^s \end{bmatrix} \text{ and } \mathbf{H}_1 = \begin{bmatrix} \mathbf{0} & & & & \\ \mathbf{CB} & \ddots & & & \\ \mathbf{CAB} & \ddots & \ddots & & \\ \vdots & \ddots & \ddots & \ddots & \\ \mathbf{CA}^{s-1}\mathbf{B} & \cdots & \mathbf{CAB} & \mathbf{CB} & \mathbf{0} \end{bmatrix},$$

then the parity space can be spanned by the row vectors of the $(q(s+1)$-rank$(\mathbf{H}_0))\times q(s+1)$ dimensional matrix $\mathbf{V}$ so that:

$$\mathbf{V}=\{\mathbf{v} \text{ independent} \mid \mathbf{v}^T\mathbf{H}_0=\mathbf{0}\}.$$

By projection of the initial equation in the parity space, $(q(s+1)$-rank$(\mathbf{H}_0))$ independent analytical redundancy relations are obtained given by:

$$\mathbf{V}\begin{bmatrix} \mathbf{y}(k-s) \\ \vdots \\ \mathbf{y}(k) \end{bmatrix} = \mathbf{VH}_1\begin{bmatrix} \mathbf{u}(k-s) \\ \vdots \\ \mathbf{u}(k) \end{bmatrix}.$$

At time instant k the residual vector which is used for FDD is then expressed by:

$$\mathbf{r}(k) = \mathbf{V}\begin{bmatrix} \mathbf{y}(k-s) \\ \vdots \\ \mathbf{y}(k) \end{bmatrix} - \mathbf{VH}_1\begin{bmatrix} \mathbf{u}(k-s) \\ \vdots \\ \mathbf{u}(k) \end{bmatrix}.$$

Ideally the residual vector is near zero when there is no fault and non zero in faulty conditions. Thus the scheme of residual generation using parity space method is shown in Figure 2-5.

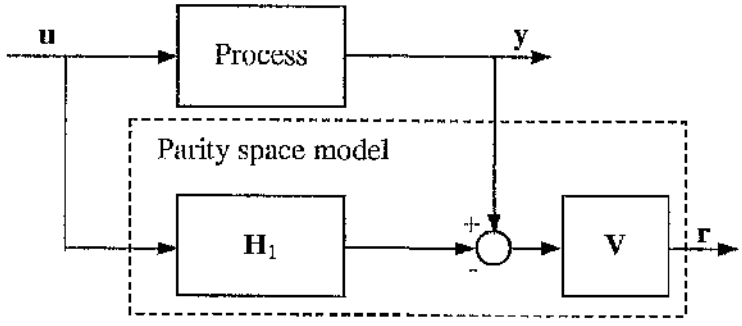


Figure 2-5: Residual generation using parity space method

2.3.3 Fault Detection Using Observers

Analytical observer-based residual generation is based on the reconstruction or estimation of outputs or states of the process of interest and on the subsequent use of the estimation error (or innovation, respectively) or a function of it as the residual. There are two kinds of observers which can be used in the FDD scheme: state observers which are needed for state feedback in the case of incomplete measurement of the state vector, and output observers which can be designed in the frequency domain without using state space theory. Different observer based residual generation schemes are shown in Figure 2-6 and Figure 2-7 respectively.

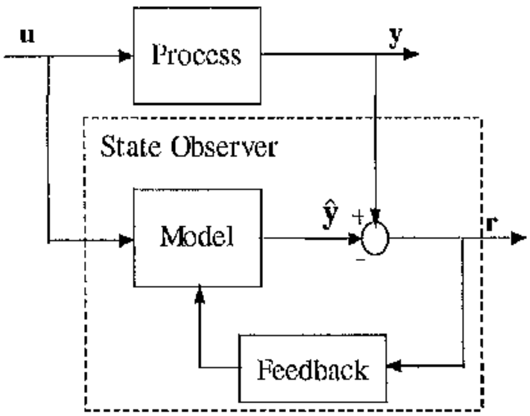


Figure 2-6: Residual generation using a state observer

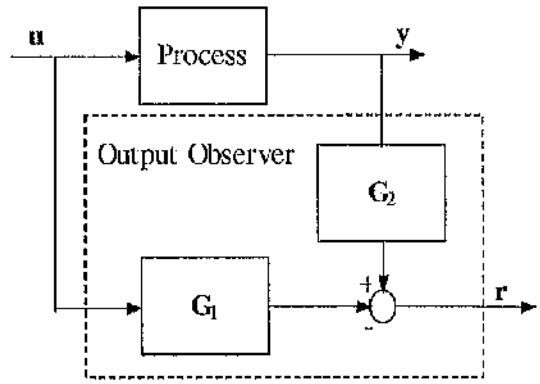


Figure 2-7: Residual generation using an output observer

2.3.4 Fault Detection Using Parameter Estimation

Parameter estimation based approaches use system identification techniques to estimate online process parameters, the results are then compared with the parameters of the reference model obtained initially under fault-free conditions. Any substantial discrepancy indicates a change in the process and may be interpreted as a fault. The procedure of parameter estimation consists of two major steps, the estimation of the mathematical parameters, $\hat{\mathbf{q}}$, and their transformation into the physical parameters, $\hat{\mathbf{p}}$, as shown in Figure 2-8.

2.3.5 Fault Isolation Issues Related to Model Based Approaches

Having detected the occurrence of a fault, it is then often important to isolate its cause. Although there are different model based fault detection approaches, there are some common fault isolation issues. Whilst a single residual signal might be sufficient for fault detection, a residual vector including a set of residuals is usually required for fault isolation. If a fault can be distinguished from others using a single residual vector, then it can be said that this fault is isolable using this residual vector. If the residual vector can isolate all faults, it can be said the residual set has the required isolability property.

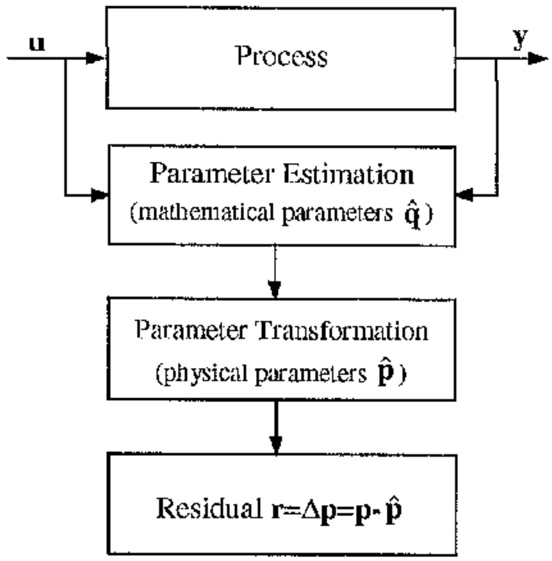


Figure 2-8: Residual generation using parameter estimation

The following sub-sections describe two fault isolation methods that are broadly acknowledged in the literature.

2.3.5.1 Fixed Direction Residual Vector

Fault isolation may be achieved by seeking the greatest correlation between the residual vector and the fault directions. If the dimension of the space spanned by the vector is less than 4, fault directions can be monitored graphically. The emphasis of this method is to design a directional residual vector which lies in a fixed and fault-specified direction (or subspace) in the residual space, in response to a particular fault. The fault isolation problem is then one of determining which of the known fault signature directions the generated residual vector lies closest to.

2.3.5.2 Binary Incidence Matrix and Structured Residual Vector

If the dimension of the space spanned by the residual vector is bigger, it is both difficult and complicated to design a directional residual vector. A binary incidence matrix is usually used to help to analyse the sensibility of the residuals against the different faults: in the matrix, each row is associated to a residual, each column to a fault. A value of 1 denotes a significant sensibility of the residual to the corresponding fault, a zero the relative insensibility of the residuals. The columns of the matrix are called the theoretical fault signatures and are compared at each instant with the experimental signature. Since each component of the residual vector is a linear combination of input and output variables of the system, any linear combination of these residuals is a residual too. A structured residual vector can be designed with structured or directional properties for easier fault isolation: each residual is designed to be sensitive to a subset of faults, whilst remaining insensitive to other faults.

The design procedure consists of two steps. The first step is to specify the sensitive-insensitive relationships between residuals and faults according to the isolation task, and the second is to design a set of residual generators according to the desired sensitive-insensitive relationships. The fault isolation is simply to determine which residual is non-zero.

It is worth mentioning the isolability structures proposed by Gertler and Anderson (1992). For each fault to be detectable, no column of the incidence matrix should contain only zero elements, and for each signature to be unique, all columns must be different, such a structure is called deterministically isolable. Under the conditions of statistical testing, deterministic isolability may not be sufficient. A fault of intermediate size may cause some of the tests to fire while others not to, in spite of a 1 in the concerned position of the incidence matrix. The resulting signature will then be a degraded version of the respective column, in that some of the 1's are replaced by 0's. If there is a fault for which this is the valid signature, then partial firing leads to misisolation of the fault. To avoid this, such structures are needed where no column can be obtained from any other column by degradation (by replacing 1's with 0's). Such structures are called statistically isolable. A column canonical structure, where each column has the same number of 0's, each in a different pattern, is statistically isolable. For example, of the following three incidence matrices, the first is not isolable, the second is isolable deterministically but not statistically and the third is statistically isolable:

$$\begin{bmatrix} 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 1 \end{bmatrix}, \quad \begin{bmatrix} 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 \end{bmatrix}, \quad \begin{bmatrix} 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & 1 \end{bmatrix}.$$

2.3.6 Criticism

Due to both technical and economic problems, model-based FDD theory that uses analytical redundancy has rarely been applied in a process industry although it has attracted much academic interest. Technically it has been demonstrated that it is difficult to develop plant models that are reliable and robust to plant disturbances because many process plants are non-linear. Economically such schemes are expensive, as each is unique and must be created and maintained by highly skilled personnel (Henry, 1995b).

2.4 Sensor, Actuator and Loop Validation

Any hybrid FDD strategy must take into account the fact that increasingly, smart (or intelligent) sensors and actuators are being designed with a self-diagnostic capability. Diagnostic data, measurements and command signals can be communicated via a high speed and bi-directional communication link such as Fieldbus, which is able to provide an integrated structure of control, maintenance and management functions as shown in Figure 2-9 (Wood, 1995). This sub-section describes the types of features that the SEVACS approach must seek to complement.

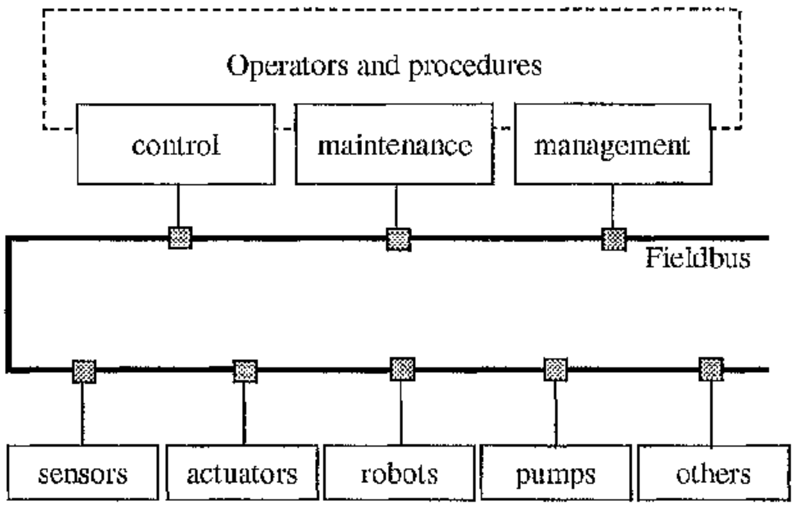


Figure 2-9: Fieldbus integration of control, maintenance and management (Wood, 1995)

2.4.1 Sensor Validation

Although, currently, most commercially available intelligent sensors that provide diagnostics generate a device-specific fault code or message (e.g. "fault 43 – fouled membrane") (Henry, 1995a), both field operators and commercial vendors are still not fully satisfied with it, the former need to know how the measurement has been affected by the device fault, the latter wonder how the code or message can be standardised so that it is device-independent and their customers can exploit the advantages of intelligent instruments without being forced into single-vendor solutions. It is therefore encouraging that the SEVA (SElf-VAlidating) framework, devised by Clarke *et al.* at Oxford University, allows any intelligent instrument to transfer measurement and validity information using a standardised message content and enables the integration of measurement validation with process control (Henry *et al.*, 1993; Henry 1995a, 1995b; Clarke, 1995).

A SEVA sensor not only employs self-diagnostics, but also provides extra stages of processing. If a fault occurs, its impact on each measurement is assessed and the measurement is corrected if necessary. Validity indices are generated which describe the resulting quality of each measurement in generic, device-independent terms. These enable the control systems to make an appropriate response to the sensor fault irrespective of the particular sensor technology or supplier. Some prototypes of self-validating sensors have been developed, such as a coriolis mass flow meter (Henry, 1994), thermocouple (Yang *et al.*, 1997a), pulse oximeter and polarographic oxgen tension meter (Leahy *et al.*, 1997) etc.

Figure 2-10 shows a SEVA sensor framework (Henry, 1995b). There are two validity indices generated for each validated measurement value (VMV, corresponding to the conventional measurement): validated uncertainty (VU) and the measurement value status (MV status). Additionally, a single device status is generated, which summarises the physical health of the sensor itself. Of course, a detailed, device-specific diagnosis of any fault is always available for the maintenance engineer.

Validated Uncertainty(VU)

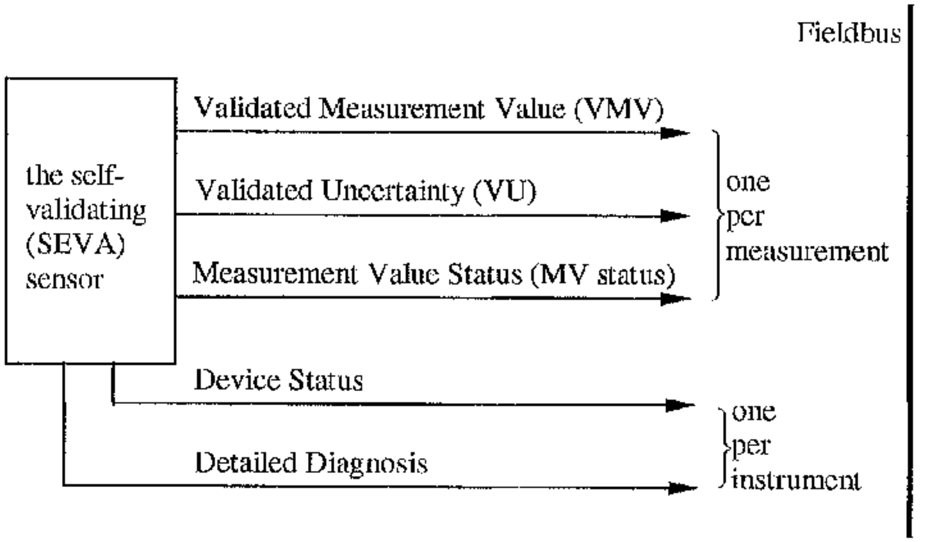


Figure 2-10: Sensor validity parameters (Henry, 1995b)

Uncertainty is a well-established engineering concept. For any measurement x, the associated uncertainty , δ_x, expresses a reasonable bound for the measurement error, at a given level of probability. In other words, it is expected that the true value of the measurand is within $x \pm \delta_x$.

The uncertainty of arbitrary functions can be calculated by the root-sum-squares rule. For instance, given the uncertainty δ_x of x and δ_y of y, the uncertainty δ_R of R which is a non-linear function f(x, y) can be calculated by

$$\delta_R^2 = \left(\frac{\partial f}{\partial x}\right)^2 \delta_x^2 + \left(\frac{\partial f}{\partial y}\right)^2 \delta_y^2$$

provided the non-linearity in the function f is not significant and the uncertainties of x and y are independent and sufficiently small.

Traditionally uncertainty has been a static analysis, assigning a single uncertainty value to an instrument, the SEVA scheme proposes that uncertainty analysis should be extended to give an on-line estimate of measurement accuracy as a function of varying operating conditions. Based on the above uncertainty analysis, the validated uncertainty VU provides the major indicator of the quality of the validated measurement value (VMV).

Measurement value status (MV status)

Under normal conditions, VMV is calculated using the latest data from the transducer, but after a fault comes, VMV may be calculated by projection from historical data while the VU will increase to accommodate the reduced accuracy of VMV. A second, discrete, validity index, called the measurement value status (MV status) is also generated with the VMV to inform the control system or supervisor in effect 'how this VMV was calculated, by live data or historical data'.

There are six possible values of the MV status, corresponding to six different scenarios for how the VMV has been generated. The principal values are:

- CLEAR indicates that there is no fault, and that the VMV has been calculated normally from the latest transducer data;
- BLURRED indicates that the measurement has been partially impaired by the presence of a sensor fault, and that a correction has been applied in the calculation of the VMV. The VU is increased appropriately to indicate the reduced accuracy of the estimate;

- BLIND indicates that a diagnosed fault has occurred which has a severe impact on the measurement , and so the current VMV is projected from historical data, not live transducer data. A BLIND measurement should never be used for feedback control;
- DAZZLED is a temporary status used when transducer data is clearly erroneous, but there is insufficient internal evidence to confirm that a substantial fault has occurred. The current VMV is projected from historical data, but the expectation is that the internal diagnosis will soon be resolved and that the status will then switch to one of the other values. DAZZLED is used to deal with the occurrence of temporary but severe effects such as a spike. It would, for example, be undesirable for a control loop to be switched to manual in response to the controlled measurement turning BLIND and then, only a few seconds later, the measurement was to return to CLEAR.

Two additional states are as follows:

- SECURE indicates that the VMV has been generated from redundant transducers or sensors, all of which are in nominal condition. This status is useful in critical applications where the user need the reassurance that, even if one transducer or sensor fails, CLEAR data will still be available;
- UNVALIDATED indicates that validation has not been in operation in the sensor which generated the measurement.

Device Status

Device Status is a generic, discrete value summarising the health of the sensor for maintenance purposes. It belongs to one of the following values:

- GOOD: the sensor is in nominal condition;
- TESTING: the sensor is performing diagnostic tests which may have caused any loss of measurement quality;
- SUSPECT: the sensor may have suffered an aberration; the condition has not yet been diagnosed;
- IMPAIRED: the sensor is suffering from a diagnosed fault which has a minor impact on performance, warranting a low priority maintenance call;

- BAD: the sensor is suffering from a diagnosed fault which has a major impact on performance, warranting a high priority maintenance call;
- CRITICAL: the sensor is in a potentially dangerous condition that may cause or have caused a hazard, such as a leak of the process fluid or a dangerous reagent, fire or explosion. It requires immediate attention.

It is stressed that the (single) Device Status refers to the health of the *sensor*, whereas the MV status refers to the quality of each (of one or more) *measurement*. Normally there will be some correlation between them, for example, if the principal measurement is BLURRED then the Device Status is likely to be IMPAIRED.

2.4.2 Actuator Validation

A similar approach has been proposed for actuators (Yang and Clarke, 1997b). The basic scheme is shown in Figure 2-11: in response to an Actuation Demand (AD), the SEVA actuator should generate the best possible actuation signal, and output the following information at each sample:

- actuation Value (AV): the best estimate.
- actuation Uncertainty (AU): as in SEVA sensors, it is believed that at a certain confidence level (say 95%) the true actuation signal u is within the range $(AV\text{-}AU) \leq u \leq (AV\text{+}AU)$;
- attainable Actuation Value (AAV): responds to a value supplied by the system, and returns the closest actuation signal that can currently be supplied because of the non-linear characteristic of the actuator;
- actuation Status (AS): this can take one of a number of states:
  - ❖ READY;
  - ❖ DEGRADED (OFFSET/HYSTERESIS);
  - ❖ UNACHIEVABLE (LIMITED/JUMP);
  - ❖ CHANGED DYNAMICS;
  - ❖ INCAPACITATED: dead;
  - ❖ UNVALIDATED.
- device Status: follows the scheme adopted by SEVA sensors;
- detailed Information: bi-directional.

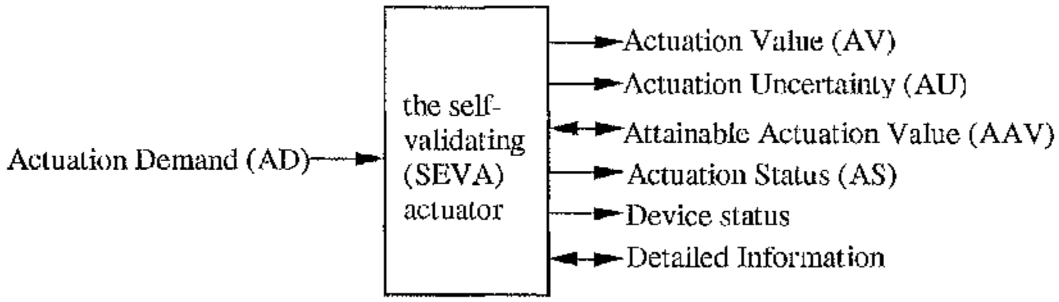


Figure 2-11: A self-validating actuator scheme (Yang *et al.*, 1997)

2.4.3 Loop Validation

According to Yung and Clarke's hierarchical validation scheme (Figure 2-12), given validated sensors and actuators it is natural to move toward loop validation. Clarke has only proposed a loop validator structure, as in Figure 2-13, and pointed out that all the tools available from FDI, signal processing and parameter estimation can be used. However, there is no generic and economical solution which can be easily and reliably implemented or embedded into commercial control systems.

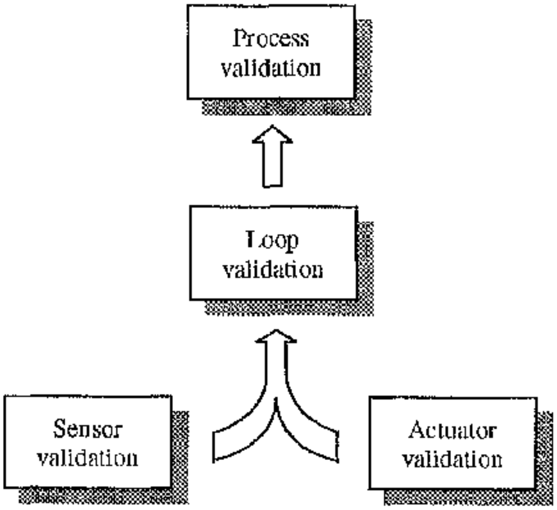


Figure 2-12: Yung and Clarke's hierarchical validation scheme (1989)

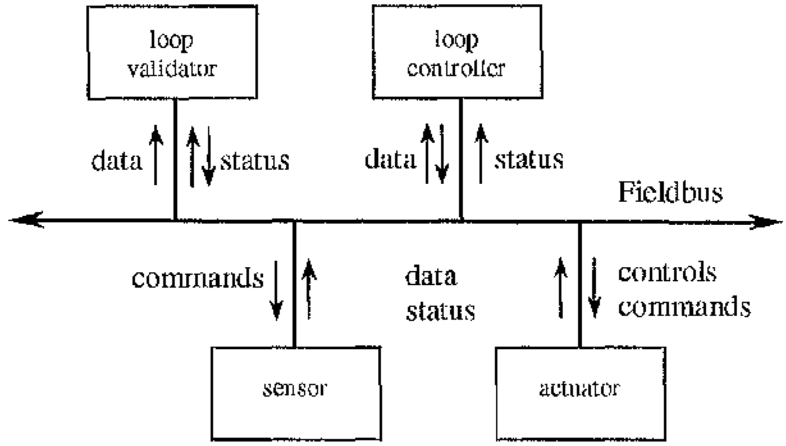


Figure 2-13: A loop validator (Henry *et al.*, 1993)

Potentially loop performance assessment may be a useful approach to loop validation. Loop performance assessment is normally related to the dynamic response of the system to a step disturbance in set-point or load upset variable. Performance is defined by measures such as integral of the absolute value of the error (IAE), maximum deviation and decay ration (Smith *et al.*, 1985) or process gain k_p, apparent dead time L and apparent time constant T (Åström, 1991). Because these methods assume that experiments or set-point changes can be made periodically on each control loop, it seems that they are not preferable for online implementation. More recently, some alternative online control system (or loop) performance monitoring approaches using various control system performance indices have been put forward and respective researches are becoming popular. By considering its link with fault detection, a control system performance index will be discussed in the next section.

2.4.4 Relevance to SEVACS

It has been envisaged in Chapter 1 that, where available, sensor and actuator validation would be included in the FDD suite. In Figure 1-2, SEVA sensors and actuators would then be used instead of normal sensors and actuators. Clearly this depends on these facilities being supplied with the sensor & actuator sub-systems. They have a number of states, which would be collected and used by the Supervisor. In this thesis, SEVACS would provide less states than those provided by the SEVA sensors and actuators. By using both approaches, some states would be cross-verified. For some states, SEVACS and SEVA components would complement each other because they provide some other information differently and they can not be replaced by each other.

2.5 A Control System Performance Index

There have been a number of papers published recently on loop performance monitoring (Smith *et al.*, 1985; Harris, 1989; Desborough *et al.*, 1992,1993; Stanfelj *et al.*, 1993; Thornhill *et al.*, 1996, 1997, 1999; Tyler *et al.*, 1996; Kesavan *et al.*, 1997). Of these Harris and Desborough have developed a technique for determining the best possible control performance for a single loop control system. They have proposed a control system performance index that provides a measure of how close the performance of an existing control system is to that for an ideal optimal controller, namely, a minimum variance controller. The performance index is updated recursively using only measurements of the controller variable. Thornhill *et al.*'s practical experiences of applying this technique to some large refinery plants have shown that the control system performance index can routinely monitor individual control loops and focus on exceptions that need attention (Thornhill *et al.*, 1996, 1997, 1999). An important theoretical advantage of the technique is that the value of the performance is not affected by load disturbances, and hence changes in the performance index can be attributed to a change in one or more of components in the feedback loop itself, e.g., a sensor or actuator 'fault'. Fasolo and Seborg have used this performance index as a fault detection technique for the online monitoring of feedback control systems and have demonstrated the feasibility via a simulation study for an HVAC heating coil subsystem (Fasolo *et al.*, 1995).

2.5.1 Definition and Estimation of The Control System Performance Index η

Figure 2-14 shows a single loop control system: $Y(i)$ is the controlled variable, $Y_{SP}(i)$ is the setpoint, $y(i)=Y(i)-Y_{SP}(i)$ is the control error, $\hat{Y}(i)$ is the forecast of $Y(i)$, $\hat{y}(i)=\hat{Y}(i)-Y_{SP}(i)$ is the forecast of $y(i)$ and $e(i)=y(i)-\hat{y}(i)=Y(i)-\hat{Y}(i)$ is the forecast error of $y(i)$ or $Y(i)$. If the minimum variance controller is used, then there is $\sigma_y^2 = var[y(i)] = var[e(i)] = \sigma_{mv}^2$ (Desborough & Harris, 1992).

Note that any other feedback controller will have a larger variance of the control error than the minimum variance controller, i.e., $\sigma_y^2 > \sigma_{mv}^2$.

A normalised performance index, η, which is bounded by [0,1] and characterises the controller performance relative to minimum variance control, was defined by Desborough and Harris (1992) :

$$\eta = 1 - \frac{\sigma_{mv}^2}{mse[y(i)]} = 1 - \frac{\sigma_{mv}^2}{\sigma_y^2 + \mu_y^2},$$

where $mse[y(i)]$ represents the mean square error of $y(i)$ and μ_y^2 is the mean deviation from the set-point.

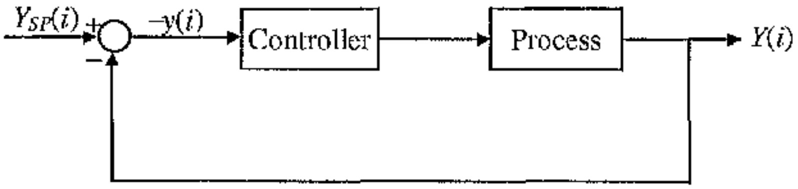


Figure 2-14: A single loop control system

If a PI controller is used, it can be assumed that μ_y=0 and η can be estimated by

$$\hat{\eta}(i) = 1 - \frac{s_{mv}^2(i)}{s_y^2(i)},$$

where variances $s_{mv}^2(i)$ and $s_y^2(i)$ are recursively calculated by exponentially weighting the squares of the forecast error $e(i)$ and the control error $y(i)$, respectively:

$$s_{mv}^2(i) = \lambda s_{mv}^2(i-1) + e^2(i)$$

$$\text{and } s_y^2(i) = \lambda s_y^2(i-1) + y^2(i),$$

the forgetting factor $\lambda \in [0,1]$ provides exponential discounting of past data.

In order to calculate $e(i)$, the forecast $\hat{y}(i)$ must be known. It can be derived as follows. Assuming that the closed-loop system is stable, the closed-loop response can be parameterised by the following form (Desborough *et al.* 1992):

$$y(i) = \xi(i) + \sum_{k=1}^{\infty} \alpha_k y(i-b-k+1),$$

where $\xi(i)$ is a linear combination of past and present disturbances $\{a_k\}$, integer b is the process delay expressed by a multiple of the sampling period. In practice, it is often feasible to truncate the infinite series in the above equation after m terms to yield an autoregressive (AR) model:

$$y(i) = \xi(i) + \sum_{k=1}^{m} \alpha_k y(i-b-k+1).$$

The AR model parameters $\{\alpha_k\}$ can then be estimated using recursive least squares (RLS). This AR model can be used to estimate $y(i)$.

Rearranging the AR model in the standard form:

$$y(i) = \phi(i)^T \theta + \xi(i)$$

where

$$\phi(i)^T = [y(i-b), \cdots, y(i-b-m+1)]$$

$$\text{and } \theta^T = [\alpha_1, \cdots, \alpha_m],$$

a RLS estimate of θ can be obtained by employing the variable forgetting algorithm of Fortescue *et al.* (1981):

$$\hat{\theta}(i) = \hat{\theta}(i-1) + \mathbf{K}(i)[y(i) - \hat{y}(i)],$$

where $\hat{y}(i) = \phi(i)^T \hat{\theta}(i-1)$ and $\mathbf{K}$(i) is updated by the following equations:

$$\mathbf{K}(i) = \frac{\mathbf{P}(i-1)\phi(i)}{1 + \phi(i)^T \mathbf{P}(i-1)\phi(i)};$$

$$\lambda(i) = 1 - \frac{[y(i) - \phi(i)^T \hat{\theta}(i-1)]^2}{\Sigma_0 [1 + \phi(i)^T \mathbf{P}(i-1)\phi(i)]};$$

$$\mathbf{P}(i) = \begin{cases} \dfrac{\mathbf{W}(i)}{\lambda(i)} & \text{if trace of } \dfrac{\mathbf{W}(i)}{\lambda(i)} \le C; \\ \mathbf{W}(i) & \text{otherwise}; \end{cases}$$

$$\mathbf{W}(i) = \mathbf{P}(i-1) - \mathbf{K}(i)\phi(i)^T \mathbf{P}(i-1).$$

In the RLS algorithm, Σ_0 and C are design parameters. The variable forgetting strategy allows small values of $\lambda(i)$ to be used when the forecast error $e(i)$ is large, while $\lambda(i)$ goes to one when $e(i)$ is small. The covariance matrix $\mathbf{P}(i)$ is designed to be prevented from becoming excessively large during periods of low excitation.

2.5.2 Fault Detection Using The Estimation of η

Fasolo and Seborg (1995) have proposed a fault detection strategy using performance index η as follows. At each sampling instant, the estimate of the performance index $\hat{\eta}(i)$ is updated via RLS as described above. The estimate is then compared to its confidence limits, $\bar{\hat{\eta}} \pm 3\sigma_{\hat{\eta}}$, where $\bar{\hat{\eta}}$ is calculated as the sample mean of $\hat{\eta}$ for the base case conditions and $\sigma_{\hat{\eta}}$ can be estimated by the approximation of the variance of $\hat{\eta}$ for n observations. This has been derived by Desborough and Harris (1992) as:

$$\hat{\sigma}_{\hat{\eta}} = \sqrt{\operatorname{var}[\hat{\eta}]} = \sqrt{\frac{4}{n}(1-\eta)^2\left(\sum_{i=1}^{b-1}[\rho(i)-\rho_e(i)]^2 + \sum_{i=b}^{\infty}\rho^2(i)\right)},$$

where ρ and ρ_e represent the output and residual autocorrelations, respectively. In practice, for a finite time series $z(1)$, $z(2)$, …, $z(n)$ of n observations, the estimate of the ith lag autocorrelation $\rho_z(i)$ can be estimated by (Box *et al.*, 1976)

$$\rho_z(i) = \frac{c_i}{c_0}$$

where

$$c_i = \frac{1}{n}\sum_{t=1}^{n-i}[z(t)-\bar{z}][z(t+i)-\bar{z}], \quad i=0, 1, \ldots, b-1$$

and $\bar{z}$ is the mean of the time series.

2.5.3 Criticism

Although the control system performance index is helpful to fault detection in feedback loops, it lacks the ability to isolate faults. Furthermore, although immunity to load disturbances is thought to be an important theoretical advantage of this approach, disturbances in a process should still be alerted.

2.6 Summary

In this Chapter, some background to process monitoring and fault diagnosis has been given. The emphasis lies in those aspects related to this thesis: functional decomposition, statistical approaches, model-based methods, the self-validating concept and control system performance monitoring.

Finch and Kramer's functional decomposition is especially beneficial to large-scale processes and is pertinent to this thesis. It will be seen in Chapter 8 that the representation of interactions between control systems is similar to theirs. However, their approach has remained on process performance as a whole. A systematic approach for distributed and detailed diagnosis is needed and is the core of this thesis.

Univariate statistical process control (USPC) is used extensively in process monitoring systems including fault detection. Multivariate statistical process control (MSPC) can be used when it is difficult for an operator to monitor a large number of inter-related variables in a plant simultaneously. However both USPC and MSPC cannot cope with fault isolation or fault diagnosis very well.

The principle behind model-based methods is general and structurally attractive. However model development costs are expensive especially in process industries. These methods suffer from the same problem as that of statistical approaches, they cannot deal with fault isolation or fault diagnosis very well. This is also the case with the control system performance index that has been of recent interest in process monitoring and fault diagnosis.

Clarke *et al.*'s self-validating concept has been accepted by many industrial partners and might become an industrial standard in the future. Their theory treats sensors, actuators, controllers and processes separately. However all of these can be viewed as a single entity in which controller/SEVACS combinations act as co-ordinators among sensors, actuators and processes because they detect and compensate for various faults or disturbances.

CHAPTER 3

THEORETICAL ANALYSIS OF SELF-VALIDATING CONTROL SYSTEMS

This chapter describes how, in theory, steady state faults can be isolated in a continuous process plant under distributed process control. The emphasis is on distributed fault isolation with a minimal role for the FDD Supervisor. Reasons as to why this approach is not practicable will then be presented. In spite of these, various results in this chapter will then be used in later chapters.

3.1 Overview

This thesis envisages a network of autonomous control systems that have the ability to self-detect and diagnose abnormalities, either specifically or as categories, and are then able to communicate their findings to a Supervisor, which would have the capacity to reason further about the information received. The distributed structure of plant-wide control systems would look something like that shown in Figure 1-1, which is copied here as Figure 3-1 for ease of reading. The process is controlled by m single loop controllers (SLC_i, $i:1 \le i \le m$) that input measurements (controlled variables) $\tilde{\theta}_{,i}$ and output demands (controller outputs) $x_{,i}$, and n cascade control systems (CC_i, $i:(m+1) \le i \le (n+m)$), each of which are composed of 2 or more controllers ($CC1_i$, $CC2_i$, ..) that input measurements $\tilde{\theta}_{1,(m+i)}$ (outer loop controlled variables) & $\tilde{\theta}_{2,(m+i)}$ (inner loop controlled variables) and output demands $x_{1,(m+i)}$ (inner loop controller outputs) & $x_{2,(m+i)}$ (outer loop controller outputs); in addition other measurements $\tilde{\phi}_i$ might be recorded from other instrumentation. Potentially, the set of observations that could be transmitted around the communications network would be $\{x_{,1}, \ldots, x_{1,(m+1)}, x_{2,(m+1)}, \ldots, \theta_{rSLC1}, \ldots, \theta_{rCC1}, \ldots, \tilde{\theta}_{,1},$

$\ldots, \tilde{\theta}_{1,(m+1)}, \tilde{\theta}_{2,(m+1)}, \ldots, \tilde{\phi}_1, \ldots\}$ where θ_{rSLC1} and θ_{rCC1} denote set-points. This represents a considerable amount of communications traffic and in order to minimise this it is hypothesised here that, as far as steady state detection and diagnosis is concerned, only the signs of any deviations in steady state values need to be communicated. In other words, an algorithm would be run on each SEVACS to ascertain whether each of the variables in its associated controller was in a steady state and if so, whether that steady state had changed by a significant amount; it would then output, for instance $x_{,1}$=normal, high or low depending on whether or not $x_{,1}$ had deviated. Some of the other SEVACS might then accept both this variable and other variables pertaining to other controllers and to additional instrumentation. Each SEVACS would then test its collection of variables regularly to see whether it could diagnose any of the deviations identified; if successful, the deviations would be declared as *explained* and messages like *normal_disturbance* would be transmitted so that the new steady state could be declared as *normal* or otherwise.

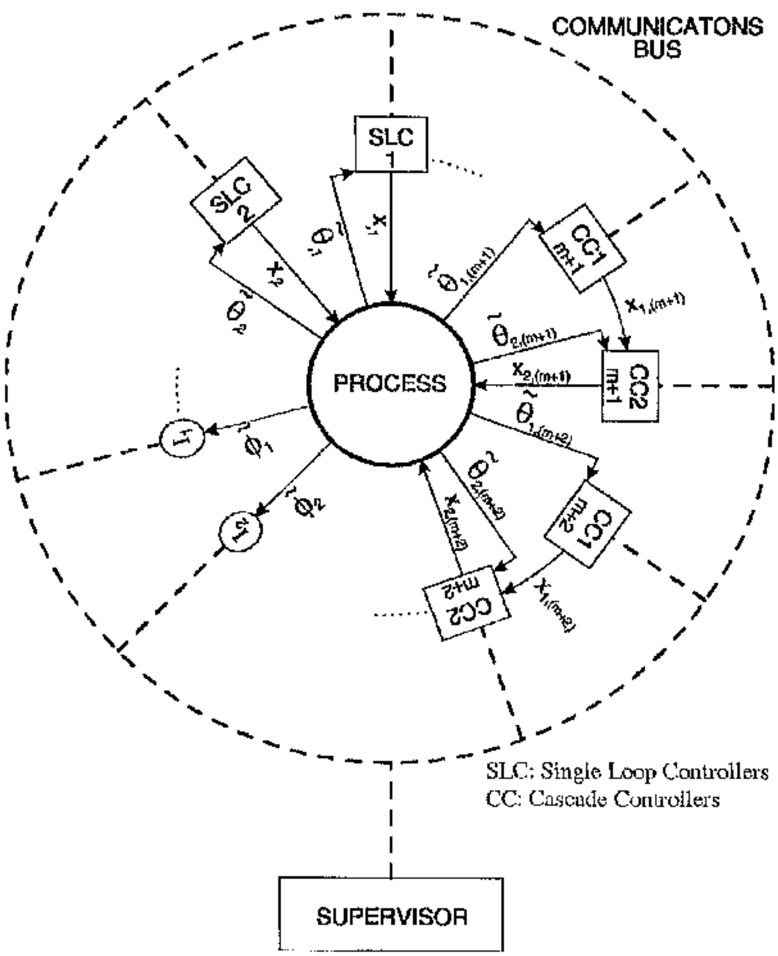


Figure 3-1: Structure of plant-wide distributed control systems

3.2 Nomenclature

The various variables used are defined before going any further. The ith single loop control system is represented by the block diagram shown in Figure 3-2: all variables represent deviations, $\theta_{r,i}$ is the deviation in the set-point/reference variable, $\theta_{,i}$ in the controlled variable, $d_{m1,i}$ in the sensor bias, $d_{v1,i}$ in the valve bias, $d_{p1,i}$ in the process disturbance and $x_{,i}$ in the controller output. Parameter $K_{c1,i}$ is the proportional gain of the controller and parameters $K_{v,i}$, $K_{p1,i}$ and $K_{d1,i}$ are respectively the valve, process and process disturbance steady state gains. $G_{c1,i}(s)$, $G_{v,i}(s)$, $G_{p1,i}(s)$ and $G_{d1,i}(s)$ are transfer functions of the controller, valve, process and disturbance respectively. Variables that pertain to a cascade control system are defined in a similar way (Figure 3-3). The approach that will be described in this chapter is based on an analysis of qualitative variables that assumes that the basic qualitative operations are as defined in Table 3-1: a qualitative variable [x] is merely defined as the sign of variable x (De Kleer & Brown, 1984; Forbus, 1984). In comparison with its normal or nominal value, [x] has four qualitative values: '+' means x deviates high; '–' means x deviates low; '0' means x has no change and '?' means the deviation of x cannot be decided.

[x]+[y]

[x] \ [y]	+	-	?	0
+	+	?	?	+
-	?	-	?	-
?	?	?	?	?
0	+	-	?	0

[x]-[y]

[x] \ [y]	+	-	?	0
+	?	+	?	+
-	-	?	?	-
?	?	?	?	?
0	-	+	?	0

Table 3-1: Definition Of Qualitative Operations

In order to implement qualitative operations, another definition is required: {K} represents the sign of the gain K and can be viewed as an operator. Qualitative operator {K} only has two values: '+' when K>0 and '–' when K<0. The operation {K} is defined as follows:

$\{-K_1\}=-\{K_1\}$;

$\{+K_1\}=+\{K_1\}=\{K_1\}$;

$-\{-K_1\}=\{K_1\}$;

$\{K_1K_2\}=\{K_1\}\{K_2\}=\{K_2\}\{K_1\}$;

$\{K_1/K_2\}=\{K_1K_2\}$.

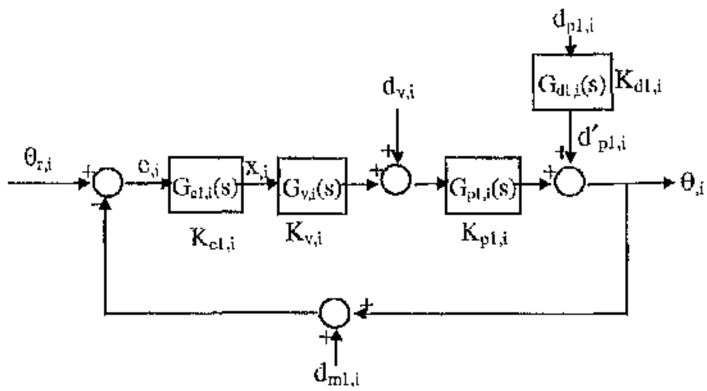


Figure 3-2: A single loop control system

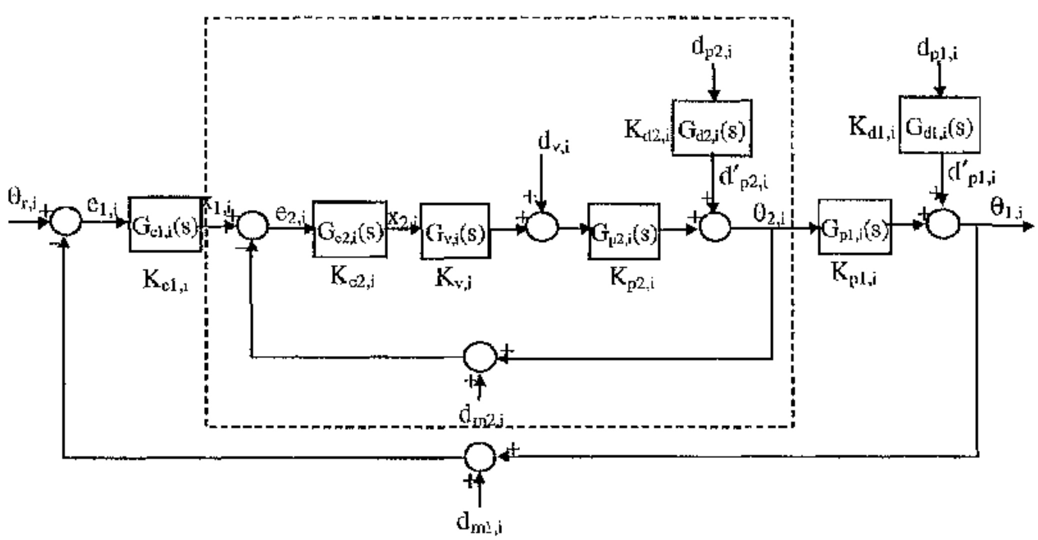


Figure 3-3: A cascade control system

3.3 Different Process Types and Their Closed-Loop Characteristics

The diagnostic approach depends on the type of process involved. This sub-section identifies those attributes that are important and needed.

3.3.1 Open Loop Stable Processes

For reasons of safety and for ease of operation, a process plant designer will seek to ensure that, whenever possible, a process plant will be open loop stable. Hence most industrial processes are open loop stable *per se*. A related PID control system block diagram is shown in Figure 3-4, in which some subscripts have been dropped for clarity and simplicity.

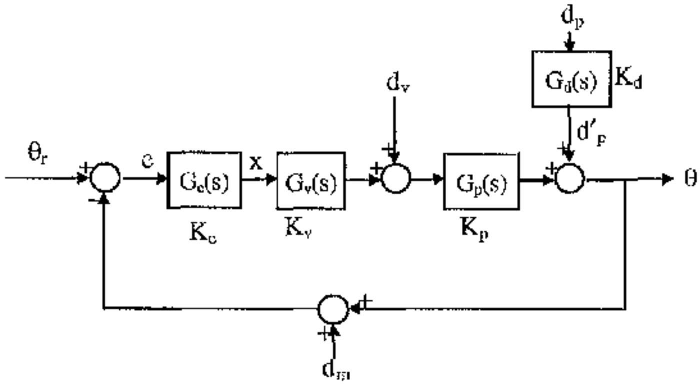


Figure 3-4: A single loop control system

Assuming that the process and disturbance models can be linearised and that the valve dynamics are first order (this is not strictly necessary), the various blocks can be represented by:

$$G_c(s) = K_c(1 + \frac{1}{T_i s} + T_d s) \qquad K_c \neq 0,\ T_i > 0,\ T_d \geq 0\ ; \tag{3-1}$$

$$G_v(s) = \frac{K_v}{T_v s + 1} \qquad K_v \neq 0,\ T_v \geq 0\ ; \tag{3-2}$$

$$G_p(s) = \frac{B_m s^m + B_{m-1} s^{m-1} + \cdots + B_1 s + B_0}{s^n + A_{n-1} s^{n-1} + \cdots + A_1 s + A_0} \quad m,n \in Z,\ m \geq 0,\ n \geq 1,\ A_j > 0 (j=0,..,n-1),\ B_0 \neq 0; \tag{3-3}$$

$$G_d(s) = \frac{D_d s^d + D_{d-1} s^{d-1} + \cdots + D_1 s + D_0}{s^n + A_{n-1} s^{n-1} + \cdots + A_1 s + A_0} \quad d,n \in Z,\ d \geq 0,\ n \geq 1,\ A_j > 0\ (j=0,..,n-1),\ D_0 \neq 0. \tag{3-4}$$

The conditions in the above two equations are necessary for open loop stability. The process dynamics can then be described as a set of state space equations:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}$$
$$\mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{u}$$

where $\mathbf{x}$ is an $n\times1$ state vector, $\mathbf{u}$ is an $m\times1$ input vector, $\mathbf{y}$ is a $p\times1$ output vector, $\mathbf{A}_{n\times n}$, $\mathbf{B}_{n\times m}$, $\mathbf{C}_{p\times n}$, $\mathbf{D}_{p\times m}$ are the coefficient matrices respectively.

The transfer function matrix $\mathbf{G(s)}$ between $\mathbf{u(s)}$ and $\mathbf{y(s)}$ can be obtained by:

$$\mathbf{G(s)} = \frac{\mathbf{y(s)}}{\mathbf{u(s)}} = \mathbf{C}(\mathbf{sI}-\mathbf{A})^{-1}\mathbf{B}+\mathbf{D}$$

If the process disturbances can be viewed as one of the elements of $\mathbf{u}$, then their characteristic polynomial will be determined by $(\mathbf{sI-A})^{-1}$. So it is reasonable to assume $G_p(s)$ and $G_d(s)$ will have the same denominator.

Equations (3-1) to (3-4) can be substituted into the normal equation for a closed loop transfer function to produce:

$$\begin{aligned}\theta(s) &= \frac{G_c(s)G_v(s)G_p(s)}{1+G_c(s)G_v(s)G_p(s)}[\theta_r(s)-d_m(s)] + \frac{G_p(s)}{1+G_c(s)G_v(s)G_p(s)}d_v(s) + \frac{G_d(s)}{1+G_c(s)G_v(s)G_p(s)}d_p(s) \\ &= \frac{K_cK_v(T_iT_ds^2+T_is+1)(B_ms^m+\cdots+B_1s+B_0)}{\Delta(s)}[\theta_r(s)-d_m(s)] \\ &\quad + \frac{T_is(T_vs+1)(B_ms^m+\cdots+B_1s+B_0)}{\Delta(s)}d_v(s) + \frac{T_is(T_vs+1)(D_ds^d+\cdots+D_1s+D_0)}{\Delta(s)}d_p(s)\end{aligned} \tag{3-5}$$

and

$$\begin{aligned}x(s) &= \frac{G_c(s)}{1+G_c(s)G_v(s)G_p(s)}[\theta_r(s)-d_m(s)] - \frac{G_c(s)G_p(s)}{1+G_c(s)G_v(s)G_p(s)}d_v(s) - \frac{G_c(s)G_d(s)}{1+G_c(s)G_v(s)G_p(s)}d_p(s) \\ &= \frac{K_c(T_iT_ds^2+T_is+1)(T_vs+1)}{\Delta(s)}\{(s^n+A_{n-1}+\cdots+A_1s+A_0)[\theta_r(s)-d_m(s)] \\ &\quad -(B_ms^m+\cdots+B_1s+B_0)d_v(s)-(D_ds^d+\cdots+D_1s+D_0)d_p(s)\}\end{aligned} \tag{3-6}$$

where,

$$\Delta(s) = T_i s(T_v s+1)(s^n + A_{n-1}s^{n-1} + \cdots + A_1 s + A_0) + K_c K_v (T_i T_d s^2 + T_i s + 1)(B_m s^m + \cdots + B_1 s + B_0).$$

It can be seen that if the Routh-Hurwitz Criterion were to be applied to the above, then one of the necessary conditions for closed loop stability would be $K_c K_v B_0 > 0$.

Because B_0/A_0 is equivalent to the steady state gain K_p of the process and $A_0 > 0$, the following is an alternative condition for stability: $K_c K_v K_p > 0$.

Suppose that a change in steady state occurs either because of a fault or because of a change of disturbance. If the controller functions properly, then from Equation (3-5) and Equation (3-6) by setting s=0,

$$\theta = \theta_r - d_m \tag{3-7}$$

and x will deviate:

$$x = \frac{\theta_r}{K_p K_v} - \frac{d_m}{K_p K_v} - \frac{K_d d_p}{K_p K_v} - \frac{d_v}{K_v}. \tag{3-8}$$

3.3.2 Purely Capacitive Processes (Processes with A Pure Integrator)

Processes with integral action most commonly encountered in a chemical process are tanks with liquids, vessels with gases, inventory systems for raw materials or products, and so on.

An uncontrolled purely capacitive process will cause serious problems, because it cannot balance itself. Take a tank as an example, we can adjust manually the speed of the constant-displacement pump, so as to balance the flow coming in and thus keep the level constant. But any small change in the flow rate of the inlet stream will make the tank flood or run dry (empty). This attribute is known as non-self-regulation (Stephanopoulos, 1984).

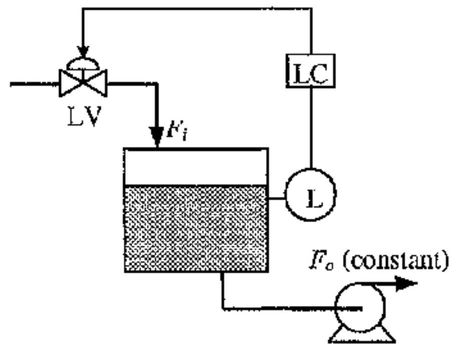


Figure 3-5: A pure capacitive process

One can recognise that a process is a purely capacitive process by viewing it either quantitatively or qualitatively.

- By quantitative equations: in Figure 3-5, the total mass balance around the tank yields

  $$A\frac{dL}{dt} = F_i - F_o \qquad (3\text{-}9)$$

  where A is the cross-sectional area of the tank.

  Because F_o is a constant, then the transfer function G(s) between the controlled variable (level L) and the control variable (inflow rate F_i) is

  $$G(s) = \frac{L(s)}{F_i(s)} = \frac{1/A}{s},$$

  which includes a pure integrator 1/s.

- By qualitative knowledge of the process: in Figure 3-5, from the qualitative knowledge of the control action, if the set-point of L is changed and the control variable F_i doesn't change in steady state at all, this indicates the process transfer function G(s) includes a pure integrator 1/s.

Generally capacitive processes can be controlled by a PID controller, the control system structure is the same as that shown in Figure 3-4 and the various transfer functions can now be represented by:

$$G_c(s) = K_c(1 + \frac{1}{T_i s} + T_d s) \qquad K_c \neq 0,\ T_i > 0,\ T_d \geq 0\ ; \qquad (3\text{-}10)$$

$$G_v(s)=\frac{K_v}{T_v s+1} \quad K_v\neq 0,\ T_v\geq 0\ ; \tag{3-11}$$

$$G_p(s)=\frac{B_m s^m+B_{m-1}s^{m-1}+\cdots+B_1 s+B_0}{s(s^n+A_{n-1}s^{n-1}+\cdots+A_1 s+A_0)} \quad m,n\in Z,\ m\geq 0,\ n\geq 0,\ A_0\neq 0,\ B_0\neq 0; \tag{3-12}$$

$$G_d(s)=\frac{D_d s^d+D_{d-1}s^{d-1}+\cdots+D_1 s+D_0}{s(s^n+A_{n-1}s^{n-1}+\cdots+A_1 s+A_0)} \quad d,n\in Z,\ d\geq 0,\ n\geq 0,\ A_0\neq 0,\ D_0\neq 0. \tag{3-13}$$

Once again, $G_p(s)$ and $G_d(s)$ have the same denominator.

Substituting equations (3-10) to (3-13) into the usual equation for a closed loop transfer function yields:

$$\begin{aligned}\theta(s)&=\frac{G_c(s)G_v(s)G_p(s)}{1+G_c(s)G_v(s)G_p(s)}[\theta_r(s)-d_m(s)]+\frac{G_p(s)}{1+G_c(s)G_v(s)G_p(s)}d_v(s)+\frac{G_d(s)}{1+G_c(s)G_v(s)G_p(s)}d_p(s)\\ &=\frac{K_cK_v(T_iT_ds^2+T_is+1)(B_ms^m+\cdots+B_1s+B_0)}{\Delta(s)}[\theta_r(s)-d_m(s)]\\ &\quad+\frac{T_is(T_vs+1)(B_ms^m+\cdots+B_1s+B_0)}{\Delta(s)}d_v(s)+\frac{T_is(T_vs+1)(D_ds^d+\cdots+D_1s+D_0)}{\Delta(s)}d_p(s)\end{aligned} \tag{3-14}$$

and

$$\begin{aligned}x(s)&=\frac{G_c(s)}{1+G_c(s)G_v(s)G_p(s)}[\theta_r(s)-d_m(s)]-\frac{G_c(s)G_p(s)}{1+G_c(s)G_v(s)G_p(s)}d_v(s)-\frac{G_c(s)G_d(s)}{1+G_c(s)G_v(s)G_p(s)}d_p(s)\\ &=\frac{K_c(T_iT_ds^2+T_is+1)(T_vs+1)}{\Delta(s)}\{s(s^n+A_{n-1}s^{n-1}+\cdots+A_1s+A_0)[\theta_r(s)-d_m(s)]\\ &\quad-(B_ms^m+\cdots+B_1s+B_0)d_v(s)-(D_ds^d+\cdots+D_1s+D_0)d_p(s)\}\end{aligned} \tag{3-15}$$

where,

$$\Delta(s)=T_is^2(T_vs+1)(s^n+A_{n-1}s^{n-1}+\cdots+A_1s+A_0)+K_cK_v(T_iT_ds^2+T_is+1)(B_ms^m+\cdots+B_1s+B_0)$$

Therefore, in order to meet the need of the stability of the closed loop, one of the necessary conditions should be: $K_cK_vB_0>0$.

In this case, the steady state gains K_p and K_d in Figure 3-4 tend to be at $\pm\infty$.

3.3.3 Processes with Unstable Open Loop Poles

Processes with unstable open loop poles also exist commonly in a chemical process. For example, consider a continuous stirred tank reactor (CSTR) in which an irreversible exothermic reaction takes place. The heat of reaction is removed by a coolant medium that flows through a jacket around the reactor. Figure 3-6 demonstrates the relation between the amount of heat released by the exothermic reaction which is a sigmodial function of the temperature T in the reactor (curve A) and the heat removed by the coolant which is a linear function of T (line B). When the CSTR is at steady state, the heat produced by the reaction should be equal to the heat removed by the coolant. So in Figure 3-6, there are three steady states P1, P2 and P3. Steady states P1 and P3 are stable, whereas P2 is unstable, from the viewpoint of control engineering, the process operated at P2 has at least one unstable pole.

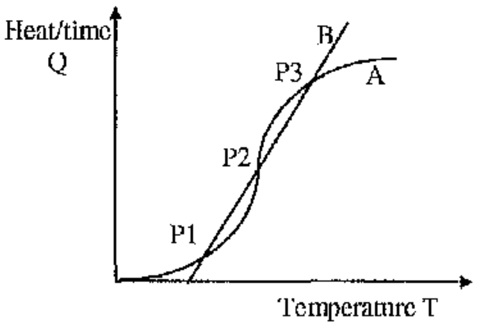


Figure 3-6: A CSTR operating states

Although the process has unstable poles, a PID controller can stabilise the process so that the closed loop system is stable.

Figure 3-4 can represent the PID control system of a linearised process with unstable open loop poles, where,

$$G_c(s) = K_c\left(1+\frac{1}{T_i s}+T_d s\right) \qquad K_c\neq 0,\ T_i>0,\ T_d\geq 0\ ; \tag{3-16}$$

$$G_v(s) = \frac{K_v}{T_v s+1} \qquad K_v\neq 0\ ,\ T_v\geq 0\ ; \tag{3-17}$$

$$G_p(s) = \frac{B_m s^m + B_{m-1}s^{m-1}+\cdots+B_1 s+B_0}{s^n + A_{n-1}s^{n-1}+\cdots+A_1 s + A_0}$$

$$m,n\in Z,\ m\geq 0,\ n\geq 1,\ A_0\neq 0,\ B_0\neq 0\ ,\ \exists A_j\leq 0\ (j=0,\ldots,n-1)\ ; \tag{3-18}$$

$$G_d(s) = \frac{D_d s^d + D_{d-1}s^{d-1}+\cdots+D_1 s+D_0}{s^n + A_{n-1}s^{n-1}+\cdots+A_1 s + A_0}$$

$$d,n\in Z,\ d\geq 0,\ n\geq 1,\ A_0\neq 0,\ D_0\neq 0\ ,\ \exists A_j\leq 0\ (j=0,\ldots,n-1)\ ; \tag{3-19}$$

Again, $G_p(s)$ and $G_d(s)$ have the same denominator.

Also

$$\begin{aligned}\theta(s) &= \frac{G_c(s)G_v(s)G_p(s)}{1+G_c(s)G_v(s)G_p(s)}[\theta_r(s)-d_m(s)] + \frac{G_p(s)}{1+G_c(s)G_v(s)G_p(s)}d_v(s) + \frac{G_d(s)}{1+G_c(s)G_v(s)G_p(s)}d_p(s)\\ &= \frac{K_c K_v (T_i T_d s^2 + T_i s+1)(B_m s^m+\cdots+B_1 s+B_0)}{\Delta(s)}[\theta_r(s)-d_m(s)]\\ &\quad + \frac{T_i s(T_v s+1)(B_m s^m+\cdots+B_1 s+B_0)}{\Delta(s)}d_v(s) + \frac{T_i s(T_v s+1)(D_d s^d+\cdots+D_1 s+D_0)}{\Delta(s)}d_p(s)\end{aligned} \tag{3-20}$$

and

$$\begin{aligned}x(s) &= \frac{G_c(s)}{1+G_c(s)G_v(s)G_p(s)}[\theta_r(s)-d_m(s)] - \frac{G_c(s)G_p(s)}{1+G_c(s)G_v(s)G_p(s)}d_v(s) - \frac{G_c(s)G_d(s)}{1+G_c(s)G_v(s)G_p(s)}d_p(s)\\ &= \frac{K_c(T_i T_d s^2 + T_i s+1)(T_v s+1)}{\Delta(s)}\{(s^n + A_{n-1}+\cdots+A_1 s+A_0)[\theta_r(s)-d_m(s)]\\ &\quad -(B_m s^m+\cdots+B_1 s+B_0)d_v(s) - (D_d s^d+\cdots+D_1 s+D_0)d_p(s)\}\end{aligned} \tag{3-21}$$

where,

$$\Delta(s) = T_i s(T_v s+1)(s^n + A_{n-1}s^{n-1}+\cdots+A_1 s+A_0) + K_c K_v (T_i T_d s^2 + T_i s+1)(B_m s^m+\cdots+B_1 s+B_0)$$

Once again, in order to meet the need of the stability of the closed loop, one of the necessary conditions should be: $K_cK_vB_0>0$.

The process steady state gain K_p is equivalent to B_0/A_0, for the stability of the closed-loop system, if $A_0>0$, which means $G_p(s)$ has an even number of poles located in the unstable right half plane, $K_cK_vK_p>0$ holds; if $A_0<0$, which means $G_p(s)$ has an odd number of poles located in the unstable right half plane, $K_cK_vK_p<0$ holds .

3.4 The Issue of Interaction Between Control Systems

In Figure 3-2 and Figure 3-3, individual control loops are influenced by their environment via process disturbances $d_{p1,i}$ for a single loop and $d_{p1,i}$ & $d_{p2,i}$ for a cascade control system. Although, in practice process disturbances can also be represented by a valve disturbance $d_{v,i}$, this possibility is ignored here because it is equivalent to applying them at $d_{p1,i}$ or at $d_{p2,i}$ having first passed through identical versions of their respective process blocks. Process disturbances might stem from other control loops or they might represent other influences like inputs into the plant. To separate these two possibilities and to focus solely on the steady state, define the following compound disturbances:

$$\begin{bmatrix} \mathbf{d}_{p1} \\ \mathbf{0}_m \\ \mathbf{d}_{p2} \end{bmatrix}' = \begin{bmatrix} \mathbf{K}_{d1}\mathbf{d}_{p1} \\ \mathbf{0}_m \\ \mathbf{K}_{d2}\mathbf{d}_{p2} \end{bmatrix} + \begin{bmatrix} \mathbf{K}_{OO} \\ \cdots \\ \mathbf{K}_{OI} \end{bmatrix} \boldsymbol{\theta}_I^* + \begin{bmatrix} \mathbf{K}_{IO} \\ \cdots \\ \mathbf{K}_{II} \end{bmatrix} \begin{bmatrix} \mathbf{0}_m \\ \cdots \\ \boldsymbol{\theta}_2 \end{bmatrix} \tag{3-22}$$

where the dash denotes the fact that these are compound disturbances; $\boldsymbol{\theta}_I^* \in \Re^{m+n}$ is composed of the m single loop controlled variables together with the n controlled variables pertaining to the outer loops of the cascade control systems (i.e. $\boldsymbol{\theta}_I^* = [\boldsymbol{\theta}_s \vdots \boldsymbol{\theta}_1]'$); $\boldsymbol{\theta}_2$ is the vector of n inner variables: $\boldsymbol{\theta}_2 \in \Re^n$; $\mathbf{d}_{p1} \in \Re^{m+n}$, $\mathbf{d}_{p2} \in \Re^n$;

$\mathbf{K}_{d1} \in \Re^{m+n,m+n}$, $\mathbf{K}_{d2} \in \Re^{n,n}$: $\mathbf{K}_{d1} = \begin{bmatrix} K_{d1,1} & & & \mathbf{0} \\ & K_{d1,2} & & \\ & & \ddots & \\ \mathbf{0} & & & K_{d1,m+n} \end{bmatrix}$ and

$$\mathbf{K}_{d2} = \begin{bmatrix} K_{d2,1} & & & \mathbf{0} \\ & K_{d2,2} & & \\ & & \ddots & \\ \mathbf{0} & & & K_{d2,n} \end{bmatrix};$$ $\mathbf{K}_{OO}$, $\mathbf{K}_{II}$, $\mathbf{K}_{IO}$,

$\mathbf{K}_{OI} \in \Re^{m+n,m+n}$: $\mathbf{K}_{IO} = \begin{bmatrix} \mathbf{0}_{m+n,m} & \vdots & \end{bmatrix}$ and $\mathbf{K}_{OI} = \begin{bmatrix} \mathbf{0}_{m,m+n} \\ \cdots \\ \end{bmatrix}$. The various subscripts are used to denote relationships e.g. OI means outer (O) to inner (I) and so on. It is likely that a large proportion of the elements of the steady state gain matrices $\mathbf{K}_{OO}$, $\mathbf{K}_{IO}$, $\mathbf{K}_{OI}$ and $\mathbf{K}_{II}$ will be relatively small and would therefore be zeroed. In addition it must be stressed that only the signs would be analysed so these gains need not be known qualitatively. Seborg, Edgar & Mellichamp (1989) suggest that the determination of the signs of the various gains should be relatively straightforward.

Two examples are given here to demonstrate the above.

A. The case of a single loop controller interacting with the inner loop of a cascade controller, in both directions:

$$\boldsymbol{\theta}_1^* = \begin{bmatrix} \theta_{,1} \\ \theta_{1,2} \end{bmatrix}, \ \boldsymbol{\theta}_2 = [\theta_{2,2}], \ \mathbf{K}_{OO} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, \ \mathbf{K}_{II} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, \ \mathbf{K}_{OI} = \begin{bmatrix} 0 & 0 \\ K_{12} & 0 \end{bmatrix} \text{ and}$$

$$\mathbf{K}_{IO} = \begin{bmatrix} 0 & K_{21} \\ 0 & 0 \end{bmatrix}$$

B. The case of the inner loops of two cascade controllers interacting, in both directions:

$$\boldsymbol{\theta}_1^* = \begin{bmatrix} \theta_{1,1} \\ \theta_{1,2} \end{bmatrix}, \ \boldsymbol{\theta}_2 = \begin{bmatrix} \theta_{2,1} \\ \theta_{2,2} \end{bmatrix}, \mathbf{K}_{OO} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, \ \mathbf{K}_{II} = \begin{bmatrix} 0 & K_{21} \\ K_{21} & 0 \end{bmatrix}, \ \mathbf{K}_{OI} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \text{ and}$$

$$\mathbf{K}_{IO} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Finally denote any steady state information that pertains to the controlled variables and is obtained from any additional sensors that are installed by

$$\boldsymbol{\phi} = \mathbf{K}_s \begin{bmatrix} \theta_1^* \\ \theta_2 \end{bmatrix} + \mathbf{d}_s \quad , \tag{3-23}$$

where $\boldsymbol{\phi}$ and $\mathbf{d}_s$ are the measurements and other sensor related influences respectively.

3.5 Steady State Deviations in Controller Outputs

Consider first the case of a single loop controller in Figure 3-2. Suppose that a change in steady state occurs either because of a fault or because of a change of disturbance. From Equations (3-7) and (3-8), if the controller functions properly, then $e_{,i}=0$ so that

$$\theta_{,i} = \theta_{r,i} - d_{m1,i} \tag{3-24}$$

and $x_{,i}$ will deviate:

$$x_{,i} = \frac{\theta_{r,i}}{K_{p1,i}K_{v,i}} - \frac{d_{m1,i}}{K_{p1,i}K_{v,i}} - \frac{K_{d1,i}d_{p1,i}}{K_{p1,i}K_{v,i}} - \frac{d_{v1,i}}{K_{v,i}} . \tag{3-25}$$

Consider, now, a cascade control system (Figure 3-3) instead. In the steady state, if $e_{1,i}=0$ and $e_{2,i}=0$, then there are:

$$x_{1,i} = \frac{\theta_{r,i}}{K_{p1,i}} - \frac{d_{m1,i}}{K_{p1,i}} - \frac{K_{d1,i}d_{p1,i}}{K_{p1,i}} + d_{m2,i} \tag{3-26}$$

$$\begin{aligned} x_{2,i} = {} & \frac{\theta_{r,i}}{K_{p1,i}K_{p2,i}K_{v,i}} - \frac{K_{d1,i}d_{p1,i}}{K_{p1,i}K_{p2,i}K_{v,i}} \\ & - \frac{d_{m1,i}}{K_{p1,i}K_{p2,i}K_{v,i}} - \frac{K_{d2,i}d_{p2,i}}{K_{p2,i}K_{v,i}} - \frac{d_{v,i}}{K_{v,i}} \end{aligned} \tag{3-27}$$

$$\theta_{1,i} = \theta_{r,i} - d_{m1,i} \tag{3-28}$$

$$\theta_{2,i} = \frac{\theta_{r,i}}{K_{p1,i}} - \frac{d_{m1,i}}{K_{p1,i}} - \frac{K_{d1,i} d_{p1,i}}{K_{p1,i}} \tag{3-29}$$

Turning to the effect of interactions, again consider first the case of a single loop controller (Controller j) affected by other controllers. Substituting equation (3-24) and the quantitative equivalent of equation (3-28) into equation (3-22) and focusing on the jth row leads to

$$d'_{p1,j} = K_{d1,j} d_{p1,j} + \sum_{\substack{i=1 \\ i \neq j}}^{m+n} \left(K_{OOj,i} + \frac{K_{IOj,i}}{K_{p1,i}} \right) \left(\theta_{r,i} - d_{m1,i} \right) - \sum_{\substack{i=1 \\ i \neq j}}^{m+n} K_{IOj,i} \frac{K_{d1,i} d_{p1,i}}{K_{p1,i}} \tag{3-30}$$

Substituting into Equation (3-25) leads to

$$\begin{aligned} x_{,j} = & \frac{\theta_{r,j}}{K_{p1,j} K_{v,j}} - \frac{d_{m1,j}}{K_{p1,j} K_{v,j}} - \frac{K_{d1,j} d_{p1,j}}{K_{p1,j} K_{v,j}} \\ & - \sum_{\substack{i=1 \\ i \neq j}}^{m+n} \left(K_{OOj,i} + \frac{K_{IOj,i}}{K_{p1,i}} \right) \frac{\theta_{r,i}}{K_{p1,j} K_{v,j}} + \sum_{\substack{i=1 \\ i \neq j}}^{m+n} \left(K_{OOj,i} + \frac{K_{IOj,i}}{K_{p1,i}} \right) \frac{d_{m1,i}}{K_{p1,j} K_{v,j}} \\ & + \sum_{\substack{i=1 \\ i \neq j}}^{m+n} \frac{K_{IOj,i}}{K_{p1,i}} \frac{K_{d1,j} d_{p1,i}}{K_{p1,j} K_{v,j}} - \frac{d_{v,j}}{K_{v,j}} \end{aligned} \tag{3-31}$$

Consider now interactions on a cascade controller: equation (3-30) still holds for the outer disturbance whereas, by repeating the above approach, the inner disturbance can be represented by

$$d'_{p2,j} = K_{d2,j} d_{p2,j} + \sum_{\substack{i=1 \\ i \neq j}}^{m+n} \left(K_{OIj,i} + \frac{K_{IIj,i}}{K_{p1,i}} \right) \left(\theta_{r,i} - d_{m1,i} \right) - \sum_{\substack{i=1 \\ i \neq j}}^{m+n} K_{IIj,i} \frac{K_{d1,i} d_{p1,i}}{K_{p1,i}} \tag{3-32}$$

This then leads to:

$$x_{1,j} = \frac{\theta_{r,j}}{K_{p1,j}} - \frac{d_{m1,j}}{K_{p1,j}} - \frac{K_{d1,j}d_{p1,j}}{K_{p1,j}} - \sum_{\substack{i=1\\ i\neq j}}^{n}\left(K_{OOj,i} + \frac{K_{IOj,i}}{K_{p1,i}}\right)\frac{\theta_{r,i}}{K_{p1,j}}$$

$$+ \sum_{\substack{i=1\\ i\neq j}}^{n}\left(K_{OOj,i} + \frac{K_{IOj,i}}{K_{p1,i}}\right)\frac{d_{m1,i}}{K_{p1,j}} + \sum_{\substack{i=1\\ i\neq j}}^{n}\frac{K_{IOj,i}}{K_{p1,i}}\frac{K_{d1,i}d_{p1,i}}{K_{p1,j}} + d_{m2,j} \tag{3-33}$$

$$x_{2,j} = \frac{\theta_{r,j}}{K_{p1,j}K_{p2,j}K_{v,j}} - \frac{d_{m1,j}}{K_{p1,j}K_{p2,j}K_{v,j}} - \frac{K_{d1,j}d_{p1,j}}{K_{p1,j}K_{p2,j}K_{v,j}}$$

$$- \sum_{\substack{i=1\\ i\neq j}}^{n}\left(K_{OOj,i} + \frac{K_{IOj,i}}{K_{p1,i}}\right)\frac{\theta_{r,i}}{K_{p1,j}K_{p2,j}K_{v,j}}$$

$$+ \sum_{\substack{i=1\\ i\neq j}}^{n}\left(K_{OOj,i} + \frac{K_{IOj,i}}{K_{p1,i}}\right)\frac{d_{m1,i}}{K_{p1,j}K_{p2,j}K_{v,j}}$$

$$+ \sum_{\substack{i=1\\ i\neq j}}^{n}\frac{K_{IOj,i}}{K_{p1,i}}\frac{K_{d1,i}d_{p1,i}}{K_{p1,j}K_{p2,j}K_{v,j}} - \frac{K_{d2,j}d_{p2,j}}{K_{p2,j}K_{v,j}}$$

$$- \sum_{\substack{i=1\\ i\neq j}}^{n}\left(K_{OIj,i} + \frac{K_{IIj,i}}{K_{p1,i}}\right)\frac{\theta_{r,i}}{K_{p2,j}K_{v,j}} + \sum_{\substack{i=1\\ i\neq j}}^{n}\left(K_{OIj,i} + \frac{K_{IIj,i}}{K_{p1,i}}\right)\frac{d_{m1,i}}{K_{p2,j}K_{v,j}}$$

$$+ \sum_{\substack{i=1\\ i\neq j}}^{n}\frac{K_{IIj,i}}{K_{p1,i}}\frac{K_{d1,i}d_{p1,i}}{K_{p2,j}K_{v,j}} - \frac{d_{v,j}}{K_{v,j}} \tag{3-34}$$

3.6 Qualitative Representations of Controller Deviations

A number of qualitative relationships must first be derived before the equations, developed in Section 3.5, can be interpreted qualitatively. For stability in a single closed loop control system with a PI controller, $K_cK_vB_0>0$ regardless of the type of the open loop process (Section 3.3). If the process is open loop stable, $A_0>0$ and $K_cK_vK_p>0$, $\{K_vK_p\}=\{K_c\}$, if the process is open loop unstable and if $A_0>0$, then $K_cK_vK_p>0$ and $\{K_vK_p\}=\{K_c\}$, otherwise if $A_0<0$, then $K_cK_vK_p<0$ and $\{K_vK_p\}= -\{K_c\}$. For the capacitive process, $\frac{1}{K_p}=0$ except that $\frac{K_d}{K_p}=\frac{D_0}{B_0}$.

In a standard cascade control system, the steady state gain of the inner loop can be viewed as 1. This means that the observations above also hold here. That is for stability of both the outer loop and inner loop systems, $K_{c1}B_{01}>0$ and $K_{c2}K_vB_{02}>0$ and therefore $\{K_{p1}\}=\left\{\frac{B_{01}}{A_{01}}\right\}=\frac{\{K_{c1}\}}{\{A_{01}\}}$ and $\{K_{p2}K_v\}=\left\{\frac{B_{02}K_v}{A_{02}}\right\}=\left\{\frac{K_{c2}}{A_{02}}\right\}$.

These relationships can now be used together with those in Section 3.3.3 to interpret qualitative versions of the equations obtained in Section 3.5. For example, in a single loop control system, Equation (3-24) can be viewed as:

$$[\theta_{,i}]=[\theta_{r,i}]-[d_{m1,i}] \tag{3-35}$$

and Equation (3-25) as

$$[x_{,i}]=\frac{[\theta_{r,i}]}{\{K_{p1,i}K_{v,i}\}}-\frac{[d_{m1,i}]}{\{K_{p1,i}K_{v,i}\}}-\frac{\{K_{d1,i}\}[d_{p1,i}]}{\{K_{p1,i}K_{v,i}\}}-\frac{[d_{v,i}]}{\{K_{v,i}\}}$$
$$=\begin{cases}\dfrac{[\theta_{r,i}]}{\{A_{01,i}K_{c1,i}\}}-\dfrac{[d_{m1,i}]}{\{A_{01,i}K_{c1,i}\}}-\dfrac{\{K_{d1,i}\}[d_{p1,i}]}{\{A_{01,i}K_{c1,i}\}}-\dfrac{[d_{v,i}]}{\{K_{v,i}\}}; & \text{the process is with a Type Number} = 0\\ -\dfrac{\{D_{01,i}\}[d_{p1,i}]}{\{K_{c1,i}\}}-\dfrac{[d_{v,i}]}{\{K_{v,i}\}} & \text{; the process is with a Type Number} > 0\end{cases} \tag{3-36}$$

where,

$$\{A_{01,i}\}=\begin{cases}+ & \text{; the process is stable or has an even number of unstable poles;}\\ - & \text{; the process has an odd number of unstable poles.}\end{cases}$$

These qualitative equations indicate that any change/fault/disturbance in $\theta_{r,i}$, $d_{m1,i}$, $d_{p1,i}$ and $d_{v,i}$ would cause the controlled variable $\theta_{,i}$ or the controller output $x_{,i}$ to deviate or both. By observing $[x_{,i}]$ and $[\theta_{,i}]$, in which the latter might not be observed directly but could be reasoned from its descendants, the fault could be detected and isolated. If ONLY one fault happens, the sign or direction of it can be determined by the equations because those qualitative gains in the equations are known once the control system is designed and process disturbances are hypothesised.

In a standard cascade control system, there are:

$$[x_{1,i}]=\frac{[\theta_{r,i}]}{\{K_{p1,i}\}}-\frac{[d_{m1,i}]}{\{K_{p1,i}\}}-\frac{\{K_{d1,i}\}[d_{p1,i}]}{\{K_{p1,i}\}}+[d_{m2,i}]$$

$$=\begin{cases}\dfrac{[\theta_{r,i}]}{\{A_{01,i}K_{c1,i}\}}-\dfrac{[d_{m1,i}]}{\{A_{01,i}K_{c1,i}\}}-\dfrac{\{K_{d1,i}\}[d_{p1,i}]}{\{A_{01,i}K_{c1,i}\}}+[d_{m2,i}] & \text{; the outer-loop process is with a Type Number} = 0\\ -\dfrac{\{D_{01,i}\}[d_{p1,i}]}{\{K_{c1,i}\}}+[d_{m2,i}] & \text{; the outer-loop process is with a Type Number} > 0\end{cases} \quad (3\text{-}37)$$

$$[x_{2,i}]=\frac{[\theta_{r,i}]-\{K_{d1,i}\}[d_{p1,i}]-[d_{m1,i}]}{\{K_{p1,i}K_{p2,i}K_{v,i}\}}-\frac{\{K_{d2,i}\}[d_{p2,i}]}{\{K_{p2,i}K_{v,i}\}}-\frac{[d_{v,i}]}{\{K_{v,i}\}}$$

$$=\begin{cases}\dfrac{[\theta_{r,i}]-\{K_{d1,i}\}[d_{p1,i}]-[d_{m1,i}]}{\{A_{01,i}A_{02,i}K_{c1,i}K_{c2,i}\}}-\dfrac{\{K_{d2,i}\}[d_{p2,i}]}{\{A_{02,i}K_{c2,i}\}}-\dfrac{[d_{v,i}]}{\{K_{v,i}\}} & \text{; both the inner and outer-loop processes are with a Type Number} = 0\\ -\dfrac{\{D_{01,i}\}[d_{p1,i}]}{\{A_{02,i}K_{c1,i}K_{c2,i}\}}-\dfrac{\{K_{d2,i}\}[d_{p2,i}]}{\{A_{02,i}K_{c2,i}\}}-\dfrac{[d_{v,i}]}{\{K_{v,i}\}} & \text{; only the outer-loop process is with a Type Number} > 0\\ -\dfrac{\{D_{02,i}\}[d_{p2,i}]}{\{K_{c2,i}\}}-\dfrac{[d_{v,i}]}{\{K_{v,i}\}} & \text{; only the inner-loop process is with a Type Number} > 0\end{cases} \quad (3\text{-}38)$$

$$[\theta_{1,i}]=[\theta_{r,i}]-[d_{m1,i}] \quad (3\text{-}39)$$

$$[\theta_{2,i}]=\frac{[\theta_{r,i}]}{\{K_{p1,i}\}}-\frac{[d_{m1,i}]}{\{K_{p1,i}\}}-\frac{\{K_{d1,i}\}[d_{p1,i}]}{\{K_{p1,i}\}}$$

$$=\begin{cases}\dfrac{[\theta_{r,i}]}{\{A_{01,i}K_{c1,i}\}}-\dfrac{[d_{m1,i}]}{\{A_{01,i}K_{c1,i}\}}-\dfrac{\{K_{d1,i}\}[d_{p1,i}]}{\{A_{01,i}K_{c1,i}\}} & \text{; the outer-loop process is with a Type Number} = 0\\ -\dfrac{\{D_{01,i}\}[d_{p1,i}]}{\{K_{c1,i}\}} & \text{; the outer-loop process is with a Type Number} > 0\end{cases} \quad (3\text{-}40)$$

where,

$$\{A_{01,i}\}=\begin{cases}+ & \text{; the related open-loop process is stable or has an even number of unstable poles;}\\ - & \text{; the related open-loop process has an odd number of unstable poles.}\end{cases}$$

$$\{A_{02,i}\} = \begin{cases} + & \text{; the related open-loop process is stable or has an even number of unstable poles;} \\ - & \text{; the related open-loop process has an odd number of unstable poles.} \end{cases}$$

Similarly, any change/fault/disturbance in $\theta_{r,i}$, $d_{m1,i}$, $d_{p1,i}$, $d_{m2,i}$, $d_{p2,i}$ and $d_{v,i}$ would cause the controlled variable $\theta_{1,i}$ and $\theta_{2,i}$ or the controller output $x_{1,i}$ and $x_{2,i}$ to deviate. By observing $[x_{1,i}]$, $[x_{2,i}]$, $[\theta_{1,i}]$ and $[\theta_{2,i}]$, in which the latter two might not be observed directly but could be reasoned from its descendants, the fault could be detected and isolated. If ONLY one fault happens, the sign or direction of it can be determined by the equations because those qualitative gains in the equations are known once the control system is designed and process disturbances are hypothesised.

The qualitative forms of other equations with interactions can be derived and explained similarly.

It is worth pointing out that the signs of the deviations in the controlled variables can also be determined from additional measurements that are available (equation 3-23), thus

$$[\boldsymbol{\phi}] = \{\mathbf{K}_s\}\begin{bmatrix} [\boldsymbol{\theta}_1^*] \\ [\boldsymbol{\theta}_2] \end{bmatrix} + [\mathbf{d}_s] \tag{3-41}$$

Equation (3-41) can then be developed further by substituting equations (3-35), (3-39) & (3-40) into it.

3.7 Fault Isolation

It is likely that more than one control system would seek to compensate for a process fault. This section examines that the various changes should be analysed to isolate the fault. It is assumed that a set of qualitative equations have been formed for each control system on the basis of equations (3-36), (3-37), (3-38) & (3-41). Note that various variables appear in more than one of the equations. A set of rules are now developed that exploit this redundancy and it is these rules that would be implemented on the controller. The rules are more likely to be implemented implicitly, rather than explicitly, because the computer program is likely to be constructed using loops and tests. However for ease of understanding here, rules are generated explicitly. To generate this set of rules first let set H_{Oj} contain those k_j controllers whose single loops interact with Controller Number j, and those k_{Oj} controllers whose outer loops interact with the Controller. Then $H_{Oj} \equiv$ {Controller $\gamma_{j,1}$, …., Controller γ_{j,k_j}, Controller $\xi_{j,1}$, …., Controller $\xi_{j,k_{Oj}}$}, let set H_{Ij} contain those k_{Ij} controllers whose inner loops interact with Controller j, then $H_{Ij} \equiv$ {Controller $\lambda_{j,1}$, …., Controller $\lambda_{j,k_{Ij}}$}, and let set $H_{\phi j}$ contain those $k_{\phi j}$ instruments that interact with Controller Number j. Then form sets that contain the all the variables that are contained in each of the equations: $C_{s,j}$ for single loop controller j, $C_{c1,j}$ for the outer loop of cascade controller j, $C_{c2,j}$ for the inner loop of cascade controller j, and $C_{\phi,j}$ for Instrument Number j, for instance:

$$
\begin{aligned}
C_{s,j} = &\left\{\theta_{r,j}, d_{m,j}, d_{p1,j}, d_{v,j}\right\} \cup \left\{\theta_{r,\gamma_{j,1}}, \ldots, \theta_{r,\gamma_{j,kj}}, \theta_{r,\xi_{j,1}}, \ldots, \theta_{r,\xi_{j,kOj}}\right\} \\
&\cup \left\{d_{m,\gamma_{j,1}}, \ldots d_{m,\gamma_{j,kj}}, d_{m1,\xi_{j,1}}, \ldots d_{m1,\xi_{j,kj}}\right\} \cup \left\{d_{p1,\lambda_{j,1}}, \ldots d_{p1,\lambda_{j,kIj}}\right\} \cup \left\{d_{m1,\lambda_{j,1}}, \ldots d_{m1,\lambda_{j,kIj}}\right\}
\end{aligned} \tag{3-42}
$$

$$
\begin{aligned}
C_{c1,j} = &\left\{\theta_{r,j}, d_{m1,j}, d_{p1,j}, d_{m2,j}\right\} \cup \left\{\theta_{r,\gamma_{j,1}}, \ldots, \theta_{r,\gamma_{j,kj}}, \theta_{r,\xi_{j,1}}, \ldots, \theta_{r,\xi_{j,kOj}}\right\} \\
&\cup \left\{d_{m,\gamma_{j,1}}, \ldots d_{m,\gamma_{j,kj}}, d_{m1,\xi_{j,1}}, \ldots d_{m1,\xi_{j,kj}}\right\} \cup \left\{d_{p1,\lambda_{j,1}}, \ldots d_{p1,\lambda_{j,kIj}}\right\} \cup \left\{d_{m1,\lambda_{j,1}}, \ldots d_{m1,\lambda_{j,kIj}}\right\}
\end{aligned} \tag{3-43}
$$

$$
\begin{aligned}
C_{c2,j} = &\left\{\theta_{r,j}, d_{m1,j}, d_{p1,j}, d_{p2,j}, d_{v,j}\right\} \cup \left\{\theta_{r,\gamma_{j,1}}, \ldots, \theta_{r,\gamma_{j,kj}}, \theta_{r,\xi_{j,1}}, \ldots, \theta_{r,\xi_{j,kOj}}\right\} \\
&\cup \left\{d_{m,\gamma_{j,1}}, \ldots d_{m,\gamma_{j,kj}}, d_{m1,\xi_{j,1}}, \ldots d_{m1,\xi_{j,kj}}\right\} \cup \left\{d_{p1,\lambda_{j,1}}, \ldots d_{p1,\lambda_{j,kIj}}\right\} \cup \left\{d_{m1,\lambda_{j,1}}, \ldots d_{m1,\lambda_{j,kIj}}\right\}
\end{aligned} \tag{3-44}
$$

Identify all the controller output variables and additional measurements associated with {Controller j}$\cup H_{Oj} \cup H_{Ij} \cup H_{\phi j}$, and generate the rule set based on all possible combinations of their having deviated. To do this let $[X_{,i}]$, $[\Phi_1]$ be the Booleans that denote $[x_{,i}] \neq$ null, $[\phi_1] \neq$ null and so on, then rules can be generated LIKE the following

$$
\begin{aligned}
&[X_{,1}] \wedge \overline{[X_{,2}]} \wedge \ldots\ldots \wedge [X_{1,(m+1)}] \wedge [X_{1,(m+2)}] \wedge \ldots\ldots \wedge \overline{[X_{2,(m+1)}]} \wedge \ldots\ldots \wedge [\Phi_1] \wedge \ldots \\
&\rightarrow C_{s,1} \cap \overline{C_{s,2}} \cap \ldots\ldots \cap C_{c1,(m+1)} \cap C_{c1,(m+2)} \cap \ldots\ldots \cap \overline{C_{c2,(m+1)}} \cap \ldots\ldots \cap C_{\phi,1} \cap \ldots \\
&\rightarrow C_{s,1} \cap \ldots\ldots \cap C_{c1,(m+1)} \cap C_{c1,(m+2)} \cap \ldots \cap C_{\phi,1} \ldots \cap \overline{C_{s,2}} \cap \ldots\ldots \cap \overline{C_{c2,(m+1)}} \cap \ldots
\end{aligned}
$$

Rule1

where the last form would be the way it is likely to be implemented in practice. Note that the consequent consists of a set of variables, the deviation in a single element of which would cause deviations in the appropriate control variables and measurements. Each rule would also contain sign information to indicate the direction each element would have to take cause the deviations observed. These rules can be refined in a number of ways:

1. knowledge pertaining to set-points may be incorporated;
2. groups of equations may be analysed for contradictory directions;
3. knowledge pertaining to correlated disturbances may be incorporated; the SDG provides a convenient representation for doing this.

Most of these aspects are demonstrated by an example in the next Section and applications in Chapter 8. Having generated a set of rules, the Supervisor then needs to combine the various consequents that are actually generated. If only single faults are to be considered, then the Supervisor need only take their intersection. However, if multiple faults are also sought, then it should be possible to isolate them provided the control systems they affect don't interact with each other directly. For example, suppose that fault F_1 affects a single loop controller i and fault F_2 affects another single controller j simultaneously, they can be detected and diagnosed so long as the equation $C_{s,i} \cap C_{s,j} = \varnothing$ (null) holds.

3.8 An Example For A Process With Two Single Control Loops That Interact

In this section we give a simple example to show how to reason about sign information, how the majority of the rules generated can be enhanced using this information and how the theory helps in process monitoring and fault diagnosis. More complicated examples and large-scale applications will be given in Chapter 8.

In this case disturbance $d'_{p1,1}$ is re-defined as

$$d'_{p1,1} = K_{d1,1}d_{p1,1} + K_{21}\theta_{,2} = K_{d1,1}d_{p1,1} + K_{21}\left(\theta_{r,2} - d_{m1,2}\right) \tag{3-45}$$

and $d'_{p,2}$ is re-defined as

$$d'_{p1,2} = K_{d1,2}d_{p1,2} + K_{12}\theta_{,1} = K_{d1,2}d_{p1,2} + K_{12}\left(\theta_{r,1} - d_{m1,1}\right) \tag{3-46}$$

where either K_{12} or K_{21} would be zero if interaction was only one-way. Thus

$$K_{OO} = \begin{bmatrix} 0 & K_{21} \\ K_{12} & 0 \end{bmatrix}, \; K_{II} = K_{IO} = K_{OI} = \mathbf{0}_{2x2}.$$

For simplicity only Type Number 0 processes are considered here. Substituting into Equation (3-36) gives

$$[x_{,1}] = \frac{[\theta_{r,1}] - \{K_{21}\}[\theta_{r,2}] + \{K_{21}\}[d_{m1,2}] - [d_{m1,1}] - \{K_{d1,1}\}[d_{p1,1}]}{\{A_{01,1}K_{c1,1}\}} - \frac{[d_{v,1}]}{\{K_{v,1}\}} \tag{3-47}$$

$$[x_{,2}] = \frac{[\theta_{r,2}] - \{K_{12}\}[\theta_{r,1}] + \{K_{12}\}[d_{m1,1}] - [d_{m1,2}] - \{K_{d1,2}\}[d_{p1,2}]}{\{A_{01,2}K_{c1,2}\}} - \frac{[d_{v,2}]}{\{K_{v,2}\}} \tag{3-48}$$

and applying equation (3-42) to the above gives $C_{s,1} = \{\ \theta_{r,1}\ ,\ \theta_{r,2}\ ,\ d_{m1,1}\ ,\ d_{m1,2}\ ,\ d_{v,1}\ ,\ d_{p1,1}\ \}$ and $C_{s,2} = \{\ \theta_{r,1}\ ,\ \theta_{r,2}\ ,\ d_{m1,1}\ ,\ d_{m1,2}\ ,\ d_{v,2}\ ,\ d_{p1,2}\ \}$. These sets indicate that there are a number of variables that are of common interest to both controllers and hence should be communicated between them. The following rules can now be generated for Controller 1:

$[X_{,1}] \wedge [X_{,2}] \rightarrow C_{s,1} \cap C_{s,2} \rightarrow \{\ \theta_{r,1}\ ,\ \theta_{r,2}\ ,\ d_{m1,1}\ ,\ d_{m1,2}\ \}$ Rule 1.1

$[X_{,1}] \wedge \overline{[X_{,2}]} \rightarrow C_{s,1} \cap \overline{C}_{s,2} \rightarrow \{\ d_{v,1}\ ,\ d_{p1,1}\ \}$ Rule 1.2

and for Controller 2:

$[X_{,1}] \wedge [X_{,2}] \rightarrow C_{s,1} \cap C_{s,2} \rightarrow \{ \theta_{r,1}, \theta_{r,2}, d_{m1,1}, d_{m1,2} \}$ Rule 2.1

$\overline{[X_{,1}]} \wedge [X_{,2}] \rightarrow \overline{C_{s,1}} \cap C_{s,2} \rightarrow \{ d_{v,2}, d_{p1,2} \}$ Rule 2.2

Rules 1.1 & 2.1 can be refined by noting that both $[\theta_{r,1}]$ and $[\theta_{r,2}]$ could be acquired at any time e.g. if Rule 1.1 has fired but neither set-point has changed, then deduce that either $d_{m1,1}$ or $d_{m1,2}$ has occurred. Next equations (3-47) & (3-48) can be compared for contradictory directions; assume that set-point deviations have been eliminated and suppose that $[x_{,1}] = + \wedge [x_{,2}] = +$, then by considering Rule 1.1 there are 2 solutions:

$$\left\{\frac{\{K_{21}\}[d_{m1,2}]}{\{A_{01,1}K_{c1,1}\}}=+,\ \frac{[d_{m1,1}]}{\{A_{01,1}K_{c1,1}\}}=-,\right\} \ \& \ \left\{\frac{\{K_{12}\}[d_{m1,1}]}{\{A_{01,2}K_{c1,2}\}}=+,\ \frac{[d_{m1,2}]}{\{A_{01,2}K_{c1,2}\}}=-,\right\}.$$

Let Boolean P_{21} denote the fact that $\{K_{21}\}$ has a positive sign, $P_{c,1}$ the fact that $\{A_{01,1}K_{c1,1}\}$ has a positive sign and so on, then to detect $d_{m1,2}$ and not $d_{m1,1}$ note that for this to happen either

$$\left[\left[\left(P_{21} \wedge P_{c,1}\right) \vee \left(\overline{P}_{21} \wedge \overline{P}_{c,1}\right)\right] \wedge \overline{P}_{c,2}\right] \wedge \left[\left(P_{12} \wedge \overline{P}_{c,1}\right) \vee \left(\overline{P}_{12} \wedge P_{c,1}\right)\right]$$
$$\Rightarrow \left[\left[P_{21} \wedge \overline{P}_{12} \wedge P_{c,1}\right] \vee \left[\overline{P}_{21} \wedge P_{12} \wedge \overline{P}_{c,1}\right]\right] \wedge \overline{P}_{c,2}$$

or

$$\left[\left[\left(P_{21} \wedge \overline{P}_{c,1}\right) \vee \left(\overline{P}_{21} \wedge P_{c,1}\right)\right] \wedge P_{c,2}\right] \wedge \left[\left(P_{12} \wedge P_{c,1}\right) \vee \left(\overline{P}_{12} \wedge \overline{P}_{c,1}\right)\right]$$
$$\Rightarrow \left[\left[P_{21} \wedge \overline{P}_{12} \wedge \overline{P}_{c,1}\right] \vee \left[\overline{P}_{21} \wedge P_{12} \wedge P_{c,1}\right]\right] \wedge P_{c,2}$$

and the same result will be obtained for $[x_{,1}] = - \wedge [x_{,2}] = -$. To detect $d_{m1,1}$ instead of $d_{m1,2}$ the following must happen:

$$\left[\left[\overline{P}_{21} \wedge P_{12} \wedge P_{c,1}\right] \vee \left[P_{21} \wedge \overline{P}_{12} \wedge \overline{P}_{c,1}\right]\right] \wedge \overline{P}_{c,2} \ \text{ or}$$

$$\left[\left[P_{21} \wedge \overline{P}_{12} \wedge P_{c,1}\right] \vee \left[\overline{P}_{21} \wedge P_{12} \wedge \overline{P}_{c,1}\right]\right] \wedge P_{c,2}$$

Thus the two disturbances can only be separated if one of these four exclusive statements are true. Combining these 4 statements leads to $\left(P_{21} \wedge \overline{P}_{12}\right) \vee \left(\overline{P}_{21} \wedge P_{12}\right)$, i.e. the signs of $\{K_{12}\}$ and $\{K_{21}\}$ must be opposite. An identical result is obtained if the two controlled variables deviate in opposite directions. Thus if $\{K_{12}\}$ and $\{K_{21}\}$ are of opposite sign additional rules like the following can be generated:

$[x_{,1}] = + \wedge [x_{,2}] = + \wedge P_{21} \wedge P_{c1,1} \wedge P_{c1,2} \wedge \overline{P}_{12} \rightarrow [d_{m1,1}] = -$ Rule 1.3

$[x_{,1}] = + \wedge [x_{,2}] = - \wedge P_{21} \wedge P_{c1,1} \wedge P_{c1,2} \wedge \overline{P}_{12} \rightarrow [d_{m1,2}] = +$ Rule 2.3

3.9 Remarks On Some Other Cases

3.9.1 Ratio Control Systems

Ratio control systems are mostly used to control the ratio of the flow rates of two streams. Both flow rates are measured but only one can be controlled by the ratio controller. Conventionally there are two different ratio control configurations for two streams:

- in Figure 3-7A, both flow rates are measured and their ratio is taken to be compared to the set-point (desired ratio) in the ratio controller;
- in Figure 3-7B, the set-point of flow rate F2 is adjusted by the product of flow rate F1 and the desired ratio.

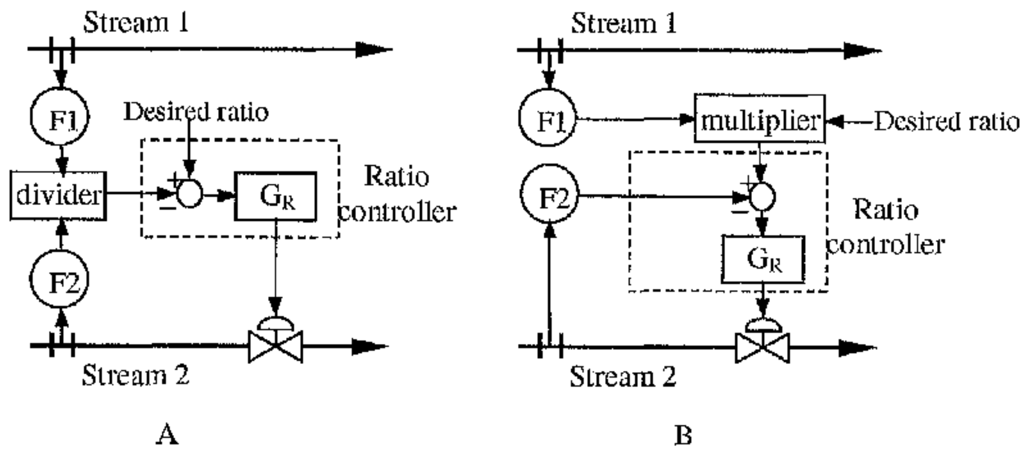


Figure 3-7: Alternative configurations of ratio control systems

No matter what the configuration is, these ratio control systems can be viewed as a single loop control system and the single loop self-validating control system based approach can be applied in fault detection and diagnosis of these ratio control systems. Whenever the ratio is controlled by another controller, the ratio control system can be viewed as an inner loop of a cascade control system.

3.9.2 Feedforward-Feedback Control Systems

In the presence of load or set-point changes, dynamic feedback control systems can never achieve perfect control of a process, that is, keep the output of the process continuously at the desired set-point because they rely on an error or rate of change of error. Feedforward control systems measure the disturbance or load directly and take control actions immediately to eliminate its impact on the process output. Therefore, feedforward controllers have the theoretical potential for perfect control.

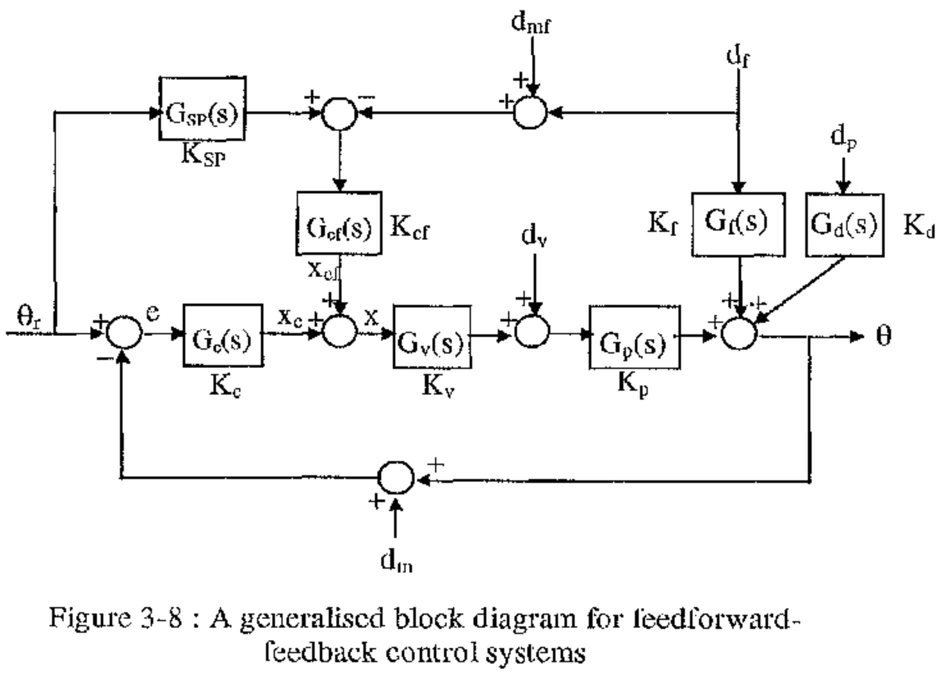


Figure 3-8 : A generalised block diagram for feedforward-feedback control systems

However, feedforward controllers cannot cope with unmeasured disturbances: combined feedforward-feedback control systems are conventionally adopted if one disturbance can be measured and a model of its impact on the process is available.

Figure 3-8 shows a generalised block diagram for feedforward-feedback control, in which, $G_{cf}(m)$ is the feedforward controller and $G_c(s)$ is the feedback controller, d_f is the measurable disturbance, $G_f(s)$ the model of its impact on the process output θ, and d_{mf} is the measurement error of the disturbance d_f.

In order to completely compensate for the process disturbance d_f or the set-point change θ_r, the feedforward system must satisfy the following equations at the design stage:

$$G_{cf}(s) = \frac{G_f(s)}{G_v(s)G_p(s)} \tag{3-49}$$

and

$$G_{SP}(s) = \frac{1}{G_f(s)} \tag{3-50}$$

Repeating the previous approach: for the feedforward-feedback control system (Figure 3-8) and assuming it is at steady state:

$$\theta = \theta_r - d_m, \tag{3-51}$$

$$x = \frac{\theta_r}{K_p K_v} - \frac{d_m}{K_p K_v} - \frac{K_d d_p}{K_p K_v} - \frac{K_f d_f}{K_p K_v} - \frac{d_v}{K_v}, \tag{3-52}$$

and

$$\begin{aligned} x_{cf} &= K_{SP} K_{cf} \theta_r - K_{cf} d_{mf} - K_{cf} d_f \\ &= \frac{\theta_r}{K_p K_v} - \frac{K_f d_{mf}}{K_p K_v} - \frac{K_f d_f}{K_p K_v} \end{aligned} \tag{3-53}$$

Qualitatively:

$$[\theta] = [\theta_r] - [d_m], \tag{3-54}$$

$$[x] = \frac{[\theta_r]}{\{K_pK_v\}} - \frac{[d_m]}{\{K_pK_v\}} - \frac{\{K_d\}[d_p]}{\{K_pK_v\}} - \frac{\{K_f\}[d_f]}{\{K_pK_v\}} - \frac{[d_v]}{\{K_v\}}$$

$$= \begin{cases} \dfrac{[\theta_r] - [d_m] - \{K_d\}[d_p] - \{K_f\}[d_f]}{\{A_0K_c\}} - \dfrac{[d_v]}{\{K_v\}} & \text{; the process is with a Type Number} = 0 \\ \dfrac{-\{D_0\}[d_p] - \{D_{0f}\}[d_f]}{\{K_c\}} - \dfrac{[d_v]}{\{K_v\}} & \text{; the process is with a Type Number} > 0 \end{cases} \tag{3-55}$$

and

$$[x_{cf}] = \frac{[\theta_r] - \{K_f\}[d_{mf}] - \{K_f\}[d_f]}{\{K_pK_v\}}$$

$$= \begin{cases} \dfrac{[\theta_r] - \{K_f\}[d_{mf}] - \{K_f\}[d_f]}{\{A_0K_c\}} & \text{; the process is with a Type Number} = 0 \\ \dfrac{-\{D_{0f}\}[d_{mf}] - \{D_{0f}\}[d_f]}{\{K_c\}} & \text{; the process is with a Type Number} > 0 \end{cases} \tag{3-56}$$

where,

$$\{A_0\} = \begin{cases} + & \text{; the process is stable or has an even number of unstable poles;} \\ - & \text{; the process has an odd number of unstable poles.} \end{cases}$$

If these equations are compared to the ones derived in a single loop control system, some additional information for fault isolation will be obtained. For example, for a process with a Type Number of 0, because a deviation in θ_r causes θ, x and x_{cf} to deviate, and one in d_m causes θ and x to deviate, then changes of θ_r and d_m can be isolated; similarly because a change in d_f causes both x and x_{cf} to deviate, whilst one in d_{mf} only causes x_{cf} to deviate, then changes of d_f and d_{mf} can be isolated.

3.9.3 Double-Cascade Control Systems

On the odd occasion a further outer loop might be added to a cascade controller resulting in three measured controller outputs, $[x_1]$, $[x_2]$ and $[x_3]$.

3.9.4 Type 1 Actuators

It is sometimes the case that the controller merely outputs a raise/lower signal to an actuator. In such cases the actuator behaves like an integrator and control action like proportional plus integral control is obtained inherently by virtue of the presence of the integration; controller output x is then effectively the position of the actuator. Diagnosis is somewhat difficult if this position is not measured because it then relies on knowledge of external effects.

3.10 Criticism

This chapter has analysed deviations in control systems, which has led to a fault diagnostic approach that is based on set operations. It considers all the controller deviations at the same time and gives a prescription based on a pre-set knowledge base which contains all the explanations for the different combinations of the controller deviations. The set operation approach can be easily explained and understood, however, it has two main drawbacks. Firstly, it is doubtful that the approach would scale to most large processes, and secondly any small deviations, which cannot be detected statistically, could result in a wrong explanation and it is not clear how these instances would be resolved. Thus it would reduce the reliability of the diagnostic system greatly and should be avoided in practice. Because of this, the approach described in the following chapters, Chapter 4, 5 and 6, is thought to be more practicable. However it is worth noting that these chapters draw on the analysis of this current chapter.

CHAPTER 4

CAUSE-EFFECT KNOWLEDGE REPRESENTATION FOR VARIOUS CONTROL SYSTEMS

In the last chapter, the SEVACS approach was presented in the form of block diagrams and equations. In practice, plant operators take advantage of cause-effect knowledge to perform process monitoring and fault diagnosis, and it is important that such knowledge can be used to complement these equations. In this chapter, a steady state based SDG approach to the representation of cause-effect knowledge is first introduced. This is then used to represent the SEVACS and by referring to these graphs and to the equations of Chapter 3, cause-effect knowledge is tabulated. Signed-directed-graph will be revisited in later chapters when there is a need to represent the interaction between SEVACS and to elaborate on the effect of process disturbances.

4.1 SDG Representation

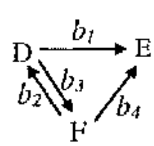
The SDG is commonly used to represent the causal effects between process variables in fault diagnosis (Iri *et al.*, 1979; Umeda *et al.*, 1980; Shiozaki *et al.* 1985; Kramer *et al.*, 1987; Chang *et al.*, 1990; Wilcox & Himmelblau, 1994a, 1994b; Lee *et al.*, 1999; Raghuraj *et al.*, 1999). Kramer and Palowitch (1987) pioneered the modern version of the SDG based fault diagnostic system when they used rule-based forward reasoning as an efficient method to identify possible causes. This has been improved by Chang and Yu (1990) who have proposed a method to deal with problems such as spurious interpretations and erroneous interpretations. A modified SDG approach (PCEG) has been suggested by Wilcox and Himmelblau (1994a, 1994b). All have focused on representation and simplification for the purpose of fault diagnosis, most haven't considered the control system as a special case. Kramer and Palowitch (1987) have discussed a rather crude classification of control loop behaviour that categorised control loops as either 'working' or 'saturated'. Chang and Yu (1990) have proposed an approach that involves checking the velocity form of the controlled variable as well as the standard form of that controlled variable when a PI controller is used. None have considered interactions between control systems and none have considered control systems involving special processes such as capacitive processes or open loop unstable processes.

An SDG can be viewed as an ordered pair, (G, s). Directed graph G can be represented as an ordered quadruple (N, B, i, t) consisting of a set of nodes N, a set of branches B, and two incidence functions i and t which map the branches to their initial and terminal nodes, respectively. The second component s of the pair (G, s) is a function that maps the branches of B to the set $\{+, -\}$, in which '+' means the initial node causes the terminal node to increase and '–' represents the former causes the latter to decrease. The state of a system is described qualitatively by a pattern p which is a function from the nodes of the graph to the set $\{+, 0, -\}$. A node mapping to qualitative value +, 0 or – indicates that the corresponding process variable is *high, normal* or *low* respectively.

An example of an SDG representation is shown in Figure 4-1. Here nodes D, E or F are mapped to +, 0 or – to indicate that the corresponding process variable is *high, normal* or *low* respectively and $s(B)$ maps each element of B either to '+' or '–'.

$N=\{D, E, F\}$

$B=\{b_1, b_2, b_3, b_4\}$



b_i	$i(b_i)$	$t(b_i)$
b_1	D	E
b_2	F	D
b_3	D	F
b_4	F	E

Figure 4-1: An example of SDG representation

Process signed directed graphs can either be constructed directly from plant data and/or from experienced operators, or from a mathematical model of the process (Iri *et al*, 1979). Clearly there might be some difficulty in obtaining the plant data and operator experiences needed to obtain a consistent representation of the process. The mathematical model approach is usually based on process models consisting of ordinary differential equations (ODEs) and algebraic equations.

In general, an ODE can be written in the form:

$$\frac{dx_i}{dt} = f_i(x_1, x_2, \cdots, x_n).$$

A branch is defined to start from x_j and end at x_i if $\frac{\partial f_i}{\partial x_j} \neq 0$. The sign of $\frac{\partial f_i}{\partial x_j}$ is assigned to the branch. No self-loop is defined even if $\frac{\partial f_i}{\partial x_i} \neq 0$ because the self-loop has nothing to do with the search for the origin of fault. Note that the signs can vary with operating points.

However, for our purposes, only a steady state representation is required. Time derivatives in the process equations are first zeroed, and then the equations are effectively linearised to form a perturbation model. The SDG is then constructed: for a linear algebraic equation of the form $x_i = \sum_{j=1}^{n} a_{ij} x_j$, a branch is defined to start from x_j and end at x_i and to take the sign of a_{ij}; no self-loops are defined because the search for the origin of a fault has nothing to do with self-loops. Process deviations or perturbations from the steady state are then transformed into qualitative states of *high, normal or low.*

4.2 SDG-Based Fault Diagnosis

The above representation helps in defining a pattern of observed symptoms on the process SDG. A nonzero node sign signifies a change in steady state in the process, and a set of nonzero signs in the SDG either represents a pattern of fault symptoms or a change in operation. It is well understood that not all the variables of the process in a complex plant can be measured or estimated due to technical and economical infeasibilities. The pattern defined is therefore always partially observed and is hence called the partial pattern, which can be used to obtain a cause-effect (CE) graph to find the structure of fault propagation.

To aid the fault diagnosis studies, a node or a cycle with no input arcs is considered to be a maximally strongly connected component (MSCC) in an SDG (Iri *et al.*, 1979). The CE graph also consists of so-called MSCCs. A branch is said to be consistent if its sign is equal to the product of both of the node signs it is connected with. And a nonzero node is marked as a valid node. When a process is decomposed into a CE graph, involving only the consistent branches and the valid nodes, the faults are assumed to originate from an element in one of the MSCCs (Iri *et al.*, 1979).

Faults in cycles are very difficult to isolate and therefore conventionally a cycle is viewed as a super-node (Raghuraj *et al.*, 1999). The task of automatic fault diagnosis would normally be stopped on encountering a super-node as the one that includes the root fault because little can be done further to analyse this super-node online. Operators would then be required to isolate the root fault on the basis of their own knowledge and experience. This procedure is unacceptable because a super-node can consist of a number of super-nodes as well as single nodes. If this situation was to arise in practice, the operators would be confused and the reliability of the automatically diagnostic system would be reduced.

Two kinds of SDG-based reasoning methods for fault diagnosis have been proposed:

(1) forward search methods, such as those of O'Shima *et al.* (Shiozaki *et al.*, 1985; Umeda *et al.*, 1980) and Kramer & Palowitch (1987), hypothesise possible root causes for observed symptoms, then examine each hypothesis in turn by searching in the direction of the graph branches to compare its consequences with the abnormal measurements;

(2) backward search methods, such as those of Kokawa *et al.* (1983), identify possible causes by working backwards from all abnormal measurements to find common explanations.

All rely on a global view of the process data, and are not easily adapted to the kind of distributed approach sought here. Although Mohindra and Clark (1993) have developed a distributed fault diagnosis method based on digraph (SDG) models, the focus is on the reasoning issues between nodes in the SDG and not on individual control systems. Derived from Kramer and Palowitch (1987), their method uses an off-line analysis of the SDG structure to develop simple diagnostic tests that can be conducted on-line by the sensors and controllers. These tests seek explanations for observed abnormalities by working backwards through the SDG.

Control systems complicate or even disable the above SDG-based fault diagnosis methods because they form cycles in an SDG and cause spurious or uncertain explanations. The cycles that arise from control systems are so different and special compared with other kinds of cycles in the SDG: on the one hand, control systems have the ability to compensate for faults or disturbances *per se*; on the other hand, there is implicit information related to them, which can be useful for fault diagnosis. In order to deal with control systems this implicit information should be taken into account while reasoning about an SDG.

4.3 Representing Control Systems By SDGs

These problems can be overcome by shifting the focus from a global representation to a separate representation of each of the individual control systems and by examining how both control loop and process faults impinge on their performance. Figure 4-2A shows an SDG representation of a typical single loop control system. In the figure, C, V, X and M represent the controller output, the valve opening, the controlled variable and the sensor measurement respectively; θ_r, d_v, d_p, d_m represent deviations in set-point, valve bias, process disturbance and sensor bias respectively. Signs of the branches in the SDG are determined from the equations in the last chapter. This SDG cannot provide complete information for fault diagnosis by itself.

It is important to note that only d_p and node X interact with nodes or variables in other parts of the plant. To indicate this, the circled parts in Figure 4-2A can be lumped together and the figure can be simplified to Figure 4-2B: θ_r and C are lumped into C node; d_v and V are lumped into V node; M and X are lumped into S node; d_p is replaced by E, which is generalised to include exogenous disturbances and other process variables. The simplified SDG doesn't compromise any understanding and reasoning processes because individual elements can still be treated separately when performing fault diagnosis. The whole control system can be viewed as a super-node and this super-node can be analysed using control system related cause-effect knowledge.

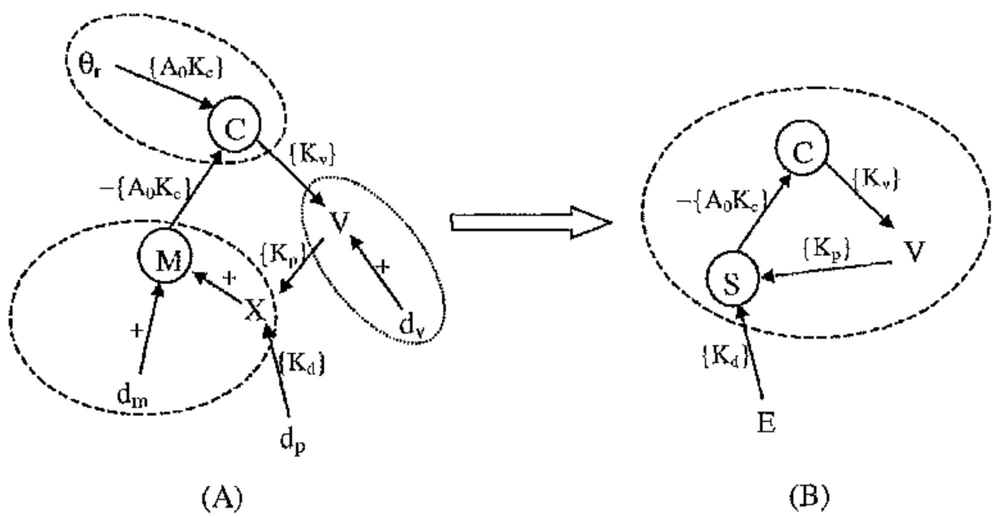


Figure 4-2: The SDG of a standard single loop control system

A standard cascade control system can be treated in a similar way. Figure 4-3 shows a cascade control system where C1, C2, V, S2 and S1 represent the output of the outer loop controller, the output of the inner loop controller, the valve opening, the inner loop sensor node and the outer loop sensor node respectively. Nodes E1 and E2 represent outer loop process disturbances and inner loop process disturbances respectively. The entire cascade control system can be viewed as a super-node in which individual elements are treated separately when performing fault diagnosis. Only nodes S1 and S2 of the super-node can interact with other nodes or variables in the plant.

It is worth pointing out that, as discussed in the previous chapter, for stability the sign product of any of the loops in the above SDGs must be '–'.

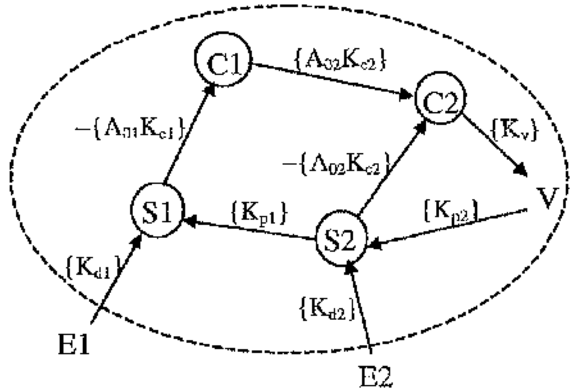


Figure 4-3: The SDG of a standard cascade control system

4.4 SEVACS Super-node Cause-Effect Knowledge

In this section, SEVACS super-node cause-effect knowledge is described that has been derived on the basis of equations in Chapter 3.

4.4.1 Cause-Effect Knowledge Pertaining To The Controlled Processes With Type Number = 0

In particular Equations (3-35) — (3-40) were referred to extensively when deriving this knowledge. Tables 4-1 and 4-2 describe the various effects that individual faults would have on the observations available for single loop and cascade loop control systems respectively. Faults like a dead sensor, or a sticking valve or a large process disturbance are not considered because, in these circumstances the steady state is unlikely to be obtained. These faults would be addressed by using other approaches (see Chapter 1). The following sub-sections discuss the determination of signs of the fault or disturbance (e.g. high or low).

Table 4-1: Cause-effect knowledge pertaining to a single loop control system

Effect/Observation	Cause
Controller deviates	• sensor bias • valve bias • process disturbance

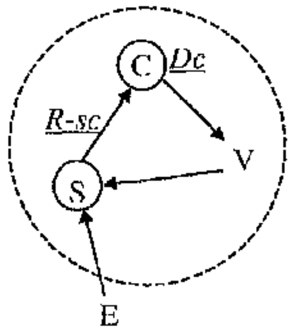
Table 4-2: Cause-effect knowledge pertaining to a cascade control system

Effect/Observation	Cause
Only inner loop controller deviates	• valve bias • inner loop process disturbance
Only outer loop controller deviates	• inner loop sensor bias
Both controllers deviate	• outer loop sensor bias • outer loop process disturbance

A sensor bias in a single loop control system or in the outer loop of a cascade control system. If the sensor biases, the controller will take action to compensate for this with the net effect that there will be a deviation in the controller output and the sensor measurement will return to its normal value. The direction of the sensor bias can then be determined by looking at the following (Figure: 4-4):

- R-sc: the steady state relation (i.e. forward or reverse acting) between the sensor measurement and the controller output defined in Figure 4-2B and Figure 4-3;
- Dc: the steady state deviation of the controller output.

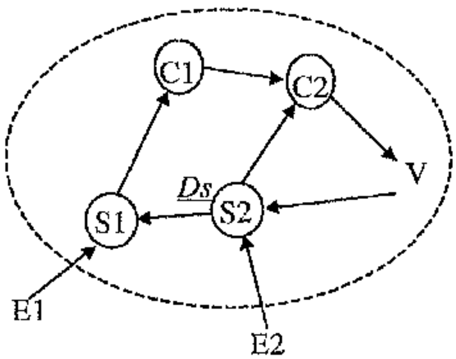
The various possibilities are listed in the decision table.



Dc	*R-sc*	Sensor bias
+	+	fails-high
-	-	fails-high
+	-	fails-low
-	+	fails-low

Figure 4-4: The effect of the sensor bias in a single loop control system and the fault-decision table

A sensor bias in the inner loop of a cascade control system. Both the inner and the outer loop controllers will attempt to compensate (Figure 4-5) with the net effect that the sensor deviation observed (Ds) will have the same direction as the (inner) sensor bias. The decision table in the Figure 4-5 summarises this.



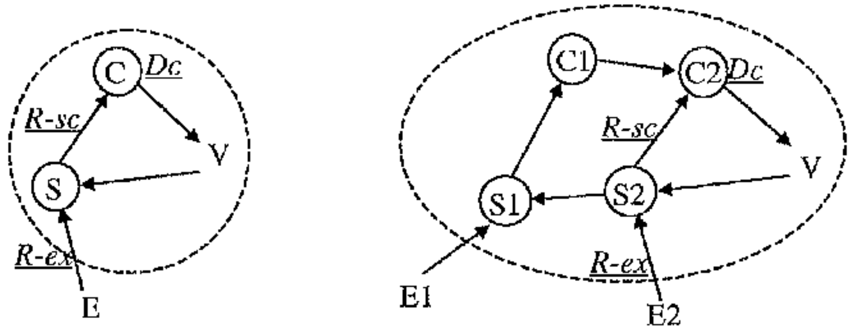
Ds	Inner sensor bias
+	fails-high
-	fails-low

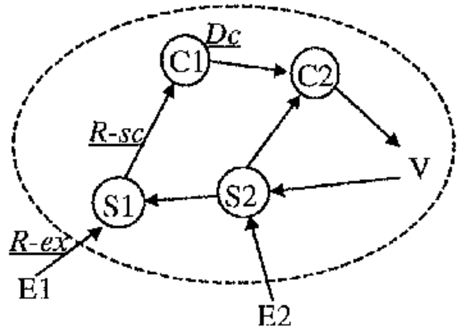
Figure 4-5: The effect of the inner loop sensor bias in a cascade control system and the fault-decision table

An exogenous/ancestor fault or disturbance. In both single and cascade loop cases, such occurrences will be compensated by the controllers with the net effect that there will be a deviation in the controller outputs. The direction of the exogenous/ancestor fault or disturbance can then be determined by looking at the following:

- *R-sc*: the steady state relation (i.e. forward or reverse acting) between the sensor measurement and the controller output defined in Figure 4-2B and Figure 4-3;
- *R-ex*: the steady state relation (i.e. forward or reverse acting) between the exogenous/ancestor variable and the sensor measurement as defined in Figure 4-2B and Figure 4-3;
- *Dc*: the steady state deviation in the controller output.

Although these 3 factors refer to the various loops differently (see Figure 4-6) the various outcomes can be represented in a single decision table as shown.





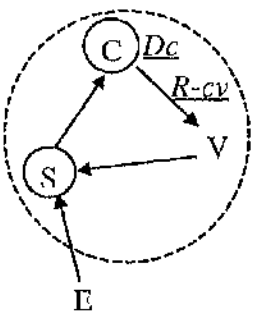
<u>*Dc*</u>	<u>*R-sc*</u>	<u>*R-ex*</u>	Exogenous/ Ancestor fault or disturbance
+	+	+	fails-high
+	-	-	fails-high
-	+	-	fails-high
-	-	+	fails-high
+	+	-	fails-low
+	-	+	fails-low
-	+	+	fails-low
-	-	-	fails-low

Figure 4-6: The effect of an exogenous/ancestor fault or disturbance and the fault-decision table

A Valve bias. If the valve biases, there will be a deviation in the controller output with the effect that the sensor measurement will return to its normal value. The direction of the valve bias can then be determined by looking at the following factors (Figure 4-7):

- <u>*R-cv*</u>: the steady state relation between the controller output and the valve opening defined in Figure 4-2B and Figure 4-3;
- <u>*Dc*</u>: the steady state deviation in the controller output.

The possible outcomes are as shown in the table.



Dc	*R-cv*	Valve bias
-	+	fails-high
+	-	fails-high
+	+	fails-low
-	-	fails-low

Figure 4-7: The effect of the valve bias in a control system and the fault-decision table

4.4.2 Cause-Effect Knowledge Pertaining To The Controlled Processes With Type Number > 0

Again Equations (3-35) — (3-40) were referred to extensively when deriving this knowledge. This depends on the type of control system and on how it is affected by the process. There are two options: i) a single loop control system or the outer loop of a cascade control system is affected, or ii) the inner loop of the cascade control system is affected instead. In the case of single and outer loops, the knowledge is as described previously but with one exception: a sensor bias needs to be distinguished differently because the output of the relevant controller doesn't deviate; although the relevant single or outer loop controller output will change transiently, it will return to the same value in the steady state. Instead the sensor bias must be viewed as a disturbance to its descendants, in which case deviations of its descendants can be analysed to determine whether the sensor has biased and in which direction (i.e. high or low). Table 4-1 should then be replaced by Table 4-3.

Table 4-3: Cause-effect knowledge pertaining to a single/outer loop capacitive process

Effect/Observation	Cause
Single / Outer loop controller deviates	• valve bias • process disturbance
Single / Outer loop controller doesn't deviate	• sensor bias • no fault

If the capacitive process is in the inner loop of a cascade control system, then the following faults will cause the outer loop controller to deviate whilst having no affect on the inner loop controller output: faults pertaining to the outer loop and an inner loop sensor bias. These faults cannot be isolated without extra information, perhaps from other controllers. However the directions of the faults might be inferred from related knowledge. With reference to a cascade control system block diagram in Figure 3-3 and its SDG in Figure 4-3, and Equations (3-37) — (3-40), in a steady state, if its outer loop process $G_{p1,i}(s)$ is a capacitive process then the outer loop sensor bias $d_{m1,i}$ will not cause the outer loop controller $G_{c1,i}(s)$ to deviate, but either an inner loop sensor bias $d_{m2,i}$ or a process fault or a disturbance $d_{p2,i}$ pertaining to this capacitive process, will cause the outer loop controller to deviate. If its inner loop process $G_{p2,i}(s)$ is a capacitive process, then faults $d_{p1,i}$ pertaining to the outer loop together with the sensor bias $d_{m2,i}$ pertaining to this capacitive process, will cause the outer loop controller to deviate but not the inner loop controller $G_{c2,i}(s)$. The net result is that Table 4-2 must be revised and that the revisions depend on the location of the capacitive process. The three alternatives are given in Tables 4-4 — 4-6.

Table 4-4: Cause-effect knowledge pertaining to a cascade control system, only the outer loop process is capacitive

Effect/Observation	Cause
Only inner loop controller deviates	• valve bias • inner loop process disturbance
Only outer loop controller deviates	• inner loop sensor bias
Both controllers deviate	• outer loop process disturbance
Controllers don't deviate	• outer loop sensor bias • no fault

Table 4-5: Cause-effect knowledge pertaining to a cascade control system, only the inner loop process is capacitive

Effect/Observation	Cause
Only inner loop controller deviates	• valve bias • inner loop process disturbance
Only outer loop controller deviates	• inner loop sensor bias • outer loop sensor bias • outer loop process disturbance

Table 4-6: Cause-effect knowledge pertaining to a cascade control system, both processes are capacitive

Effect/Observation	Cause
Only inner loop controller deviates	• valve bias • inner loop process disturbance
Only outer loop controller deviates	• inner loop sensor bias • outer loop process disturbance
Controllers don't deviate	• outer loop sensor bias • no fault

4.5 Summary

Cause-effect knowledge for a SEVACS has been described by referring to an SDG representation. If SDGs are to be referred to whilst performing fault diagnosis through the SDG, control systems should be viewed as super-nodes and the knowledge pertaining to the super-nodes should be used. In Chapter 5, fault isolation issues based on this chapter will be discussed in detail.

CHAPTER 5

FAULT ISOLATION

Although the problems of fault isolation and interacting control systems have been probed in Chapter 3, the solutions are rather general and abstract. This Chapter re-investigates them from an SDG representation perspective. A fault isolation principle and general procedure will be expounded. Different types of control system interactions will be discussed so that the fault isolation procedure can be improved. A modified representation of interacting control systems will then be proposed in order that the fault isolation procedure can deal with different process types in an unified manner.

5.1 The Fault Isolation Principle and General Procedure

The following paragraph describes a principle, which can be deduced from either the basic equations in Chapter 3 or the knowledge in Chapter 4.

Any steady state deviation in any control system must be caused either by a fault in a loop element such as in the sensor or in the actuator/valve or by a process disturbance. Although, by the application of appropriate simple heuristic rules, it is very easy to isolate faults like a dead sensor, or a large exogenous fault/disturbance, or a sticking valve, it is more difficult to isolate faults like a sensor bias, or a small exogenous fault/disturbance. In these circumstances, the controlled variable, and its effect on descendants, is arguably the key to fault isolation: with a sensor bias, the controlled variable will deviate from its nominal value and descendants of the controlled variable will be affected; with a valve bias, or with an exogenous fault/disturbance, the controlled variable will remain at its nominal value and its descendants will not be affected.

The above fault isolation principle suggests that the search and test strategy shown in Figure 5-1 could be used.

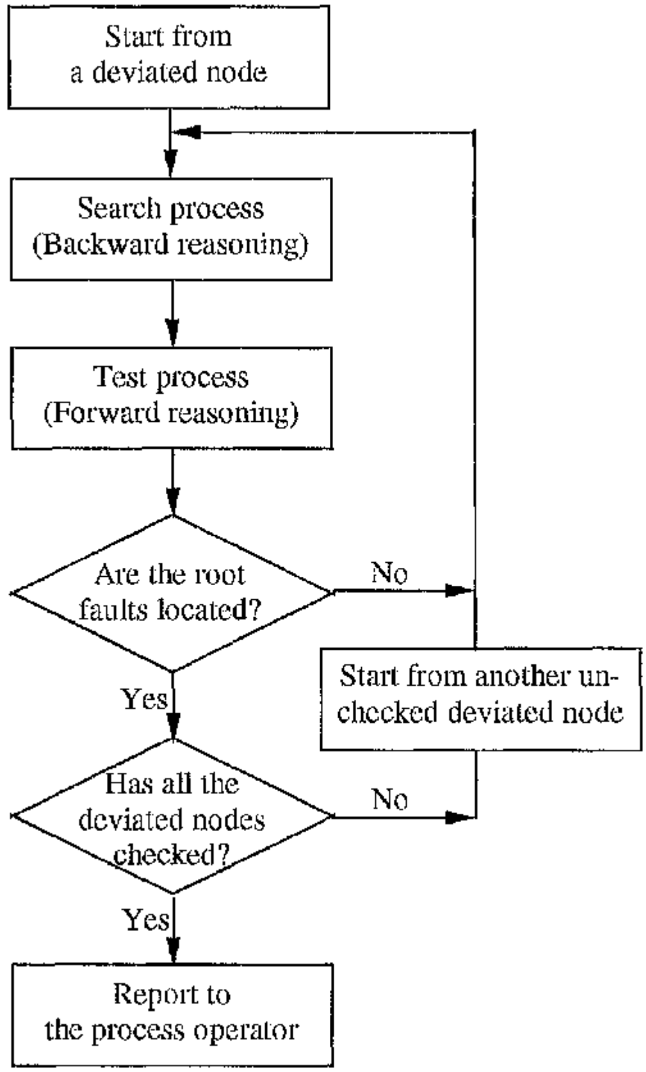


Figure 5-1: The general procedure for fault isolation

Starting from a deviated control system and by referring to the process SDG and SEVACS knowledge (Chapters 3 and 4), a search strategy first finds all possible faults or disturbances. This is followed by a strategy that tests which of the faults or disturbances would result in the observed deviations. Backward reasoning is used to carry out the search strategy and forward reasoning is used to carry out the test strategy. The two strategies iterate through all the deviated nodes. This general procedure would be easily implemented at the Supervisor level in a distributed process monitoring and fault diagnosis system so long as the individual control system information as well as other available measurements information at the lower level could be communicated to it (see Figure 1-1). The procedure would be configured during the SEVACS configuration and supervisor configuration stage in Figure 1-3. Obviously an operator can be viewed as the Supervisor if the procedure is carried out by the operator.

However the general procedure is somewhat cumbersome, Sections 5.2 and 5.3 describe ways in which the search and test processes can be improved by identifying interactions from a simple SDG representation of a plant.

The following section describes the method dealing with interactions, which depends on whether or not any two controlled nodes interact bi-directionally and on whether or not these relationships are actually 'invoked' when a particular fault arises.

5.2 Improving The Fault Isolation Procedure by Considering Control System Interactions

5.2.1 Control Systems with Uni-directional Interactions

A simple set of rules can be derived for those control systems with uni-directional interactions that have the fairly general feature shown in Figure 5-2. Of importance here are the relationships between a measured control variable and its neighbouring measured nodes: S1 is a controlled variable, S2 is a measured descendant of S1 (it could be another controlled variable), E1 is an ancestor of both S1 and S2 (as their process disturbance), it affects S1 and S2 simultaneously, E2 is an ancestor of S1 and only affects S1. Thus S1-sensor-bias should be viewed as a process disturbance to S2, the descendant of S1.

If S1 is pertaining to a Type Number 0 controlled process and its control loop deviates (any element in the control loop deviates), then, initially, the fault candidate will be {S1-sensor-bias, E1, E2, valve-bias in the S1 control loop}. There are now two possibilities:

- S2 is affected: because E1 is the common ancestor of S1 and S2 and according to the fault isolation principle, the fault candidate set shrinks to {S1-sensor-bias, E1}; if the direction of the deviation of S2 contradicts that expected from the S1-sensor-bias, {E1} is the only fault root.
- S2 is not affected: the fault candidate set shrinks to {E2, valve-bias in the S1 control loop}. If there is no more information about E2, then these two possibilities can not be separated. Otherwise, if E2's descendants deviate, E2 will be the only root fault.

It should be noted that when S2 is in another control loop, if that controller deviates, S2 should be viewed as being affected, though the sensor measurement of S2 itself doesn't deviate.

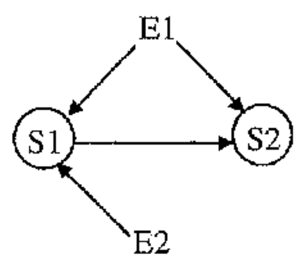


Figure 5-2: Uni-directional interaction

If S1 is pertaining to a Type Number > 0 controlled process instead then, although S1-sensor-bias doesn't cause the S1 control system to deviate, it causes S1 descendants to deviate. Therefore in this case, only the valve-bias in the S1 control loop and the S1 process disturbances such as E1 and E2 can cause S1 control loop to deviate, S1-sensor-bias cannot be deduced from the deviation of any element in the S1 control loop but from the deviation of S2, the S1 descendant.

5.2.2 Control Systems with Bi-directional Interactions

Here the controlled variables S1 and S2 affect each other (Figure 5-3); either can pertain to a single loop (s.l.) control system or to the inner loop (i.l.) or to the outer loop (o.l.) of a cascade control system. Then three different types of interactions must be considered: Type A interaction involves s.l./s.l., s.l./o.l. or o.l./o.l.

interactions, Type B interaction occurs when one, and only one, of the loops is an inner loop and Type C interaction occurs when both are inner loops. Note that the treatment of single and outer loops is the same because, in the latter, the non-interacting inner loop can be viewed as a virtual valve node. This can be seen in Figure 5-4 where V2′ is a virtual valve node.

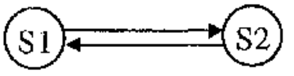


Figure 5-3: Interacting control systems

5.2.2.1 Type A Interaction: Solely Single/Outer Loops Interact

Referring to Figure 5-4, S1 is one controlled variable that is controlled by the controller C1 and manipulated by the valve/actuator V1; S21 is the other controlled variable which interacts with S1, here S21 is controlled by a cascade control system that includes an outer loop controller C21 and an inner loop controller C22, S22 is as the inner loop controlled variable, V2 is as the manipulated valve/actuator. Nodes C22, S22 and V2 can be lumped together as a super-node V2′ (as a virtual valve node) so that this cascade control system can be viewed or analysed as a single loop control system. Signs α and β represent the directions of the interactions between the two controlled variables S1 and S21.

First consider the case that the controlled processes belong to Type Number 0 processes. If only one of the control systems deviates, then the fault is local to that control system so the fault can be isolated using the method above; if both the control systems deviate, there are two possibilities:

- if S1 and S21 have at least one common ancestor, the fault candidate set is {S1-sensor-bias, S21-sensor-bias, one of the common ancestors' faults};
- if S1 and S21 have no common ancestor, the fault candidate set is {S1-sensor-bias, S21-sensor-bias}.

If the directions of the interactions between S1 and S21 are opposite, S1-sensor-bias and S21-sensor-bias in the above fault candidate sets can be separated by the knowledge related to the two control systems, as shown in Table 5-1; otherwise they cannot be separated without further information. Table 5-1 has been derived by modifying and subsequently analysing equations (3-47) and (3-48).

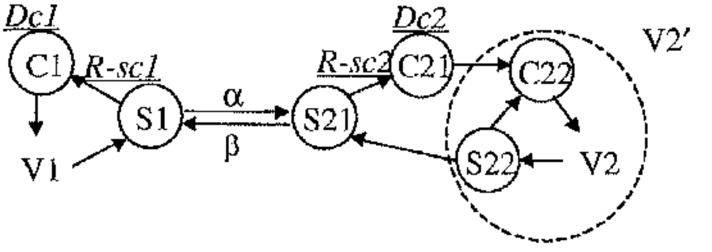


Figure 5-4: Type A interaction

If either or both the S1 controlled process and the S21 controlled process are capacitive, both sensor biases above cannot cause both control systems to deviate. However one sensor bias can be viewed as a process disturbance to the other controlled process and cause the respective control system to deviate; if both controlled systems deviate, there must be at least one common ancestor, which is the fault.

Table 5-1: A sensor bias decision table for Figure 5-4 when {α}= '+' and {β}= '–'

R-sc1	*R-sc2*	*Dc1*	*Dc2*	Sensor bias fault
+	+	+	-	S1 fails high
+	-	+	+	S1 fails high
-	-	-	+	S1 fails high
-	+	-	-	S1 fails high
+	+	-	+	S1 fails low
+	-	-	-	S1 fails low
-	-	+	-	S1 fails low
-	+	+	+	S1 fails low
+	+	+	+	S21 fails high
+	-	+	-	S21 fails high
-	-	-	-	S21 fails high
-	+	-	+	S21 fails high
+	+	-	-	S21 fails low
+	-	-	+	S21 fails low
-	-	+	+	S21 fails low
-	+	+	-	S21 fails low

5.2.2.2 Type B Interaction: The Inner Loop of Only One of The Control Systems Interacts

For Type B interaction, a single control loop or the outer loop of a cascade control system interacts with an inner loop of a cascade control system. For example, in Figure 5-5, S1 is a single loop controlled variable that is controlled by controller C1 and manipulated by valve/actuator V1. Node S1 interacts with S22. S22 is the inner loop controlled variable in a cascade control system in which C21 is the outer loop controller, C22 is the inner loop controller, S21 is the outer loop controlled variable and V2 represents the valve/actuator of the control system. Signs α and β represent directions of the interactions between the two controlled variables S1 and S22. Node E2 represents the process disturbance to S21.

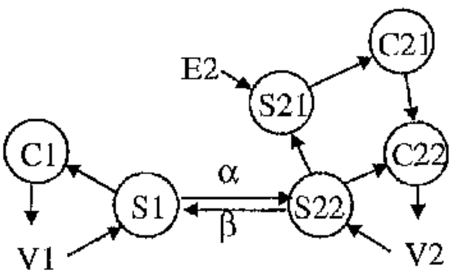


Figure 5-5: Type B interaction

For convenience, suppose there is no common ancestor between the two control systems. According to the theoretical analysis in Chapter 3, a sensor bias on S1 can be viewed as an external disturbance/fault to the inner loop of the cascade control system, but an inner loop sensor bias on S22 has no effect on the single control system in the steady state. An external disturbance/fault to the outer loop of the cascade control system, say E2 in Figure 5-5, or a sensor bias on S21 can cause the single loop control system to deviate.

So, S1-sensor-bias, S22-sensor-bias, E2 or S21-sensor-bias can be isolated no matter what the relations between S1 and S22 are. For example, suppose all controlled processes here are not capacitive, if only C21 deviates, S22-sensor-bias is the fault; if only C1 and C22 deviate, S1-sensor-bias is the fault; if C1, C21, C22 deviate, E2 or S21-sensor-bias is the fault. The fault directions can be inferred from the cause-effect knowledge described in Chapter 4.

It is worth pointing out that the knowledge or rules above will be different if some of the controlled processes are capacitive. However faults can still be isolated: if the S1 controlled process is capacitive, S1-sensor-bias doesn't cause C1 to deviate but it can affect the cascade control system and only cause C22 to deviate; if the inner loop controlled process is capacitive, C22 cannot be affected by E2 or S21-sensor-bias; if the outer loop controlled process is capacitive, C1 cannot be affected by S21-sensor-bias.

5.2.2.3 Type C Interaction: Inner Loops of Both Cascade Control Systems Interact

A Type C interaction is shown in Figure 5-6: one inner loop controlled variable S12 interacts with the other inner loop controlled variable S22. Node S12 is the inner loop controlled variable in a cascade control system in which C11 is the outer loop controller, C12 is the inner loop controller, S11 is the outer loop controlled variable and V1 represents the valve/actuator of the control system. Node S22 is the inner loop controlled variable in the other cascade control system in which C21 is the outer loop controller, C22 is the inner loop controller, S21 is the outer loop controlled variable and V2 represents the valve/actuator of the control system. Signs α and β represent directions of the interactions between the two controlled variables S12 and S22. Node E1 represents the process disturbance to S11 and E2 represents the process disturbance to S21.

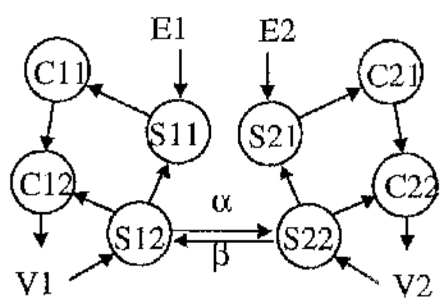


Figure 5-6: Type C interaction

Again, for convenience, suppose there is no common ancestor between the two control systems. The inner loop sensor bias of one cascade control system will not affect the other cascade control system in the steady state. First consider the situation in which the controlled processes here are not capacitive. If only C11 deviates, S12-sensor-bias is a possible fault; if only C21 deviates, S22-sensor-bias is a possible fault. An outer loop process disturbance or outer loop sensor bias of one cascade control system can cause the other system to deviate, in which case the fault can be isolated using the following: if C11, C12 and C22 deviate, S11-sensor-bias or E1 is a possible fault; if C21, C22 and C12 deviate, S21-sensor-bias or E2 is a possible fault. Once again, the above faults directions can be inferred from the cause-effect knowledge in Chapter 4.

The knowledge or rules above will be also different if some of the controlled processes are capacitive: if the S12 inner loop controlled process is capacitive, C12 cannot be affected by E1 or S11-sensor-bias; if the S11 outer loop controlled process is capacitive, C22 cannot be affected by S11-sensor-bias; if the S22 inner loop controlled process is capacitive, C22 cannot be affected by E2 or S21-sensor-bias; if the S21 outer loop controlled process is capacitive, C12 cannot be affected by S21-sensor-bias.

5.3 An Alternative Way of Reasoning about Control System Interactions

The procedures described in the last section require different knowledge or rules for different processes. In this section, an SDG-based fault isolation approach will be developed that is applicable to all processes. In addition this approach is easier to realise as an auto-reasoning algorithm in a real-time fault diagnosis system because it does not rely on a large number of rules. The approach is to modify the SDGs by breaking the interactions between the control systems, and then to use the knowledge relating to the single or cascade control systems to isolate the faults. Thus the effect of one control system on the other is viewed as a process disturbance to that control system. Having modified the relevant SDGs, fault isolation pertaining to individual controllers can now be applied as before. Having isolated a fault, and if it is identified by more than one controller, then this hypothesis would be accepted provided that associated signs do not contradict. The rest of this section examines each type of interaction in turn.

5.3.1 The Modified SDG of Type A Interaction

The SDG of two control systems with Type A interaction can be modified as shown in Figure 5-7. The sensor biases (i.e. S1-sensor-bias and S21-sensor-bias) are represented by special process disturbances. Relationships *R-11* and *R-22* are always '+' unless the process pertaining to S1 or S21 is capacitive. If the process pertaining to S1 is capacitive, S1-sensor-bias doesn't affect S1 in the steady state, so the link from the node S1-sensor-bias to S1 doesn't actually exist. Thus *R-11* can be assigned as '0'; if the process pertaining to S21 is capacitive, *R-22* = '0' instead. Relationships *R-12* and *R-21* depend on the relation between S1 and S21. For example if S1 sensor biases high, then the respective controlled variable will be controlled at a value less than its nominal value and the controlled variable S21 will see this effect as a negative going disturbance. It follows that, if the relations between S1 and S21 are as shown in Figure 5-4, then *R-12*=–α and *R-21*=–β.

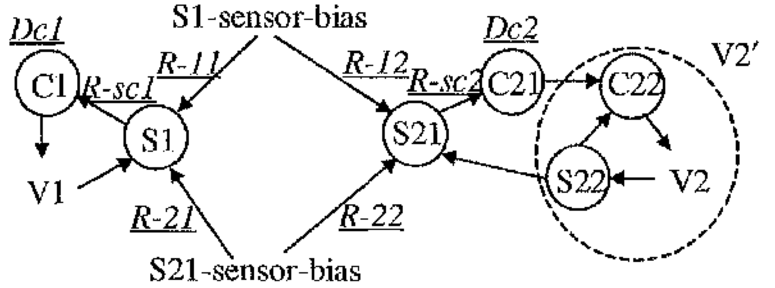


Figure 5-7: The modified SDG of Type A interaction in Figure 5-4

5.3.2 The Modified SDG of Type B Interaction

The SDG of two control systems with Type B interaction can be modified as shown in Figure 5-8. Again the sensor biases (i.e. S1-sensor-bias and S21-sensor-bias) are represented by special process disturbances. S22-sensor-bias doesn't cause the other control system to deviate in the steady state because the effect of this inner sensor bias can be compensated by the output of the outer loop controller C21. Variable E2 is represented as an exogenous disturbance to both S1 and S21 because although E2 affects S21 directly, it affects S1 indirectly via C22 and S22 and hence through the relations β1 and β2. Suppose the relations between S1 and S22 are as shown in Figure 5-5 and suppose that α, β, β2, η are known, then the signs of α1, α2, β1, γ1, γ2 can be determined.

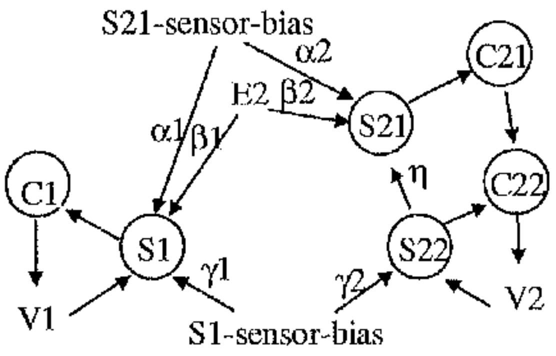


Figure 5-8: The modified SDG of Type B interaction in Figure 5-5

Equation (3-37) can be analysed to consider how the S21-sensor-bias can affect S1 via the inner loop controlled variable of S22. If the outer loop process is not capacitive, the outer loop controller C21 will deviate in the direction of $-\frac{[d_{m1,2}]}{\{K_{p1,2}\}}$ and so will S22. Comparing Figure 5-8 and Figure 4-3, it can be seen that $\{K_{pi}\}$ of controller 2 is the same as η i.e. $\{K_{p1,2}\}$; if the outer loop process is capacitive, the outer loop controller C21 doesn't deviate with the sensor bias and neither does S22. This leads to the following relation:

$$\alpha 2 = \begin{cases} + & \text{; the process pertaining to S21 is not capacitive;} \\ 0 & \text{; the process pertaining to S21 is capacitive.} \end{cases}$$

and

$$\alpha 1 = \begin{cases} -\beta \cdot \eta & \text{; the process pertaining to S21 is not capacitive;} \\ 0 & \text{; the process pertaining to S21 is capacitive.} \end{cases}$$

Similarly:

$$\beta 1 = -\beta \cdot \beta 2 \cdot \eta$$

$$\gamma 1 = \begin{cases} + & \text{; the process pertaining to S1 is not capacitive;} \\ 0 & \text{; the process pertaining to S1 is capacitive.} \end{cases}$$

and

$$\gamma 2 = -\alpha .$$

5.3.3 The Modified SDG of Type C Interaction

The SDG of two control systems with Type C interaction can be modified as shown in Figure 5-9. Again the sensor biases (i.e. S11 bias and S21 bias) are represented by special process disturbances. Variable E1 is represented as an exogenous disturbance to both S11 and S22 because although E1 affects S11 directly, it affects S22 indirectly via C12 and S12 and hence through the relations β1 and β2. Similar relationships can be constructed for E2.

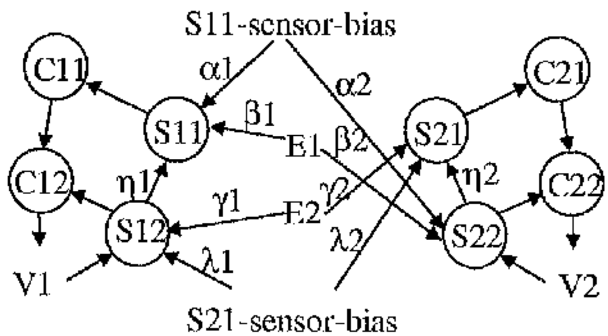


Figure 5-9: The modified SDG of Type C interaction in Figure 5-6

Suppose the relation between S12 and S22 is as shown in Figure 5-6 and suppose that α, β, $\beta1$, $\gamma2$, $\eta1$, $\eta2$ are known, then the signs of $\alpha1$, $\alpha2$, $\beta2$, $\gamma1$, $\lambda1$, $\lambda2$ can be determined. Again by referring to Equation (3-37) and Figure 4-3 the following relations can be obtained:

$$\alpha1 = \begin{cases} + & \text{; the process pertaining to S11 is not capacitive;} \\ 0 & \text{; the process pertaining to S11 is capacitive.} \end{cases}$$

$$\alpha2 = \begin{cases} -\alpha \cdot \eta1 & \text{; the process pertaining to S11 is not capacitive;} \\ 0 & \text{; the process pertaining to S11 is capacitive.} \end{cases}$$

$$\beta2 = -\alpha \cdot \beta1 \cdot \eta1$$

$$\gamma1 = -\beta \cdot \gamma2 \cdot \eta2$$

$$\lambda1 = \begin{cases} -\beta \cdot \eta2 & \text{; the process pertaining to S21 is not capacitive;} \\ 0 & \text{; the process pertaining to S21 is capacitive.} \end{cases}$$

and

$$\lambda 2 = \begin{cases} + & ;\text{ the process pertaining to S21 is not capacitive;} \\ 0 & ;\text{ the process pertaining to S21 is capacitive.} \end{cases}$$

5.4 Summary

In this chapter, the fault isolation procedures have been discussed, which can be improved by appropriate reasoning about interacting control systems. Some examples of various methods will be given in Chapter 8.

For the interacting control systems, two sorts of fault isolation improvements have been introduced. One is to make use of different knowledge for different processes, the other is to make use of the modified SDGs and to reason about them. The latter doesn't rely on a lot of rules. However both methods build on the theory of Chapter 3. In essence they are the same.

CHAPTER 6

KNOWLEDGE ACQUISITION AND EVOLUTION

When implementing these distributed tasks it is intended that individual modules would start from with a minimum amount of knowledge. The intention is then that this knowledge would grow with operational experience. That is the signed directed graphs are expected to evolve with time. This Chapter describes a framework and some guidelines for knowledge evolution so that the approach can have a learning and updating capability. A method is also introduced to acquire the initial knowledge by applying step tests. A CSTR process will be used as an application for illustrating the method and the framework.

6.1 Evolutionary Signed Directed Graphs (E-SDG)

Traditionally, SDG-based fault diagnosis assumes that the SDG reflects the system completely and accurately. It is unlikely that this assumption is ever satisfied in practice with the net effect that there is a lack of confidence with diagnostic results obtained. When coupled with the amount of effort required to produce an SDG in the first place, it is hardly surprising that SDG-based diagnosis has not found much support in industry. To elaborate on this further, consider the incomplete SDG shown in Figure 6-1A where A is a controlled variable in a SEVACS super-node, and B is a measured variable. Suppose a fault now occurs that causes A and B to deviate, according to the SEVACS approach and assuming that the SDG is complete, it can be inferred that the fault is A-sensor-bias. This may be wrong if there exists a common ancestor C of A and B (Figure 6-1B), or there is a link from B to A (Figure 6-1C), which is implicit.

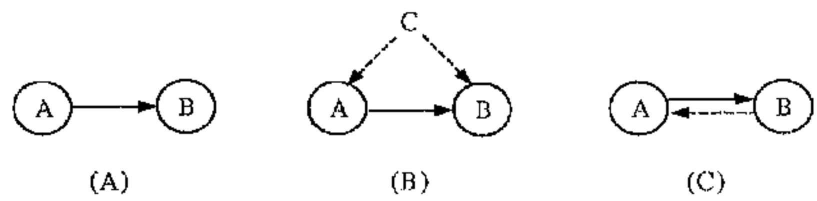


Figure 6-1: A probably incomplete SDG

Thus, it is important that

1) if readily available, any knowledge should be incorporated into the initial implementation;
2) erroneous diagnostic conclusions must be fedback to enable the knowledge to be refined;
3) a structure is in place to enable evolution to take place.

An alternative to the SDG, the evolutionary SDG (E-SDG) is proposed to facilitate this. Built by a mixed method (Figure 6-2), it would be constructed by combining mathematical models, empirical knowledge, process step test experiments and SEVACS-based knowledge together. It can be updated by learning.

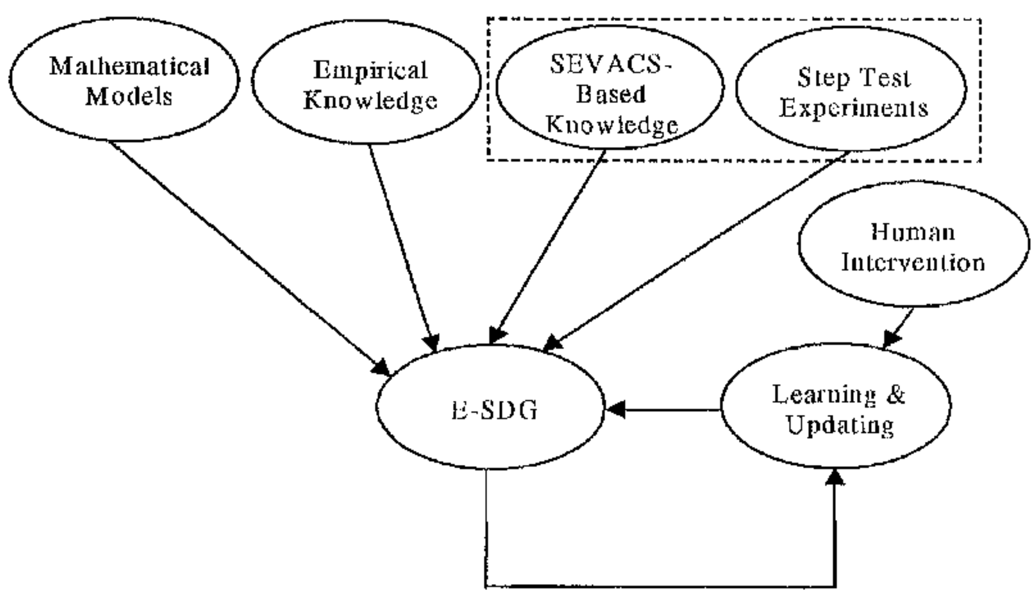


Figure 6-2: Constructing and updating an E-SDG

6.2 Step Testing

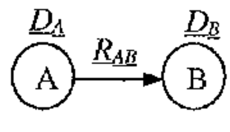
The SEVACS based knowledge can help to identify the open loop characteristics of the process in a feedback control loop. A step test can be applied to the set-point of the controlled variable, by observing the steady state change of the output of the controller, the open loop process characteristics can be obtained:

- if the output of the controller doesn't change, the related open loop process is capacitive;
- otherwise, according to Equation (3-36), if $[x_{,i}]=\{K_{c1,i}\}[\theta_{r,i}]$, then $\{A_{01,i}\}$='+', which means the related open loop process is stable or includes an even number of unstable poles; if $[x_{,i}]=-\{K_{c1,i}\}[\theta_{r,i}]$, then $\{A_{01,i}\}$='−', which means the related open loop process includes an odd number of unstable poles.

This section explores how step tests can be used to obtain SEVACS interactions and to examine how process disturbances affect the SEVACS. This then leads to a procedure for the construction of an E-SDG and an example of how it can be applied is given in Section 6.5. Various E-SDGs will then be considered when deriving SEVACS for various applications in Chapter 8.

6.2.1 A Single-Loop Control System to A Measured Variable

In Figure 6-3, suppose node A is controlled by a single control system or the outer-loop of a cascade control system and node B is a measured (but not controlled) variable. A step test can be applied to the set-point of node A, and interaction $\underline{R_{AB}}$ can be obtained by looking at deviations $\underline{D_A}$ and $\underline{D_B}$ in the steady state. The decision table is shown in Figure 6-3.



$\underline{D_A}$	$\underline{D_B}$	$\underline{R_{AB}}$
+	+	+
+	–	–
–	+	–
–	–	+
+/–	0	0

Figure 6-3: Identify the effect from a single control system to a measured variable

6.2.2 The Interaction between Two Single-Loop Control Systems (or Outer Loops)

Suppose A and B are controlled by two single-loop control systems or the outer loops of cascade control systems (Figure 6-4). Step tests can be applied to the set-points of A and B separately, the change in one controlled variable can be viewed as a process disturbance to the other, and then $\underline{R_{AB}}$ and $\underline{R_{BA}}$ can be determined by the SEVACS cause-effect knowledge described in previous chapters.

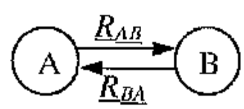


Figure 6-4: Identify the interaction between two single-loop control systems

6.2.3 A Cascade Control System to A Measured Variable

Suppose A1 is controlled by the outer-loop controller A1C, A2 is controlled by the inner-loop controller A2C (Figure 6-5) and apply a step test to the set-point of A1. If there is a change in B, it indicates that B is affected by this cascade control system. It is very difficult to decide whether A1, A2 or both affect B, so if possible, other related knowledge should then be used, e.g. if the outer loop process is capacitive, it is certain that A1 affects B. If the outer loop process is not capacitive, for robust fault isolation, it is quite acceptable to assume it is the inner loop controlled variable A2 that affects B. This is because this assumption can accommodate the situation in which A1 is the true cause: if A2 affects B, then when

B deviates, the fault candidate is {A1-set-point-change, A1-sensor-bias, process-disturbance-to-A1}; if A1 affects B, then when B deviates, the fault candidate is {A1-set-point-change, A1-sensor-bias}, the former can accommodate the latter.

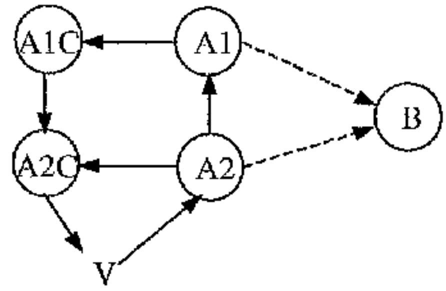


Figure 6-5: Identify the effect from a cascade control system to a measured variable

It should be noted that although A2 can be assumed to be one of ancestors of B just for the purpose of fault diagnosis, it is possible that it is not A2 at all but A1 actually affects B. For example, if in one case, either controllers A1C or A2C or both deviate but B is not affected, process disturbances to A1 cannot be rejected due to an observation that B is not affected under the assumption that A2 affects B. This is because it is still possible that A1 affects B, and thus in this case, the control system compensates for the fault, B is not affected. However an A1-set-point-change and an A1-sensor-bias can be rejected due to the previous observation if the process pertaining to A1 is not capacitive.

6.2.4 The Interaction between A Cascade Control System and Another Control System

Three sub-cases are considered.

(1) A single-loop control system or the outer loop of a cascade control system affects another cascade control system. Suppose A is controlled by a single-loop control system, B1 is controlled by the outer-loop controller B1C and B2 is controlled by the inner-loop controller B2C (Figure 6-6). If a step test is applied to the set-point of A and the cascade control system is affected, it indicates A affects this cascade control system. If the outer loop controller B1C deviates, A affects B1 or both B1 and B2 and in the latter case, the link from A

to B2 can be neglected because it doesn't affect the final diagnostic result. If only the inner loop controller B2C deviates, A only affects B2.

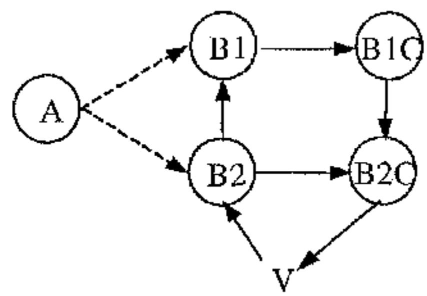


Figure 6-6: Identify the effect from a single-loop control system to a cascade control system

(2) <u>A cascade control system affects a single-loop control system</u>. Suppose A1 is controlled by the outer loop controller A1C, A2 is controlled by the inner loop controller A2C and B is controlled by a single-loop controller (Figure 6-7). The case is quite similar to that in Section 6.2.3. If a step is applied to the set-point of A1, and the single control system deviates, it indicates B is affected by this cascade control system. It is very difficult to decide whether A1, A2, or both, affects B and in this situation, if possible, process knowledge should be used, e.g., if the outer loop process is capacitive, it is quite certain that A1 affects B. For the same reason as before, if the outer loop process is not capacitive, for robust fault isolation, it is acceptable to assume it is A2 that affects B. However, similar to the case in the last paragraph of Section 6.2.3, this is only an assumption and faults like process disturbances to A1 should not be rejected deliberately because of this assumption.

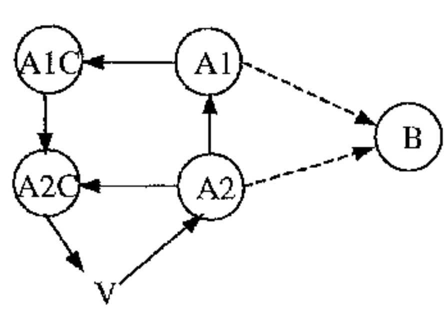


Figure 6-7: Identify the effect from a cascade control system to a single-loop control system

(3) <u>A cascade control system affects another cascade control system (Figure 6-8)</u>. The interaction between them can be determined by the combination of (1) and (2).

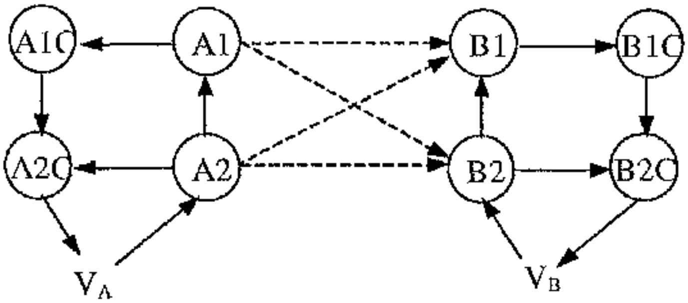


Figure 6-8: Identify the interaction between two cascade control systems

6.2.5 Summary of The Identification of Process Interactions

The identification of process interactions can be guided and summarised as the following.

(1) The question as to whether or not a deviation in a controlled variable (not a slave variable in a cascade control system) will affect a measured variable, controlled or not, can be investigated by applying a step test to the set-point of the controlled variable. It is more difficult to determine whether a deviation in an uncontrolled variable will affect another variable because an appropriate step test is not likely to be realised. It might be possible to obtain this from related process knowledge.

(2) If there exists two controlled variables (not a slave variable in a cascade control system), A and B, the interactions between them can be determined by a step test. There are four possible relationships between A and B (Figure 6-9). The link directions can be determined by the step test and by referring to the cause-effect knowledge of the SEVACS. If the change in A set-point can cause B related control system to deviate, it indicates A is an ancestor of B, and vice versa. If neither a change in A set-point can cause B related control system to deviate nor a change in B set-point can cause A related control system to deviate, it indicates A and B are independent of each other.

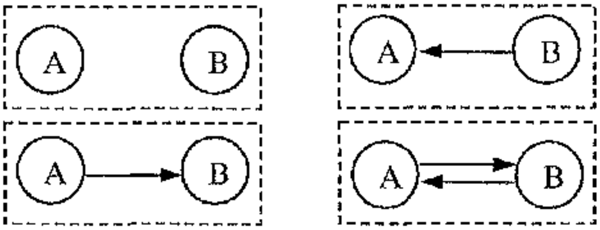


Figure 6-9: Four possible relationships between two controlled variables

(3) If a step applied to the set-point of A doesn't cause B or its related control system to deviate, there are two possibilities: (1) A and B are independent of each other; (2) A is not an ancestor of B, but B may be an ancestor of A. If a step, applied to the set-point of A, causes B or its related control system to deviate, there are also two possibilities: (1) A is an ancestor of B, but not vice versa; (2) A is an ancestor of B, B may be an ancestor of A.

(4) For a cascade control system, there exists some ambiguities.

6.3 Constructing and Modifying An E-SDG

An E-SDG can be constructed as follows:

(1) classify nodes into controller related nodes (including controlled nodes, valve nodes and controller output nodes) and other measured nodes;

(2) apply step changes to controlled nodes one by one, observe and record how other nodes change in steady state;

(3) identify process characteristics, interactions and construct the E-SDG;

(4) update the E-SDG by learning.

Learning can be realised by:

(1) expert knowledge;

(2) reasoning about contradictory cause-effects: for example, suppose a plant is thought to have interactions as in Figure 6-1A, the A related controller output and B deviate, A-sensor-bias-high is inferred from knowledge of SEVACS, and

A-sensor-bias-low is inferred from testing, then this contradiction might be explained as either Figure 6-1B or Figure 6-1C interaction instead;

(3) comparing a diagnostic result with a known fault or disturbance: if they contradict, then something unknown exists. For example, in Figure 6-1, if A-sensor-bias is inferred, then the operator should check and confirm whether it is true. If it is not true, then either Figure 6-1B or Figure 6-1C is possible;

(4) applying other possible methods, for example, add additional measurements or observers etc.

Human investigation and intervention should be incorporated into the learning and updating process.

6.4 A CSTR Case Study

This section describes how the above procedure would be applied to a CSTR process that might, or might not, be open loop unstable. Hence two possibilities are examined: with stable parameters, with unstable parameters. Consider the simulated CSTR process shown in Figure 6-10: there are two outlets, the flow rate, F_1, is manipulated to regulate level, L, whilst a nominally constant flow rate, F, is drawn for a separate purpose; the reactor temperature, T, is maintained by varying the flow rate, FJ, through a heat exchanger installed in the CSTR and, in addition, concentration C_A is measured. The detail model of this CSTR process is described in Appendix 1. Note that there are three control systems, two of which have single loops, the other has a cascade arrangement.

(1) Classify nodes: there are three main controlled nodes F, L and T, in addition, FJ is an inner loop controlled node. There are three main controllers FC, LC and TC, plus one inner loop controller, FJC, three valve nodes FV, LV and FJV and one additional measurement node C_A. This example is somewhat simple because SDGs pertaining to the three control systems can be derived at the design stage. However this might not always be the case so here it is assumed that this is not possible.

(2) Step tests: step changes are applied to L , F and T respectively, all the set-points are increased and the deviation directions of other variables are then observed in the steady state (Table 6-1). Note that steps are only applied to outer loops.

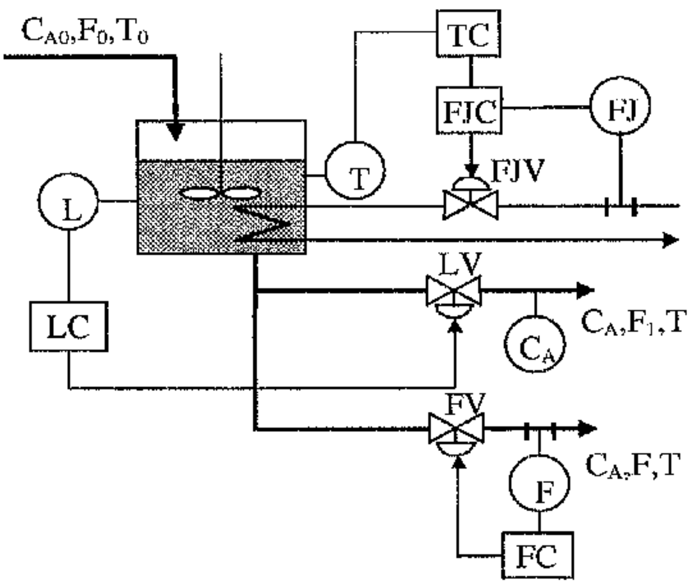


Figure 6-10: A simulated CSTR process

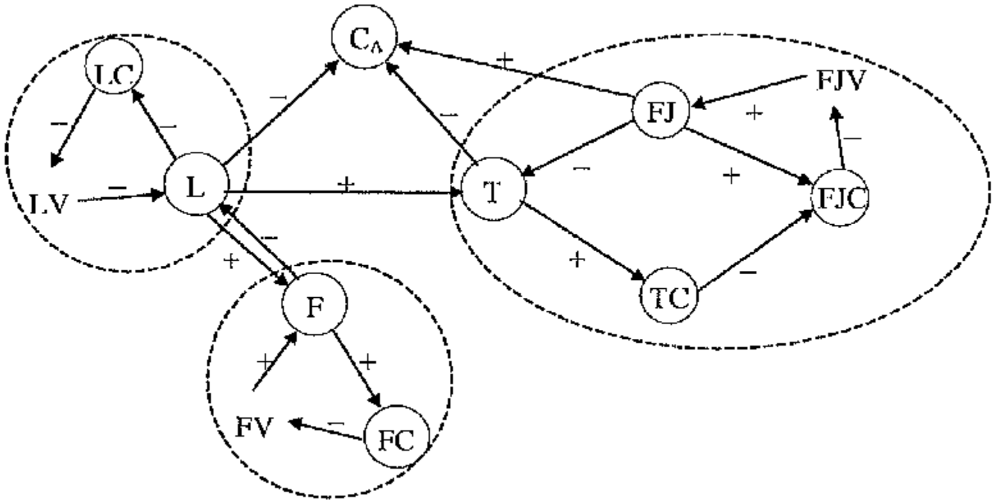
Table 6-1: Step tests

Step changes	Observed deviation directions
LC set-point(+)	FC(+), C_A(−), TC(+), FJC(−), FJ(+), LC(+), L(+)
TC set-point(+)	Unstable parameters: C_A(−), TC(−), FJC(+), FJ(−), T(+)
	Stable parameters: C_A(−), TC(+), FJC(−), FJ(+), T(+)
FC set-point(+)	FC(−), LC(+), F(+)

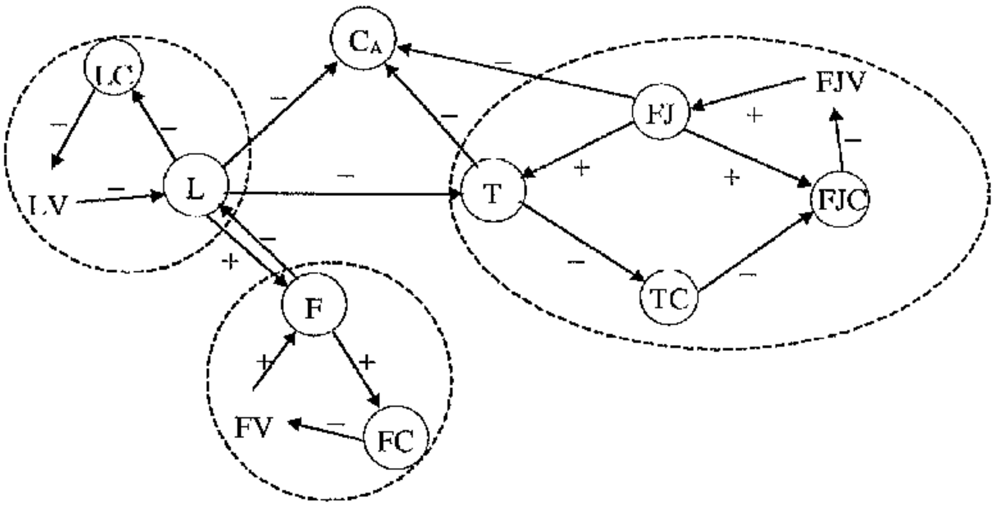
(3) Construct super-nodes for control systems: by referring to Equations (3-36) to (3-38), it can be deduced that the open loop processes of L, F and FJ are either stable or have even numbers of unstable poles. Turning to the open loop process that affects T: for the case where stable parameters are present, it is either stable or has an even number of unstable poles; for the case where unstable parameters are present, it has an odd number of unstable poles. All the open loop processes here have a type number of zero.

(4) Identify process interactions: using SEVACS knowledge, the super-nodes constructed and the deviation directions in Table 6-1, process interaction can be established and an E-SDG of the CSTR can be built as in Figure 6-11. Note that a set-point change can cause either positive or negative deviations depending on the sign of $\{A_0K_c\}$ (Figure 4-2) or $\{A_0K_{c1}\}$ (Figure 4-3).

(5) Learn and modify the E-SDG: for instance if there is expert knowledge that FJ can only affect C_A indirectly through T, then the direct link from FJ to C_A can be removed from the E-SDG. Or for instance if there is a disturbance or fault that causes $C_A(-)$, TC(+), FJC(–), FJ(+) and LC(+), it is unlikely that the cause is L-sensor-bias because T control system deviates and C_A deviates, but F control system doesn't deviate. To infer this fault note that there must be a common ancestor of L, T and C_A. After investigation, the common ancestor is found to be F_0 because the decrease of F_0 can cause those variables to deviate in those directions. Now the E-SDG can be updated as in Figure 6-12.

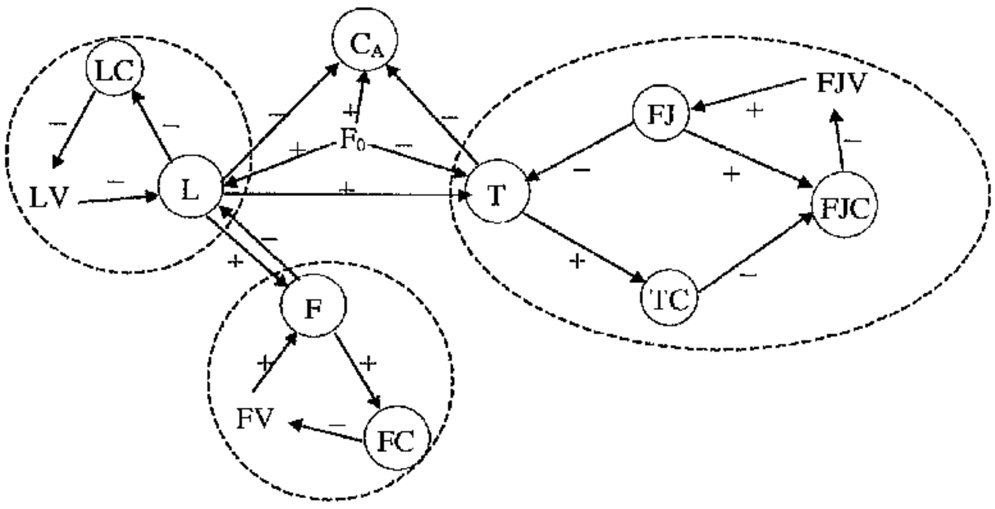


(A) With stable parameters

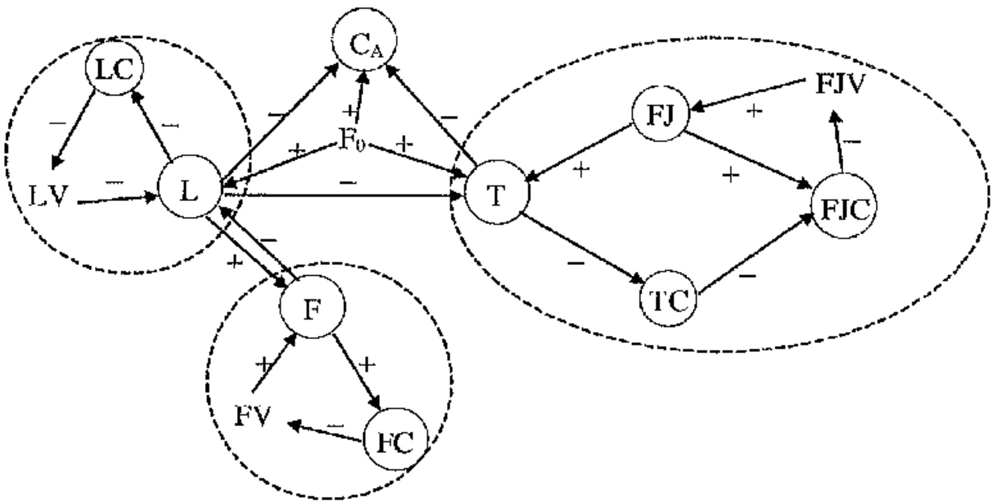


(B) With unstable parameters

Figure 6-11: Constructing an E-SDG for the CSTR



(A) With stable parameters



(B) With unstable parameters

Figure 6-12: The updated E-SDG for the CSTR

CHAPTER 7

STEADY STATE IDENTIFICATION AND CHANGE DETECTION

The approach described in this thesis relies on the fact that faults cause sustainable changes to the steady state and that a change in the steady state can be detected and quantified. In practical terms this means that the process must be continually monitored to observe whether it is in a steady state or not. Having detected that the process has entered a 'non-steady' phase, and having waited for this phase to end, a decision must then be made as to whether the process has returned to its previous steady state or to a new one. Qualitative deviations can then be obtained. Figure 7-1 summarises this procedure.

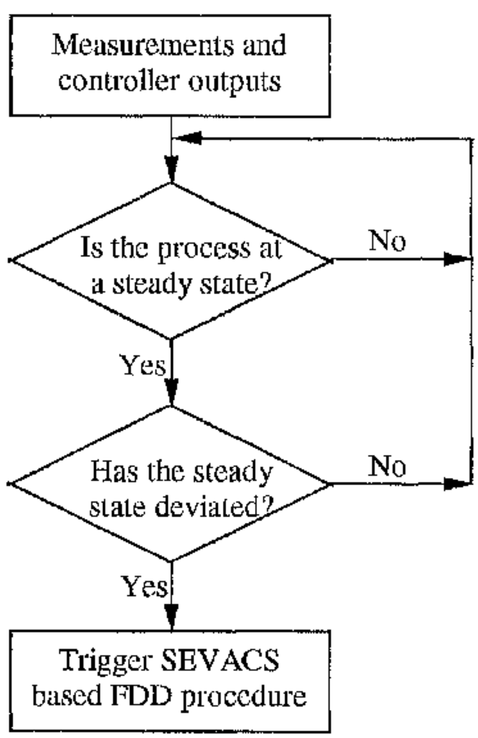


Figure 7-1: Steady state identification and change detection

7.1 Steady State Identification

The steady state identification algorithm described here is due to Cao & Rhinehart (1995). They assume that the measured variable from a real process can be viewed as representing the true process value corrupted by additive noise. If the true process value remains unchanged at every sampling time during a certain time interval, it can be considered that the corresponding variable is at a steady state (or pseudo steady state if steady state is too strict) during this time interval. As far as this thesis is concerned, if all measured variables of a process are at a steady state, it can be considered that the corresponding process is at a steady state. It should be noted that the concept of *steady state* here is less strict than *stationary* or *strictly stationary* in statistics. In statistics, *stationary* requires not only the mean of the time series data to be constant but also the distribution and autocorrelation, if any, to remain unchanged with time.

There are three main approaches to steady state identification based on different statistics as follows:

- *t-statistic*: the idea is to perform a linear regression over a data window and then to perform a *t*-test on the regression slope. If the slope is significantly different from zero, the considered data variable is almost certainly not at a steady state, otherwise, it is at a steady state;
- *F-statistic*: this is to use an *F-test* type statistic, a ratio of variances as measured on the same set of data by two different methods. The data in the most recent window are averaged and the variance is first conventionally calculated as the mean-square-deviation from the average. The variance can also be calculated from the mean of squared differences of successive data. If the time series is stationary (i.e. if the relevant variable is at a steady state), then ideally the ratio of these two variances will be unity. Alternatively, the ratio will be unusually large if the data variable is not at a steady state;
- *R-statistic*: which was developed by Cao and Rhinehart (1995) and is styled after the *F-test* type of statistic. *R* is also the ratio of variances as measured on the same set of data by two different methods. However this time *R-statistic*'s

first estimate of the variance (or numerator) is based on the filtered squared deviation from previous filtered value.

The first two approaches are usually used offline because their online versions require considerable data storage, associated computational effort and user expertise. For instance, there are no universal rules to choose the length of the data window and the selection will be judgmental, these two approaches could suffer false alarms often because of noise change and autocorrelation.

The *R-statistic* based approach is intentionally designed to be used online because it is computationally inexpensive and does not suffer from the other drawbacks mentioned above. It has proved to be effective when applied to several chemical processes online. Thus the *R-statistic* is recommended for the SEVACS. Details of the *R-statistic* are given in the next section and the reader is referred to Cao and Rhinehart (1995, 1997) for more details.

7.1.1 The *R-statistic*

The primitive way of estimating variance is:

$$\hat{\sigma}^2 = \frac{1}{N-1}\sum_{i=1}^{N}(X_i - \overline{X}_N)^2 . \tag{7-1}$$

If an EWMA (exponentially weighted moving average) filtered value $X_{f,i-1}$ where

$$X_{f,i} = \lambda_1 X_i + (1-\lambda_1)X_{f,i-1} \tag{7-2}$$

and

$$0 < \lambda_1 \leq 1 ,$$

is used to replace the sample mean $\overline{X}_N$, a mean squared deviation can be defined as the expectation:

$$\nu^2 = E((X_i - X_{f,i-1})^2)$$

and can be estimated by :

$$\hat{\nu}^2 = \frac{1}{N-1}\sum_{i=1}^{N}(X_i - X_{f,i-1})^2 . \tag{7-3}$$

Assuming $\{X_i\}$ is uncorrelated, then there is no autocorrelation between X_i and $X_{f,i-1}$ and σ^2 can easily estimated from ν^2.

Define:

$$d_i = X_i - X_{f,i-1}, \tag{7-4}$$

suppose the process is at a steady-state condition and there is no autocorrelation in the sequential measurement, then X_i and $X_{f,i-1}$ are independent, so that the variance on d is related to the variance on X and X_f :

$$\sigma_d^2 = \sigma_X^2 + \sigma_{X_f}^2. \tag{7-5}$$

Further, for the EWMA, when $\{X_i\}$ are independent and stationary, the variance on X_f becomes:

$$\sigma_{X_f}^2 = \frac{\lambda_1}{2-\lambda_1}\sigma_X^2. \tag{7-6}$$

From the above two equations, we have:

$$\sigma_X^2 = \frac{2-\lambda_1}{2}\sigma_d^2 = \frac{2-\lambda_1}{2}\nu^2, \tag{7-7}$$

and so:

$$\hat{\sigma}_X^2 = \frac{2-\lambda_1}{2}\hat{\nu}^2 \tag{7-8}$$

If we use a filtered value instead of the traditional average $\hat{\nu}^2$ as represented in equation (7-3):

$$\nu_{f,i}^2 = \lambda_2 (X_i - X_{f,i-1})^2 + (1-\lambda_2)\nu_{f,i-1}^2, \tag{7-9}$$

$$(0 < \lambda_2 \leq 1)$$

and suppose the process is stationary:

$$E(\nu_{f,i}^2) = E((X_i - X_{f,i-1})^2) = \nu^2$$

we have :

$$\mathrm{var}(\nu_{f,i}^2) = \frac{\lambda_2}{2-\lambda_2}\mathrm{var}((X_i - X_{f,i-1})^2)$$

which means that $\nu^2_{f,i}$ provides a computationally efficient, unbiased estimate of $(X_i - X_{f,i-1})^2$.

Then the estimate of the noise variance from this first approach will be:

$$s_{1,i}^2 = \frac{2-\lambda_1}{2}\nu_{f,i}^2 \tag{7-10}$$

Using this method, $s_{1,i}^2$ will be increased from its steady-state value by a recent shift in the mean. Such a measure could be used to trigger the *not-at-a-steady-state* condition; however, the threshold is dependent on both the measurement units and the unknown process noise variance.

The second method to estimate the variance uses the mean squared differences of successive data. Define:

$$\delta^2 = E((X_i - X_{i-1})^2) \tag{7-11}$$

and

$$E(s_{2,i}^2) = \frac{1}{2}E((X_i - X_{i-1})^2). \tag{7-12}$$

If we use the filtered data:

$$\delta_{f,i}^2 = \lambda_3 (X_i - X_{i-1})^2 + (1-\lambda_3)\delta_{f,i-1}^2, \tag{7-13}$$

$(0 < \lambda_3 \le 1)$

obviously we have the estimate of the variance:

$$s_{2,i}^2 = \frac{\delta_{f,i}^2}{2}, \tag{7-14}$$

then the ratio expressed by

$$R_i = \frac{s_{1,i}^2}{s_{2,i}^2} = \frac{(2-\lambda_1)\nu_{f,i}^2}{\delta_{f,i}^2} \tag{7-15}$$

can be used to be the criteria for a steady state as follows:

1. if the process data is at a steady state (process mean is constant, additive noise is independent and identically distributed), then R_i will be near 1;
2. if the process data mean shifts, or if the noise is autocorrelated, then R_i will be greater than 1. When there is a shift in mean, both the calculations of the variance will be influenced temporally. The first calculation will increase more and persist longer, so R_i will be greater than 1 for a period of time, and that is the way that the *not-at-a-steady-state* condition can be identified;
3. if the sequentially sampled process data alternate between high and low extremes, then R_i will be less than 1. This would be very uncommon in chemical processes. Hence the work only tests whether R_i is greater than a critical value R_{crit}.

7.1.2 Correlated Processes

The preceding algorithm is available for uncorrelated processes. If the process is autocorrelated, then Cao and Rhinehart recommend that an appropriate sampling interval should be selected to 'eliminate' the influence of autocorrelation efficiently. For example, for a first-order autoregressive process which is sampled every P data points:

$$X_i = \phi X_{i-1} + a_i \,, \tag{7-16}$$

where $a_i = \mu + n_i$, n_i is zero mean noise and $0 \le \phi < 1$ for the process to be stable, Cao and Rhinehart (1995) give:

$$E(s_{2,i}^2) = \frac{1}{2}E(\delta_{f,i}^2) = \frac{1}{2}E((X_i - X_{i-P})^2) = (1-\rho_P)\sigma_X^2 \tag{7-17}$$

and

$$E(s_{1,i}^2) = E(\frac{2-\lambda_1}{2}\cdot \nu_{f,i}^2) = \frac{2-\lambda_1}{2}E((X_i - X_{f,i-P})^2) = \frac{1-\rho_P}{1-(1-\lambda_1)\cdot\rho_P}\sigma_X^2 \tag{7-18}$$

where $\rho_P = \phi^P$ is the autocorrelation coefficient at lag P for the first-order autoregressive process.

For stable autoregressive processes, the bigger the step size P, the smaller the ρ^P. So, the above equations indicate that a big sampling interval could make the means of those estimations close to the true process variance; and, as a result, R, the ratio of those two estimates will be centred towards unity and the probability density function of R will be close to that of uncorrelated cases.

7.1.3 Choice of Critical Values

Cao and Rhinehart (1997) have proven that the distribution of the *R-statistic* is effectively only a function of λ_1, λ_2 and λ_3 so that the critical value R_{crit} need only be calculated for different combinations of λ_1, λ_2 and λ_3 values. A table of R_{crit} is given below (Table 7-1). Its construction is based on the probability density functions of R calculated by simulation using computer generated pseudo-random numbers.

Note from Table 7-1 that, if λ_1=0.01, λ_2=0.02 and λ_3=0.02, an R_{crit} value of 1.27 would be required to be 99% confident that the process is in steady state. However, it will be seen in the next section that the approach fails to accommodate the long term fluctuations that are prevalent in real plants. Although this effect has been recognised by Cao and Rhinehart, they failed to recommend a solution and hence the approach here is to choose R_{crit} on the basis of actual performance. In addition they fail to point out that an EWMA is a filter with filter like attributes, which need to be taken into account. The following sub-section examines these attributes, in particular the interdependence between the λ's, the sampling time interval ΔT and the filter time constant.

Table 7-1: Critical values of the *R-statistic* (Cao and Rhinehart, 1997)

λ_1	λ_2	λ_3	α=0.50	α=0.25	α=0.10	α=0.05	α=0.01
0.5	0.5	0.5	0.99	1.29	1.70	2.01	2.72
0.2	0.5	0.5	0.96	1.43	2.21	2.93	4.97
0.1	0.5	0.5	0.94	1.47	2.40	3.29	6.05
0.05	0.5	0.5	0.94	1.49	2.50	3.50	6.69
0.02	0.5	0.5	0.93	1.49	2.56	3.63	7.11
0.01	0.5	0.5	0.93	1.50	2.57	3.66	7.21
0.5	0.2	0.2	1.00	1.15	1.32	1.45	1.72
0.2	0.2	0.2	1.00	1.22	1.51	1.74	2.32
0.1	0.2	0.2	0.99	1.24	1.57	1.84	2.57
0.05	0.2	0.2	0.99	1.25	1.60	1.90	2.70
0.02	0.2	0.2	0.99	1.25	1.62	1.93	2.79
0.01	0.2	0.2	0.99	1.26	1.63	1.95	2.82
0.5	0.1	0.1	1.00	1.10	1.21	1.28	1.43
0.2	0.1	0.1	1.00	1.15	1.32	1.44	1.73
0.1	0.1	0.1	1.00	1.16	1.35	1.49	1.83
0.05	0.1	0.1	1.00	1.17	1.37	1.52	1.89
0.02	0.1	0.1	1.00	1.17	1.38	1.53	1.93
0.01	0.1	0.1	1.00	1.17	1.38	1.55	1.95
0.5	0.05	0.05	1.00	1.07	1.14	1.18	1.28
0.2	0.05	0.05	1.00	1.10	1.21	1.28	1.44
0.1	0.05	0.05	1.00	1.11	1.23	1.31	1.50
0.05	0.05	0.05	1.00	1.11	1.24	1.33	1.52
0.02	0.05	0.05	1.00	1.12	1.24	1.34	1.54
0.01	0.05	0.05	1.00	1.12	1.25	1.34	1.55
0.5	0.02	0.02	1.00	1.04	1.08	1.11	1.16
0.2	0.02	0.02	1.00	1.06	1.12	1.16	1.24
0.1	0.02	0.02	1.00	1.07	1.14	1.18	1.27
0.05	0.02	0.02	1.00	1.07	1.14	1.19	1.28
0.02	0.02	0.02	1.00	1.00	1.14	1.19	1.29
0.01	0.02	0.02	1.00	1.07	1.14	1.19	1.30
0.5	0.01	0.01	1.00	1.03	1.06	1.07	1.11
0.2	0.01	0.01	1.00	1.04	1.08	1.11	1.16
0.1	0.01	0.01	1.00	1.05	1.09	1.12	1.18
0.05	0.01	0.01	1.00	1.05	1.10	1.13	1.19
0.02	0.01	0.01	1.00	1.05	1.10	1.13	1.19
0.01	0.01	0.01	1.00	1.05	1.10	1.13	1.19

7.1.4 The Balance between $\lambda_1, \lambda_2, \lambda_3$ and The Sampling Interval ΔT

Parameters $\lambda_1, \lambda_2, \lambda_3$ and ΔT should be chosen so that noise effects are abated efficiently and the statistics reflect the truth in time. To explain this, compare the EWMA to the conventional first order filter (Figure 7-2).

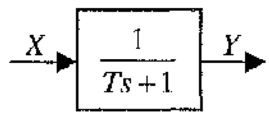


Figure 7-2: The first-order filter

The first-order filter can be represented by the continuous form:

$$Y + T\frac{dY}{dt} = X \ , \tag{7-19}$$

or the discrete form:

$$Y_i + T\frac{Y_i - Y_{i-1}}{\Delta T} = X_i \,, \tag{7-20}$$

where X_i is the input at the *ith* instant,

Y_i is the filtered output at the *ith* instant,

T is the time constant of the filter,

and ΔT is the sampling time or time interval of the filter.

Then Y in recursive form:

$$\begin{aligned} Y_i &= \frac{\frac{\Delta T}{T}}{1+\frac{\Delta T}{T}} \cdot X_i + \frac{1}{1+\frac{\Delta T}{T}} \cdot Y_{i-1} \,, \\ &= \lambda X_i + (1-\lambda) Y_{i-1} \end{aligned} \tag{7-21}$$

where $0 < \lambda \leq 1$ is the filter factor.

It can be seen that if λ is kept constant, whilst changing the time interval ΔT, the time constant T is changed as well. The smaller the time constant T, the better the tracking ability of the filter but the worse the de-noising ability of the filter, and *vice versa*. Because T can affect the performance of the filter significantly, ΔT can have a great influence on the identifier performance.

7.1.5 The Application of The *R-statistic*

The *R-statistic* based steady state identifier has been applied to a simulated CSTR process (see Appendix). At time 1hr, the temperature (TEMP) set-point was changed from 600 °R to 597 °R, *R-statistics* of the temperature (TEMP) and the output of the FJ controller (FJC) under different sampling intervals are shown in Figures 7-4A — 7-4H. These statistics have been generated using λ_1=0.01, λ_2=0.02 and λ_3=0.02. Note that a threshold of R_{crit}=2 has been drawn. It has been increased from 1.3 since this value would result in an unacceptable level of false detection and R_{crit} was raised to 2 to accommodate this.

It has been seen that the bigger the sampling interval the less difference between *at-a-steady-state* and *not-at-a-steady-state* conditions (Figure 7-4C), and also the longer the time duration of the transient response (Figure 7-4G).

Autocorrelation of TEMP is not an issue because sensor dynamics are not modelled so that the only autocorrelation will be due to the process time constant [500 secs, 2000 secs] which is very long relative to the sampling interval (Figure 7-4E). One step lag autocorrelation coefficients of TC, FJC, TEMP and Ca have been calculated for different sampling intervals (Table 7-2). Only point of interest are the two controllers' (TC and FJC) autocorrelations, though still very small. It can be seen from the Figure 7-3 that they could be decreased effectively by increasing their time intervals.

Table 7-2: One step lag autocorrelation coefficients

	Sampling intervals			
	1 sec	2 secs	5 secs	≥10 secs
TC	0.0107	0.0095	0.0061	≈0
FJC	0.0026	0.0025	0.0021	≈0
TEMP	≈0	≈0	≈0	≈0
Ca	≈0	≈0	≈0	≈0

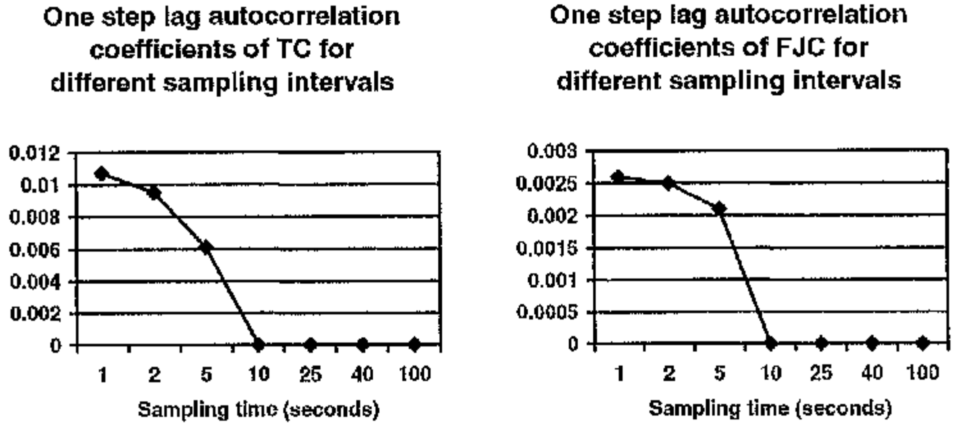
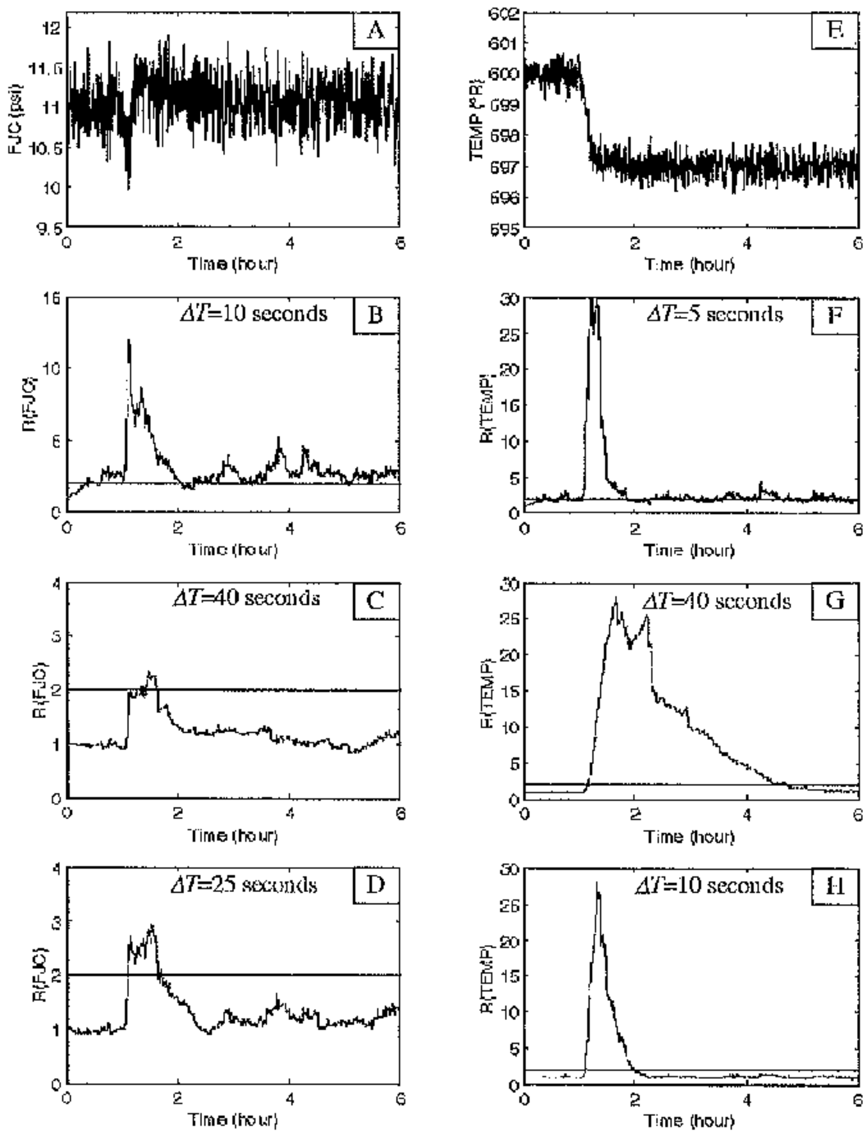


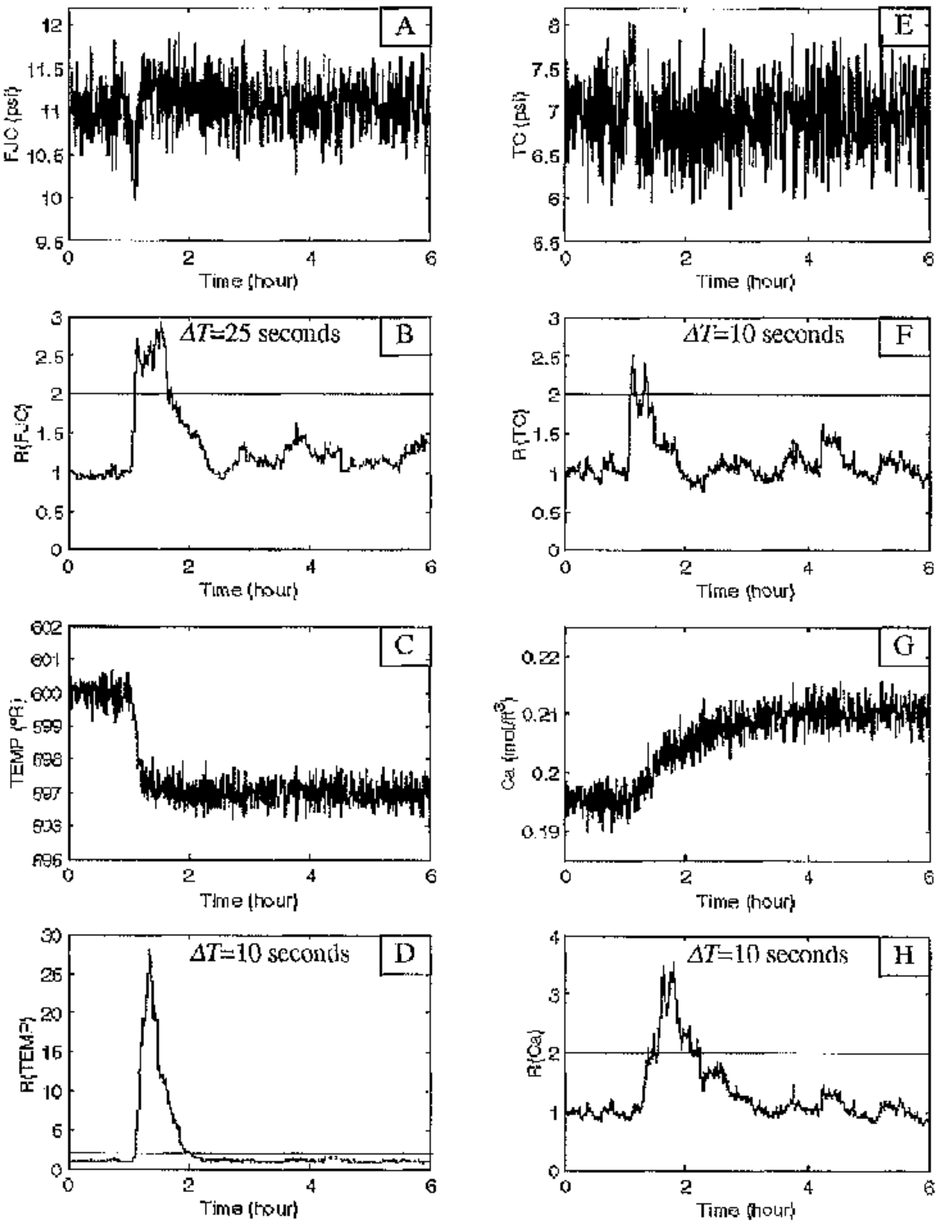
Figure 7-3: Autocorrelation tests

Sampling intervals should be reasonably selected for optimal steady state identification performance. For example, the average value of R is bigger than its critical value even when the process is actually in steady state if the sampling interval is too small (Figure 7-4B and 7-4F), but increasing the sampling interval will cause R to decrease and the transient response time duration to increase (Figure 7-4C and 7-4G). As shown in the Figures, the best sampling interval is 25 seconds for FJC (Figure 7-4D), and 10 seconds for TEMP (Figure 7-4H). Four steady state identifiers for FJC, TC, TEMP and Ca under the above set-point change are shown in Figures 7-5A — 7-5H with λ_1=0.01, λ_2=0.02 and λ_3=0.02. The various sampling intervals 25 seconds, 10 seconds, 10 seconds and 10 seconds are compromise-balanced. Note in Figure 7-5F that the statistic returns to *at-a-steady-state* for a short while before returning to *not-at-a-steady-state*; as will be explained in the next section, this occurrence is ignored when deriving the qualitative changes in steady state. So the performances in Figures 7-5A — 7-5H are acceptable.

To summarise, it is suggested that λ1, λ2, λ3, AT and R_{crit} should be tuned reasonably and scrupulously for the best steady state identification performance on a real application.



Figures 7-4A — 7-4H: *R-statistics* for FJC and TEMP under different sampling intervals (TEMP set-point changed from 600 °R to 597 °R at the 1 hour time)



Figures 7-5A — 7-5H: Satisfied *R-statistics* for FJC, TC, TEMP and Ca (TEMP set-point changed from 600 °R to 597 °R at the 1 hour time)

7.2 Steady State Change Detection

This section examines how steady states can be compared to determine qualitative deviations. The procedure is in 2 parts, a quantitative test is applied followed by a qualitative one. The quantitative part is a common hypothesis test in statistics, the aim is to compare the difference between the sample means of two independent SRSs (simple random samples) with unknown variances.

Suppose there are two independent SRSs X_1 with size n_1 and X_2 with size n_2, which are drawn from different normal populations with unknown means μ_1 and μ_2 and unknown variances σ_1^2 and σ_2^2 respectively. In order to test the hypothesis H_0: $\mu_1 \gtreqless \mu_2$, a two-sample *t-statistic* can be used:

$$t = \frac{\overline{X}_2 - \overline{X}_1}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}, \tag{7-22}$$

with

estimated sample means $\overline{X}_1 = \frac{\sum_{i=1}^{n_1} X_{1i}}{n_1}$ and $\overline{X}_2 = \frac{\sum_{i=1}^{n_2} X_{2i}}{n_2}$,

estimated sample variances $s_1^2 = \frac{\sum_{i=1}^{n_1} (X_{1i} - \overline{X}_1)^2}{n_1 - 1} = \frac{n_1 \sum_{i=1}^{n_1} X_{1i}^2 - \left(\sum_{i=1}^{n_1} X_{1i} \right)^2}{n_1(n_1 - 1)}$

and $s_2^2 = \frac{n_2 \sum_{i=1}^{n_2} X_{2i}^2 - \left(\sum_{i=1}^{n_2} X_{2i} \right)^2}{n_2(n_2 - 1)}$.

These sample means and variances can be easily calculated online. For a confidence level C, $t^* = t(k)$ is the upper $\frac{1-C}{2}$ critical value for the *t-statistic*, where $t(k)$ is the value from the table of t distribution critical values with k the smaller of n_1-1 and n_2-1.

Note that there will then be periods of time when the test cannot be applied because the sample means and variances are in the process of being formed i.e. there will be blackout periods. Obviously there will also be other times when the test cannot be applied because the process is not in a steady state. Suppose that a variable enters an unsteady state at time T_u and arrives at a new steady state at a time T_0. Then there will be an unsteady period fro T_u to T_0, which would be followed by a blackout period until $T_0+n_2\Delta T$. At that time the t-statistic would be computed on the basis of data collected during the two time periods from $T_u-n_1\Delta T$ to T_u and from T_0 to $T_0+n_2\Delta T$. Comparing with t^* , a threshold evaluated at a certain confidence level C, if $t>t^*$, the variable is said to be *at-a-high-value* with confidence level C; if $t<-t^*$, the variable is said to be *at-a-low-value* with confidence level C; otherwise the variable is said to be unchanged or normal with confidence level C. Any deviation or change in status would be reported to a higher level system, e.g. the SEVACS based FDD system (see Figure 7-1), which would acknowledge its occurrence. On acknowledgement, all statuses would be reset to normal so that the procedure could be repeated. The procedure would then enter a blackout period immediately to ensure that it had sample means and variances prior to the occurrence of another unsteady phase. If an unsteady phase did arise during this period, then the reset would be cancelled i.e. effectively the variable would be deemed to be in the same unsteady phase as before.

To demonstrate this consider the same CSTR process data as before. The various stages are shown in Figures 7-6A — 7-6F. Figures 7-6A & 7-6D show the raw data, 7-6B & 7-6E their *R-statistics* and 7-6C & 7-6F their *t-statistics*. Focusing on FJC change detection (Figures 7-6A — 7-6C):

(1) $[0, t_A]$, the first nominal steady state test: FJC is in its nominal steady state, but since the program has just been activated, data is collected to derive the statistics for X_1, and hence *blackout* is output;

(2) $[t_A, t_B]$: the state remains unchanged and so *at-a-normal-value* is output until a change is detected on the basis of the *R-statistic* at time t_B; this is as a result of a change in TEMP set-point at time 1 hour;

(3) $[t_B, t_C]$: *not-at-a-steady-state* is now output until a time shortly before t_C when the *R-statistic* exceeds its threshold transiently causing the output to switch

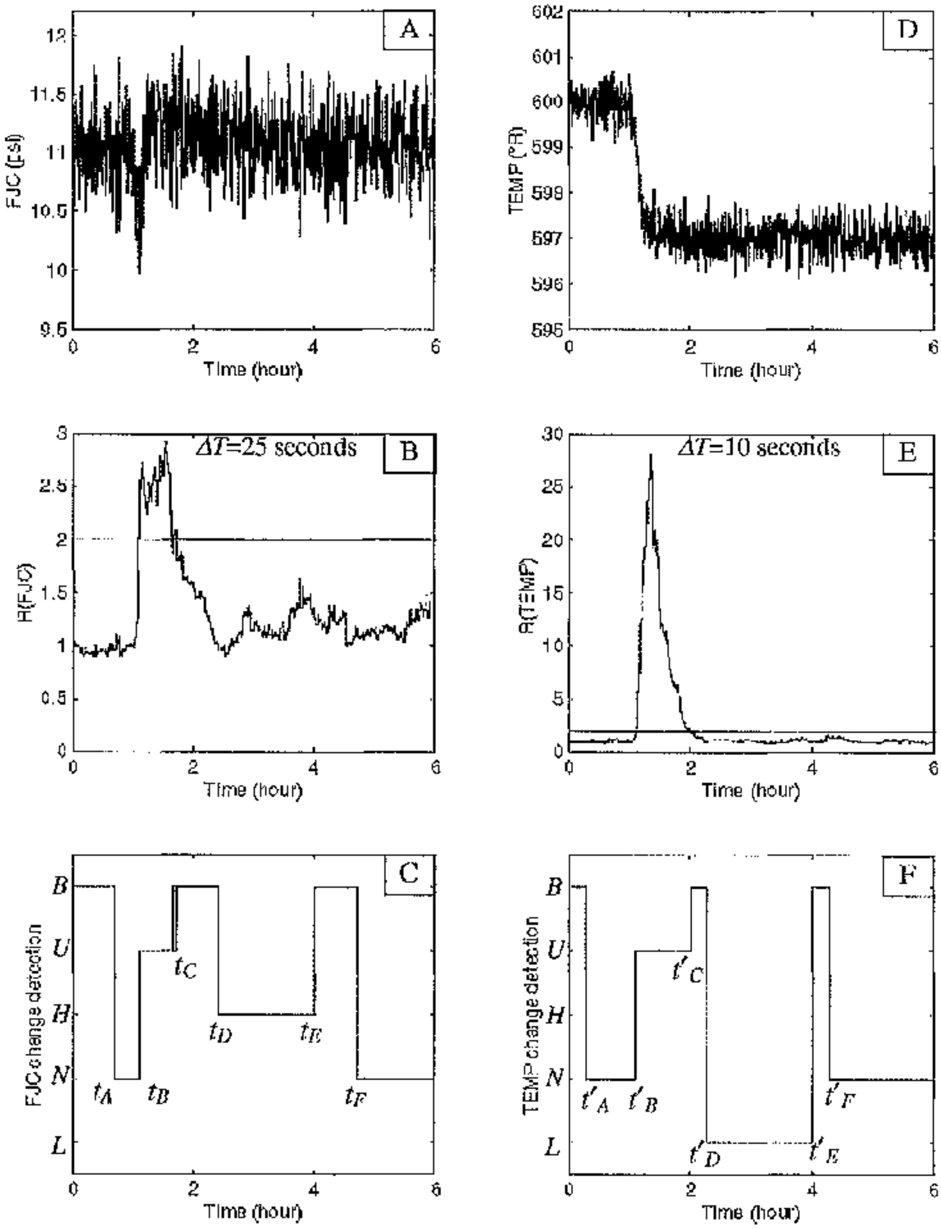
between *not-at-a-steady-state* and *blackout*. Under these two states, the high level FDD system won't do anything and consequently short-term fluctuations into and out of steady state are effectively ignored.

(4) [t_C, t_D]: The output is at *blackout* for $n_2\Delta T$ hours where n_1=101and n_2=101. A change in steady state is now detected, using the confidence level C=95% and a threshold of $t^*=t(100)=1.984$, and the output changes to *at-a-high-value*.

(5) [t_D, t_E]: This output remains until it is acknowledged at t_E.

(6) [t_E, t_F]: The mean and sample variances are obtained so the output is *blackout*. Finally the output returns to *at-normal-value*.

Note that the FDD program starts to diagnose the fault at times t_D and t'_D .



Figures 7-6A — 7-6F: Steady state change detection of FJC and TEMP (TEMP set-point changed from 600 °R to 597 °R at the 1 hour time) (in C and F, *B*: *blackout*; *U*: *not-at-a-steady-state*; *H*: *at-a-high-value*; *N*: *at-a-normal-value*; *L*: *at-a-low-value*)

CHAPTER 8

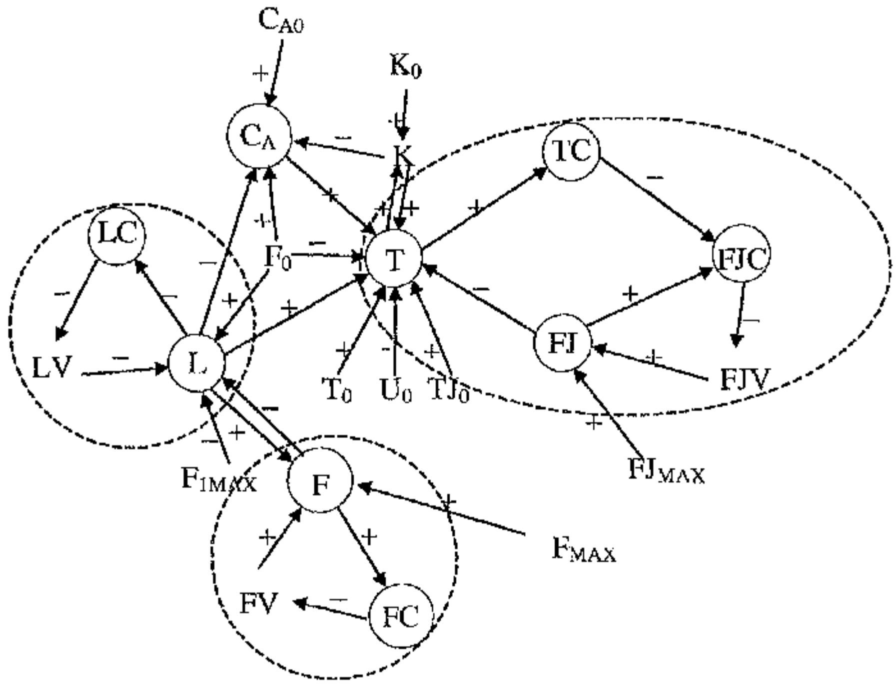
APPLICATIONS

For better understanding of the SEVACS based approach to process monitoring and fault diagnosis, two applications will be investigated in this Chapter, one is to a simulated CSTR, the other is to the Tennessee Eastman Process Benchmark.

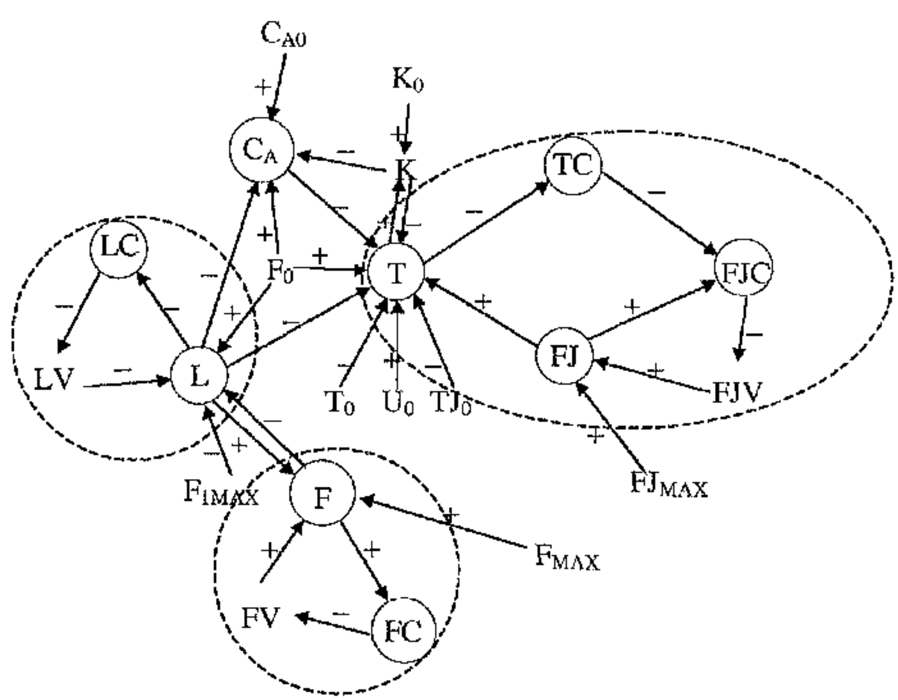
8.1 Application to The CSTR Process

8.1.1 The SDG Representation and Simulated Faults

The CSTR process has already been introduced in Chapter 6, Chapter 7 and Appendix 1. Figures 8-1(a) & (b) show its signed directed graph (SDG) representation, for both stable and unstable parameters, that have been constructed from the equations given in the Appendix 1. Note that there are three control systems (enclosed by dashed lines), two of which have single loops, the other has a cascade arrangement. Compared to the stable case, the unstable case requires a number of changes, the signs of the branches from FJ to T, T to TC and all the disturbances to T are inverted. It is assumed that the output from each circled node can be recorded either because it can be measured, as is usually the case for sensors and valves, or because it has been calculated, as in the case of a digital control output. The list of faults considered is given in Table 8-1 together with their consequent deviations in the various measurements that can be recorded. These were obtained from a simulation.



(a) With stable parameters



(b) With unstable parameters

Figure 8-1: The SDG of the CSTR example (circled variables are measured)

Table 8-1: Simulated faults and steady state deviations in the CSTR

FAULT		LC	FC	TC	FJC	FJ	C_A
(1) L-sensor-bias-high		–	–	–	+	–	+
(2) T-sensor-bias-high	stable			+	–	+	+
	unstable			–	+	–	+
(3) F-sensor-bias-low		+	–				
(4) FJ-sensor-bias-low				–		–	
(5) LV-valve-bias-high		+					
(6) FV-valve-bias-high			+				
(7) FJV-valve-bias-low					–		
(8) Low F_{1MAX}		–					
(9) Low FJ_{MAX}					–		
(10) Low F_{MAX}			–				
(11) Low F_0		+		–	+	–	–
(12) Low K_0				–	+	–	+
(13) High C_{A0}				+	–	+	+
(14) Low U_0				+	–	+	

8.1.2 SEVACS Analysis

Label the L controller as controller 1 with output x_1, F as controller 2 with output x_2 and T/FJ as a cascade controller 3 with its outer loop output $x_{1,3}$ and inner loop output $x_{2,3}$, and refer to the nomenclature in Chapter 3, then take the stable case as an example:

$$\mathbf{K_{OO}} = \begin{bmatrix} 0 & K_{FL} & 0 \\ K_{LF} & 0 & 0 \\ K_{LT} & 0 & 0 \end{bmatrix}, \ \mathbf{K_{II}} = \mathbf{K_{IO}} = \mathbf{K_{OI}} = \mathbf{0_{3x3}},$$

$$[x_1] = \frac{[\theta_{r,1}]}{\{K_{c1,1}\}} - \frac{[d_{m1,1}]}{\{K_{c1,1}\}} - \frac{[d'_{p1,1}]}{\{K_{c1,1}\}} - \frac{\{K_{FL}\}[\theta_{r,2}]}{\{K_{c1,1}\}} + \frac{\{K_{FL}\}[d_{m1,2}]}{\{K_{c1,1}\}} - \frac{[d_{v,1}]}{\{K_{v,1}\}},$$

$$[x_2] = \frac{[\theta_{r,2}]}{\{K_{c1,2}\}} - \frac{[d_{m1,2}]}{\{K_{c1,2}\}} - \frac{[d'_{p1,2}]}{\{K_{c1,2}\}} - \frac{\{K_{LF}\}[\theta_{r,1}]}{\{K_{c1,2}\}} + \frac{\{K_{LF}\}[d_{m1,1}]}{\{K_{c1,2}\}} - \frac{[d_{v,2}]}{\{K_{v,2}\}},$$

$$[x_{1,3}] = \frac{[\theta_{r,3}]}{\{K_{c1,3}\}} - \frac{[d_{m1,3}]}{\{K_{c1,3}\}} - \frac{[d'_{p1,3}]}{\{K_{c1,3}\}} - \frac{\{K_{LT}\}[\theta_{r,1}]}{\{K_{c1,3}\}} + \frac{\{K_{LT}\}[d_{m1,1}]}{\{K_{c1,3}\}} + [d_{m2,3}] \text{ and}$$

$$[x_{2,3}] = \frac{[\theta_{r,3}]}{\{K_{c1,3}\}\{K_{c2,3}\}} - \frac{[d_{m1,3}]}{\{K_{c1,3}\}\{K_{c2,3}\}} - \frac{[d'_{p1,3}]}{\{K_{c1,3}\}\{K_{c2,3}\}} - \frac{\{K_{LT}\}[\theta_{r,1}]}{\{K_{c1,3}\}\{K_{c2,3}\}} + \frac{\{K_{LT}\}[d_{m1,1}]}{\{K_{c1,3}\}\{K_{c2,3}\}} - \frac{[d'_{p2,3}]}{\{K_{c2,3}\}} - \frac{[d_{v,3}]}{\{K_{v,3}\}},$$

where $\{K_{c,1}\} = +$, $\{K_{c,2}\} = -$, $\{K_{c1,3}\} = -$, $\{K_{c2,3}\} = -$, $\{K_{FL}\} = -$, $\{K_{LF}\} = +$, $\{K_{LT}\} = +$, $\{K_{v,1}\} = -$, $\{K_{v,2}\} = -$ and $\{K_{v,3}\} = -$ so that

$$[x_1] = [\theta_{r,1}] - [d_{m1,1}] - [d'_{p1,1}] + [\theta_{r,2}] - [d_{m1,2}] + [d_{v,1}],$$

$$[x_2] = -[\theta_{r,2}] + [d_{m1,2}] + [d'_{p1,2}] + [\theta_{r,1}] - [d_{m1,1}] + [d_{v,2}],$$

$$[x_{1,3}] = -[\theta_{r,3}] + [d_{m1,3}] + [d'_{p1,3}] + [\theta_{r,1}] - [d_{m1,1}] + [d_{m2,3}] \text{ and}$$

$$[x_{2,3}] = [\theta_{r,3}] - [d_{m1,3}] - [d'_{p1,3}] - [\theta_{r,1}] + [d_{m1,1}] + [d'_{p2,3}] + [d_{v,3}].$$

From Section 3.7, to generate a set of rules first let set H_{Oj} contain those k_j controllers whose single loops interact with Controller Number j, and those k_{Oj} controllers whose outer loops interact with the Controller. Then $H_{Oj} \equiv$ {Controller $\gamma_{j,1}$, ..., Controller γ_{j,k_j}, Controller $\xi_{j,1}$, ..., Controller $\xi_{j,k_{Oj}}$}, let set H_{Ij} contain those k_{Ij} controllers whose inner loops interact with Controller j, then $H_{Ij} \equiv$ {Controller $\lambda_{j,1}$, ..., Controller $\lambda_{j,k_{Ij}}$}, and let set $H_{\phi j}$ contain those $k_{\phi j}$ instruments that interact with Controller Number j. Then those sets that contain the all the variables that are contained in each of the equations can be formed: $C_{s,j}$ for single loop controller j, $C_{c1,j}$ for the outer loop of cascade controller j, $C_{c2,j}$ for the inner loop of cascade controller j, and $C_{\phi,j}$ for Instrument Number j.

Consider first the case where no additional instrumentation is available, then H_{O1}={Controller 2, Controller 3}, H_{O2}={Controller 1}, H_{O3}={Controller 1}, $H_{I1}=H_{I2}=H_{I3}$={ }, and there are sets

$$C_{s,1} = \{\theta_{r,1}, \theta_{r,2}, d_{m1,1}, d_{m1,2}, d'_{p1,1}, d_{v,1}\},$$

$$C_{s,2} = \{\theta_{r,1}, \theta_{r,2}, d_{m1,1}, d_{m1,2}, d'_{p1,2}, d_{v,2}\},$$

$$C_{c1,3} = \{\theta_{r,1}, \theta_{r,3}, d_{m1,1}, d_{m1,3}, d'_{p1,3}, d_{m2,3}\},$$

$$\text{and } C_{c2,3} = \{\theta_{r,1}, \theta_{r,3}, d_{m1,1}, d_{m1,3}, d'_{p1,3}, d'_{p2,3}, d_{v,3}\}.$$

The next step is to identify all the controller output variables and additional measurements associated with {Controller j}$\cup H_{Oj} \cup H_{Ij} \cup H_{\phi j}$, and generate the rule set based on all possible combinations of their having deviated. To do this let $[X_i]$, $[\Phi_1]$ be the Booleans that denote $[x_i] \neq$ null, $[\phi_1] \neq$ null and so on, then there are:

Controller 1: $[X_1] \wedge [X_2] \wedge [X_{1,3}] \wedge [X_{2,3}] \rightarrow \{\theta_{r,1}, d_{m1,1}\}$ Rule 8-1.1

$[X_1] \wedge \overline{[X_2]} \wedge \overline{[X_{1,3}]} \wedge \overline{[X_{2,3}]} \rightarrow \{d_{v,1}, d'_{p1,1}\}$ Rule 8-1.2

Controller 2: $[X_1] \wedge [X_2] \rightarrow \{\theta_{r,2}, d_{m1,2}\}$ Rule 8-2.1

$$\overline{[X_1]} \wedge [X_2] \rightarrow \{d_{v,2}, d'_{p1,2}\} \qquad \text{Rule 8-2.2}$$

Controller 3:

$$\overline{[X_1]} \wedge \overline{[X_{1,3}]} \wedge [X_{2,3}] \rightarrow \{d_{v,3}, d'_{p2,3}\} \qquad \text{Rule 8-3.1}$$

$$\overline{[X_1]} \wedge [X_{1,3}] \wedge [X_{2,3}] \rightarrow \{\theta_{r,3}, d_{m1,3}, d'_{p1,3}\} \qquad \text{Rule 8-3.2}$$

$$\overline{[X_1]} \wedge [X_{1,3}] \wedge \overline{[X_{2,3}]} \rightarrow \{d_{m2,3}\}. \qquad \text{Rule 8-3.3}$$

In this particular case, the consequences are identical to those that would be generated if the loops were non-interacting; exchanging knowledge about controller outputs has failed to separate the various possibilities any further. Greater separation can only be obtained by either representing correlated disturbances and/or making use of additional measurements and/or making use of sign information. An example of the first possibility involves elaborating on $d_{p,1}$ and $d_{p1,3}$ by replacing these elements by their components, i.e. $\{F_0,\ F_{1MAX}\}$ for $d_{p,1}$ and $\{C_A, K, F_0, T_0', U_0, T_0\}$ for $d_{p1,3}$. Then Rule 8-1.2 can be re-written as

$$[X_1] \wedge \overline{[X_2]} \wedge \overline{[X_{1,3}]} \wedge \overline{[X_{2,3}]} \rightarrow \{d_{v,1}, d'_{p,1}\} \rightarrow \{d_{v,1}, F_0, F_{1MAX}\} \qquad \text{Rule 8-1.2a}$$

and the following extra Rules can be added:

Controller 1: $[X_1] \wedge \overline{[X_2]} \wedge [X_{1,3}] \wedge [X_{2,3}] \rightarrow \{F_0\}$, Rule 8-1.3

Controller 3: $[X_1] \wedge [X_{1,3}] \wedge [X_{2,3}] \rightarrow \{F_0\}$. Rule 8-3.4

That is, it is possible to isolate F_0. Turning to the possibility of incorporating additional measurements, if a measurement of concentration C_A is now made available then knowledge of its relationships with other variables can be exploited to separate the possible options further. For instance the following relationship can be obtained from the SDG in Figure 8-1:

$$[C_A] = \{K_{LCA}\}[\theta_{,1}] + [F_0] + [C_{A0}] - [K]$$

$$= -[\theta_{r,1}] + [d_{m,1}] + [F_0] + [C_{A0}] - [K_0] - [\theta_{1,3}]$$

where $[\theta_{1,3}] = [\theta_{r,3}] - [d_{m1,3}]$.

Then let $[\phi_1]=[C_A]$, $H_{\phi,1}=\{C_A\}$, $H_{\phi,2}=\{\}$, $H_{\phi,3}=\{C_A\}$, and $C_{\phi,1} = \{\theta_{r,1}, \theta_{r,3}, d_{m,1}, d_{m1,3}, F_0, C_{A0}, K_0\}$; replace C_A by all elements of $C_{\phi,1}$ in the subset for $d_{p1,3}$, similarly replace K by $\{K_0, \theta_{r,3}, d_{m1,3}\}$. Rules 8-1.2a, 8-1.3 and 8-3.4 above can now be revised to separate F_0 from F_{1MAX}:

Controller 1: $[X_1] \wedge \overline{[X_2]} \wedge [X_{1,3}] \wedge [X_{2,3}] \wedge [\Phi_1] \rightarrow \{F_0\}$ Rule 8-1.3a

$$[X_1] \wedge \overline{[X_2]} \wedge \overline{[X_{1,3}]} \wedge \overline{[X_{2,3}]} \wedge \overline{[\Phi_1]} \rightarrow \{d_{v,1}, F_{1MAX}\} \quad \text{Rule 8-1.2b}$$

Controller 3: $$[X_1] \wedge [X_{1,3}] \wedge [X_{2,3}] \wedge [\Phi_1] \rightarrow \{F_0\} \quad \text{Rule 8-3.4a}$$

and parameter K_0 can be separated by splitting Rule 8-3.2 above as

Controller 3: $$\overline{[X_1]} \wedge [X_{1,3}] \wedge [X_{2,3}] \wedge \overline{[\Phi_1]} \rightarrow \{T_0, U_0, TJ_0\} \quad \text{Rule 8-3.2a}$$

$$\overline{[X_1]} \wedge [X_{1,3}] \wedge [X_{2,3}] \wedge [\Phi_1] \rightarrow \{C_{A0}, K_0, \theta_{r,3}, d_{m1,3}\} \quad \text{Rule 8-3.2b}$$

Rules 8-1.1, 8-2.1, 8-2.2, 8-3.1 & 8-3.3 still apply but do not involve C_A. As in Section 3.7, sign information can also be incorporated, for instance faults in $d_{m1,3}$ (i.e. temperature sensor, T) can be separated from faults in $d_{p1,3}$ (e.g. K_0). Finally an example of the method's ability to diagnose multiple faults can be observed by considering the simultaneous occurrence of faults in FJ_{MAX} and F_{MAX}. Although the condition $C_{s,2} \cap C_{e2,3} = \varnothing$ (see Section 3.7) doesn't hold, in this case it is possible to diagnose both faults separately because $F_{MAX} \in d_{p1,2}$, $FJ_{MAX} \in d_{p2,3}$, $d'_{p1,2} \in C_{s,2}$ only and $d'_{p2,3} \in C_{e2,3}$ only.

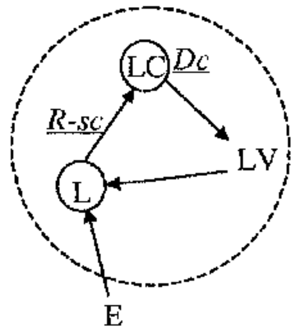
It has been pointed out in Section 3.9 that it is doubtful that the above set operation approach would scale to most large processes. The procedures proposed in Chapter 5 are thought to be more practicable and are applied in the next section.

8.1.3 Fault Isolation Examples

To save space, a detailed description of the isolation process for Fault 1 will be described, less will be given for the other 13 faults. Only single faults will be discussed.

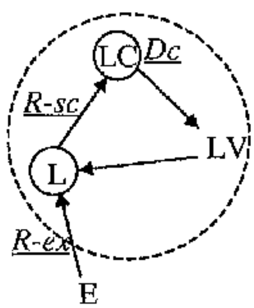
Fault 1: L-sensor-bias-high. If L sensor biases, then in the steady state all control systems will deviate (Table 8-1). If the general procedure of Section 5.1 is applied then the following would take place.

1. The reasoning process can start from any deviated controller node.
2. Start, say, at the level controller LC: by assessing Table 4-1 and tables in Figure 8-2, Figure 8-3 and Figure 8-4, which have been adapted from Figure 4-4, Figure 4-6 and Figure 4-7 accordingly, the search process would produce the following possibilities: {L-sensor-bias-high, LV-valve-bias-low, high-F_0, low-F_{1MAX}, F-sensor-bias-high/low-F}.



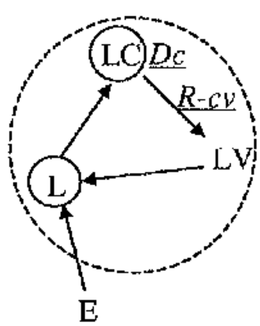
Dc	*R-sc*	L-sensor
+	+	fails-high
-	-	fails-high
+	-	fails-low
-	+	fails-low

Figure 8-2: The effect of L-sensor-bias in the level control system and the fault-decision table



Dc	*R-sc*	*R-ex*	E
+	+	+	fails-high
+	-	-	fails-high
-	+	-	fails-high
-	-	+	fails-high
+	+	-	fails-low
+	-	+	fails-low
-	+	+	fails-low
-	-	-	fails-low

Figure 8-3: The effect of an exogenous/ancestor fault or disturbance to the level control system and the fault-decision table



Dc	*R-cv*	LV
-	+	fails-high
+	-	fails-high
+	+	fails-low
-	-	fails-low

Figure 8-4: The effect of the valve bias in the level control system and the fault-decision table

3. Refer to the fault isolation principle in Section 5.1, in the steady state, a valve bias and process disturbances wouldn't cause the corresponding controlled variable to deviate and thus wouldn't affect descendants of that controlled variable; a sensor bias would cause the controlled variable to deviate and its

descendants would be affected. Therefore the test process would eliminate the LV-valve-bias-low, high-F_0 and low-F_{1MAX} because the descendants of L (T and F) have been affected. This leaves L-sensor-bias-high and F-sensor-bias-high.

4. Further examine the flow rate controller FC in the test process, F-sensor-bias-high would be eliminated because only L-sensor-bias-high/low-L would cause FC to deviate negatively (refer to tables in Figure 8-2 and Figure 8-3). Thus the root fault L-sensor-bias would be located.

If the procedure is started from the deviated temperature controller TC, then initially T-sensor-bias as well as process disturbances including changes in C_A, F_0, L, K, T_0, U_0 and TJ_0 would form a fault candidate set (see Section 4.4) in the search process. In the test process, the fault candidate set would shrink to be {L-sensor-bias-high, high-F_0} and other elements would be rejected because LC deviates. High-F_0 would be further rejected in the test process because the flow rate control system has been affected. Thus the root fault L-sensor-bias would be also located.

As has been said in Section 5.1, the above procedures are somewhat cumbersome. Note that both the level and the flow rate control systems have single loops and the interaction between L and F is of Type A. This means that either the improvements of Section 5.2 or of Section 5.3 could be applied.

If Section 5.2 is applied (and in particular Section 5.2.2.1) and it is started from the level (L) controller LC, then initially the fault candidate set is {L-sensor-bias-high, F-sensor-bias-high} because both controllers deviate and there is no common ancestor for L and F. In addition the effects between L and F are opposite (Table 5-1), so it would be possible to reject F-sensor-bias-high and only leave L-sensor-bias-high, which can be further tested by forward reasoning about the temperature cascade control system.

If Section 5.2 is applied instead (and in particular Section 5.3.1), the fault isolation procedure can be improved by constructing the modified Type A interaction shown in Figure 8-5. Here L-sensor-bias and F-sensor-bias can both be viewed as process disturbances to L and F. The LC deviation (–) implies that the fault candidate set could be {L-sensor-bias-high, F-sensor-bias-high}, after using the test strategy, F-sensor-bias-high can be rejected because the FC deviation (-) implies that the fault candidate set could be {L-sensor-bias-high, F-sensor-bias-low}. Therefore L-sensor-bias-high is the only possible fault.

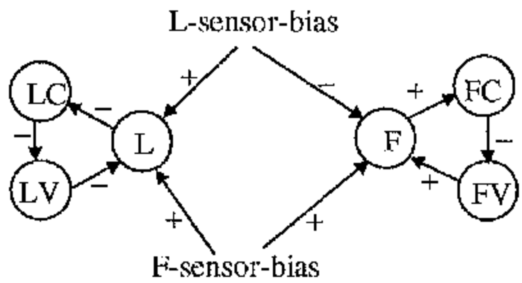


Figure 8-5: Type A modified SDG for L & F interaction

Fault 2: T-sensor-bias-high. If T sensor biases, then in the steady state both the outer loop and the inner loop controllers of the temperature cascade control system will deviate. However neither the level control system nor the flow rate control system will be affected although concentration C_A will also deviate. It is worth noting that, if the temperature is open loop unstable, then the controller deviations will be opposite to those of the stable case.

Starting from deviated TC, in the search process, initially the fault candidate set would be {high-C_{A0}, low-K_0, low-F_0, T-sensor-bias-high, high-T_0, low-U_0, high-TJ_0} (Section 4.4.1). Then in the test process, high-T_0, low-U_0 and high-TJ_0 can be removed from the fault candidate set because C_A deviates and these variables cannot cause C_A to deviate according to the fault isolation principle in Section 5.1. Low-F_0 can also be removed from the candidate set by noting that LC controller doesn't deviate. High-C_{A0}, low-K_0 or T-sensor-bias-high can all cause C_A to deviate high. Low-K_0 and T-sensor-bias-high are not distinguishable from the SDG. High-C_{A0} can only be eliminated if it meets the latter condition of the following:

- if the temperature process is open loop stable or has an even number of open loop unstable poles, then a high C_{A0} will cause the same deviations as T-sensor-bias-high so a C_{A0} fault can not be separated and eliminated;
- if the temperature process includes an odd number of open loop unstable poles, the deviations caused by high C_{A0} contradict with the deviations caused by T-sensor-bias-high so C_{A0} can be separated and eliminated.

Fault 3: F-sensor-bias-low. Similar to the L-sensor-bias-high, this can cause both the level and the flow rate control systems to deviate. The interaction between these two control systems is of Type A (Section 5.2.2.1), they have opposite effects so that L-sensor-bias-high would be diagnosed either from Table 5-1 or by applying the general fault isolation procedure (Section 5.1 or Section 5.3.1).

Fault 4: FJ-sensor-bias-low. FJ sensor is located in the inner loop of the temperature cascade control system. Refer to Table 4-2 and Figure 4-5, if only the outer loop controller deviates, inner loop sensor bias is the fault and the sensor bias has the same direction as the deviation of that sensor measurement.

Fault 5: LV-valve-bias-high. A valve bias only causes its own control system to deviate. Refer to Table 4-1, Figure 8-2 and Figure 8-4, and according to the fault isolation principle, the fault candidate here is {LV-valve-bias-high, low-F_{1MAX}}.

Fault 6: FV-valve-bias-high. Similar to Fault 5; the fault candidate is {FV-valve-bias-high, high-F_{MAX}}.

Fault 7: FJV-valve-bias-low. FJV valve is located in the inner loop of the temperature cascade control system. According to Table 4-2, if only the inner loop controller deviates then the fault relates to the inner loop. Refer to Figure 4-6 and Figure 4-7, the fault candidate set is {FJV-valve-bias-low, low-FJ_{MAX}}.

Faults 8 to 10: low-F_{1MAX}, low-FJ_{MAX}, low-F_{MAX}. These three faults cannot be separated from their related valve biases as Faults 5 — Faults 7.

Fault 11: low-F0. If F_0 is low, both the level and the temperature control systems deviate. Flow rate F_0 can be isolated in the test process because the flow rate control system doesn't deviate and F_0 is the only common ancestor of the level and temperature control systems. The direction of F_0 can be determined from either the deviation in the level or in the temperature controller outputs.

Fault 12: low-K_0. Both the outer and the inner loop controllers of the temperature control system will deviate, as will C_A. In the search process, based on Table 4-2, the fault candidate set would be {low-C_A, low-K, high-F_0, T-sensor-bias-low, low-T_0, high-U_0, low-TJ_0}({low-C_A, low-K, high-F_0, T-sensor-bias-high, low-T_0, high-U_0, low-TJ_0} for the unstable process). In the test process, low-C_A contradicts with the observed C_A that deviates positively and low-C_A would be eliminated. The positive deviation of C_A also eliminates faults in T_0, U_0, TJ_0 because, these are not the direct ancestors of C_A, they just affect C_A via the controlled variable T. High-F_0

can be eliminated as well because it is the ancestor of L and LC doesn't deviate. Further separation depends on the stability of the open loop process:

- if the temperature process is open loop stable or has an even number of open loop unstable poles, T-sensor-bias-low would be eliminated because it should cause C_A to deviate negatively, which contradicts with the observed C_A. And low-K_0 would be diagnosed because low-K has already been located.
- if the temperature process has an odd number of open loop unstable poles, now the fault candidate is {low-K, T-sensor-bias-high} and then it should be {low-K_0, T-sensor-bias-high}.

Fault 13: high-C_{A0}. Concentration C_A will be high and both the outer and the inner loop controllers of the temperature control system will deviate. In the search process, based on Table 4-2, the fault candidate set would be {high-C_{A0}, high-K, low-F_0, T-sensor-bias-high, high-T_0, low-U_0, high-TJ_0}({high-C_{A0}, high-K, low-F_0, T-sensor-bias-low, high-T_0, low-U_0, high-TJ_0} for the unstable process). In the test process, high-K would cause C_A to deviate negatively, which contradicts with the observed C_A that deviates positively and high-K would be eliminated. The positive deviation of C_A also eliminates faults in T_0, U_0, TJ_0 because, these are not the direct ancestors of C_A, they just affect C_A via the controlled variable T. low-F_0 can be eliminated as well because it is the ancestor of L and LC doesn't deviate. Further separation depends on the stability of the open loop process:

- if the temperature process is open loop stable or has an even number of open loop unstable poles, high-C_{A0} and T-sensor-bias-high cannot be separated;
- if the temperature process has an odd number of open loop unstable poles, T-sensor-bias-low would be eliminated because it should cause C_A to deviate negatively, which contradicts with the observed C_A. And high-C_{A0} would be located.

Fault 14: low-U_0. Both controllers in the temperature cascade control system deviate. In the search process, the fault candidate is {high-T_0, low-U_0, high-TJ_0, low-F_0, high-K, L-sensor-bias-low, T-sensor-bias-high}({high-T_0, low-U_0, high-TJ_0, low-F_0, high-K, L-sensor-bias-low, T-sensor-bias-low} for the unstable process). However, in the test process, C_A, the descendant of F_0, T and K_0, doesn't deviate, enabling low-F_0, high-K and T-sensor-bias-high (T-sensor-bias-low for the unstable process) to be removed from the fault candidate. The L-sensor-bias-low can also be removed because the level control system doesn't deviate. High-T_0, low-U_0 and high-TJ_0 cannot be separated further.

8.2 Application to The Tennessee Eastman Process Benchmark

Besides being of larger scale, and highly interactive, the main difference between this and the previous CSTR application is that a list of faults/disturbances actually come with the benchmark. A wide range of scenarios are hypothesised and only a number of these would be diagnosed by the new approaches described here. Thus it provides an opportunity to show how the new approaches would form part of a hybrid strategy. Another difference is that it would be extremely difficult to form a complete, detailed SDG representation of the plant and hence is an ideal candidate for the methods proposed here.

8.2.1 Process Description

The Tennessee Eastman (T-E) process benchmark is a simulation of a real plant that has been disguised for proprietary reasons, the flow diagram and its basic control scheme is shown in Figure 8-6. The process produces two products, G and H, from four reactants, A, C, D and E. Also present are an inert B and a by-product F. The process has five major units: a reactor, a product condenser, a vapour/liquid separator, a recycle compressor and a product stripper. The gaseous reactants are fed to the reactor where they react to form liquid products. The gas phase reactions are catalysed by a non-volatile catalyst dissolved in the liquid phase. The products leave the reactor as vapours along with unreacted feeds and the catalyst remains in the reactor. The process has 41 measurements and 12 manipulated variables. A plant-wide decentralised control scheme has been developed by McAvoy *et al.* It is based on multiple single-input-single-output (SISO) control loops. Many of them are standard cascade control systems. Further details of the process and its control systems can be found in (Downs & Vogel, 1993; McAvoy & Ye, 1994; McAvoy *et al.*, 1995; Howell *et al.*, 1997).

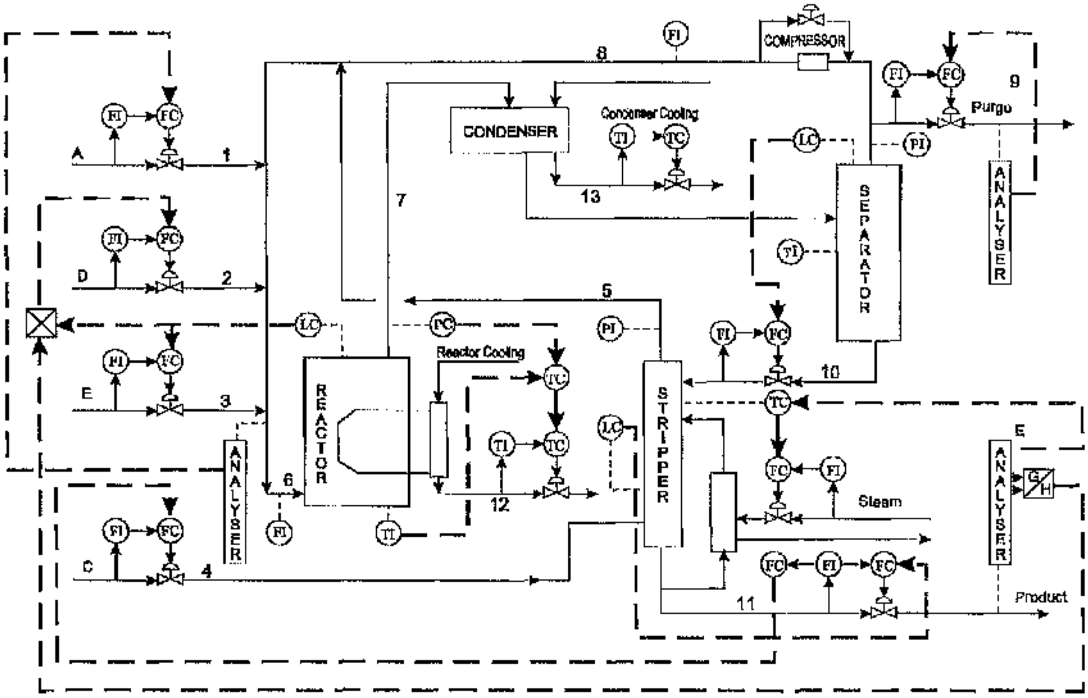


Figure 8-6: The flow diagram and basic control of the T-E process benchmark

8.2.2 The SEVACS Nodes

There are 9 distributed SEVACS as shown in Table 8-2.

Table 8-2: The nine SEVACS

Tag	SEVACS
SV1	A/C composition — A flow rate cascade control system
SV2	G/H composition — reactor level — D,E flow rate control system
SV3	Reactor pressure — temperature cascade control system
SV4	Condenser cooling control system
SV5	Purge composition B — purge flow rate cascade control system
SV6	Separator level — underflow rate cascade control system
SV7	Stripper level — product flow rate cascade control system
SV8	Product flow rate — C flow rate cascade control system
SV9	Product composition E — stripper temperature cascade control system

It can be seen that SV4 is a single loop control system, SV1, SV5, SV6, SV7 and SV8 are standard cascade control systems, SV3 and SV9 are cascade control systems with two inner loops, and SV2 is a much more complicated control system.

All three level processes are open loop capacitive.

8.2.3 Faults/Disturbances

Table 8-3 shows the 28 faults or disturbances hypothesised, IDV(1) — IDV(20) are from the original benchmark, F(1) — F(8) are new.

Table 8-3: Disturbances or faults injected into the plant

Tag	Process variable	Type
IDV(1)	A/C feed ratio, B compositon constant (stream 4)	Step
IDV(2)	B composition, A/C constant (stream 4)	Step
IDV(3)	D feed temperature (stream 2)	Step
IDV(4)	Reactor cooling water inlet temperature	Step
IDV(5)	Condenser cooling water temperature	Step
IDV(6)	Partial A feed loss (stream 1)	Step
IDV(7)	C header pressure loss — reduced availability (stream 4)	Step
IDV(8)	A, B, C feed composition (stream 4)	Random variation
IDV(9)	D feed temperature (stream 2)	Random variation
IDV(10)	C feed temperature (stream 4)	Random variation
IDV(11)	Reactor cooling water inlet temperature	Random variation
IDV(12)	Condenser cooling water inlet temperature	Random variation
IDV(13)	Reaction kinetics	Slow drift
IDV(14)	Reactor cooling water valve	Sticking
IDV(15)	Condenser cooling water valve	Sticking
IDV(16)	Unknown	Unknown
IDV(17)	Unknown	Unknown
IDV(18)	Unknown	Unknown
IDV(19)	Unknown	Unknown
IDV(20)	Unknown	Unknown
F(1)	Purge composition B measurement (stream 9)	Bias-low
F(2)	Reactor pressure measurement	Bias-high
F(3)	Reactor level measurement	Bias-low
F(4)	A/C composition ratio (stream 6)	Bias-low
F(5)	Product flow rate measurement	Bias-low
F(6)	D flow rate measurement (stream 2)	Bias-high
F(7)	E flow rate measurement (stream 3)	Bias-high
F(8)	G/H composition ratio measurement (stream 11)	Bias-low

Note that IDV(8) — IDV(12) are intended to assess control system performance and hence, are of no interest here. Similarly IDV(16) — IDV(20) have also been ignored because it is not known whether they are intended for performance assessment or for fault detection and diagnosis studies.

Some of the graphs obtained by running the benchmark simulation when subjected to the various faults/disturbances are given in Appendix 4. Some examples for steady state identification and change detection are shown in Appendix 5. Note that in certain circumstances, not all variables achieve a steady state and hence the steady state detector described in Chapter 7 would remain in its '*not-at-a-steady-state*' mode. However, as can be seen from the graphs, these variables have deviated in one direction and are merely taking a long time to reach a new steady state. Thus as far as SEVACS are concerned they can be viewed as having deviated and the problem is therefore with steady state detection rather than with the SEVACS approach in general. This will be discussed in the section on future work in Chapter 9.

8.2.4 The Hybrid Strategy

The hybrid strategy adopted to detect and isolate the above faults is described in this sub-section.

8.2.4.1 Basic Heuristic Rules

Being based on observed changes in steady state, the SEVACS approach is not suited to diagnosing faults like a dead sensor, or a large exogenous fault (or disturbance), or a sticking valve, which cause the plant to 'run-away'. Such faults can be isolated by the application of appropriate simple heuristic rules. This technique has been widely adopted by many expert system based process monitoring and fault diagnosis systems and has proven to be efficient.

The T-E process benchmark is particularly amenable to a heuristic approach because of the relatively high density of instrumentation installed (Howell *et al.*, 1997). However there is a fundamental problem when producing heuristics to detect faults in a benchmark: there is a temptation to examine benchmark results with a view to generating heuristics; clearly these will then fire on the same benchmark but that is no guarantee that they would do so on the real plant. Typical rules are like, in G2 format:

FOR any flow-sensor LS
IF the sensor-reading of LS during the last 5 minutes has no value
THEN conclude that the status of LS is FAILED

FOR any flow-sensor LS
IF the maximum value of the sensor-reading of LS during the last 5 minutes = the minimum value of the sensor-reading of LS during the last 5 minutes
THEN conclude that the status of LS is DEAD

IF the valve-position of any control-valve CV = 100
THEN conclude that the status of CV is SATURATED

Other rules can relate to the performance of individual control loops: a change in the controller's output should result in a change in the sensor-reading and also in the measurement of valve opening (if available). It is relatively easy to detect faults such as frozen/failed sensors and locked/stuck valves, e.g., IDV(14) and IDV(15), by means of the simple heuristic rule:

1. examine the maximum and the minimum output of the controller during the last few minutes; if the difference between them is large enough, then perform next step;
2. examine the maximum and minimum measurement of the sensor during the last few minutes; if the difference between them is too small, then conclude that there might be something wrong with either the sensor or the valve: if the maximum is close to zero, it is most likely that the sensor failed, otherwise either the sensor froze or the valve locked/stuck.

Much extremely useful insight into the interactions and relationships in a process is confined to reports in the drawers of engineers and scientists or gathers dust in the archives (Mjaavatten, 1994). Much of this knowledge could be used to formulate effective heuristics.

8.2.4.2 Heuristic Rules to Identify Faults Through Global Changes

Some faults or disturbances can cause global changes in a plant. It is a good strategy to identify these before applying the distributed SEVACS approach because it can take less time to locate them and this will lead to less ambiguous diagnostic results.

Global changes are always caused by those faults or disturbances that can affect the entire process, i.e. from beginning to end. This need not be the actual beginning of the plant but can be a complete section where its input and output variables have changed. Expert knowledge and heuristic rules can be applied to identify these situations.

For example, the change in the throughput of the T-E process or F(5) causes global changes, all the flow rates of the reactants A, C, D and E will be affected and so will most of the variables in the process. If a global change strategy is applied, the fault can be located correctly in time.

8.2.4.3 SEVACS

The SEVACS approach is used wherever possible. Note that the T-E benchmark contains control schemes not met previously in this thesis and these will be discussed in detail in sub-section 8.2.6.

8.2.4.4 Governing Equations

For industrial processes, the governing equation based method (Kramer, 1987a) is often used to do fault detection or gross error identification and data reconciliation. The principle is to make use of a set of mathematical equations, normally these equations hold, they could be violated if a fault or disturbance happens. For instance, for a flow system in Figure 8-7, the sum of the outputs of the system should be equal to those of the inputs of the system in steady state, normally $\sum F_{Ii} = \sum F_{Oj}$ holds, otherwise something is wrong, e.g, a leak happens.

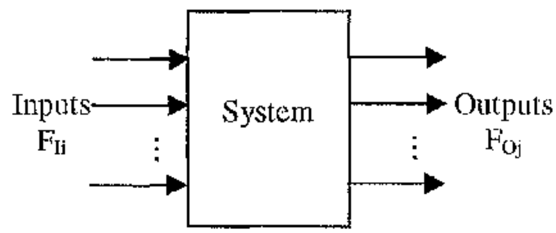


Figure 8-7: Governing equation between system inputs and outputs

For every measurement, we assume that

true value (F) + sensor bias (B) = sensor reading (R)

Reconsidering the governing equation, we have

$$\sum_{i=1}^{I}(R_{Ii} - B_{Ii}) = \text{Leak} + \sum_{j=1}^{J}(R_{Oj} - B_{Oj})$$

or

$$E = \sum_{i=1}^{I} R_{Ii} - \sum_{j=1}^{J} R_{Oj} = \text{Leak} + \sum_{i=1}^{I} B_{Ii} - \sum_{j=1}^{J} B_{Oj},$$

where

R_{Ii} is the sensor reading of the ith input,

B_{Ii} is the sensor bias of the ith input,

R_{Oj} is the sensor reading of the jth output,

B_{Oj} is the sensor bias of the jth output,

Leak is any 'loss' from the system: Leak≥ 0

and

E is the difference between the sum of sensor readings of the inputs and outputs.

Suppose there is one fault at a time, if $E = 0$, there is no fault; if $E < 0$, there is no Leak, the fault can be one of sensor biases of the inputs and the outputs, i.e., $\{ B_{I1}, \ldots, B_{Ii}, \ldots, B_{II}, B_{O1}, \ldots, B_{Oj}, \ldots, B_{OJ} \}$ would be the fault candidate set; if $E > 0$, the fault can be Leak or one of sensor biases of the inputs and the outputs, i.e., $\{\text{Leak}, B_{I1}, \ldots, B_{Ii}, \ldots, B_{II}, B_{O1}, \ldots, B_{Oj}, \ldots, B_{OJ} \}$ would be the fault candidate set.

Take an example, let $F1-F2=0$ represent the mass balance of a process unit, $F1$ is the sensor reading of its inflow mass and $F2$ is the sensor reading of its outflow mass. If the left-hand side of this expression is significantly less than zero, then the inference (*F1-SENSOR-BIAS-LOW*) $\vee$ (*F2-SENSOR-BIAS-HIGH*) can be established; if the expression is significantly greater than zero, then the inference (*F1-SENSOR-BIAS-HIGH*) $\vee$ (*F2-SENSOR-BIAS-LOW*) $\vee$ (*SYSTEM-LEAK*) can be established. Importantly, these conditions are the only explanations for violation of the constraint (assuming no leaks into the system). Logical combination of the inference drawn from the full set of process constraints yields the pertinent diagnosis.

For the T-E process benchmark, if the material accumulations in the vessels are ignored, then the following mass balance equations can be obtained (it is assumed there are additional measurements for Stream 5 and Stream 7):

$$Stream1 + Stream2 + Stream3 + Stream5 + Stream8 - Stream6 = 0 \tag{8-1}$$

$$Stream6 - Stream8 - Stream9 - Stream10 = 0 \tag{8-2}$$

$$Stream4 + Stream10 - Stream5 - Stream11 = 0 \tag{8-3}$$

$$Stream1 + Stream2 + Stream3 + Stream4 - Stream9 - Stream11 = 0 \tag{8-4}$$

$$Stream6 - Stream7 = 0 \tag{8-5}$$

Values, averaged over the relatively short period time, say 5 minutes, are used to overcome random deviations, disturbances and uncertainties in the process. In addition, the benchmark's 'chemical' units of flow rate (kscmh and m^3/h) are changed to kg/h to perform mass balances.

Any of the constraints is then deemed to be in conflict if it is in error by more than 5% of the total mass either into or out of the node (e.g. Stream6 in Equations (8-1) & (8-2)). The percentage can be chosen by trial and error. When conflict arises, various logical statements can be formulated based on the various balances; for instance, suppose that the second governing equation has a discrepancy less than its lower limit of tolerance, then the statement can be established: (*Stream6-BIAS-LOW*) $\vee$ (*Stream8-BIAS-HIGH*) $\vee$ (*Stream9-BIAS-HIGH*) $\vee$ (*Stream10-BIAS-HIGH*), i.e., [U_1 U_1 U_1 U_1 U_1 L_1 U_1 H_1 H_1 H_1 U_1 N_1 N_1 N_1 N_1 U1] where each element denotes a different stream from Stream 1 to Stream 11 and five respective system leaks; N denotes normality, H denotes high, L denotes low and U denotes undetermined; the subscript denotes likeliness of the fault, the bigger the number, the more likely the fault. These statements can then be combined by applying the operator defined in Table 8-4 where R is the ambiguous result of L^H.

Table 8-4: Combining

^	L_i	N_i	H_i	R_i	U_i
L_i	L_{i+1}	N_i	R_i	R_i	L_i
N_i	N_i	N_i	N_i	N_i	N_i
H_i	R_i	N_i	H_{i+1}	R_i	H_i
R_i	R_i	N_i	R_i	R_i	R_i
U_i	L_i	N_i	H_i	R_i	U_i

For example, suppose that, on one occasion, the governing equation (8-2) has a discrepancy less than its lower limit of tolerance whilst the governing equation (8-3) has a discrepancy greater than the upper limit of tolerance whilst the other equations are within the limits of their tolerances. Five governing vectors v1, v2, ..., and v5 can be inferred from the hypothesis:

$$v1=[N_1\ N_1\ N_1\ U_1\ N_1\ N_1\ U_1\ N_1\ U_1\ U_1\ U_1\ U_1\ U_1\ U_1\ U_1\ U_1],$$

$$v2=[U_1\ U_1\ U_1\ U_1\ U_1\ L_1\ U_1\ H_1\ H_1\ H_1\ U_1\ N_1\ N_1\ N_1\ N_1\ U_1],$$

$$v3=[U_1\ U_1\ U_1\ H_1\ L_1\ U_1\ U_1\ U_1\ U_1\ H_1\ L_1\ U_1\ U_1\ U_1\ U_1\ H_1],$$

$$v4=[N_1\ N_1\ N_1\ N_1\ U_1\ U_1\ U_1\ U_1\ N_1\ U_1\ N_1\ N_1\ N_1\ N_1\ N_1\ N_1],$$

and

$$v5=[U_1\ U_1\ U_1\ U_1\ U_1\ N_1\ N_1\ U_1\ U_1\ U_1\ U_1\ N_1\ U_1\ U_1\ U_1\ U_1].$$

Thus,

$$v1\wedge v2\wedge v3\wedge v4\wedge v5=[N_1\ N_1\ N_1\ N_1\ N_1\ N_1\ N_1\ N_1\ N_1\ H_2\ N_1\ N_1\ N_1\ N_1\ N_1\ N_1]$$

can be obtained, the 10th element of the vector is H_2 and it indicates that the sensor value of stream 10 is most likely to have failed high.

In Table 8-3, faults F(5) — F(7) would violate the governing equations and hence could be detected using this approach. This can be achieved by combining the governing equations with SEVACS and this approach is discussed in the next sub-section.

8.2.4.5 Combining Governing Equations with SEVACS

The approach is first to generate a set of fault candidates by analysing the appropriate governing equations. Various possibilities are then eliminated by referring to SEVACS knowledge.

For example, if fault F(5) happened, then the governing equations (8-3) and (8-4) would be violated whilst the others would not. Thus according to the logical operation, C-flow-rate-sensor-bias-high (stream 4), product-flow-rate-sensor-bias-low (stream 11) and the system leak would form a fault candidate set. Because C flow rate sensor is in the inner loop of a cascade system and referring to SEVACS knowledge in Table 4-2, this sensor bias shouldn't cause the inner loop controller to deviate and thus this sensor bias would be rejected.

If fault F(6) happened, the governing equations (8-1) and (8-4) would be violated whilst the others would not. Then A-flow-rate-sensor-bias-high (stream 1), D-flow-rate-sensor-bias-high (stream 2), E-flow-rate-sensor-bias-high (stream 3) and the system leak would form a fault candidate set. These three flow rate sensors are all in inner loops, referring to Table 4-2, any inner loop sensor bias would cause the respective outer loop controller to deviate, thus both A-flow-rate-sensor-bias-high (stream 1) and E-flow-rate-sensor-bias-high (stream 3) would be rejected.

Fault F(7) is very similar to the fault F(6) and would be diagnosed similarly.

8.2.5 Identification of Process Type Numbers And Control System Interactions

This sub-section focuses on the preliminary work that must be carried out to apply the SEVACS approach to the T-E benchmark. A more formal approach is needed because of the increased complexity compared with, e.g., the CSTR example. Clearly the first step is to identify the various SEVACS, their process Type numbers, and their interactions. It is then sensible to construct a simple SDG to describe these interactions.

Another complication is that control systems other than with single and double loop are used and this is addressed first before going any further. SEVACS SV3 and SV9 can be viewed as normal cascade control systems if the most inner loop is viewed as a virtual valve node (see Section 5.2.2). Node SV2 can be viewed similarly.

8.2.5.1 Identification of Process Type Numbers

Process types and interactions can be identified by doing step tests on the process control systems' set-points one by one. As a result of doing these tests, it was found that the three level processes are capacitive (Type 1 processes) because their related controller outputs don't change or deviate in steady state when their set-points' are step changed. All the other SEVACS related processes are open-loop stable or have an even number of unstable poles ($A_0>0$).

8.2.5.2 Identification of SEVACS Interactions

This is carried out in two parts, first the fact that two SEVACS interact is sought, secondly the type of interaction is established. Section 8.2.5.2 describes the first, Section 8.2.5.3 the second. If a set-point change in a SEVACS results in any steady state change of an element in another SEVACS, then the latter SEVACS is affected by the former. If each SEVACS is viewed as a super-node (see Section 4.3), a branch or a link from the former super-node to the latter one can be assigned. A simple SDG representing process interactions can then be constructed by repeating this operation for all SEVACS. Figure 8-8 shows that derived for the T-E benchmark.

For example, the positive change of A/C composition set-point in the A-feed flow results in steady state changes in the outputs of the reactor pressure controller (–), the product flow rate controller (–), the condenser cooling controller (+), the purge flow rate controller(−) and the stripper temperature controller (+); it indicates that the super-node SV1 affects the super-nodes SV3, SV8, SV4, SV5 and SV9. Branches from SV1 to those nodes can be assigned (Figure 8-8).

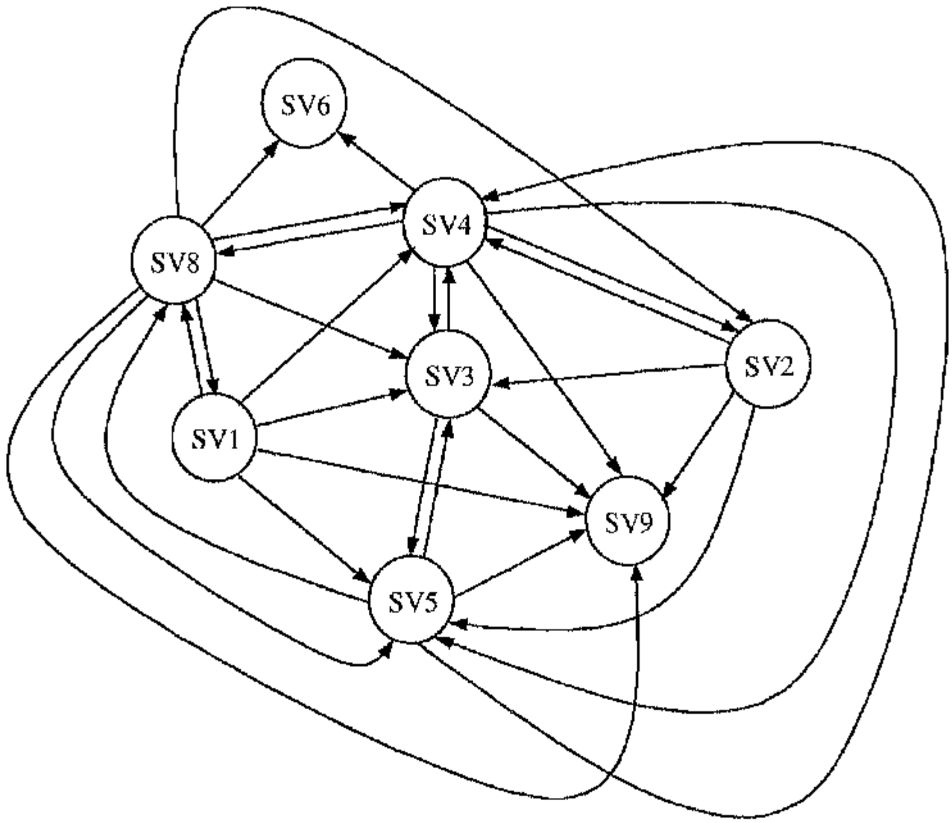


Figure 8-8: T-E process interactions

8.2.5.3 Describing The Process Interactions

As discussed previously, process interactions have causal signs and can affect control systems in different ways. In addition it is sometimes sensible to describe interactions in a different way so that the right faults can be accommodated. This is particularly important here because of the prevalence of cascade control systems. For cascade control systems, and as discussed in Section 6.2.3, interactions can be treated as always stemming from the inner loop. Thus for example, there is a cascade arrangement in SV1 (see Figure 8-6), so the effects given in the previous sub-section can be treated as stemming from the inner loop set-point F_A (Figure 8-9).

Having identified the causal element of SV1, those elements directly affected are now identified. For instance, the outermost/main controller node (PC_R) in SV3 has deviated, so F_A can be viewed as an exogenous disturbance to the controlled node, reactor pressure P_R (Figure 8-9). It is also possible that F_A is an exogenous disturbance to the two inner loops in SV3, but these effects can be ignored because if F_A is the true fault, it can still be inferred from the change of the outermost controller output (Section 6.2.4). Directions can now be inferred. For instance, F_A has a negative impact on P_R because the positive change of F_A causes a negative change of output of the reactor pressure controller and because of the negative proportional gain of this controller. For the same reason, F_A has a positive impact on the product flow rate Fo in SV8, a positive impact on the condenser cooling temperature T_{CCW} in SV4, a positive impact on the purge flow rate F_{PRG} in SV5 and a negative impact on the stripper temperature T_{STR} in SV9.

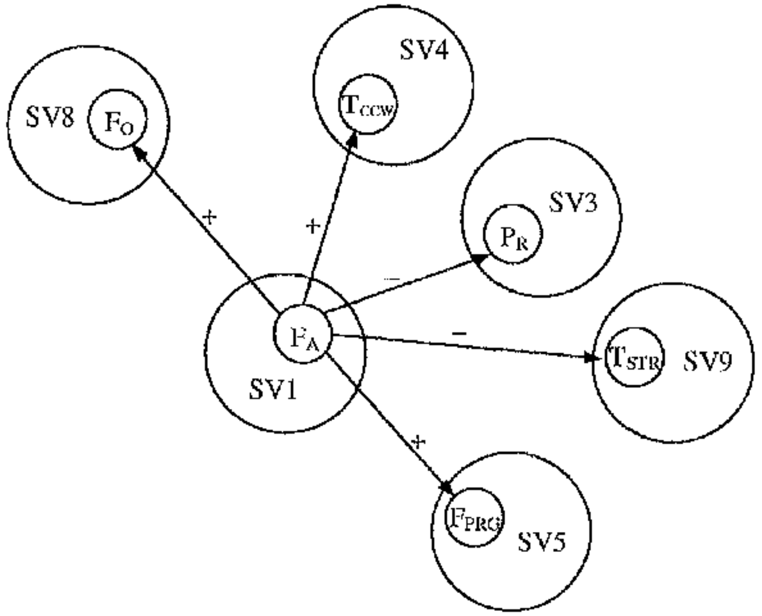


Figure 8-9: Elements involved in the interactions

Other effects or interactions between internal nodes in different super-nodes can be determined in a similar way. Table 8-5 shows the various results.

Additional measurements, which are not within any control systems, are useful and might therefore be considered in fault isolation. These include the temperature and pressure in the separator, the pressure in the stripper, the compressor work and the recycle flow rate. This can be viewed as 'sink' nodes on the simple SDG.

In a similar way, disturbances can be viewed as 'source' nodes. For instance, if IDV(1) occurs, A, C composition ratio in SV1 would change, as would Purge B composition in SV5 and product flow rate in SV8; similarly IDV(2) would affect A, C composition ratio in SV1, the G, H composition ratio and the reactor level in SV2, the reactor pressure in SV3, Purge B composition in SV5, product flow rate in SV8, the stripper temperature in SV9 and the additional measurement of the stripper pressure.

Table 8-5: Interactions between nodes

Beginning_node	Ending_node	Branch_sign
A feed flow rate in SV1	Reactor pressure in SV3	–
	Condenser Cooling Temperature in SV4	+
	Purge flow rate in SV5	+
	Product flow rate in SV8	+
	Stripper temperature in SV9	–
D, E flow rate ratio in SV2	Reactor pressure in SV3	–
	Stripper temperature in SV9	–
Reactor level in SV2	Reactor pressure in SV3	+
	Condenser Cooling Temperature in SV4	–
	Purge flow rate in SV5	–
	Stripper temperature in SV9	+
Reactor cooling temperature in SV3	Condenser Cooling Temperature in SV4	–
	Purge flow rate in SV5	–
	Stripper temperature in SV9	+
Condenser cooling temperature in SV4	G,H product composition ratio in SV2	–
	Reactor pressure in SV3	+
	Purge B composition in SV5	–
	Separator level in SV6	+
	Product flow rate in SV8	–
	Stripper temperature in SV9	+
Purge flow rate in SV5	Reactor pressure in SV3	–
	Condenser Cooling Temperature in SV4	+
	Product flow rate in SV8	+
	Stripper temperature in SV9	–
C feed flow rate in SV8	A, C composition ratio in SV1	–
	Reactor level in SV2	+
	Reactor pressure in SV3	+
	Condenser Cooling Temperature in SV4	+
	Purge B composition in SV5	–
	Separator level in SV6	+
	Product composition E in SV9	+

8.2.6 SEVACS Analysis

This section describes the fault candidates that would be generated by each of the SEVACS if any of the faults/disturbances considered here, were to occur. Section 8.2.7 then summarises these candidates and Section 8.2.8 discusses how individual candidates might then be isolated. For simplicity, the nomenclature in this chapter is somewhat different from that in Chapter 3.

(1) SV1 (A/C composition — A flow rate cascade control system)

This is a standard cascade control system, A/C composition is controlled by manipulating A flow rate into the process. Faults or disturbances only affecting its inner loop can be compensated by the control system, their effects are only local to this system and are irrelevant to other systems. IDV(6) (partial feed A loss), the valve bias and A flow rate sensor bias belong to this category. If only its inner loop controller deviates, IDV(6) or the valve bias is the fault, however they are not distinguishable. If only its outer loop controller deviates, A flow rate sensor bias is the fault. If both controllers deviate, the fault comes from its outer loop disturbances. For instance, IDV(1), IDV(2) and F(5) (see Section 8.2.4.2), or the outer loop sensor bias, i.e., the A/C composition analyser bias F(4).

A decision table is given in Table 8-6. Fault or disturbance directions can be determined as described in Chapter 3 and Chapter 4.

Table 8-6: The knowledge pertaining to SV1

If only the inner loop controller deviates, then the fault can be:

- IDV(6)
- The valve bias

If only the outer loop controller deviates, then the fault should be:

- A flow rate sensor bias

If both the controllers deviate, then the fault can be:

- outer loop disturbances such as IDV(1), IDV(2) and F(5).
- A/C composition analyser bias

(2) SV2 (the G/H composition — reactor level control system)

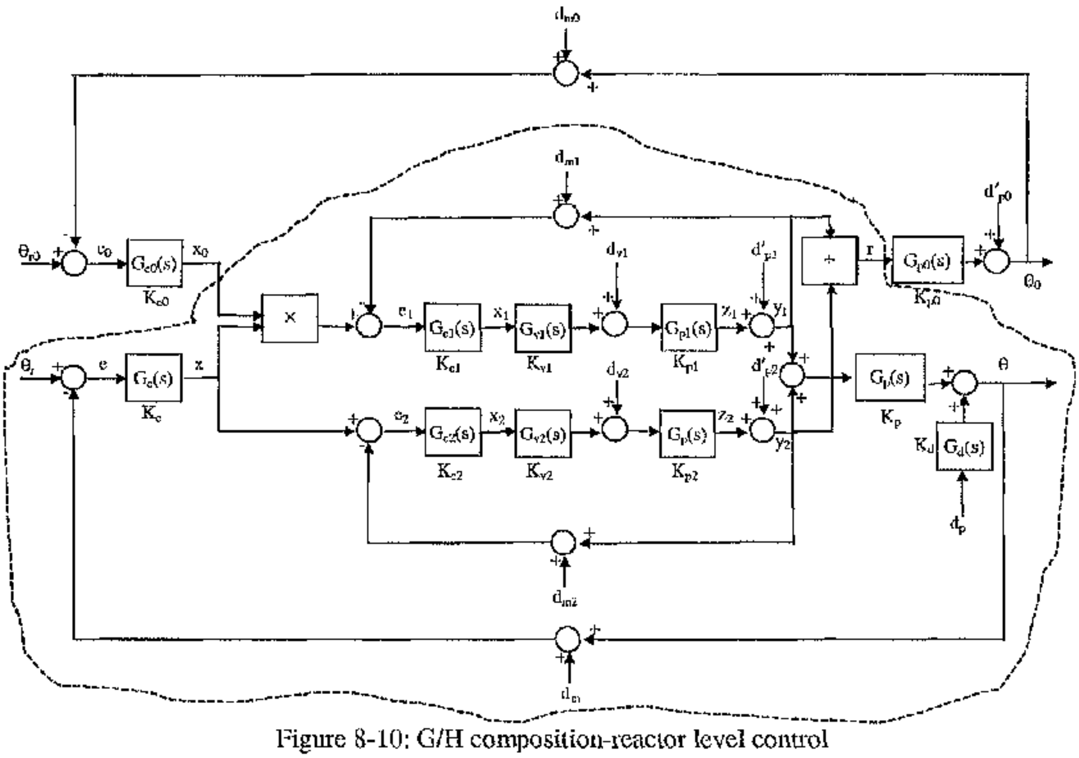


Figure 8-10: G/H composition-reactor level control

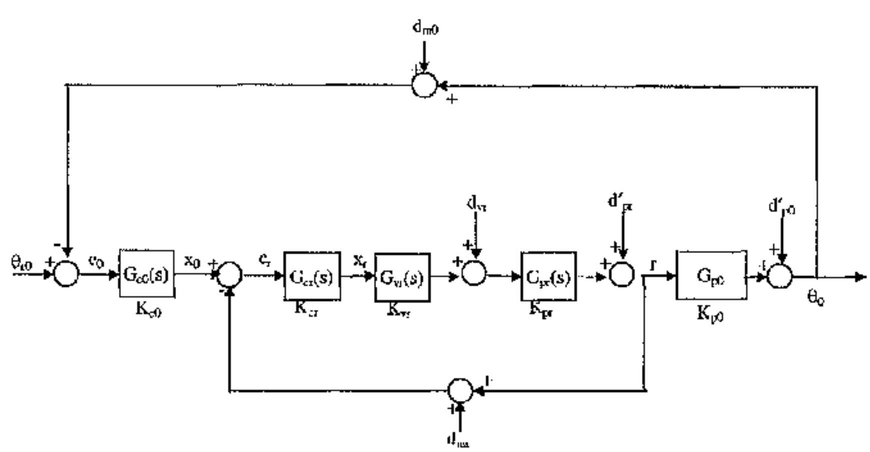


Figure 8-11: The simplified G/H composition-reactor level control

SV2 is quite a complicated control system, Figure 8-10 shows a block diagram representation that is pseudo-linear because it contains '×' and '÷'. D flow rate (y_1) and E flow rate (y_2) are controlled and should be kept in a ratio x_0 for two purposes, one is to maintain the G/H composition ratio in the final product θ_0 at its set-point

θ_{r0}, the other is to maintain the reactor level θ at the set-point θ_r. Four controllers, two valves, four processes are involved here. The four controllers are the G/H composition controller $G_{c0}(s)$, which has proportional gain K_{c0} and output x_0, the reactor level controller $G_c(s)$, which has proportional gain K_c and output x, the D flow rate controller $G_{c1}(s)$, which has proportional gain K_{c1} and output x_1, and the E flow rate controller $G_{c2}(s)$, which has proportional gain K_{c2} and output x_2. The two valves are the D flow rate valve $G_{v1}(s)$, which has gain K_{v1} and the E flow rate valve $G_{v2}(s)$, which has gain K_{v2}. The four processes are the D flow rate process $G_{p1}(s)$, which has gain K_{p1}, the E flow rate process $G_{p2}(s)$, which has gain K_{p2}, the G/H composition process $G_{p0}(s)$, which has gain K_{p0} and the reactor level process $G_p(s)$, which is a capacitive process with an infinite gain K_p. In the figure, d_{m0}, d_{m1}, d_{m2} and d_m represent respective sensor biases, d_{v1} and d_{v2} represent respective valve biases, d'_{p0}, d'_{p1}, d'_{p2} and d_p represent respective process disturbances. K_d is the steady state gain of the level process disturbance transfer function $G_d(s)$, similar to K_p, it also tends to infinity. All variables represent deviations from their nominal values.

The circled part in Figure 8-10 can be viewed as the D/E flow ratio (r) control system, which can then be viewed as the inner loop of the cascade system shown in Figure 8-11. Because D/E flow ratio should be maintained, around its nominal point and after linearisation, there are $r=\alpha y_1-\beta y_2$ and $d_{mr}=\alpha d_{m1}-\beta d_{m2}$ ($\alpha>0$, $\beta>0$). Because $G_p(s)$ is a capacitive process, at a steady state,

$$y_1+y_2=\gamma d_p\left(\gamma=-\frac{K_d}{K_p}\right).$$

$$r=\frac{\theta_{r0}-d'_{p0}-d_{m0}}{K_{p0}}$$

$$y_1=\frac{\beta\gamma d_p+r}{\alpha+\beta}$$

$$y_2=\frac{\alpha\gamma d_p-r}{\alpha+\beta}$$

$$x_0=\alpha d_{m1}-\beta d_{m2}+r$$

$$x=y_2+d_{m2}$$

$$x_1 = \frac{y_1 - d'_{p1} - K_{p1} \cdot d_{v1}}{K_{p1} \cdot K_{v1}}$$

$$x_2 = \frac{y_2 - d'_{p2} - K_{p2} \cdot d_{v2}}{K_{p2} \cdot K_{v2}}$$

Some observations that can be derived from these equations are summarised in Table 8-7. It can be seen that the change of d_{v1} and d'_{p1} can only cause x_1 to change and the change of d_{v2} and d'_{p2} can only cause x_2 to deviate because all of them are in the innermost loops in the control system. Change of d_{m1}, i.e. F(6), can only cause x_0 to deviate and d_{m2}, i.e. F(7), can cause both x_0 and x to deviate. The change in d_p, e.g. F(5) can cause x , x_1 and x_2 to deviate. The changes in θ_{r0}, d'_{p0}, d_{m0}, i.e. F(8) can cause x_0, x , x_1 and x_2 to deviate. IDV(2) is a very complicated disturbance that can be viewed as both d_p and d'_{p0}, it causes x_0, x and x_2 to deviate. The directions of the faults or disturbances can be determined from the equations developed in this section. However, the reactor level sensor bias F(3) cannot be detected and diagnosed by this SEVACS.

Table 8-7: The knowledge pertaining to SV2

Combination of deviations				Fault
x	x_0	x_1	x_2	Candidate
	✓			$\{d_{m1}(F6)\}$
✓	✓			$\{d_{m2}(F7)\}$
		✓		$\{d_{v1}, d'_{p1}\}$
			✓	$\{d_{v2}, d'_{p2}\}$
✓		✓	✓	$\{d_p$(e.g., F(5) and IDV(2))$\}$
✓	✓	✓	✓	$\{\theta_{r0}, d'_{p0}$(e.g., IDV(2)), d_{m0}(F(8))$\}$

(3) SV3 (the reactor pressure — temperature cascade control system)

This is a cascade control system with double inner loops. The SDG of this system is shown in Figure 8-12. In this system, the reactor pressure P_R is controlled by the controller PC_R by manipulating the reactor temperature T_R, which is controlled by the controller TC_R by manipulating the reactor cooling water temperature T_{RC}, which is controlled by the controller TC_{RC} by manipulating the cooling water valve opening V_R. θ_{PR} is the set-point of the reactor pressure.

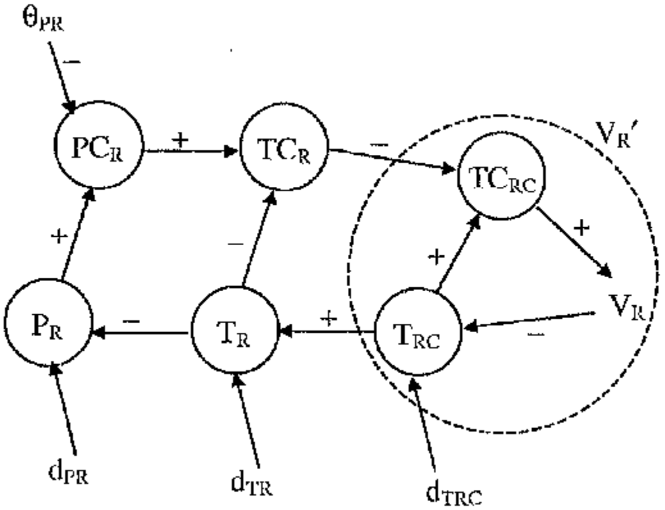


Figure 8-12: The SDG of SV3

The circled part of the system in Figure 8-12 can be viewed as a virtual valve V_R' enabling the standard cascade SEVACS analysis approach to be applied to this system. Note that IDV(4) is a disturbance to the innermost loop (d_{TRC}), i.e., the cooling water temperature control loop; IDV(3) is a disturbance to the second inner loop (d_{TR}), i.e. the reactor temperature loop; F(3) would cause a disturbance to the outermost loop (d_{PR}), i.e., the reactor pressure loop. These three disturbances can be distinguished by the SEVACS theory because they affect the control system from different nodes. However each of them might not be distinguishable or isolatable from other faults or disturbances that affect the system from the same node. For instance, IDV(3) may not be distinguished from E feed temperature disturbance or the fault due to the deterioration of the heat transfer coefficient of the reactor.

In some circumstances the same fault or disturbance will affect different loops in SV3, e.g. a change in reactor level will affect both d_{PR} and d_{TR}. In this case, the fault or disturbance would still be determined by its effect to the outer loop from node d_{PR} for two reasons (see Section 6.2.4). One is that once both the outer loop and the inner loop deviate, the fault should not be from or related to the inner loop directly; the other is that although the fault or disturbance can cause both the inner and outer loop controller to deviate, the direction of the fault should be determined by the deviation in the outer loop controller because the direction of the deviation in the inner loop controller might be ambiguous, the fault direction is not easily determined by it.

A decision table is given in Table 8-8. Fault or disturbance directions can be determined from the equations or knowledge in Chapter 3 or Chapter 4.

Table 8-8: The knowledge pertaining to SV3

If only the controller TC_{RC} deviates, then the fault could be:

- d_{TRC} such as IDV(4)
- the valve-bias

If only the controller TC_R deviates, then the fault should be:

- the cooling-water-temperature-sensor-bias (T_{RC}-sensor-bias)

If only controllers TC_{RC} and TC_R deviate, then the fault should be:

- d_{TR} such as IDV(3)

If only the controller PC_R deviates, then the fault should be:

- the reactor-temperature-sensor-bias (T_R-sensor-bias)

If all the controllers TC_{RC}, TC_R and PC_R deviate, then the fault could be:

- d_{PR} such as F(3)
- the reactor-pressure-sensor-bias (P_R-sensor-bias)

(4) SV4 (Condenser cooling control system)

SV4 is a single loop control system, IDV(5) can be easily detected but it might not be isolated from other faults or disturbances like the maximum flow rate of the condenser cooling water and the heat transfer effect of the heat exchanger in the condenser.

(5) SV5 (Purge composition B — purge flow rate cascade control system)

SV5 is a standard cascade control system, B purge composition is controlled by manipulating the purge flow rate leaving the separator. Faults or disturbances affecting the outer loop such as IDV(1), IDV(2) and F(5), and the outer loop sensor bias F(1) can cause both the two controllers in this control system to deviate. Faults or disturbances only affecting its inner loop such as F(2), F(3), F(4) and the valve bias can only cause the inner loop controller to deviate. Inner loop sensor bias can only cause the outer loop controller to deviate.

A decision table is given in Table 8-9. Fault or disturbance directions can be determined from the equations or knowledge in Chapter 3 or Chapter 4.

Table 8-9: The knowledge pertaining to SV5

If only the inner loop controller deviates, then the fault could be:

- the inner loop disturbances such as F(2), F(3), F(4)
- the valve bias

If only the outer loop controller deviates, then the fault should be:

- inner loop flow sensor bias

If both controllers deviate, then the fault could be:

- outer loop disturbances such as IDV(1), IDV(2) and F(5)
- the outer loop sensor bias F(1)

(6) SV6 (Separator level — underflow rate cascade control system)

Again, SV6 is another standard cascade control system, the separator level is controlled by manipulating its under flow rate leaving the separator. It should be noted that the level process in the outer loop of this control system is a capacitive process. Faults or disturbances affecting the outer loop, such as F(5), can cause both the two controllers in this control system to deviate. However the outer loop level sensor bias won't cause the two controllers to deviate in the steady state because of the capacitive level process. The valve bias can only cause the inner loop controller to deviate. Inner loop flow sensor bias can only cause the outer loop controller to deviate.

A decision table is given in Table 8-10. Fault or disturbance directions can be determined from the equations knowledge in Chapter 3 or Chapter 4.

Table 8-10: The knowledge pertaining to SV6

If only the inner loop controller deviates, then the fault can be: • inner loop process disturbances • the valve bias If only the outer loop controller deviates, then the fault should be: • inner loop flow sensor bias If both the controllers deviate, then the fault can be: • outer loop disturbances such as F(5) If none of the controllers deviate, then there might be: • the outer loop level sensor bias

(7) SV7 and SV8 (Stripper level — product flow rate cascade control system and Product flow rate — C flow rate cascade control system)

Nodes SV7 and SV8 are so tightly coupled that they have to be analysed together. This can be seen from Figure 8-13, which shows a block diagram for these two control systems when linearised. Broadly speaking the upper part represents SV8 and the lower one represents SV7. Variables $\theta_{1,1}$ and $\theta_{1,2}$ represent the product flow rate and the stripper level, $\theta_{r,1}$ and $\theta_{r,2}$ are their set-points respectively. Although SV7 and SV8 are two standard cascade control systems, they have a common controlled variable, product flow rate $\theta_{1,1}$, which is the inner loop controlled variable in SV7 as well as the outer loop controlled variable in SV8. The stripper level is controlled by manipulating the product flow rate out of the stripper through processes $G_{z11}(s)$ and $G_{z22}(s)$ and by manipulating the C flow rate into the stripper through the process $G_{z12}(s)$. Steady state gains are as shown. The product flow rate is controlled by manipulating the level of the stripper through processes $G_{z12}(s)$ and $G_{z21}(s)$ and via the product valve opening through $G_{z11}(s)$.

Controller outputs $x_{1,1}$ and $x_{2,1}$ relate to the outer loop controller $G_{c11}(s)$, which has proportional gain $K_{c1,1}$, and the inner loop controller $G_{c21}(s)$, which has proportional gain $K_{c2,1}$. These two controllers have control errors $e_{1,1}$ and $e_{2,1}$ respectively. Deviations $d_{v,1}$, $d'_{p2,1}$, $d'_{p1,1}$, $d_{m2,1}$ and $d_{m1,1}$ represent the bias of the valve $G_{v1}(s)$, which has steady state gain $K_{v,1}$, the disturbance to the inner loop process $G_{p21}(s)$, which has steady state gain $K_{p2,1}$, the disturbance to the product flow rate related processes $G_{z11}(s)$ and $G_{z21}(s)$, which have steady state gains $K_{z1,1}$ and $K_{z2,1}$ respectively, the inner loop sensor bias and the outer loop sensor bias in SV8, in which $d_{m1,1}$ is also the inner loop sensor bias in SV7.

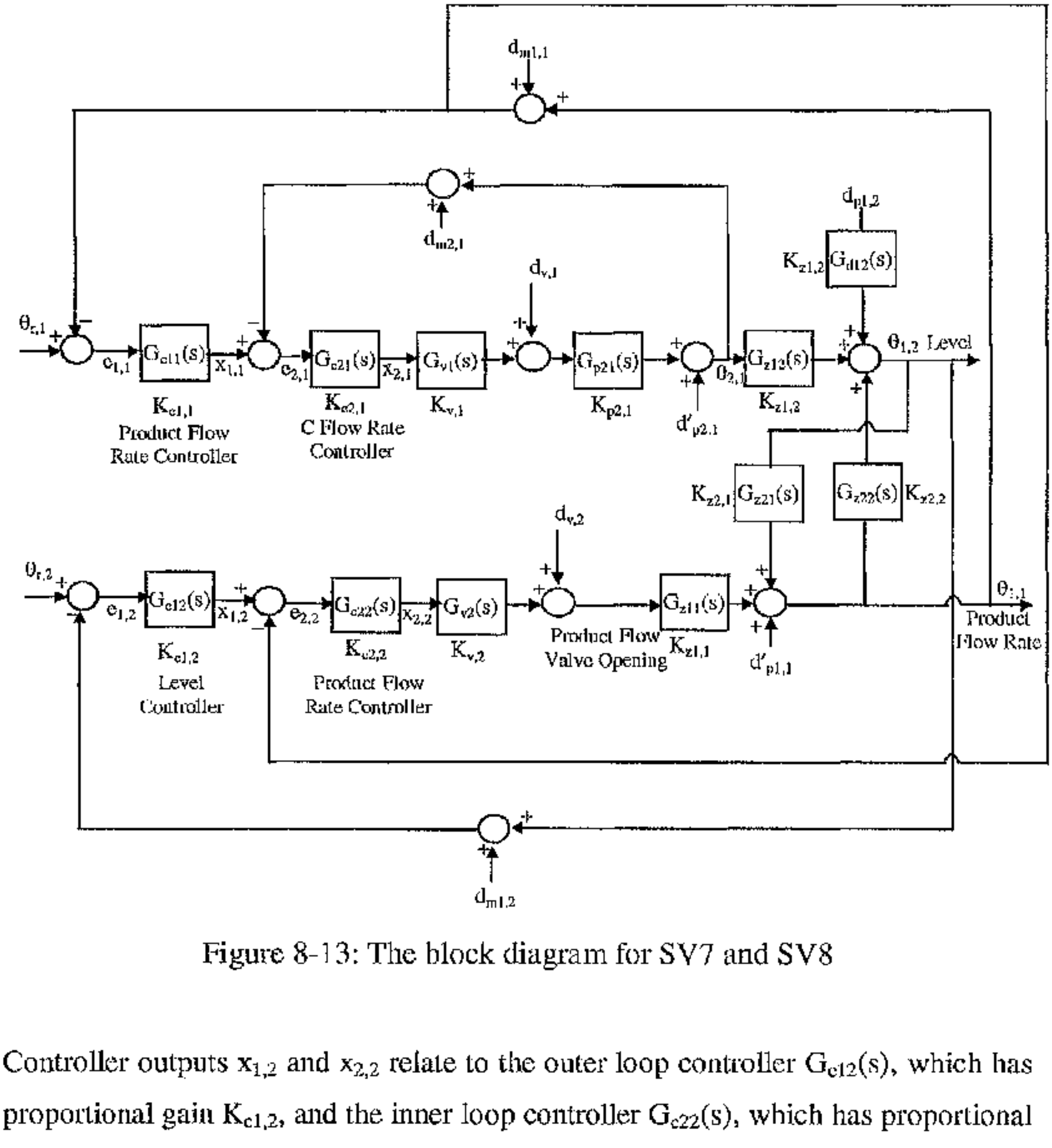


Figure 8-13: The block diagram for SV7 and SV8

Controller outputs $x_{1,2}$ and $x_{2,2}$ relate to the outer loop controller $G_{c12}(s)$, which has proportional gain $K_{c1,2}$, and the inner loop controller $G_{c22}(s)$, which has proportional gain $K_{c2,2}$. These two controllers have control errors $e_{1,2}$ and $e_{2,2}$ respectively. Deviations $d_{v,2}$, $d_{p1,2}$ and $d_{m1,2}$ represent the bias of the valve $G_{v2}(s)$ which has steady state gain $K_{v,2}$, the disturbance to the level related processes $G_{z12}(s)$ and $G_{z22}(s)$, which have steady state gains $K_{z1,2}$ and $K_{z2,2}$ respectively, and the level sensor bias in SV7. Transfer function $G_{d12}(s)$ has a steady state gain $K_{d1,2}$ and represents a disturbance process from $d_{p1,2}$ to the level $\theta_{1,2}$.

All the controllers have an integral action in the steady state,

$e_{1,1}=0$

$e_{2,1}=0$

$e_{1,2}=0$

$e_{2,2}=0$

Controller outputs are given by

$$x_{1,1} = \frac{-K_{z2,2}\theta_{r,1} + \theta_{r,2} + K_{z2,2}d_{m1,1} - d_{m1,2} - K_{d1,2}d_{p1,2}}{K_{z1,2}} + d_{m2,1}$$

$$x_{2,1} = \frac{-K_{z2,2}\theta_{r,1} + \theta_{r,2} + K_{z2,2}d_{m1,1} - d_{m1,2} - K_{d1,2}d_{p1,2}}{K_{p2,1}K_{v,1}K_{z1,2}} - \frac{d'_{p2,1}}{K_{p2,1}K_{v,1}} - \frac{d_{v1}}{K_{v,1}}$$

$x_{1,2} = \theta_{r,1}$

$$x_{2,2} = \frac{\theta_{r,1} - K_{z2,1}\theta_{r,2} - d_{m1,1} + K_{z2,1}d_{m1,2} - d'_{p1,1}}{K_{v,2}K_{z1,1}} - \frac{d_{v2}}{K_{v,2}}$$

To analyse the above equations qualitatively, first note that the level related processes are capacitive, which means that steady state gains $K_{z1,2} \to +\infty$, $K_{z2,2} \to -\infty$ and $K_{d1,2} \to \pm\infty$. However, any ratio between two of these three steady state gain should be finite. Thus,

$$[x_{1,1}] = [\theta_{r,1}] - [d_{m1,1}] - \left\{\frac{K_{d1,2}}{K_{z1,2}}\right\}d_{p1,2} + [d_{m2,1}]$$

$$[x_{2,1}] = \frac{[\theta_{r,1}]}{\{K_{p2,1}K_{v,1}\}} - \frac{[d_{m1,1}]}{\{K_{p2,1}K_{v,1}\}} - \frac{[d'_{p2,1}]}{\{K_{p2,1}K_{v,1}\}} - \left\{\frac{K_{d1,2}}{K_{p2,1}K_{v,1}K_{z1,2}}\right\}[d_{p1,2}] - \frac{[d_{v1}]}{\{K_{v,1}\}}$$

$[x_{1,2}] = [\theta_{r,1}]$

$$[x_{2,2}] = \frac{[\theta_{r,1}]}{\{K_{v,2}K_{z1,1}\}} - \left\{\frac{K_{z2,1}}{K_{v,2}K_{z1,1}}\right\}[\theta_{r,2}] - \frac{[d_{m1,1}]}{\{K_{v,2}K_{z1,1}\}}$$
$$+ \left\{\frac{K_{z2,1}}{K_{v,2}K_{z1,1}}\right\}[d_{m1,2}] - \frac{[d'_{p1,1}]}{\{K_{v,2}K_{z1,1}\}} - \frac{[d_{v2}]}{\{K_{v,2}\}}$$

Based on the above qualitative equations, a decision table for fault detection and diagnosis can be made (Table 8-11). Directions of various faults or disturbances can be also determined from these equations.

Consider the fault scenarios in Table 8-3 and the simulation results in Appendix 4, F(1), IDV(1) and IDV(2) can cause $x_{1,1}$ and $x_{2,1}$ to deviate and thus can be detected and diagnosed as $d_{p1,2}$. F(5), namely as $d_{m1,1}$ would be detected and diagnosed from deviations in $x_{1,1}$, $x_{2,1}$ and $x_{2,2}$. IDV(7) would be detected and diagnosed as $d'_{p2,1}$ from a deviation in $x_{2,1}$ only.

Table 8-11: The knowledge pertaining to SV7 and SV8

Combination of deviations				Fault Candidate
$x_{1,1}$	$x_{2,1}$	$x_{1,2}$	$x_{2,2}$	
✓				$\{d_{m2,1}\}$
✓	✓			$\{d_{p1,2}$ (e.g., F(1), IDV(1) and IDV(2)) $\}$
	✓			$\{d'_{p2,1}(\text{IDV}(7)), d_{v,1}\}$
			✓	$\{d'_{p1,1}, d_{v,2}, \theta_{r,2}, d_{m1,2}\}$
✓	✓		✓	$\{d_{m1,1}(\text{F}(5))\}$
✓	✓	✓	✓	$\{\theta_{r,1}\}$

(8) SV9 (Product composition E — stripper temperature cascade control system)

Like SV3, SV9 is another cascade control system with double inner loops. The SDG of this system is shown in Figure 8-14. In this system, the E composition in the product E_P is controlled by the controller EC_P by manipulating the stripper temperature T_P, which is controlled by the controller TC_P by manipulating the stripper heating steam flow rate F_{PS}, which is controlled by the controller FC_{PS} by manipulating the steam valve opening V_{PS}. θ_{EP} is the set-point of the E composition in the product.

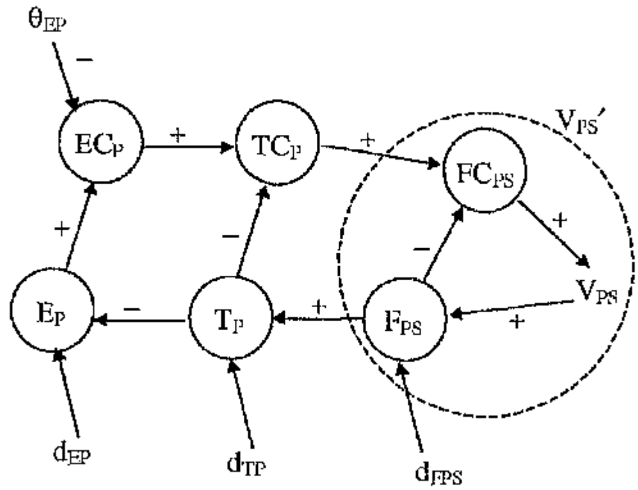


Figure 8-14: The SDG of SV9

If the circled part of the system in Figure 8-14 is viewed as a virtual valve V_{PS}', then the standard cascade SEVACS analysis approach can be applied to this system. For example, IDV(2), F(1), F(2), F(3), F(4) and F(8) can cause the temperature of the material, fed into the stripper from the separator, to deviate and thus can be viewed as the faults or disturbances (d_{TP}) to the second inner loop, the stripper temperature loop; F(5) can cause the outermost controller EC_P to deviate and can be seen as the disturbance (d_{EP}) to the outermost or primary controlled variable and can be isolated from the foregoing faults or disturbances.

A decision table is given in Table 8-12. Fault or disturbance directions can be determined from the equations or knowledge in Chapter 3 or Chapter 4.

Table 8-12: The knowledge pertaining to SV9

If only the controller FC_{PS} deviates, then the fault could be:

- d_{FPS}
- the valve-bias

If only the controller TC_P deviates, then the fault should be:

- F_{PS}-sensor-bias

If only controllers FC_{PS} and TC_P deviate, then the fault should be:

- d_{TP} such as IDV(2), F(1), F(2), F(3), F(4) and F(8)

If only the controller EC_P deviates, then the fault should be:

- T_P-sensor-bias

If all the controllers FC_{PS}, TC_P and EC_P deviate, then the fault could be:

- d_{EP} such as F(5)
- E_P-sensor-bias

8.2.7 Distributed Diagnosis of 9 SEVACS

9 SEVACS have been analysed when subjected to different faults or disturbances. The overall fault and disturbance effects on the SEVACS of the T-E benchmark can be summarised in Table 8-13.

From the table, it can be seen that each SEVACS has its own diagnostic capability so that distributed diagnosis can be realised. However this is not to say that they could be individually isolated. Overall isolation would be achieved in a Supervisor by a search and test strategy. By referring to 2 examples, this is elaborated on in the next section.

Table 8-13: Faults and disturbances effects' on the SEVACS of the T-E benchmark

	SV1	SV2	SV3	SV4	SV5	SV6	SV7	SV8	SV9
IDV(1)	✓				✓			✓	
IDV(2)	✓	✓	✓	✓	✓			✓	✓
IDV(3)			✓						
IDV(4)			✓						
IDV(5)				✓					
IDV(6)	✓								
IDV(7)								✓	
F(1)			✓	✓	✓			✓	✓
F(2)	✓		✓	✓	✓				✓
F(3)			✓	✓	✓				✓
F(4)	✓		✓	✓	✓				✓
F(5)	✓	✓	✓	✓	✓	✓	✓	✓	✓
F(6)		✓							
F(7)		✓							
F(8)		✓	✓	✓					✓

8.2.8 Two Isolation Examples

- IDV(1): lower A/C feed ratio and constant B composition in stream 4.

In the steady state, SV1, SV5 and SV8 will be affected (Table 8-11):

SV1: the A, C composition ratio (A/C) controller and the A feed flow rate controller have positive deviations;

SV5: the purge B composition controller and the purge rate controller have negative deviations;

SV8: the product flow rate controller and the C feed flow rate controller have negative deviations (see Appendix 4).

If the fault isolation procedures described in Chapter 5 were to be applied then:

search process: starting from the super-node SV1, A/C-sensor-bias-low and process disturbances including product-flow-rate-sensor-bias-high, IDV(1) and IDV(2) would form a fault candidate set because of the outer-loop controller deviation;

test process: from Figure 8-8, A/C-sensor-bias-low would be rejected because it should cause SV1, SV3, SV4, SV5, SV8 and SV9 to deviate; product-flow-rate-sensor-bias-high would be rejected because it should cause SV1, SV2, SV3, SV4, SV5, SV6, SV8 and SV9 to deviate; IDV(2) would be also rejected because it should cause SV1, SV2, SV3, SV5, SV8 and SV9 to deviate (Section 8.2.5.3). This leaves IDV(1), which can cause SV1, SV5 and SV8 to deviate in the above directions.

Note the emphasis on 'should' rather than 'would'. This is because some of the deviations sought by the search process didn't actually happen in the simulation. However sufficient super-nodes did deviate to enable the process to eliminate the alternatives. Also, as always, it is worth pointing out that IDV(1) is just one disturbance, other disturbances might exist that have similar effects and this possibility should not be ruled out. It is therefore important that a dialogue takes place with the operators to ensure that the system 'learns'.

- F(3): reactor-level-sensor-bias-low.

In the steady state, although the fault actually occurred in SV2, this would not be apparent, locally, because the level process is capacitive and nothing wrong would be observed in SV2. However SV3, SV4, SV5, and SV9 will be affected:

SV3: the reactor pressure controller and the reactor temperature controller have positive deviations, and the reactor cooling controller has a negative deviation;

SV4: the condenser cooling controller has a negative deviation;

SV5: the purge flow rate controller has a positive deviation;

SV9: the stripper temperature controller and the stripper steam controller have negative deviations.

The additional measurements, the compressor work and the recycle flow rate will also deviate, negatively.

Similar to the previous example, if the fault isolation procedures described in Chapter 5 were to be applied then:

search process: starting from the super-node SV3, the fault candidate set would be {reactor-pressure-sensor-bias, condenser-cooling-temperature-sensor-bias, purge-B-composition-sensor-bias, reactor-level-sensor-bias, other process disturbances including IDV(2)}. Note that this contains the outer loop sensor bias for SV2 i.e. reactor-level-sensor-bias because the reactor level process is capacitive and hence the sensor bias can be viewed as a process disturbance to SV3 (see Section 5.2.1).

test process: the reactor-pressure-sensor-bias in SV3 can be rejected because the additional measurements such as the separator pressure and the stripper pressure don't deviate. The condenser-cooling-temperature-sensor-bias in SV4 can be rejected because it should lead to deviations in SV2, SV6 and SV8. The purge-B-composition-sensor-bias in SV5 can be rejected because it should lead to a deviation in SV8. Since there are no deviations in SV2 and IDV(2) is a disturbance to SV2, IDV(2) can be rejected. This leaves reactor-level-sensor-bias in SV2, which can cause SV3, SV4, SV5 and SV9 to deviate in the observed directions.

Once again it is unlikely that the observed effects can be attributed, uniquely, to one fault, so it is important that a dialogue takes place with the operators to ensure that the system 'learns'.

8.3 Summary

In this Chapter, two applications have been demonstrated for control system based distributed diagnosis, in which each individual SEVACS has its own diagnostic capability and the Supervisor performs the overall isolation. The first application is to a simple CSTR process, in which in the Supervisor level, the set-operation based isolation approach of Chapter 3 is used. However, the set-operation approach is clearly limited by scale. For the second application, which is more complex, a search and test strategy has to be used in the Supervisor.

It should be mentioned that, in practice, accurate isolation may not be possible if there is not enough process knowledge. However, at least the approach can be successful in finding the locality of the fault or disturbance and further isolation can be done with more knowledge. Finally the human being is still important in such an isolation process.

CHAPTER 9

CONCLUSIONS AND FUTURE RECOMMENDATIONS

9.1 Conclusions

Process monitoring and fault diagnosis is an important R & D issue for industries. For example, Honeywell Inc., a global leader in control technology, is currently leading the $20 million ASM (Abnormal Situation Management) project that seeks to demonstrate the technical feasibility of collaborative decision support technologies for improving the performance of operations personnel. Although there has been considerable research into process monitoring and fault diagnosis (Chapter 2)it is clear that solutions are still sought. Statistical process control can offer little help to fault isolation or fault diagnosis. Analytical redundancy techniques are unpopular because it is very difficult and expensive to obtain process models. In addition, as with the statistical process control method, it is also difficult to isolate a fault even when a discrepancy has been detected. The self-validating concept proposed by Henry and Clarke *et al.* (1995) looks practicable but only focuses on sensors and on actuators. Control system performance assessment might be useful for fault detection but not for isolation.

This thesis proposes an original, generic and systematic approach to the distributed diagnosis of faults and disturbances. The approach has some distinguishing features (Table 9-1). Its inspiration derives from the structure of various distributed control systems that are used widely in process industries and from the self-validating concept of Henry & Clarke (1993). The approach is control system based and hence is directly relevant to distributed systems. The theoretical philosophy that underpins the approach is described in Chapter 3. In particular equations that describe how one controller responds to faults and disturbances that originate elsewhere are derived. Chapter 3 also describes a fault isolation approach that is largely not practicable.

Table 9-1: Features of the SEVACS based approach

— distributed;
— qualitative model based;
— knowledge based;
— steady state based;
— easy, cheap and widely applicable;
— can work with a minimal amount of knowledge, although the more the better;
— learning and updating capability.

In general, knowledge is the key to fault diagnosis. Thus knowledge acquisition and knowledge representation for distributed diagnosis are of great interest. This is considered in Chapter 4, which focuses on fault diagnostic knowledge for single loop and cascade controllers. Of importance is the need to know the process Type number and whether it is stable or not. Having gained an understanding of controllers and how they respond to faults, a search and test strategy for fault isolation is proposed in Chapter 5. This is found to be somewhat cumbersome so various improvements are then made.

Although the approach would produce some form of diagnosis when given a minimal amount of knowledge, clearly greater resolution can be obtained with more knowledge. Chapter 6 introduces a method to acquire the minimum knowledge by applying step tests and gives a framework and some guidelines for knowledge evolution so that the SEVACS based approach can have a learning and updating capability. A CSTR process is used to illustrate the method.

Being steady state based, algorithms are needed to detect when a plant is in steady state and then to ascertain whether this steady state has changed.. Chapter 7 describes a steady state identifier, the *R-statistic*, which is the ratio of two variances as measured on the same set of data by two different methods, and a steady state change detection procedure. The *R-statistic* is a ratio in which the numerator is estimated from the filtered squared deviation from previous filtered values and the denominator is estimated from the mean of squared differences of successive data. The *R-statistic* can be calculated online and has proved to be an effective steady state identifier when applied to several chemical processes online (Cao and Rhinehart, 1995, 1997). Steady state change detection is based on the *t-statistic*, which compares the difference between the sample means of two independent SRSs (simple random samples) with unknown variances. The *R-statistic* is sensitive to various parameters, which should be carefully selected in order to differentiate between steady and unsteady states. The change detection performance depends on sample sizes. The smaller the sample sizes, the less the *blackout* period although the less the ability to get rid of the wrong state indication from the *R-statistic*.

As can be seen in Chapter 8, the approach has been applied to two applications, to a simulated CSTR process and to the Tennessee Eastman (T-E) process benchmark. The small size of the CSTR application is convenient for developing a process SDG from process equations. This graph can then be used to obtain sign information for the set-operation based fault isolation approach of Chapter 3. Although successful this is clearly limited by scale and the T-E benchmark is too large and complicated for this approach to be practicable. Instead a kind of hierarchical approach where an outline SDG describing controller super-nodes and interactions is first constructed, and then each super-node is elaborated on in turn. Both design information and step tests might provide appropriate knowledge. The set-operation based approach is then replaced by a search and test strategy. Once again the CSTR application can provide a simple example of this strategy. Its application to the T-E benchmark shows that the sets of possible faults & disturbances can be reduced effectively. However it is appreciated that it will always be difficult to say 'this is the fault' although 'the fault' should always have the same symptoms as those hypothesised. As such it is most important that the operator is involved in the decision making process. Clearly this is only one part of a hybrid strategy combining other techniques such as heuristic rules, sensor and actuator validation, governing equations.

9.1.1 Pros and Cons

The main strengths and weaknesses of the approach can be summarised in 4 points.

(1) Notionally it requires the process to be in steady state before any decision can be made. Thus the time to make a decision might be quite long, which might be a serious problem in some situations. However as seen in the applications chapter, this requirement is not strictly necessary. Further work is needed to determine how the steady state algorithms of Chapter 7 might be 'relaxed' to accommodate this.

(2) It is qualitative-based. Its reasoning processes are based on just three states [–, 0, +], which requires thresholds to switch between them. As can be seen in the applications it is sometimes difficult to detect small changes and the approach needs to be lenient towards cases where a certain deviation is not observed.

(3) Complicated, quantitative mathematical equations that are difficult and expensive to be developed are not necessary for the approach, although they can contribute to knowledge acquisition for the approach.

(4) The qualitative steady state based method means simple algorithms that can be easily understood, implemented and maintained.

In principle, the approach can form the basis for the diagnosis of faults in both control systems and in the process itself. One of the key features is that the approach can work at different levels of detail. Diagnosis is based on knowledge of the signs of steady state interactions (gains) between individual control loops, additional measurements and on the steady state effects of disturbances. Both faults and disturbances (e.g. a load change) can be diagnosed, although diagnostic detail, i.e. degree of isolation, is clearly dependent on the measurements and knowledge that is available. For instance it would not be possible to isolate a 'hidden' process fault if nothing is known about the process itself. This, then, is the core of the problem: there is a conflict between the need for, and cost of this knowledge; the cost would be in terms of both the loss of generality and in acquisition. To address this problem, and in order to keep costs down, it is proposed that the initial implementation on a plant should require a minimal amount of knowledge requisition. Driven by normal plant disturbances, the distributed systems would then acquire additional knowledge for the knowledge base. In addition successes and failures at fault diagnosis together with conflicts (contradictory diagnoses) between distributed systems would also be interpreted to acquire new knowledge.

The following recommendations are made for the future research.

9.2 Future Work

9.2.1 Knowledge Representation for Distributed Diagnosis

The SDG representation has been used to determine the sources of the observable effects. Although, in theory, SDGs can be constructed on the basis of process mathematical models, in practice the construction of a mathematically strict SDG is considerably difficult and expensive. Even if some equations are available, only an incomplete SDG can be obtained, thus the diagnostic result based on the incomplete SDG would be wrong. For the purpose of fault diagnosis, the initial implementation would be based on a minimal SDG which has not been researched enough yet, hence the first task would be to establish its form. The overall aim would be to provide appropriate knowledge for the configuration of individual SEVACS.

9.2.2 Incremental Knowledge Acquisition

Knowledge would be acquired from mathematical models, process step test experiments, process operators and associated support staff, and from the performance of the SEVACS. Each route would be considered in turn and an appropriate method developed. For instance, research would first be carried out into the actual specification of step tests so that appropriate additional knowledge can be obtained, the method of knowledge acquisition would then be examined in detail. Knowledge might be acquired simultaneously by more than one distributed system. Although some work has been done in Chapter 6, it needs more research. The focus should be on how to carry out incremental knowledge acquisition and how to keep updated.

That proposed is essentially an instance of the Frame Problem (Cawsey, 1998), which centres on issues of representation, completeness and knowledge acquisition.

9.2.3 Conflict Resolution

There are two kinds of conflict that are of relevance here:

a) the first derives from the incompleteness of the SDG, the diagnostic result may be different from the real fault which is investigated and confirmed by operators;

b) due to statistical uncertainties, if some deviations are insufficiently large to be detected, the deviation information in a SDG may conflict.

Item a) can be used to acquire new knowledge whilst Item b) is needed to ensure correct performance. Fuzzy logic may help to solve the conflict problem.

9.2.4 The Supervisor or Co-ordinator

Like with distributed control systems, distributed fault detection & diagnosis still requires a Supervisor or Co-ordinator to collect and display information and to enable the plant operator to interact with the systems. Certain aspects of conflict resolution would be performed at this level as would fault appraisal/evaluation.

9.2.5 Fault Appraisal/Evaluation

It is important that the approach is attractive to the end-user. It is better that before the result is presented to operators, each fault can be evaluated and ordered quantitatively so that operators can make use of this information to locate the true fault reasonably and rapidly. Bayes Theorem has a good reputation for doing this.

9.2.6 Ergonomic Considerations

So far, only the technical problems have been considered, however there is nothing is as wise as a human being, all process monitoring and fault diagnosis systems need human operators' co-operation. It is very important to ensure that human operators are involved in the decision making process.

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APPENDIX 1

THE MODEL OF A SIMULATED CSTR PROCESS

A1.1 The Description of A Simulated CSTR

A simulated CSTR process undergoing an irreversible first-order exothermic reaction is used to test the effectiveness of the proposed approach in this thesis (Figure A1-1): the reactant A is fed into the reactor with the initial concentration C_{A0}, flow rate F_0 and temperature T_0, after the reaction, A leaves the reactor with the final concentration C_A and temperature T which is viewed as the same as that in the reactor, note there are two outlets, the flow rate, F_1, is manipulated to regulate the level, L, whilst a nominally constant flow rate, F, is drawn for a separate purpose; the reactor temperature, T, is maintained by varying the cooling water flow rate, FJ, through a heat exchanger installed in the CSTR and, in addition, concentration C_A is measured. There are three control systems, two of which have single loops, the other has a cascade arrangement. Thus four PI controllers, the level controller LC, the outlet flow rate controller FC, the temperature controller TC and the cooling water flow rate controller FJC, are employed to manipulate three valves LV, FV and FJV.

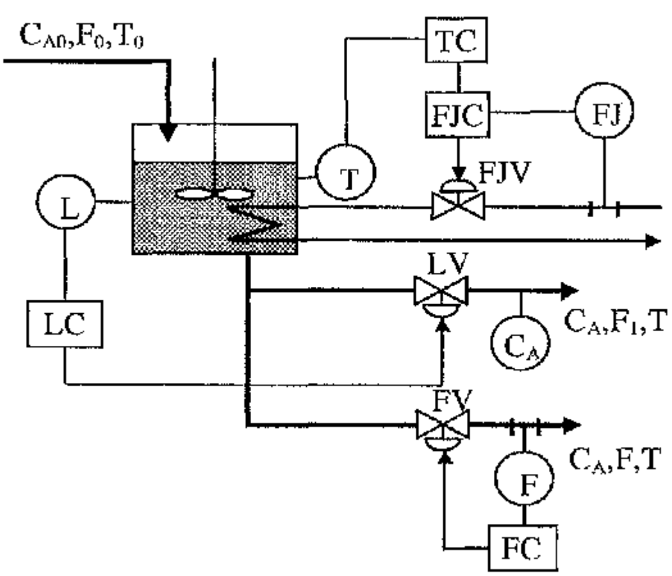


Figure A1-1: A simulated CSTR process

A1.2 The Reactor Model

The dynamic model of the CSTR is as the following:

$$\frac{dV}{dt} = F_0 - F - F_1$$

$$\frac{dC_A}{dt} = \frac{F_0}{V}(C_{A0} - C_A) - k_0 e^{\frac{-E}{RT}} C_A$$

$$\frac{dT}{dt} = \frac{F_0}{V}(T_0 - T) - \frac{\lambda k_0 e^{\frac{-E}{RT}} C_A}{\rho C_p} - \frac{U_0 A}{V \rho C_p}(T - TJ)$$

$$\frac{dTJ}{dt} = \frac{FJ}{V_j}(TJ_0 - TJ) + \frac{UA}{V_j \rho_j C_{pj}}(T - TJ)$$

After linearization around the nominal operating point, there are:

$$\frac{dC_A}{dt} = a_{11} C_A + a_{12} T + b_{11} C_{A0} + b_{13} F_0$$

$$\frac{dT}{dt} = a_{21} C_A + a_{22} T + a_{23} TJ_0 + b_{22} T_0 + b_{23} F_0$$

$$\frac{dTJ}{dt} = a_{32} T + a_{33} TJ + b_{34} TJ_0 + b_{35} FJ$$

where:

$$a_{11} = -(\frac{\overline{F}_0}{V} + k_0 e^{-E/(R\overline{T})})$$

$$a_{12} = -\frac{\overline{C}_A k_0 e^{-E/(R\overline{T})} E}{R\overline{T}^2}$$

$$b_{11} = \frac{\overline{F}_0}{V}$$

$$b_{13} = \frac{\overline{C}_{A0} - \overline{C}_A}{V}$$

$$a_{21} = -\frac{\lambda k_0 e^{-E/(R\overline{T})}}{\rho C_p}$$

$$a_{22} = -(\frac{\overline{F}_0}{V} + \frac{UA}{V\rho C_p} + \frac{\lambda k_0 \overline{C}_A e^{-E/(R\overline{T})} E}{\rho C_p R \overline{T}^2})$$

$$a_{23} = \frac{UA}{V\rho C_p}$$

$$b_{22} = \frac{\overline{F}_0}{V}$$

$$b_{23} = \frac{\overline{T}_0 - \overline{T}}{V}$$

$$a_{32} = \frac{UA}{V_j \rho_j C_{pj}}$$

$$a_{33} = -(\frac{\overline{FJ}}{V_j} + \frac{UA}{V_j \rho_j C_{pj}})$$

$$b_{34} = \frac{\overline{FJ}}{V_j}$$

$$b_{35} = \frac{\overline{TJ}_0 - \overline{TJ}}{V_j}$$

In the above, $\overline{X}$ means the nominal value of the variable X.

The above equations can be represented as the state space equation matrix:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}$$

where

$$\mathbf{x} = [C_A \quad T \quad TJ]^T$$

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & 0 \\ a_{21} & a_{22} & a_{23} \\ 0 & a_{32} & a_{33} \end{bmatrix}$$

$$\mathbf{B} = \begin{bmatrix} b_{11} & 0 & b_{13} & 0 & 0 \\ 0 & b_{22} & b_{23} & 0 & 0 \\ 0 & 0 & 0 & b_{34} & b_{35} \end{bmatrix}$$

$$\mathbf{u} = [C_{A0} \quad T_0 \quad F_0 \quad TJ_0 \quad FJ]^T$$

then the denominator of $(s\mathbf{I}-\mathbf{A})^{-1}$ (where $\mathbf{I}$ is an identity matrix of dimension 3) represents the process characteristic polynomial, the characteristic equation is:

$$\Delta(s) = s^3 + B_2 s^2 + B_1 s + B_0 = 0$$

where

$$B_2 = -(a_{11} + a_{22} + a_{33})$$

$$B_1 = a_{11}a_{22} + a_{11}a_{33} + a_{22}a_{33} - a_{12}a_{21} - a_{32}a_{23}$$

$$B_0 = a_{12}a_{21}a_{33} + a_{32}a_{23}a_{11} - a_{11}a_{22}a_{33}$$

So the open loop process is stable if all the roots of the characteristic equation have negative real parts; the open loop process is unstable if any root of the characteristic equation has real part zero or positive, in other words, if either B_2 or B_1 or B_0 is negative, the characteristic equation has at least one root which has positive real part, the open loop process is unstable.

A1.3 The Control Model

$$TC = bias(1) + KC(1)\cdot\left(\bar{T} - T\right) + \frac{KC(1)}{\tau_i(1)}\int\left(\bar{T} - T\right)dt$$

$$FT = 12\frac{FJ}{FJ_{MAX}} + 3$$

$$FJC = bias(2) + KC(2)(TC - FT) + \frac{KC(2)}{\tau_i(2)}\int(TC - FT)dt$$

$$FJV = \frac{15 - FJC}{12}$$

$$FJ = FJ_{MAX} \times FJV$$

$$L = \frac{V}{A}$$

$$FC = bias(3) + KC(3)\cdot\left(\bar{F} - F\right) + \frac{KC(3)}{\tau_i(3)}\int\left(\bar{F} - F\right)dt$$

$$FV = \frac{15 - FC}{12}$$

$$LC = bias(4) + KC(4)\cdot\left(\bar{L} - L\right) + \frac{KC(4)}{\tau_i(4)}\int\left(\bar{L} - L\right)dt$$

$$LV = \frac{30 - LC}{24}$$

$$F = F_{MAX} \times \sqrt{\frac{V}{\overline{V}}} \times FV$$

$$F_1 = F_{1MAX} \times \sqrt{\frac{V}{\overline{V}}} \times LV$$

A1.4 Parameters for The Open Loop Stable Process

Parameters for the open loop stable process are shown in Table A1-1. The process characteristic polynomial is $\Delta(s)=s^3+191s^2+253s+322$.

Table A1-1: Parameters for the open loop stable process

$F = 40\ ft^3/h$	bias(1) = 7.75 psi
$V = 72\ ft^3$	bias(2) = 10.25 psi
$C_{A0} = 0.5\ mol/ft^3$	bias(3) = 11.3 psi
$C_A = 0.1952\ mol/ft^3$	bias(4) = 18.3 psi
$T = 600\ °R$	$U_0 = 150\ Btu/(h \cdot ft^3 \cdot °R)$
$TJ = 597\ °R$	$A = 250\ ft^2$
$FJ = 79\ ft^3/h$	$TJ_0 = 575\ °R$
$VJ = 3.85\ ft^3$	$T_0 = 575\ °R$
$K_0 = 7.08 \times 10^{10}\ h^{-1}$	$\lambda = -30000\ Btu/mol$
$E = 30000\ Btu/mol$	$C_p = 0.75\ Btu/(lb_m \cdot °R)$
$R = 1.99\ Btu/(mol \cdot °R)$	$C_{pj} = 1.0\ Btu/(lb_m \cdot °R)$
$FJ_{MAX} = 199.6\ ft^3/h$	$\rho = 50\ lb \cdot mol/ft^3$
$F_{MAX} = 64.8\ ft^3/h$	$\rho_j = 62.3\ lb \cdot mol/ft^3$
$F_{1MAX} = 41\ ft^3/h$	
KC(1) = −1.2 psi/°R	$\tau_i(1) = 353$ sec
KC(2) = −0.5	$\tau_i(2) = 2$ sec
$KC(3) = -600\ psi \cdot sec/ft^3$	$\tau_i(3) = 60$ sec
KC(4) = 300 psi/ft	$\tau_i(4) = 900$ sec

A1.5 Parameters for The Open Loop Unstable Process

Parameters for the open loop unstable process are shown in Table A1-2. The process characteristic polynomial is $\Delta(s)=s^3+184s^2-384s-69$.

Table A1-2: Parameters for the open loop stable process

$F = 40\ ft^3/h$	bias(1) = 7 psi
$V = 72\ ft^3$	bias(2) = 11.008 psi
$C_{A0} = 0.5\ mol/ft^3$	bias(3) = 11.3 psi
$C_A = 0.1952\ mol/ft^3$	bias(4)= 18.3 psi
$T = 600\ °R$	$U_0 = 150\ Btu/(h{\cdot}ft^3{\cdot}°R)$
$T_j = 593\ °R$	$A = 250\ ft^2$
$F_j = 66.4\ ft^3/h$	$T_{j0} = 530\ °R$
$V_j = 3.85\ ft^3$	$T_0 = 530\ °R$
$K_0 = 7.08\times10^{10}\ h^{-1}$	$\lambda = -30000$ Btu/mol
E = 30000 Btu/mol	$C_p = 0.75\ Btu/(lb_m{\cdot}°R)$
$R = 1.99\ Btu/(mol{\cdot}°R)$	$C_{pj} = 1.0\ Btu/(lb_m{\cdot}°R)$
$FJ_{MAX} = 199.6\ ft^3/h$	$\rho = 50\ lb{\cdot}mol/ft^3$
$F_{MAX} = 64.8\ ft^3/h$	$\rho_j = 62.3\ lb{\cdot}mol/ft^3$
$F_{IMAX} = 41\ ft^3/h$	
KC(1) = −1.2 psi/°R	$\tau_i(1) = 353$ sec
KC(2) = −0.5	$\tau_i(2) = 2$ sec
$KC(3) = -600\ psi{\cdot}sec/ft^3$	$\tau_i(3) = 60$ sec
KC(4) = 300 psi/ft	$\tau_i(4) = 900$ sec

APPENDIX 2

THE STABLE CSTR PROCESS RESPONSES UNDER DIFFERENT FAULTS

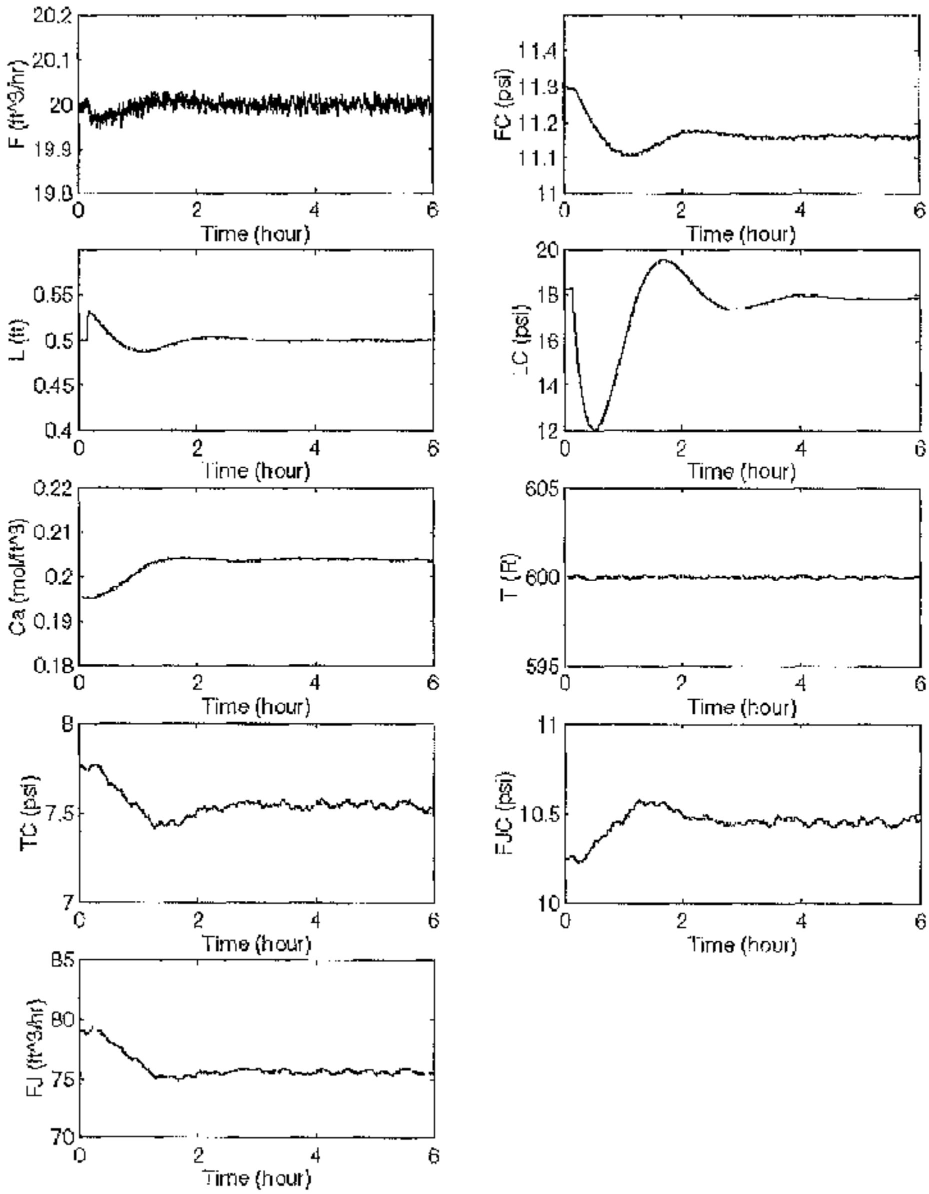


Figure A2-1: The stable CSTR process responses under L-sensor-bias-high

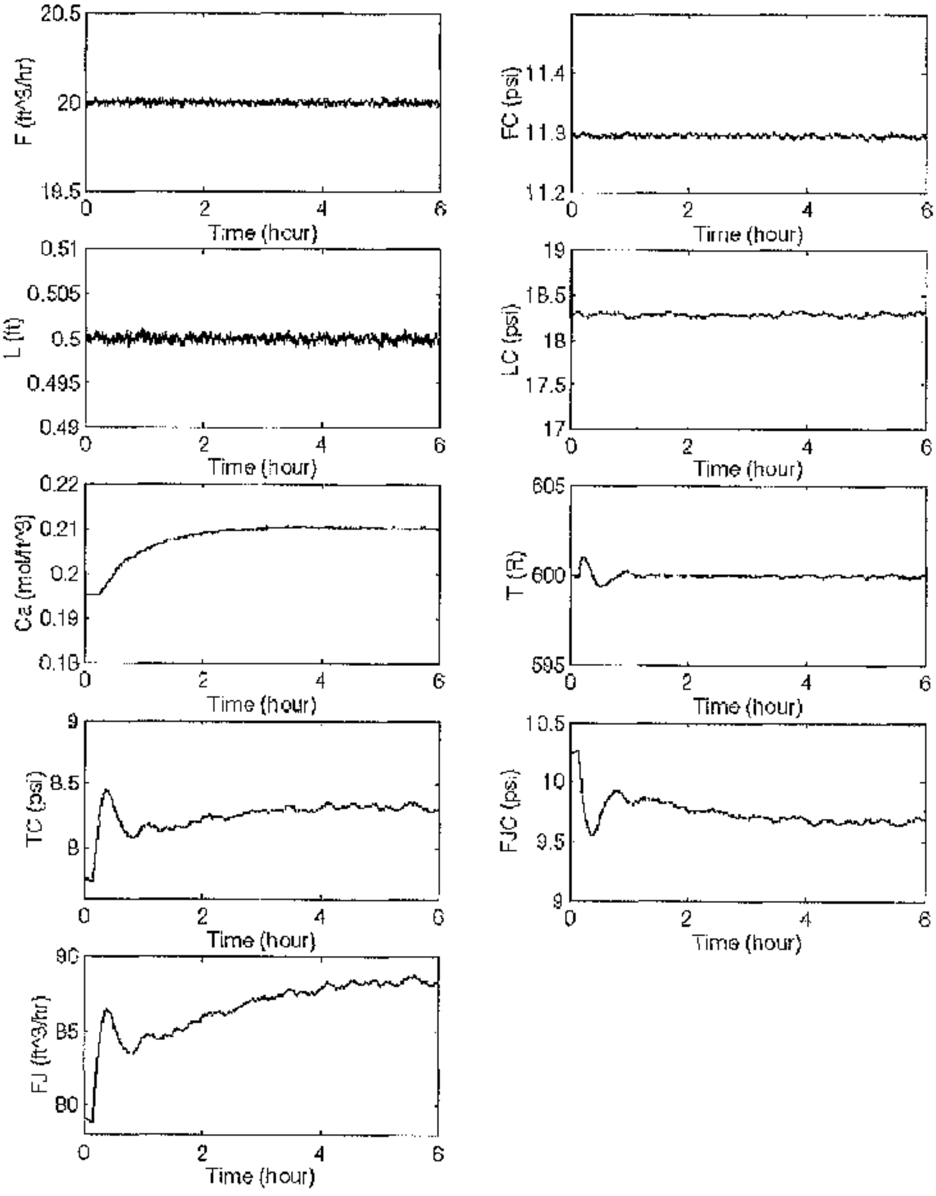


Figure A2-2: The stable CSTR process responses under T-sensor-bias-high

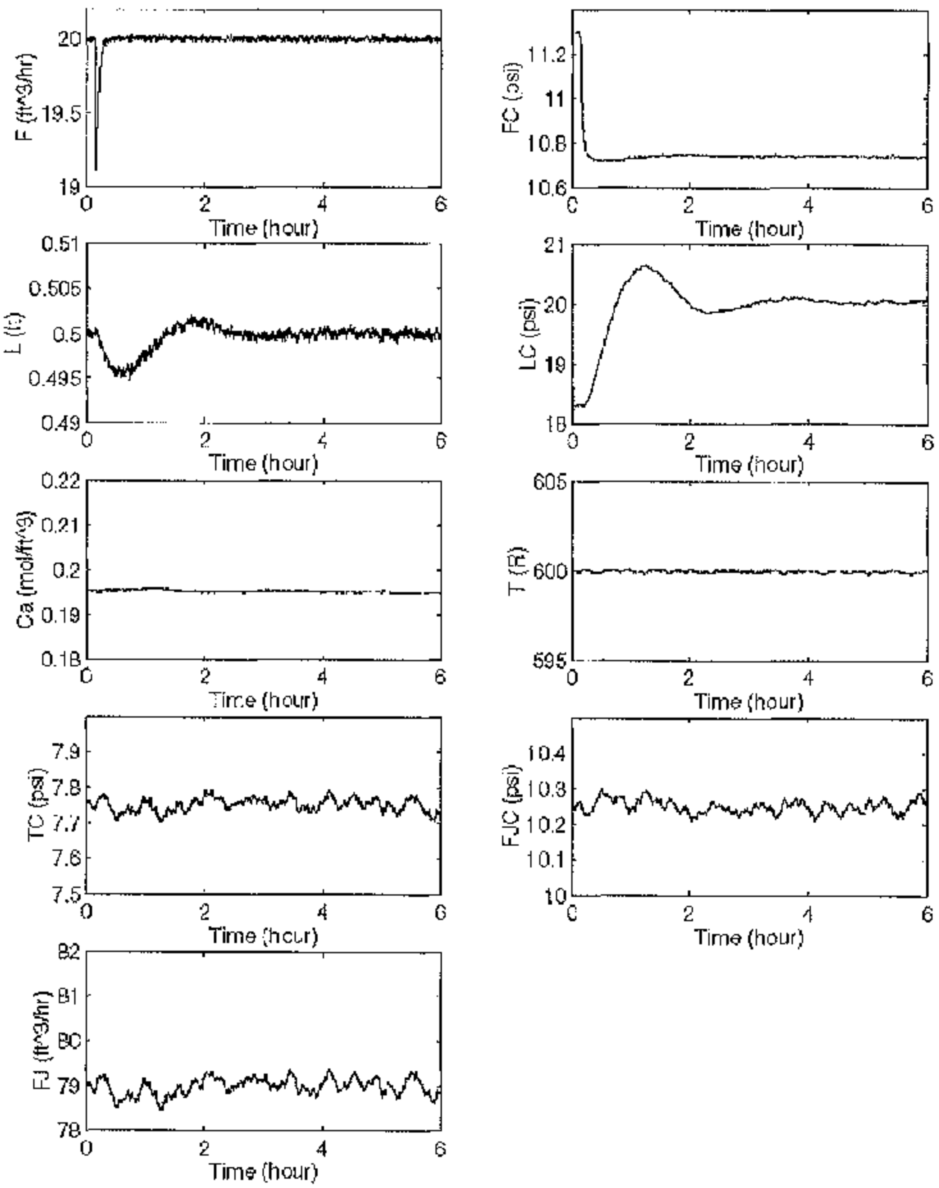


Figure A2-3: The stable CSTR process responses under F-sensor-bias-low

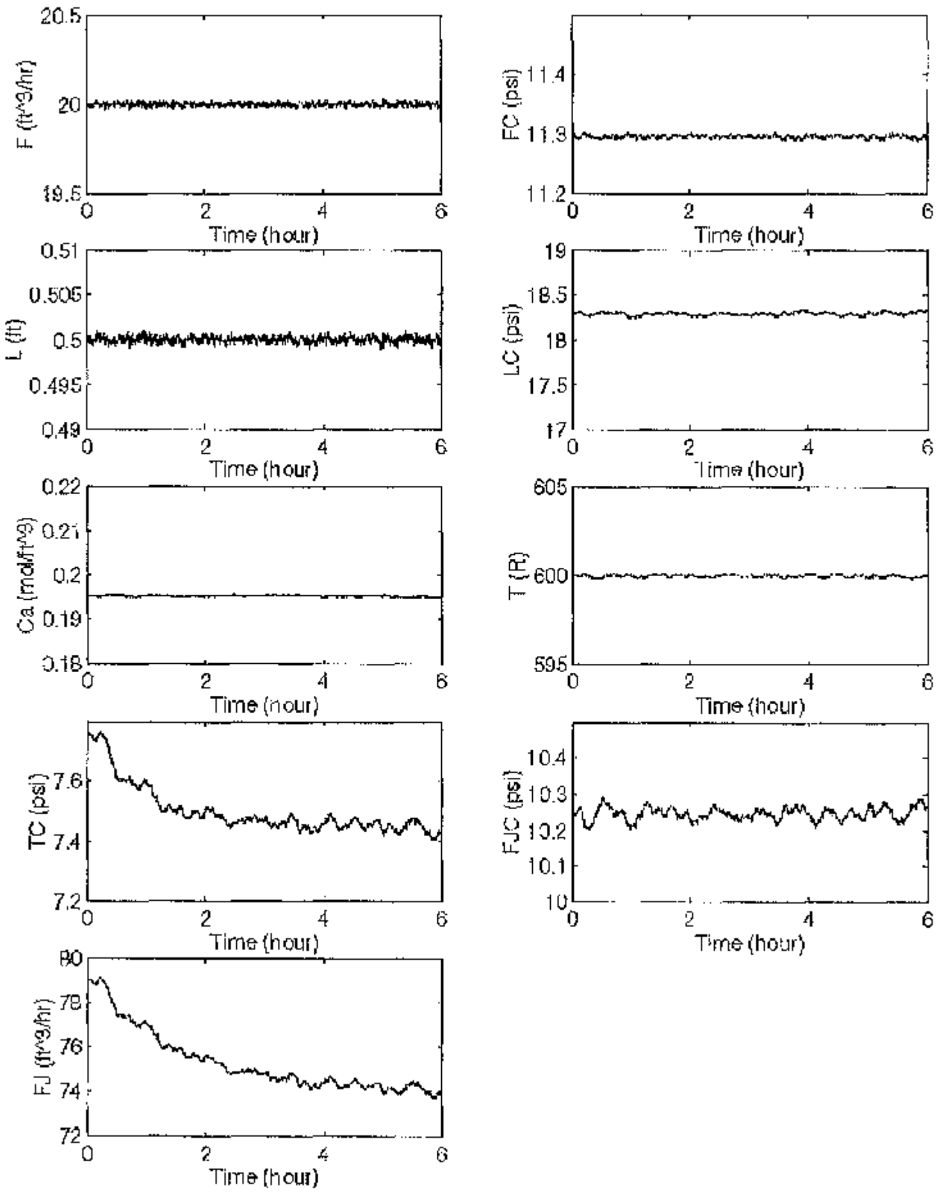


Figure A2-4: The stable CSTR process responses under FJ-sensor-bias-low

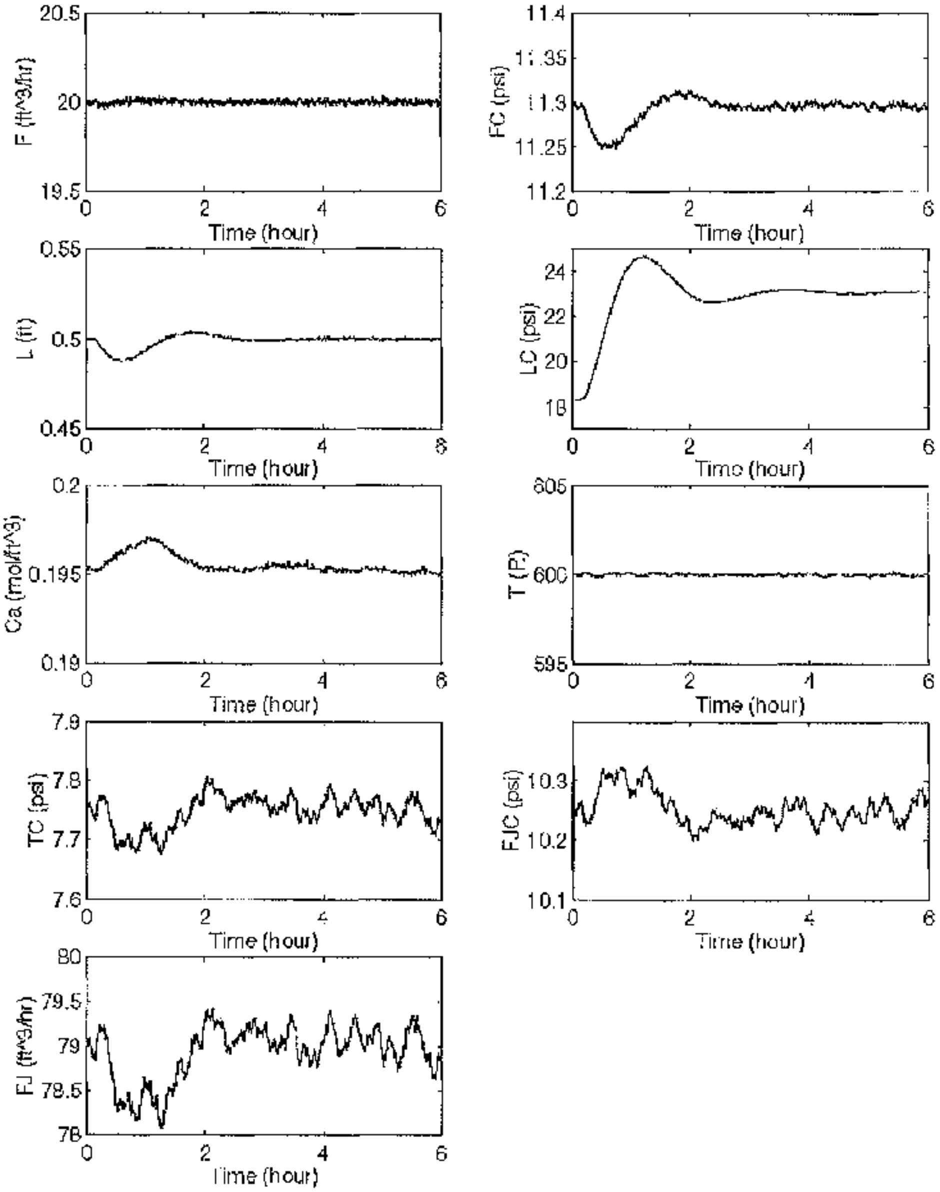


Figure A2-5: The stable CSTR process responses under LV-valve-bias-high

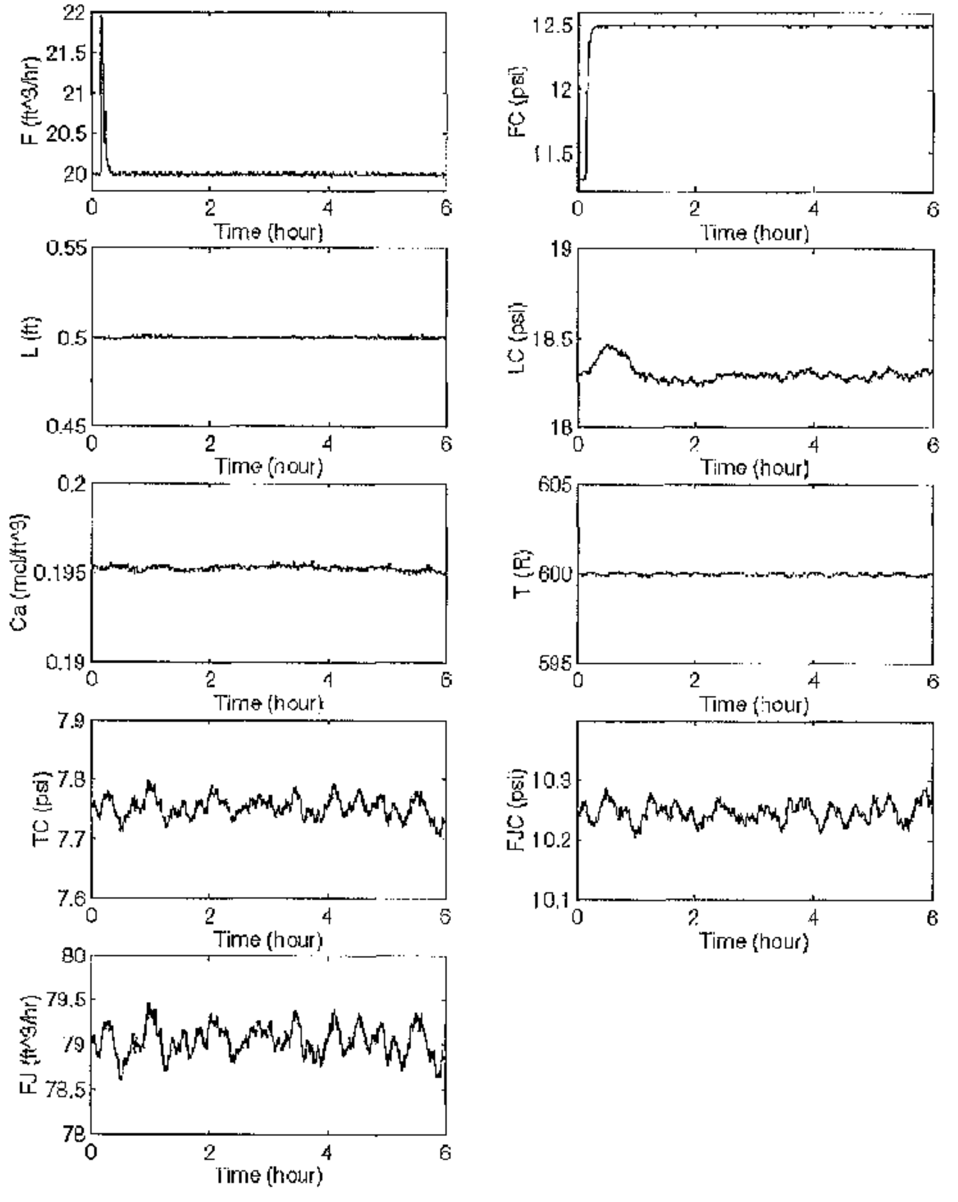


Figure A2-6: The stable CSTR process responses under FV-valve-bias-high

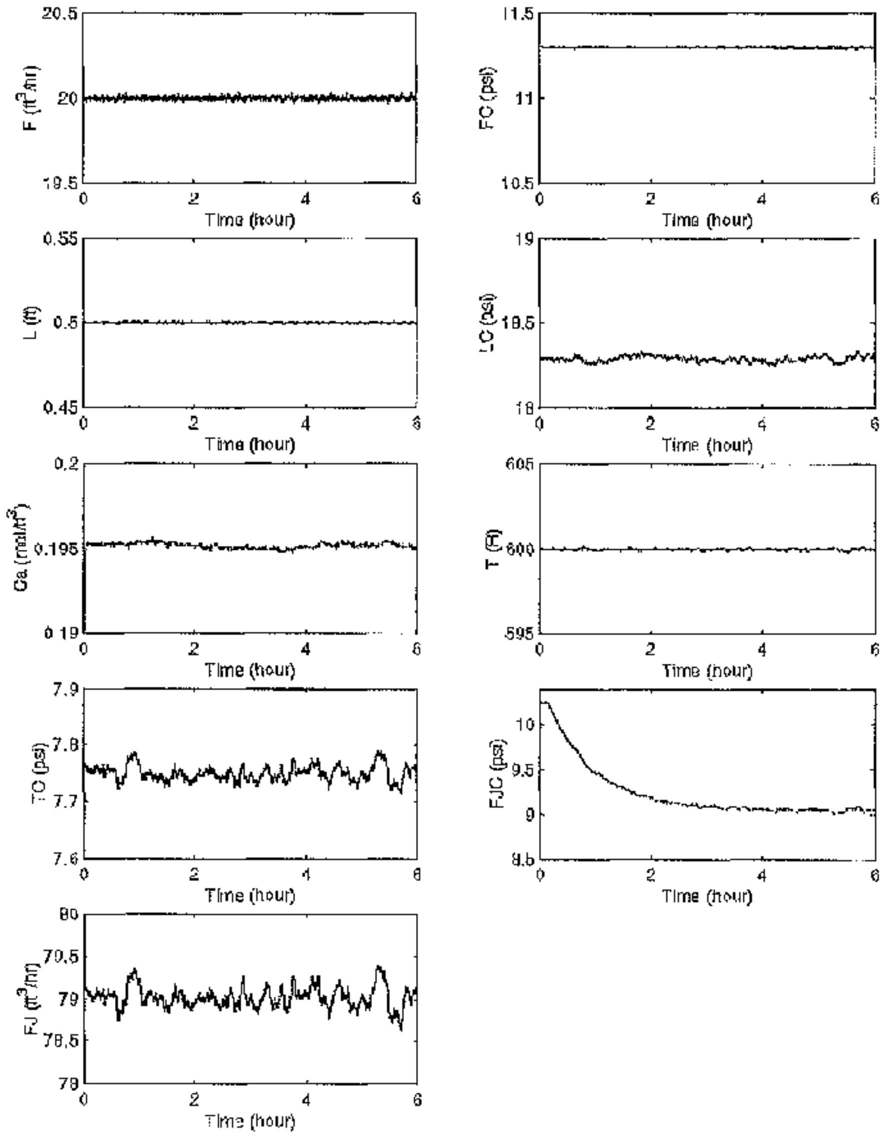


Figure A2-7: The stable CSTR process responses under FJV-valve-bias-low

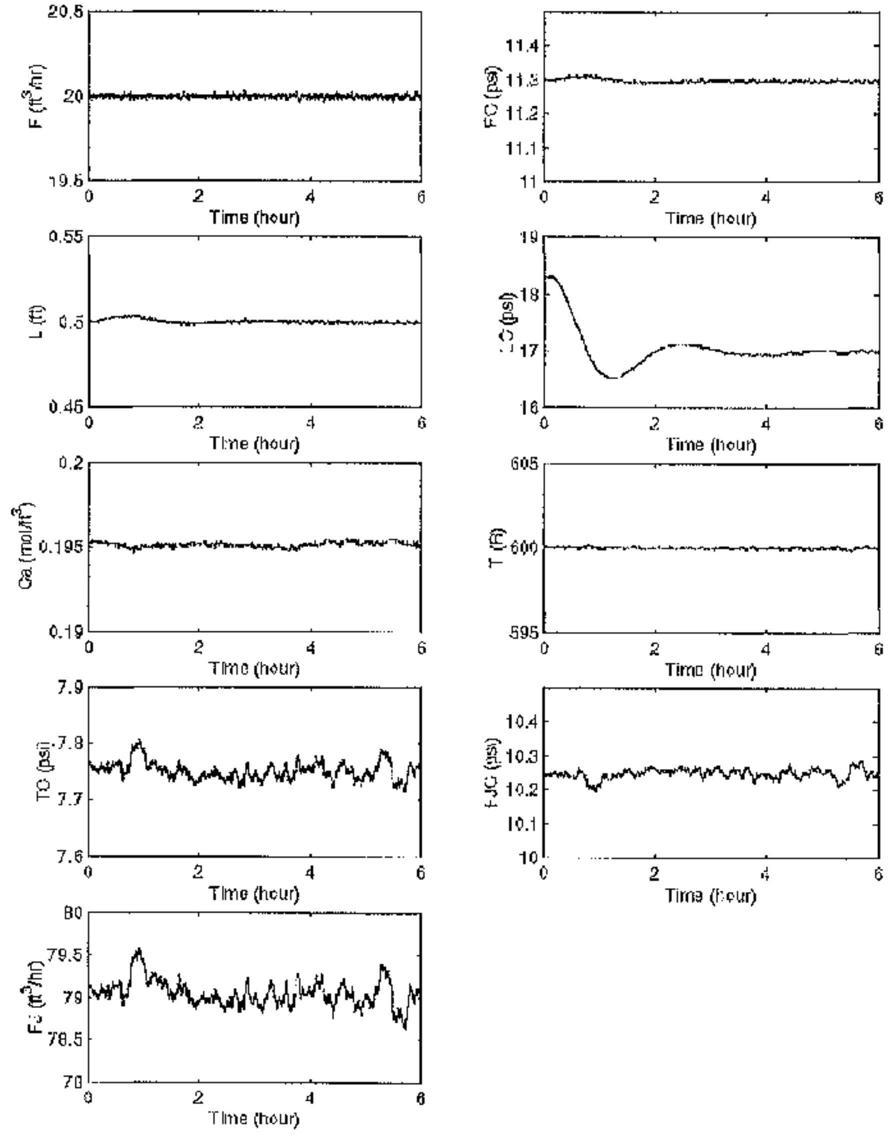


Figure A2-8: The stable CSTR process responses under low F_{IMAX}

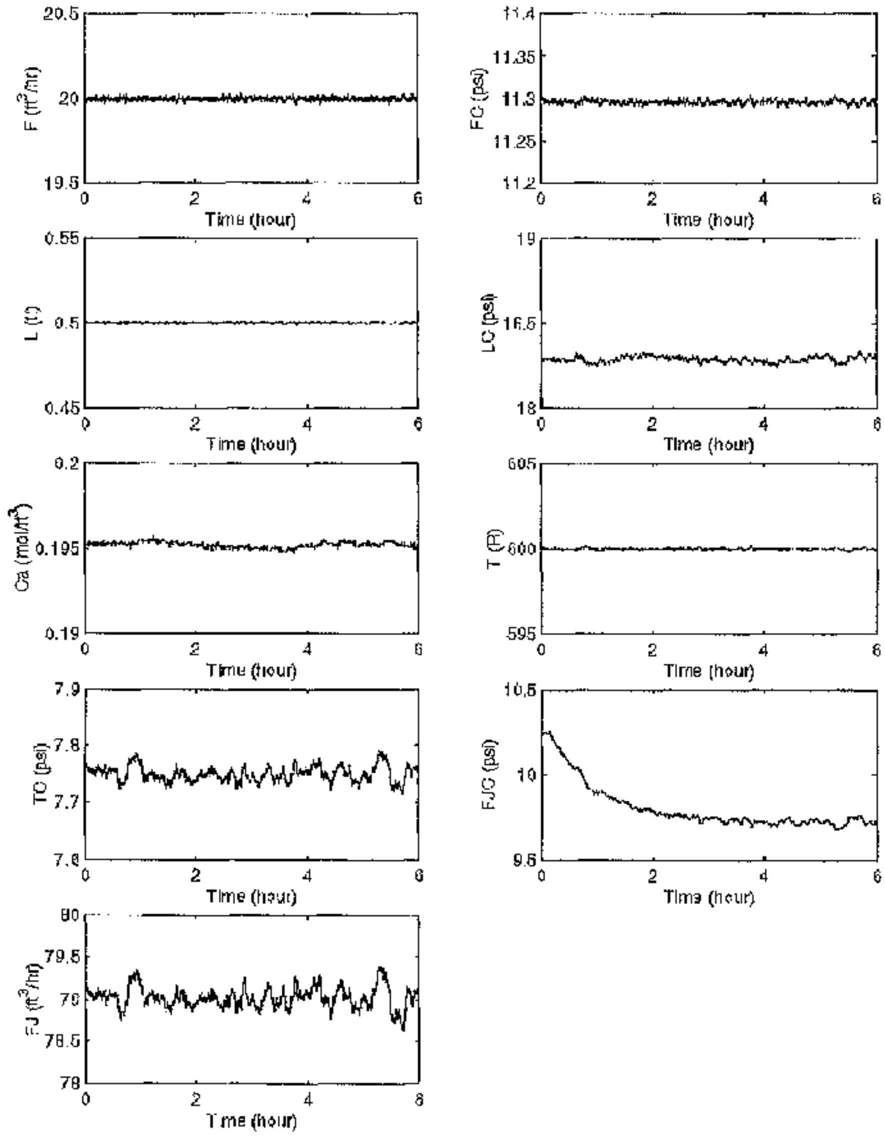


Figure A2-9: The stable CSTR process responses under low FJ_{MAX}

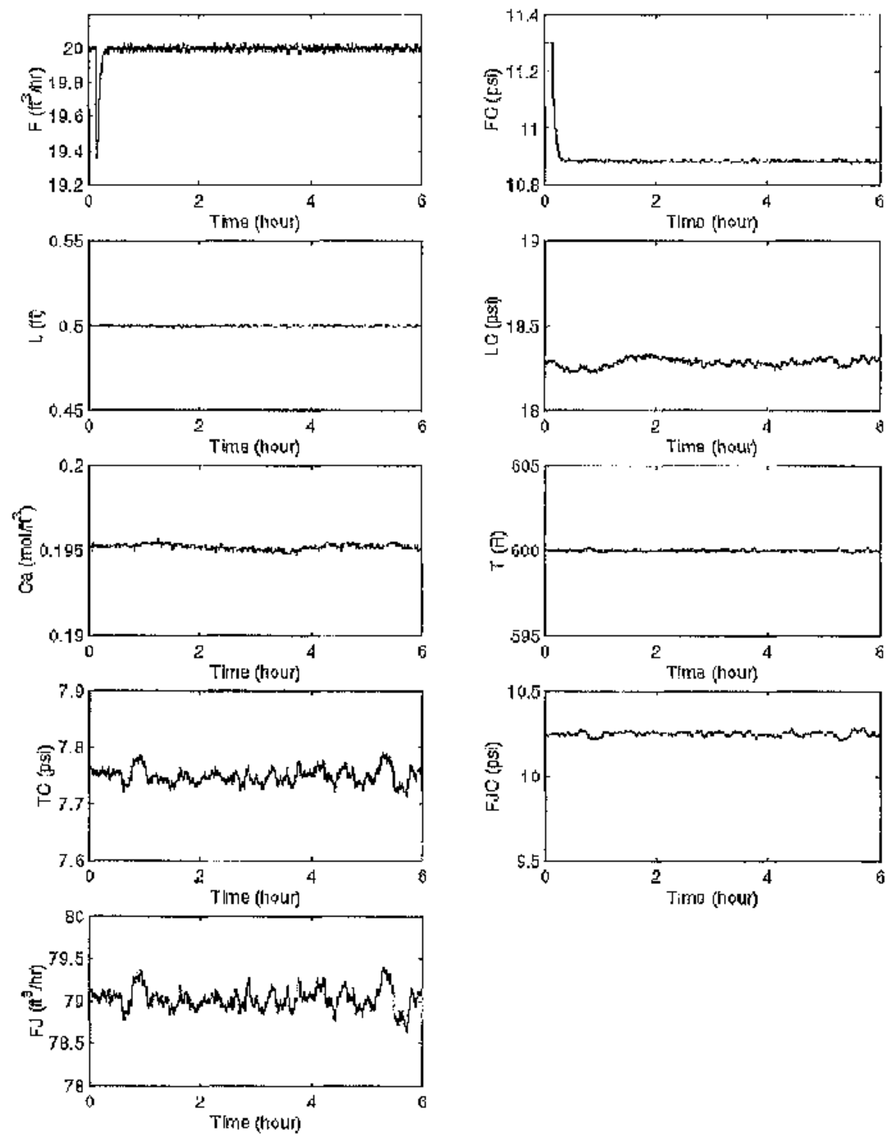


Figure A2-10: The stable CSTR process responses under low F_{MAX}

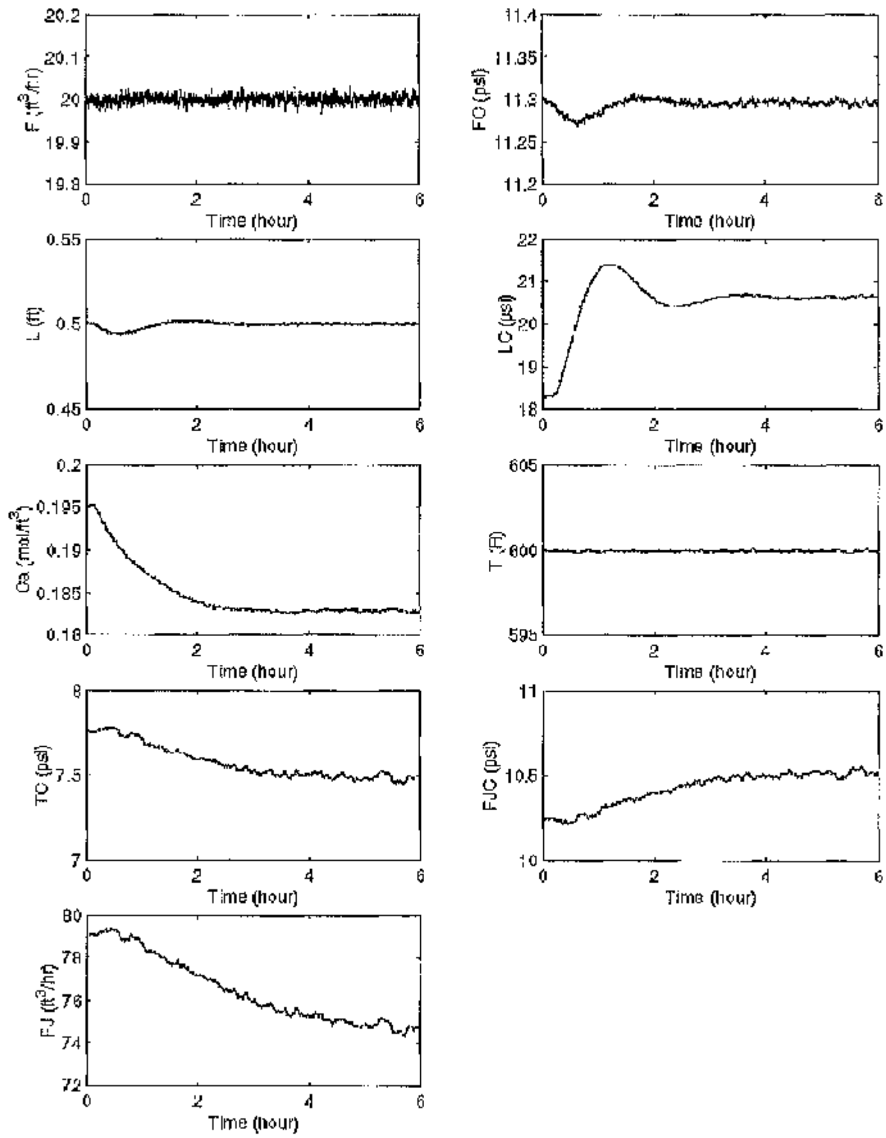


Figure A2-11: The stable CSTR process responses under low F_0

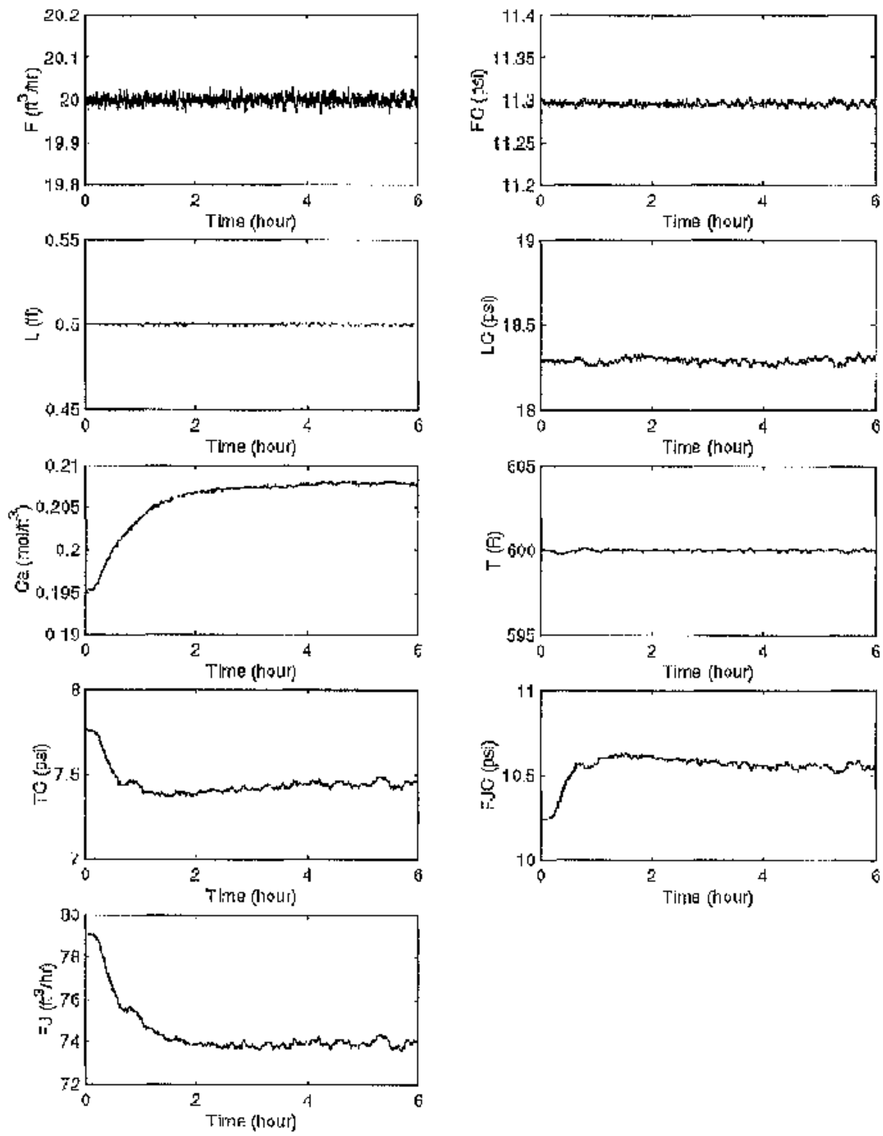


Figure A2-12: The stable CSTR process responses under low K_0

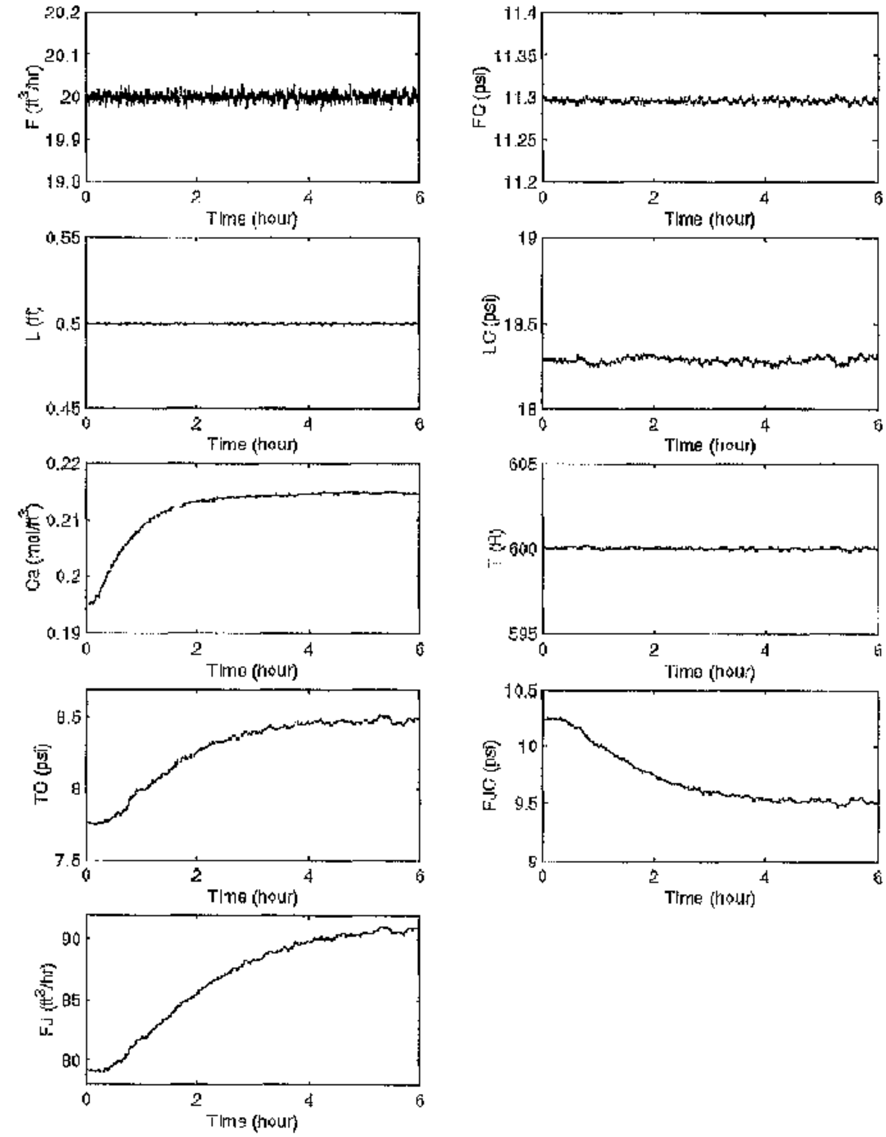


Figure A2-13: The stable CSTR process responses under high C_{A0}

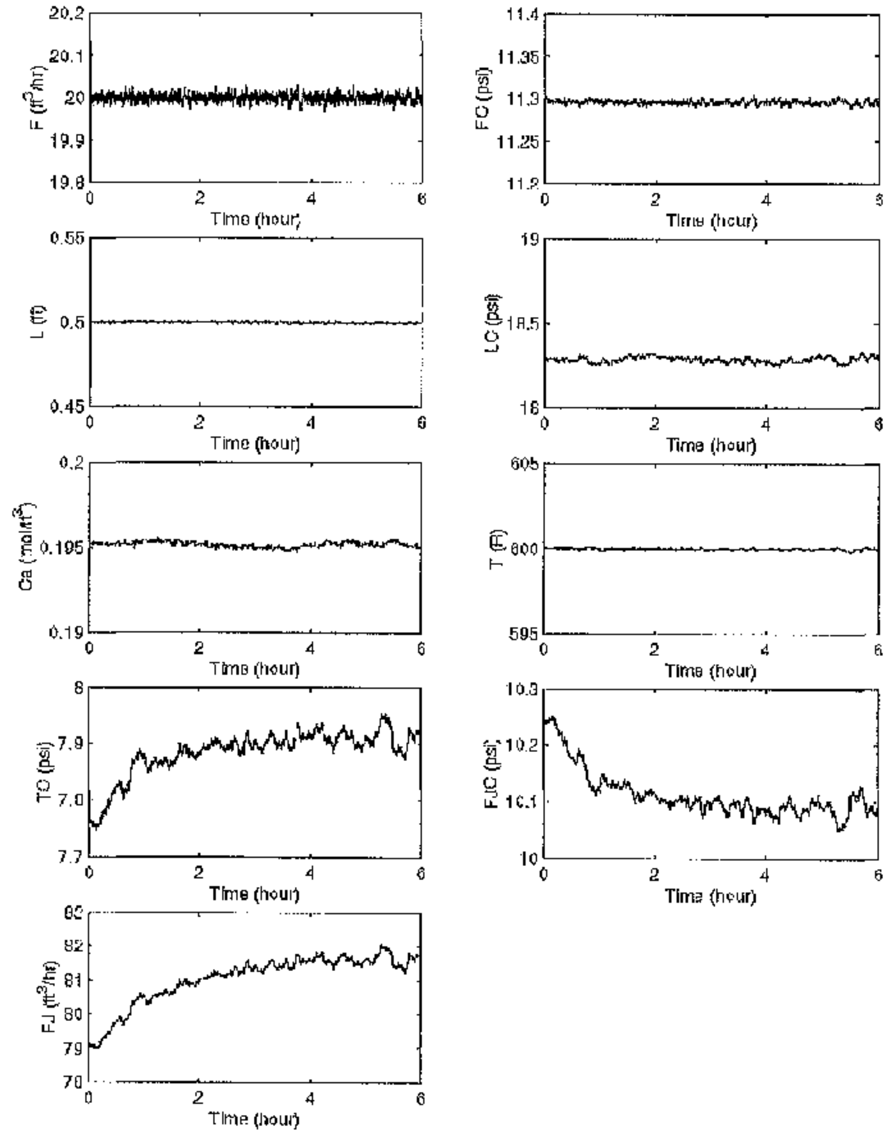


Figure A2-14: The stable CSTR process responses under low U_0

APPENDIX 3

THE UNSTABLE CSTR PROCESS RESPONSES UNDER DIFFERENT FAULTS

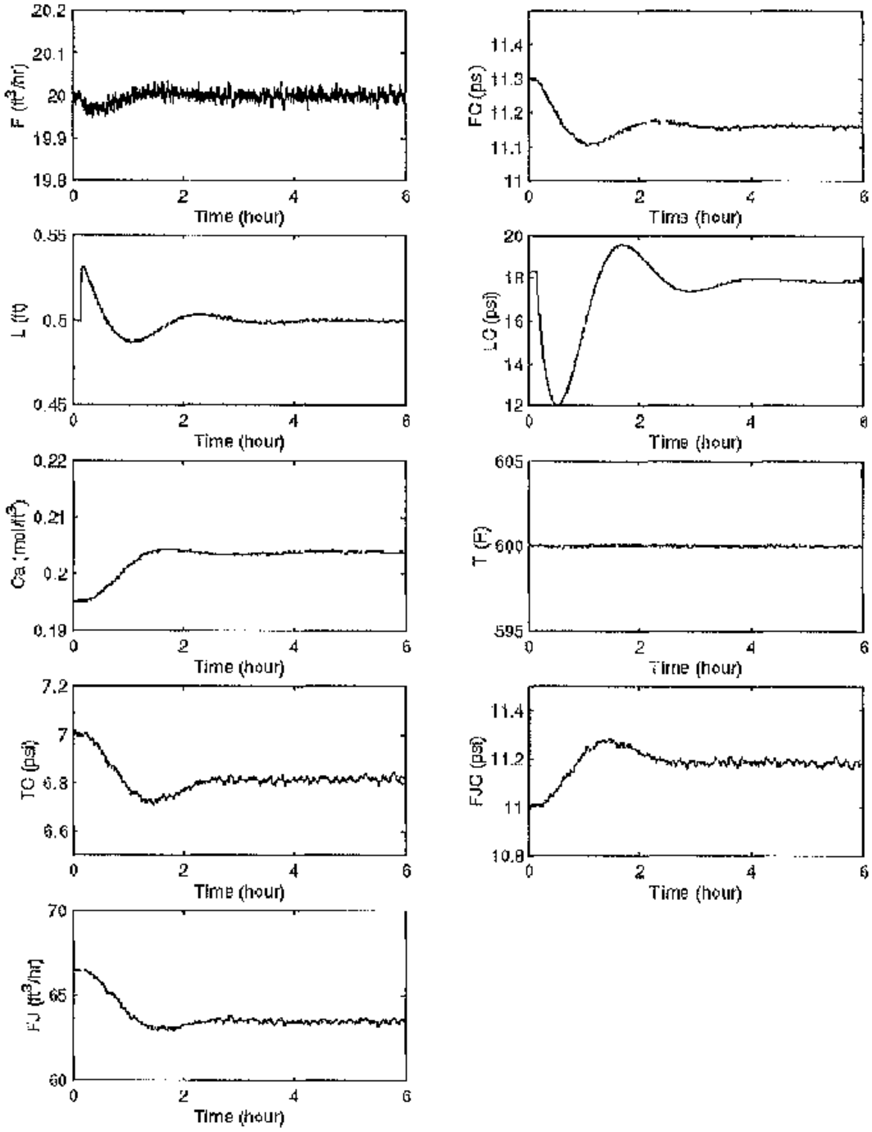


Figure A3-1: The unstable CSTR process responses under L-sensor-bias-high

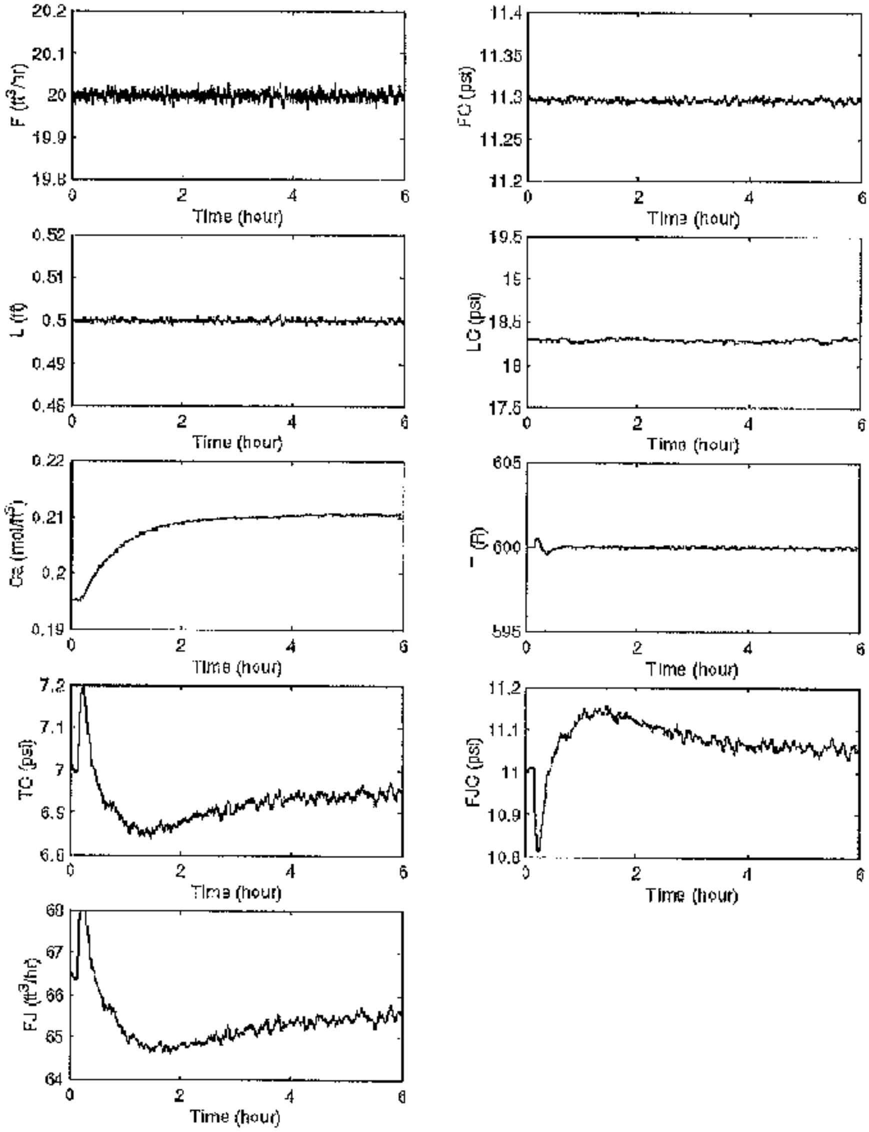


Figure A3-2: The unstable CSTR process responses under T-sensor-bias-high

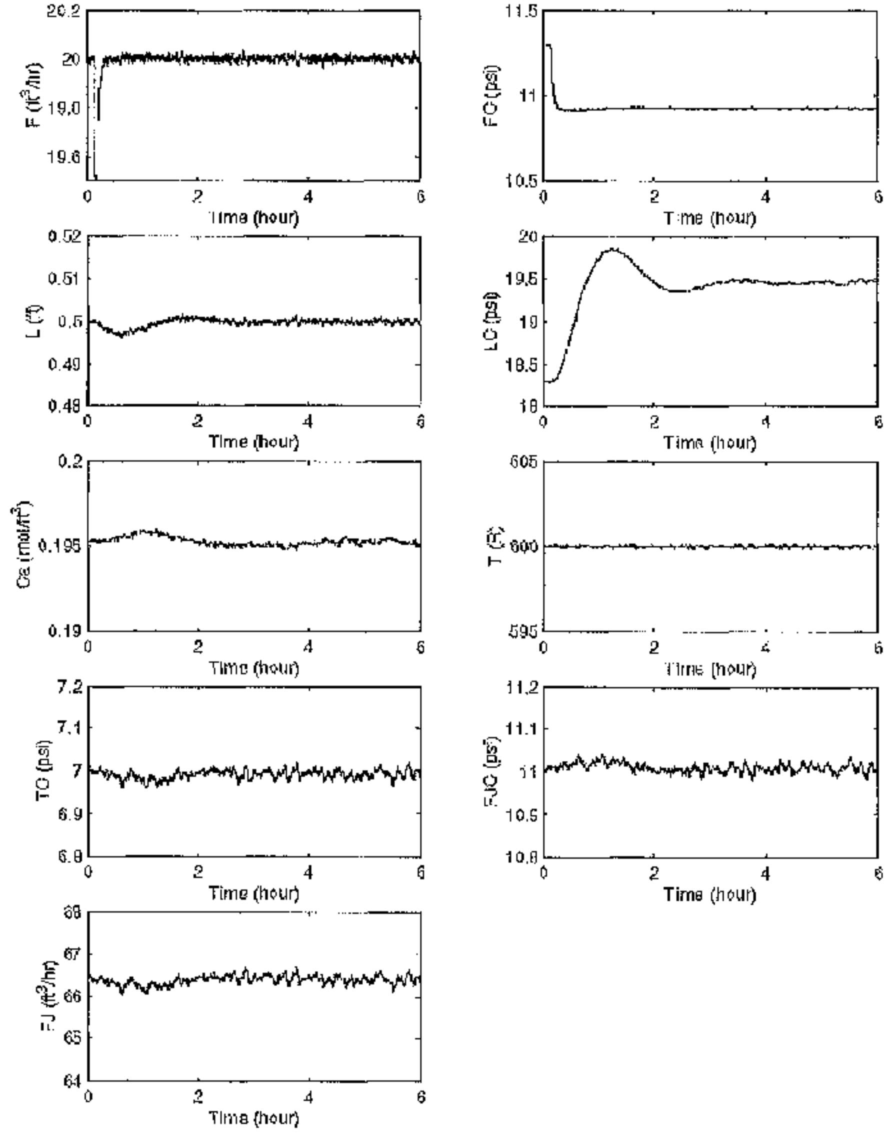


Figure A3-3: The unstable CSTR process responses under F-sensor-bias-low

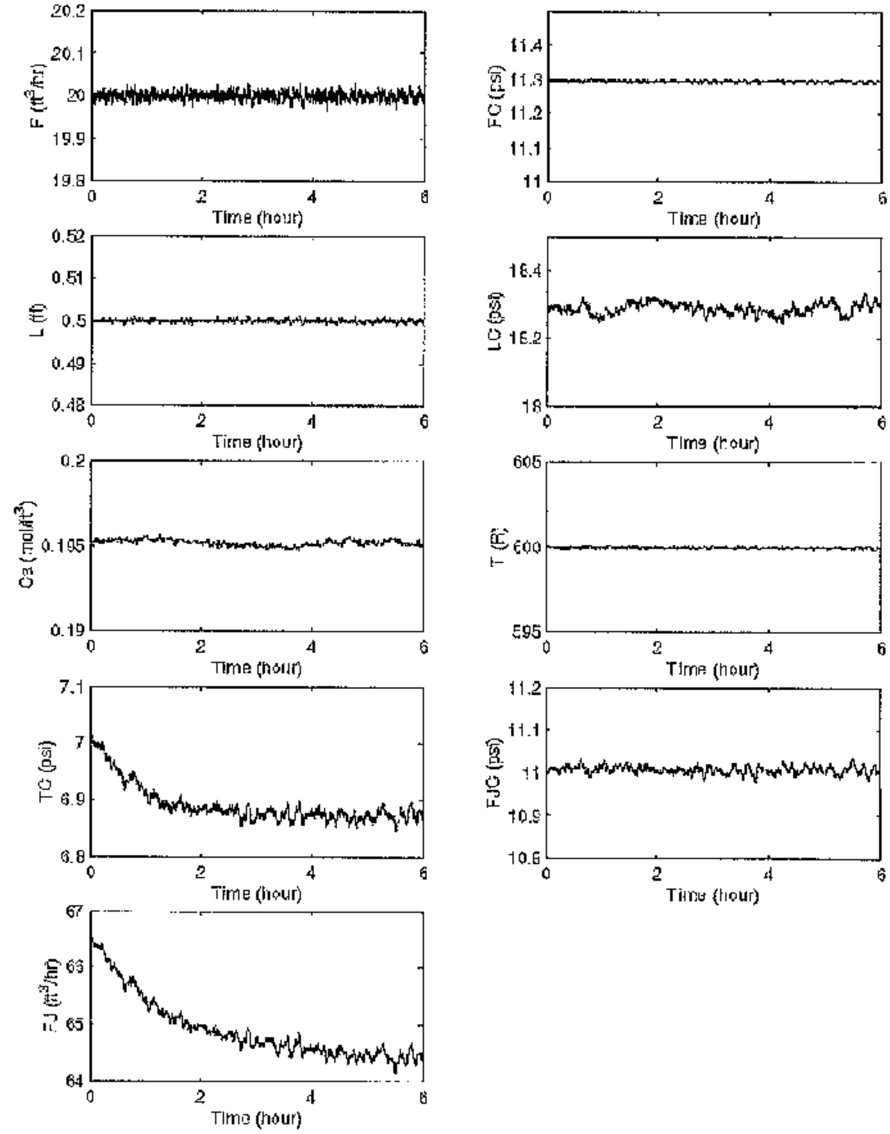


Figure A3-4: The unstable CSTR process responses under FJ-sensor-bias-low

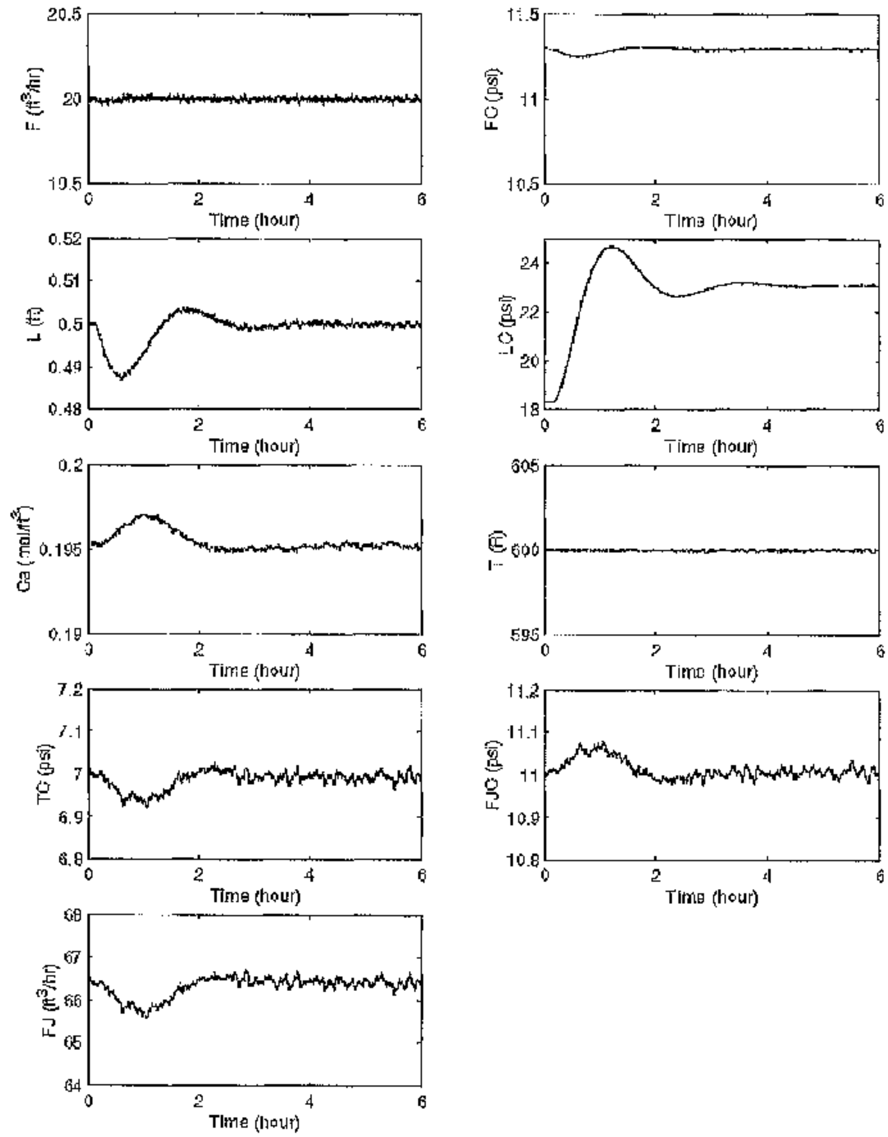


Figure A3-5: The unstable CSTR process responses under LV-valve-bias-high

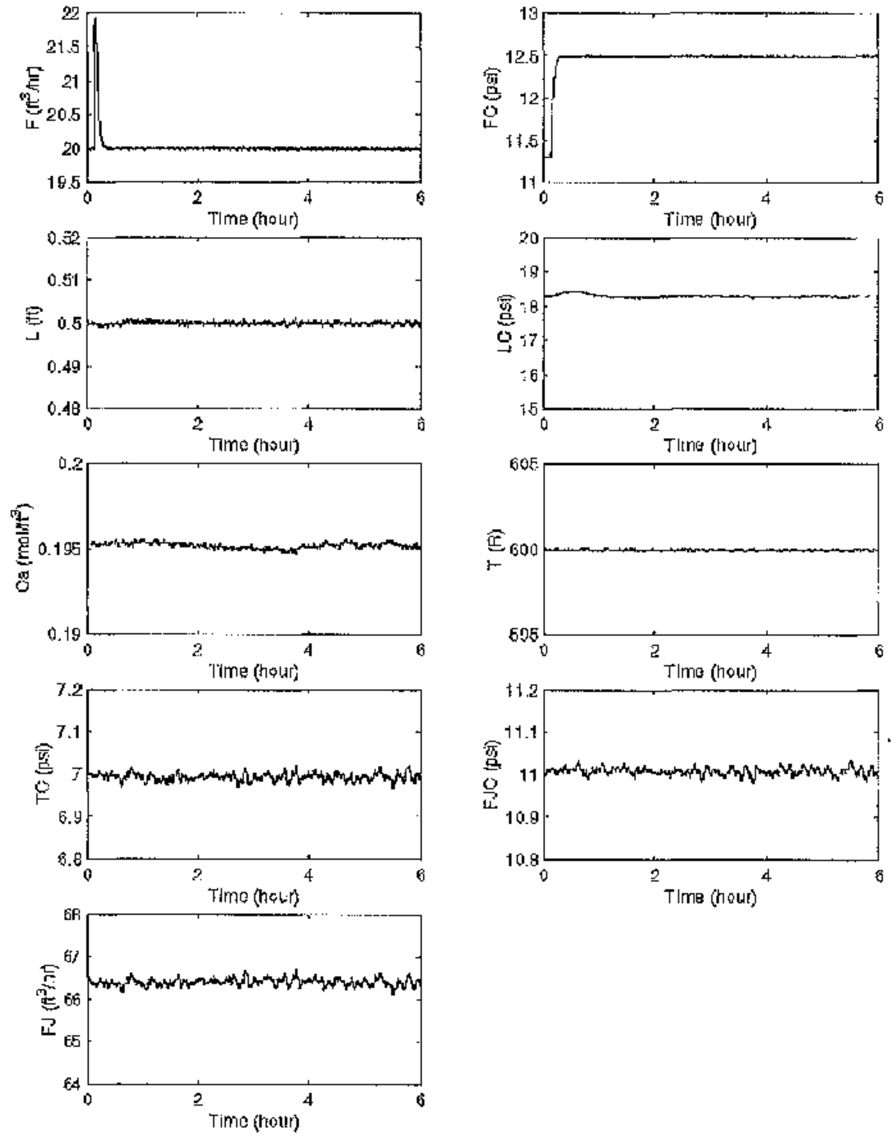


Figure A3-6: The unstable CSTR process responses under FV-valve-bias-high

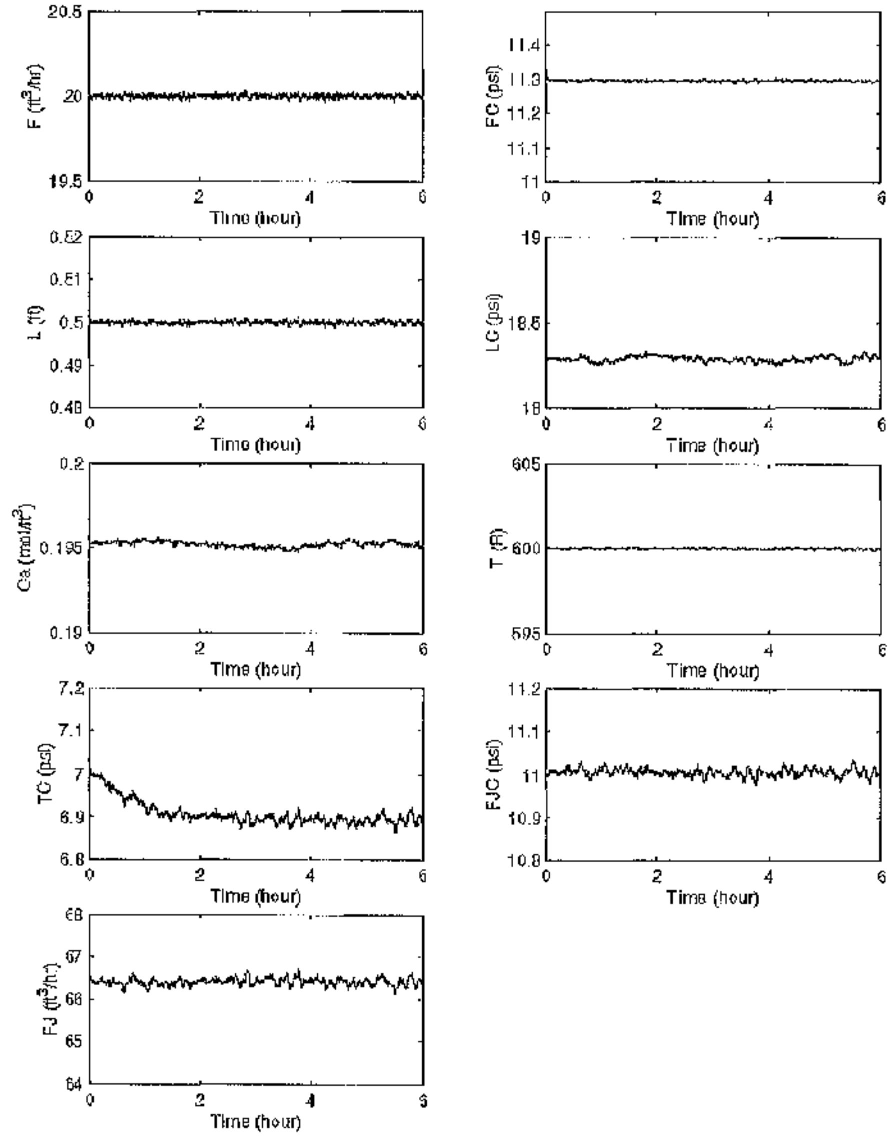


Figure A3-7: The unstable CSTR process responses under FJV-valve-bias-low

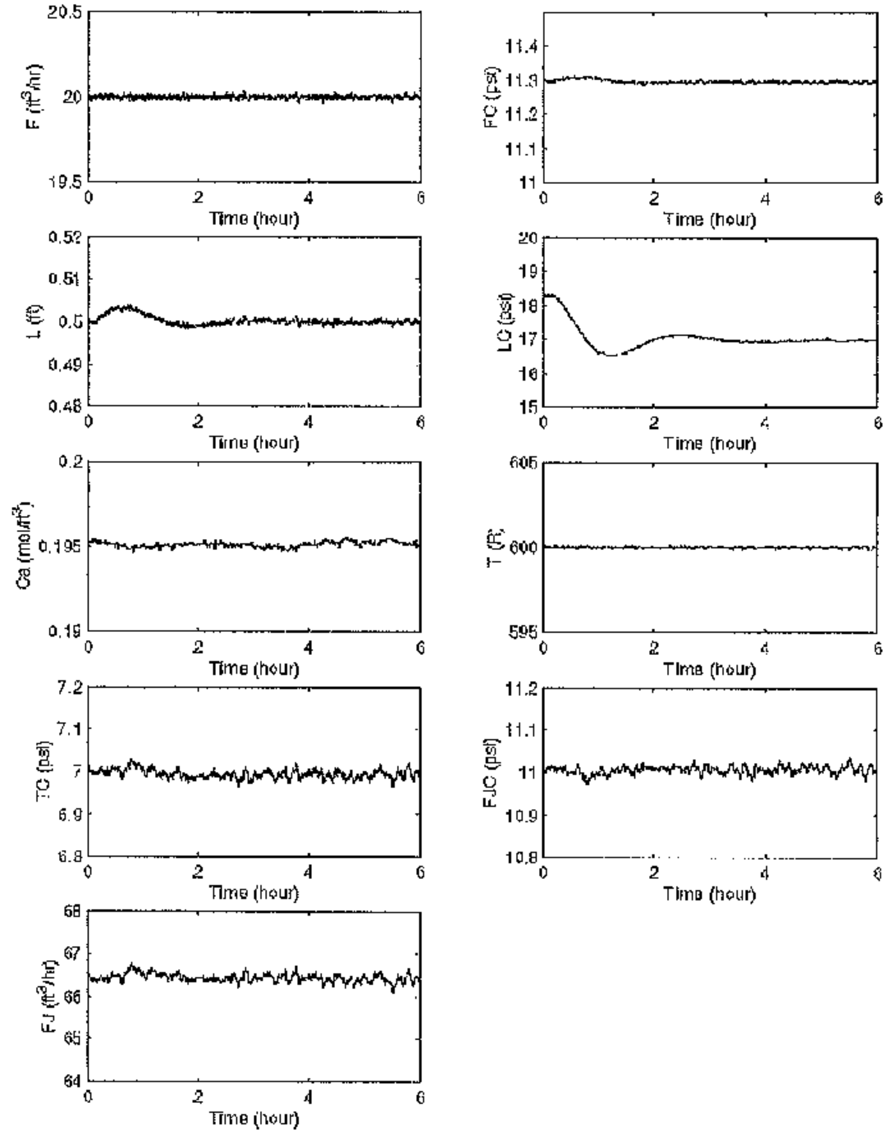


Figure A3-8: The unstable CSTR process responses under low F_{JMAX}

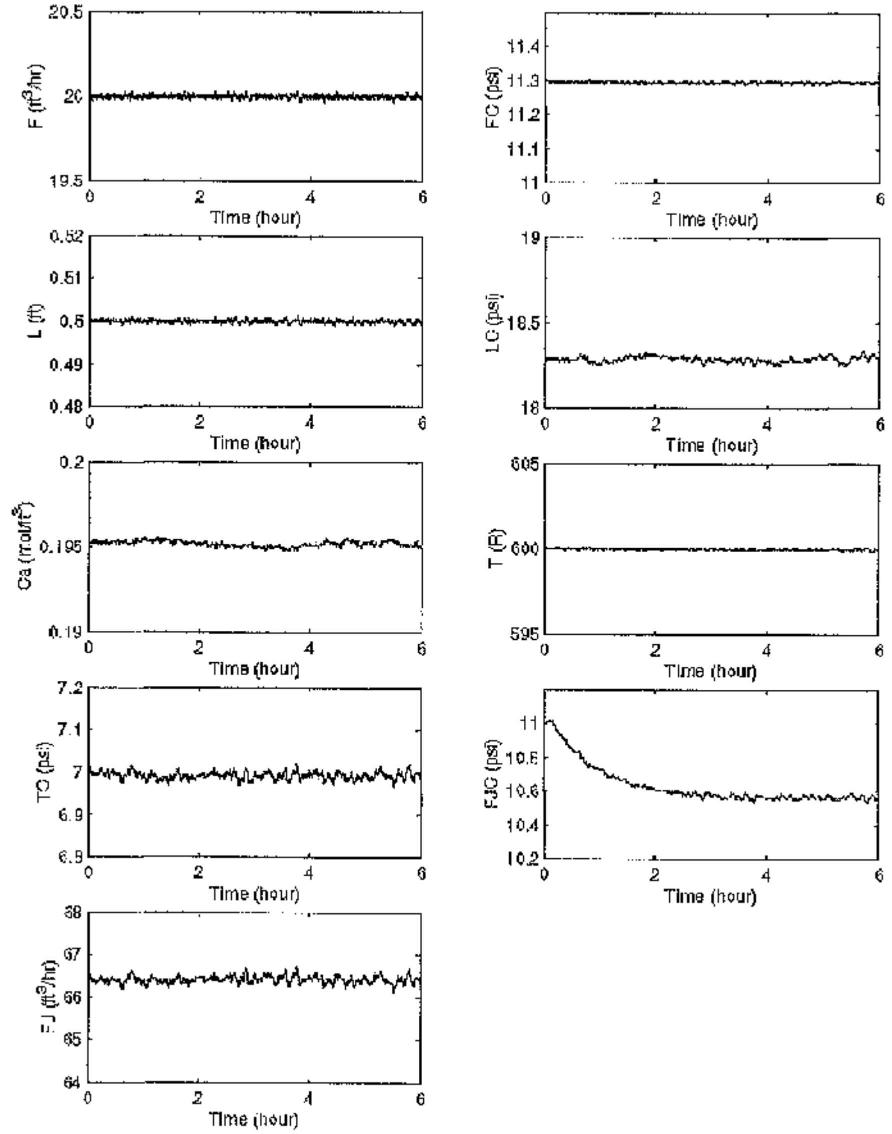


Figure A3-9: The unstable CSTR process responses under low FJ_{MAX}

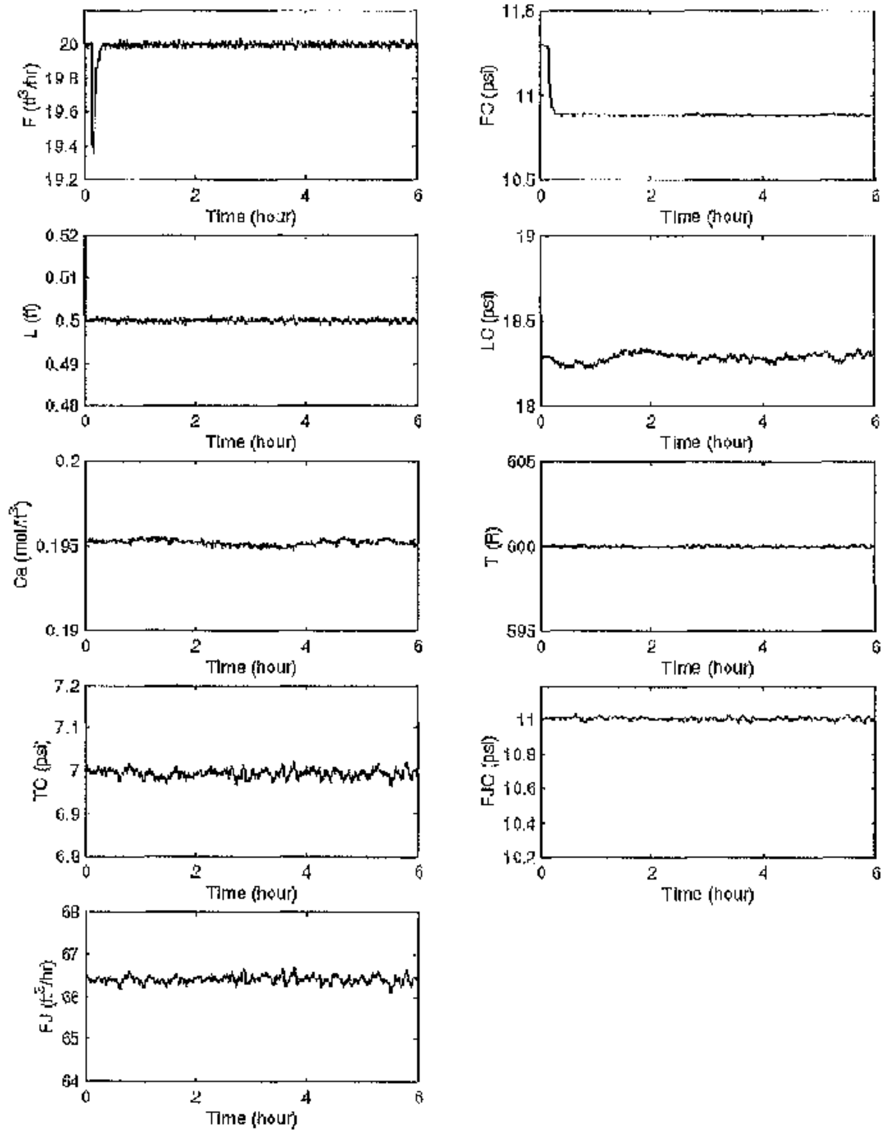


Figure A3-10: The unstable CSTR process responses under low F_{MAX}

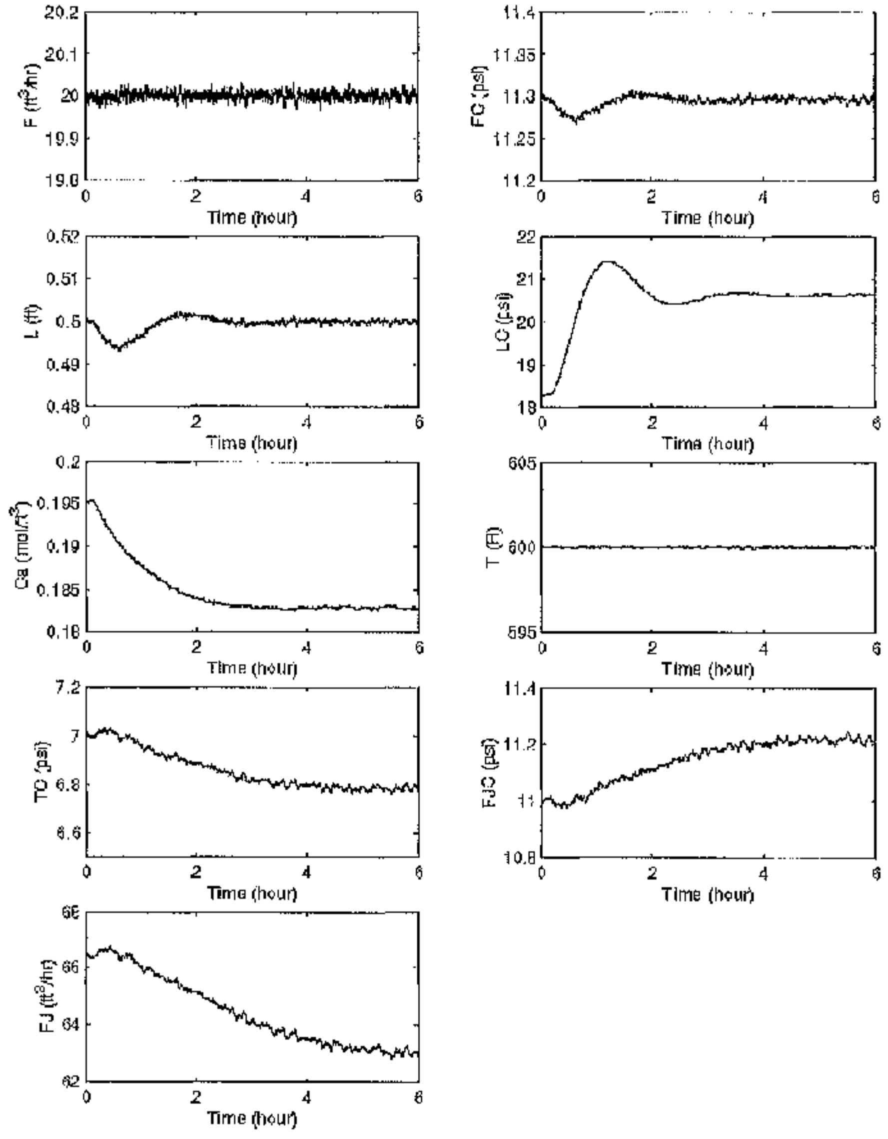


Figure A3-11: The unstable CSTR process responses under low F_0

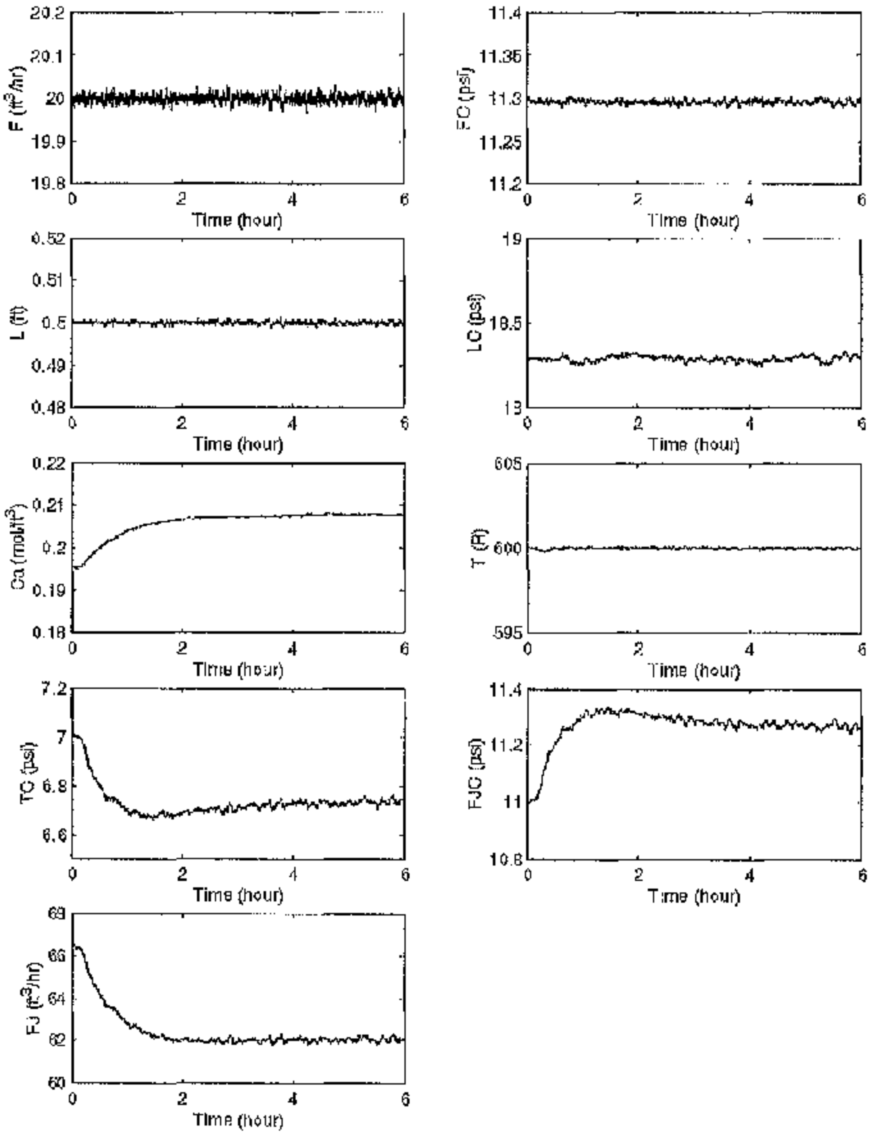


Figure A3-12: The unstable CSTR process responses under low K_0

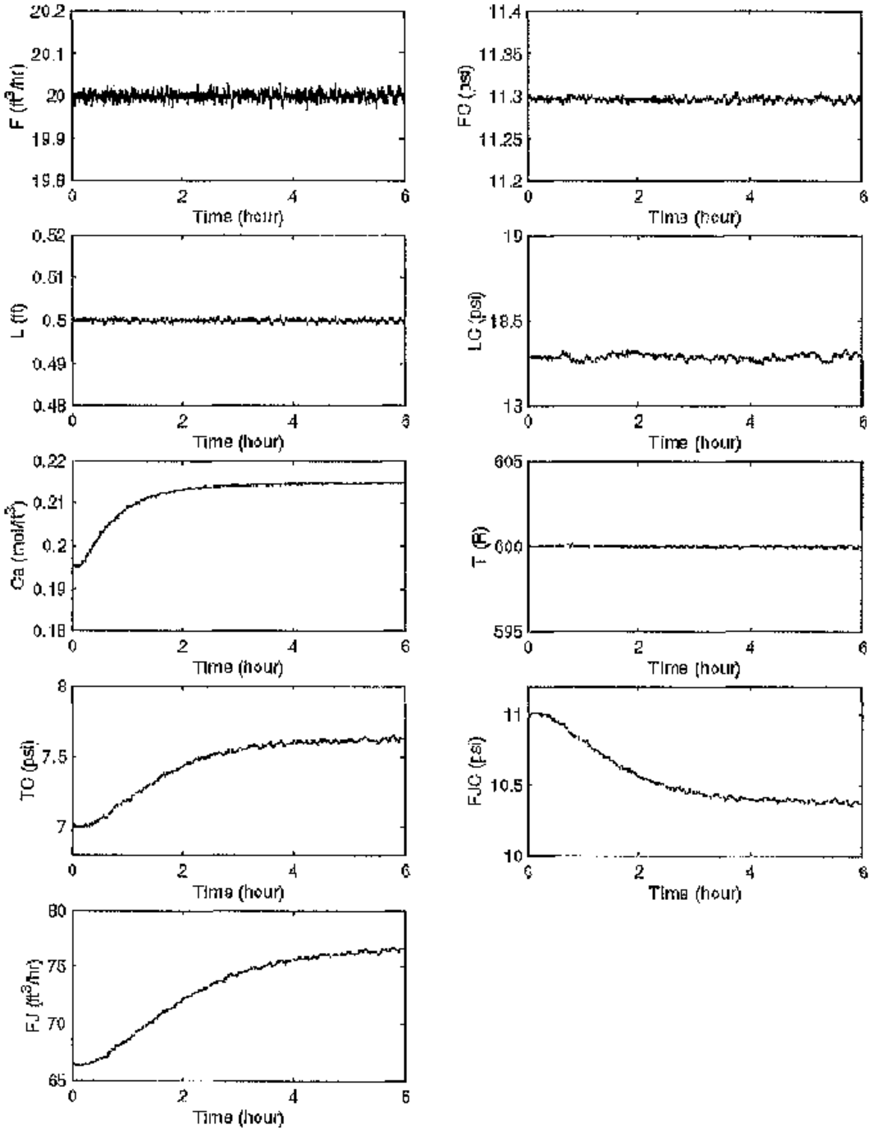


Figure A3-13: The unstable CSTR process responses under high C_{A0}

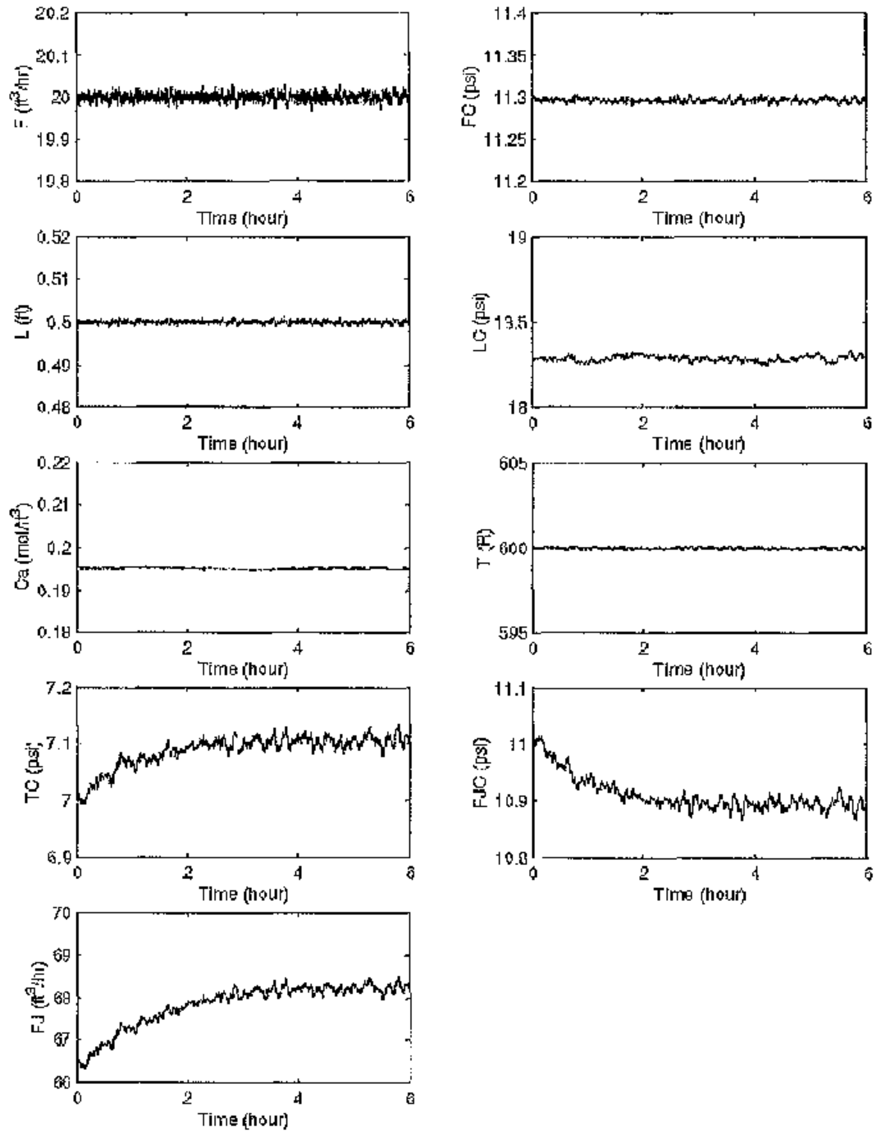


Figure A3-14: The unstable CSTR process responses under low U_0

APPENDIX 4

THE TENNESSEE EASTMAN PROCESS BENCHMARK

A4.1 Process Measurements and Manipulated Variables

Table A4-1: Process manipulated variables

Variable name	Variable number	Base case Value (%)	Low limit	High limit	Units
D feed flow (stream 2)	XMV(1)	63.053	0	5811	kgh^{-1}
E feed flow (stream 3)	XMV(2)	53.980	0	8354	kgh^{-1}
A feed flow (stream 1)	XMV(3)	24.644	0	1.017	kscmh
A and C feed flow (stream 4)	XMV(4)	61.302	0	15.25	Kscmh
Compressor recycle valve	XMV(5)	22.210	0	100	%
Purge valve (stream 9)	XMV(6)	40.064	0	100	%
Separator pot liquid flow (stream 10)	XMV(7)	38.100	0	65.71	m^3h^{-1}
Stripper liquid product flow (stream 11)	XMV(8)	46.534	0	49.10	m^3h^{-1}
Stripper steam valve	XMV(9)	47.446	0	100	%
Reactor cooling water flow	XMV(10)	41.106	0	227.1	m^3h^{-1}
Condenser cooling water flow	XMV(11)	18.114	0	272.6	m^3h^{-1}
Agitator speed	XMV(12)	50.000	150	250	rpm

Table A4-2: Continuous process measurements

Variable name	Variable number	Base case value	Units
A feed (stream 1)	XMEAS(1)	0.25052	kscmh
D feed (stream 2)	XMEAS(2)	3664.0	kgh^{-1}
E feed (stream 3)	XMEAS(3)	4509.3	kgh^{-1}
A and C feed (stream 4)	XMEAS(4)	9.3477	kscmh
Recycle flow (stream 8)	XMEAS(5)	26.902	kscmh
Reactor feed rate (stream 6)	XMEAS(6)	42.339	kscmh
Reactor pressure	XMEAS(7)	2705.0	kPa gauge
Reactor level	XMEAS(8)	75.000	%
Reactor temperature	XMEAS(9)	120.40	°C
Purge rate (stream 9)	XMEAS(10)	0.33712	kscmh
Product separator temperature	XMEAS(11)	80.109	°C
Product separator level	XMEAS(12)	50.000	%
Product separator pressure	XMEAS(13)	2633.7	kPa gauge
Product separator underflow (stream 10)	XMEAS(14)	25.160	m^3h^{-1}
Stripper level	XMEAS(15)	50.000	%
Stripper pressure	XMEAS(16)	3102.2	kPa gauge
Stripper underflow (stream 11)	XMEAS(17)	22.949	m^3h^{-1}
Stripper temperature	XMEAS(18)	65.731	°C
Stripper steam flow	XMEAS(19)	230.31	kgh^{-1}
Compressor work	XMEAS(20)	341.43	kW
Reactor cooling water outlet temperature	XMEAS(21)	94.599	°C
Separator cooling water outlet temperature	XMEAS(22)	77.297	°C

A4.2 The Process Responses Under Different Faults/Disturbances

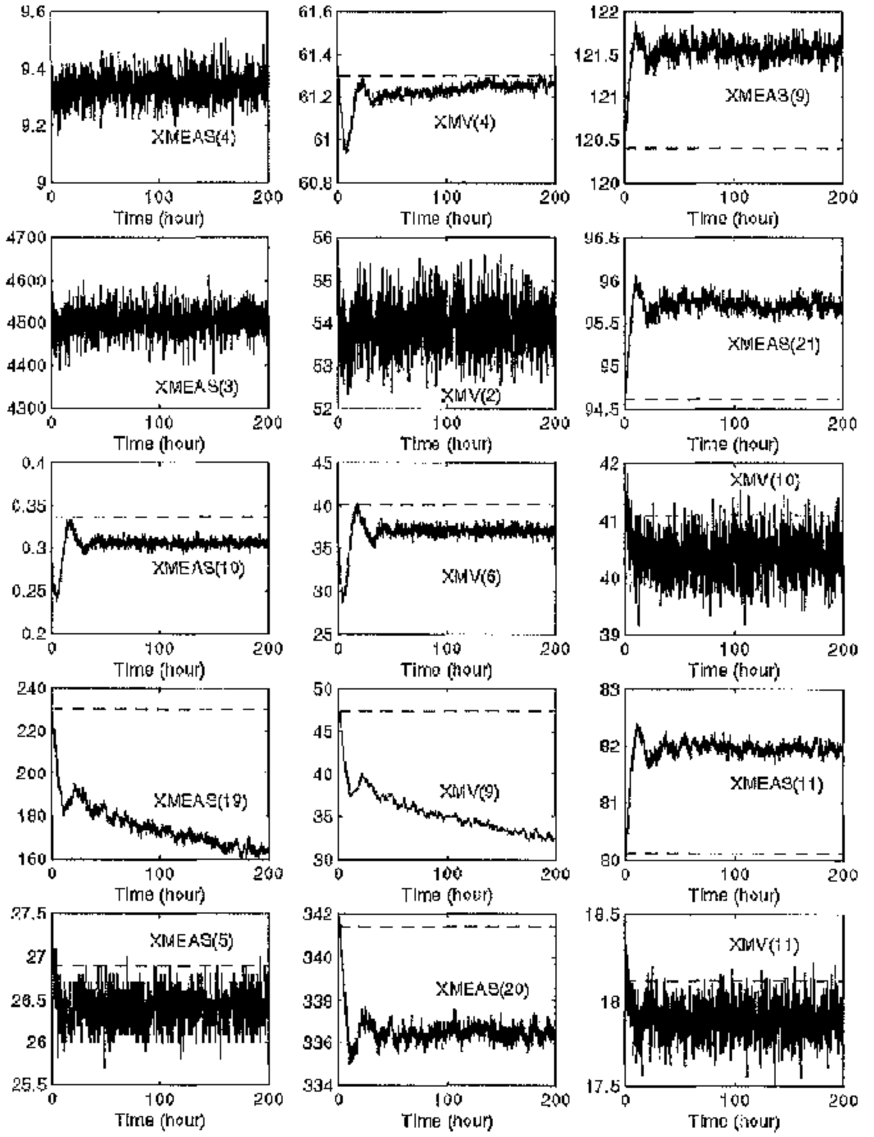


Figure A4-1: Some Tennessee Eastman Process responses under F(1)

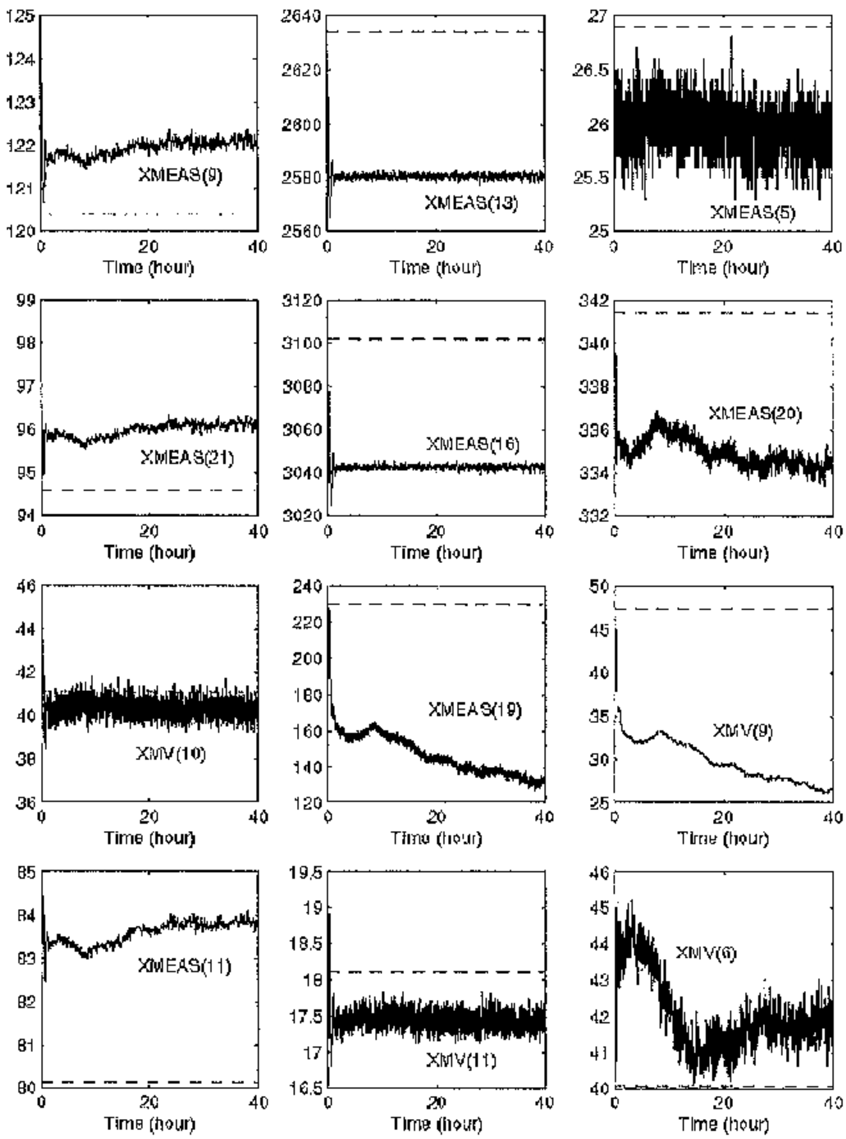


Figure A4-2: Some Tennessee Eastman Process responses under F(2)

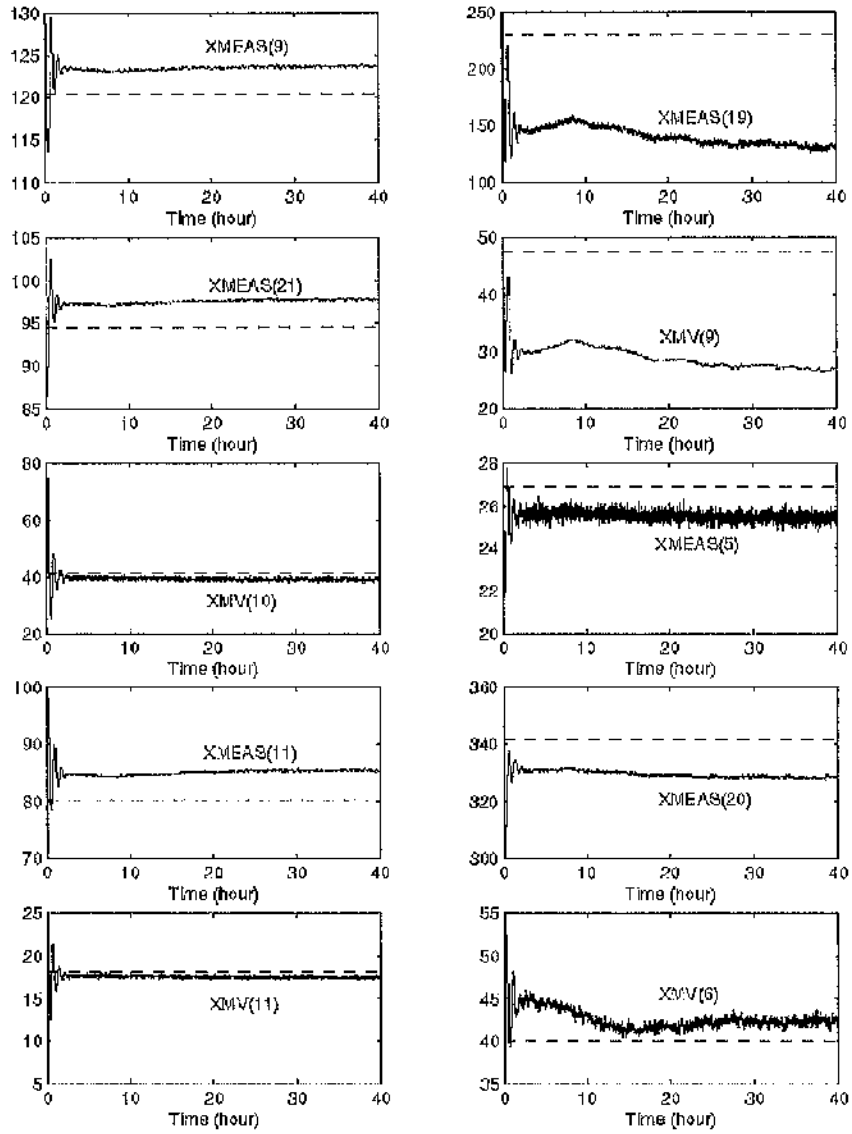


Figure A4-3: Some Tennessee Eastman Process responses under F(3)

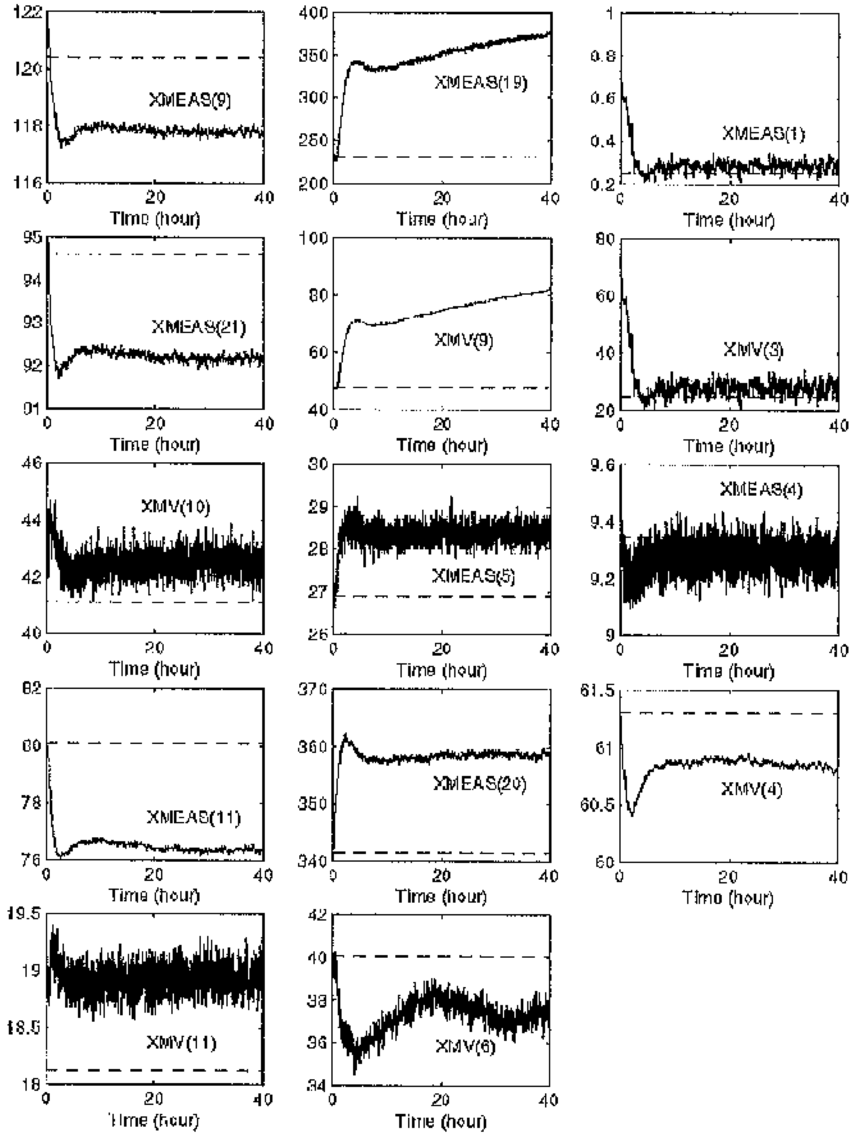


Figure A4-4: Some Tennessee Eastman Process responses under F(4)

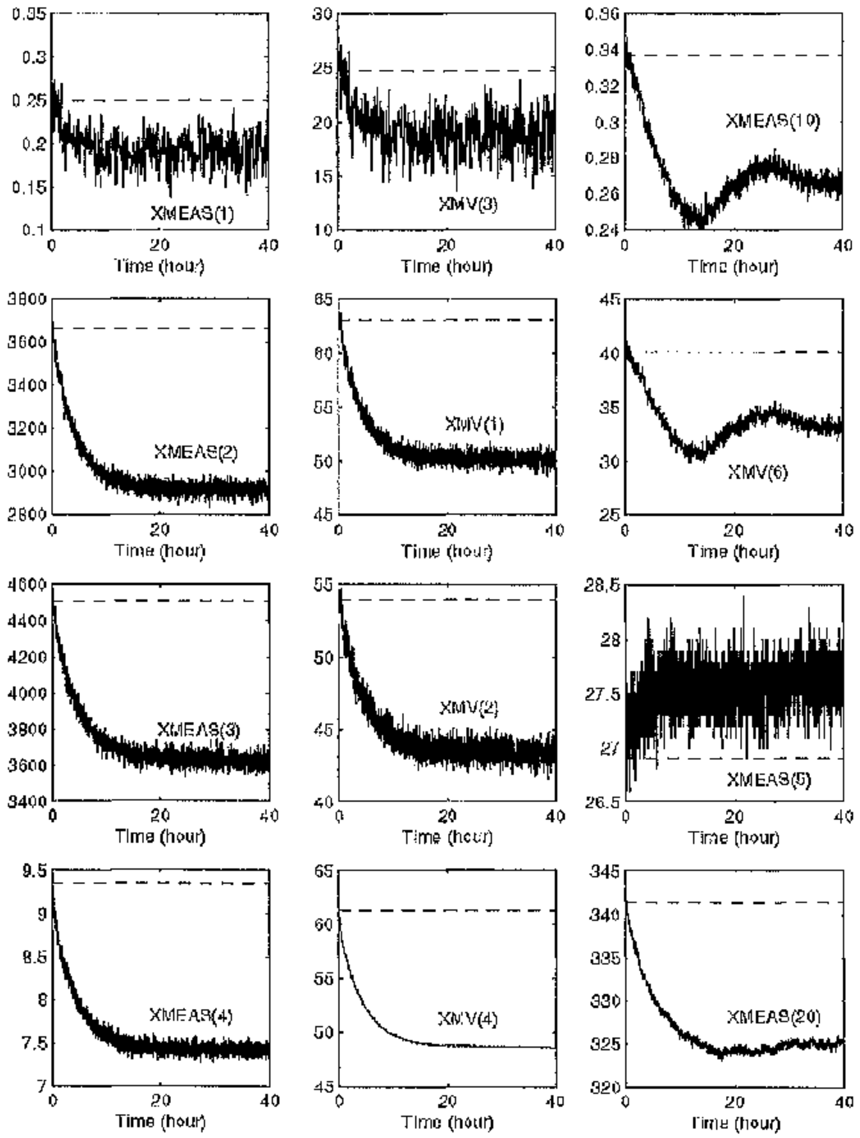


Figure A4-5: Some Tennessee Eastman Process responses under F(5) (to be continued)

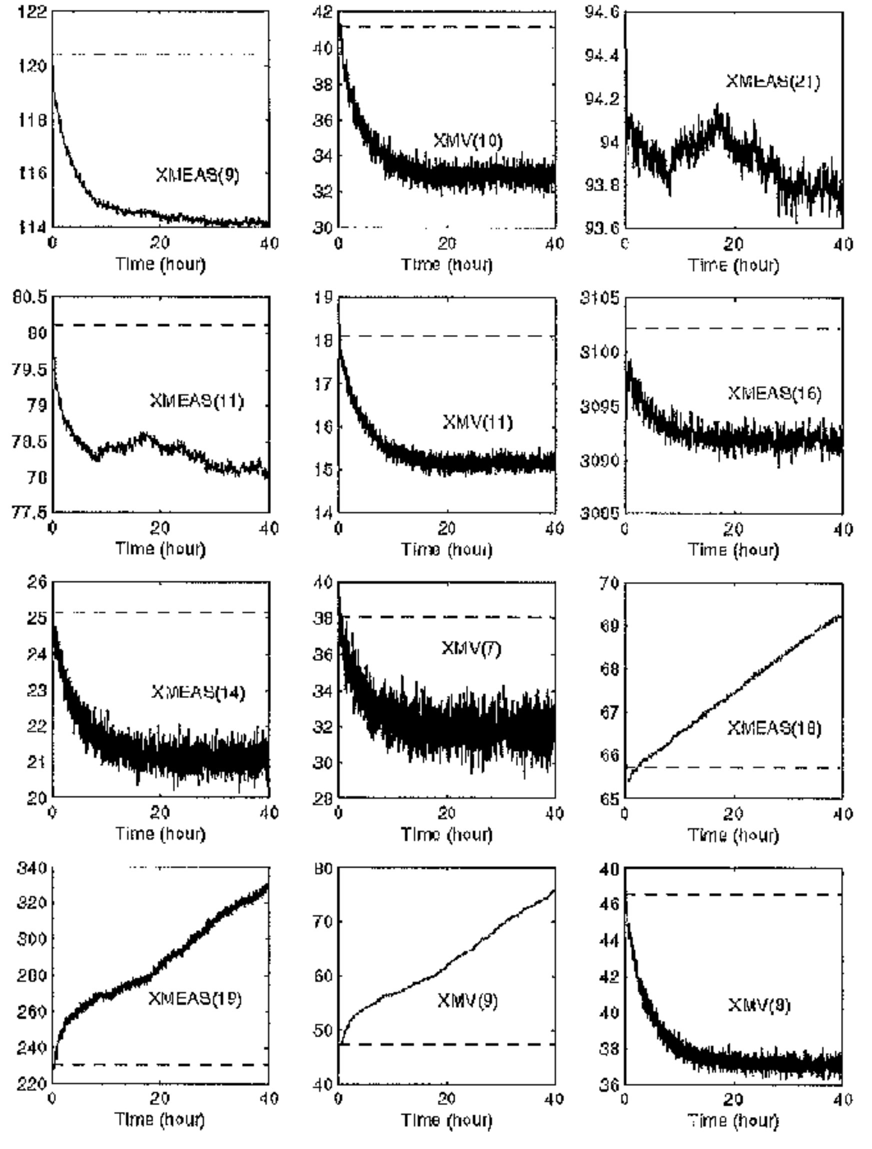


Figure A4-5: Some Tennessee Eastman Process responses under F(5) (continued)

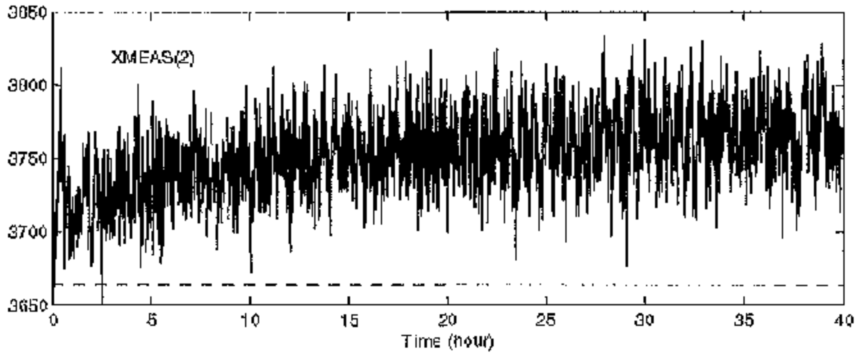


Figure A4-6: XMEAS(2) response under F(6)

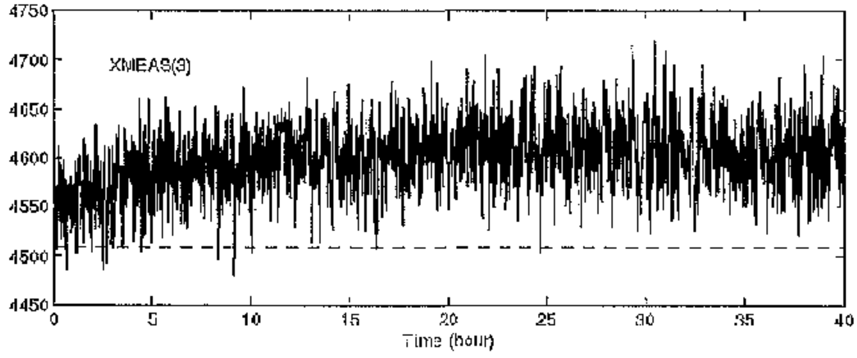


Figure A4-7: XMEAS(3) response under F(7)

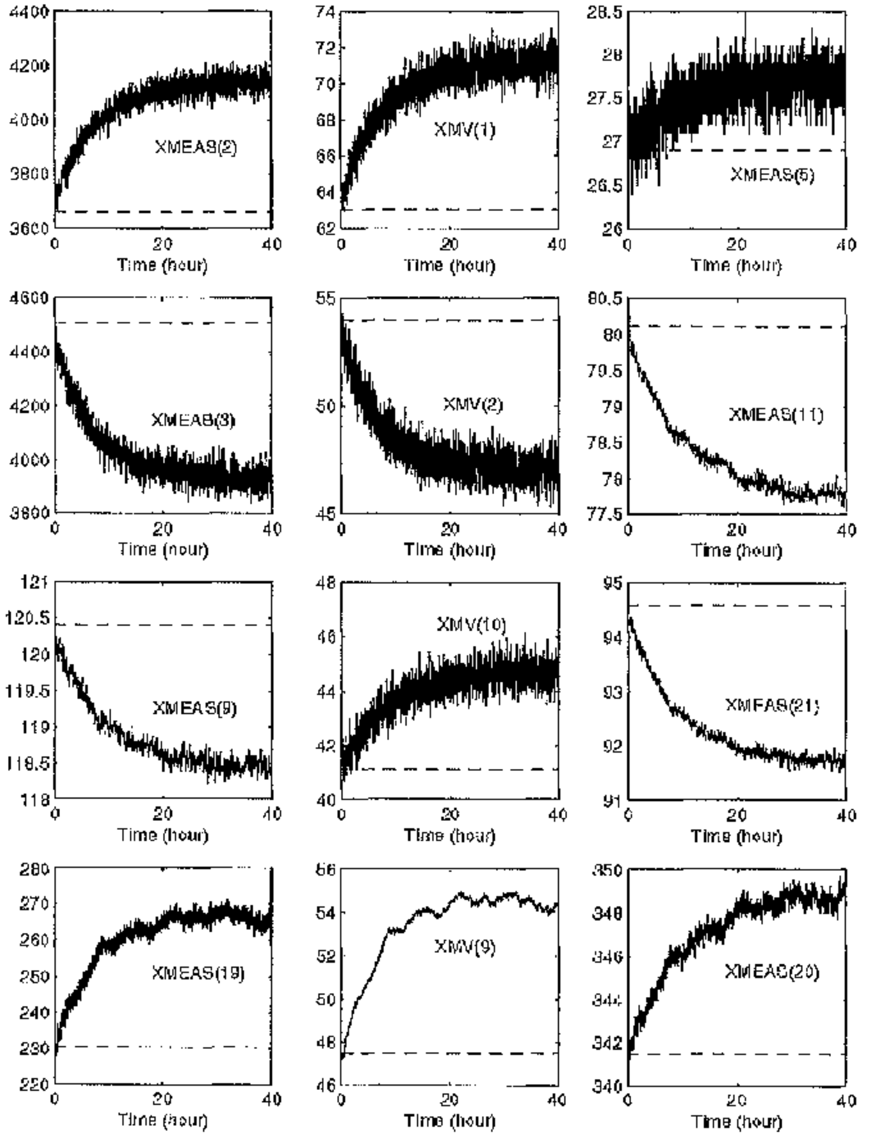


Figure A4-8: Some Tennessee Eastman Process responses under F(8)

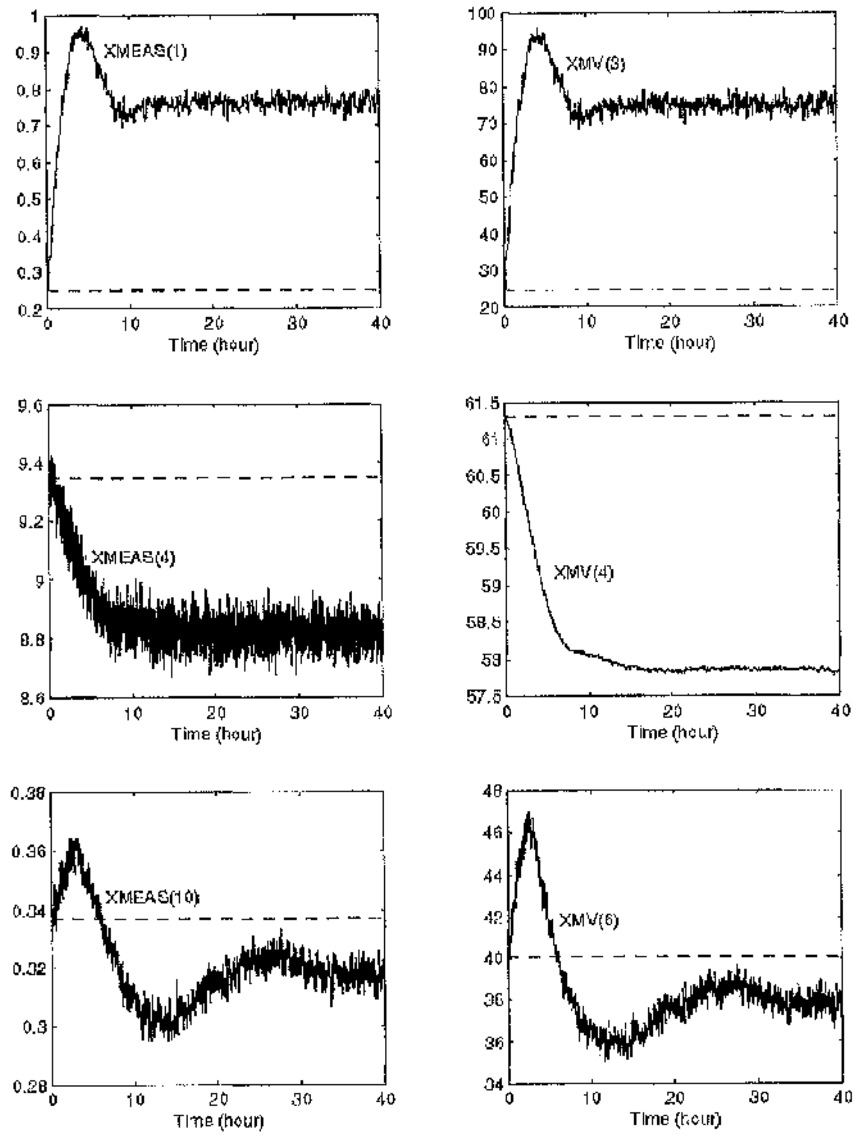


Figure A4-9: Some Tennessee Eastman Process responses under IDV(1)

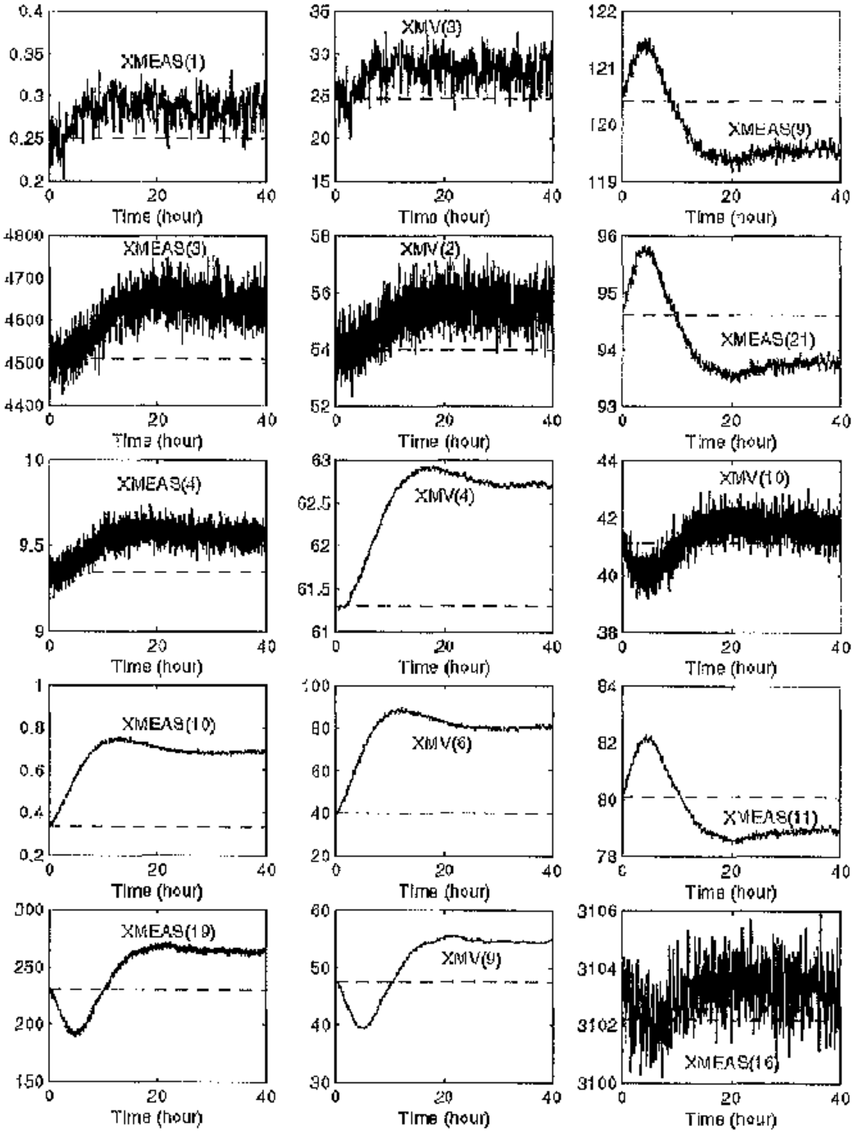
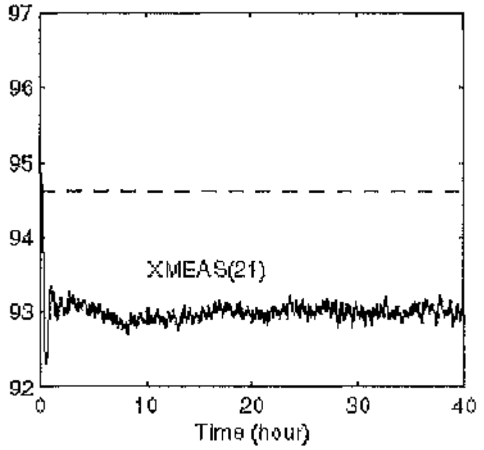


Figure A4-10: Some Tennessee Eastman Process responses under IDV(2)



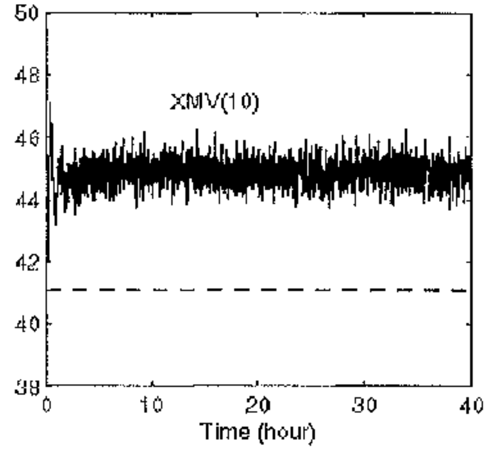


Figure A4-11: XMEAS(21 and XMV(10) under IDV(3)

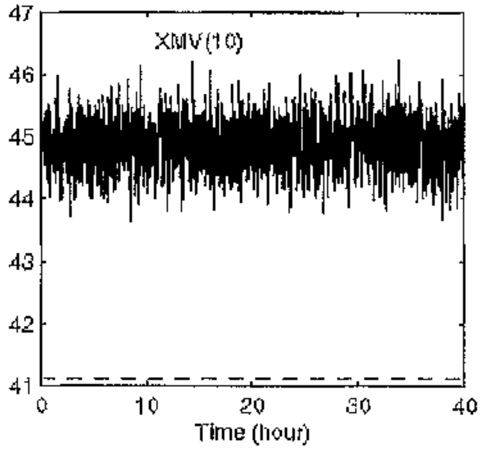


Figure A4-12: XMV(10) under IDV(4)

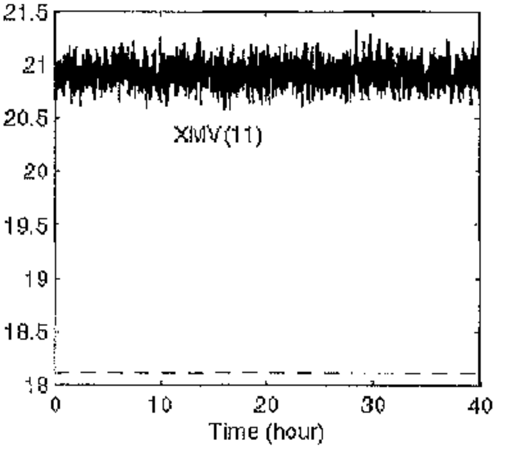


Figure A4-13: XMV(11) under IDV(5)

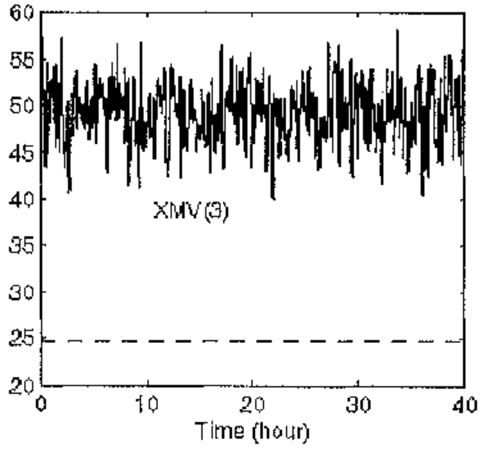


Figure A4-14: XMV(3) under IDV(6)

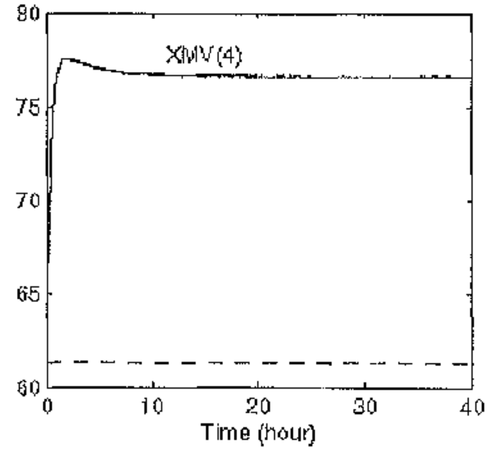
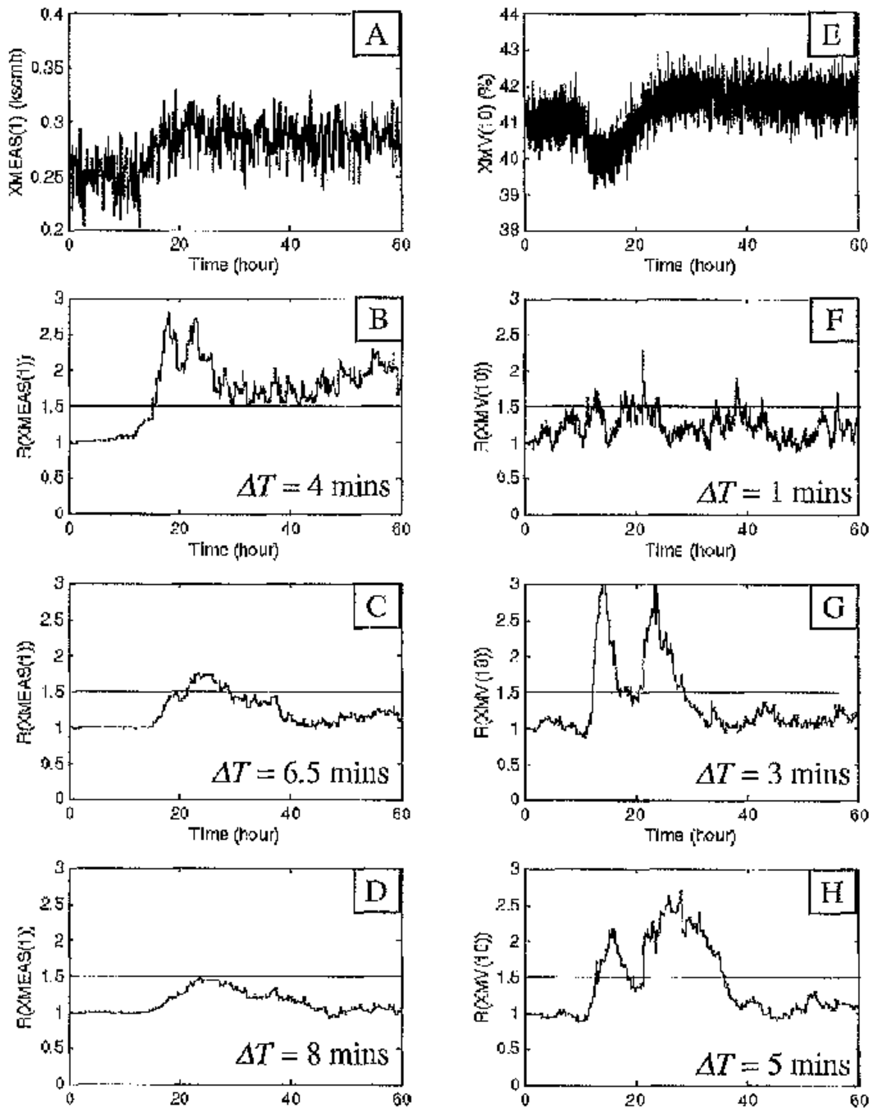


Figure A4-15: XMV(4) under IDV(7)

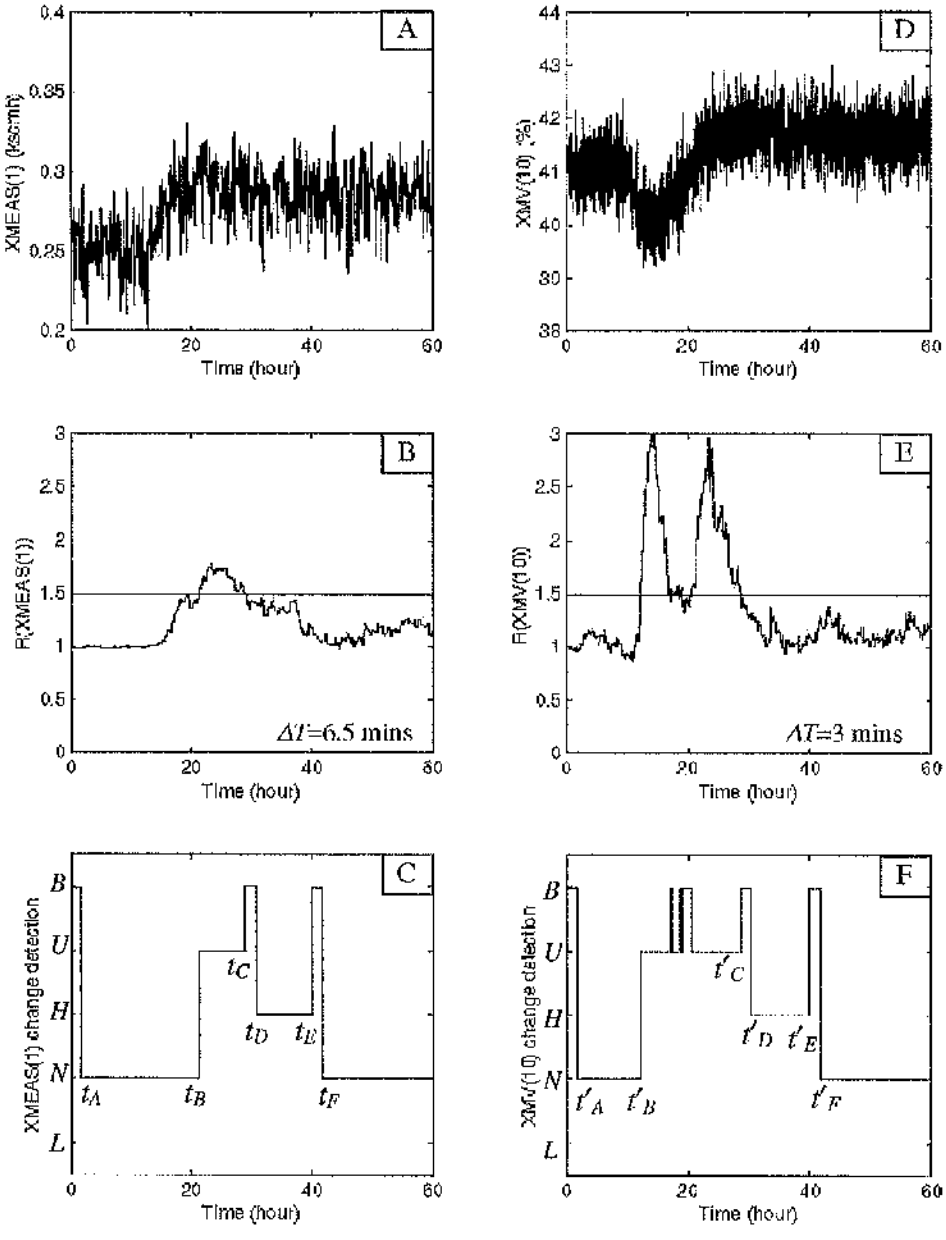
APPENDIX 5

STEADY STATE IDENTIFICATION AND CHANGE DETECTION EXAMPLES FOR THE T-E PROCESS



Figures A5-1A — A5-1H: *R-statistics* for XMEAS(1) and XMV(10) of the T-E process under different sampling intervals (IDV(2) happened at the 10 hours time, $\lambda_1=\lambda_2=\lambda_3=0.02$)

It can be seen that a threshold (Section 7.1.5) of 1.5 and a sampling time of 6.5 mins for XMEA(1) and of 3 mins for XMV(10) would be suitable.



Figures A5-2A — A5-2F: Steady state change detection of XMEAS(1) and XMV(10) of the T-E process (IDV(2) happened at the 10 hours time, $\lambda_1=\lambda_2=\lambda_3=0.02$, $n_1=n_2=101$) (in C and F, *B*: *blackout*; *U*: *not-at-a-steady-state*; *H*: *at-a-high-value*; *N*: *at-a-normal-value*; *L*: *at-a-low-value*)