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A parallel, fault-tolerant control and diagnostics system for nuclear power plants

Evren Eryurek

To the Graduate Council:

I am submitting herewith a dissertation written by Evren Eryurek entitled "A parallel, fault-tolerant control and diagnostics system for nuclear power plants." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Nuclear Engineering.

Belle R. Upadhyaya, Major Professor

We have read this dissertation and recommend its acceptance:

Rafael B. Perez, J.A.M. Boulet

Accepted for the Council:

Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

To the Graduate Council:

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Belle R Upadhyaya

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We have read this dissertation
and recommend its acceptance:

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[illegible]

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Associate Vice Chancellor
and Dean of the Graduate School

A Parallel, Fault-Tolerant Control and Diagnostics System for Nuclear Power Plants

A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Evren Eryürek
August 1994

DEDICATED TO

My mother Şenay, my sister Bige and my late father Mete...

Sen Evren'sin

Sen Büyüksün Oğlum
Yüreğin büyük
Dünyadaki tüm sevgileri içine alacak kadar
Sende yalnız yavan bir bilim aşkı değil
Dostluk var insanlık var
İçinde sadece gelecek değil
Geçmiş de yaşar
Sen sensin esensin sevecensin
Sen küçücük kalplere sığmayı bilmiş
Bir büyük evrensin

Başarın büyük Oğlum
Sen büyüksün
Büyüksün dünyalar kadar
Dünyalar yetmez gönlümdeki ölçün için
Guneşsin aysın gezegensin
Hepsi birdensin
Sende nice güneşler yanar
Nice yıldız parıldar
Çünkü senin içinde onlar
Çünkü sen evrensin

Amacın büyük Oğlum
Eserin büyük
Bilime gönül verensin
Yalnız bugünü yaşayan değil
Yarını görensin
Birgün Nobel ödülü alırsın belki
Ama bilki başarıdan yana
Yetişemezsin bana
Çünkü sen Evren'sin
Ve benim eserim sensin

To my pride, my hope, my son, Evren
With my love ...

Şenay Eryürek
February 10, 1993

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ABSTRACT

A new integrated fault-tolerant control and diagnostics system was developed and applied to the feedwater flow regulation system of a pressurized water reactor (PWR). Control, signal and command validation, monitoring and diagnostic tasks were integrated into one large-scale system.

The control module of the Fault-Tolerant Control and Diagnostics System (FCDS) includes two nonlinear control algorithms, in addition to conventional controllers. A software-based parallelism was implemented in the design of the control module. The parallel control includes a model-based adaptive controller, two fuzzy logic controllers, and proportional-integral (PI) controller. Each algorithm was designed to handle the same control task using different strategies and different sets of plant measurements.

Using family of control solutions requires a systematic approach to select the most suitable control action for the present demand. A new concept, called Command Validation, was developed as part of the Fault-Tolerant Control and Diagnostics System. Command validation is a prediction scheme in which the objective is to provide an estimate of the expected control action using relevant plant variables. The prediction is then used to cross-examine the output of the control algorithm before the final decision is made by the Decision-Making module. This approach enables the control system to detect anomalies in the sensors, actuators and in the control actions.

A Signal Validation module was also developed for validating the plant measurements before they were utilized by the control algorithms. A software-based parallelism was also included in the signal validation and command validation modules by incorporating two different modeling techniques: process empirical models and

artificial neural network models. The estimations of selected plant signals were made via a set of process measurements and the developed models.

The FCDS was tested using an application to the feedwater flow regulation system of a typical four-loop Westinghouse type PWR. In order to test the system, a nonlinear feedwater flow system was modeled with 96 state equations. The model includes four steam generators, two main feed pumps, piping and their control systems. There are two control systems in the feedwater flow regulation of a PWR: the steam generator water level controller and the main feed pump speed controller. Both of these controllers were included in the model.

Reconstructive Inverse Dynamics (RID) and the Fuzzy Logic controllers were developed for water level control and pump speed control systems. The RID controller is a model-based controller and is found to be exceptionally accurate if the control problem is of a trajectory-following type. The fuzzy logic controllers give excellent results during unexpected changes in the behavior of the plant as well as during trajectory-following problems. An extensive testing of the fuzzy logic controller was performed to demonstrate the robustness of the fuzzy logic control approach, since the application of this technique is considerably new in the nuclear industry. The development of fuzzy logic controllers for such highly nonlinear systems was one of the objectives of this dissertation.

The utilization of more than one algorithm not only improves the availability of the control system during sensor failures or inadequacies in the control algorithms, but also provides alternate approaches for different plant operating conditions. The Fault-Tolerant Control and Diagnostics System improves the availability of the control system and provides fault-tolerance through multiple control strategies and the incorporation of signal and command validation features.

List of Acronyms

- AI: Artificial Intelligence
- ANN: Artificial Neural Networks
- BPN: Backpropagation Network
- BWR: Boiling Water Reactor
- CECo: Commonwealth Edison Company
- CV: Command Validation
- CVB: Command Validation Block
- DAS: Data Acquisition System
- DCS: Distributed Control System
- FCDS: Fault-Tolerant Control and Diagnostics System
- FPL: Florida Power & Light
- ES: Expert Systems
- FL: Fuzzy Logic
- FOTL: First-Order Transport-Lag
- GUI: Graphical User Interface
- IFR: Integrated Fast Reactor
- LHS: Left Hand Side
- MISO: Multiple Input Single Output

- PDS: Plant Display System
- PE: Processing Element
- PEM: Process Empirical Modeling
- PID: Proportional-Integral-Differential
- PNC: Power Reactor and Fuel Development Corporation, Japan
- PWR: Pressurized Water Reactor
- RHS: Right Hand Side
- RID: Reconstructive Inverse Dynamics
- SDS: Shut Down System
- SG: Steam Generator
- SSM: Safety System Monitor
- SVB: Signal Validation Block
- TVA: Tennessee Valley Authority
- UTSG: U-Tube Steam Generator
- WA: Weight Assigner

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Chapter 1

Introduction

The design of fault-tolerance has become an important requirement for power plant control because of safety and availability considerations. Typical applications in the process control industry employ redundant hardware for data acquisition and processing, in order to guarantee continued operation even in the presence of anomalies in instrument channels.

Digital technology implementation issues are being considered in the design of advanced reactors, and in the recent upgrades in some of the existing nuclear power plants such as TVA's Sequoyah Nuclear Plant [2]. Although a major benefit of digital technology is its computational power and the capability to incorporate a large number of algorithms, the current implementations mostly emulate the principles of analog control and data processing methods. An objective of this dissertation is to utilize the computational advantages of digital systems to develop fault-tolerant control algorithms.

A number of new and advanced methods including inverse dynamics, fuzzy logic, artificial neural networks, and expert systems were used in this research for the development of fault-tolerant control algorithms. The architecture, employing "**Software**

Fault-Tolerance" differs from the conventional philosophy by requiring minimal redundancy in the measurements.

The fault-tolerant control principle is implemented with parallel control and command and signal validation functions. **Parallel control** includes a number of control algorithms, each designed to accomplish the same control task using different sets of plant signals. A family of control solutions is evaluated to select the best combination of solutions as the final control action. Therefore, the development requires the design of a family of controllers and a criterion for the final control selection. **Command validation** is based on a prediction scheme. The objective is to estimate the expected control actions via process variables. The prediction is used to cross-examine the control solutions. With this capability, the control system can detect anomalies in sensors, actuators, and in the software platform [1].

The integration of the control design, signal and command validation, and monitoring and diagnostics into a large-scale system is the primary objective of this dissertation. The use of signal and command validation modules with parallel control architecture has shown the benefit of reducing system failures which arise due to inadequacies in plant measurements. An effective signal validation module increases the possibility of overcoming measurement problems in the control system, since the signal validation module has the ability to estimate parameter values over a period of time.

1.1 Importance of the Research

The purpose of this research is to develop a parallel, fault-tolerant control and diagnostics system (FCDS) for enhancing nuclear reactor operations. The objective is to combine monitoring and diagnostics tasks with control tasks so that the overall control strategy and its implementation may be more effective. The interactions between the diagnostics and control systems are automated while retaining a capability for operator intervention at all times. The advanced methods used in this study include artificial intelligence techniques such as neural networks and fuzzy logic, signal processing techniques such as process empirical modeling, and nonlinear control techniques such as inverse dynamics [16].

The existing digital systems in operating power plants do not fully utilize the advanced methods in control, signal processing, and artificial intelligence. Most of the existing automatic control systems lack a cross-talk feature with diagnostics systems which may prevent plants from reaching an undesired condition; presently, the coordination and supervision are generally handled by reactor operators [17]. One important reason for not utilizing the advanced systems in existing power plants is the "proven" old technology versus "unknown complexity" of new algorithms with a potential of not being easily understood by the operators. The reliability of digital software systems must also be tested extensively, before they can be implemented in operating plants.

The research presented here demonstrates the feasibility of integrating two existing tasks, signal validation and control, and a new concept – the command validation, into one system. Signal validation is a proven useful tool that establishes a systematic way to demonstrate the accuracy of sensor readings. The FCDS offers a signal validation approach in which two different methodologies are utilized to overcome their individual inadequacies. Cross-checked results of the signal validation schemes provide better reliability for control input signals.

The FCDS houses two nonlinear control algorithms, in addition to the conventional proportional-integral (PI) control system. One of the nonlinear algorithms is a model-based adaptive controller which gives excellent results for trajectory following problems. The second nonlinear control algorithm is based on fuzzy logic, and gives exceptionally accurate results during unexpected behavior of the process. The control module of the FCDS utilizes these nonlinear algorithms to offer a better control system for the feedwater flow regulation of a pressurized water reactor. The parallel design of the control algorithms is an enhancement to the existing control systems and provides an alternative solution in the event of controller failure. The inverse dynamics controller is found to be excellent for trajectory following problems, and the fuzzy logic controller is found to be very robust during transients for which the current control systems fail to give accurate results. The use of multiple control algorithms not only improves the availability of the control system in the event of a sensor failure or a controller failure, but also provides alternate control strategies which may be utilized during different operating conditions.

The command validation is the third module of the FCDS. It is a new validation scheme that checks the quality of the control solutions and ensures the validity of the final control action. A decision making procedure is part of the command validation module. Decision making is used to select the best control signal based on the availability and accuracy of the control input and output signals. The command validation module includes another module called **Decision Making** where the selection of the most suitable controller is made. The selection of the controller is based on the availability and accuracy of the controller signals. Some controllers may be more suitable for different operating regimes. Simulation tests have shown that the Reconstructive Inverse Dynamics (RID) controller is a better controller for trajectory following and steady-state operations. Based on this a priori knowledge, the decision making module selects the RID controller (unless there is an inaccurate control input signal) to complete the operation. The fuzzy logic controller is found to be more suitable during transients where the system model does not give good estimations about the status of the plant. Since fuzzy logic does not rely on a model-based information, the control action produced by the fuzzy logic controller is more accurate during transients for which the system dynamics may contain uncertainties. Figure 1.1 gives the overall structure of the FCDS.

1.2 Statement of the Problem

In this dissertation, the application of the Fault-Tolerant Control and Diagnostics System is demonstrated for the regulation of the feedwater system in pressurized water reactors (PWRs). The speed control problem in turbine-driven pumps is related to the regulation of pressure difference (ΔP) across the feedwater valve around set points during feedwater maneuvers. The present speed and level controllers in PWRs do not include a direct communication between the two control systems: the three-element level control and the ΔP control. The lack of communication between these two controllers [2] [34] may be resolved by utilizing different control strategies for the level and speed control systems of pressurized water reactors. The inverse dynamics controller and the fuzzy logic controller developed for the feedwater regulation system include feedforward measurements of the feedwater flow rate and the pump speed signals. A common reactor trip occurs during a plant startup when the feedwater flow is being switched from the main feedwater bypass control valves to the main feedwater control valves. During the switchover, an uncontrollable swing caused by improper measurements in the steam generator level results in a reactor trip at low levels [2].

Another good example is the problem of oscillations in the steam generator water level. In the case of a higher feedwater demand the three-element controller tries to open the feedwater valve. Since there is a long time constant (some about 30 minutes [33]) in the existing proportional-integral (PI) controllers, this demand is not

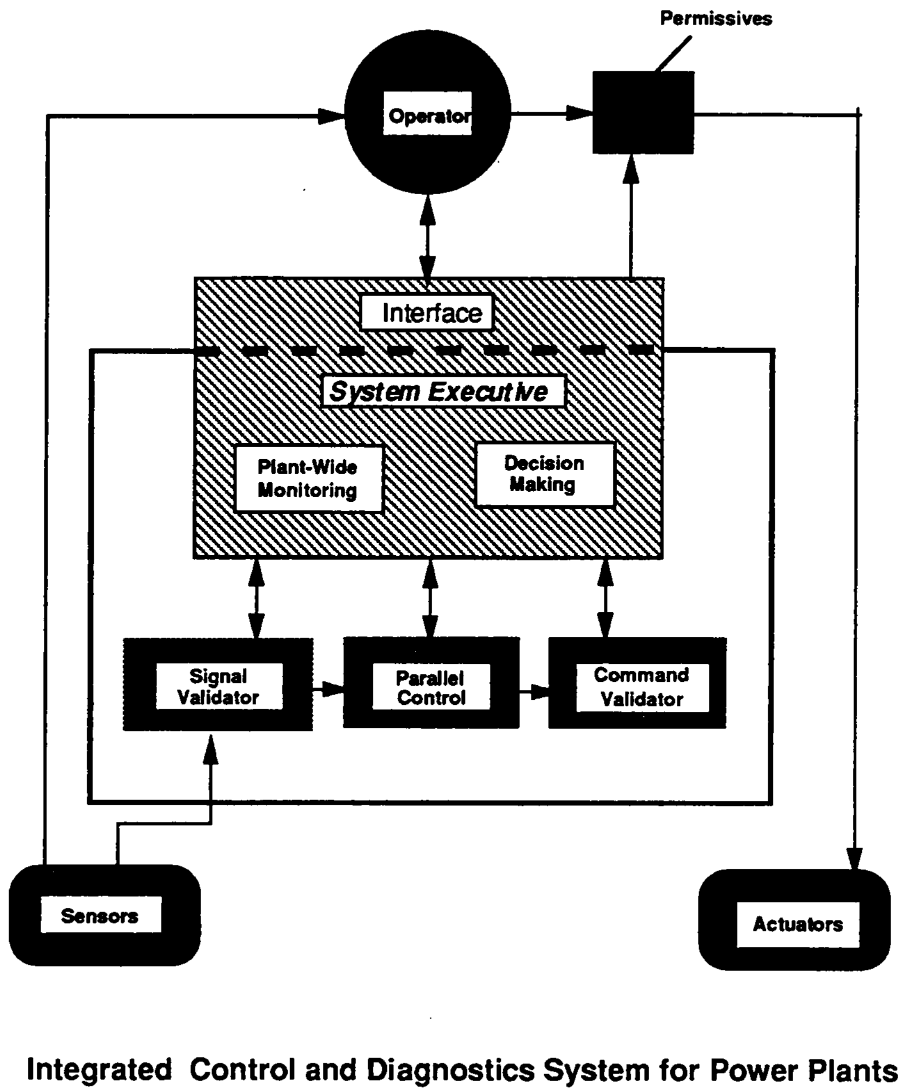

Figure 1.1: Fault-Tolerant Control and Diagnostics System.

satisfied immediately. At the time the (ΔP) controller realizes that more feedwater is needed, the three-element controller again changes the position of the feedwater valve in order to maintain the water level at a desired value. The new change does not affect the (ΔP) controller command and the (ΔP) controller tries to meet the higher water demand for the steam generator. Sometimes similar actions create major swings in each steam generator, and the operators switch the control systems to manual mode so that the problem can be solved without shutting down the plant [2].

A wide range of sensor/signal validation, diagnostics, monitoring, and control applications for large scale, complex systems is found in the literature [61] [43] [41] [40] [39] [38]. In most cases these tasks are performed individually. Recently, a few studies have tried to combine several of these tasks into one system, such as the combination of validation and monitoring functions for large scale systems [43] [40]. A common objective of these studies is to "simplify" the operation of industrial processes; another objective is to reduce system failures or process discontinuities due to sensor failure or invalid control actions.

This dissertation research involves the development and evaluation of a system which integrates sensor/signal validation, diagnostics, and most importantly the control schemes into one. In addition to these tasks, it also provides "command validation", which validates the control actions based on the observation of state variables. A new, software-based, parallel control strategy design is part of the research. Integrating these tasks will significantly reduce the system failures due to missing signals or invalid control actions.

1.3 Contributions of the Dissertation Research

Traditionally, a process control task is performed with one software system or one hardware system. Studies in which hardware redundancies were introduced in signal measurements and especially in control systems were reported recently [43] [46]. These redundant systems receive identical signals and use identical strategies to perform their tasks. In addition to hardware redundancy, the FCDS offers *software redundancy* for sensor/signal validation, command validation, and most importantly for the control task. Thus the FCDS may be referred to as a "smart" controller. The contributions of this research include the following.

1. Development of a software-based parallel control system.

2. Development of a nonlinear four-loop PWR feedwater flow regulation system model, including four steam generators, two main feed steam turbine driven pumps, and their controllers.

3. Development of model-based adaptive control, and fuzzy logic control for steam generator water level and (ΔP) controllers, in addition to the existing PI controllers.

4. A detailed testing of the fuzzy logic control for its robustness.

5. Development of signal validation models for selected parameters of the feedwater flow regulation system.

6. Development of command validation models for feedwater valve and turbine governor valve positions.

7. Implementation of an expert system-based decision making module for choosing an appropriate control input to the actuators.

8. Integration of the control, signal/sensor validation, command validation and decision making modules into one large system.

9. Development of a workstation-based graphical user interface.

10. Application of the FCDS to the secondary side of a four-loop PWR.

1.4 Organization of the Dissertation

A literature review and background of advanced control systems for power plants, monitoring and diagnostics, artificial intelligence and fault-tolerant control systems are given in Chapter 2. In Chapter 3, the feedwater flow regulation system of a pressurized water reactor (PWR) and modeling of the U-tube steam generator, main feed pump, feedwater control and main feed pump speed control systems are presented.

Chapter 4 gives a detailed description of the new Fault-Tolerant Control and Diagnostics System (FCDS). This chapter discusses each of the module and the development of models for signal and command validation.

Chapter 5 is dedicated to the control modules of the FCDS. The development of the control algorithms, and the theory of fuzzy logic control are discussed in this chapter.

Analysis of the integrated control system, applications to the feedwater flow regulation system and performance testing of the fuzzy logic controller are given in Chapter 6. The results obtained from signal validation, command validation, decision-making and parallel control systems are also presented in this chapter. A summary of the dissertation is presented in Chapter 7, including conclusions and suggestions for future research.

Chapter 2

Literature Review and Background

A review of the literature, related to feedwater regulation systems, monitoring and diagnostics, artificial intelligence, and fault-tolerant control systems is presented in this chapter. The purpose of this discussion is to present the current status of the topics of interest. Although most of the operating power plants utilize similar control techniques, namely the PID controllers in their feedwater regulation systems, a number of studies have been conducted to try to improve the current systems and minimize plant trips [42] [55] [46]. Along with the feedwater flow regulation system studies, there is also a number of studies related to diagnostics and monitoring systems in power plant operations [41] [40] [43].

Applied artificial intelligence methodologies are being increasingly used for control, monitoring and diagnostics. There are studies involving on-line monitoring systems using artificial neural networks in power plants. There is also an ongoing research using artificial intelligence (AI) for developing control systems for feedwater flow regulation and reactor power control for nuclear power plants. The following sections discuss these topics and give an overview of the approaches used.

2.1 Advanced Control Systems for Power Plants

Recent emphasis on nuclear plant surveillance and control suggests that future power plants would require fault-tolerant control strategies that can cope with varying plant conditions and instrumentation malfunctions. There are two important reasons for this trend from the nuclear power generation point of view: safety and availability. New "passive" reactor designs such as the PIUS, the simplified BWR [14], and the IFR [15], and the AP-600 PWR have introduced a significant margin of improvement in reactor safety. These designs have inherent capabilities for safe shut down under adverse operational problems. In addition, the design of emergency shut down and plant protection systems has been improved to handle a wide range of problems. These advances have slightly shifted the objective of reactor control design from primarily assuring safe operation, to avoiding plant operation close to trip conditions. Accordingly, if undesired regimes can be avoided by control, both safety and availability requirements are satisfied.

The identification of an abnormal status of components and inappropriate control strategies can prevent a plant from drifting into the vicinity of trip conditions. This constitutes a challenging diagnostics task which undoubtedly requires on-line computational capability for handling numerous sensor readings, extracting useful information, and providing decision aids to operators. An accurate diagnosis is only part of the solution to the trip avoidance problem. A control decision based on diagnostics results is required to maneuver around the problems. The trend in the integration of diagnosis and control may be seen in the form of computer-controlled design in western Europe, Japan and Canada [3] [38] [40] [61].

The current modular power plant designs do not incorporate a fully automated startup control strategy. Automatic load-following control systems are being designed for pressurized water reactor (PWR) plants by Mitsubishi Atomic Power Industries [3] in Japan. The primary objective here is to control core axial power distribution using load-following control rods. Automation in the Canadian heavy water reactors (CANDU) is the most advanced in the industry [43]. The goal is to achieve 100 % digital control and protection in the new plants, such as the Darlington units of Ontario Hydro.

The CANDU reactors were the first systems that incorporate digital technology. In the most recent Canadian reactor designs, the Darlington plant, nearly 100% of the reactor and process control is digital. In the early 1980's CANDU reactor designers implemented the trip decision logic for the process trip in the CANDU 600 design. Darlington units, which have been on-line since 1990, have 100 % digital control systems. The centralized dual process controller is implemented in the Darlington plant. One of the two control systems is on-line during the entire process. Both of these controllers have their own databases and do not utilize each other's information in case of an anomaly. If any failure or abnormality is detected in the control system, the second system would be activated for on-line operation.

The switching is done simply by a fast reacting electronic component. Since both the systems utilize identical control strategies, and use the same signals for producing the control signals for the entire plant, a simple switching system seems feasible for the CANDU reactors [35]. CANDU reactors are designed with a number of systems to shut down the reactor, to maintain cooling, and other functions. Each reactor has two shutdown systems (called SDS-1 and SDS-2) to increase the reliability of the overall system. Every system is independent of the other, each utilizes different sensors, logic, devices, and more importantly they are physically separated. Both of the shut down systems are completely independent of the plant control systems.

An advanced feedwater flow regulation systems has been developed for the Fugen Nuclear Power Station in Japan. The system utilizes fuzzy logic for the steam drum water level control. The first stage of the study was simulation and the second stage was development of the prototype system for an on-line support system. Validation tests were performed in 1989 and the fuzzy logic control system for the steam drum level control was implemented in the Fugen Nuclear Reactor in July 1992. In Fugen Reactor, a three-element PI controller is used for the water level control in the power range between 10 % and 100 %. The control system is taken over by a single-element PI controller in the lower power range. Since the lower flow rate valve cannot cope with the rapid changes in the reactor output, sometimes manual operation is necessary for a faster adjustment of the steam generator water level. During these manual operations, feedwater flow rate and steam flow rate measurements are difficult to perform since they are too small to sense accurately. Therefore, a corrective action for valve openings was introduced by the operators based upon their personal experiences. Since fuzzy logic can easily formulate these qualitative features and the subtle human reactions into the control rules, a fuzzy logic control system for the feedwater flow regulation was developed by the Power Reactor and Fuel Development Corporation (PNC) [55].

An advanced digital feedwater control system was introduced at the Commonwealth Edison Company's (CECo) LaSalle County Nuclear Station. Numerous feedwater control system hardware failures occurred during the operation, resulting in many high reactor water level feed pump trips and plant scrams [42]. The digital control system was designed to recognize failed sensor inputs, control elements, and take automatic actions to prevent the feedwater system from water level transients. This system replaces the analog feedwater level control system and the turbine speed control system. The new system is expected not to allow more than one plant scram in 10 years of operation. Three different narrow range sensors are used in the water level control system, and two-out-of-three trip logic for the feed pumps and the main turbine control is used at the LaSalle County Nuclear Station.

2.2 Monitoring and Diagnostics

In the CANDU reactors, control and monitoring are combined into one system so that the duty of the operators can be eased in case of an anomaly. The MONITOR computer in the shut down systems performs different identification and communication functions related to monitoring. A safety system monitor computer acquires data, alarm messages and test results at the Darlington plant. The basic function of this computer is the storage of historical data. There is only one computer for this monitoring unit.

Two computers collect most of the plant data for the distributed control system (DCS) and the CANDU plant display system (PDS). The information from the safety system monitor (SSM) is sent to two operator workstations. Data acquisition and process control functions for the non-safety systems are performed by an advanced distributed digital control system. The system controls low-level and interlocking functions for individual process devices such as pumps, valves, and others. High-level control functions, steam generator level control, system pressure control, inventory control, and others are also performed by the same system. Automatic and manual mode changes, set point changes, and control actions in response to operator commands are within the scope of this control system.

Many utilities have developed advanced monitoring systems for their power plants. Florida Power & Light (FPL) has developed an on-line monitoring system to improve their current system. FPL's new performance monitoring system is expected to offer reduction in fuel consumption to generate the same capacity, improve their current data collection and archiving system to reduce operator errors, offer enhancement to their maintenance program, and others [67].

PC-based operator interface systems for plant-wide monitoring are being introduced to power stations by many different agencies to improve operations and to reduce plant trips. Some features of these systems are performance analysis for feedwater heaters and condensers, heat rate monitoring, equipment performance monitoring, core monitoring, and safety parameter display [40] [41].

2.3 Artificial Intelligence

Artificial intelligence has become one of the most-utilized methods for monitoring, diagnostics and control. Artificial intelligence includes Expert Systems (ES), Artificial Neural Networks (ANN), and Fuzzy Logic (FL) as major branches. Expert systems have been used in many different areas, including the nuclear industry for many years. Recently, a better understanding of new neural network paradigms and more powerful computers has lead to the utilization of neural network modeling in the areas of validation, monitoring, diagnostics, and control. The applicability of neural networks in the nuclear industry for monitoring and validation has been demonstrated in a number of studies [36] [49].

2.3.1 Neural Networks

For effective control strategies in many process industry systems, it is necessary to perform validation and monitoring of important variables. Early applications of validation and diagnostics systems utilized model-based techniques where polynomial fits were used to capture the relationships among the variables. The Kalman filtering technique uses a physical model of the system for state estimation. A new approach, artificial neural network modeling, has broadened the capabilities of validation, monitoring, and diagnostics systems even further. This approach provides an opportunity to develop a nonlinear model between the related parameters.

Artificial neural networks are models inspired by the architecture of the human brain. A neural network consists of a large number of highly interconnected processing elements (PEs). A PE, analogous to a neuron, has a number of input paths. It combines the values of the weighted inputs, modifies the combination with a transfer function, and produces an output. In an artificial neural network, the processing elements are organized in a sequence of layers.

The generation of an accurate model, using model-based techniques, requires an effort which is proportional to the size of the complexity of the system. Neural networks offer several advantages for signal validation, monitoring, and diagnostics when compared to traditional techniques [7].

1. It is not required to define a functional form to relate a set of process variables.
2. The functional form developed by an Artificial Neural Network (ANN) is implicitly nonlinear.
3. Neural networks do not require detailed system specifications.
4. Neural networks are more fault-tolerant in the presence of anomalies.

Neural networks are intrinsically parallel and non-algorithmic methods. These features of neural networks make real-time processing of data and information more feasible. Some of the current applications include nuclear fuel management, multi-sensor information fusion, sensor validation, diagnostics, and pattern recognition [49].

Although, today's computers are still not as fast as one would like them to be, artificial neural networks provide fast responses or solutions to complex problems such as plant-wide monitoring or model-based sensor/actuator validation. They are easy to implement and they can be used as real-time failure detection tools due to their inherently robust and parallel computational architecture.

2.3.2 Fuzzy Logic

Although fuzzy logic has gained most of its recognition recently, fuzzy set theory was established by Zadeh [11] as the "dialectical synthesis of continuously graded degree of membership to a set" in the year, 1965. The mathematical foundations of the *fuzzy set theory* can be seen as the generalized form of the *classical set theory.* The fuzzy logic theory was essentially introduced by Zadeh to describe the systems that are "too complex or too ill-defined to admit precise mathematical analysis." The major characteristics of fuzzy logic are the use of linguistic rather than numerical variables and establishing the relationships among variables by fuzzy conditional statements.

Fuzzy set theory offers major advantages compared to the crisp theory of numbers. No artificial precision is needed to avoid the borderline problems. For example, it is not necessary to define the concept of "tall" as a person whose height is greater than 1.834523 m. In other words there is no need for clear-cut distinction between the borderlines. Fuzzy logic enables us to define relationships that we use during our daily lives. The definition of a "tall person" can change from person to person, from region to region.

In process control, the main difference between the fuzzy logic approach and the traditional techniques is that the former uses qualitative information whereas the latter require rigid mathematical relationships to describe the process. Control action in a rule-based system is performed by first measuring the relevant parameters and then defining their membership grades in the appropriate subsets.

2.3.3 Expert Systems

Expert systems are computer programs designed to "mimic human expertise." Expert system programs are used to solve a well-defined problem by utilizing the human expertise in the related area. Uhrig [73] [72] lists a number of advantages of expert systems. Some of the advantages are

- Experts do not have to be present for a possible consultation. Expert systems may be delivered to other locations where needed.
- Expert systems do not get tired or careless if they are utilized for long hours.
- They are more efficient in terms of searching larger data bases or finding out more appropriate data bases.

Like many other systems, expert systems also have some serious disadvantages.

- Experts systems mostly handle static situations.
- They must be updated as more information becomes available.
- Results are highly dependent on the accuracy of the collected knowledge base.
- Expert systems are limited to their domain of expertise, and in many cases they are unable to detect the limitations of their domain [73] [72].

The main components of an expert system are the inference engine, and the interface between the expert system and the users. The inference engine collects the information from the human expert and/or from a data base, and leads a search after which a conclusion is drawn.

Although there is a vast number of expert systems available in different areas including power plant operations and control [74] [71], only a few expert systems interact with plant operators or provide information in the control rooms. Decision support systems, diagnostics systems, training programs, monitoring, maintenance, and advisory systems are some of the available expert systems in industry. Real-time applicability is one of the appealing features of the expert systems to the nuclear industry [71]. Another feature of expert systems which captures the attention of the nuclear industry is that the capability of providing an explanation of the conclusion reached by the system, and the ease of updating the knowledge base.

Artificial intelligence (AI) technology is still a growing and maturing area. Although they are not routinely used in many areas of the industry, especially in the nuclear industry, there is a growing trend towards understanding the capabilities of these relatively new techniques: artificial neural networks, fuzzy logic, and experts systems. These systems may eventually become a part of the "critical" tools in most areas of the industry.

2.4 Fault-Tolerant Control Systems

Control systems which retain acceptable performance in the presence of failures are said to be "robust" systems. Reconfigurable systems are those control systems in which the original structure or some of the parameters may be altered in response to a system failure which is identified by that control system. If a system is fault-tolerant due to its reconfigurability, it is adaptive and redundant. It is redundant since the system can overcome the existing problems with its remaining resources, it is adaptive because it can adjust to those new states [47] [61].

The major expected enhancement of fault tolerance is the improvement of system reliability, availability, and survivability. Reliability of a system is the ability of that system to perform or complete its task at a given time in its operation. A control system that helps to complete the normal task of a plant after a component failure or system failure, improves the reliability of that system. Survivability is mainly the concern for a system to operate within the design safety limits without creating any danger to the environment, and especially to human lives. Lower performance due to a component failure or a control system failure is acceptable as long as the system or the plant is brought back to its normal operational state [47] [61].

In principle, control system failures can be minimized if two or more sensors, actuators, or computers are used for controlling a complex system, provided each of them is able to control that system individually. A voting system is used in different control systems such as in aerospace, power plant, and process industries. For example, a two-channel system is considered "fail-safe", since failures can be detected. The weak point of two-channel systems is that, identifying the failed system is left to a built-in logic. The three-channel systems are called "fail-operational" since the task of the system can be completed after a single failure. Systems with four-channels are called "fail-op/fail-op" since two failures can be overcome by the system and yet the overall system will still be operating normally within its nominal performance [47].

Detection and isolation of faults usually can be achieved by using built-in test systems. A practical solution to this problem can be found, within the ability of control computers to compare the expected response to the actual response. Failure identification for sensors and actuators usually require sophisticated tests that are costly and time consuming.

Chapter 3

Feedwater Flow Regulation System of a PWR

3.1 Introduction

In order to understand and develop an effective control system for a plant subsystem, one needs a detailed model. For example, such a model may be used to study the thermodynamic behavior of the balance-of-plant. The secondary side of a Pressurized Water Reactor (PWR) was modeled with emphasis on the U-tube steam generator. The model could be further developed if necessary, by including the condenser, main turbine, drain tanks, feedwater heaters, and the reactor core. The present simulation code combines four U-tube steam generators, two turbine driven main feedwater pumps, piping, and their controllers. A conventional three-element PID controller is used for regulating the water level in each steam generator. An adaptive controller, using the Reconstructive Inverse Dynamics (RID) algorithm, and a Fuzzy Logic controller were also developed for this system.

U-tube steam generator and turbine driven main feedwater pump models are presented in some detail. The design of a control strategy for a turbine-driven main feedwater pump for an operating nuclear power plant was undertaken as part of the Fault-Tolerant Control and Diagnostics System (FCDS) development. This research task is important in contributing to the improved transient performance that combines steam generator level control and main feedwater valve differential pressure regulation.

The control problem in turbine-driven feedwater pumps is related to the regulation of pressure difference (ΔP) across the feedwater valve around set points during feedwater maneuvers. In the conventional strategy, the feedwater valve position is adjusted to satisfy a feedwater demand whereas the turbine valve position is adjusted to maintain the ΔP close to its set point.

In order to offer a better solution for the problem, it is necessary to simulate the existing control system of an operating nuclear power plant. A computer code was developed and used to simulate the dynamics of the steam generator and the feedwater system. The code consists of models for a U-tube steam generator, main feedwater pump turbine, feedwater pump, and their related control and bypass valves.

Although the development of the code was carried out on a SUN Sparc workstation, the code is completely system independent (except the graphical user interface, GUI) so that it could be executed in personal computers as well as workstations.

There are two controllers involved in adjusting the valve positions:

1. Three-element controller for feedwater valve actuation.
2. Turbine governor valve control to adjust the speed of the turbine driven pump.

The existing controllers in most of the plants are based on analog technology and do not include direct communication between the two control systems. During some steam generator transients where a rapid change in feedwater flow is required for level control, these control systems may go out of phase due to the sluggish behavior of the turbine controller. Thus, a major improvement in feedwater operations requires a coupling between the turbine valve control system and the feedwater/steam generator system to improve the turbine speed adjustment.

The solution to this control problem includes the utilization of more process variables as the input to the turbine valve control system in a feedforward fashion, and/or utilizing different algorithms with different strategies. A number of control algorithms (including PID, fuzzy logic, inverse dynamics) were developed to solve this problem within a fault-tolerant architecture. Although fuzzy logic and inverse dynamics controllers use signals similar those used in the current PID controllers. Since their strategy is different than the PID, an improvement in the feedwater flow regulation is expected. The water level signal, feedwater flow, and pump speed signals are included as a feedforward control input signals in the development of fuzzy logic and inverse dynamics controllers to overcome the lacking communication between the ΔP controller and feedwater valve controller.

An operating four-loop PWR's current three-element PID controller and turbine governor valve PID controller are duplicated in the model. Controller gains and time constants match closely those used in the plant controllers. The primary goal is to develop a system model whose overall behavior is similar to that subsystem of the actual plant. These PID controllers in the simulation use the same form of input signals as those used in plant actuators. The controller generates actuation signals in milliamps (mA) current units. Since the final goal is to have a parallel fault-tolerant control system, adaptive controllers for both the steam generator water level and turbine governor valve controllers were developed. The second controller, Reconstructive Inverse Dynamics (RID), has a faster response compared to the PID controller. This faster response comes from its adaptive nature. The RID controller is a model based controller, and essentially follows the plant dynamics; possible changes that might occur within the plant is directly reflected to the RID controller since the inverse dynamics behavior of the plant is the driving force of the RID controller. The adaptive nature of the RID controller comes from its model-based inverse dynamics feature. A constraint on the rate of change of actuator response can be imposed to match the real system response.

The third controller is the fuzzy logic controller. Two different controllers were developed using the fuzzy logic approach. First controller uses inputs similar to those used in the current PID controller of the plant, namely, level error and flow mismatch. The second approach is an alternative to the existing control system. Level error and the change in level error are the only two inputs to the fuzzy logic controller. The comparison of simulation test results are discussed in the following Chapter.

3.2 Steam Generator System Modeling

A typical U-tube steam generator was modeled for simulation studies. This model is particularly developed for an operating typical four-loop Westinghouse PWR. The primary coolant enters the steam generator through an inlet nozzle at the bottom of the inlet planum. The coolant flows inside the U-tubes first upward and then downward, and transfers heat to the secondary fluid in the shell side of the steam generator. The primary fluid leaves the outlet plenum through an outlet nozzle into the cold leg piping.

Feedwater enters the downcomer shell at a level just above the U-tube region. It flows down through an annulus inside the shell and mixes with water coming from the drum section. The water enters the tube bundle region where heat is transferred to the fluid. As it flows over the outside of the U-tubes, a mixture of steam and water is formed. The mixture enters the riser region where the nozzle effect increases the natural driving force. As the flow passes through the steam separator region, water is separated from the steam and returned to the drum section [30]. Figure 3.1 gives a typical U-tube steam generator.

3.2.1 Steam Generator Model

The steam generator is one of the most important components of a PWR system. It provides a dynamic link between the reactor and turbine-generator systems. It is necessary to understand and model the steam generator to further analyze the PWR systems. There are many different studies performed for the U-tube steam generator, (UTSG), itself and for the PWR systems as a whole [30] [31] [32]. Almost all the models use lumped parameter formulation. In this study four steam generators, two main feedwater pumps and internal piping, and valves have been included. The theoretical simulation is based on the conservation equations (mass, energy, and momentum) [30]. The following assumptions are made for the derivations of the model equations:

- Both water and steam are considered to be saturated.
- Density and specific heat of the feedwater, subcooled region, and the primary side are assumed to be constant.
- Heat transfer coefficients are constant.
- Steam leaving the UTSG is assumed to be 100 % saturated.
- Heat transfer between the downcomer and the tube bundle regions is negligible.

The thermodynamic properties of the saturated water and steam are assumed to be linear functions of the steam pressure for a range of $\pm$ 100 *psi* from the normal

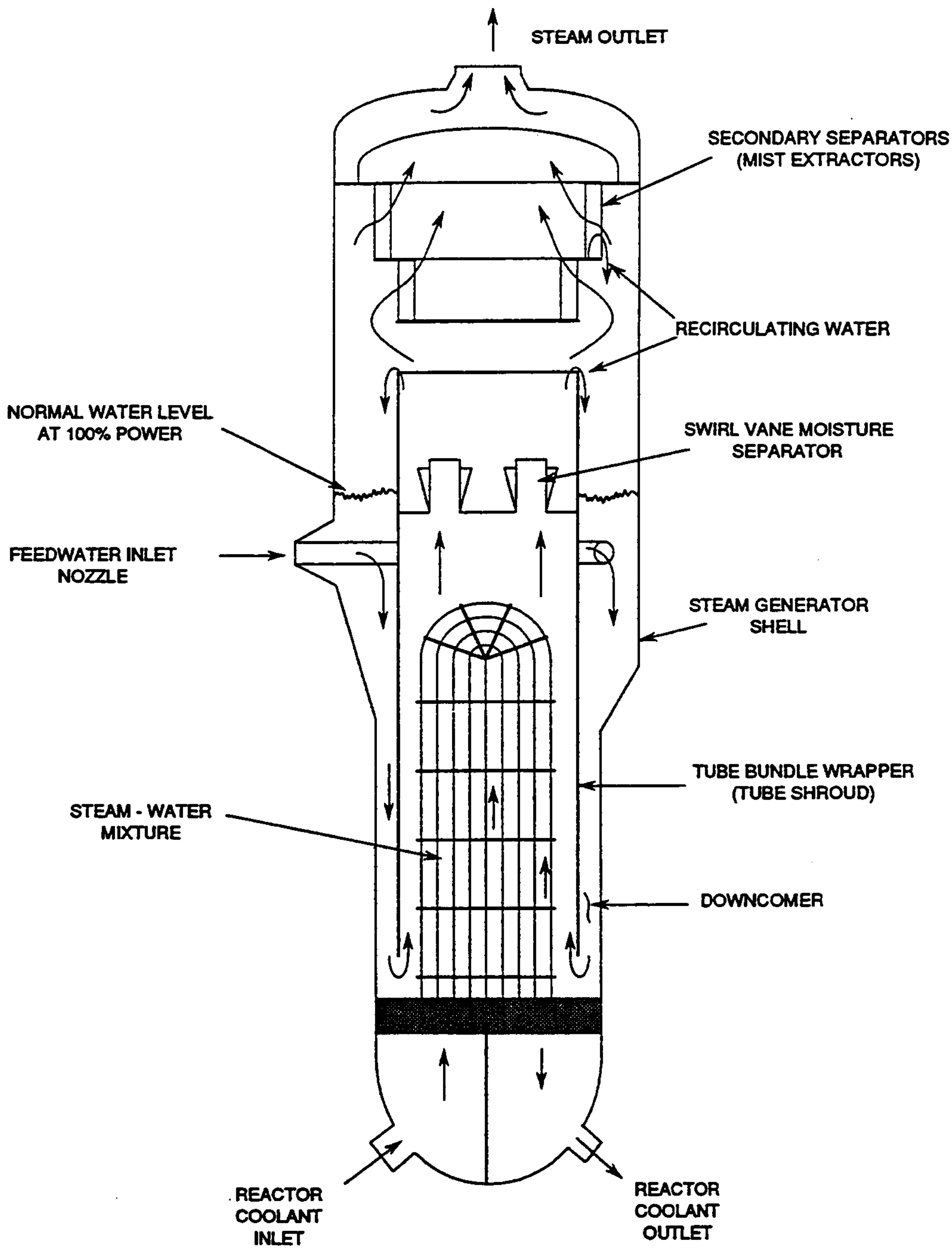

Figure 3.1: A Typical U-tube Steam Generator.

operating point. Equation (3.1) describes the mathematical expression of the above assumption.

$$F_p = X_m + K_n P \tag{3.1}$$

where

F_p is saturated water or steam property.

X_m is a constant of the equation.

$K_n = \frac{\partial F_p}{\partial P}$.

P is steam pressure.

The steam flow leaving the UTSG is considered to be a critical flow. The flow is defined in terms of steam pressure and steam valve coefficient.

$$W_s = C_l P \tag{3.2}$$

where

W_s is the steam flow rate.

C_l is the steam valve coefficient, and P is steam pressure.

A complete description of the UTSG model is given in Appendix A. The forcing functions of the isolated UTSG model are:

(a) primary coolant inlet temperature,

(b) steam valve coefficient,

(c) feedwater temperature.

3.2.2 The Steam Generator Feedwater Control System

The steam generator feedwater control system maintains the steam generator level at its set point and the main valve differential pressure program by controlling the feedwater flow rate through the regulation of the position of feedwater control valve and the speed of the turbine driven main feed pump. The conventional three-element controller generates an error signals from the deviation of the water level from its set point, and steam flow and feedwater flow rates. The error signals are used in a PI controller to actuate the feedwater valve to regulate the water level according to its set points.

In order to minimize the duty on the feedwater control valve, the variable speed main feed pump turbine controls the differential pressure between the feedwater header and the steam header according to a ΔP program which is a function of the main steam flow rate. Figure 3.2 gives the ΔP set point program. This control action tries to keep the differential pressure at a constant value during the steady-state operation. The conventional ΔP controller generates its error signal from the pressure differential between feedwater header pressure and steam header pressure, and from its set point and is used in a proportional-integral controller.

The steam control valve ahead of the feed pump turbine adjusts the pump speed to its set point by regulating the extraction steam flow through the control valve. The basic momentum balance for each feedwater loop is represented as

$$\frac{d}{dt}[M\,U] = [P_{suc} + \frac{F\,\rho}{144} - (f_1 + f_2 + f_3 + \frac{f_v}{A_v^2})\,W_f^2 - P_{sg}]A\,144\,g_c \qquad (3.3)$$

where

M = mass of fluid in this system,

U = velocity of fluid,

A = area of the pipe,

P_{suc} = suction pressure of the main feed pump,

P_{sg} = steam generator pressure,

W_f = feedwater flow rate,

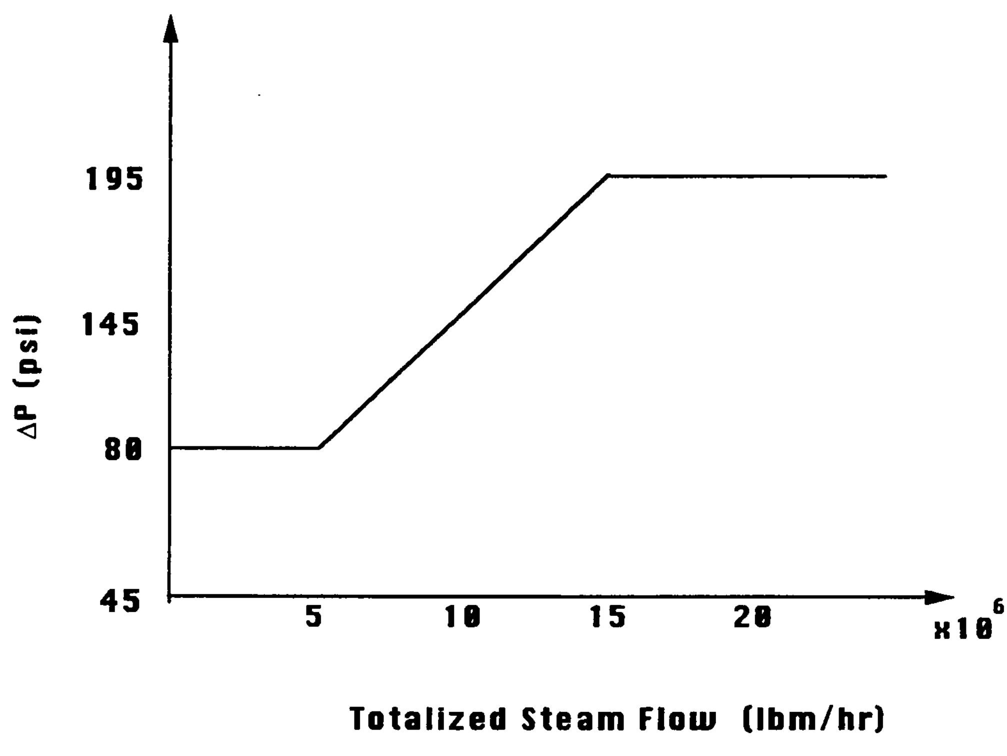

Figure 3.2: ΔP Set Point Program.

f_1, f_2, f_3 = constants related to the pipes,

f_v = constant related to the valve,

A_v = feedwater control valve opening,

The momentum change may be represented as

$$\frac{d(M\,U)}{dt} = \frac{d(\rho\,A\,L\,U)}{dt} = L\,\frac{dW_f}{dt} \tag{3.4}$$

where

L = length of pipe.

3.2.3 Feedwater Control Valves

One feedwater control valve is used in the feedwater line for each steam generator. The valve for a particular steam generator is operated by an automatic control system which regulates feedwater flow to maintain desired water level in that steam generator. There is an independent conventional PI control system for each steam generator. Manual control for each of the valves is also used in case of a malfunction of the automatic controller.

3.2.4 Main Feedwater Pumps

There are two, 60 percent capacity, variable speed, turbine-driven, centrifugal main feed pumps that raise the pressure of the condensate to a value that is high enough to feed the steam generators [28]. The main feed pumps discharge to a common header which supplies the high-pressure heaters. The feed water then flows into a common header which supplies feedwater to the steam generators. Figure 3.3 displays the schematic of the feedwater system of a typical PWR nuclear station.

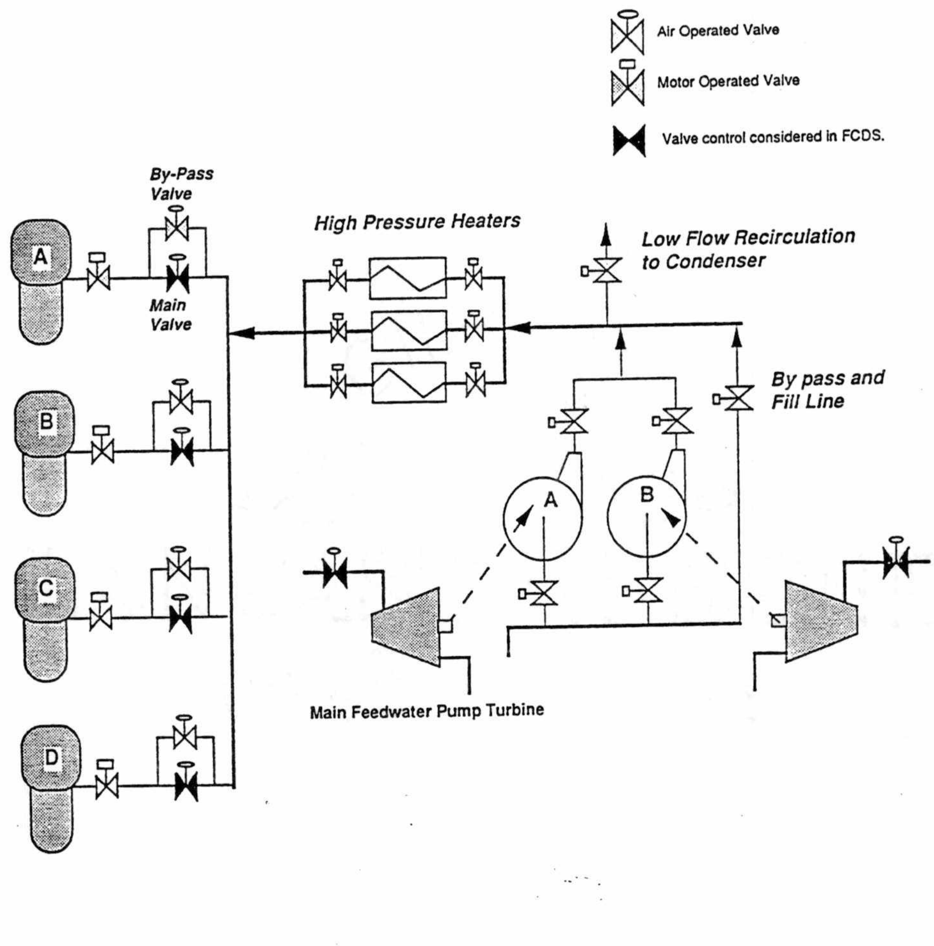

Figure 3.3: Feedwater System of a PWR.

3.3 Pump Model

The pumps are modeled using their characteristic curves. The characteristics curves show the variation of pump head, H, and pump efficiency, $eff = N/N_0$, to be a function of both volumetric flow rate, Q and pump speed, N.

$$H = a_1\,(\frac{Q}{Q_0}) + a_2\,(\frac{Q}{Q_0})\,(\frac{N}{N_0}) + a_3\,(\frac{N}{N_0})^2 \tag{3.5}$$

where 0 indicates the full power condition; the coefficients a_1,a_2, and a_3 are obtained from the characteristic curves at full power condition which are supplied by the manufacturer [32].

The outlet enthalpy, h_0, is represented as

$$h_0 = h_i + \frac{H}{778\,eff} \tag{3.6}$$

where

h_i = enthalpy of fluid at inlet,

For a constant speed pump, the pump head is considered to be a function of the volumetric flow rate. The pump speed is determined by the driving torque and pump torque.

$$I\,\frac{2\pi}{60}\,\frac{dN}{dt} = T_d - T_l \tag{3.7}$$

where

I = pump moment of inertia,

N = pump speed in RPM,

T_d = driving torque,

T_l = pump load torque.

The pump load torque is given by

$$T_l = \frac{H\,W_f}{eff\,2\pi\,N} \tag{3.8}$$

where

W_f = feedwater mass flow rate in lbm/sec.

3.4 Pipe Model

A very simple approach is used for modeling an insulated pipe with incompressible liquid flowing through the pipe. Balance of momentum equation gives the following:

$$\frac{L}{A}\frac{dW}{dt} = P_2 - P_1 + \frac{f\,W^2\,L}{2\,A\,D\,\rho} + (Z_1 - Z_2)\,\rho\,\frac{g}{g_c} \tag{3.9}$$

where

P_1 = pressure at position 1,

P_2 = pressure at position 2,

f = Darcy-Weisbach friction coefficient of the pipe,

W = liquid mass flow rate through the pipe,

ρ = density of the liquid,

A = cross sectional area of the tube,

L = length of the tube,

D = diameter of the tube,

Z_1 = elevation at point 1,

Z_2 = elevation at point 2,

g = the gravity acceleration,

g_c = conversion factor ($32.2\ \frac{lbm-ft}{lbf-sec^2}$).

3.5 Feedwater Pump Speed Control System

The feedwater pump speed control circuitry is shown on Figure 3.4. A load signal, derived from the total steam flow, is used to generate a ΔP program (steam pressure - feedwater header pressure). This signal and a preset minimum differential pressure

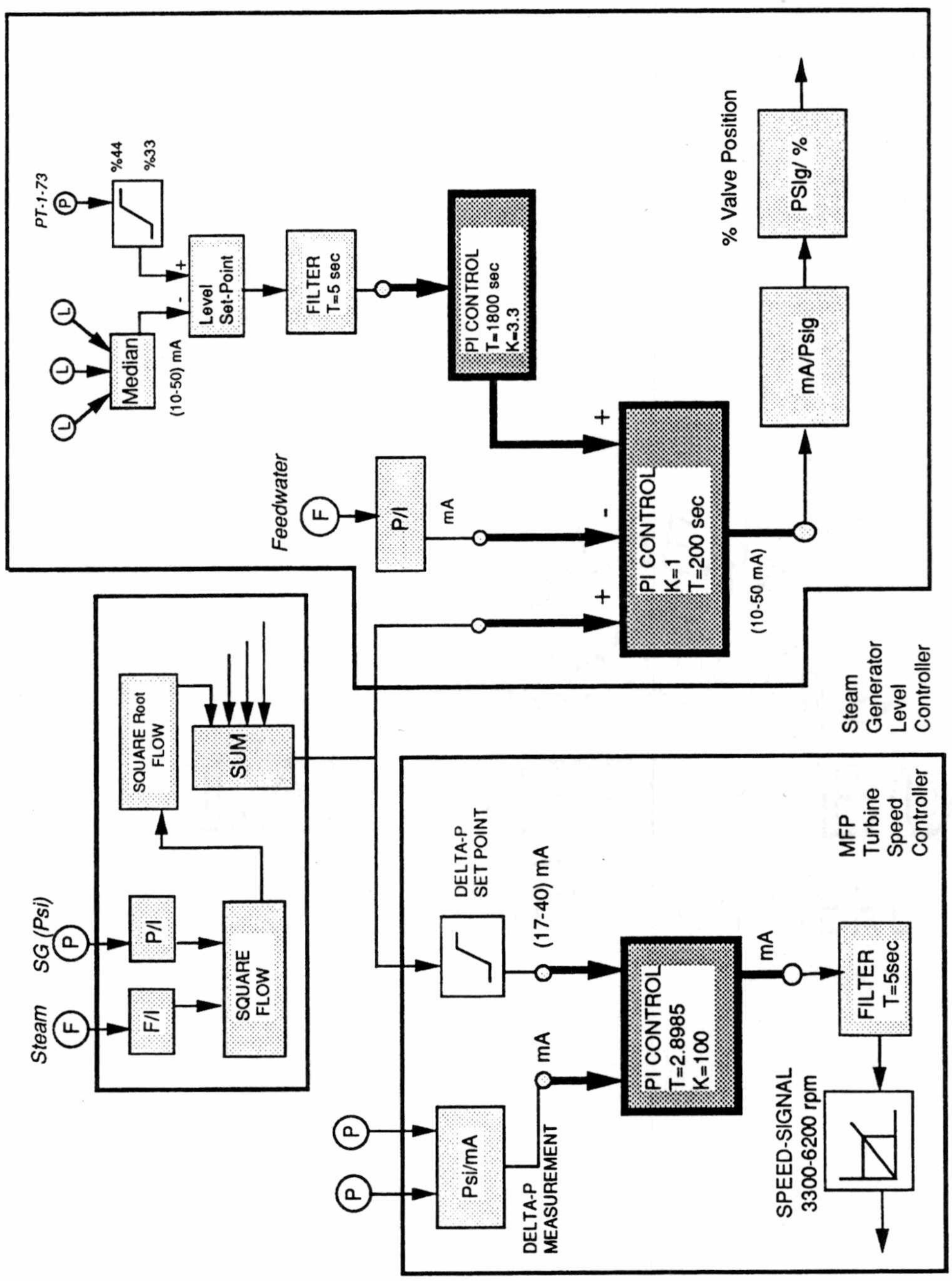

Figure 3.4: Schematic of the Main Feedwater Control System.

signal are supplied to a high value gate in the PWRs, the output of which is the programmed differential pressure.

Actual steam and feedwater header pressures are compared and the actual differential pressure is computed. The program and actual differential signals are then compared to produce a differential error signal which controls feedwater pump speed. The feedwater pump speed control system consists of the following three interrelated components.

1. The set point calculators which sum the four steam flows, provide the lag on set point changes, and contain the basic scaling adjustments.
2. The differential pressure controller which compares the steam header pressure, feedwater header pressure, and the calculated set point to determine the required speed signal (a fairly slow reset action is provided in this controller to reduce the steady-state operating error).
3. The feed pump manual/auto stations which provide the operator with the flexibility of choosing various operating modes.

Feedwater flow to the individual steam generators is controlled automatically above 15 % load by adjustment of a feedwater regulator valve in the piping to each steam generator. The valve's position is determined by a conventional three-element controller that uses steam generator water level, steam flow, and feedwater flow as the inputs. During startup and operation below 15 % load, additional control is available from small bypass valves. The bypass valve's position is determined by a single element controller using steam generator water level as the input [29].

Simulation and operational experiences have shown that a large load reduction is the governing transient in the design of the feedwater control system [27]. The closing of the turbine governor valve results in an increase in the steam header pressure (and consequently a decrease in the steam generator level). The increased pressure results in a decreased flow rate from the feed pumps, as long as the valve position and the pump speed remain unchanged. To minimize the duty on the valve, the control system should increase the speed of the pump so that the pump discharge pressure increases by at least as much as the pressure in the steam generator. To achieve this, the pressure difference between feedwater header and steam header is used as a control variable, to be compared with a set point in order to generate a pump speed signal.

To provide a given flow margin at any load, the steady-state ΔP may be reduced at lower loads. Therefore, the header-to-header ΔP set point varies with load, increasing as the load increases. As an index of load, steam flow is used. To avoid a momentary drop in the steam flow during the time period between the closing of the turbine valve and the opening of the steam dump valves, the pressure difference set point is delayed. This delay provides a constant pressure set point during the first stage of the transient.

3.5.1 The Pump Control System Model

An operating four-loop PWR's current three-element controller and turbine governor valve controller were simulated. The controller gain constants and time constants closely match those used in the plant controller. The mathematical derivation of the ΔP controller is given in this section. The pump speed control system model is stated in the following equations.

$$\Delta P = P_{hd} - P_{ave} \tag{3.10}$$

$$P_{err} = \Delta P_{set} - \Delta P \tag{3.11}$$

$$W_{mfp} = K_a\, A_s\, P_{in} \tag{3.12}$$

$$I\,\frac{dN}{dt} = \frac{W_{mfp}\,(h_{in} - h_{out})\,778}{N} - \frac{H\,W_f}{eff\,N} \tag{3.13}$$

$$H = f(W_f, N) \tag{3.14}$$

$$P_{dis} = P_{suc} + \frac{\rho\,H}{144} \tag{3.15}$$

$$P_{hd} = P_{dis} - f_1\,W_f^2 \tag{3.16}$$

$$P_{uv} = P_{hd} - f_2\,W_f^2 \tag{3.17}$$

$$P_{dv} = P_{sg} + f_3\,W_f^2 \tag{3.18}$$

where

$f_1 = (P_{dis0} - P_{hd0})/W_{f0}^2$

$f_2 = (P_{hd0} - P_{uv0})/W_{f0}^2$

$f_3 = (P_{dv0} - P_{sg0})/W_{f0}^2$

P_{hd} = Pressure at feedwater header

$P_{ave} = \sum_{i=1}^{4} P_{sg}(i)/4$, Average pressure of the four steam generators

N = Pump speed

A_s = Steam control valve opening

W_{mfp} = Extraction steam to main feed pump turbine

eff = Efficiency of turbine

h_{in} = Inlet enthalpy to turbine

h_{out} = Enthalpy at the turbine exhaust

P_{in} = Inlet pressure to turbine

I = Inertia of turbine-pump

H = Pump head

P_{dis} = Pressure at pump outlet

P_{suc} = Suction pressure of feed pump

P_{uv} = Pressure at upstream of feedwater control valve

P_{dv} = Pressure at downstream of feedwater control valve

Table 3.1 gives the steam valve control model variables [30].

Table 3.1: Steam Valve Control Model Parameters.

No:	*Variable Name*	*Description*
1.	P_{sg}, Steam generator pressure	857 Psi
2.	P_{dis}, Discharge pressure of feed pump	989.17 Psi
3.	P_{uv}, Pressure at the Upstream of valve	917 Psi
4.	P_{dv}, Pressure at the Downstream of valve	877 Psi
5.	W_f, Feedwater flow rate (each loop)	1035.125 lbm/s
6.	N, Pump speed	5362 RPM
7.	L_{dw}, Water level (from the top of the tubes)	9.63 ft
8.	ρ, Density of water	50 $\frac{lbm}{ft^3}$
9.	I, Pump turbine inertia	160
10.	h_{in}, Inlet enthalpy of turbine	1271.4 Btu/lbm
11.	h_{out}, Enthalpy at the turbine exhaust	976.2 Btu/lbm
12.	P_{suc}, Suction pressure of feed pump	360 psia
13.	P_{in} Inlet pressure to turbine	160 psia
14.	a_1, Pump head coefficient	2440
15.	a_2, Pump head coefficient	241.19
16.	a_3, Pump head coefficient	-869.17

Chapter 4

Parallel, Fault-Tolerant Control and Diagnostics System

4.1 Introduction

A nuclear power plant is a complex system with the various subsystems fulfilling the needs of process control and safety. Continued operation of these systems has both economic and safety implications. Electric utilities seek continuously to improve the operation of power generating stations. The various studies in control, monitoring, diagnostics, validation, and performance analysis of these systems are reviewed in Chapter 2.

The primary focus of this dissertation research is to develop and apply advanced techniques to some of the problems identified by utilities in the areas of instrumentation and control. An integrated approach for control, diagnostics, and monitoring is the major contribution of this work. In this chapter, the design of a parallel, fault-tolerant control strategy for the main feedwater flow regulation system is discussed. The goal is to combine the steam generator water level controller and the main feed pump speed controller, and develop an integrated system consisting of control, signal validation, and command validation modules. The resultant fault-tolerant control system consists of five major components.

1. Control module,
2. Signal validation module,
3. Command validation module,
4. Decision making module,
5. System executive module.

Figure 4.1 shows the general architecture of the FCDS design. Each module has multiple approaches in its implementation. In order to offer fault tolerance at the control level, FCDS utilizes three different control algorithms in a parallel manner. The control module incorporates reconstructive inverse dynamics control, fuzzy logic control, and the conventional PID control for feedwater flow regulation of a pressurized water reactor (PWR). Reconstructive inverse dynamics (RID) is a model-based adaptive nonlinear control algorithm. Fuzzy logic is a nonlinear controller where the qualitative information of the process and approaches of human operators are utilized. In addition to these nonlinear controllers, existing PID controllers of a PWR are also developed as part of the control module in the FCDS. During normal operation, the multiple controllers provide a choice of a controller suitable for operation.

The objective of the signal validation system is to monitor outputs from sensors, detect and isolate faulty sensors, and if necessary provide estimation of control and protection system signals. Two different methods are used for validating the signals in the FCDS: (a) Process empirical modeling (PEM), a model-based technique where polynomial empirical models are used to present the relationships among the measurements, (b) artificial neural networks (ANN), a non-algorithmic approach which has the ability to capture the nonlinear relationship between a set of inputs and one or many output variables.

The purpose of the command validator is to verify the control signals (to the actua-

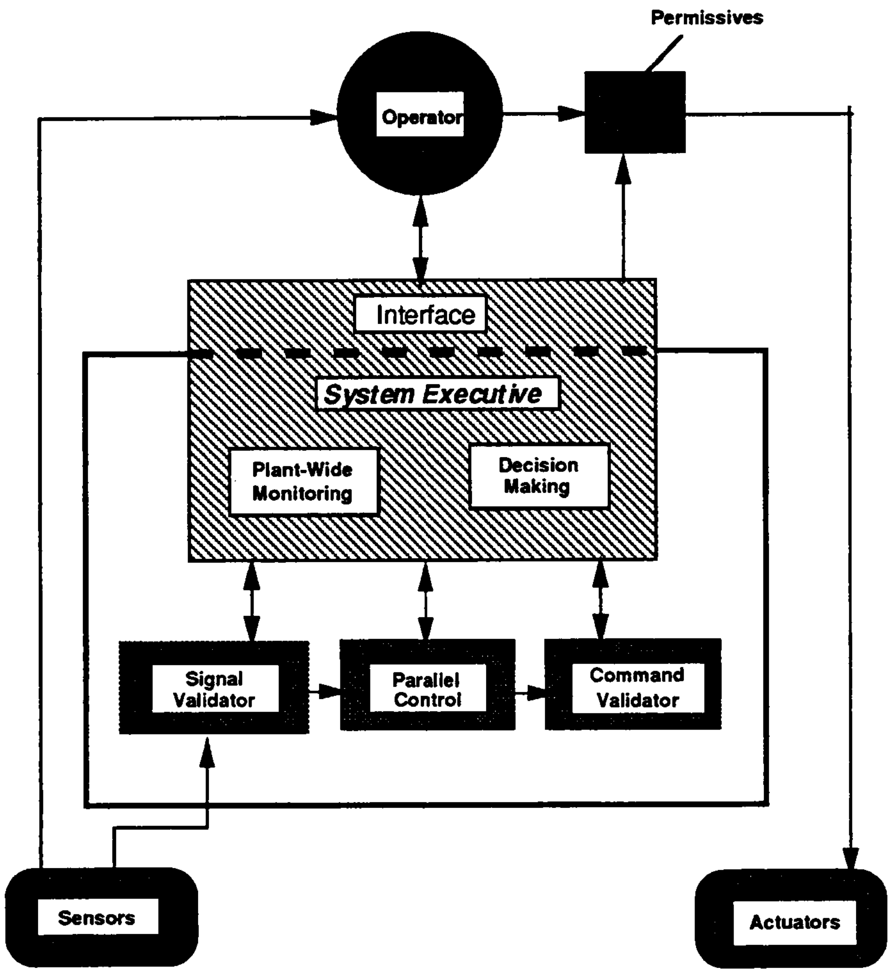

Figure 4.1: Integrated-System Components for Advanced Plant Control.

tors) and outputs of the actuators. Although command validation is a new approach that improves the reliability of the control actions, it can be envisioned as signal validation in which the signals are either the control actions produced by the control algorithms or by the operators. Similar to the signal validation module, both PEM and ANN techniques are used for developing the models.

The system executive module serves as a high-level decision support unit. It analyzes the overall performance and selects appropriate controllers based on the command validation and decision making modules, displays the signals and allows the user (operator) to interact with the FCDS.

4.2 General Features of the Fault-Tolerant Control and Diagnostics System (FCDS)

The fault-tolerant control and diagnostics system introduces parallelism to validation and control by utilizing different algorithms, and increased reliability and fault-tolerance due to the integrated systems approach. The following sections discuss the fault-tolerance, parallel architecture, and command validation features of the FCDS design.

4.2.1 Fault-Tolerance

The FCDS architecture shown in Figure 4.2 represents a fault-tolerant strategy to circumvent problems which may cause reactor trips in conventional systems. The fault-tolerant capability in the FCDS is designed to solve problems in an anticipatory fashion before their effect causes or induces reactor trip. It is important to note that the definition of fault-tolerance does not include any trip avoidance maneuvers in the vicinity of the prescribed safety limits.

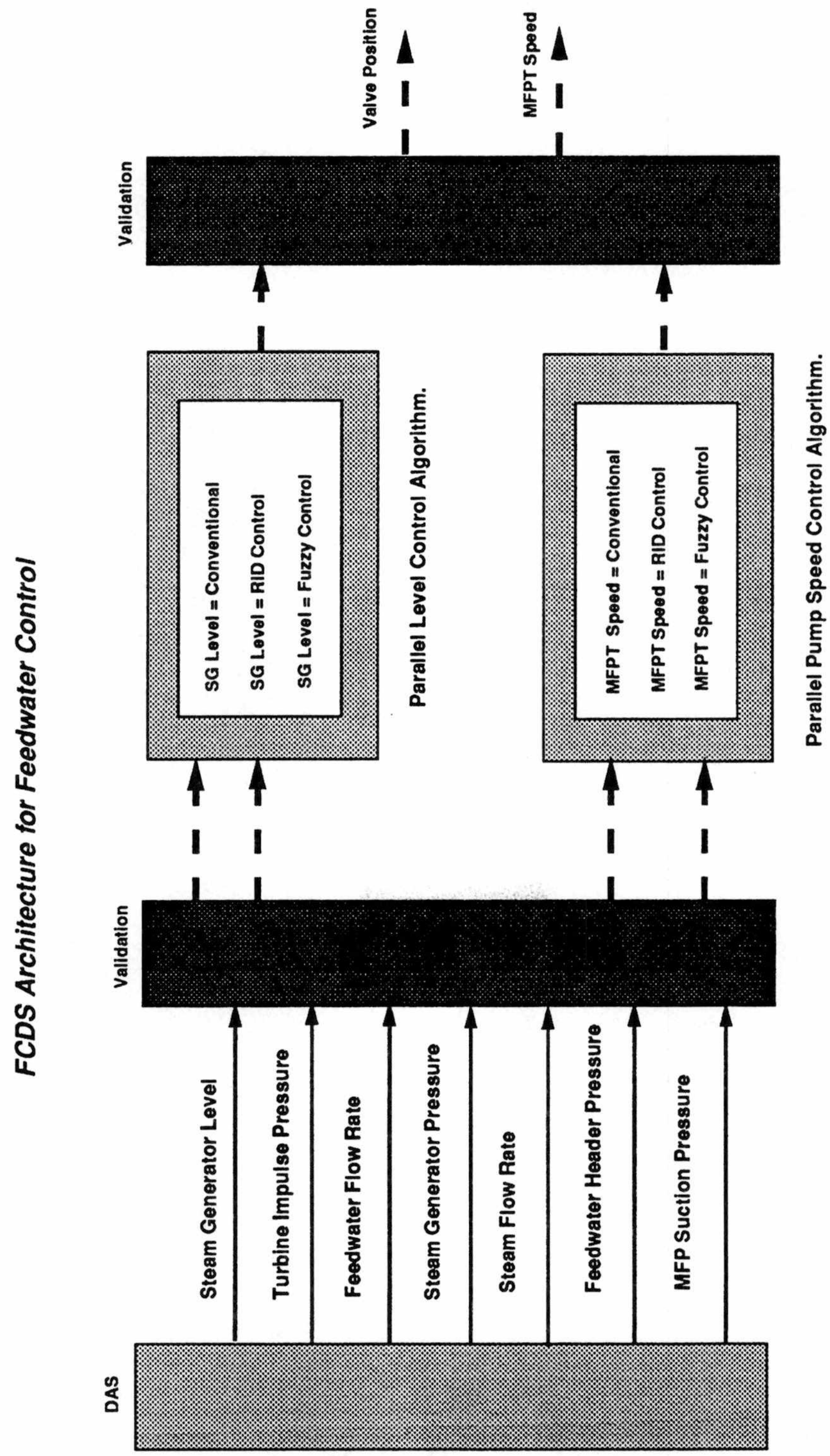

Figure 4.2: Structural Fault-Tolerant Nature of the FCDS.

The FCDS includes signal and command validation blocks. Their major contribution to the fault-tolerant strategy comes from the fault detection capability. This can be performed continuously so that anomalies do not propagate in time. For example, the signals that are used in control systems are analyzed on-line to check their validity. Anomalies are detected promptly and the relevant systems are warned. A similar logic holds for the command validation task. The commands which are not appropriate to the system are not allowed to affect the system. Thus, the validation blocks function as an early failure detection system. However, the early detection does not complete the fault-tolerant logic since the question of "what to do next" has to be answered.

The decision about the actions to be taken following the detection of an anomaly constitutes one of the most significant issues. This problem is solved in the FCDS design by creating redundancies in control systems that operate in parallel. The redundancy built in the FCDS not only introduces a software fault-tolerance, but also offers a number of solutions in case of anomalies. The control block houses three different controllers, each of which

1. Uses a different set of plant measurements,
2. Uses a different control law,
3. Has different robustness characteristics and,
4. Produces the same (or different) output(s).

A signal anomaly can be bypassed by activating one of the controllers which do not utilize the faulty signal. This solution holds if the anomaly is caused by the measurement system. Similarly, if the on-line controller starts generating unacceptable commands, an alternative control system takes over. There exist a jump condition as part of the decision making process. This measure indicates if the jump condition from one controller to the other is acceptable. The FCDS fault-tolerant logic cannot resolve equipment malfunctions (except verifying actuator output) since it is not an expected capability of any control system, in general. In addition, the multiple anomalies occurring simultaneously may not be avoidable; however, the proposed design, in general, offers a better solution than the existing designs.

Figure 4.2 shows the fault-tolerant feature of the parallel control system interacting with the validation blocks. The three controllers use different sets of measurements. The decision making continuously receives the status information from signal and command validators. In case of anomalies, the destination of the corresponding signals is disabled. When there is no signal or command anomaly, the FCDS is expected to drive the plant along the pre-determined trajectories. The fault-tolerance built into the FCDS can also handle software/hardware failures. This requires isolating redundant control algorithms from each other by using different computers, and different operating systems.

4.2.2 Parallel Control Systems

In general, a parallel architecture consists of multiple information processing systems each with the same functional objective. The objective may include the generation of one control signal or the prediction of one process variable. This is illustrated in Figure 4.3-a, where Y is the output, $\{X_n\}$ is the n_{th} subset of measurements, and $F_n(X_n)$ is the algorithm of the n_{th} processor. Referring to Figure 4.3, the parallelism can be categorized in two ways: vertical redundancy and horizontal redundancy.

1- Vertical Redundancy

The simplest parallel form, called vertical redundancy, utilizes the same subset of

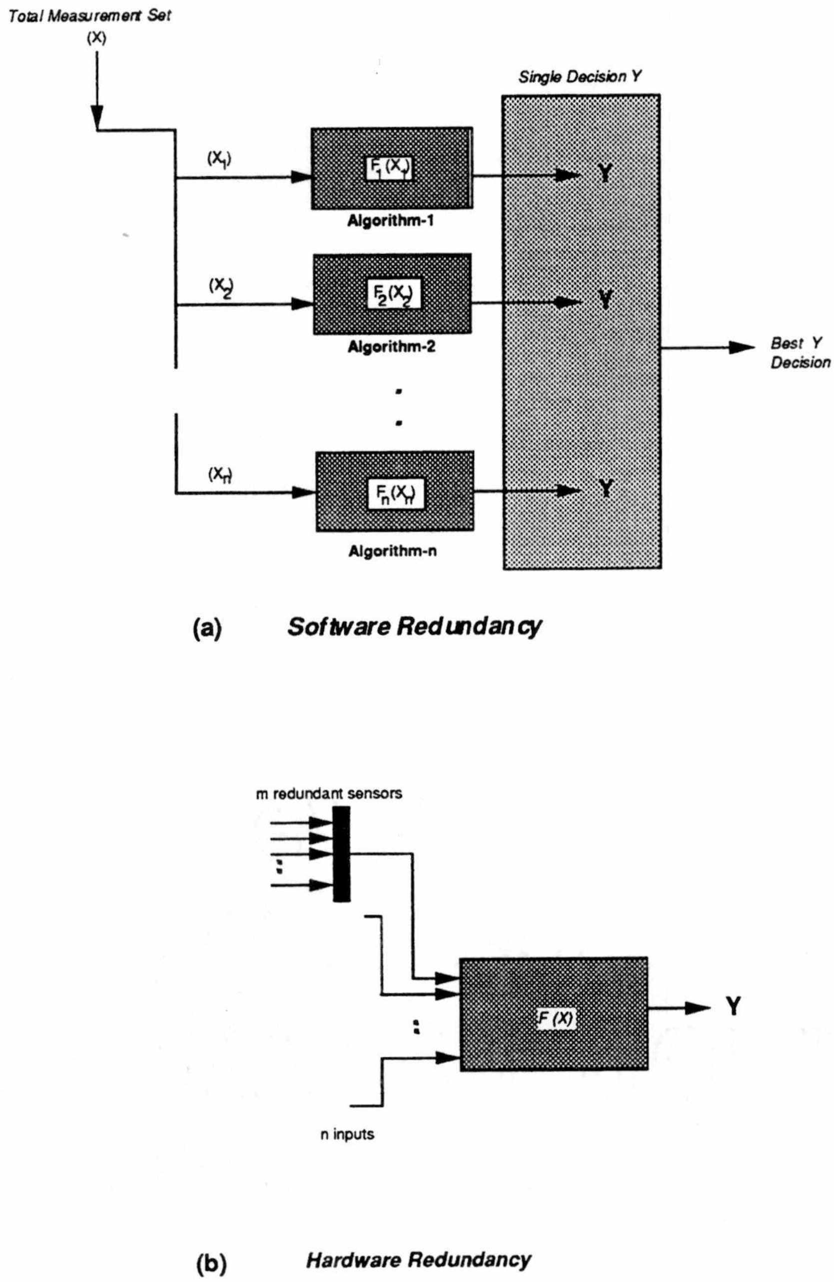

Figure 4.3: Parallel Architecture for the Generation of Decision. (a) Software Redundancy, (b) Measurement Hardware Redundancy.

measurements and the same algorithm.

$$\{X_1\} = \{X_2\} = \ldots = \{X_n\}$$

$$F_1(X_1) = F_2(X_2) = \ldots = F_n(X_n) = Y.$$

This form of parallelism implies that fault-tolerance can only be improved by physically isolating the processors from each other. Stand-by systems used in various industrial applications fall into this category [53].

2- Horizontal (Functional) Redundancy

This architecture utilizes different subsets of measurements along with different algorithms.

$$\{X_1\} \neq \{X_2\} \neq \ldots \neq \{X_n\}$$

$$F_1(X_1) \neq F_2(X_2) \neq \ldots \neq F_n(X_n).$$

The parallel system above suggests n possible solutions for the generation of the output Y. Note that the fault-tolerance property introduced here serves a different purpose compared to that of the vertical redundancy. First, n possible solutions constitute an opinion poll for the decision of Y. Thus, Y is potentially more reliable than the single opinion suggested by vertically redundant processors. Second, there are different combinations of measurements utilized by different processors which provide an avoidance capability in case of a measurement anomaly. Because there are alternative processors not utilizing a corrupted signal, the generation of output Y by those processors will not be affected by signal anomaly.

The feasibility of developing n valid algorithms for single objective depends solely on the specific problem. Similarly, the selection of measurements is not arbitrary. The measurement subsets determined in accordance with each algorithm may include some measurements at the input of every processor. Thus, avoidance against every possible signal failure may not be feasible.

Horizontal (functional) redundancy improves the survival capability in case of measurement anomalies, and enhances decision making via multiplicity of opinions without the requirement of physical isolation of hardware. Hence, it is also called "software-based fault-tolerance".

4.2.3 Command Validation and Decision Making

As shown in Figure 4.3-a, the functionally redundant control system produces multiple solutions of the control (output) Y. The decision of choosing a control strategy requires the validation of each solution independently. Thus, the final decision criterion may reduce to the selection of the best solution, or a combination of reasonable solutions [50] [54].

Within the command validation module, there is a sub-module called, the *Checker*; these two, command validator and checker, work very closely. The Checker evaluates and compares the control signals generated by different control algorithms. Each control signal is compared with the estimations of the PEM and ANN models. If the control output agrees with the estimation results, then the on-line control strategy is kept unchanged. In the event of a disagreement, an alternate control signal is sought. Since it is shown that the PID controller can handle most of the current problems in nuclear power plants, using PID results as a guidance would be reasonable. On the other hand, there are problems such as sluggish behavior, slow response time, and lack of communication between the controllers that PID controllers cannot handle.

The objective of this study is to overcome these current problems, therefore, using PID responses as a standard is not appropriate at each stage. In order to overcome this problem, it is necessary to evaluate each control signal using the command validation and decision making systems so that the best control signal, or combination of two signals is sent to the actuators. Finally, it is also important to realize that the control signal that will be chosen must be generated by an algorithm that is not likely to fail in the following stages of the operation; that is, there should not be a degrading signal, or failed sensor in the input signal set of that control algorithm. The necessary information identifying the current status of each signals is provided by the Signal Validator and Weight Assigner blocks. Weight assigner block assigns values to the validated signals indicating the confidence in the signals based on the signal validation models. Figure 4.4 shows the integration of Command Validator and Checker blocks. Figure 4.5 shows an example of designing different control strategies to achieve the same final goal. The approach studied in this dissertation utilizes different control algorithms which are using different sets of input signals. If one of the signals used in a controller is inaccurate, then this information becomes available through the signal validation block to the decision making and command validation blocks. An alternative controller whose input signals are valid will be available, and the output signal of this control algorithm will be sent to the actuators.

4.2.4 System Description

The fault-tolerant control and diagnostics system includes five major components: system executive, signal validation module, command validation module, decision making module and control module. In this section each of these modules is discussed, the developments of the modules and their individual results are given. These modules are highly interactive, and share information. Although each of the four modules can operate separately, they are organized under a system executive. Signal validation, control, and command validation modules operate as one big module. On-line validation of the signals which are used in the control module

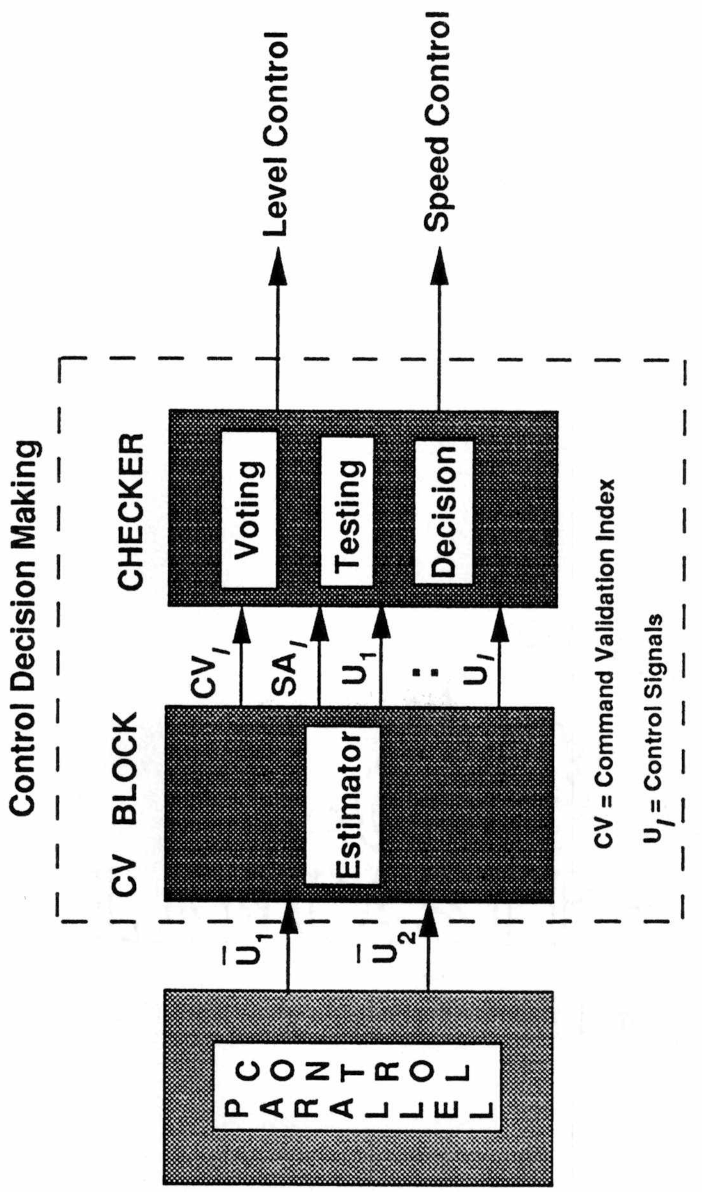

Figure 4.4: Command Validation and Checker Blocks in the FCDS.

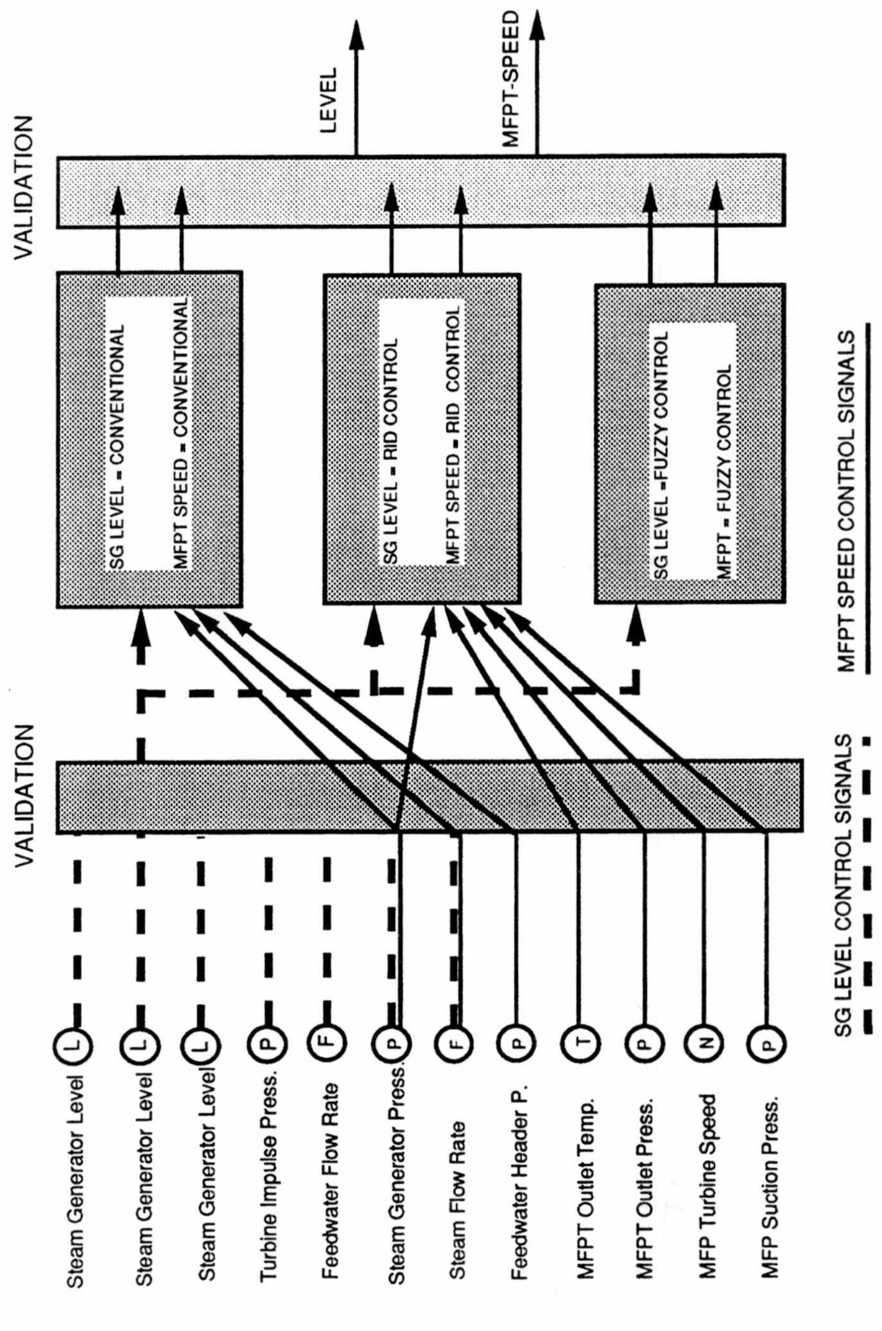

Figure 4.5: Fault-Tolerant Control Using Software Redundancy.

are completed and sent to the decision making module. Command validation and decision making modules select the most appropriate control action calculated by three different control algorithms, and sends the signal to the actuators.

4.3 System Executive

The FCDS combines various modules into one large scale system where control, validation, decision making, and monitoring take place. Although each of these modules can operate individually, every module produces a series of output which is shared by the other modules. Information sharing is one of the important features that makes this integrated system fault-tolerant. The validation module broadcasts information about the control input signals which helps decision making and control modules to determine which controller to use in the event of an invalid sensor.

The estimation results of the signal validation models along with the actual measurements are broadcast and stored in a data file which can later be used. Actual values of selected parameters are displayed by the graphical user interface (GUI). The results of the command validation and decision making modules are also stored in a file for further use after the simulation is completed. The information produced by the modules is not only stored in external files, but is also shared among the other modules. Command validation and decision making modules receive the estimation results of the signal validation module along with the actual measurements of the parameters.

The display of the selected parameters is handled by the system executive via the graphical user interface. Plotting various parameters of the plant, graphical displays of the control systems, and subsystems are also handled by the system executive. The FCDS system executive is a menu-driven system, where the graphical user interface is developed using a commercial software package on a SUN SPARC workstation. The details of the GUI is given in the next section with sample displays of the system executive.

4.3.1 Graphical User Interface

A graphical user interface is developed to provide user friendly access to the FCDS. The GUI is developed on a SUN SPARC workstation using a commercially available software, WINGZ [70]. The GUI displays the various results of modules, validation, monitoring, control actions, and simulation results. The GUI allows the user (operator) to interact with the code at each stage. The flow logic and the organization of the GUI are give in Figure 4.6. Figure 4.7 displays the main menu of this graphical interface.

If simulation is selected, then simplified graphical display of the secondary side of the PWR will appear along with manual/automatic (control mode) control options and steam generator water level and differential pressure control set point switches. This display is given in Figure 4.8. If user selects the *Control* box from Figure 4.8, a new display *FCDS Architecture for Feedwater Control of a PWR* appears on the screen (Figure 4.9).

If the user selects the upper box (*Conventional Controllers* for both steam generator level and main feedwater pump speed control), control diagrams for the conventional PID controllers will be displayed (Figure 4.10). If the second box (*Conventional and RID*) is chosen, a control diagram which shows PID controller for the level, and RID controller for the speed will be displayed (Figure 4.11).

Initially, the program uses the automatic control with predefined set points. The GUI allows the user to change each of the following set points: steam generator

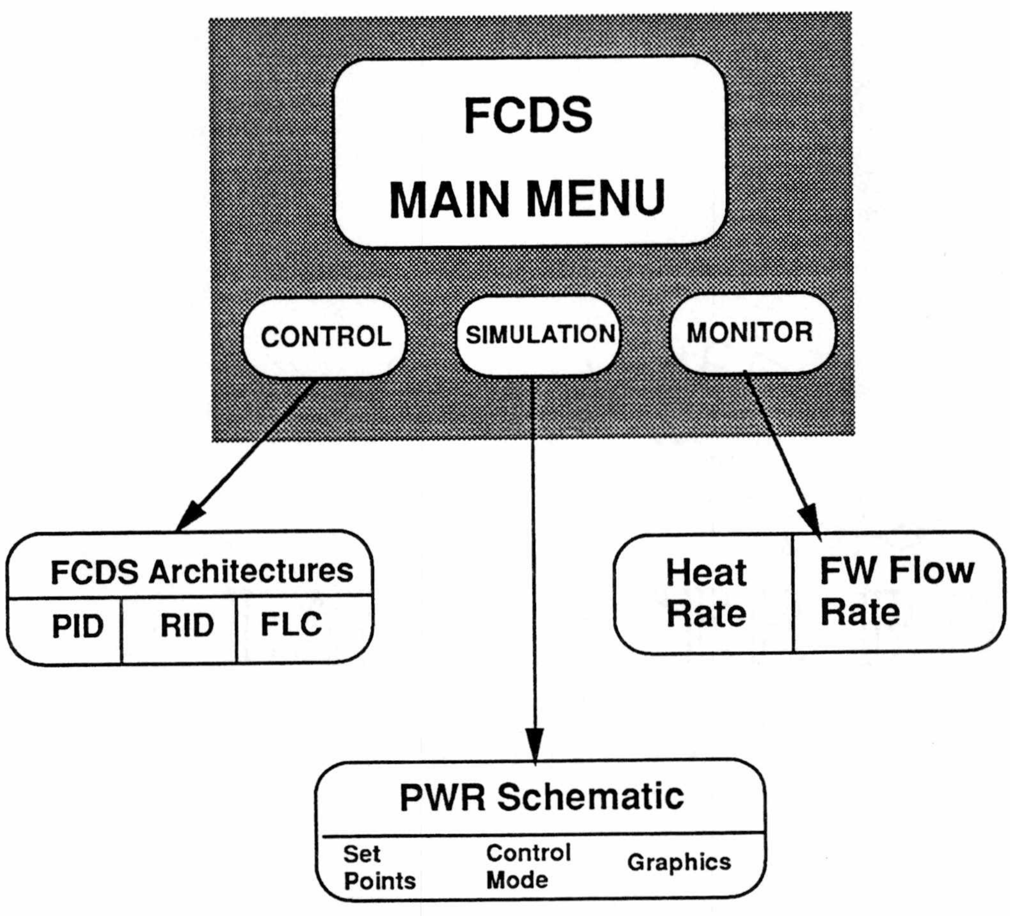

Figure 4.6: Schematic of the Graphical User Interface (GUI) and the Flow Diagram.

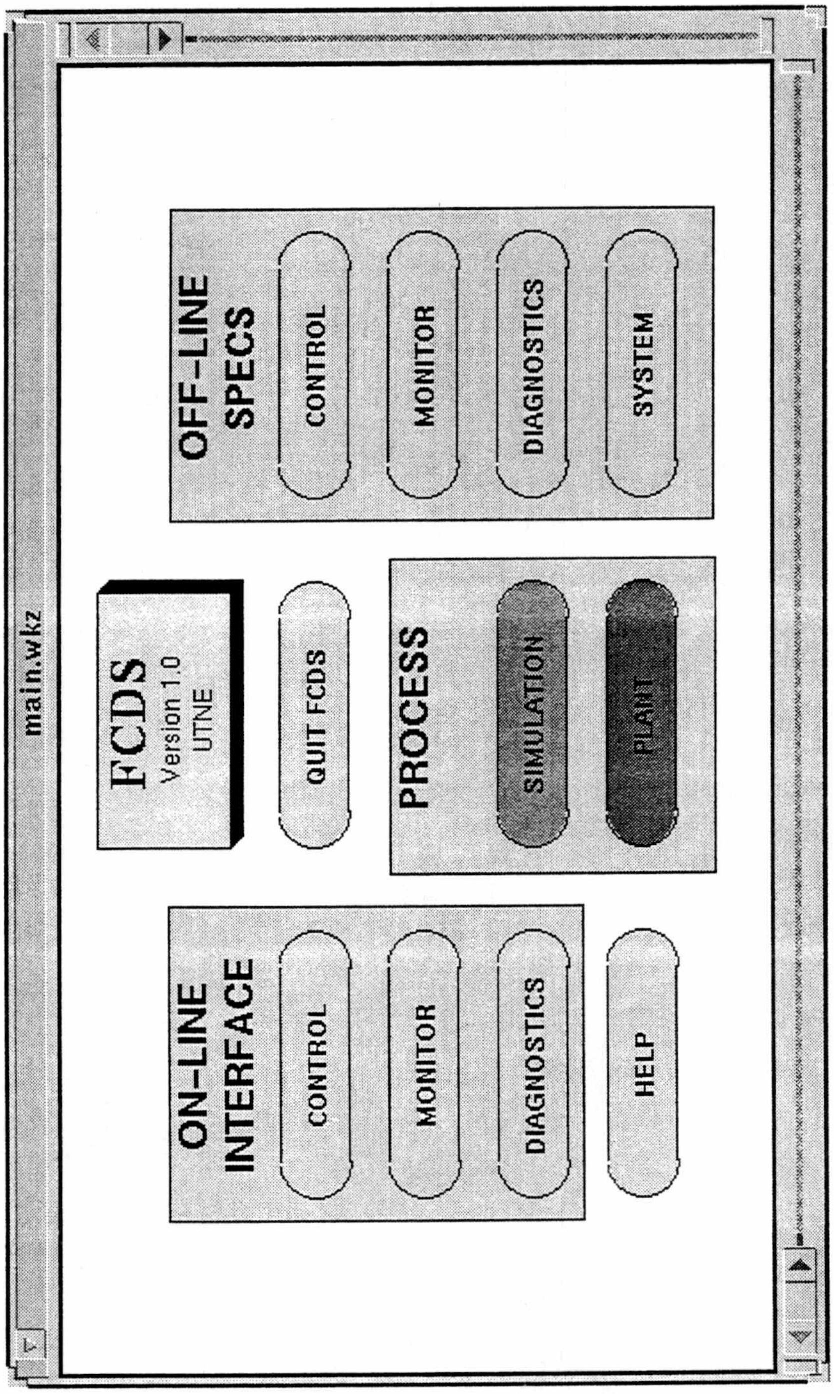

Figure 4.7: Main menu of the graphical user interface (GUI).

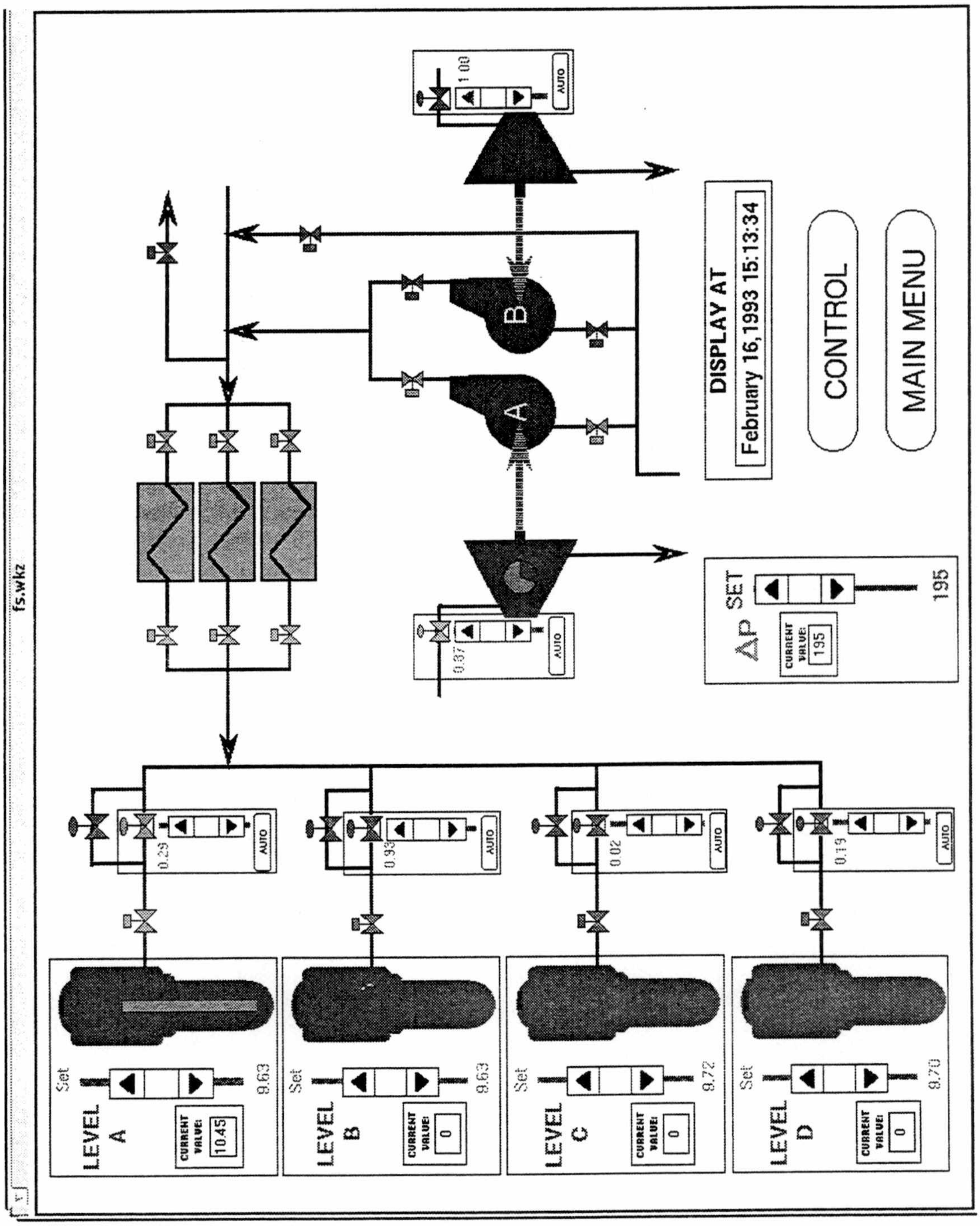

Figure 4.8: Simulation Display of GUI.

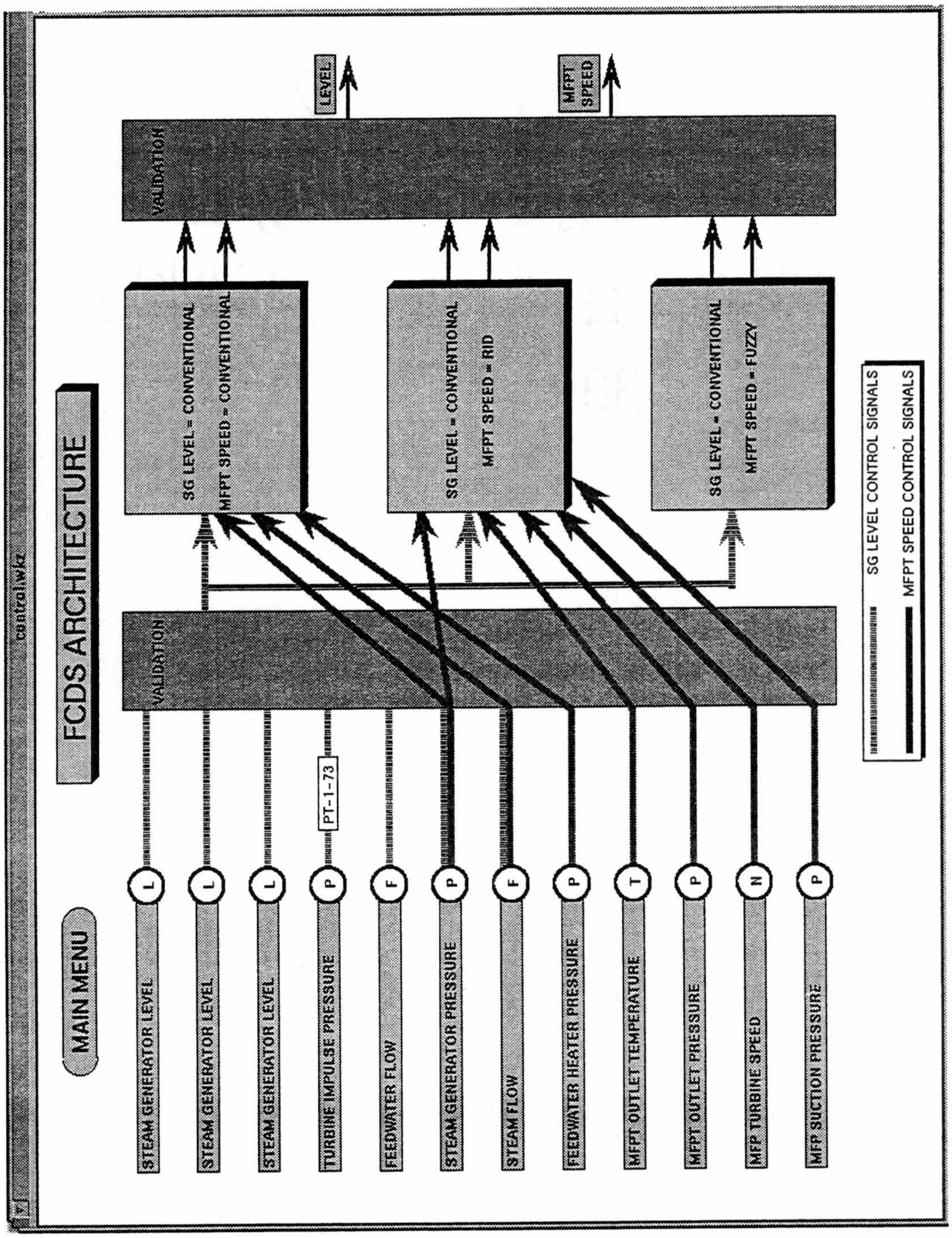

Figure 4.9: FCDS Architecture for Feedwater Control of a PWR.

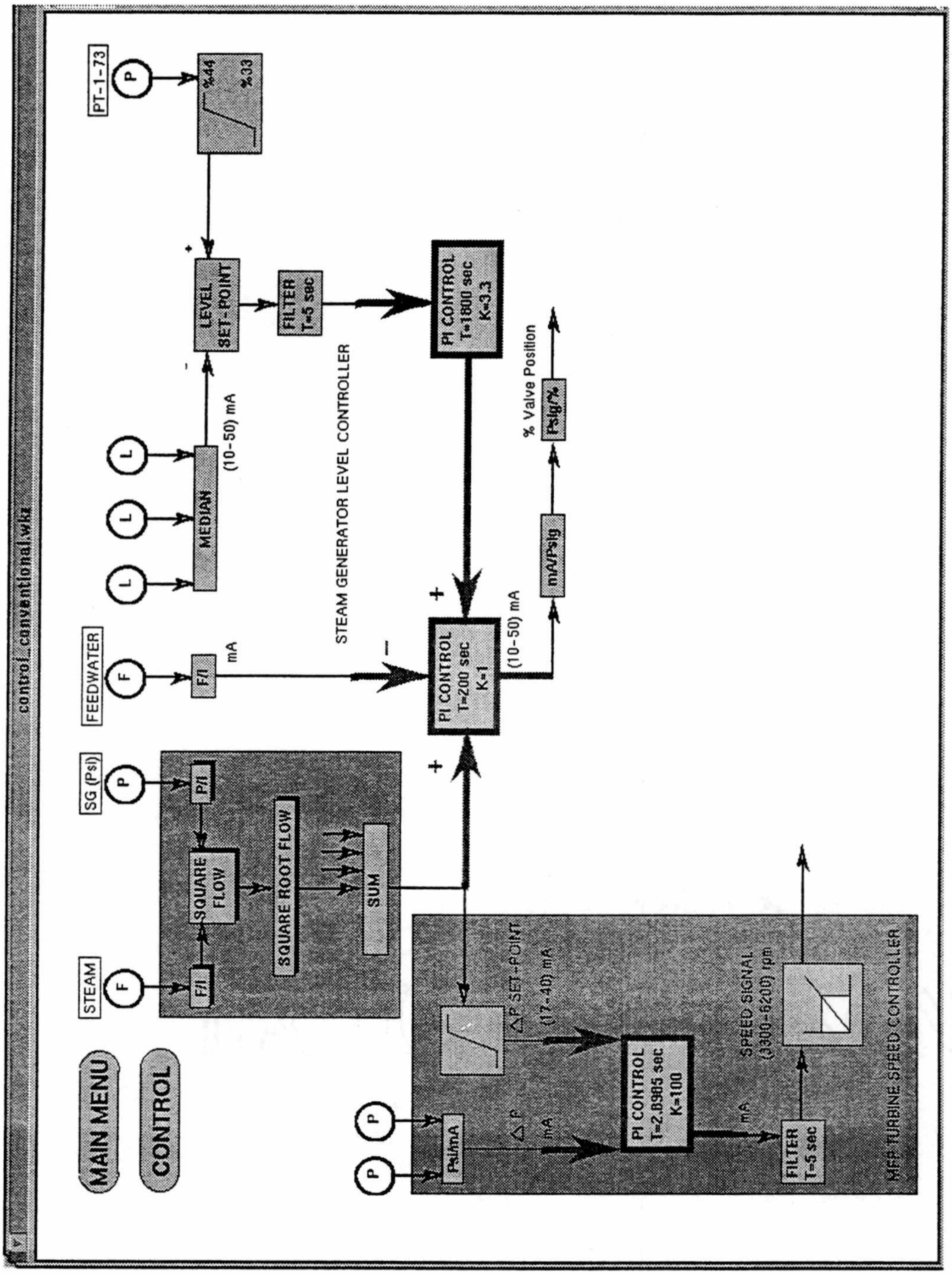

Figure 4.10: Conventional PID Controller Diagram for Level and Speed Controllers.

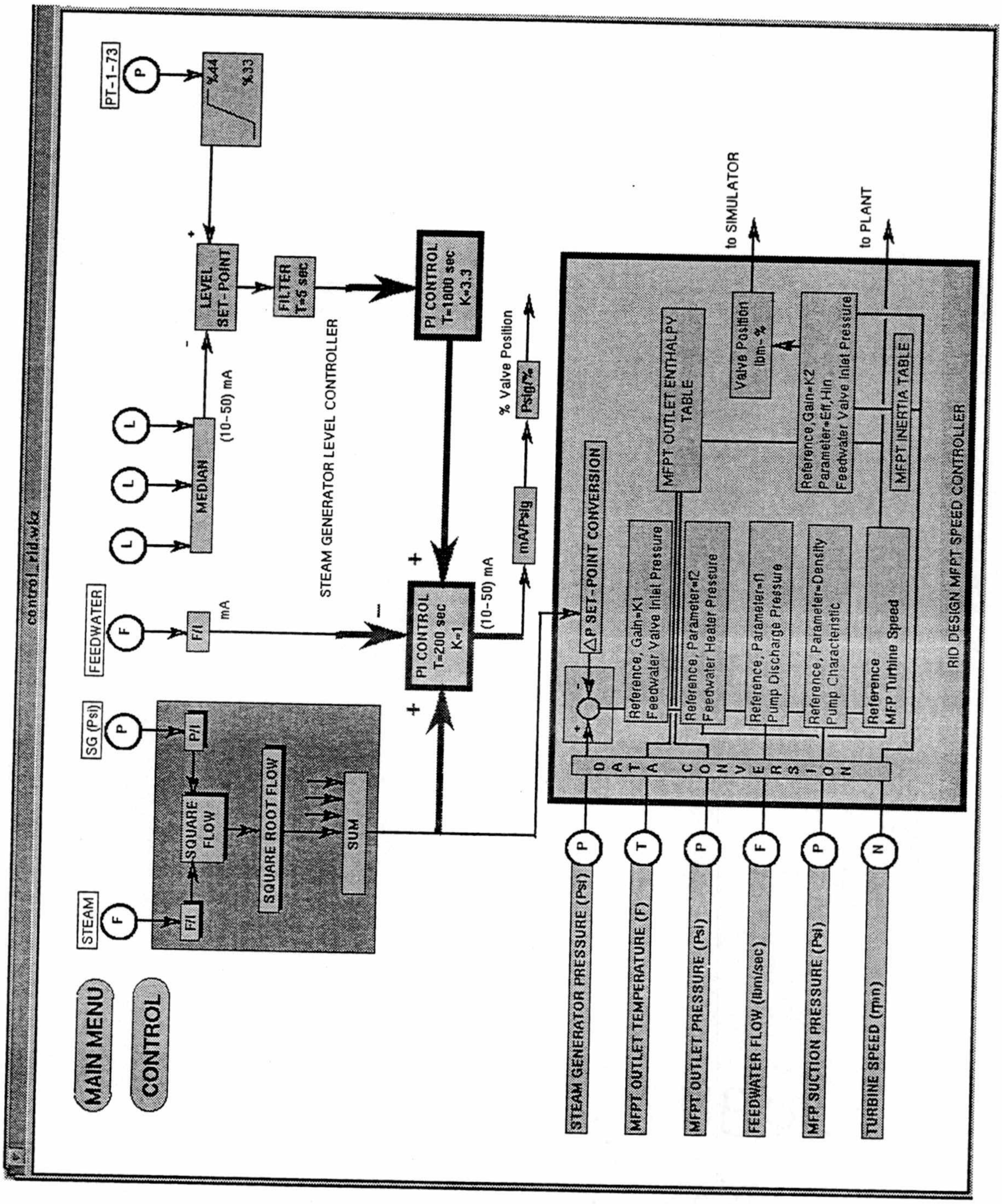

Figure 4.11: Conventional PID Controller for Level and RID Controller for Speed.

water level set point, differential pressure set point, during simulation. The user may also switch the controllers from automatic to manual. During the simulation, seven different graphs are displayed and updated each second. These displays are feedwater valve position, steam valve position, steam generator level and its set point, differential pressure and its set point, main feedwater pump turbine speed, feedwater flow rate, and steam generator pressure. The GUI also displays the levels of the four steam generators, speeds of the turbines, and positions of the valves for each component. While the simulation is being run on the SUN workstation, the results may be displayed on the PC as well as on the workstation.

4.4 Signal Validation

In large power generating systems and process control systems, sensor outputs from many different channels are used in control systems, protection systems, and plant-wide monitoring systems. It is necessary to validate the outputs of these sensors to increase the reliability of operator decision and improve the plant productivity. Signal validation is one of the means which can help to increase the reliability of the control systems. "Signal validation is used to check the consistency of the redundant measurements of selected process variables, estimate their expected values from measurements, and detect, isolate and characterize the type of anomaly in the instrument channel outputs [20]."

The routine validation of critical signals in a reactor system is useful for monitoring incipient changes in sensor behavior and for improving the control strategy with less challenge to the control systems. Signal validation and process monitoring require the prediction of one or more process variables in a system. The prediction of system state variables is performed traditionally using either physical or empirical models. Empirical models require knowledge of all variables having a significant effect on the signal to be modeled. The model characterizes a signal as a function of a set of other measurements which influences the behavior of the signal under consideration.

Model-based prediction assumes a fixed structure for characterizing relationships among process variables. The generation of an accurate model requires an effort which is proportional to the size and complexity of the system. An alternative method, artificial neural networks offers modeling without defining a functional form for relating process variables [7]. In this dissertation research, both the approaches were utilized for developing models of critical signals which are used in the control systems.

The signal validation block contains multiple methods for processing raw sensor data and generating validated data for specific use. Multiple validation techniques are used concurrently to check the data. An intelligent supervisor then votes or weights the outcomes of the various techniques to arrive at a validity parameter. Data samples and validated parameters are broadcast to a specified destination.

Operational records of PWRs indicate various measurement problems encountered during their operation. The feedwater flow elements are subjected measurement errors due to venturi fouling. The steam flow measurement used in the present automatic feedwater control system is also subjected to inaccuracies due to calibration and sensor problems. Steam generator (SG) narrow-range level is another critical measurement for both feedwater control system and reactor protection system. Instrument inaccuracies in the narrow-range SG level measurements impose indirect limitations on the feedwater control system by reducing the margin between the programmed level and the low-low level reactor trip point. Feedwater and steam header pressure measurements are also important parameters used in the feed pump speed control system, a failure of either one of these signals will cause a transient which may result in a reactor trip. Especially non-redundant measurements may sometimes provide misleading information due to sensor degradation or measurement noise. Thus, an on-line signal validation capability is necessary for a fault-tolerant control strategy.

4.4.1 On-line Signal Validation Strategy

The signal validation consists of creating a set of *base* signals. The signals obtained from redundant-measurements are called base signals. The validation strategy also includes empirical models to estimate signals using the non-redundant measurements. The empirical models are developed off-line using data obtained during the previous states of the power plant. These data include the base signals. Thus, the empirical models are developed only using the base signals. This is because redundant measurements are more reliable than non-redundant measurements.

The signal validation block (SVB) shown in Figure 4.12 includes two different routines that check independently the validity of the signals. The first routine uses a nonlinear, process empirical modeling (PEM) technique developed previously [20]. The second routine uses a well-known artificial neural network paradigm called the backpropagation network (BPN). This routine was also developed for diagnostics purposes [7]. Thus, the SVB includes two modules (PEM and BPN) for each set of measurements, and also for other important parameters. Development of the empirical models requires off-line computations.

The PEM routine uses a nonlinear curve-fitting method and is known to provide a very good prediction [68] [20]. It is suitable for rapid updating since the development process takes relatively short CPU time. The BPN is a learning algorithm which requires off-line training. The training period can be long, thus it is not updated easily on-line. However, it is robust against abnormal situations. It is also known to

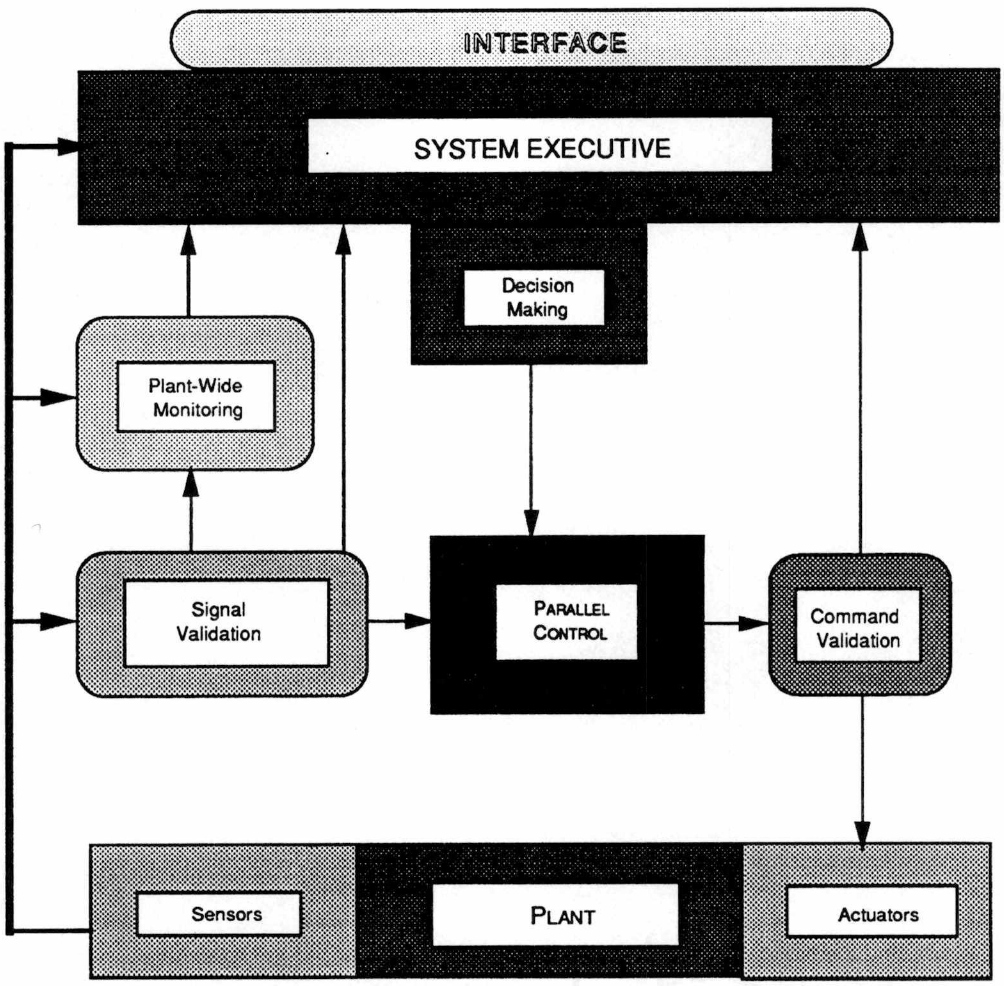

Figure 4.12: Fault-Tolerant Control and Diagnostics System Configuration.

be a powerful generalization tool. The different characteristics of the two methods cover a variety of anomalies so that the fault-tolerance can be handled by, at least, one of the two routines.

During the on-line implementation, the SVB block receives the selected signals. It uses the base signals as the inputs to the models to estimate one or more variables. A comparison takes place between the estimated value and the actual reading. If the deviation exceeds a pre-defined band, then the SVB disqualifies the corresponding signal.

4.4.2 Process Empirical Modeling

The process empirical modeling (PEM) module generates nonlinear multiple-input single-output (MISO) models [68] [20]. The measurements of a sensor output may then be compared against the estimation from the PEM model. The PEM module provides an independent estimate of the process variables. The PEM models are utilized to determine the sensor degradations or drift by on-line monitoring of the sensor readings.

Figure 4.13 demonstrates the schematic way of formulating a critical signal as a function of related variables. The analytical measurement or prediction of a signal y as a function of related variables in a subsystem is given by

$$y = f(\underline{x}) = f(x_1, x_2, \ldots, x_m) \tag{4.1}$$

Empirical Modeling Algorithm

The empirical modeling method creates an optimal nonlinear multiple-input single-output (MISO) model from the given data set. The form of the data driven predic-

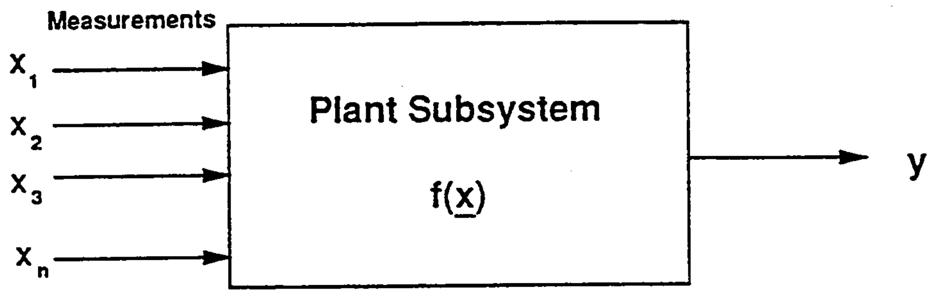

Figure 4.13: Empirical Modeling of a Critical Signal.

tive models is given by

$$y = C_0 + \sum_{i=1}^{N} C_i \Phi_i(\underline{x}) \tag{4.2}$$

where

y = output signal,

$\underline{x}$ = vector of input signals,

Φ_i = nonlinear formation of input signals,

C_i = coefficients.

A geometrical description of the nonlinear modeling algorithm, developed previously [20] [68], follows.

"The closest nonlinear cross-product vector relative to the output vector is determined. New nonlinear vectors (terms) are subsequently selected by projecting the remaining unselected vectors onto a subspace of the original vector space orthogonal to the selected vector(s). This procedure continues until N terms (vectors) are chosen. The final step is to fit a linear type model using the selected terms to compute the coefficients [68]." Figure 4.14 gives the schematic of the empirical modeling.

4.4.3 Artificial Neural Networks

In this section one of the most widely used neural network training algorithms, namely the Backpropagation Network (BPN), is discussed [7]. BPN is a multi-layer fully connected training algorithm. Figure 4.15 shows a typical topology of a three-layer artificial neural network (ANN) architecture. The first layer, usually referred to as the input buffer, receives the information, and feeds it to the inner layers. The second layer, in a three-layer network, commonly known as a hidden layer, receives the information from the input layer, modified by the weights on the connections and propagates this information forward. The hidden layer is used to characterize the nonlinear properties of the system analyzed. The last layer is the output layer where the calculated outputs (estimations) are presented to the environment.

The BPN algorithm was utilized to develop "models" for the "Signal Validation Module." The neural network modeling has the distinct advantage of generating the relationship between two information sets. Thus, it is not necessary to make an assumption about the type of nonlinearity. Model-based prediction assumes a fixed structure for characterizing either steady-state or dynamic relationships among process variables. Relationships between signals in a subsystem of a plant can be modeled using neural networks which provide fault-tolerant estimates of process variables. Neural network models when compared to model-based techniques are more robust against the anomalies in the input signals, and they can give better estimations outside their modeling domain. The drawback in the neural network modeling is the longer model development time. Adjustments of the connection weights between the processing elements (PEs), the basic units of artificial neural networks, is an iterative procedure where the series of input and desired output

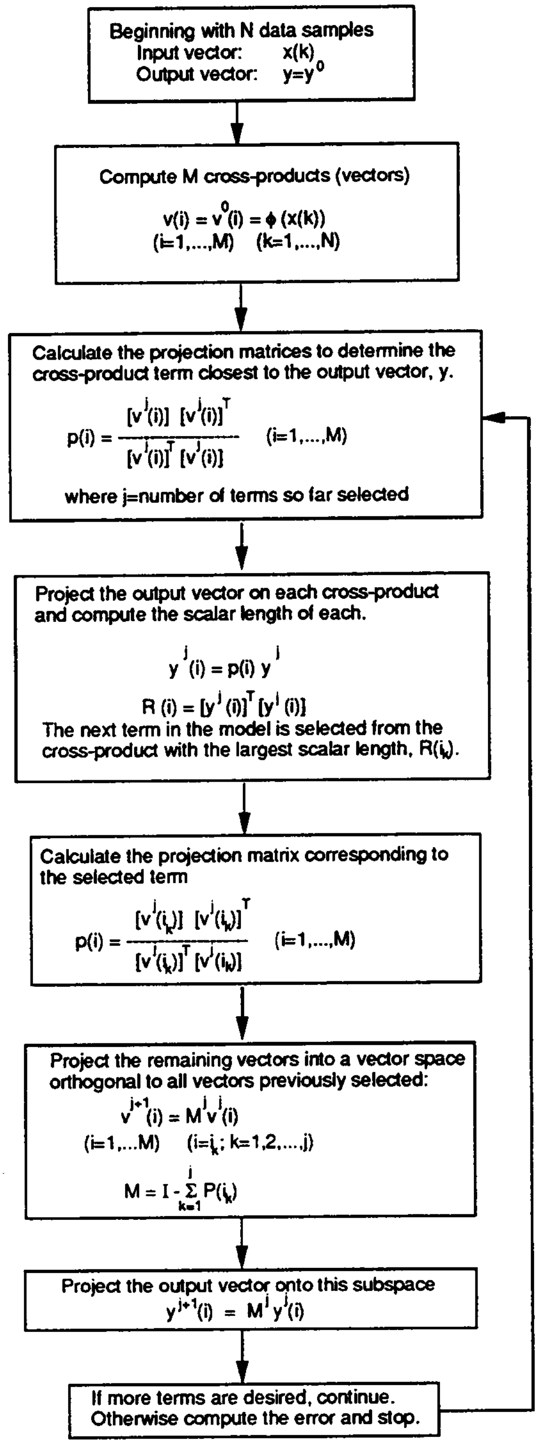

Figure 4.14: Process Empirical Modeling (PEM) Schematic.

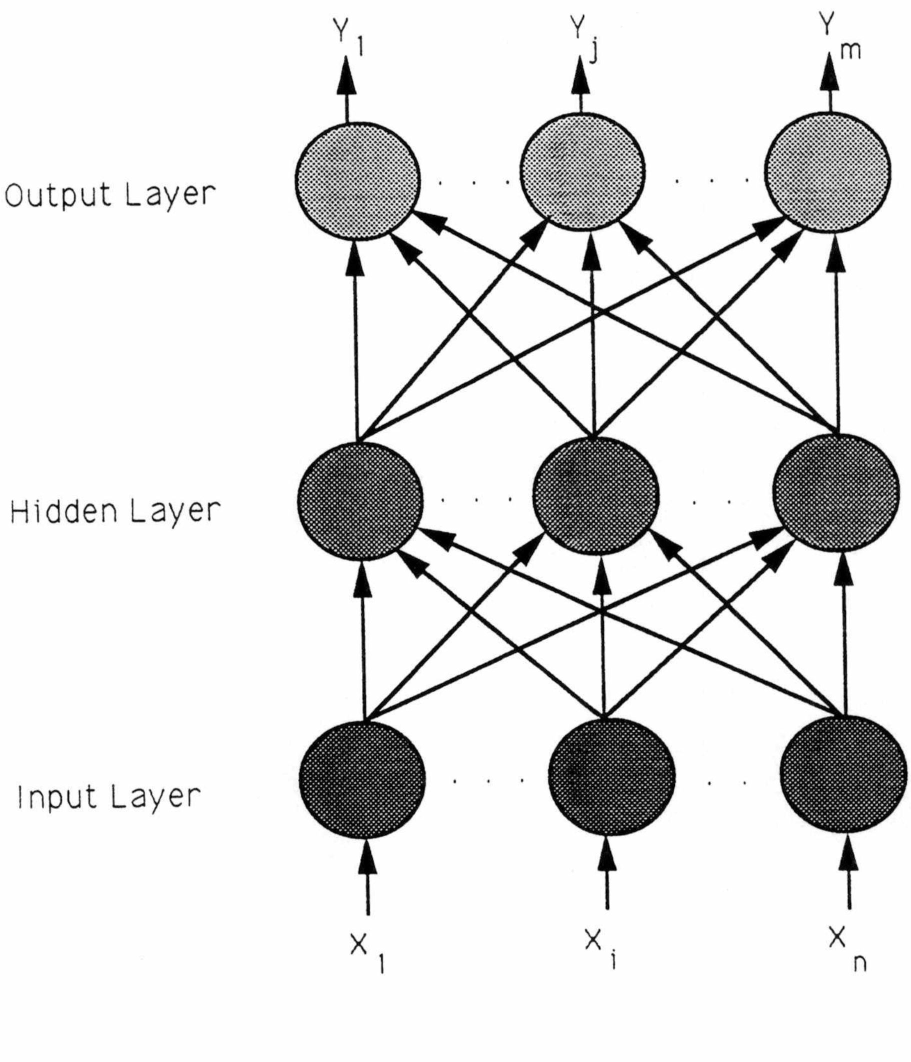

Figure 4.15: Topology of a Three-Layer Perceptron.

signals are presented to the learning algorithm respectively.

The Backpropagation Network Algorithm

The Backpropagation Network (BPN) algorithm uses the generalized delta rule for training. Figure 4.15 shows the topology of a network. The algorithm as presented in [21] is outlined below.

1. Assign a random number r (uniformly distributed) in the range [+1,-1] to all the connection weights w_{ij}^l, and bias θ_j^l of all processing elements (PEs).

2. Present the normalized input vector to the first layer and propagate it to the output layer as

$$x_{jp}^l = \frac{1}{1 + e^{-\beta(\sum_i x_{ip}^{l-1} w_{ij}^l + \theta_j^l)}} \tag{4.3}$$

   after which each PE in every layer of the network will have an associated value of x_{jp}^l. β is the shaping parameter of the sigmoidal thresholding function.

3. For each PE compute the local error at the output layer between the desired value and the calculated value using the generalized delta rule

$$\delta_{jp}^l = x_{jp}^l(1 - x_{jp}^l)(t_{jp}^l - x_{jp}^l) \tag{4.4}$$

   where, t_{jp}^l is the target value.

4. For each PE in the hidden layers, starting at the layer below the output layer ending above the input layer, compute the local error by using

$$\delta_{jp}^l = x_{jp}^l(1 - x_{jp}^l) \sum_i \delta_{jp}^{l+1} w_{ij}^{l+1} \tag{4.5}$$

5. Compute all the connection weight corrections by using

$$\Delta_p w_{ij}^l(n+1) = \alpha(\delta_{jp}^l x_{ip}^{l-1}) + \mu \Delta_p w_{ij}^l(n) \tag{4.6}$$

where n indexes the presentation number, μ is a coefficient called *momentum term*, α is the learning coefficient, and the bias corrections are given by

$$\Delta\theta_j^l(n+1) = \alpha\delta_j^l \tag{4.7}$$

6. Update all the connection weights by adding the weight corrections to the old weights as

$$w_{ij}^l(n+1) = w_{ij}^l(n) + \Delta_p w_{ij}^l(n+1) \tag{4.8}$$

7. Update all the PE bias values by adding the bias corrections to the previous bias values as

$$\theta_j^l(n+1) = \theta_j^l(n) + \Delta\theta_j^l \tag{4.9}$$

8. Present the next pattern, p, to the network until all the patterns are presented.

9. Repeat (step 2) until the error between the desired and the calculated value of the output is sufficiently small.

4.4.4 Signal Validation Database

Prior to developing the signal validation modules using process empirical modeling (PEM) and artificial neural network (ANN) techniques, a database is created using the simulation data and some operational data which were collected from an operating Westinghouse four-loop pressurized water reactor (PWR). Simulation data covered a wide range of level perturbations. The reason for using such data is to include as wide dynamic range about the system in the models as possible. Including a wide range of dynamics enables the signal validation models to give better results in the event of sensor failure, drift, or any other anomalies. The signal validation modules are especially created for those signals that are vital for the operation of the plant and for the feedwater flow regulation control system. Some of the signals included in the signal validation database were: steam generator water level, feedwater flow rate, steam flow rate, steam pressure, coolant temperature in the outlet plenum, drum water temperature, downcomer temperature, feedwater header pressure. These signals were selected to develop the signal validation models, since the focus of this dissertation is on the feedwater regulation system of a PWR.

Using the base data PEM and ANN models were generated for steam generator water level, feedwater flow, coolant temperature, and feedwater header pressure. The models are developed off-line and are utilized within the signal validation block as part of the fault-tolerant control system design. Before the signals are sent to the control module, they are validated and cross-examined by the PEM and ANN models. If the error between the predictions and the measured signals exceed a predefined error, a lower validation measure is assigned to that particular sensor reading by the Weight Assigner and this information is broadcast to the points of interest such as the decision making block where the final decision about the controller to be used is made. Results of the signal validation models developed using PEM are presented in Chapter 6.

4.4.5 Weight Assigner

In order to decide what signals or sensors to use in the control block, a procedure is needed to separate corrupt signals from good signals. The Weight Assigner block designates a value (between 0 and 1) to each signal and/or sensor which will be used in the parallel control block. Weighting is done according to the availability of the sensors and based on the Signal Validation block evaluations. If the estimations of the PEM and ANN models closely match with the measurements (based on defined tolerances), then a high confidence factor (1.0) is assigned. If the measurements differ greatly from the estimations, then a value close to (0.0) is assigned indicating a possible sensor error. The WA is especially useful along with a generalized consistency checking system when the FCDS is to be tested with real plant data. The final result is then sent to the Decision Making block for further use. Figure 4.16 displays the integrated form of the Data Acquisition System (DAS), the Signal Validation Block (SV) and the Weight Assigner (WA).

4.5 Command Validation

The purpose of the command validation block is to determine the accuracy of the command generated by the control system or by the operator, and to validate the resulting output of the actuator system. A command validator as a distinct function is a relatively new concept in process control. It parallels, to some extent, the signal validation black. The overall command validation involves verification of control signal input (to actuator) and actuator system output (plant response). A classic example of a command validator is the conflict resolver circuit of a traffic-light controller. Should the timers and phase sequencers produce simultaneous *green* lights at an intersection, the conflict resolver overrides the situation to produce flashing red or yellow lights.

A definition of the requirement for valid control strategy is that the controller's output to the actuator and the actuator's output must remain within certain bands of a desired strategy or trajectory. The procedure for command validation consists of

- identifying faulty control signals (input and output)
- isolating plant actuator malfunction
- quantifying the control signal's variation from its nominal value.

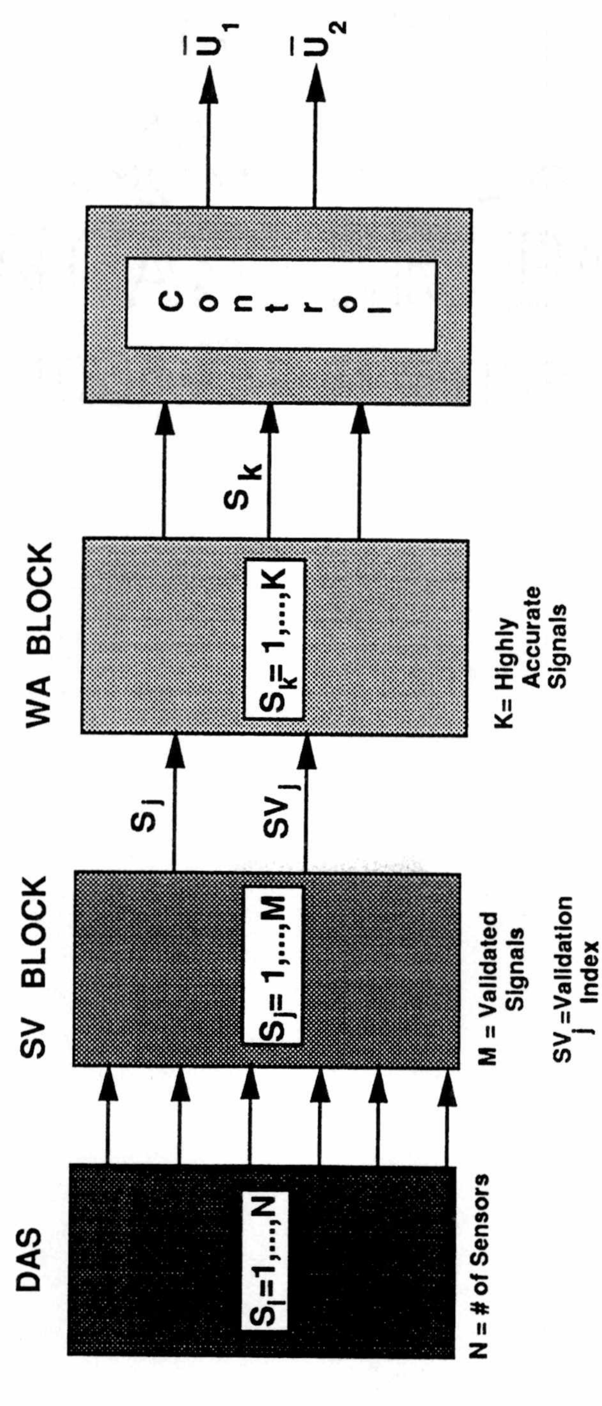

Figure 4.16: Integration of Data Acquisition System (DAS) with Signal Validation (SV) and Weight Assigner (WA) Blocks.

The purpose of command validation is to provide an intermediate confirmation stage before the commands are sent to the plant actuators. From a practical point of view, the command validation is similar to signal validation, except that the signals to be validated are obtained from the operator, controller and/or actuator. The concept of command validation covers the failure possibilities of the command generating components such as the hardware, software, and the operator.

The command validation block (CVB) shown in Figure 4.12 also utilizes two empirical models for each command. The routines used for the CVB are the same as those used in the SVB. Similarly, the models in CVB are developed off-line using available data. The strategy consists of utilizing base signals to estimate the commands. The estimations are compared with actual command signals. When a large deviation occurs between the estimated and actual commands, CVB disqualifies the corresponding command strategy.

Along with the CV block, there is a checker to verify the control signals by either comparing the results of different algorithms, or by comparison with the estimates of the CV block. This dissertation research concentrates on the feedwater regulation of a four-loop PWR. Command validation schemes are applied to feedwater valve and to turbine governor valve control signals. Since the actuator signals are not archived by the data acquisition system at Sequoyah, necessary data for guidance were obtained from TVA's Sequoyah Nuclear Station Simulator [34]. Various simulator transients such as main turbine trip and maximum rate power ramp, and level perturbations were considered during the development of the command validation modules.

4.5.1 Feedwater Valve Validation Models

Two input signals, steam generator water level and feedwater flow are used for this PEM model of the form, $U1 = f(level, W_{feedwater})$. Equation (4.10) gives the formulation of the model.

$$U1 = a_0 + a_1x^2 + a_2y + a_3y^2 + a_4x \tag{4.10}$$

where,

$U1$ = Feedwater valve position (%)

x = Feedwater flow rate (lbm/sec)

y = Steam generator water level (feet)

a_0 = 14.79513

a_1 = 0.06148146

a_2 = -0.4696181

a_3 = 0.02457267

a_4 = -1.744343

Modeling Error (%) = 0.96 %

Along with the PEM model, an artificial neural network (ANN) model for the feedwater valve opening is developed as part of the command validation module. Table 4.1 gives the model specifications. Results of the command validation using PEM and ANN models are given in Chapter 6.

4.5.2 Turbine Governor Valve Validation Models

This model is developed with data that were collected during a ΔP set point change. Four input signals were used to develop the PEM model for the governor steam valve validation: feedwater header pressure, pump speed, steam generator pressure, and feedwater flow rate. Equation (4.11) gives the formulation of the model for the

Table 4.1: ANN Model for Feedwater Valve Opening

Input Signals	*SG Water Level* *Feedwater Flow*
Number of Training Patterns	150
Number of Hidden Nodes	10
Training Standard Deviation	8.61 x 10^{-4}

governor steam valve validation.

$$U2 = a_0 + a_1x + a_2y + a_3z + a_4w \tag{4.11}$$

where

$U2$ = Turbine governor valve position (%)

x = Feedwater header pressure (psi)

y = Feedwater flow rate (lbm/sec)

z = Steam pressure (psi)

w = Pump speed (RPM)

a_0 = -1517.08

a_1 = -18.69873

a_2 = 58.23101

a_3 = -5.689079

a_4 = 24.18062

Modeling Error (%) = 0.4529714

A neural network model was also generated for validating governor steam valve openings. A similar input set was used to develop the model: feedwater header pressure (P_{uv}), pump speed (N_{pump}), steam generator pressure (P), and feedwater flow rate (wf). Details and the accuracy of the neural network model are given in

Table 4.2: ANN Model for Governor Steam Valve Opening

Input Signals	*Feedwater Header Pressure* *Pump Speed* *Steam Pressure* *Feedwater Flow*
Number of Training Patterns	150
Number of Hidden Nodes	15
Training Standard Deviation	1.64×10^{-3}

Table 4.2. The comparative estimation results of both PEM and ANN models are presented in Chapter 6.

Chapter 5

The Control Module

5.1 Introduction

The Fault-Tolerant Control and Diagnostics System, developed as part of this research provides two alternative controllers to the existing conventional controllers used in the feedwater flow regulation system in PWRs. The first controller developed is a model-based adaptive controller which uses the inverse dynamics approach. Reconstructive Inverse Dynamics (RID) controller was developed for both level and (ΔP) control systems. In addition to a model-based control approach, a fuzzy logic (FL) concept is also utilized in this dissertation as part of the control module. Two different fuzzy logic controllers were developed for the steam generator water level control system and one controller for ΔP control. During the simulations, both the level controller and the speed controller are in action. Any combination of the control algorithms can be selected as the initial control strategy. PID, RID, and FL controllers are designed to operate interchangeably during normal operating conditions and during transients. The following sections discuss the control algorithms and give their derivations.

5.2 Reconstructive Inverse Dynamics (RID) Controller

Inverse problems in various fields of applied sciences exhibit differences in mathematical formulation. Despite the variations, the similarities are significant enough to treat them as a single class of problems. The following discussion of the inverse dynamics controller is taken from Berkan [25].

Consider a mathematical model representing a physical process. Typical architecture consists of principal quantities such as input, system parameters, and output. The description of the process is often characterized by a set of equations (ordinary and/or partial differential/integral equations) with bounded parameters. The analysis of the given process via the mathematical model may be separated into three distinct types of problems.

(A) The *direct* problem. Given the input and the system parameters, determine the output of the model. Also known as the *forward* problem.

(B) The *reconstruction* problem. Given the system parameters and the output, determine which input has led to this output.

(C) The *identification* problem. Given the input and output, determine the system parameters which are in agreement with the relationship between input and output.

The problem of types (B) and (C) are called inverse problems because known consequences are used to determine unknown causes. The mathematical representation of the forward and the inverse problems can be carried out by defining:

X = space of input quantities,

Y = space of output quantities,

$\Re$ = space of system parameters,

$A(p)$ = system operator from X into Y associated to $p \in \Re$.

Using the terminology above we can formulate the three types of problems.

(A) Given $x \in X$ and $p \in \Re$, find $y := A(p)x$.

(B) Given $y \in Y$ and $p \in \Re$, solve the equation

$$Ax = y \qquad (x \in X)$$

where $A := A(p)$

(C) Given $y \in Y$ and $x \in X$, find $p \in \Re$ such that

$$A(p)x = y.$$

The reconstruction problem for the linear case, that is if A is a linear map, has been studied extensively, and its theory is well-developed. The situation in the nonlinear case is somewhat less satisfactory. Linearization is very successful to find an acceptable solution to a nonlinear problem for small dynamic perturbations but in general this principle provides only a partial answer.

A typical example of the type **(B)** inverse problems consists of dynamic forces acting on a mechanical system. The problem statement is as follows.

> **Determine the unknown dynamic force having a measured vibration response of a system, whose parameters are considered to be known.**

Considering a one-degree-of freedom mechanical system, the dynamics may be described by the following ordinary differential equation

$$m\ddot{x}(t) + kx(t) = f(t) \tag{5.1}$$

where m and k are the mass and stiffness constant, respectively. The driving force $f(t)$, which is also considered as a control variable, can be solved provided the displacement measurement $x(t)$ exists and is twice differentiable.

$$f(t) = m\ddot{x}(t) + kx(t) \tag{5.2}$$

The solution would not work in practice if the measurement $x(t)$ is contaminated by noise ϑ for which the derivatives do not exist. Even if ϑ is regular enough $m\ddot{\vartheta}$ may be a highly oscillating function.

The underlying principle of the RID controller includes creating the inverse dynamics of the process using a set of equations (linear or nonlinear) that describe the system dynamics [25]. The technique yields algebraic control laws that are easily implementable in a digital environment. The derivation of the control law may be illustrated by considering a simple, nonlinear system where x and u are state and control variables.

$$\dot{x}(t) = F\left[x(t), u(t)\right] \qquad t > 0 \tag{5.3}$$

The reconstruction problem defined by Baumeister [23] states that the unknown control u can be found in terms of the state x and its derivative via an inverse solution G.

$$u(t) = G\left[x(t), \dot{x}(t)\right] \tag{5.4}$$

The existence of such a solution strictly depends on the explicit nature of F. The equilibrium of control for a given time t_0 is given by

$$u(t_0) = G\left[x(t_0), \dot{x}(t_0) = 0\right] \tag{5.5}$$

The condition $\dot{x}(t_0) = 0$ represents a stable solution. In a similar fashion, a dynamic equilibrium of control is given by

$$u_{eq}(t) = G\left[x(t), \dot{x}(t) = 0\right], \; t > 0 \tag{5.6}$$

where u_{eq} denotes the dynamic equilibrium. It was later shown by Berkan [25] that such an inverse solution yields the dynamic equilibrium of control when a desired dynamics $E(t)$ is substituted for $\dot{x}$. A first-order lag dynamics is sufficient to follow a continuous trajectory $x_r(t)$ with an adjustable constant k.

$$E(t) = k[x_r(t) - x(t)] = \dot{x} \tag{5.7}$$

The final form of the control is found by substituting (5.7) into (5.4)

$$u(t) = G\left[E(t), x(t)\right] \tag{5.8}$$

When G is the exact inverse dynamics of the plant dynamics F and when the measurement $x(t)$ is available, the closed-loop dynamics coincides with the definition of the desired plant behavior given by Equation (5.7). Previous studies showed that the closed-loop performance is highly robust against inexact inverses [24]. Adaptive features are incorporated within the theory to enhance performance in case of significant uncertainties. If there are non-measurable state variables required by the control law, an on-line model can be used for state estimation. The example presented here is for a single input and output, but the technique can be extended to multiple variables.

State Reconstructing Inverse Control Law

The reconstruction principle defined by Baumeister [23] states that u_{eq} in Equation (5.6) can be computed provided measurement $x(t)$ is available and G is known. The primary goal in nonlinear control is to **find an appropriate reconstruction of u for the trajectory following case where the effect of imperfect measurements and partially unknown G are guaranteed to be insignificant for all**

practical purposes.

Referring to Equation (5.7), we define a new dynamics for the process which allows a trajectory following in a first-order-transport-lag (FOTL) fashion. The definition is given by

$$\dot{x}(t) = k[x_r(t) - x(t)] = E(t) \tag{5.9}$$

where k is an adjustable constant, x_r is the reference trajectory and $E(t)$ is the dynamic error in trajectory following. Then, the reconstruction problem may be stated as follows:

$$\textit{Find } u(t) \textit{ such that } k[x_r(t) - x(t)] = F[x(t), u(t)]$$
$$\textit{where } x(t) \textit{ is the solution of } \dot{x}(t) = k[x_r(t) - x(t)],$$
$$\textit{for } k > 0 \textit{ and } t > 0.$$

Solution to the problem requires combining Equation (5.3) with Equation (5.9). Eliminating $\dot{x}(t)$ between these two equations gives

$$E(t) = F[x(t), u(t)] \tag{5.10}$$

The reconstruction of $u(t)$ from the above requires "inverse" G such that

$$u(t) = G[E(t), x(t)]. \tag{5.11}$$

Thus, Equation (5.11) is the control design for a system described by Equation (5.3) that requires the knowledge of G and measurement $x(t)$. The closed-loop dynamics can be found by substituting $u(t)$ in Equation (5.3)

$$\dot{x}(t) = F\{x(t), G[E(t), x(t)]\} \tag{5.12}$$

which further reduces to

$$\dot{x}(t) = E(t) = k[x_r(t) - x(t)]$$

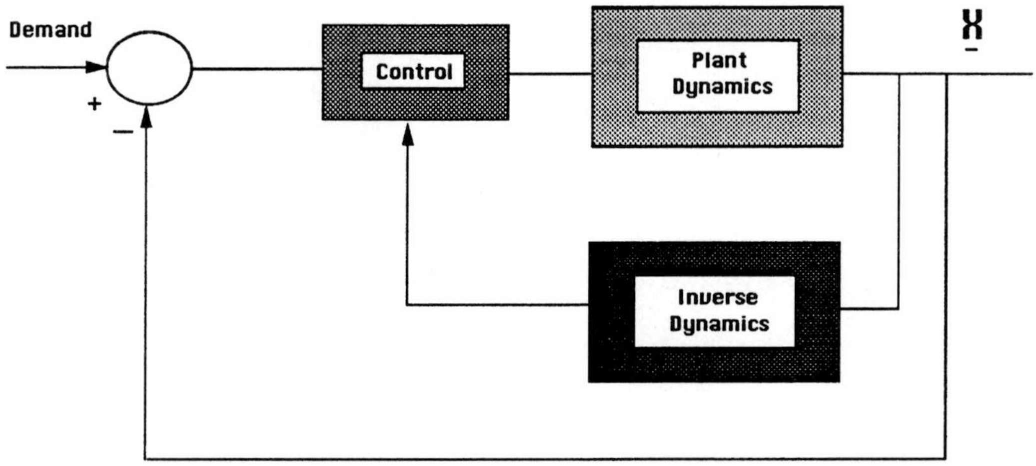

Figure 5.1: Feedback Arrangement of Inverse Dynamics Control.

as defined in Equation (5.9), because G is the inverse dynamics of the forward plant dynamics F. Comparing controls given by Equation (5.6) and Equation (5.11), it can be interpreted that the latter is a dynamic equilibrium of control along the bounded trajectory $\dot{x}(t) = E(t)$ instead of $\dot{x}(t) = 0$.

Adaptive Nature of the RID Controller

The RID control law given by Equation (5.11) operates on the measurement vector $\underline{x}$ in a unique form defined by the inverse dynamics operator G which yields a feedback-control structure shown in Figure 5.1. The two possible problems (1) corrupted or lack of measurements, and (2) inexact operator G, <u>may</u> deteriorate the closed-loop performance. Therefore, a model-reference adaptive method is employed. Both the problems stated above can be handled by incorporating an on-line model where the state variables are estimated. Only the estimation of unmeasurable state variables is required.

5.2.1 RID Control Design Steps

The RID control design requires an adequate knowledge of the dynamics of the system under consideration. Although RID is very robust against modeling errors, accurate modeling facilitates the task of the adaptive part and improves the robustness against anomalies. The RID control design includes the following steps.

- **Modeling:** A nonlinear model must be developed using the state space representation. The model should include all the known nonlinearities as well as the uncertainties [25].

- **Control Law Derivation:** Using the nonlinear model, the control law is derived as discussed previously in Equations (5.3) - (5.8). The analytical derivation, even if there are many solutions to satisfy a given demand, should be performed. The derivation step is completed by defining which state variables are not available as measurements. If state variables are not available, then an on-line model needs to be part of the control system to provide the estimation of the missing state variables.

- **Tuning:** This step includes simulations in which the complete RID control design is included within the model. Tuning is very straight forward since the gain parameters can only have positive values. The tuning takes place only to solve the cost of control, and the stiffness condition restrictions.

- **Final Testing:** Once the controller is tuned, the robustness of the RID controller may be tested against various perturbation and uncertainties.

5.2.2 The Water Level Controller

A nonlinear, state-space model was previously developed to represent the feedwater flow regulation system of a PWR. In this section, the derivation of the inverse dynamics controller for the steam generator water level control is discussed. Steam generator water level model is given as:

$$\frac{d\ell}{dt} = \frac{wf + (1-xe)w4 - w1}{\rho Adw} \tag{5.13}$$

where, xe is the exit quality of the steam leaving the boiling region, $w4$ and $w1$, are the riser and separator flow rates, respectively. ρ and Adw are the density of water and the effective area of the drum water section, and wf is the feedwater flow rate. The details of the U-tube steam generator model are given in Appendix A. The first step in deriving the RID control equation is to define an equation to represent the level model. The control system uses state information from the duplicate model. This approach enables the control system to test its robustness against unknown dynamics. The duplicate model uses a new notation to indicate that it is the on-line estimator of the RID control design.

$$\frac{d\ell_0}{dt} = Gain1(l_{set} - \ell) \tag{5.14}$$

where l_{set} is the level set point, ℓ is the level measurement and $Gain1$ is an adjustable quantity. The design of the RID control law depends on the distribution of the control variables versus trajectory assignments. Solution to the trajectory following control problem requires additional reconstruction through an auxiliary state [25]. Equation (5.14) gives the first auxiliary state which yields replacement of the dynamic error $\frac{d\ell}{dt}$ with $\frac{d\ell_0}{dt}$. Substituting Equation (5.14) in (5.13) gives the following equation.

$$Gain1(l_{set} - \ell) = \frac{wf + (1-xe)w4 - w1}{\rho Adw} \tag{5.15}$$

Solving Equation (5.15) for wf and renaming it as wf^* gives us the first RID model-based feedwater flow control equation. wf is the feedwater flow measurement and wf^* is the auxiliary state variable for the feedwater flow rate.

$$wf^* = Gain1(l_{set} - \ell)\rho Adw - (1-xe)w4 + w1 \tag{5.16}$$

In the feedwater flow regulation model, the feedwater flow rate is given by the following equation

$$\frac{dwf}{dt} = Area[P_{dis} - (f1 + f2 + f3 + \frac{fv}{/U1^2})wf^2 - P_{sg}]\frac{144 * 32.2}{L} \tag{5.17}$$

Details of this equation are given in Chapter 3 and in Appendix A. In order to derive the second RID equation, for the feedwater valve control action, U1, a new equation, auxiliary state variable, for the feedwater flow is defined as

$$\frac{dwf}{dt} = Gain2(wf^* - wf) \tag{5.18}$$

Replacing Equation (5.17) with Equation (5.18) yields the feedwater valve control action of RID controller, $U1$, which is given as:

$$U1 = \frac{fv}{-(f1 + f2 + f3) - \frac{1}{wf^2}(\frac{Gain2(wf^* - wf)L}{Area*144*32.2} - P_{dis} + P_{sg})} \tag{5.19}$$

where $Gain1$ and $Gain2$ are the tuning parameters and can only have positive values. As discussed previously, using large values for gains, results in a better performance of the controller [25]. A value of 100 for $Gain1$ and $Gain2$ was determined from simulation studies.

5.2.3 The Pump Speed Controller

This section discusses the derivation of the RID controller for the pump speed controller. The details of the pump model are given in Chapter 3. The differential pressure is defined as the difference between the feedwater header pressure and the steam pressure. The equation for the differential pressure ΔP is

$$P^*_{hd} = \Delta P + P_{sg} \tag{5.20}$$

where P_{sg} is the average steam header pressure, and P_{hd} is the feedwater header pressure. The first order lag equation for P_{hd} is

$$\frac{dP_{hd}}{dt} = \frac{1}{\tau}(P_h - P_{hd}) \tag{5.21}$$

The derivation of the RID controller for the speed control requires the construction of an auxiliary state variable, P_h^*. The next step gives a new formulation for Equation (5.21) as a first-order transport lag

$$\frac{1}{\tau}(P_h - P_{hd}) = Gain3(P_{hd}^* - P_{hd}) \tag{5.22}$$

Solving Equation (5.22) for P_h and renaming it P_h^* gives the auxiliary state variable for the RID ΔP controller.

$$P_h^* = Gain3(P_{hd}^* - P_{hd})\tau + P_{hd} \tag{5.23}$$

From the pump model given in Chapter 3, solving for the pump head, H, and renaming it H_s gives the following

$$H_s = \frac{(P_{hd}^* - P_{suc} + f1wf^2 + f2wf^2)144}{\rho_1} \tag{5.24}$$

where P_{hd}^* is the pressure at upstream of feedwater control valve, P_{suc} is suction pressure of feed pump, $f1$ and $f2$ are constants given in Chapter 3, wf is the feedwater flow rate, and ρ_1 is the density of water. Similarly, from the pump model, solving for the pump speed, and renaming it N_s, yields the following

$$N_s^2 + (\frac{a2}{a1})(\frac{wf}{wf0})N_s + (\frac{a3}{a1})(\frac{wf}{wf0})^2 - (\frac{H_s}{a1}) = 0 \tag{5.25}$$

There are two solutions for Equation (5.25); the one with the physical meaning has the positive sign, and is given by

$$N_{s1} = \frac{-\frac{a2}{a1}\frac{wf}{wf0} + \sqrt{(\frac{a2}{a1}\frac{wf}{wf0})^2 - 4(\frac{a3(\frac{wf}{wf0})^2 - H_s}{a1})}}{2} \tag{5.26}$$

The pump speed model equation is given as

$$\frac{dN_{pump}}{dt} = \frac{X_{pt} - X_{pump}}{I} \tag{5.27}$$

RID formulation for the pump speed model requires the construction of the auxiliary state variable N_{pump}^*, and is given as

$$\frac{dN_{pump}}{dt} = \frac{X_{pt} - X_{pump}}{I} = Gain4(N_{pump}^* - N_{pump}) \tag{5.28}$$

where X_{pt} is the driving torque and X_{pump} is the pump load torque.

$$X_{pt} = \frac{W_{mfp}(h_{in} - h_{out})778}{N_{pump}} \tag{5.29}$$

$$X_{pump} = \frac{H\,wf}{eff\,N_{pump}} \tag{5.30}$$

where h_{in} and h_{out} are the inlet and outlet enthalpies of the turbine, H is the pump head, eff is the efficiency of the turbine, and W_{mfp} is the extraction steam flow rate to the main feed pump turbine.

$$W_{mfp} = U2\,P_{r0}\,K_r \tag{5.31}$$

Substituting Equations (5.29), (5.30), and (5.31) into Equation (5.28) and solving for $U2$ gives the RID control variable for the pump speed control.

$$U2 = \frac{I\,Gain4\,(N^*_{pump} - N_{pump})\,N_{pump} + \frac{H\,wf}{eff}}{P_r\,K_r\,(h_{in0} - h_{out})\,778} \tag{5.32}$$

where N^*_{pump} is

$$N^*_{pump} = (N_{s1})(N_{pump0}) \tag{5.33}$$

The values of the gain constants are found from simulation tests as 100 for both $Gain3$ and $Gain4$. The details and definitions of the pump model are given in Chapter 3.

5.3 Fuzzy Logic Controller

The important difference between the fuzzy logic approach and the traditional approaches for control design is that, the former uses qualitative information where as the latter requires rigid mathematical relationships describing the process. The control action in a rule-based system is performed by first measuring the relevant parameters and then defining their membership grades in the appropriate subsets.

There are two types of applications of fuzzy sets in control theory. In the approach developed by Bellman and Zadeh [56] [10] the performance criterion is a combination of subjectivity and computational tractability. The second approach is Zadeh's linguistics approach, which motivated many researchers in developing fuzzy logic controllers for large, complex systems [56].

"The optimal control is to find a sequence of inputs (possibly of a fixed length) in order to reach a prescribed final state (the goal) [56]." The purpose of controllers is to compute action variables from the observation of the state variables during a process. The relationship between the state variables and action variables can be a set of logical rules. An example of a fuzzy rule is *"if level error is positive large or positive medium then feedwater valve opening is medium small."* Positive large, positive medium, medium small are different sets defined on various universes.

The main advantage of using fuzzy control is that it is not necessary to have a mathematical model of the observed system. Mathematical models in this research were used for simulation purposes. Their robustness comes from human experience. Fuzzy controllers, when compared with the traditional PID controllers in highly non-linear systems, have given better results [44]. Recently, fuzzy controllers have been very successful in applications to complex systems. Examples of fuzzy logic controller include automatic fast-train controllers, feedwater flow regulation systems, and cement kiln controllers [55] [48] [44]. As Zadeh [10] has pointed out, an intelligent control is descriptive and relies on the operating experience via a rule-based representation such as fuzzy rules, whereas the conventional control is prescriptive and relies on a crisp logic. Thus, the fuzzy logic is well-suited for the management of uncertainty present in the context of complex behavior which cannot be properly handled by a crisp logic [18].

A fuzzy logic is characterized by a linguistic variable whose values are words or sentences in a synthetic language. A linguistic variable includes an adjective-like term (and its antonym), a modifier and a connective. The modifier is a measure of intensity which is associated with a possibility distribution. This is often referred to as the *membership function* in the literature. The fuzzy control policy is represented by a finite collection of rules of the form "*if X is A then Y is B*" where the truth value of the antecedent *if X is A* is determined by the grade of membership.

In fuzzy logic control, a fuzzy relationship between the information about the system and the current conditions of the system is developed. Traditionally control algorithms work with crisp numbers which represent the condition of a system. In fuzzy control the algorithm is composed of *if-then* statements. These statements are called *fuzzy rules.* There is a group of fuzzy control rules that calculates the control output for the actual data. This calculation is performed using a *fuzzy inference.* There are various methods of fuzzy inferences [62]. The fuzzy control inference usually uses numerical values as an actual input to the controller, and not fuzzy values. Fuzzy rules are derived using fuzzy subsets which describe the controlled process and the output of the fuzzy controller.

A fuzzy subset A of a universe of discourse U is characterized by a membership function $\mu : U \rightarrow (0,1)$ which associates with each element u of U a number $\mu(u)$ in the interval (0,1), representing the grade of membership of u in A. The fuzzy set A of $U = \{u_1, u_2, \ldots, u_n\}$ is denoted by

$$A = \sum_{i=1}^{n}[\mu(u_i)/u_i] = \sum_{i} \mu_A(u_i) \tag{5.34}$$

where $\sum$ denotes union.

Two basic operators are used in the steam generator water level control. The union of fuzzy subsets A and B is shown by $A+B$ and is defined as

$$A + B = \sum_i \mu_A(u_i) \vee \mu_B(u_i) \tag{5.35}$$

where $\vee$ stands for maximum. The union corresponds to the operator *OR*. The second operation, the intersection of fuzzy sets A and B is denoted by $A \cdot B$ and is defined as

$$A \cdot B = \sum_i \mu_A(u_i) \wedge \mu_B(u_i) \tag{5.36}$$

where $\wedge$ means minimum. The intersection corresponds to the operator *AND*. The definition of fuzzy sets permits one to assign values to fuzzy variables [63]. An aggregated value of control can be found by a voted average among the contributing rules. The design of a fuzzy control for dynamic systems includes a table of fuzzy rules that relates the state variables to the control variables. Every fuzzy rule corresponds to a unique relationship among the state and control variables of the system. Control is determined by an interpolative method when the input to the control system does not match with the canonical structure of the table (fuzzy predicate). The membership functions are usually triangular or trapezoidal on the universe that lies between two connecting points of the truth table. As plant states change in time, membership functions are shifted to a new universe. This approach saves computational costs by minimizing the number of membership functions for the trajectory following case. For example, a ramp trajectory can be divided into n intervals in which the same control logic holds. Instead of using $n \times k$ membership functions (k is the number of propositions in each interval), we can use only k memberships applicable to n different universes. A control law Y calculated in terms of trainable weights W_i, and partial controls U_i is given by

$$Y = \frac{\sum_{i=1}^{n} W_i U_i}{\sum_{i=1}^{n} W_i} \tag{5.37}$$

Each partial control U_i is based on a unique relationship among the state variables of the plant.

5.3.1 Fuzzy Variable

Let us consider a continuous variable Y which can have the values between -10 and 10. If this variable is defined in a crisp logic, then the information that can be obtained from this variable will also be crisp as expected. For example, if Y denotes temperature, then the information $Y = 5$ will simply say that the temperature is 5 ^oC. On the other hand, consider the heuristic approach in which the range (universe of discourse) of Y divided into several regions is defined by an interpretable term. Suppose the intervals -10 to -4, -5 to 5, 4 to 10 are defined as *low*, *medium*, and *high* regions of Y, respectively. Then, the variable Y is defined as a fuzzy variable which can take linguistic values of low, medium, and high. Figure 5.2 displays the universe of the fuzzy variable Y and its regions. The fuzzy representation contains more information about a variable than that of the standard representation in calculus. Using the same example, the information $Y = low$ means that the temperature is within a range of -10 and -5 ^oC and it is defined as low with respect to the other values it can take. The variable *temperature* is now defined by a range of numbers, rather than a crisp value such as $Y = 5$. This representation is closer to the human reasoning than that using crisp values.

5.3.2 Fuzzy Membership Function

Let X be a classical set of objects, called *universe*, whose generic elements are denoted by x [56]. The membership in a classical subset A of X is often viewed as a characteristic function μ_A from X to {0,1} such that

$$\mu_A(x) = \begin{cases} 1 & iff \quad x \in A, \\ 0 & iff \quad x \notin A. \end{cases}$$

{0,1} is called a valuation set, $\in$ means "is a set of" and *iff* means "if and only if."

If the valuation set is allowed to be the real interval [0,1], A is called a *fuzzy set* [11].

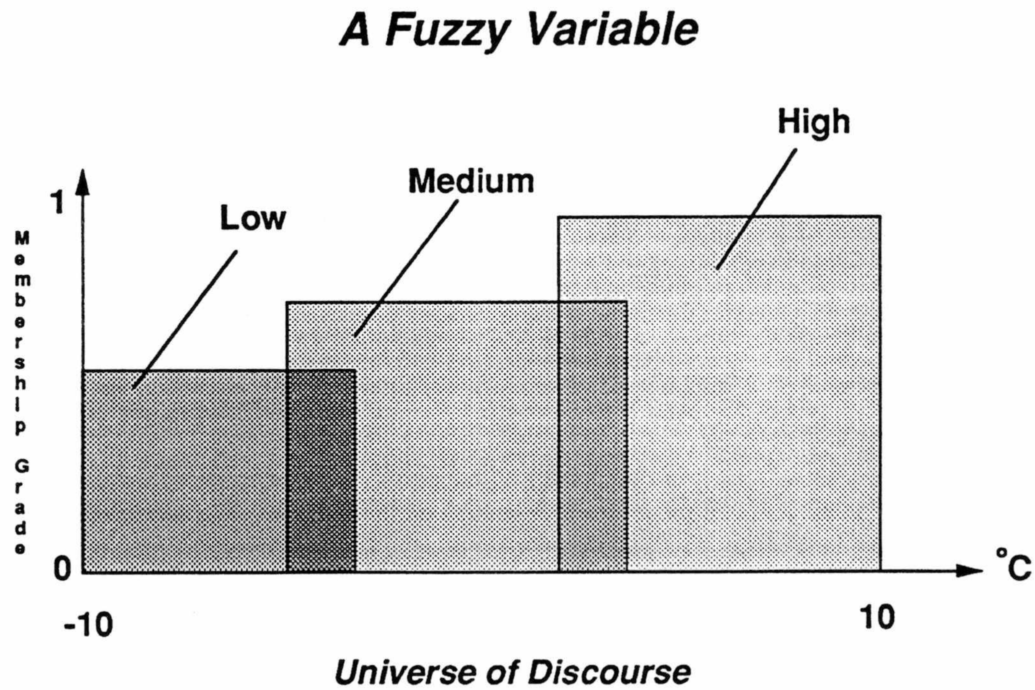

Figure 5.2: A Fuzzy Variable with Three Linguistic Values.

In the fuzzy set theory $\mu_A(x)$ is the grade of membership of x in A. The closer the value of $\mu_A(x)$ is to 1, the greater is the belonging of x in A.

A is completely characterized by the set of pairs

$$A = \{(x, \mu_A(x)),\ x \in A\} \tag{5.38}$$

When X is a finite set $\{x_1, \ldots, x_n\}$, a fuzzy set on X is expressed as

$$A = \mu_A(x_1)/x_1 + \cdots + \mu_A(x_n)/x_n = \sum_{i=1}^{n} \mu_A(x_i)/x_i \tag{5.39}$$

When X is not finite, we write

$$A = \int_X \mu_A(x)/\,x \tag{5.40}$$

Two fuzzy sets A and B are said to be equal (denoted $A = B$) iff

$$\forall\, x \in X,\ \mu_A(x) = \mu_B(x)$$

where $\forall$ means "for every." In Section 5.3.1 a fuzzy variable Y as temperature was defined. Now the definition of *low* and other values of temperature are discussed. The definition of *low* or any other term simply depends on the person defining the fuzzy variables. In the fuzzy logic, the judgement of this definition is formulated with a possibility distribution, taking values between 0 and 1. This distribution is called a *membership function*. In the temperature example, the membership function *low* must give 1 (or the maximum value defined for *low*) at a certain point on the universe of discourse which best represents *low*. Figure 5.3 displays an example of membership function distribution of Y between -10 and 10. The shape of the membership function may have any form, as long as it represents the relationship of interest [66]. Trapezoidal fuzzy membership functions have been utilized in this dissertation research.

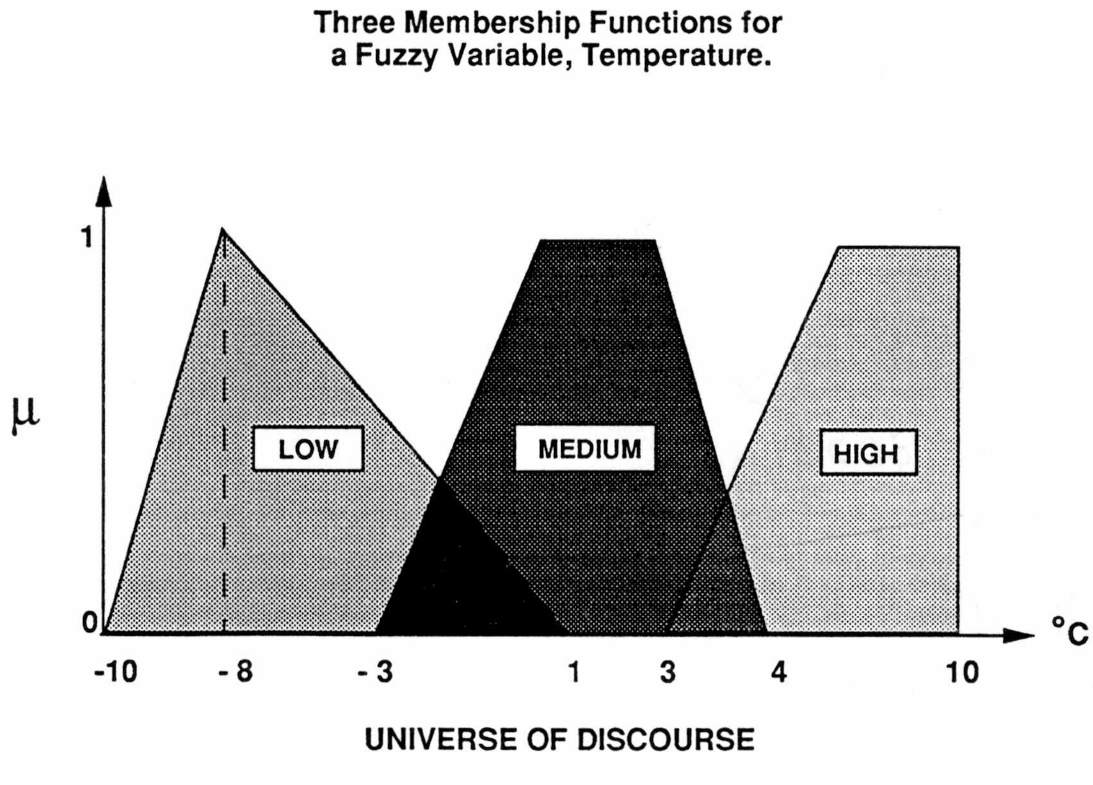

Figure 5.3: An Illustration of Membership Functions Low, Medium and High.

5.3.3 Implementation of a Fuzzy Controller

In this section membership cuts and principle of implications are discussed. There are two major steps in implementing a fuzzy algorithm: fuzzification and defuzzification. Fuzzification is a process in which the variables are transformed into fuzzy variables, and defuzzification is simply the opposite of the fuzzification process. After defuzzification the results will again be real values. Since the goal is to develop a controller using real values obtained from the plant, real values are used as inputs and outputs.

Fuzzy Inference Engine

A fuzzy inference engine is a rule-based system (which can be a computer program, an integrated circuit, or an information system in other media) that implements the fuzzy logic. It must have both inputs and outputs. It performs a nonlinear mapping between the input domain and the output domain. Its objective function can be a control, classification, pattern recognition, filtering, prediction, diagnostics or modeling. The fuzzy inference engine can be viewed as a decision making tool in general. Figure 5.4 shows an example of a fuzzy inference engine. It receives numerical values of measurements such as Flow Error and Level Error, and produces a numerical output such as Valve Opening.

Rule Composition

Rule composition refers to the organization of the left-hand-side (LHS) statements using logic operators such as (OR) and (AND). For example, consider the following fuzzy rule:

$$IF\, X = low\ AND\ Y = high\ THEN\ U = medium$$

Here, the LHS statements (*X=low and Y=high*) are connected by the AND operator. Suppose that the membership functions for $X = low$ and $Y = high$ are designed

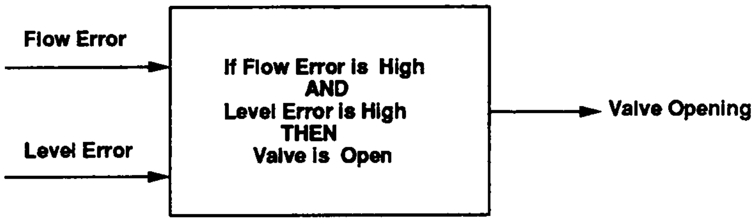

Figure 5.4: Fuzzy Inference Engine.

as triangles as given in Figure 5.5. When there are entries (inputs) of $X = 1.5$ and $Y = 8.5$, the corresponding values of the membership functions (μ) are found as shown in the Figure. The values of $X = 1.5$ and $Y = 8.5$ yield 75% and 100% possibility for X being low and Y being high, respectively.

The AND operator uses the values of $\mu = 0.75$ and $\mu = 1.0$ to compute the output of the composition which is the minimum of the two entries, 0.75. This output is then used in the implication process by the THEN operator.

Fuzzy Projections

The evaluation of membership functions (sometimes called cuts) for a given numerical value is different for the input and action variables. The evaluation of a membership function of an input fuzzy variable is similar to that of calculus (i.e. calculate $y = f(x)$ given values of x). Once the inputs of an inference engine are projected onto the contours of membership functions, they may be considered as being mapped onto a fuzzy space or fuzzy clusters (*fuzzification*). Consider a

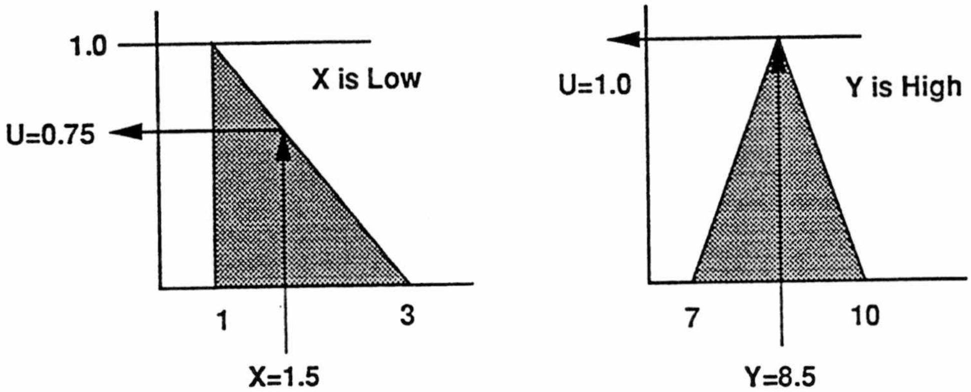

Figure 5.5: Rule Composition for Two Fuzzy Input Variables.

membership function called LOW that lies between 10 and 30 of the universe of composition left-hand-side (LHS) variable called FLOW. If FLOW is 23.5 lbm/sec then the membership function will take a value between 0 and 1. Figure 5.6 displays the fuzzy cuts of the membership functions. Similarly, if FLOW is an implication right-hand-side (RHS) variable the results of rule composition will be projected onto the contours of the membership function. The cut will be side-ways, leaving a shape underneath often in the form of a trapezoid. Another way of implementing cuts is to place a new triangle inside the trapezoidal. If there are N rules, each of those rules will produce a similar shape, and the final decision will be made through the implication process which takes into account all the resultant trapezoids and computes the center of gravity [66]. Figure 5.7 gives the method of placing a triangle below the cutting line, the fuzzy cut is found with the product of the contributing fuzzy variable entries.

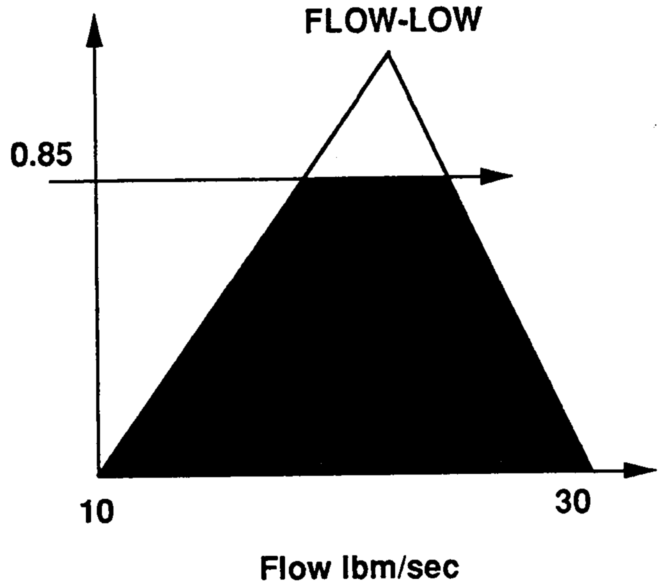

Figure 5.6: Membership Function Cuts in the Form of Trapezoidal.

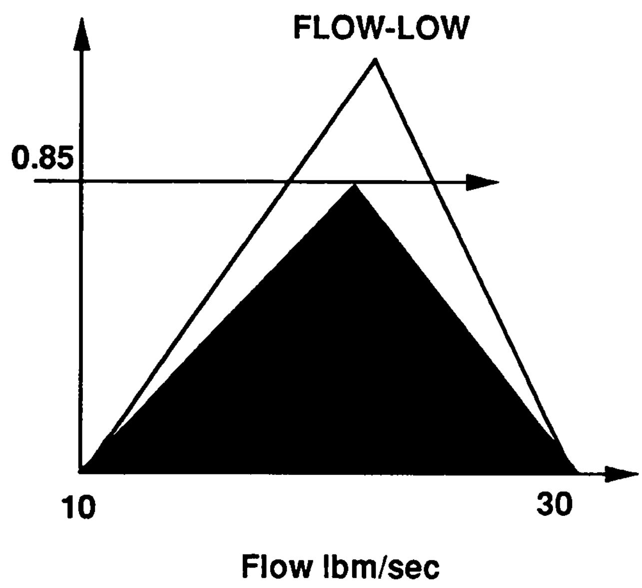

Figure 5.7: Membership Function Cuts by Placing a New Triangle.

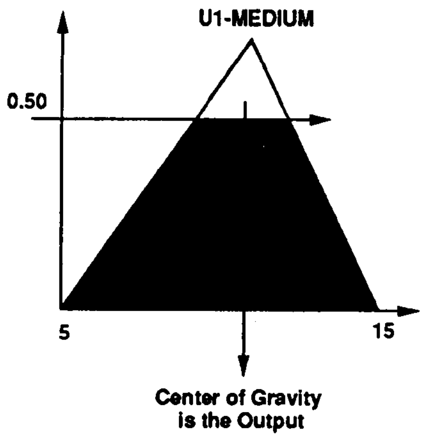

Figure 5.8: Implication Principle of the THEN Operator for one Variable.

Implication of Rules

In this section interpretation of the operator THEN is discussed. One of the common approaches for interpreting THEN is to calculate the center of gravity of the final shape obtained by cutting the right-hand-side (RHS) membership function with the results of the rule composition. For example, if the composition result is 0.75 from the LHS, this yields a cut in the output variable's membership function from 0.75. The center of gravity of the new trapezoidal area of the output membership function is the result. Often this process is called "defuzzification", and the RHS variable is called "action variable" [66]. The real value of the action variable is within the universe of discourse of that action variable which is defined during the fuzzification process, along with the input variables. When there is more than one rule for the same action variable, the resulting areas overlap. The final shape is used to calculate the center of gravity as the result of the action variable. Figure 5.8 displays the implication principle of THEN operator. Figure 5.9 gives the resulting action variable which is obtained by combining three different cuts.

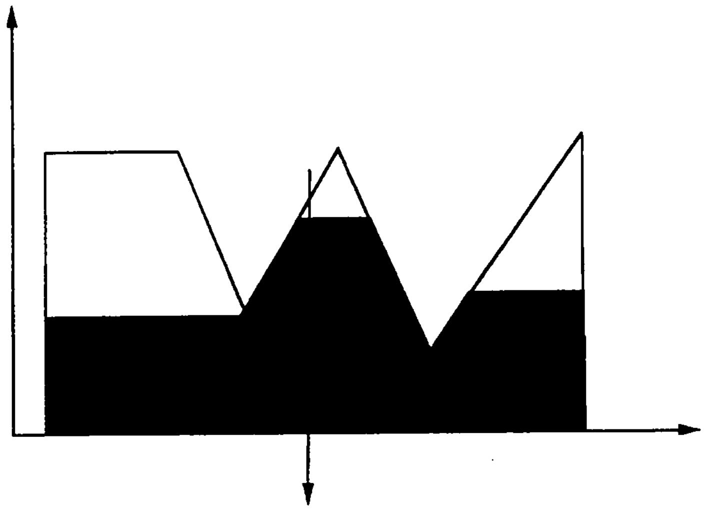

Figure 5.9: Resulting Form of the Action Variable by Combining Various Fuzzy Cuts.

5.3.4 Fuzzy Inferencing Methods

This section discusses two different inferencing methods which are used in the fuzzy logic applications, namely *min-max gravity* and *product-sum gravity* [44] [64] [56] [45]. These methods combine the fuzzy relations defined on different Cartesian products and compose a new relationship. Fuzzy if/then rules or fuzzy algorithms are mathematically equivalent to fuzzy relations and the problem of inferencing (or evaluation for specific inputs) is equivalent to composition.

Min-Max Gravity Method

Most of the existing fuzzy logic controllers use Mamdani's "min-max" fuzzy reasoning method. There are two relations in this method, (*max* $\vee$) and (*min* $\wedge$). Let there be two fuzzy relations $A(x,y)$ and $B(y,z)$ defined over $X \times Y$ and $Y \times Z$, respectively. The *min-max* composition of A and B is a new relation shown as $A \circ B$

defined on $X \times Z$ with

$$A \circ B \equiv \int_{X \times Z} \vee [\mu_A(x, y) \wedge \mu_B(y, z)] \, / (x, z) \tag{5.41}$$

where "o" stands for *min-max* composition method. When the product $X \times Y$ is discrete then the integral (union) is replaced by summation. Consider the following multiple reasoning form for a better understanding of the min-max method:

Rule 1: A1 and B1 => C1

Rule 2: A2 and B2 => C2

... .

Rule n: An and Bn => Cn

Facts: x_0 and y_0

Result: z_0

where A_i is a fuzzy set defined in a set X, and similarly B_i is a fuzzy set in a set Y, and C_i is the resultant fuzzy set in a set Z. Figure 5.10 displays the membership functions for $A1$, $B1$, and $C1$, and the *min-max* composition of membership functions. The resulting membership functions for the rules is given by

$$\mu_{A_i and B_i => C_i}(x, y, z) = \mu_{A_i}(x) \wedge \mu_{B_i}(y) \wedge \mu_{C_i}(z) \tag{5.42}$$

where $\wedge$ stands for *min*. The inference result C_i', which is obtained from the facts x_0, y_0, and the fuzzy rule A_i and $B_i => C_i$, can be displayed as

$$\mu_{C_i}'(z) = \mu_{A_i}(x_0) \wedge \mu_{B_i}(y_0) \wedge \mu_{C_i}(z) \tag{5.43}$$

The final form of the n rules, C_i', will be aggregated by taking the union ($\cup$) of $C1', C2', \ldots Cn'$ as shown in Equation (5.43).

$$C' = C1' \cup C2' \cup \ldots \cup Cn' \tag{5.44}$$

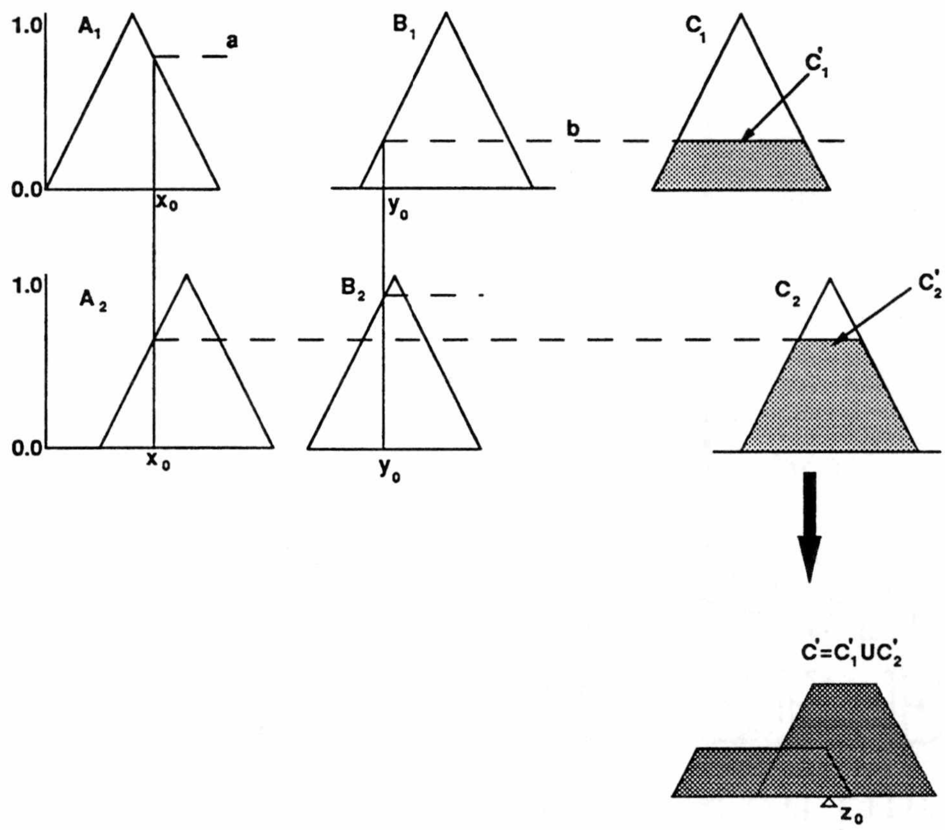

Figure 5.10: Min-Max Gravity Composition Method.

which is,

$$\mu_{C'}(z) = \mu_{C1'}(z) \vee \cdots \vee \mu_{Cn'}(z) \tag{5.45}$$

where $\vee$ stands for *max*. From Equation (5.41) the grade of membership functions of each (x, z) pair can also be displayed by

$$\mu_{A \circ B}(x, z) = \vee_y[\mu_A(x, y) \wedge \mu_B(y, z)] \tag{5.46}$$

The representation of the point z_0 (displayed in Figure 5.10) for the resulting fuzzy set C' is obtained as the center of gravity of C'

$$z_0 = \frac{\int z \cdot \mu_{C'}(z)dz}{\int \mu_{C'}(z)dz} \tag{5.47}$$

This fuzzy composition method is known as Mamdani's method [64] and called the "*min-max gravity method*".

Product-Sum Gravity Method

The second method was introduced by Mizumoto as an alternative to the min-max method of Mamdani. The *product-sum gravity method* proposes a placement of a triangle for the fuzzy cuts. This method replaces the *min* function with *product*, $(\cdot)$, and *max* function with *sum* in the min-max method. The product-sum gravity method is shown in Figure 5.11. The inference result of C_i' from the facts x_0, y_0, and the fuzzy rule A_i and B_i => C_i is given by

$$\mu_{C_i'}(z) = \mu_{A_i}(x_0) \cdot \mu_{B_i}(y_0) \cdot \mu_{C_i}(z) \tag{5.48}$$

Aggregated form of C' is given by

$$C' = C1' + C2' + \cdots + Cn' \tag{5.49}$$

The resulting membership function for the aggregated form of C' is given with

$$\mu_{C'}(z) = \mu_{C1'}(z) + \cdots + \mu_{Cn'}(z) \tag{5.50}$$

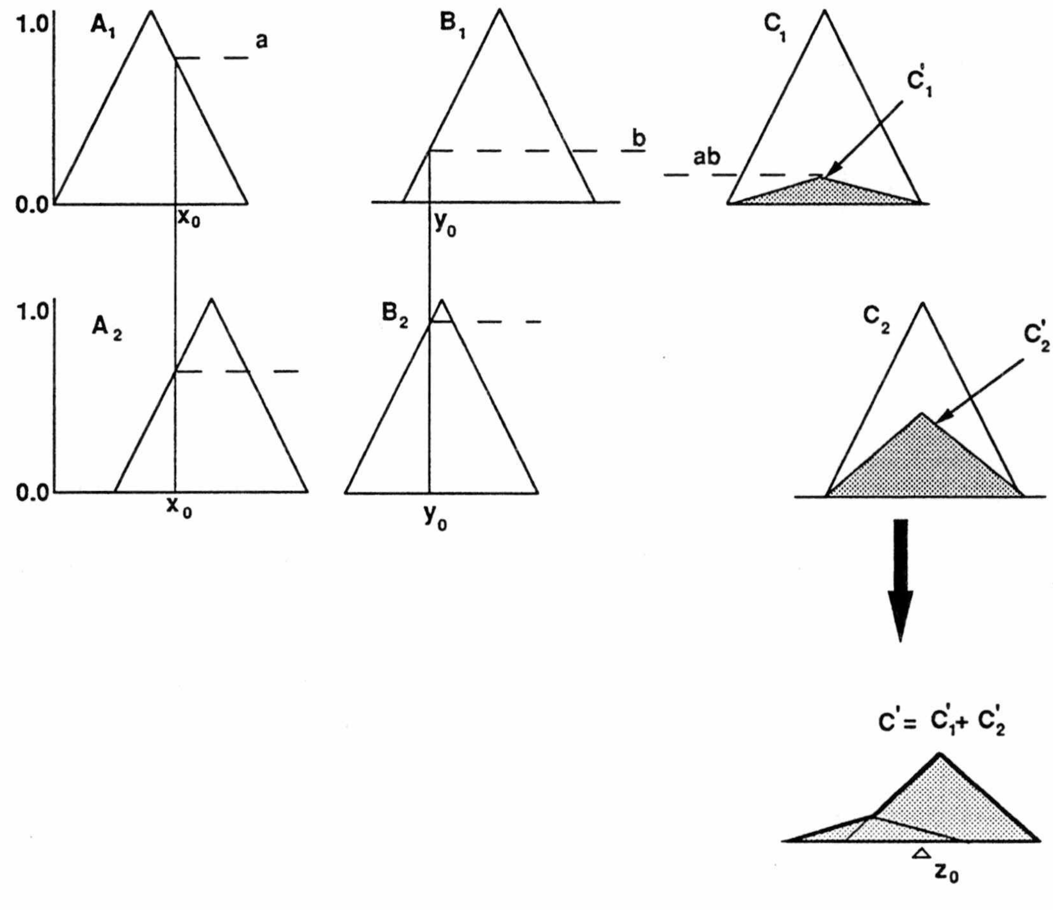

Figure 5.11: Product-Sum Gravity Composition Method.

The representative point, z_0, of the C' is obtained using the center of gravity method, similar to the min-max method. However, the center of gravity for the product-sum gravity method is derived as follows.

Let z_i be the center of gravity of the inference result C_i' of Equation (5.48) and S_i be the area of C_i' (see Figure 5.11), which is given with

$$z_i = \frac{\int z \cdot \mu_{C_i'}(z)dz}{\int \mu_{C_i'}(z)dz} = \frac{\int z \cdot \mu_{C_i'}(z)dz}{S_i} \tag{5.51}$$

which yields

$$\int z \cdot \mu_{C_i'}(z)dz = S_i\, z_i \tag{5.52}$$

Center of gravity, z_0, of the final form of C' given with the Equation (5.50) can be displayed as

$$\begin{aligned} z_0 &= \frac{\int z \cdot \mu_{C_i'}(z)dz}{\int \mu_{C_i'}(z)dz} = \frac{\int z \cdot [\mu_{C1'}(z) + \cdots + \mu_{Cn'}(z)]dz}{\int [\mu_{C1'}(z) + \cdots + \mu_{Cn'}(z)]dz} \\ &= \frac{\int z \cdot \mu_{C1'}(z)dz + \cdots + \int z \cdot \mu_{Cn'}(z)dz}{\int \mu_{C1'}(z)dz + \cdots + \int \mu_{Cn'}(z)dz} \\ &= \frac{S_1 z_1 + S_2 z_2 + \cdots + S_n z_n}{S_1 + S_2 + \cdots + S_n} \end{aligned} \tag{5.53}$$

The center of gravity, z_0, therefore is the weighted average of z_i's (center of gravity of C_i') with weights S_i's (area of C_i'). The described method also corresponds to the *area method* of defuzzification [44].

Comparison of Min-Max and Product-Sum Gravity Methods

A comparison of the two composition methods described above will be given with an example in this section [45] [44]. Let z_1, z_2, z_3, and z_4 be the heights at the lattice points $(x1, y1), (x1, y2), (x2, y1)$, and $(x2, y2)$, respectively, in which $x1 < x2$, and $y1 < y2$. For simplicity four fuzzy rules will be considered in this example:

$$\text{Rule 1: } \tilde{x}1 \text{ and } \tilde{y}1 => \tilde{z}1$$

$$\text{Rule 2: } \tilde{x}1 \text{ and } \tilde{y}2 => \tilde{z}2$$

$$\text{Rule 3: } \tilde{x}2 \text{ and } \tilde{y}1 => \tilde{z}3$$

$$\text{Rule 4: } \tilde{x}2 \text{ and } \tilde{y}2 => \tilde{z}4$$

$$\text{Facts : } x_0 \text{ and } y_0$$

$$\text{Result : } z_0$$

where $\tilde{x}1$ is a fuzzy set representation of "about x1". Fuzzy sets $\tilde{x}1$ and $\tilde{x}2$ are of the triangular type and intersect each other at the height 0.5, the same holds for $\tilde{y}1$ and $\tilde{y}2$. Fuzzy sets $\tilde{z}1$, $\tilde{z}2$, $\tilde{z}3$, and $\tilde{z}4$ have the same width, although it is not restricted. Figure 5.12 displays the resulting center of gravity point, z_0, for both methods.

In the applications of fuzzy logic, both inferencing methods are widely used. Although the results of these methods are most of the time very close to each other, some application dependent advantages and disadvantages of these approaches exist [45] [44].

5.3.5 The Water Level Controller

In the application to a steam generator water level control three fuzzy variables are used:

- LE → Level Error, defined as the difference between the level set point and the present value of the steam generator water level.
- FE → Flow Error, defined as the mismatch between the feedwater flow and the steam flow.
- U1 → Feedwater Valve Opening (control action variable).

These variables are defined with a number of points to cover the universe of discourse, and values to the variables are assigned using seven fuzzy subsets:

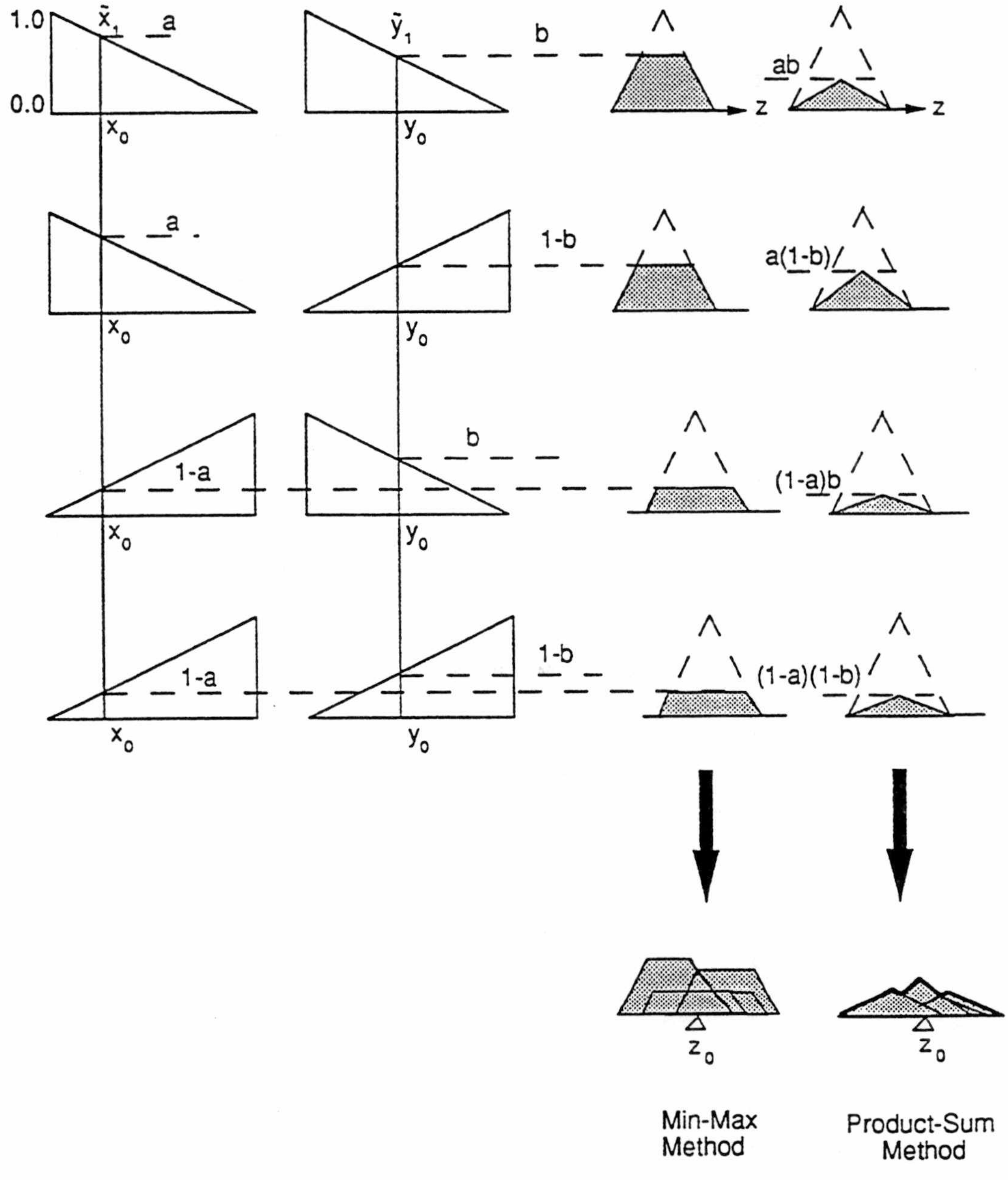

Figure 5.12: Inference Results of Min-Max and Product-Sum Gravity Methods.

- PB → Positive Big
- PM → Positive Medium
- PS → Positive Small
- ZO → Zero
- NS → Negative Small
- NM → Negative Medium
- NB → Negative Big

Two different fuzzy logic level controllers were developed as part of the parallel, fault-tolerant control design. The first design uses variables similar to those used in the conventional PI controller, namely *level error* and *flow mismatch.* The second fuzzy controller is an alternative controller where, instead of using flow mismatch, the *change in level error* is used along with the level error signal. This approach enables the control design to overcome not only the sensor failures, but also possible swings that may occur during plant operation. Since the change in level error has ± sign, this indicates not only how much change takes place, but also the direction of the change. Figures 5.13 through 5.15 display the fuzzy variables *Level Error, LE, Flow Mismatch, FE, and Valve Opening, U1.* Seven membership functions were used for covering the effective domains of each fuzzy variables changing from NB to PB. The control rules were implemented by using the fuzzy conditional statements.

$$IF\ LE\ is\ NB\ and\ FE\ is\ PS\ then\ U1\ is\ NM$$

$$IF\ LE\ is\ NM\ and\ FE\ is\ NB\ then\ U1\ is\ PS$$

$$IF\ LE\ is\ ZO\ and\ FE\ is\ PS\ then\ U1\ is\ NM$$

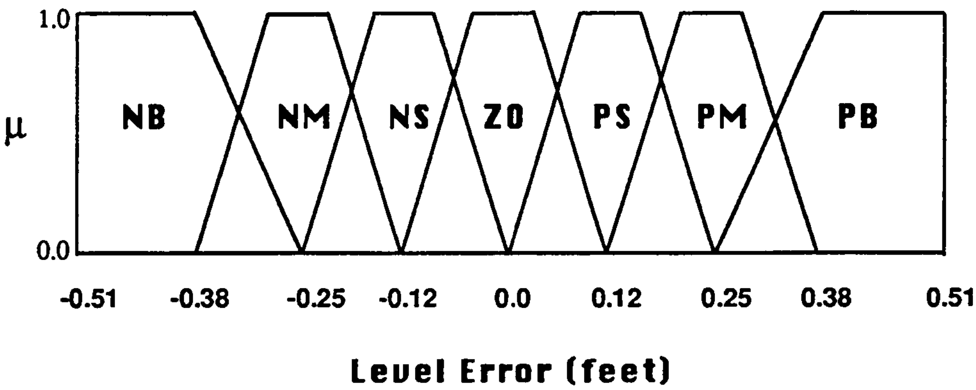

Figure 5.13: Fuzzy Variable Level Error, LE.

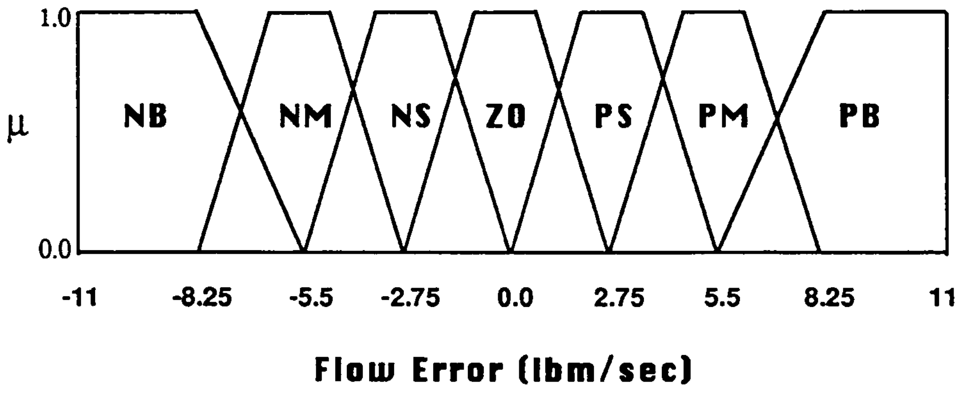

Figure 5.14: Fuzzy Variable Flow Mismatch, FE.

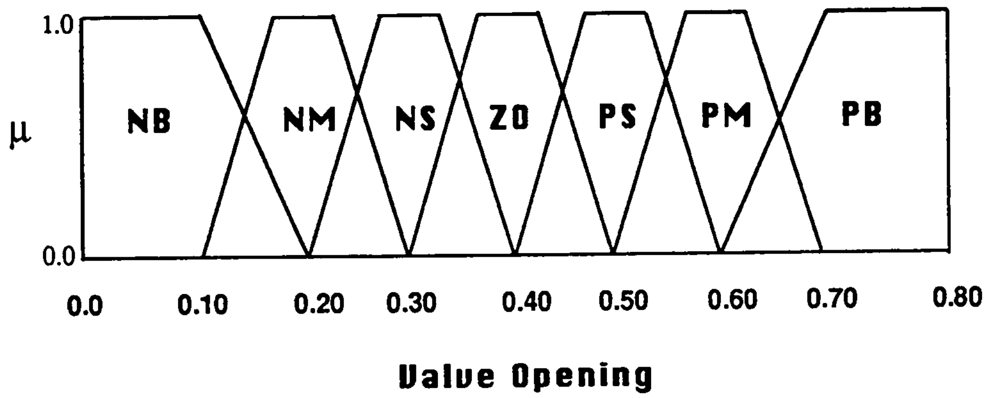

Figure 5.15: Fuzzy Control Variable, Valve Opening, U1.

Table 5.1 gives the rules for the first fuzzy logic controller for the steam generator water level control of a four-loop PWR. The definition of the fuzzy variable domains and the tuning of the fuzzy rules were completed with extensive tests and trials. Numerous simulation tests were completed to determine the effective ranges of the variables and the rules. A single rule implication from Table 5.1 presented in this section. First fuzzy logic water level controller has two inputs, namely *Level Error, LE* and *Flow Mismatch, FE.* Suppose the value coming from the plant for LE falls between 0.25 and 0.51, for which the membership function PB is defined. Similarly a value for FE falls between 5.5 and 11 for which the membership function PB is defined. The following fuzzy rule will be fired according to these incoming fuzzy variable values: "If LE is PB AND FE is PB THEN U1 is NB." During the fuzzification stage, the minimum of the two fuzzy cuts from LE and FE will be found, since the operator AND is used, then the fuzzy cut within the fuzzy variable *Valve Opening (U1)* will be found as it was discussed in the previous sections. Defuzzification will take place according to the cut within the fuzzy membership function NB which covers the domain of 0.0 and 0.20. The centroid of the area will be found according

Table 5.1: Steam Generator Water Level Fuzzy Control Rules I

		Flow Mismatch (FE)						
	U1	NB	NM	NS	ZO	PS	PM	PB
	NB	PM	PM	ZO	ZO	NM	NM	NM
	NM	PS	PS	PS	PS	NM	NM	NM
Level Error	NS	NS	NS	NS	NS	NS	NS	NS
(LE)	ZO	PB	NM	NM	NM	NM	NM	NM
	PS	NB	NB	NB	NB	NB	NB	NB
	PM	NM	NB	NB	NB	NB	NB	NB
	PB	NM	NM	NM	NM	NM	NM	NB

to the fuzzy cut, and the centroid value will be the control action for water level controller. If there are more than one fuzzy membership functions contributing to the same action, then the areas of each trapezoid (obtained from the fuzzy cuts) will be added, and the resultant centroid of the area will be the control output. Fuzzy inferencing was discussed in detail in Section 5.3.4. Figures 5.16 through 5.18 show the fuzzy variables for the second fuzzy logic controller. Table 5.2 gives the second fuzzy logic controller rules for the steam generator water level control of a four-loop PWR. The results of the fuzzy controllers for the steam generator water level are presented in Chapter 6.

5.3.6 The Pump Speed Controller

One of the objectives of this study is to develop a better feedwater regulation system for Westinghouse-type four-loop Pressurized Water Reactors (PWRs). In order to overcome the sluggish nature of the current pump speed controllers, an alternative control design using fuzzy logic is presented. The nature of the fuzzy control design,

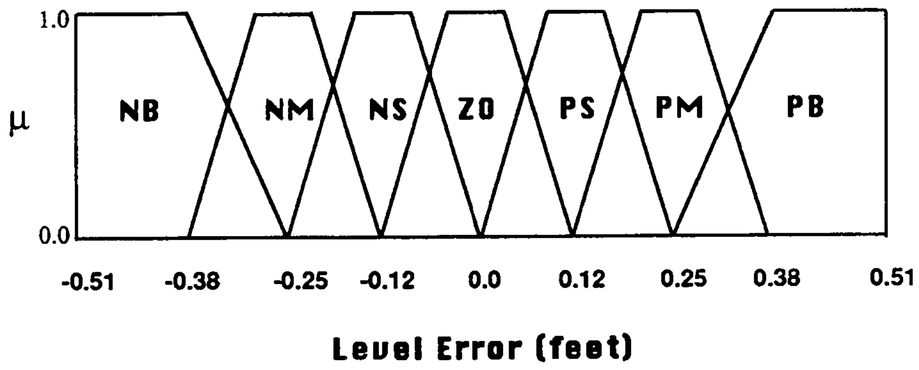

Figure 5.16: Fuzzy Variable Level Error, LER.

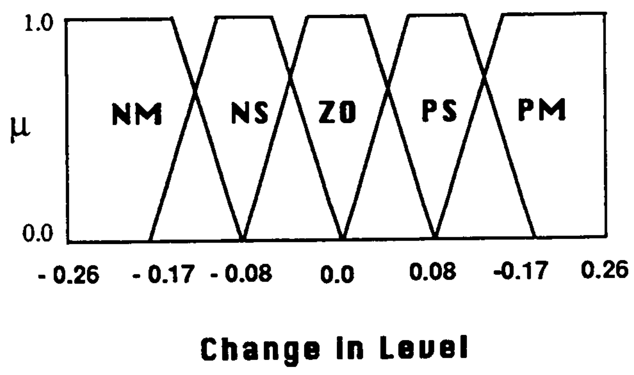

Figure 5.17: Fuzzy Variable Change in Level, Δ L.

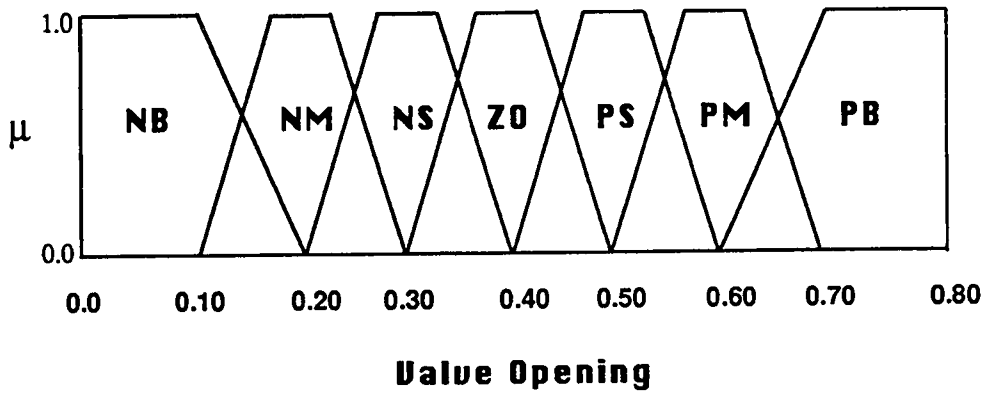

Figure 5.18: Fuzzy Control Variable, Valve Opening, U2.

Table 5.2: Steam Generator Water Level Fuzzy Control Rules II

		Level Error (LER)				
	U2	NM	NS	ZO	PS	PM
Change in Level (ΔL)	NM	PB	PM	NS	NM	NB
	NS	PM	ZO	PS	NB	NB
	ZO	PM	NS	NM	NB	NB
	PS	NS	NS	NM	NB	NB
	PM	NM	NM	NB	NB	NB

allows us to develop a controller that has a smoother response when compared to the conventional PID controllers [12]. Fuzzy variables are defined with overlapping membership functions, therefore each of these membership functions contribute to the resulting control action. A fuzzy controller also allows us to use signals in the feedforward fashion. This further enables the controller to overcome the possible problems that occur in the event of steam generator transients. The pump speed fuzzy controller, has two inputs, feedwater flow and differential pressure. The feedwater flow signal indicates the flow demand during a certain operating power level. The differential pressure is the difference between the feedwater header pressure and the steam header pressure, and is set according to a differential pressure program. Fuzzy variables for the pump speed controller are defined similar to those for the water level controller. Seven membership functions are used for each variable to cover the effective domain of the controller.

The pump speed fuzzy controller has two inputs, *feedwater flow* and *differential pressure error* (ΔP_{err}). Fuzzy variables for the controller are shown in Figures 5.19 through 5.21. Table 5.3 gives the fuzzy rules for the controller. Feedwater flow signal is used as feedforward signal, and the effective domain of the fuzzy variable WF is determined based on the possible transients that might occur during the normal operation of a PWR. The range of the feedwater flow variable covered was with seven overlapping membership functions from 975 lbm/sec to 1100 lbm/sec. Similarly, ΔP_{err} and $U3$ are defined using seven membership functions, and their effective domains were determined with simulation tests. Performance test results of the pump speed controller are presented in Chapter 6.

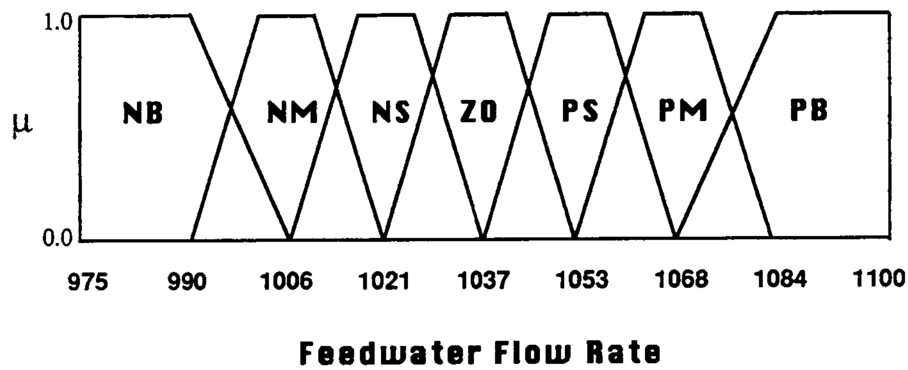

Figure 5.19: Fuzzy Variable Feedwater Flow (WF).

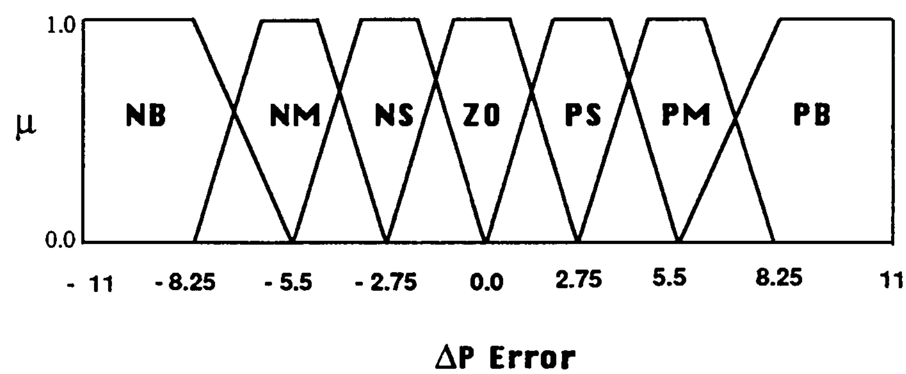

Figure 5.20: Fuzzy Variable Differential Pressure Set Point Error, ΔP_{err}.

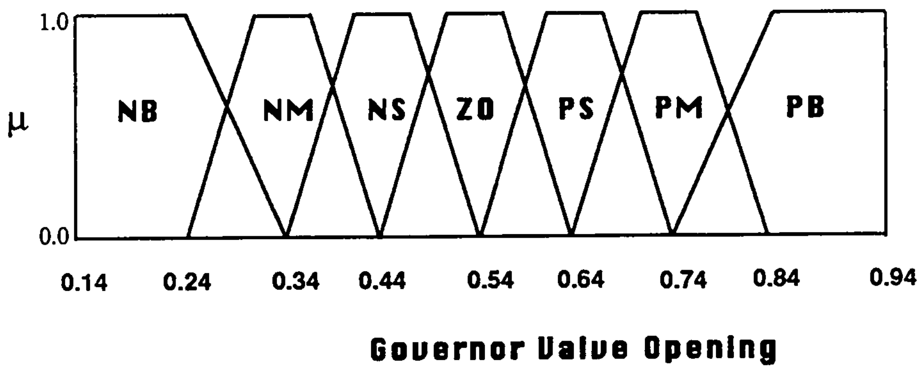

Figure 5.21: Fuzzy Control Variable, Main Feed Pump Turbine Valve Opening, U3.

Table 5.3: The Pump Speed Fuzzy Control Rules

Feedwater Flow (WF)

	U3	NB	NM	NS	ZO	PS	PM	PB
	NB	ZO	ZO	ZO	ZO	ZO	ZO	ZO
	NM	ZO	ZO	ZO	ZO	ZO	ZO	ZO
ΔP_{err}	NS	PS	PS	PS	PS	PS	PS	PS
	ZO	PS	PS	PS	PS	PS	PS	PS
	PS	PM	PM	PM	PM	PM	PM	PM
	PM	PB	PB	PB	PB	PB	PB	PB
	PB	PB	PB	PB	PB	PB	PB	PB

5.4 Conventional PID Controller

In a PWR plant, a standard three-element controller regulates each steam generator water level individually. Water level, pressure, feedwater flow, and steam flow readings compose the instrumentation for each controller. The three-element control system uses the measurements of steam generator water level, feedwater flow, and steam flow. The control system maintains the feedwater flow at a value equal to the steam flow, when the steam generator water level is equal to the level setpoint [27]. Feedwater flow is controlled automatically above 15 % power [27]. The main feedwater pump speed controller responds to the error between the actual differential pressure at the main valve and its set point. The feed pump turbine valve is regulated to provide proper pump head.

5.4.1 The Water Level Controller

The three-element controller regulates the main feedwater valve position such that sufficient feedwater flows into the steam generator to maintain the programmed level value. The level error signal indicates the deviation of the water level signal from the desired setpoint. The setpoint is derived from the first-stage turbine impulse pressure [28]. The signal representing the measured level passes through a filter ($\frac{1}{1+\tau_{l1}s}$) to remove any high frequency oscillations. The narrow range level indicator reading is compared with the desired level signal, and the error is sent to a proportional-integral (PI) controller, $K_{l1}(1+\frac{1}{\tau_{l2}s})$, which eliminates the steady-state level errors. The output of this first PI controller goes to the three-mode valve controller. The controller subtracts the feedwater flow from the steam flow, adds the level error signal and sends the final signal to another PI controller, $K_{l2}(1+\frac{1}{\tau_{l3}s})$, to eliminate steady-state errors in feedwater flow. The output of the PI controller is the final main feedwater valve position signal. Figure 5.22 gives the block diagram of the conventional three-element controller [28].

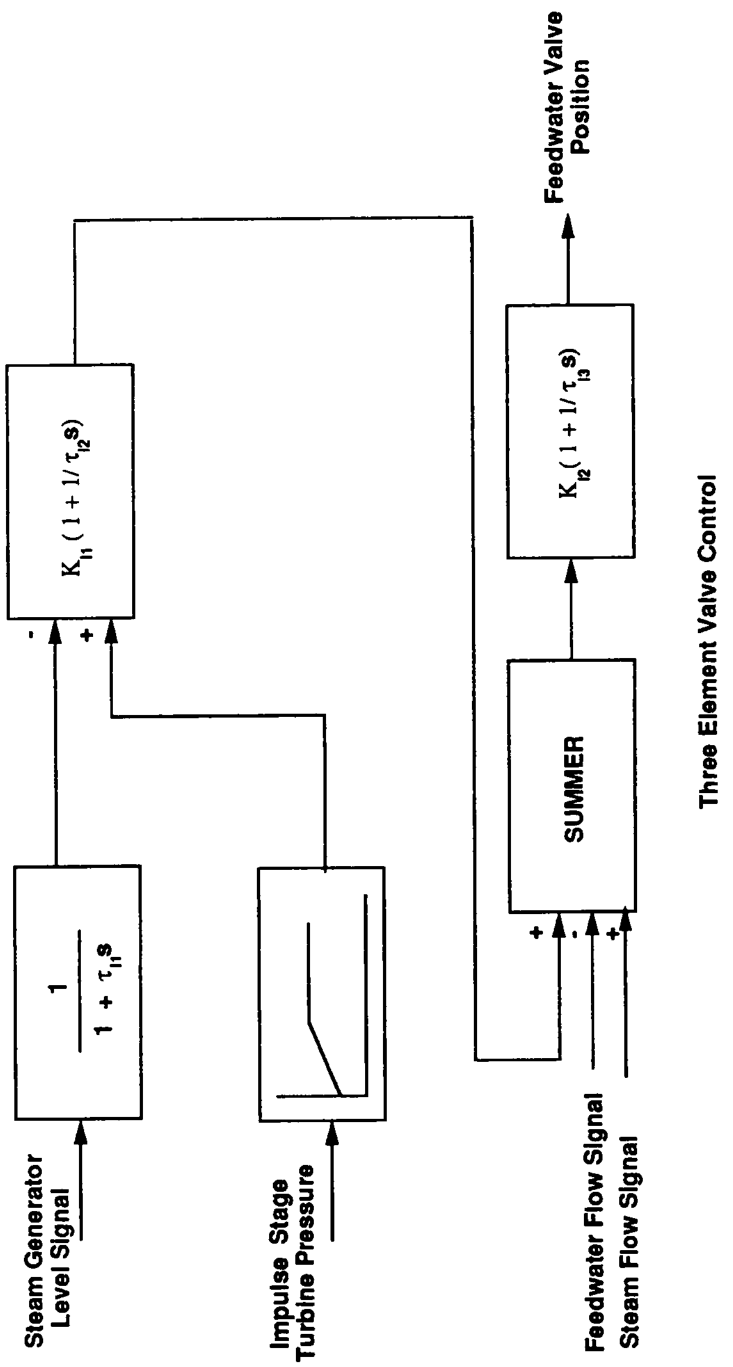

Figure 5.22: Block Diagram of the Conventional Three-Element Steam Generator Water Level Controller.

5.4.2 The Pump Speed Controller

The feedwater pump speed control system maintains a programmed differential pressure between the feedwater pump's discharge and the steam header by controlling the speed of the feedwater pump turbine drives [28]. A single controller governs the speed of both turbine-driven main feedwater pumps. The programmed pressure difference is maintained as a function of plant load in order to:

- Maintain feedwater control valve position in the linear range at part power
- Reduce pump power requirements at part load
- Reduce the possibility of valve plug erosion due to excessive closure at part load.

Description of the Pump Speed Control System

The functional diagram of the pump speed control is given in Figure 5.23. The programmed differential pressure between the feedwater header and steam header is derived as a function of the plant load as measured by the total steam flow. Figure 5.24 shows the differential pressure program. The programmed pressure difference signal passes through a lag unit $\frac{K_{p1}}{1+\tau_{p1}s}$ to slow the effect of large steam flow perturbations, and it is summed with a bias signal to allow feedwater flow against static head losses at no-load conditions. The programmed pressure difference is then compared with the actual pressure difference signal (feedwater header pressure - steam header pressure) to generate an error signal. The error signal is sent to a PI controller, $K_{p2}(1 + \frac{1}{\tau_{p2}s})$ which eliminates the steady-state error. The output of the controller is the actuation to change the pump speed by throttling the feed pump turbine valve.

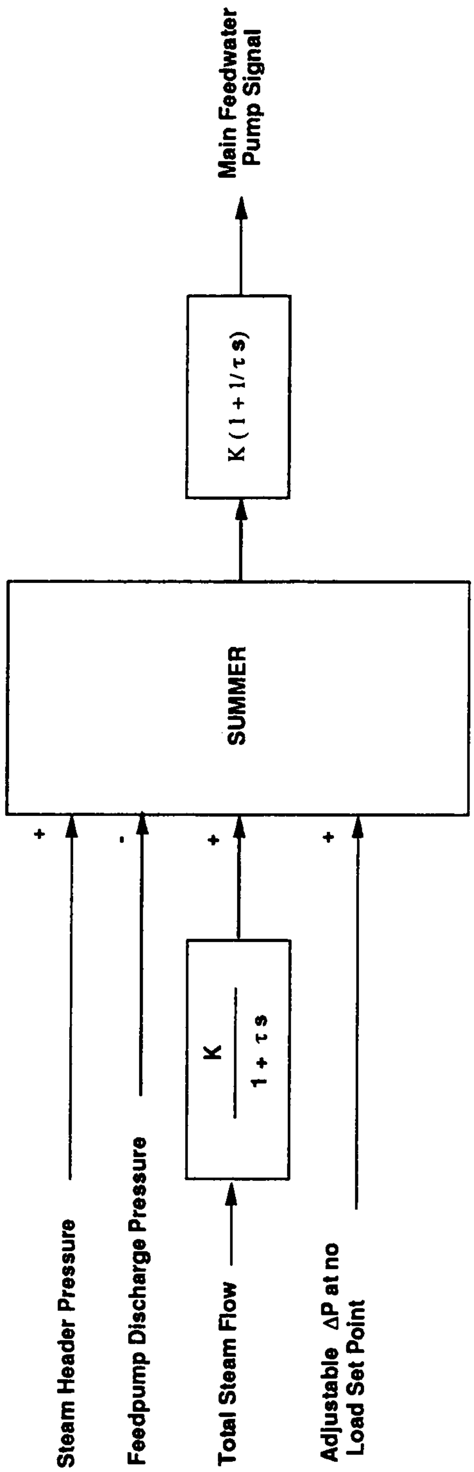

Figure 5.23: Functional Block Diagram of the Pump Speed Control System.

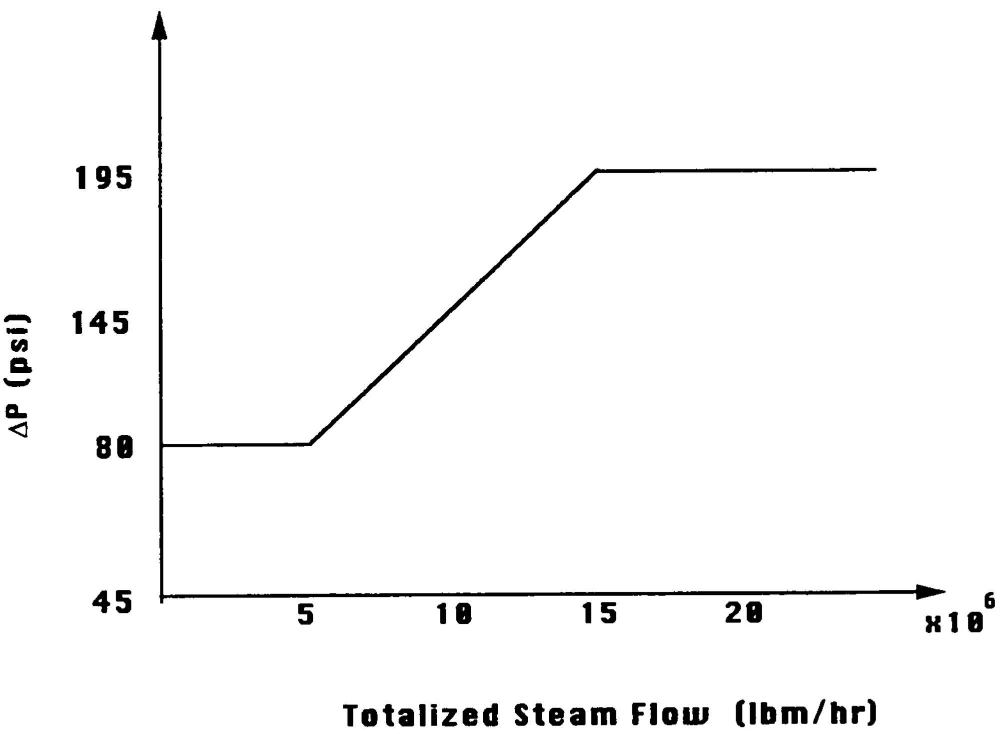

Figure 5.24: Differential Pressure Set Point Program.

5.5 Summary of the Chapter

This Chapter presented the control module of the Fault-Tolerant Control and Diagnostics System developed for the feedwater flow regulation of a PWR. Three different control algorithms were developed as part of the parallel control approach introduced in this research, namely the conventional PI controller, the Reconstructive Inverse Dynamics (RID) controller, and the Fuzzy Logic Controller (FLC). The feedwater flow regulation consists of two major control systems: the steam generator water level control and the main feed pump speed control. Both of these control systems were included in the FCDS. The development of the control algorithms and details were presented in this Chapter.

Chapter 6

Results of Analysis of the Integrated Control System

6.1 Introduction

Unknown plant dynamics, time-delay in measurements, actuator constraints, flow and temperature perturbations, and main feed pump failure are the most common causes for plant trip in PWRs. The robustness of the FCDS control algorithms was demonstrated by simulating these cases. The performance of the existing PI controller, inverse dynamics and fuzzy logic controller for water level set point and steam valve perturbation tests were also analyzed. The results are compared in the following sections. The test of ΔP set point perturbation for the pump speed controller is also discussed in this chapter to illustrate the robustness of the RID and the fuzzy logic controllers.

Since one of the objectives of this research is to demonstrate the feasibility of using multiple controllers for the same task, the case of water level perturbation is used to integrate all the three control algorithms for the feedwater control system. The results of the command validation and the decision-making modules, and the signal validation module are also presented in this chapter.

6.2 Fuzzy Logic Controller

One of the important contributions of this dissertation research is the design of Fuzzy Logic Controllers (FLC) for the steam generator water level control and the turbine-driven feedwater pump speed control in pressurized water reactors (PWRs). Although fuzzy logic controllers have been developed for various systems such as electric trains, cement kilns, water purification plants, and many others, there is no real application of fuzzy logic in the nuclear industry, except in the Fugen reactor in Japan. This dissertation research introduces a new control system for the feedwater flow regulation with the development of water level control and pump speed control. These two controllers work individually as part of the FCDS, and operate jointly to regulate the feedwater flow in PWRs.

Fuzzy controllers were introduced by Mamdani and Assilian in 1975 for the control of complex processes, especially when no precise model of the process exists [56]. The fuzzy controllers were designed to handle a process similar to a human operator's actions. Since the fuzzy logic controller follows the actions of a human operator, the stability analysis of fuzzy controllers is not straight forward. Stability analysis of a control system relies on the availability of mathematical models of processes [56]. The main advantage of a fuzzy controller is that its synthesis does not require the existence of any model. Therefore the stability analysis of fuzzy logic controllers cannot be carried out in the traditional manner. They are assumed to be implicitly robust because they are based on human experiences [56] [62][63] [65].

Dynamic models of a PWR steam generator and controllers were used in this research in order to simulate the feedwater system responses. Based on the model, and using the possible real world failures, the performance and the stability of the fuzzy controllers can be evaluated. Since the transient steam generator dynamics is highly nonlinear, and there are various factors that might change during the operation of a power plant which challenge the control systems, testing the fuzzy logic controllers will enhance the reliability of the controllers. The details of the fuzzy logic controllers for both the steam generator water level control and the differential pressure control are given in Chapter 5. In addition to the perturbation tests which are discussed in the following sections, a set of performance tests were also carried out to show the robustness of the fuzzy logic controllers.

The following cases are chosen to test the fuzzy logic controller performance, since these situations are more likely to occur during the operation of a power plant.

- Unknown plant dynamics.
- Measurement delays.
- Constraints in the control actions.
- Boundary condition perturbations.

6.2.1 Unknown Plant Dynamics

Some of the design parameters change during the normal operation of a power plant. These are usually handled by the operators without challenging the control systems. Three different parameters were selected to test the robustness of fuzzy controllers. The heat transfer coefficients from primary side to metal side (U_{pm}), from metal side to subcooled region (U_{ms1}), and from metal side to boiling region (U_{ms2}), are considered. The details of the U-tube steam generator model and how these coefficients affect the modeled system are given in Appendix A. These parameters may degrade due to changes in the design values such as deposit build up, breaks, concentration deviations, or possible turbulence in the flows. Four different external disturbances are applied to each of the coefficients varying from 0.5 % ramp change within 50 seconds to nearly 100 % change. The fuzzy logic controller is able to handle the disturbances without creating further complication to the feedwater system. This test also evaluates the robustness of the fuzzy logic control.

Figure 6.1 shows the perturbations ($\sim$ 100 %) applied to the heat transfer coefficients from the primary side to the metal side (U_{pm}), from the metal side to subcooled region (U_{ms1}), and from the metal to the boiling region (U_{ms2}). After the analysis of the effects of changing three coefficients, it is concluded that the primary to metal side transfer coefficient, U_{pm}, has the most impact on the water level control. The fuzzy logic controller is able to handle all disturbances with no steady-state error, or negligible steady-state error in the water level. Figures 6.2 through 6.4 give the corresponding steam generator water level responses for the first $\sim$ 100 % parameter disturbances.

In addition to the 100 % disturbance that was introduced to U_{pm}, a final test was simulated by increasing the coefficient to 3 times its original value within 50 seconds. In order to understand the effective domain of the fuzzy logic controller, this unrealistically large perturbation test was performed (see Figure 6.5). These disturbances are much greater than those that might occur during the operation of a nuclear power plant. The fuzzy logic water level controller showed a robust response to the disturbance and controlled the water level within the design limits with a negligible steady-state error (see Figure 6.6). In conclusion to these unknown plant dynamics tests, the fuzzy logic controller is robust against these types of disturbances.

6.2.2 Measurement Time-Delay Problem

One of the problems associated with control systems is their robustness against the abnormalities in measured signals. Sensors often undergo a gradual degradation before they become completely non-operational. Although the FCDS offers a

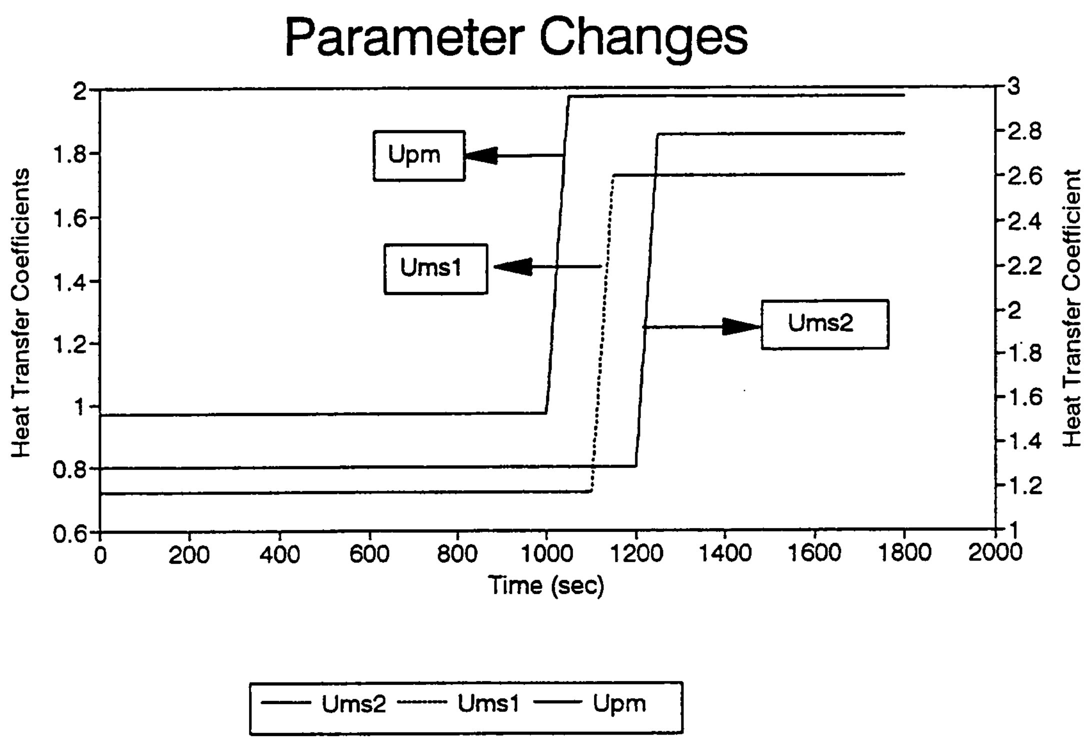

Figure 6.1: Changes in Heat Transfer Coefficients During Parametric Test of Fuzzy Logic Controller.

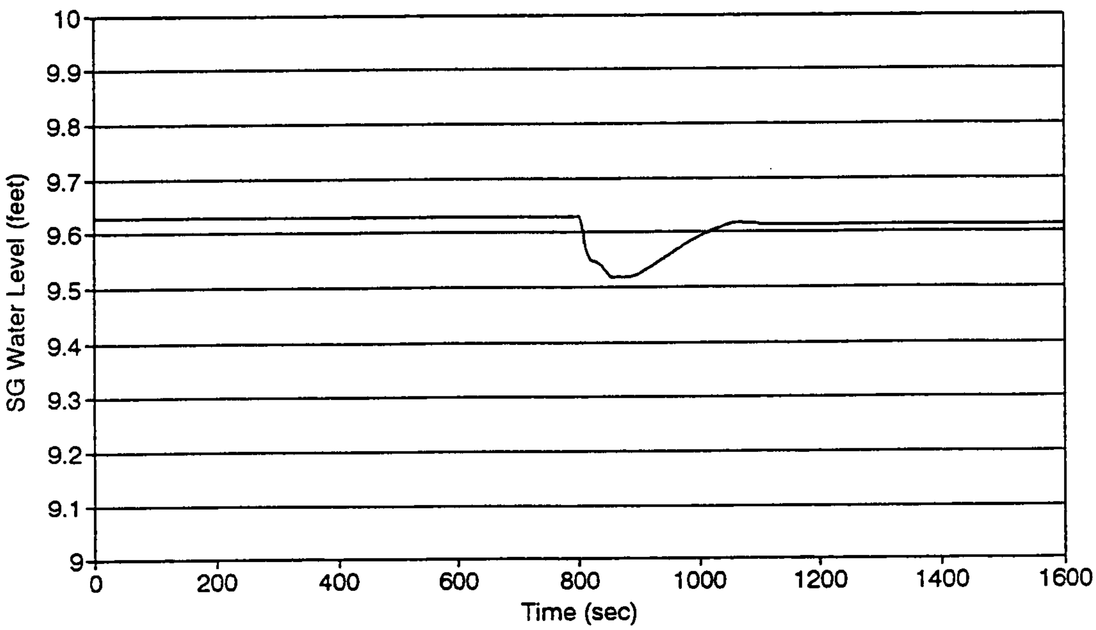

Figure 6.2: Steam Generator Water Level Response During, U_{pm} Parameter Change Test.

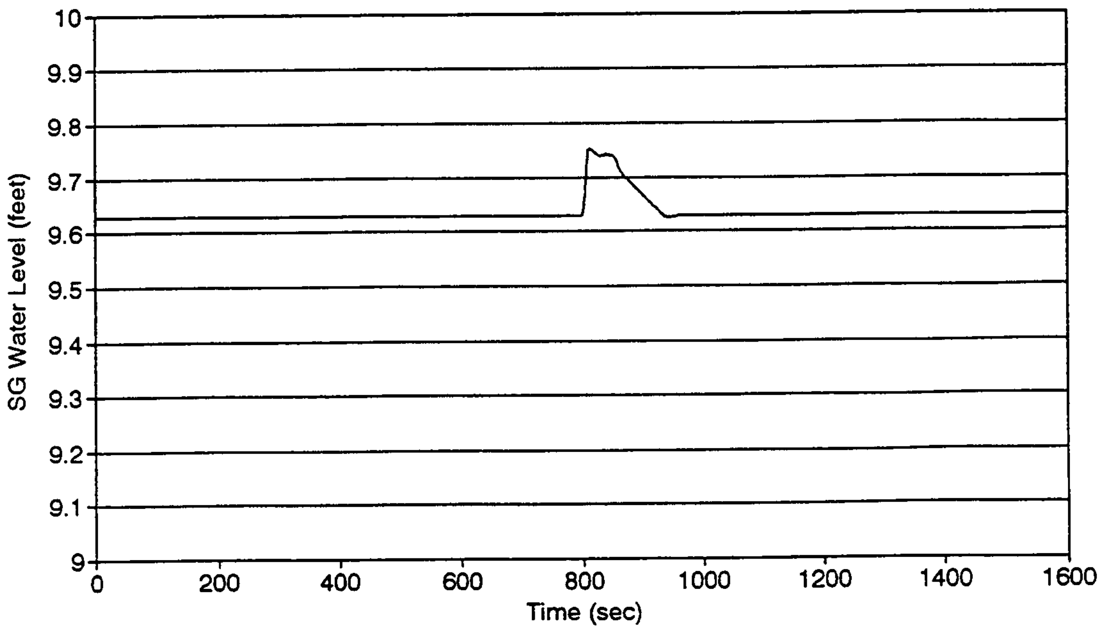

Figure 6.3: Steam Generator Water Level Response During, U_{ms1} Parameter Change Test.

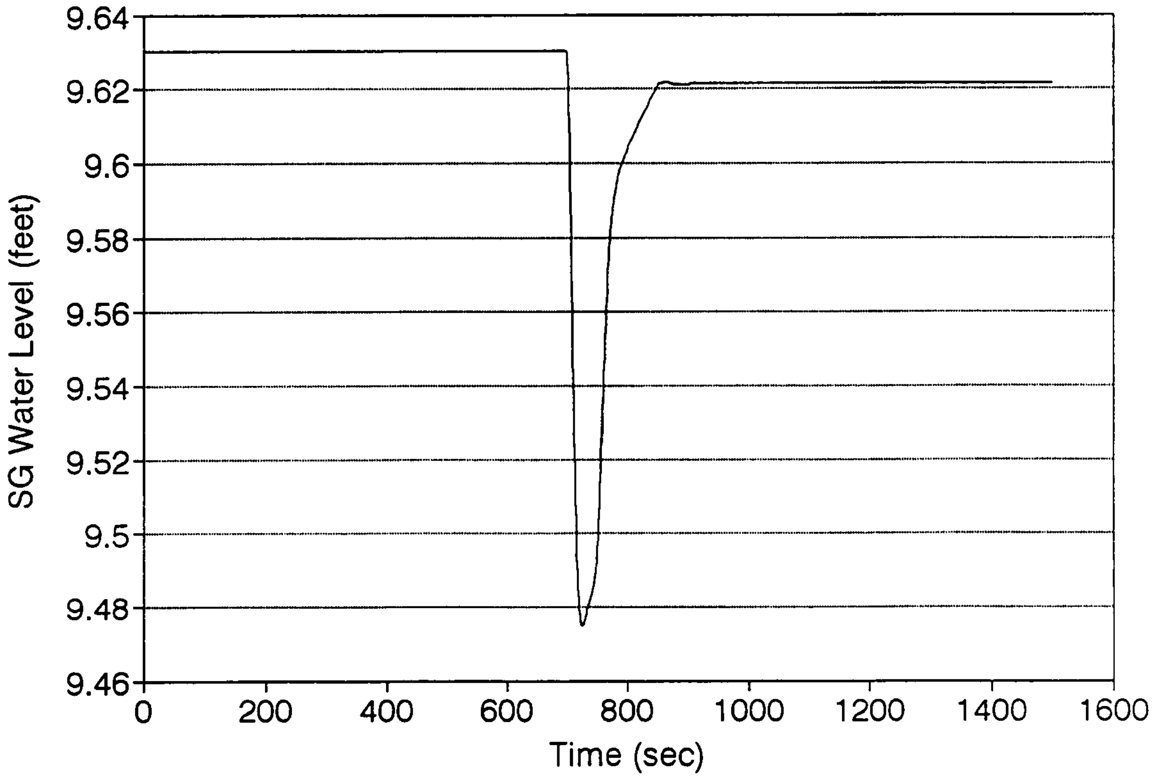

Figure 6.4: Steam Generator Water Level Response During, U_{ms2} Parameter Change Test.

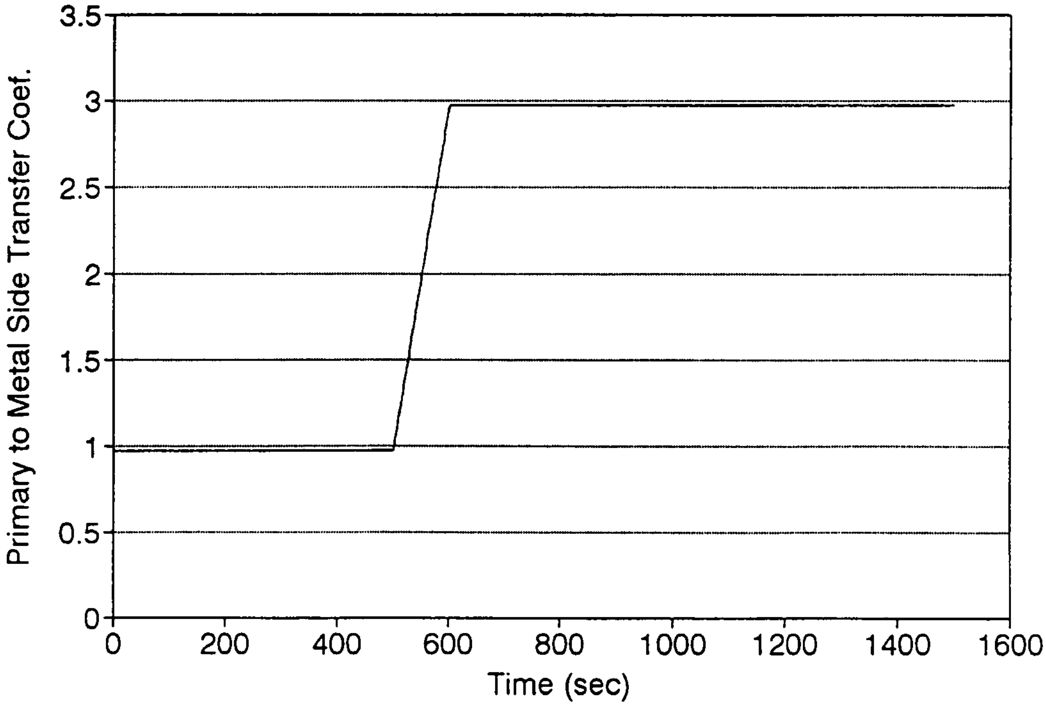

Figure 6.5: Largest Change Applied to the Primary to Metal Side Heat Transfer Coefficient, U_{pm}, During Parameter Test of Fuzzy Logic Controller.

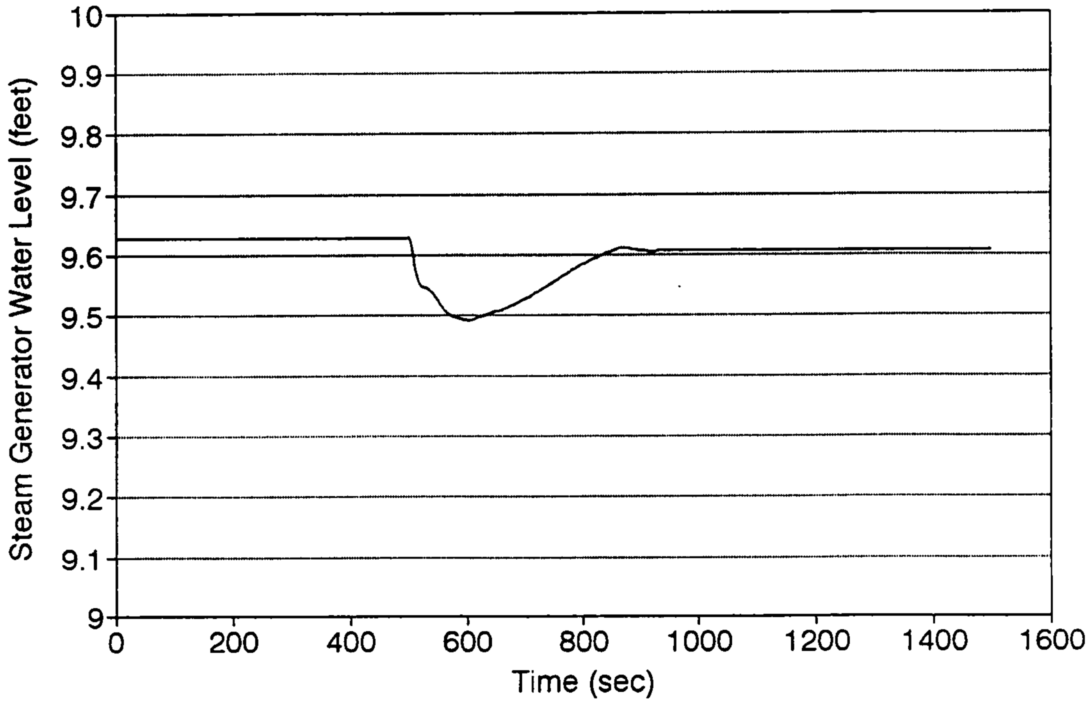

Figure 6.6: Steam Generator Water Response During Parameter Change Test for the Largest Change given to U_{pm}.

sensor/signal validation module to overcome this problem within its fault-tolerant design, it is necessary to show the robustness of the individual controllers against measurement delays that often occur during the operation of a power plant. Since the emphasis is given to the fuzzy logic controllers in this dissertation, various measurement delay tests were applied to the fuzzy logic steam generator water level controller.

Before a sensor anomaly is detected by any signal validation technique, it is important that control systems respond properly during the period in which one or more sensors are degrading. In this test, the simulations include time-delays in water level measurement and feedwater flow measurement. The measurement time-delay is modeled using a first-order delay dynamics given by

$$\frac{dL_d}{dt} = \frac{1}{\tau}(L - L_d) \tag{6.1}$$

where L_d, L, and τ are the measured signal, plant state variable, and sensor time-constant, respectively. The first time-delay test simulation introduces a 100 millisecond delay in both of the control inputs: flow error and level error signals. These delays are defined to be in addition to the normal time constants of the sensors in the plants. Figure 6.7 shows the steam generator water level response during a level perturbation. Level perturbation is a set point change in which the level set point was increased 16 % from 9.63 feet (measured from the top of the U-tube bundle) to 11.13 feet within 300 seconds. The second simulation was made with 5 second delay in the level error signal and a 100 millisecond delay in the flow error signal. The result of this simulation test is shown in Figure 6.8. The third test was made with a 5-second delays in both of the control input signals. Figure 6.9 gives the responses of the water level signal when there is a 5-second delay in the control input measurements. The results of the simulation tests have shown the robustness of the fuzzy logic controller against possible time-delays in measurements. Although

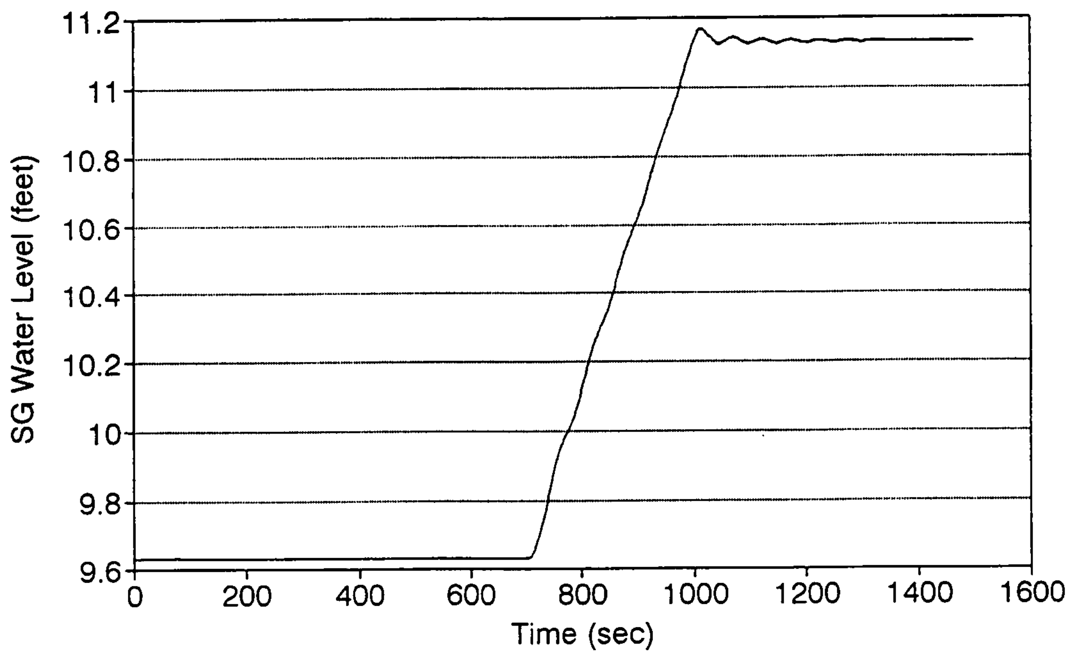

Figure 6.7: Steam Generator Water Level Response with 100 Millisecond Time-Delay in the Control Input Signals.

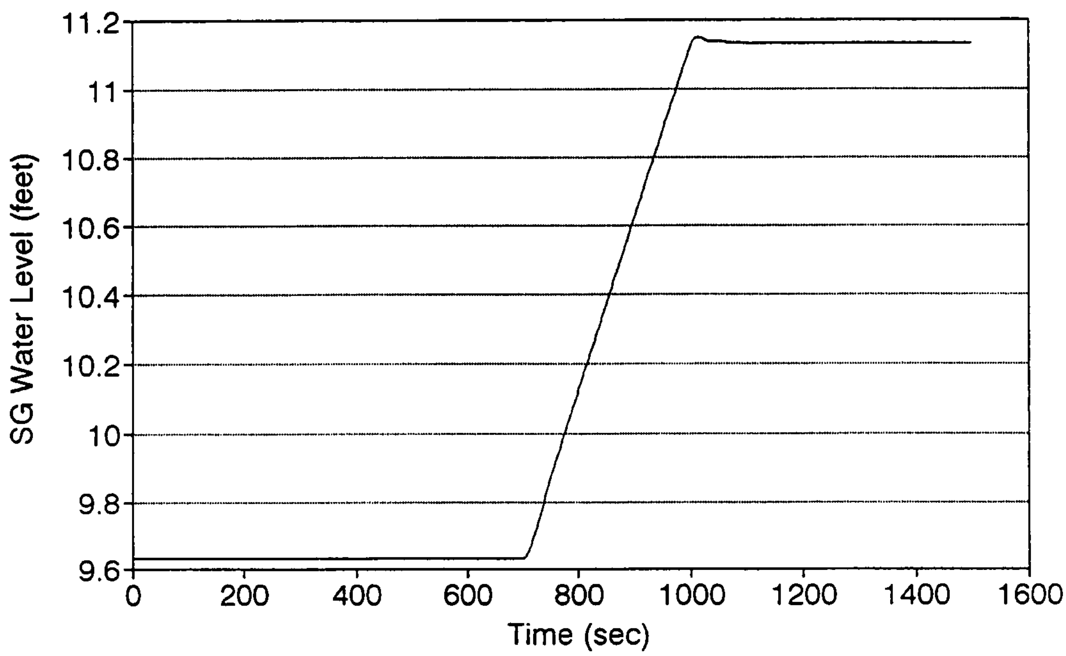

Figure 6.8: Steam Generator Water Level Response with 5 Second Delay in Level Error, and 100 Millisecond Delay in Flow Error Signals.

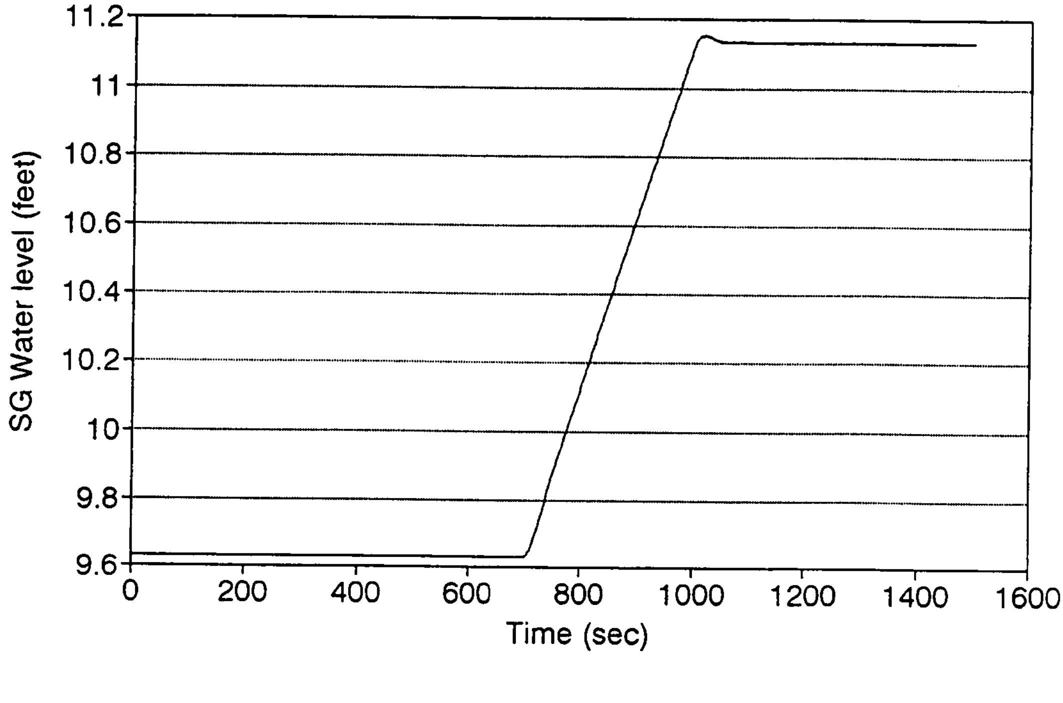

Figure 6.9: Steam Generator Water Level Response with 5 Second Time-Delay in the Control Input Signals.

the time delay in the control input signals caused small fluctuations in the level signal, the fluctuations were insignificant, and the fuzzy logic controller completed the perturbation successfully.

6.2.3 Actuator Constraints

Actuator constraints limit the capability of control systems because of electromechanical or safety-related constraints. The error between the desired trajectory and the system response must be minimized by modifying the trajectory such that the actuator limitations are not exceeded. There is a maximum rate for the control-rod motion, pump discharge, and valve openings in nuclear reactors where the safety limitation often imposes more restrictions. Therefore, the trajectories must be designed so that violations of these limits are avoided. Fast changes in the control action may cause actuator hardware problems. Protecting the actuators from an excessive control signal can be accomplished by using input limiters. Although such fast control actions have not occurred during the various perturbation tests discussed later in this chapter, constrained actuator tests were applied to show the robustness of the fuzzy logic controllers.

The actuator dynamics can be expressed as

$$\frac{dz}{dt} = R_{max}, \qquad k_v(u - z) \geq R_{max} \tag{6.2}$$

$$\frac{dz}{dt} = k_v(u - z), \qquad R_{max} > k_v(u - z) > R_{min} \tag{6.3}$$

$$\frac{dz}{dt} = R_{min}, \qquad k_v(u - z) \leq R_{min} \tag{6.4}$$

where R_{max} and R_{min} represent the upper and lower boundaries of the actuator signal rate respectively, $\frac{dz}{dt}$, and k_v is the time-constant of the actuator.

Although the fuzzy logic controllers do not have control actions that require actuator constraints to save the control valves, various limitations to control actions have been placed to test the performance of the controller. In operating nuclear power plants, the feedwater control valves are designed to handle a 10 % step increase, and a 50 % step decrease in the flow demand [34]. This indicates that the existing control valves have very fast response capability in the event of transients. A number of simulations were performed to test the fuzzy logic controller during a level perturbation. The actuator limitations varied from ± 10 % change in the control action to ± 0.1 % change. When the control action limits were higher than ± 0.001, the fuzzy logic controller handled the perturbations without causing any disturbance to the system. If the control action changes were limited to as low as ± 0.001, the fuzzy logic controller would fail to handle the perturbations. It is obvious that a ± 0.001 change in control actions is not logical for power plant operations. Therefore, the failure is not due to the design or the logic of the controller, it is due to the external restrictions that were added to the control valve dynamics. Figure 6.10 displays the comparative normalized control actions for the fuzzy logic controller with and without applying the constraints on the actuators. Figure 6.11 displays the steam generator water level response for the constrained (± 0.005) and unconstrained controllers during a perturbation. It is concluded that the fuzzy logic controller is able to operate with very restricted control actions.

6.2.4 Boundary Condition Perturbations

The nonlinear modeling of the feedwater flow control system used the following forcing functions.

- Feedwater temperature
- Primary flow
- Steam valve coefficient.

The perturbation results of the steam valve coefficient are presented in the following sections along with the PID and RID controllers of the FCDS. In this section, as

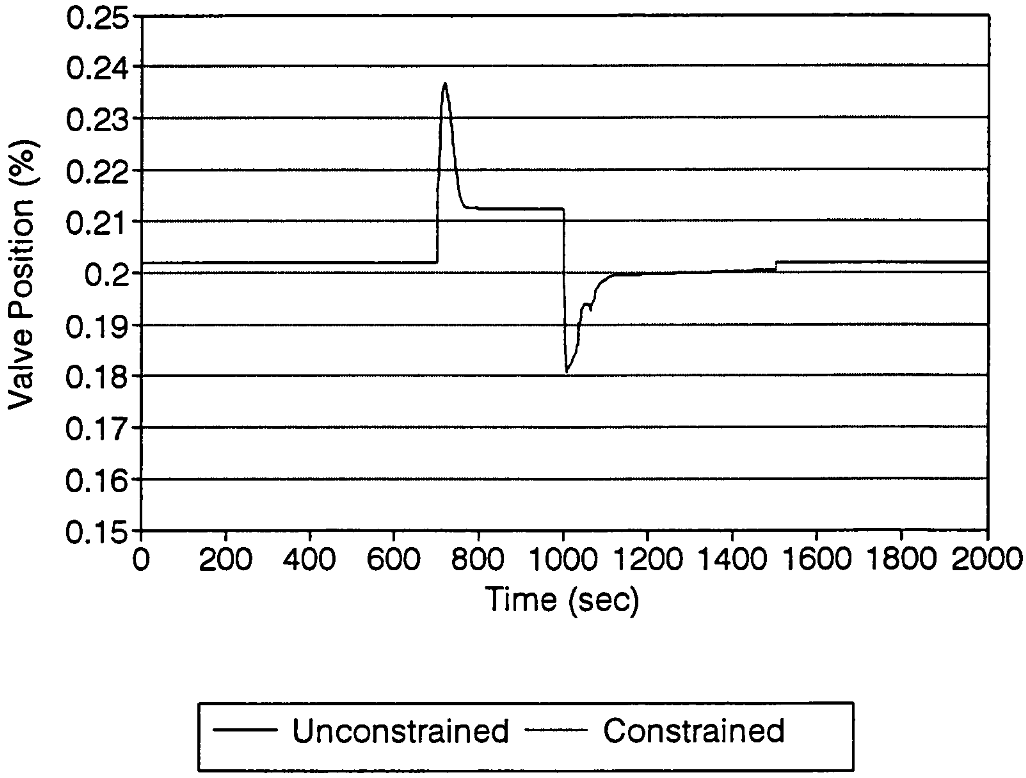

Figure 6.10: Constrained and Unconstrained Control Actions of the Fuzzy Logic Controller.

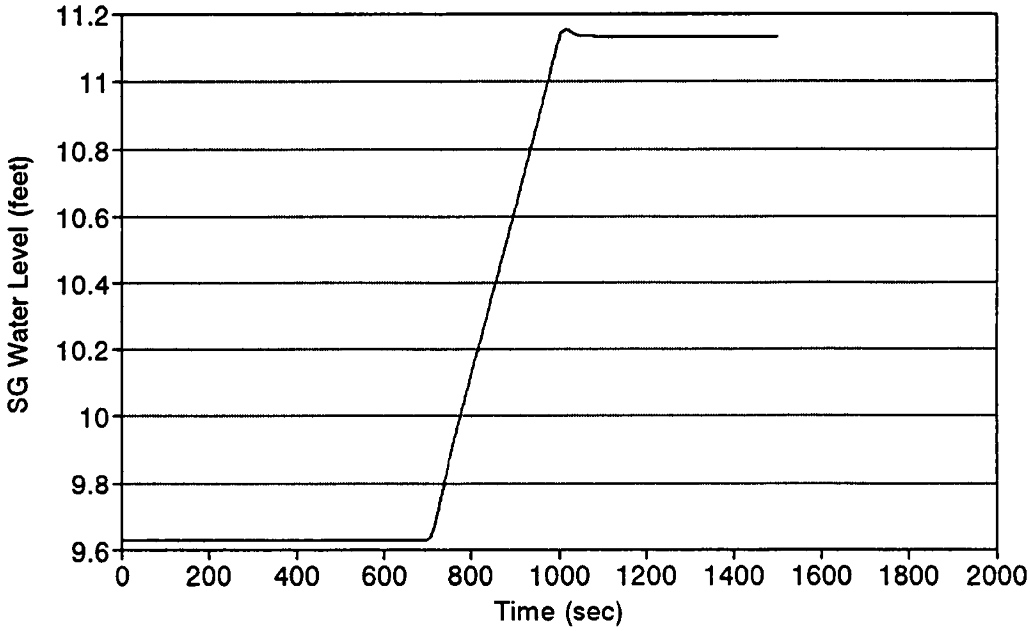

Figure 6.11: Water Level Responses for the Constrained and Unconstrained Fuzzy Logic Control Actions.

part of the performance analysis of the fuzzy logic controller, perturbation test results for the feedwater temperature, and the primary inlet flow are discussed. The possible disturbances that might occur in these parameters should be handled without causing further problems to the feedwater system.

Feedwater Temperature Perturbation

A number of simulations were completed to analyze the robustness of the fuzzy logic controller in the event of feedwater temperature disturbance. The design value for the feedwater inlet temperature is set to 434.3 ^0F at full power normal operation of a PWR. During the test 5 % to 25 % changes lasting for 50 seconds were simulated and the performance of the fuzzy logic controller was observed. The fuzzy logic controller was able to handle the disturbances less than 25 % increase in feedwater temperature. When the feedwater temperature was increased by 25 % (from 434 ^0F to 543 ^0F), the control system is not able to handle the transient. A 100 ^0F change in feedwater flow temperature is not likely to occur under normal operating conditions of a PWR. Figure 6.12 shows the 20 % increase in the feedwater temperature for 50 seconds, and Figure 6.13 shows the steam generator water level response during the perturbation. A sudden increase in the feedwater inlet temperature is not very likely to happen during the normal operation of a PWR.

In order to study a transient which is more likely to occur, decrease in the feedwater inlet temperature was also considered as part of this study. Feedwater inlet temperature may decrease due to various reasons during normal operations (feedwater heater outage for example). Similar to the previous simulation tests, a range of disturbances were introduced to the feedwater control system. The fuzzy logic level controller was able to handle even a 25 % decrease in the inlet temperature which would disturb the feedwater system significantly. Figure 6.14 shows the introduced 25 % feedwater inlet temperature decrease, and Figure 6.15 shows the steam gener-

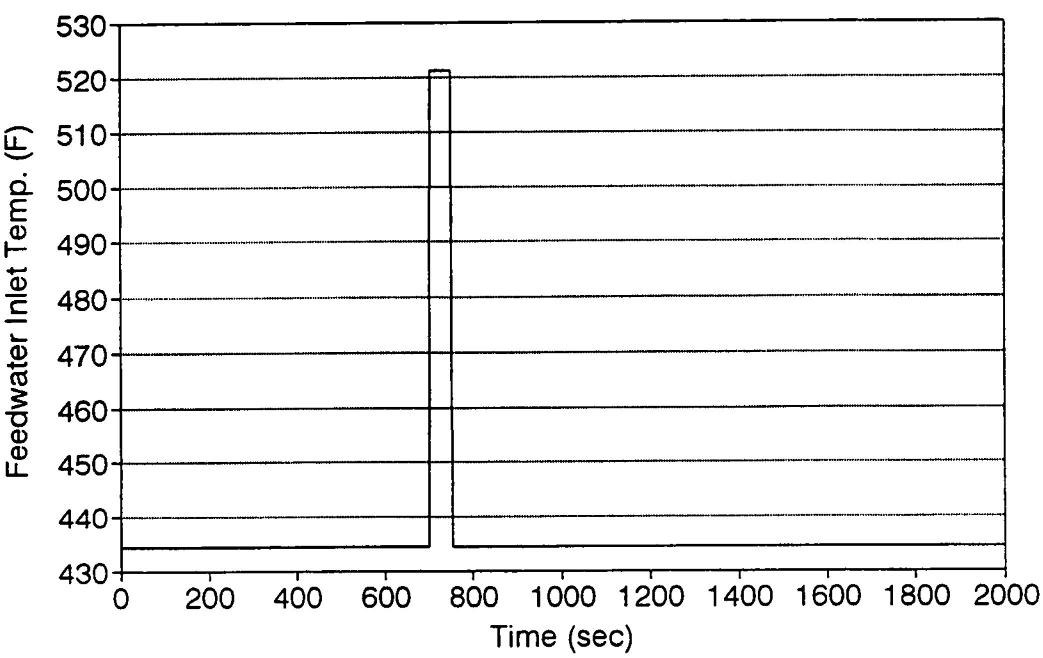

Figure 6.12: Feedwater Inlet Temperature Perturbation, 20 % Increase.

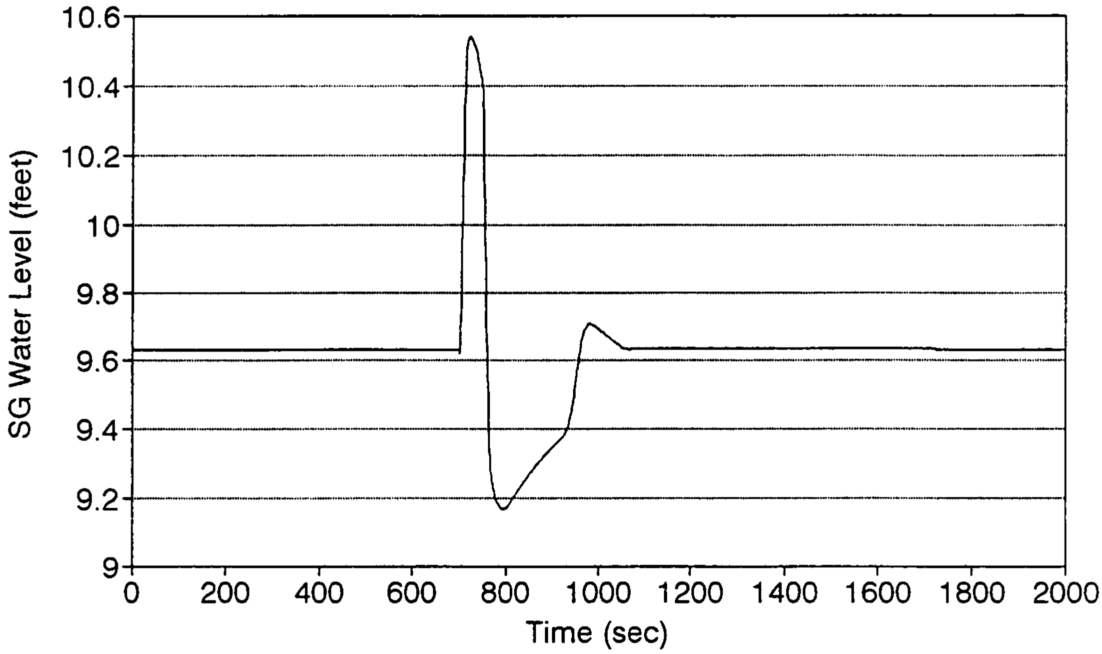

Figure 6.13: Steam Generator Water Level Response During a Feedwater Inlet Temperature Perturbation.

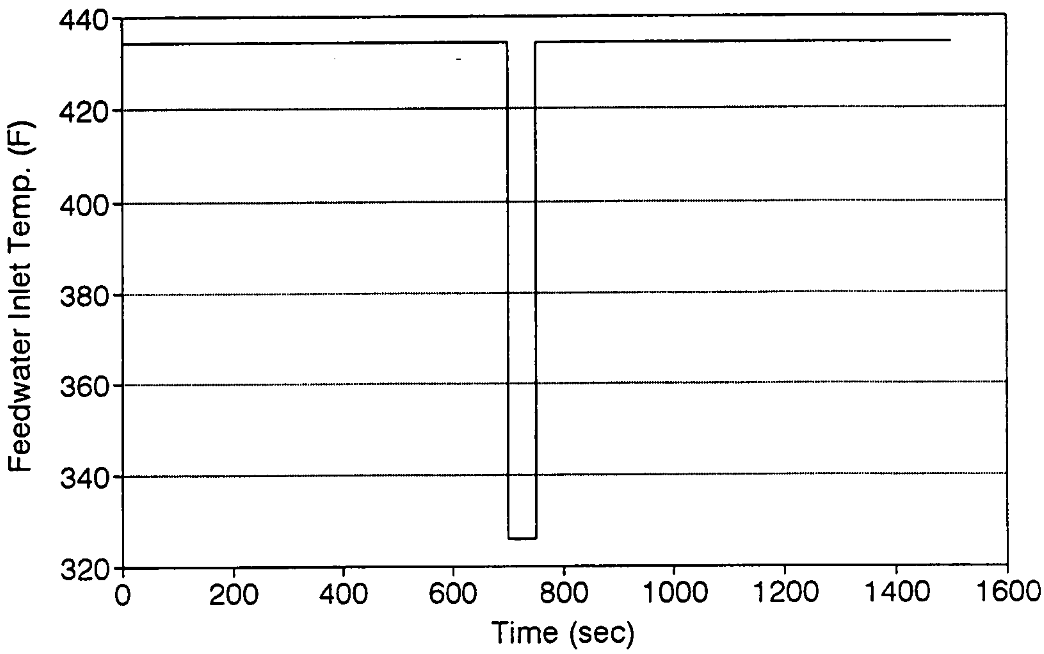

Figure 6.14: Feedwater Inlet Temperature Perturbation, 25 % Decrease.

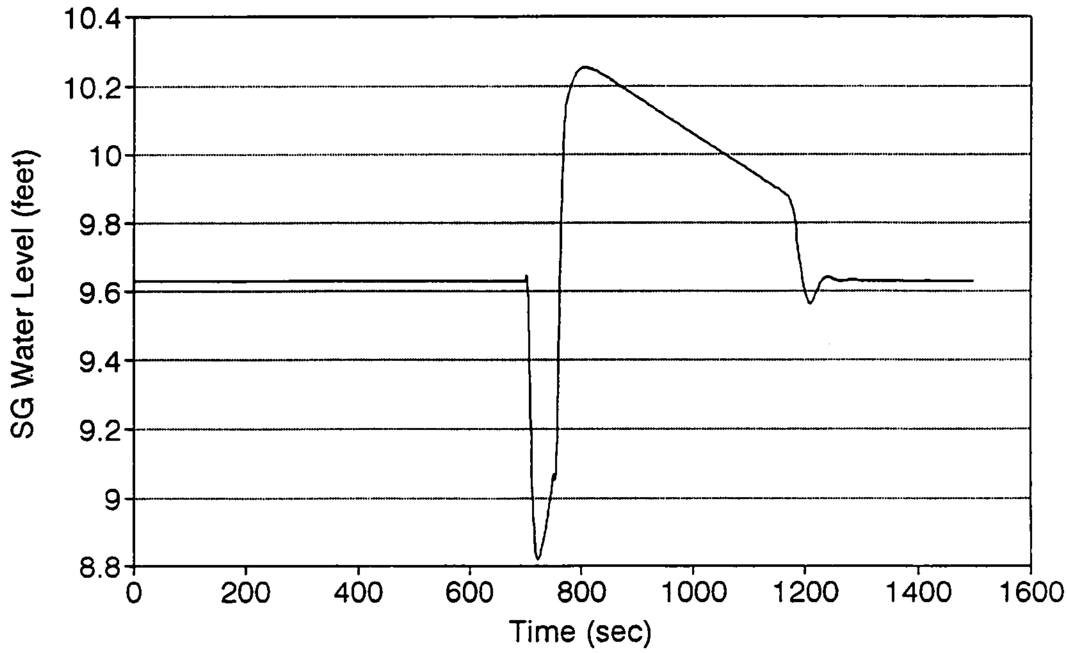

Figure 6.15: Steam Generator Water Level Response During a Feedwater Inlet Temperature Perturbation.

ator water level behavior in response to the disturbance.

These simulations demonstrate the ability of the fuzzy logic controller to handle significant temperature changes in the feedwater flow without causing trip conditions. The robustness of the fuzzy logic design against sudden changes in the inlet temperature is shown using these various simulation tests.

Primary Flow

Although changes in the primary flow are not likely to occur, two different simulation tests were completed to test the fuzzy logic level controller. Primary flow may be disturbed due to a pump failure or loss of coolant. If there is any change in the primary flow, the auxiliary pumps are activated to compensate for the loss of flow. One of the simulation tests demonstrates the loss of flow for a short period of time. The primary flow was decreased from 11000 lbm/sec to 8500 lbm/sec, and the water level controller was observed. Figure 6.16 gives the transient that occurred in the primary flow. The steam generator water level response to the transient is given in Figure 6.17. Although the water level has a sudden drop, the fuzzy logic controller was able to bring the water level to its set point without causing a trip. The feedwater pump speed is shown in Figure 6.18. As expected the pump speed increased to compensate for the flow loss.

Feed Pump Failure

The second simulation test demonstrates the possible main feed pump failure. According to the surveys carried out by various agencies [27] [2] [34] the plant trips caused by main feed pumps make nearly 35 % of the total trips in PWRs. The application of FCDS to the feedwater system tries to offer a better control system to overcome the existing problems. There are two 60 % capacity, variable speed, turbine driven centrifugal main feed pumps that raise the pressure of the condensate

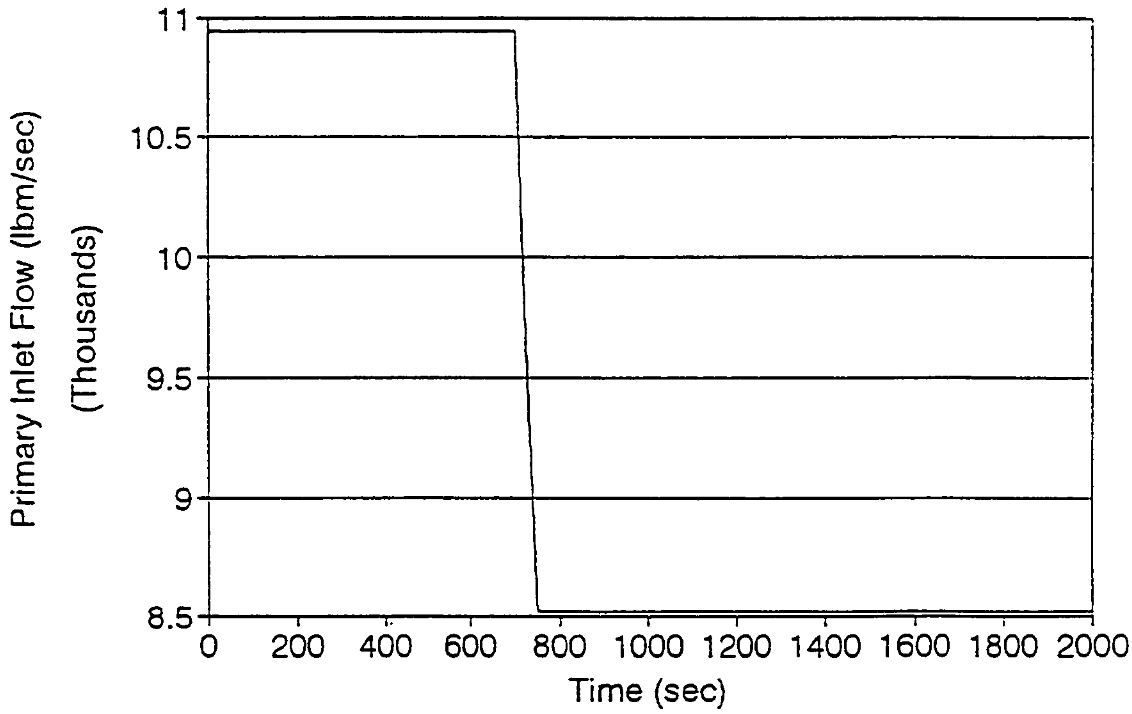

Figure 6.16: Primary Flow Loss Transient Simulation.

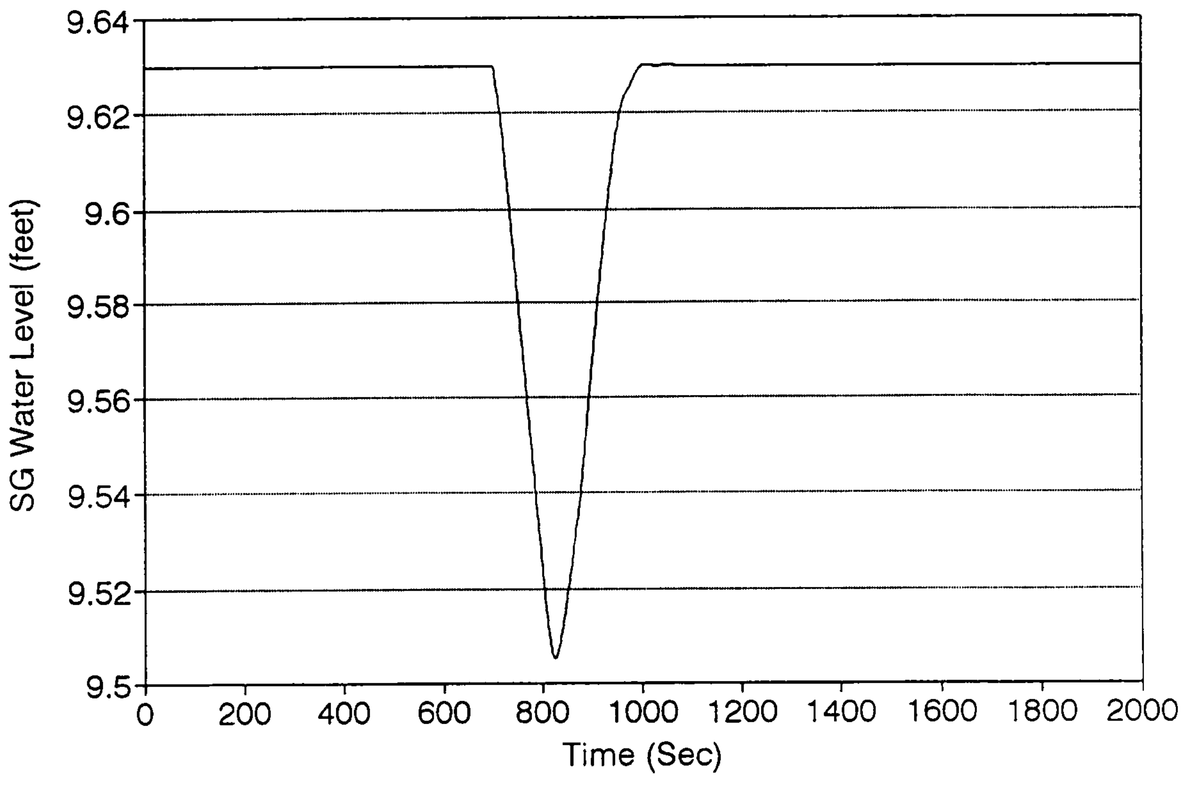

Figure 6.17: Steam Generator Water Level During Primary Flow Loss.

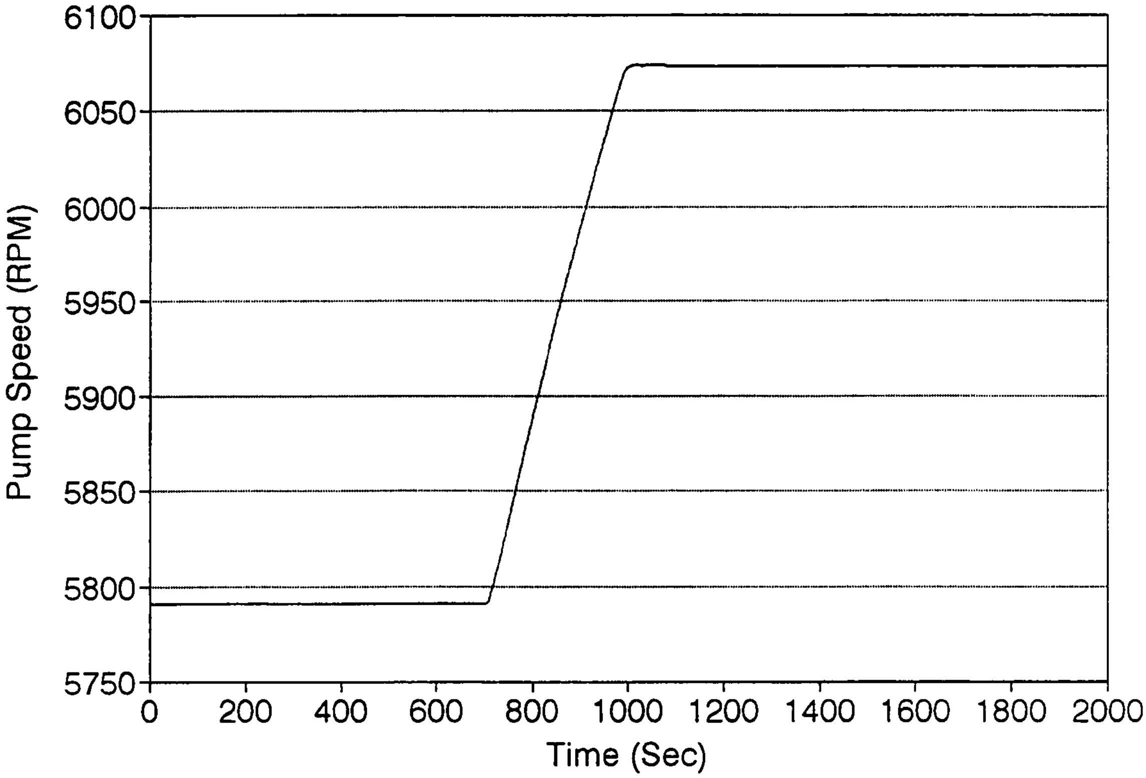

Figure 6.18: Pump Speed Change During Primary Flow Loss.

to a value that is high enough to feed the steam generators. Failure of one of these pumps causes a loss in feedwater flow, even though one feed pump can handle nearly 80 % of the flow demand by itself.

Since the pump head is very large (the decrease in the feed flow is not sudden) a slowly decreasing flow loss is simulated to demonstrate the robustness of the fuzzy controller in the event of pump failures. Steam generator water level and pump speed responses for the simulation test are given in Figures 6.19 and 6.20, respectively. Figure 6.21 shows the change in the feedwater flow rate. The fuzzy logic controller shows a robust response to a pump failure and flow disturbance that might occur during normal operations in PWRs.

6.3 Control Applications

The design of a control strategy for feedwater flow regulation of a four-loop pressurized water reactor (PWR) was undertaken as part of the Fault-Tolerant Control and Diagnostics System. This research task is of importance in contributing to the improved transient performance that combines steam generator level control and main feedwater valve differential pressure regulation.

The control problem in turbine-driven feedwater pumps is related to the regulation of pressure difference (ΔP) across the feedwater valve around set points during feedwater maneuvers. In the conventional strategy, the feedwater valve position is adjusted to satisfy a feedwater demand, whereas the turbine valve position is adjusted to maintain the ΔP close to its set point.

A computer code was developed and used to simulate the dynamics of the steam generator and the feedwater system. The code consists of models of a U-tube steam

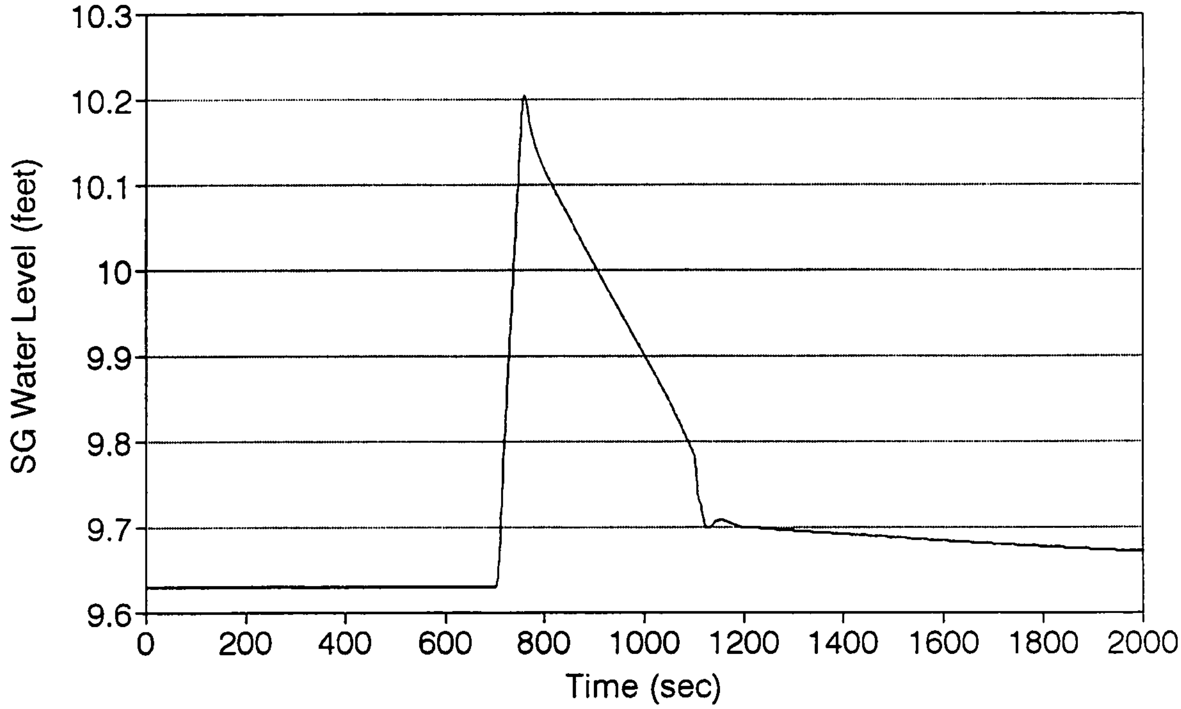

Figure 6.19: Steam Generator Water Level During Feed Pump Failure.

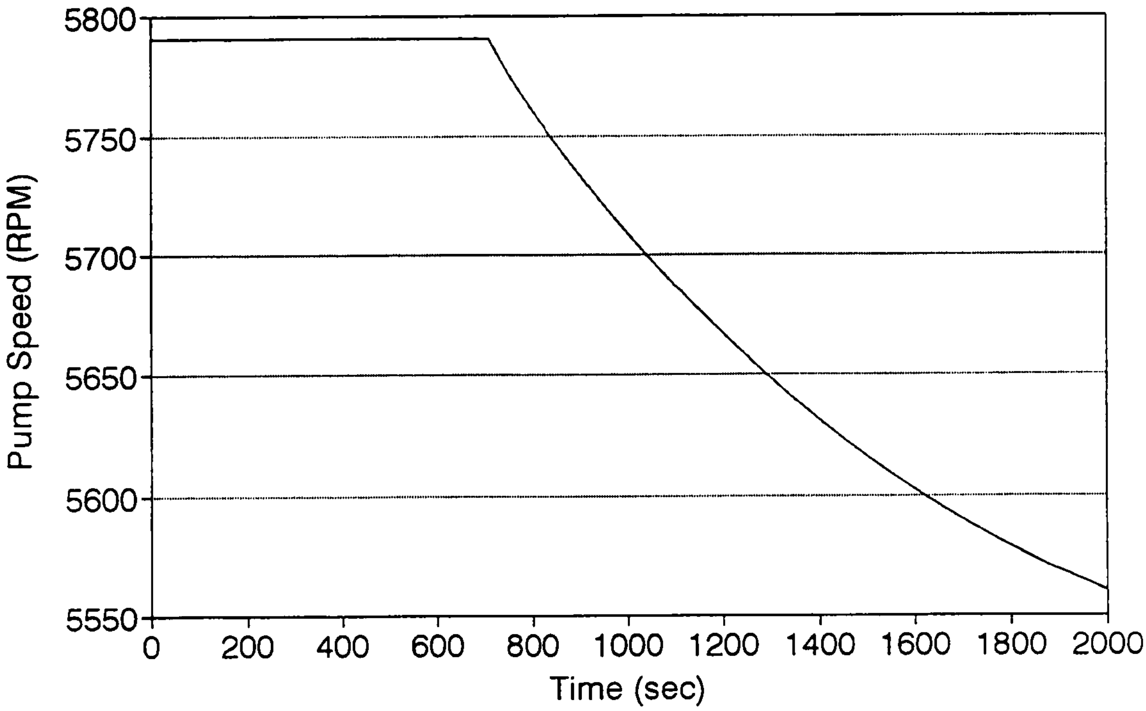

Figure 6.20: Pump Speed Change During Main Feed Pump Failure.

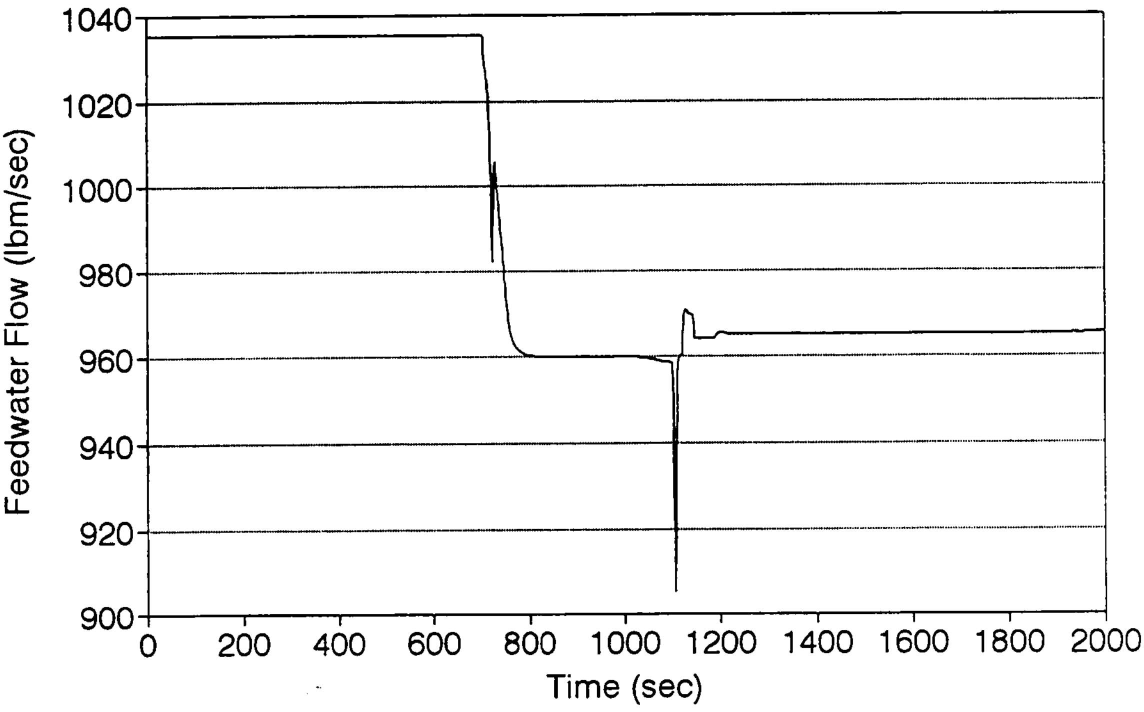

Figure 6.21: Feedwater Flow Loss Due to Main Feed Pump Failure.

generator, main feedwater pump, and their related control valves. There are two controllers involved in adjusting the valve positions:

1. A three-element controller for feedwater valve actuation.
2. A turbine governor valve controller (to maintain a desired ΔP across the feedwater valve).

Existing controllers in operating PWRs are based on analog technology and do not include direct communication between the two control systems. During some steam generator transients, where a rapid change in feedwater flow is required for level control, these control systems may go out of phase due to the sluggish behavior of the turbine-driven pump speed controller. Thus, a major improvement in feedwater operations requires communication between the turbine valve control system and the feedwater/steam generator system in order to improve the pump speed adjustment.

The solution to this control problem includes the development of advanced nonlinear control designs which utilize different control strategies. An operating nuclear power plant's current three-element PID controller and turbine governor valve PID controller were also simulated. The controller gains and time constants are closely matched to those used in the plant controllers. The primary concern was to develop a system model whose behavior is similarly to the actual plant.

These PID controllers in the simulation use the same form of input signals as those used in plant actuators. The controller generates actuation signals in mA (milliamp) current units. Since the final goal is to have a parallel fault-tolerant control system, adaptive controllers for both three-element and turbine governor valve controllers were developed. No changes were made to the existing control strategy.

The second controller, Reconstructive Inverse Dynamics (RID), has a faster response compared to the PID controller. This faster response comes from its adaptive nature. A constraint on the rate of change of actuator response can be imposed to match the real system response. Finally, the third controller uses a fuzzy logic. Two different controllers were developed using the fuzzy logic. One uses control input signals similar to the current three-element controller (level error and flow mismatch). The second fuzzy logic controller was developed as an alternative for possible sensor failures or control system failures. Control inputs are rate of change of level error and level error signals.

The RID and the fuzzy logic controllers provide improved communication between the level control and the differential pressure control systems. The derivation of the RID controller clearly shows that the changes which might occur in the feed pump system will be directly observed by the level controller since the feedwater flow rate, steam generator water level signal, and pump speed signals are directly included in the RID water level and pump speed controllers. Similarly, the fuzzy logic controller provides improved communication between the two systems, since the feedwater signal is an input signal in the development of the differential pressure controller. During the simulation tests both the water level and the pump speed controllers utilized, therefore the communication between the two control system existed continuously.

6.3.1 Level Control Perturbation Test Results

In this section, comparative results of PID, RID, and Fuzzy Logic controllers during steam valve perturbation and level change are presented. Since the purpose of this research is to utilize the new concept of software parallelism, different control algorithms were employed to control the steam generator water level. In order to test the robustness of the controllers, two different perturbations were used during simulations. The first perturbation was a 5 % steam valve opening for 50 seconds, and the second one was a water level set point change. Water level set point was changed 16 % within 300 seconds. Initial level set point was 9.63 feet (measured above the U-tube bundle) during both of these perturbations. The set point was increased to 11.13 feet during the level perturbation. Figures 6.22 and 6.23 display the results of the PID controller. As shown in the figures there is a negligible steady-state error when the PID controller is used. This error could be minimized by changing the gains and time constants of the controller. Since the goal of this research is not to improve the current controller of the plant, there was no attempt to change the PID controller design. Figures 6.24 and 6.25 present the results of the model-based adaptive controller, Reconstructive Inverse Dynamics (RID). Figures 6.26 and 6.27 show the responses of the Fuzzy Logic Controller (FLC) for steam valve perturbation and level change, respectively. The results for the steam valve perturbation and level change using the second fuzzy logic control are given in Figures 6.28 and 6.29.

It is easy to see that both the RID and the FLC gave desirable results for both of the perturbations. The FLC performed even better during the steam valve perturbation when compared to the RID. Since the RID is a model-based system, it requires a trajectory to calculate the desired control output. Although it is within an acceptable range, feedwater flow has a larger swing during steam valve perturbation. The variations in the feedwater flow rate during steam valve perturbation of the corresponding loop are given in Figures 6.30 through 6.33 for the PID, RID and FLC controllers, respectively.

6.3.2 Pump Speed Control Perturbation Test Results

In order to overcome the sluggish nature of the current pump speed controllers, an alternative control design using fuzzy logic was developed. The nature of the fuzzy control design, allows us to develop a controller that has a faster and smoother re-

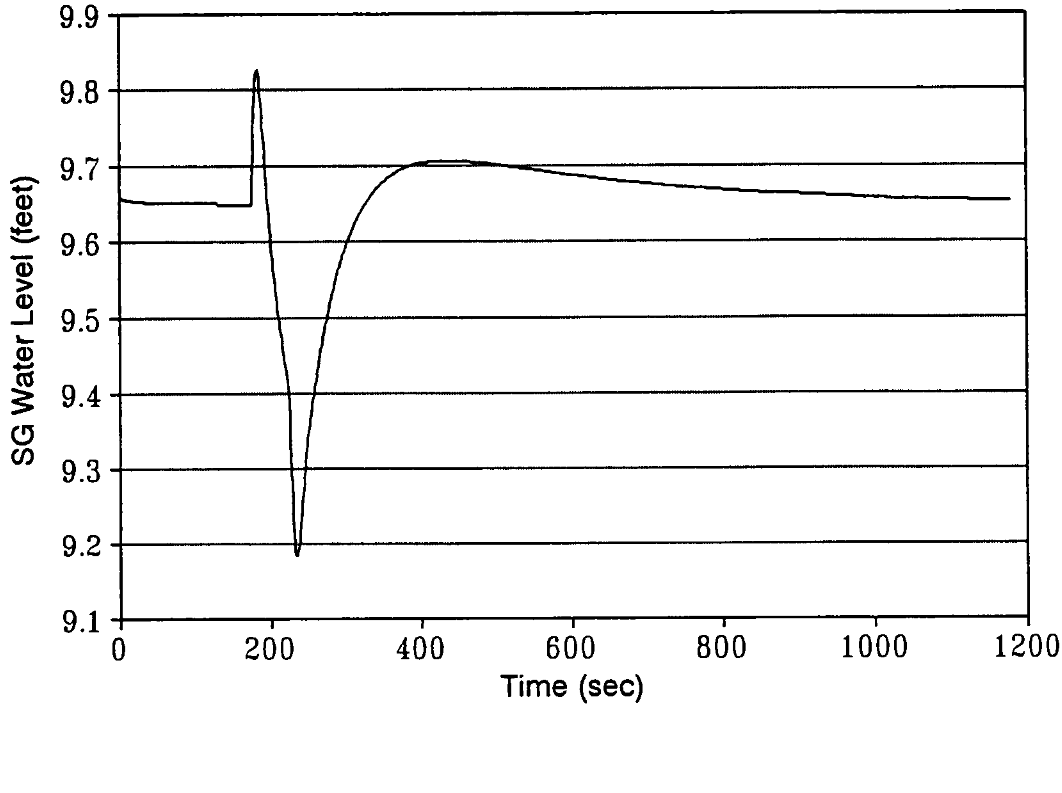

Figure 6.22: Steam generator water level response using PID, during a 5% steam valve perturbation.

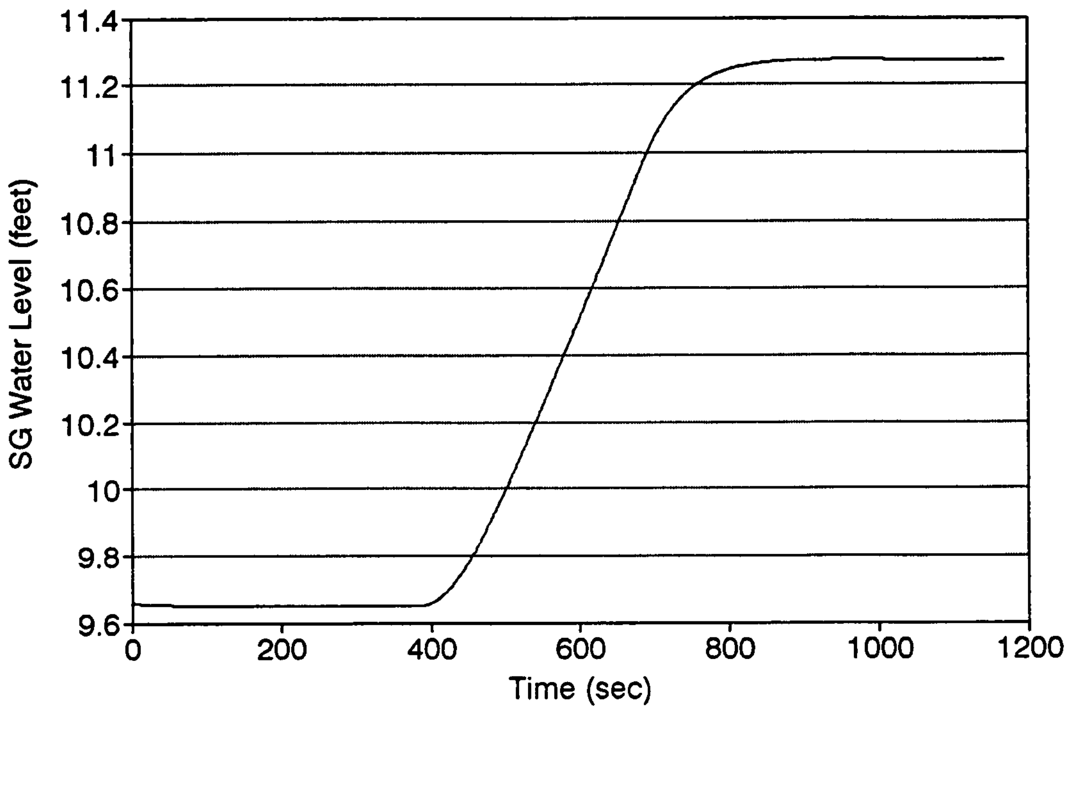

Figure 6.23: Steam generator water level response using PID, during a level set point change.

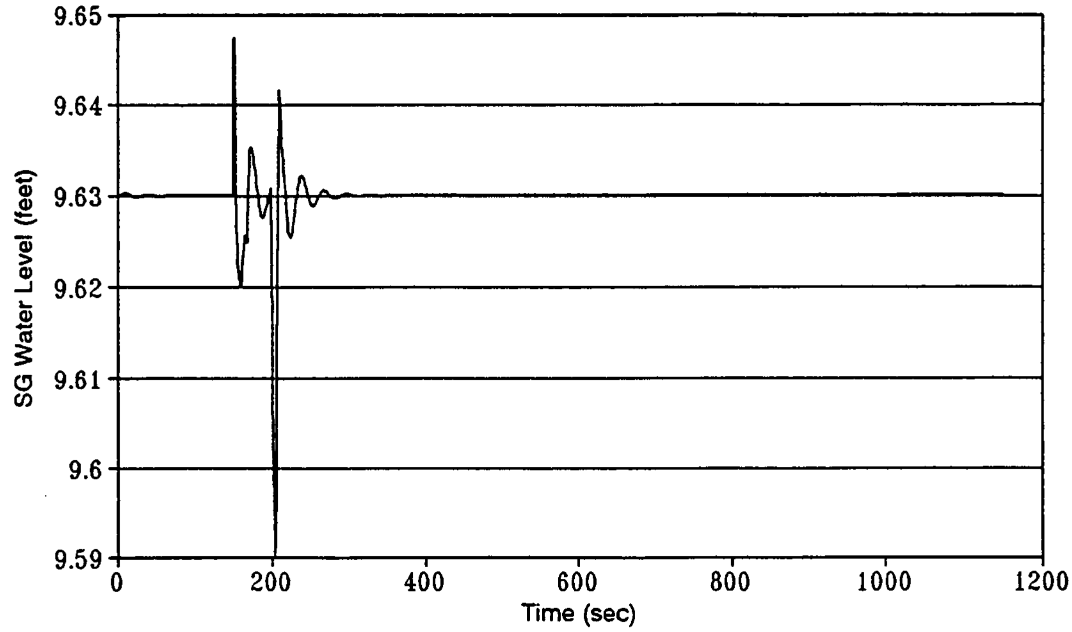

Figure 6.24: Steam Generator Water Level Response Using RID, During a 5% Steam Valve Perturbation.

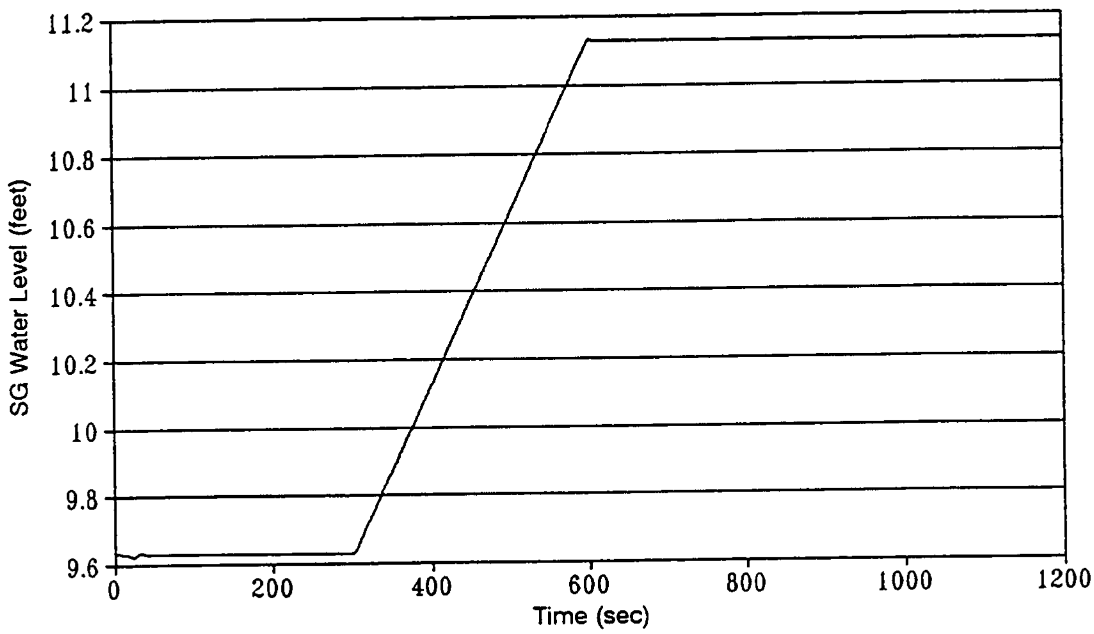

Figure 6.25: Steam Generator Water Level Response Using RID, During a Level Set Point Change.

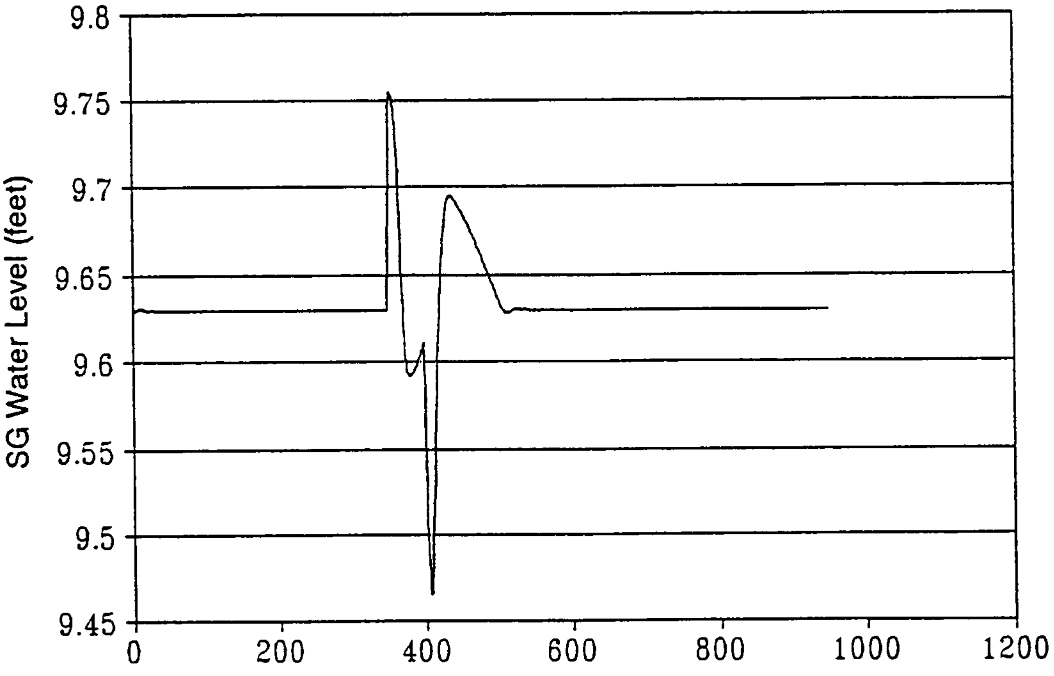

Figure 6.26: Steam Generator Water Level Response Using FLC, During a 5% Steam Valve Perturbation.

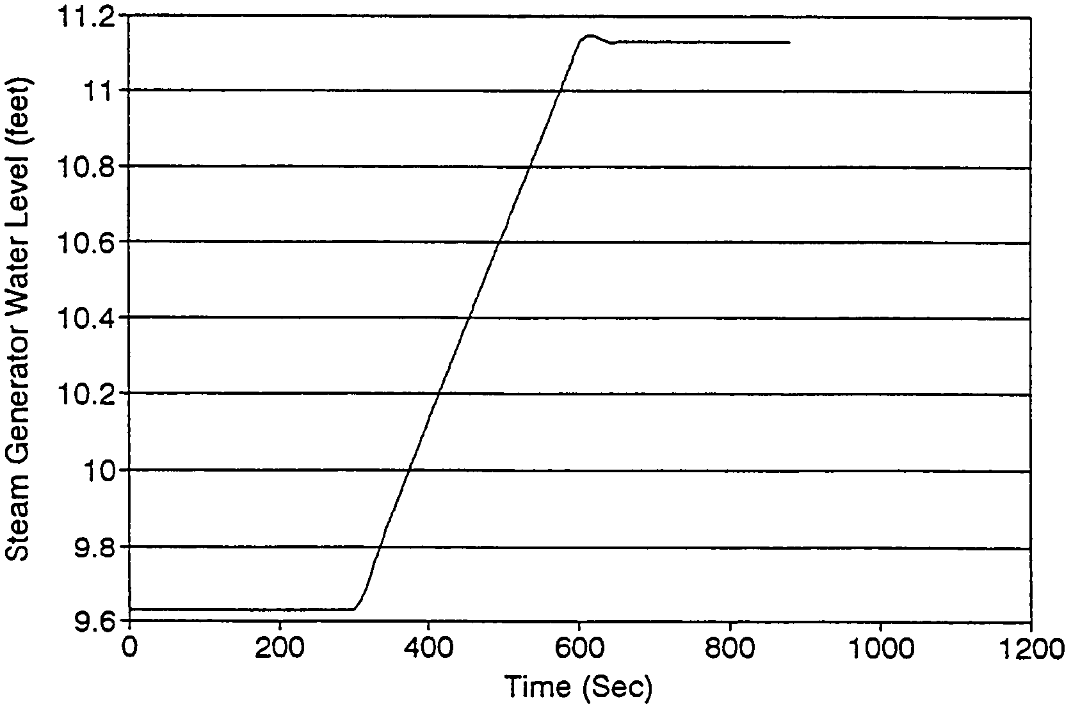

Figure 6.27: Steam Generator Water Level Response Using FLC, During a Level Set Point Change.

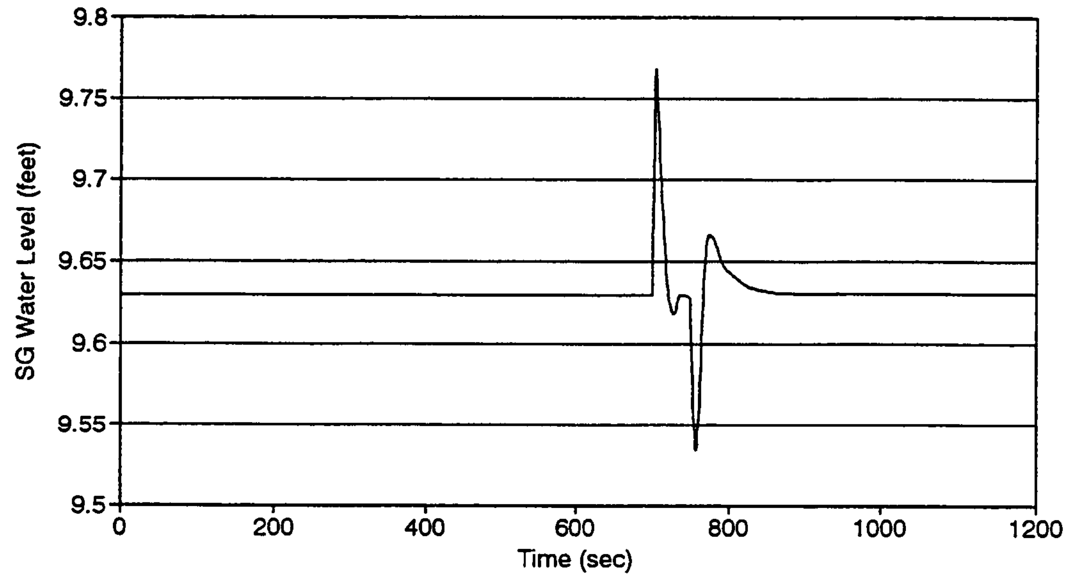

Figure 6.28: Steam Generator Water Level Response of the Second FLC, During a 5% Steam Valve Perturbation.

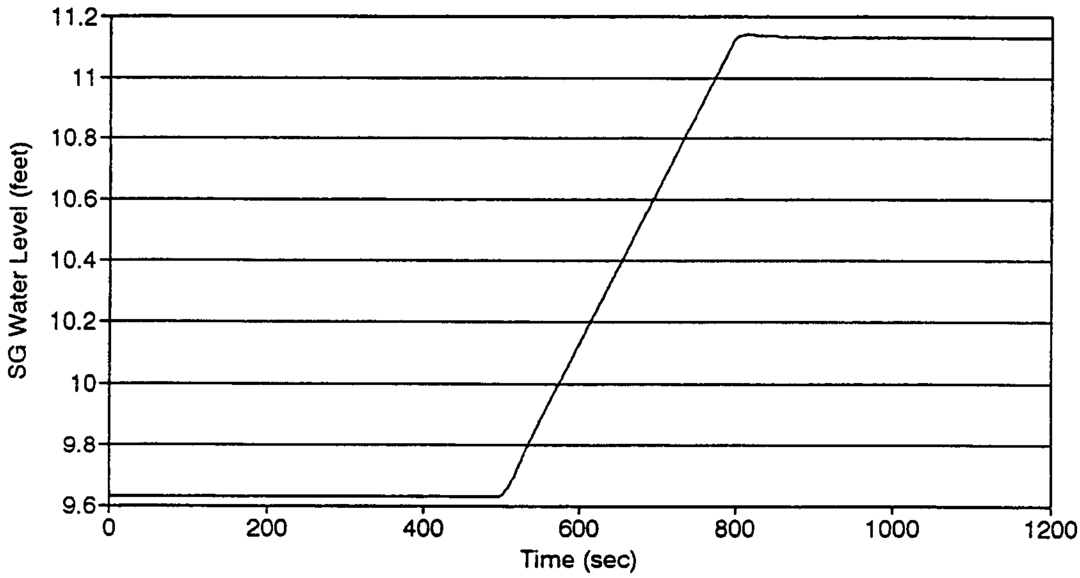

Figure 6.29: Steam Generator Water Level Response of the Second FLC, During a Level Set Point Change.

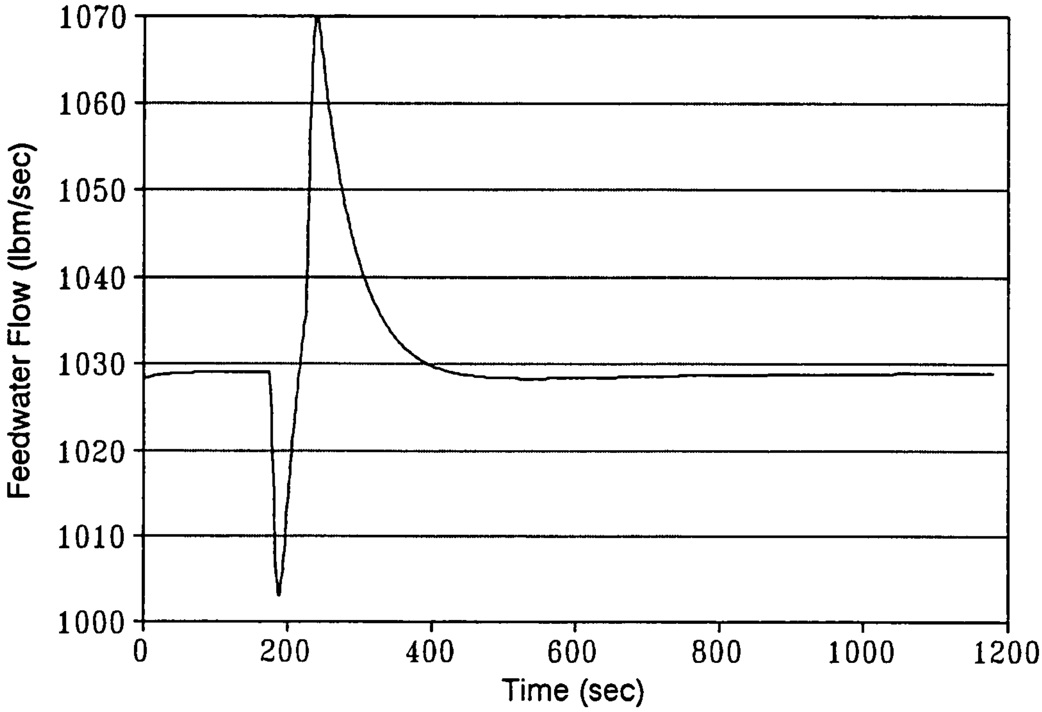

Figure 6.30: Feedwater Flow Using PID, During a 5% Steam Valve Perturbation.

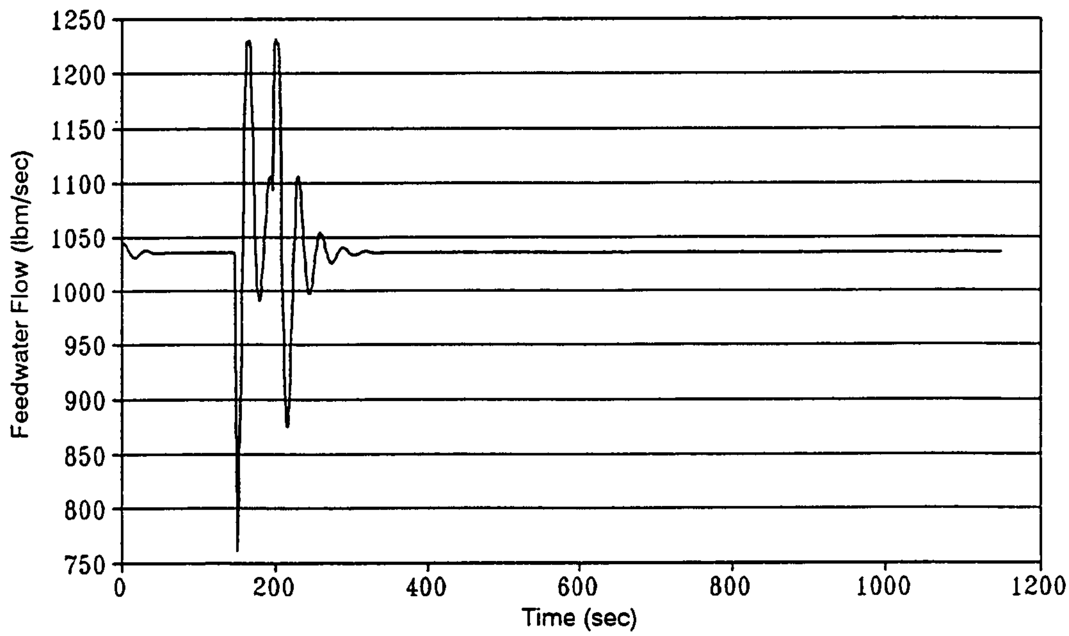

Figure 6.31: Feedwater Flow Using RID, During a 5% Steam Valve Perturbation.

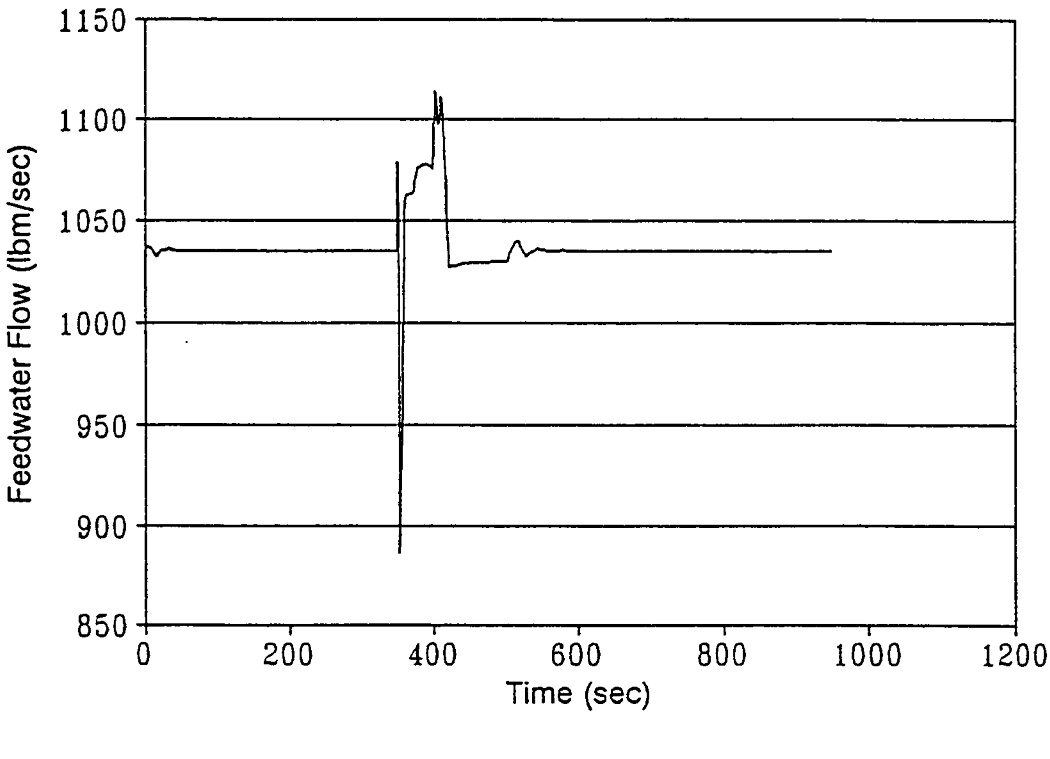

Figure 6.32: Feedwater Flow Using FLC, During a 5% Steam Valve Perturbation.

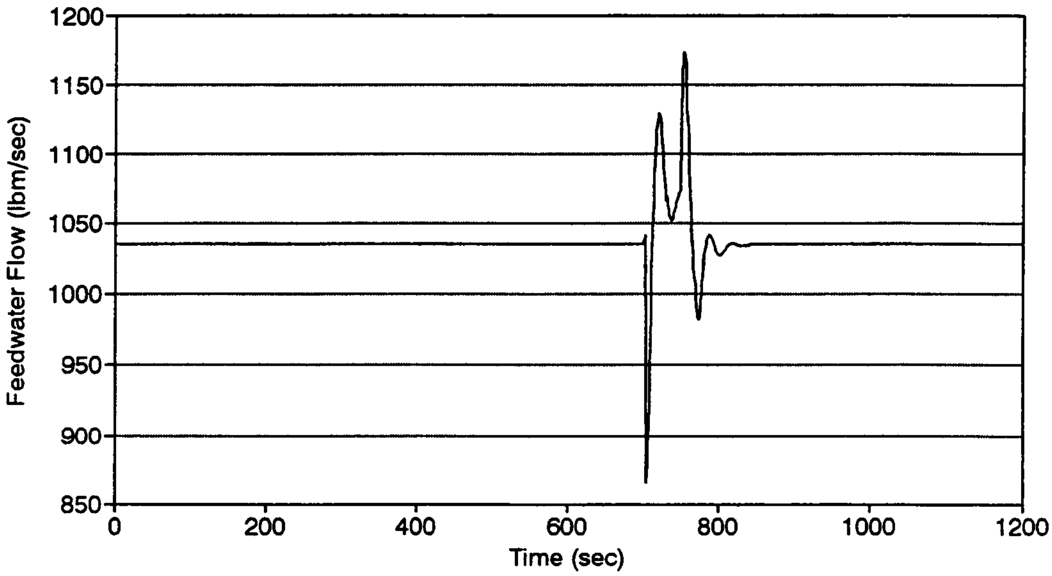

Figure 6.33: Feedwater Flow Using the Second FLC, During a 5% Steam Valve Perturbation.

sponse than a conventional PID controller. The fuzzy logic control also allows us to use signals in a feedforward fashion; this further enables the controller to overcome the possible problems that occur in the event of steam generator transients. The pump speed fuzzy controller, has two inputs: feedwater flow and differential pressure error. The feedwater flow signal indicates the flow demand as well as possible transients that might occur. The differential pressure error is the difference between the desired ΔP and the actual difference between the feedwater header pressure and the steam header pressure.

Along with the fuzzy logic control for improving the performance of the pump speed control system, the model-based RID controller was also developed. The details of each of these controllers are given in Chapter 5. One of the common transients that occur during the normal operation of PWRs is the set point change of the ΔP controller. The normal operating range of ΔP set point is between 195 psi (100 % load) and 45 psi (no load). Due to operational difficulties during startup, the differential pressure control domain is often changed and the lower limit is set to 80 psi. This adjustment has eliminated the transients that occurred during start up [33].

Each algorithm was tested with a ΔP reduction, where the set point is reduced from 195 psi to 165 psi (see Figure 6.34). Figures 6.35 through 6.39 give the responses of the steam header pressure, feedwater header pressure, pump speed, feedwater flow rate, and one of the steam generator water level signals during this perturbation, and using the RID controller.

A similar analysis was also carried out using the Fuzzy Logic Controller. The performance of the fuzzy logic controller was as good as the model-based adaptive controller (RID). During the simulation tests both the water level control and the

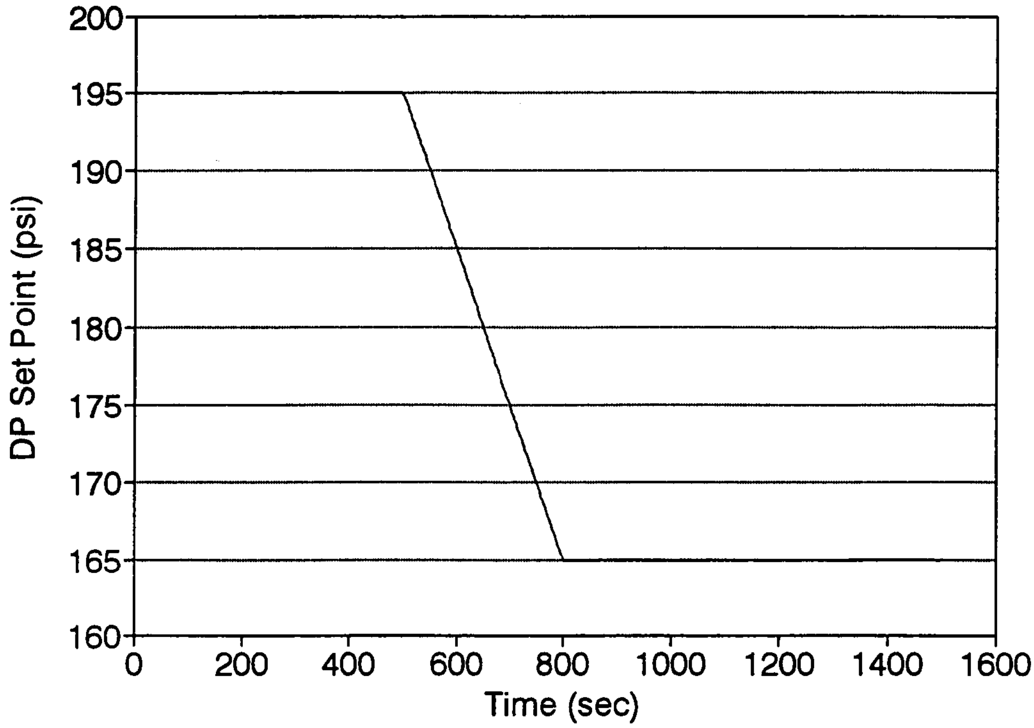

Figure 6.34: Differential Pressure Set Point.

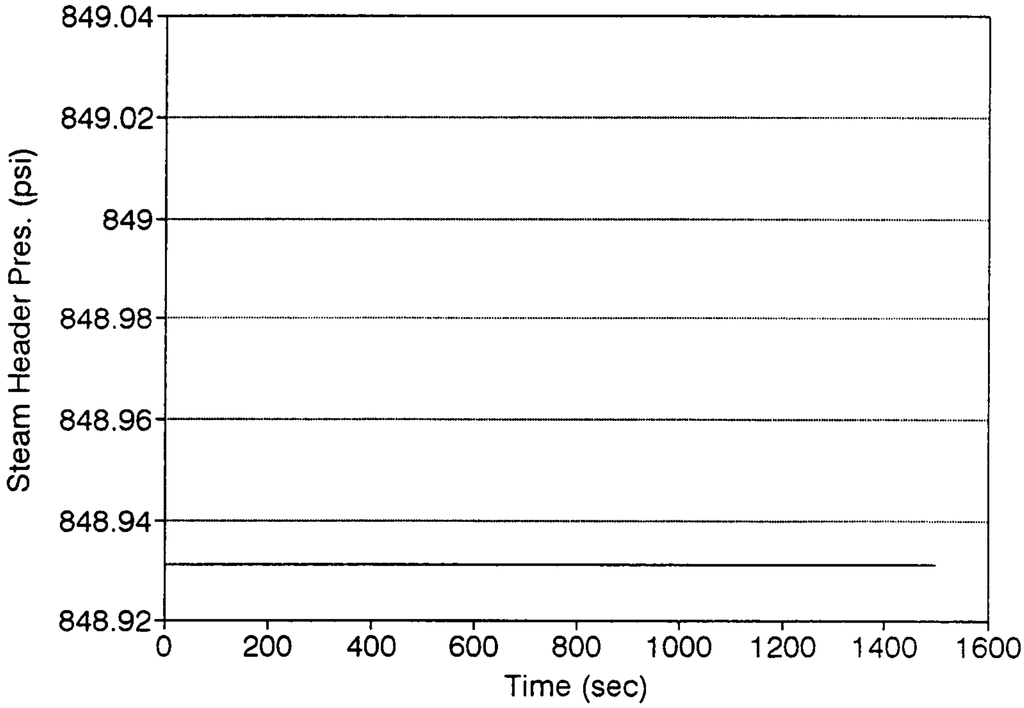

Figure 6.35: Steam Header Pressure Signal Using RID, During ΔP Set Point Change.

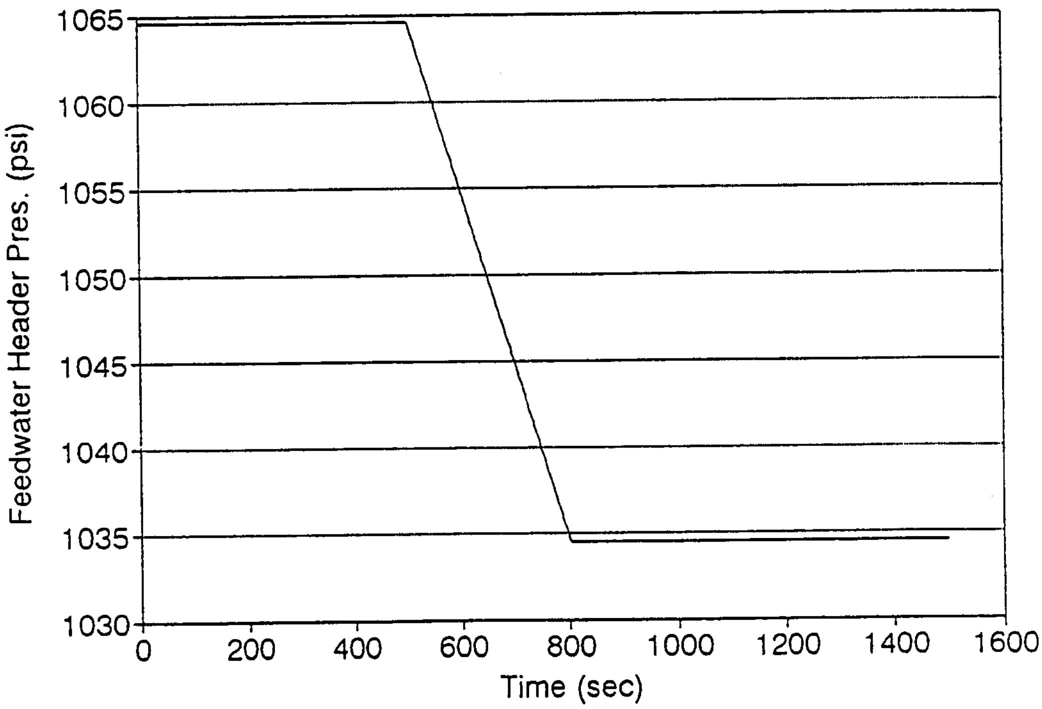

Figure 6.36: Feedwater Header Pressure Signal Using RID, During ΔP Set Point Change.

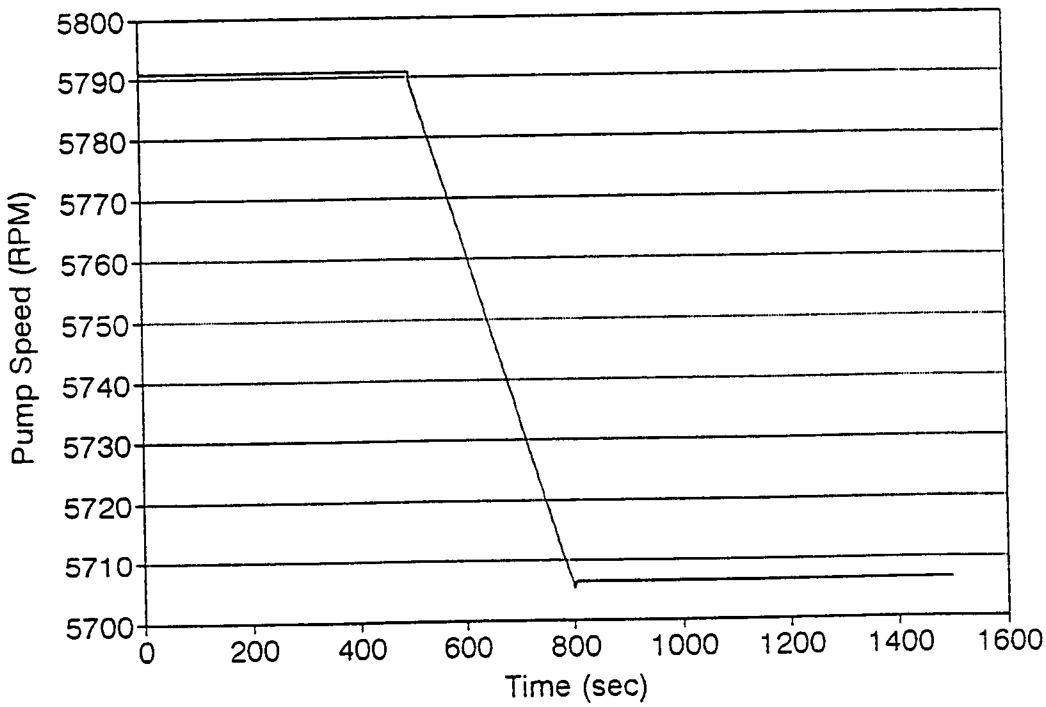

Figure 6.37: Pump Speed Signal Using RID, During ΔP Set Point Change.

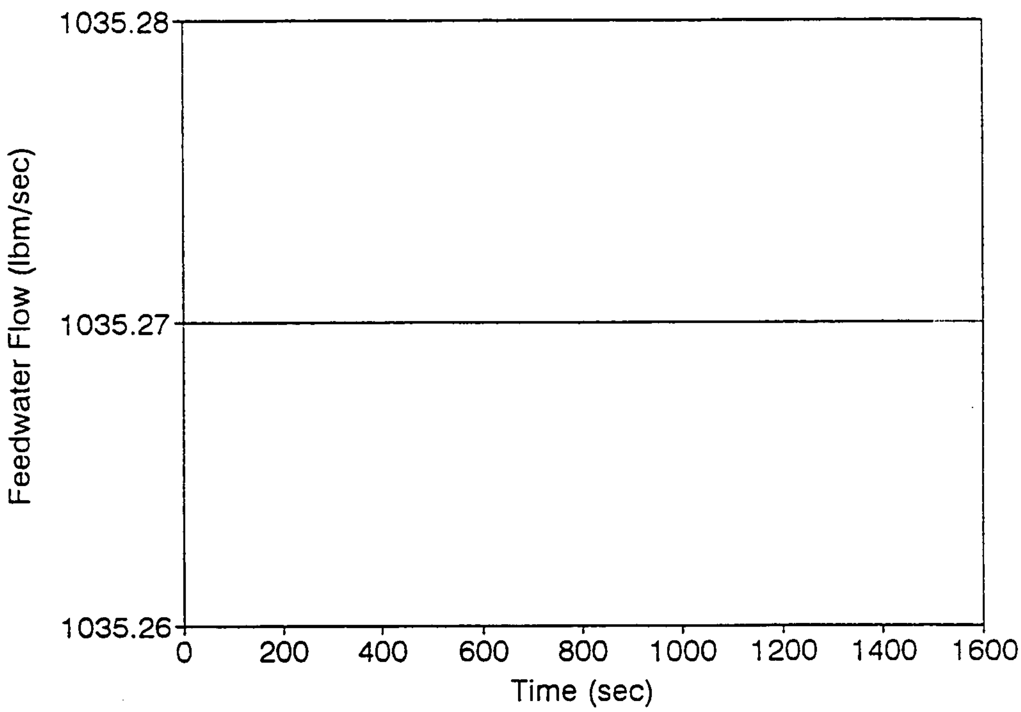

Figure 6.38: Feedwater Flow Signal Using RID, During ΔP Set Point Change.

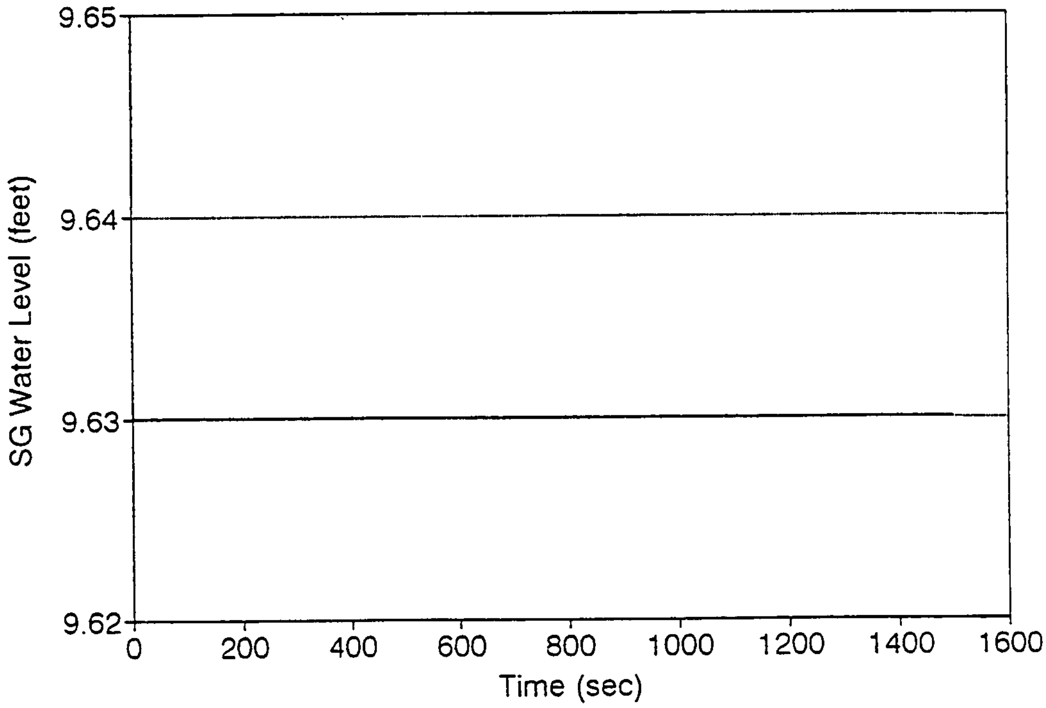

Figure 6.39: Steam Generator Water Level Signal Using RID, During ΔP Set Point Change.

pump speed control systems were active. The goal is to keep steam header pressure, feedwater flow rate, and steam generator water level at their set points during the ΔP reduction test. The results obtained from the (RID) controller were excellent. Pump speed was reduced smoothly without causing any disturbance to the water level, feedwater flow rate and steam header pressure. The trajectory-following capability of the fuzzy logic controller was excellent for this perturbation. As can be seen from the results, the steam generator water level has a negligible steady-state error which is within the dead bands that are used in the power plants. Feedwater flow has no error, and ΔP is taken down to the new setpoint, with negligible set point error. Figures 6.40 through 6.44 display the responses of the steam header pressure, feedwater header pressure, pump speed, feedwater flow rate, and one of the steam generator water level signals during perturbations when fuzzy logic controllers was used in the control systems. Similar to the RID results, the FLC was also able to keep the water level, feedwater flow rate, and steam header pressure at their respected set point values with negligible errors, and pump speed was reduced smoothly without causing any disturbances.

6.3.3 Parallel Control Application

The application of the FCDS is demonstrated for the regulation of the feedwater system in pressurized water reactors (PWRs). There are two main controllers in the feedwater regulation system of a PWR. The steam generator water level control and the main turbine governor valve control (to maintain a desired ΔP across the feedwater valve). The FCDS utilizes three different control algorithms for the steam generator water level control and the differential pressure control: the traditional PID, the reconstructive inverse dynamics (RID), and the fuzzy logic control (FLC). Each algorithm runs independently in the FCDS, and the decision making module selects the appropriate controller using the results of the Signal and Command Validation blocks. In order to test the robustness of the controllers two different

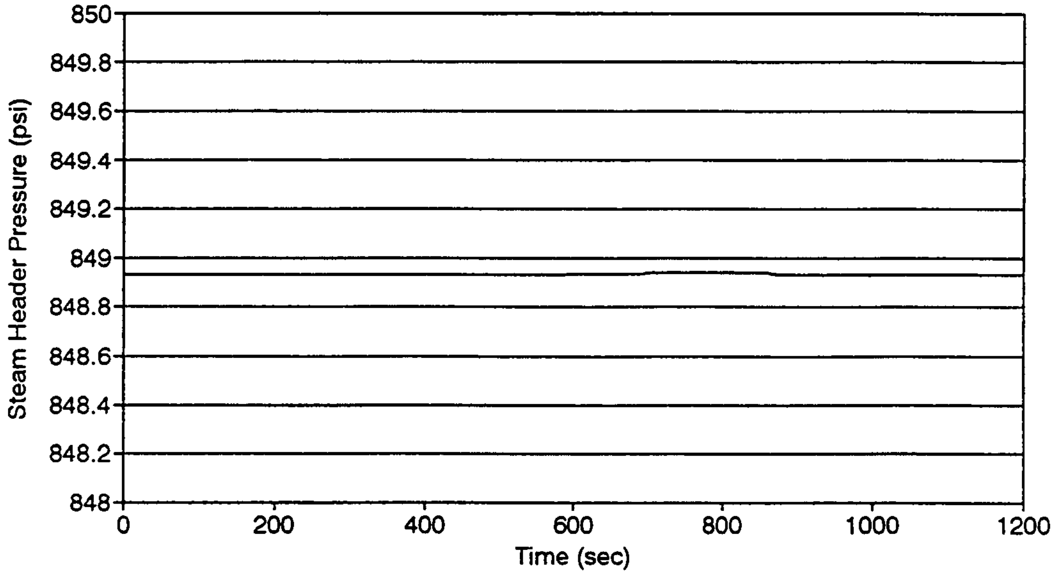

Figure 6.40: Steam Header Pressure Signal Using FLC, During ΔP Set Point Change.

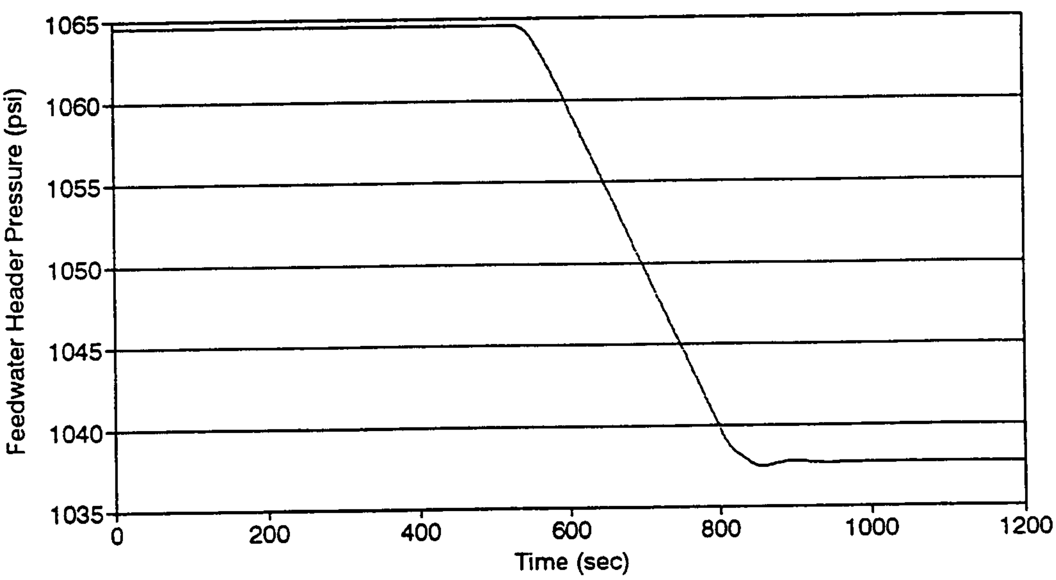

Figure 6.41: Feedwater Header Pressure Signal Using FLC, During ΔP Set Point Change.

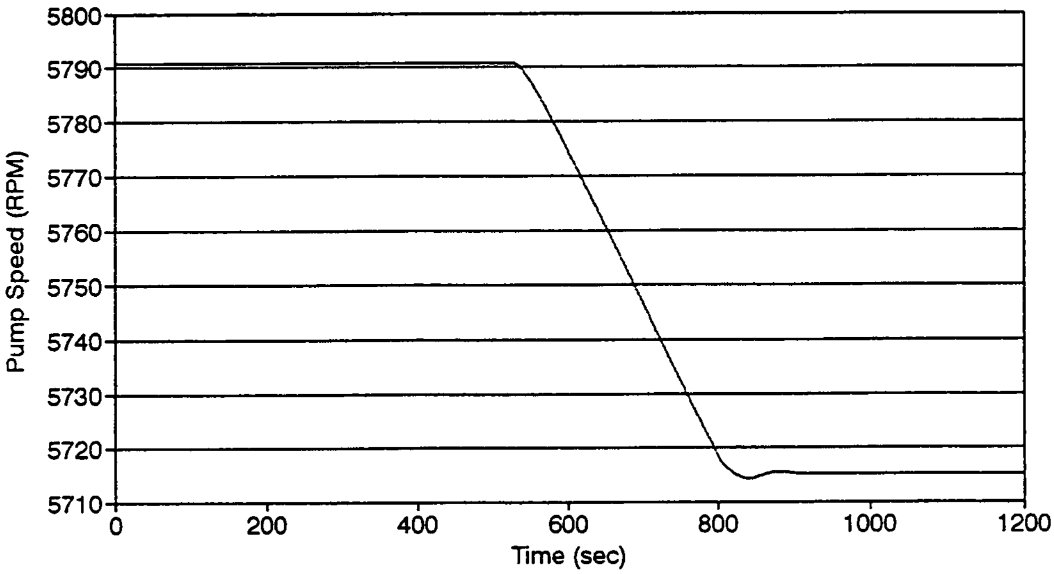

Figure 6.42: Pump Speed Signal Using FLC, During ΔP Set Point Change.

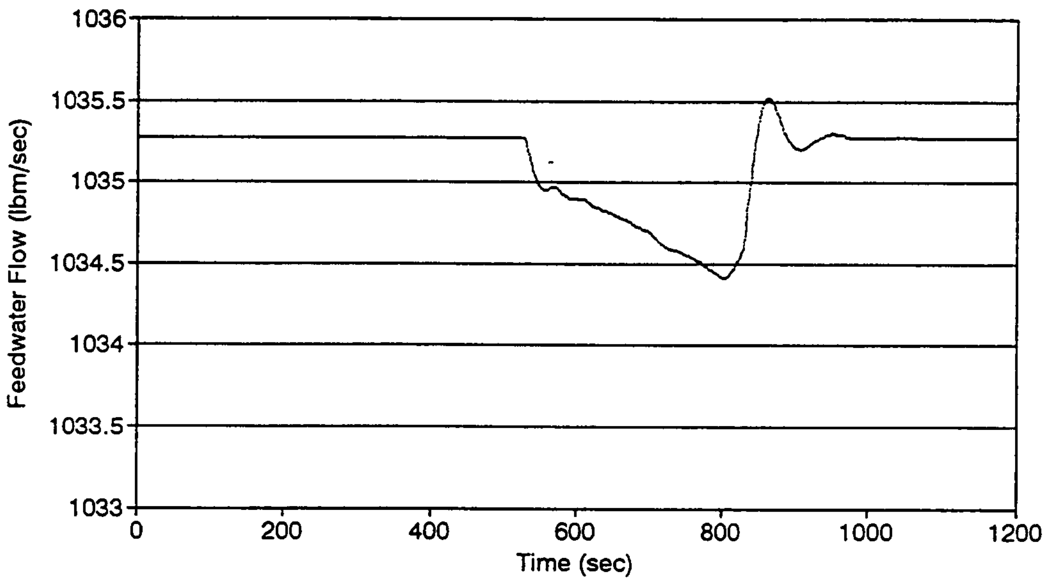

Figure 6.43: Feedwater Flow Signal Using FLC, During ΔP Set Point Change.

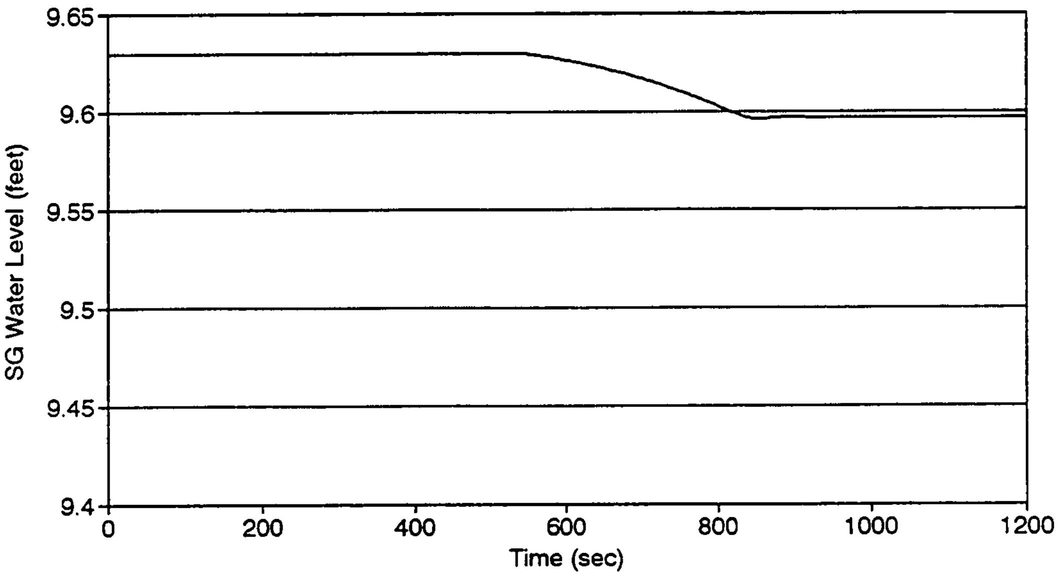

Figure 6.44: Steam Generator Water Level Signal Using FLC, During ΔP Set Point Change.

perturbations were simulated.

The first perturbation is a 5% steam valve opening for 50 seconds, and the second is a water level set-point change. The initial set point level was 9.63 feet during both of these simulations. The water level set point was changed 16% in 300 seconds, to a level of 11.13 feet. Figure 6.45 displays the results of level perturbation. The simulation starts with the FLC controller. Due to high error between the level set point and the actual value, the decision making block starts evaluating the other control algorithms. The command validation block provides a combination of fuzzy logic control and RID control around the 20^{th} second of the simulation. The combination of these two algorithms was used until the decision making block switches from a combination control to fuzzy logic control, during the early stages of the simulation. If the error between the level set point and the results of FLC is the smallest among other controllers, then the decision making block switches from the combination of two algorithms to the FLC controller exclusively. During level perturbation, an artificial error was introduced to feedwater flow rate signal, one of the fuzzy logic control inputs, and the signal validation block immediately relayed this information to the decision block, which switched the control algorithm from the FLC to the RID controller, since there are no invalid signals used in the RID controller.

The RID controller is used for the level perturbation after that point. A similar application is also completed, where the RID controller was used at the beginning of the level perturbation. An artificially introduced error to the feedwater flow rate signal, one of the control input signals, was detected by the signal validation block, and caused the decision making block to switch the controller from RID to FLC (see Figure 6.46). These applications illustrate the feasibility of using parallel control during transients in power plant operations. The parallel control not only reduces

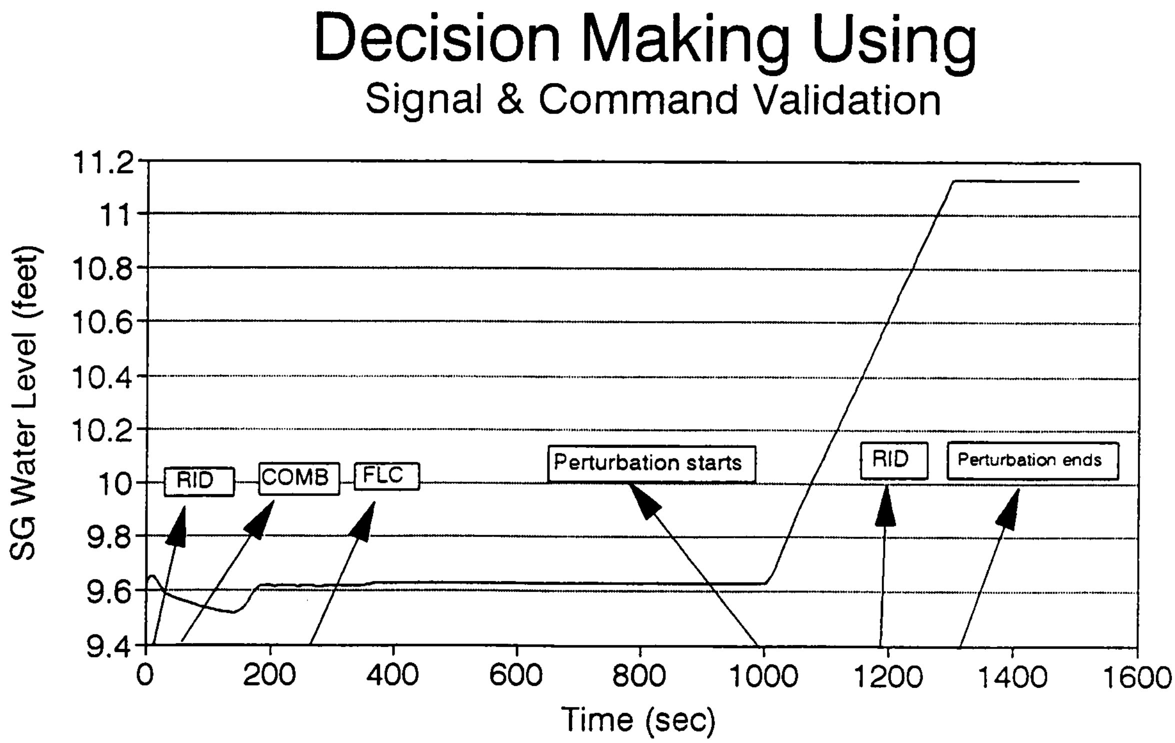

Figure 6.45: Steam generator water level (feet) regulation using parallel control and command validation, during a level set point change.

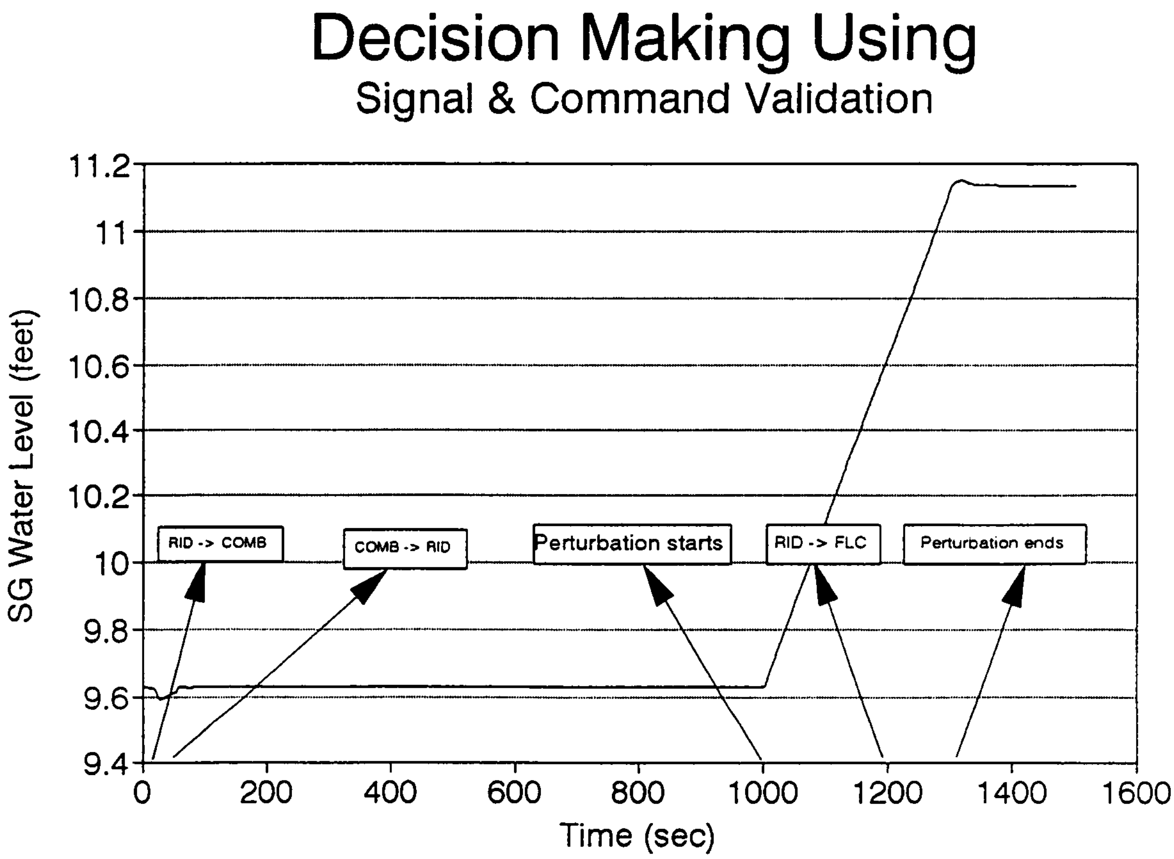

Figure 6.46: Steam generator water level (feet) regulation using parallel control and command validation, during a level set point change.

the set point error, but also provides flexibility of selecting a different controller in the event of inconsistencies in the control system.

Integration of signal validation, control, and command validation enables the control system to detect and isolate the faulty sensors and continue the operation in the event of a controller failure without disturbing the system. One of the important points to be noticed during the application of the parallel control system is that, switching does not cause any disturbance to the system. The controllers were able to handle the steam generator water level set point even in the presence of sensor degradation. One reason for this smooth switching from one controller to another is that, each algorithm performs the computation independently within the FCDS. Parallel controllers, validation modules and decision making system are highly integrated. Each module broadcasts information indicating its individual results. Information broadcasting is kept at a minimum, so that this process would not cause any further delays in the system. Decision making works in a way so that, there is no switching among the control algorithms, unless there is no other way to overcome the existing problem.

6.4 Command Validation and Decision Making

The objective of the command validation block is to determine the accuracy of the commands generated by the control system or by the operator, and to validate the outputs of the actuator systems. The command validator, as a distinct function, is a relatively new concept in process control. It parallels signal validation to some extent. The command validation block utilizes two empirical models for each command. A process empirical modeling (PEM) technique and a backpropagation neural network (BPN) were used to develop the models. In Chapter 4 the models developed by PEM and BPN are discussed.

6.4.1 Evaluation of the Signals

Decision making is performed according to the results of the signal and command validation blocks. The decision making block receives information on the accuracy of the control input signals from each signal validation module before any conclusion is drawn about the final control signal. The results of the models are then cross-checked with each other to observe possible discrepancies.

If the signals used in the control algorithms are valid, control actions are then calculated by the control algorithms. After calculating the control actions, each action is evaluated by the command validation module. The command validation module also incorporates two models for feedwater valve and turbine governor valve positions. Command validation and signal validation results provide the most important information in the process of making the final control decisions. Figure 6.47 displays the estimations for both PEM and BPN models versus the actual measurements of the normalized control action of feedwater valve during a level perturbation.

6.4.2 Final Control Decision

Provided that the signals used in the control algorithms are valid and the commands produced by the controllers are accurate, the decision making block evaluates each algorithm to decide which one gives the least error with respect to the set points. If the set point error is within an acceptable range, then there is no switching among the controllers; if the error exceeds the threshold (defined previously), then the decision making block determines which control algorithm to use.

The decision-making and command validation module of the system, is in charge of choosing the appropriate control action, or a reasonable combination of actions, using the set of solutions calculated by the controllers. The simple average of the

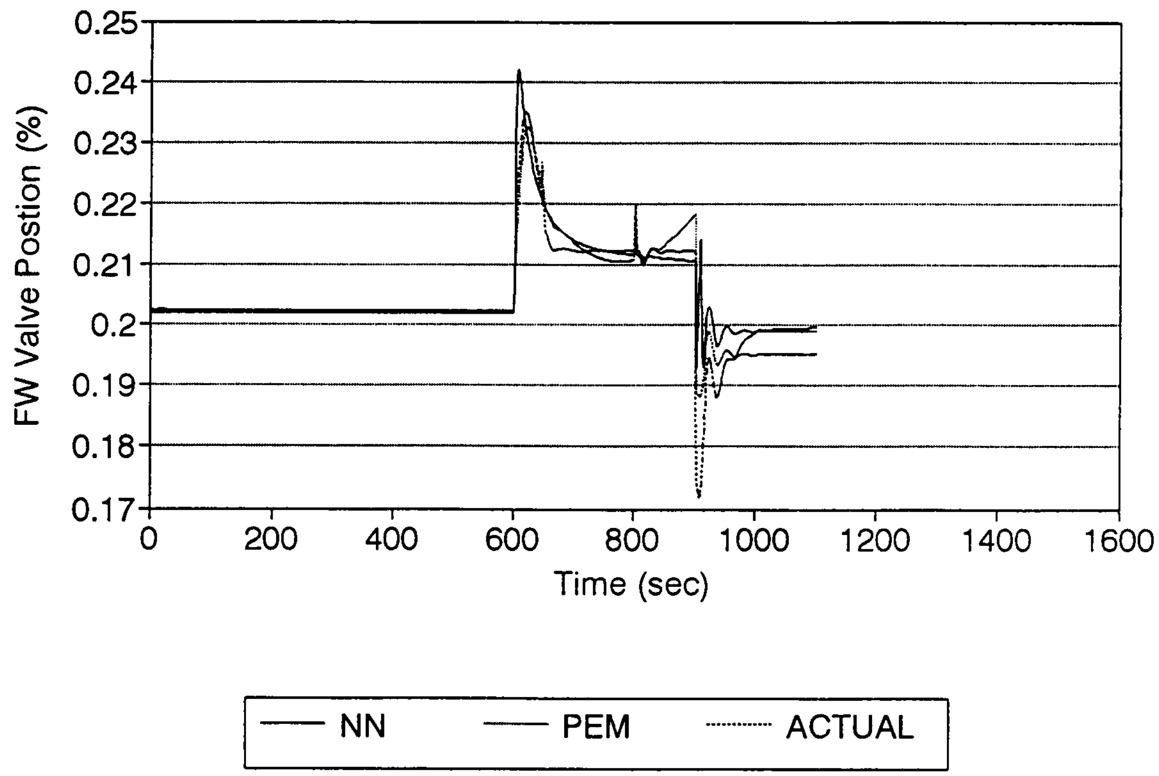

Figure 6.47: Comparative Command Validation Results of PEM and ANN Models.

control actions is utilized if and only if two controllers give similar accuracies for the same operating condition. The final decision is made according to the quality and availability of signals from the plant, the system state, and a priori information about the performance of the control algorithms under different operating conditions. Once the decision has been made by the expert system, it is sent to the actuators for execution.

The performance of a control strategy also depends on the knowledge of control trajectory. The individual performance tests of the control algorithms have indicated operating domains where each of the algorithms give better results when compared to the others. Simulation tests have shown that the RID controller gives the best results when the control task is trajectory-following. Based on this a priori knowledge, the results of the decision making module is weighted more towards selecting the RID controller if the operation mode is identified as trajectory following. The state of the operation was identified from the steam generator water level signal and its corresponding set point. Since the signal validation module provides information on the critical signals such as steam generator water level, feedwater flow, and steam pressure, transients other than trajectory following (i.e. set point changes) are easily identified and observed before any control action is taken.

The fuzzy logic controller gave extremely robust results during various simulation tests such as unknown dynamics, measurement time delays and parameter perturbations. A high confidence factor was given to the fuzzy logic controller if a transient other than a trajectory following is identified. Although a wide operational range was included in the fuzzy logic controllers during their development, fuzzy logic controllers did not give accurate results outside their domain. In order to prevent the complete failure of the fuzzy logic controllers, an external preventive measure was embedded in the FCDS. If a transient causes control input signals to go out of the fuzzy logic controller operation domain, control actions corresponding to the boundaries of their normal operation domain are provided. This prevents the fuzzy controllers from failing completely. If the input signals for both RID and fuzzy logic controllers are valid, and the control actions of these algorithms are both accurate, then a simple average of RID and fuzzy logic control actions is sent to the actuators.

The decision making block was designed to handle steam generator water level perturbations without challenging any of the controllers. In the event of a steam valve perturbation (similar to the power runback tests of operating power plants), the decision making module selects either a PI controller or one of the fuzzy logic controllers, depending on the availability of control input signals. This conclusion was reached after the individual tests of the control algorithms. Since RID is a trajectory following algorithm, it did not give the desired accuracy in controlling the steam generator water level during a steam valve perturbation. During steam valve perturbations there was no specific trajectory for model-based controllers to follow. PI and fuzzy logic controllers were able to handle the perturbation with desired accuracy in the level control. If both PI and fuzzy logic controllers fail, and a disturbance similar to steam valve perturbation occurs, then RID can be used as an alternate controller for the transient.

Table 6.1 gives the effective control domains for each controller. RID is the model-based adaptive controller, FLC1 is the first fuzzy logic controller which uses level error and flow mismatch as control inputs, and FLC2 is the second fuzzy logic controller where level error and change in error are the control input signals. The conventional PI controller is not included in the table since it is a proven control system currently used in operating power plants.

Table 6.1: Effective Ranges of the FCDS Control Algorithms

Control Tests	*RID*	*FLC1*	*FLC2*
Trajectory Following	1	1	1
Steam Valve Perturbation	3	2	1
Boundary Condition Perturbations	2	1	1
Unknown Dynamics	2	1	1
Level Sensor Failure	3	1	2
Flow Sensor Failure	3	2	1

1 = Highly Accurate

2 = Moderately Accurate

3 = May Challenge the Control System.

Figure 6.48 is a flow chart showing the decision making process of the FCDS. Signal and command validation results, and control set points are among the inputs to the decision making block. The control action is the output of the module.

6.5 Signal Validation Results

In this section the results of process empirical models and artificial neural network models are presented. Two different models were developed for each signal. Water level, feedwater flow, coolant temperature, feedwater header pressure, steam pressure, drum water temperature, and downcomer temperature are the signals selected from the feedwater flow regulation system of a PWR.

The validation of these signals is essential to provide an uninterrupted operation for the feedwater flow regulation. Studies have shown that some of the plant trips

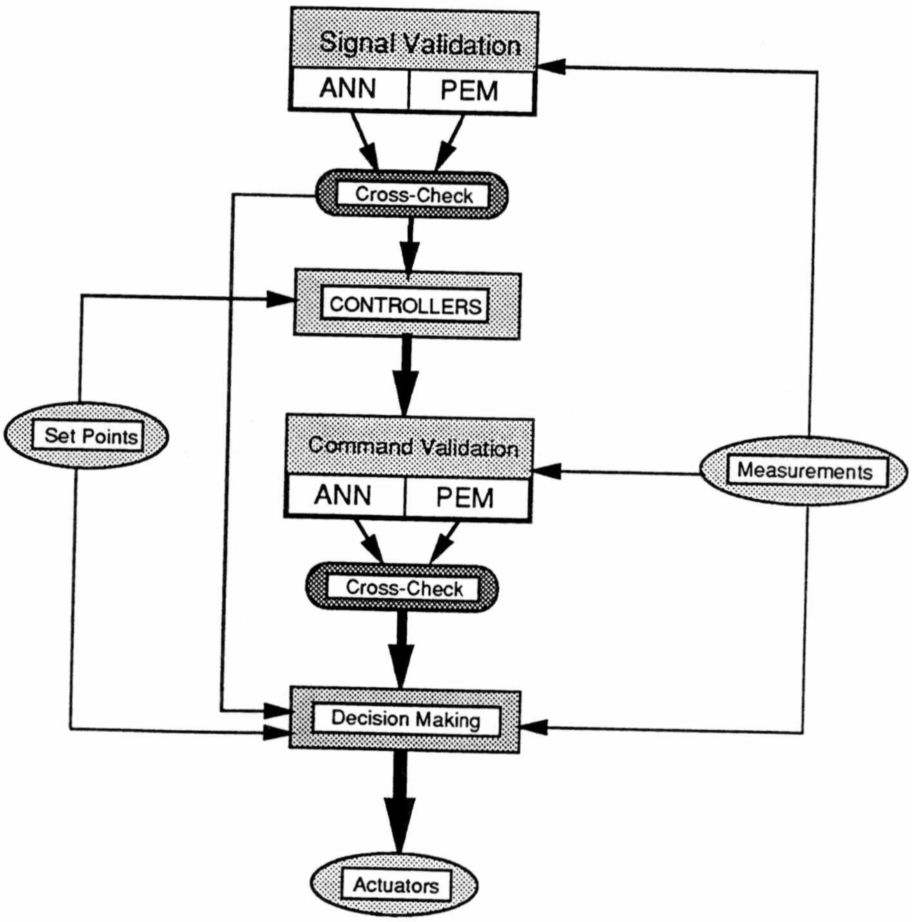

Figure 6.48: Decision Making Process of the FCDS.

are caused by the malfunctioning sensors or invalid control input signals [34] [28]. The FCDS provides a redundant signal validation module where the results of the algorithms are cross-checked to provide the best result to the operators and the control module.

Details of the PEM and ANN models are given in Appendix B. Figures 6.49 through 6.55 display the results of PEM and Figures 6.56 through 6.62 give the ANN model results for each signal collected during the trajectory following tests. The estimations of these models provide very important information to the control module either to help identify the state of the operation or to check the validity of the signals. When the PEM results and the ANN results were compared, less prediction error was seen in the ANN results, especially during the beginning and at the end of each transient. This is because the disturbances coming from the input measurements and PEM models are not as robust as ANN models against these uncertainties. The models for both PEM and ANN would give better results if more information becomes available about the system. Using real measurements would also improve the signal validation results, since the nonlinear model developed for this study has its modeling limitations.

6.6 Summary of the Chapter

This chapter presented the results of the integrated control system with application to the feedwater flow regulation of a PWR. The Fault-Tolerant Control and Diagnostics System includes three control algorithms as part of the software-based parallel control module. The results of the individual control algorithms, namely, the conventional PI controller, the Reconstructive Inverse Dynamics controller, and the Fuzzy Logic controller are illustrated in this chapter. Various simulations were completed to test the performance of the controllers. Two different control strate-

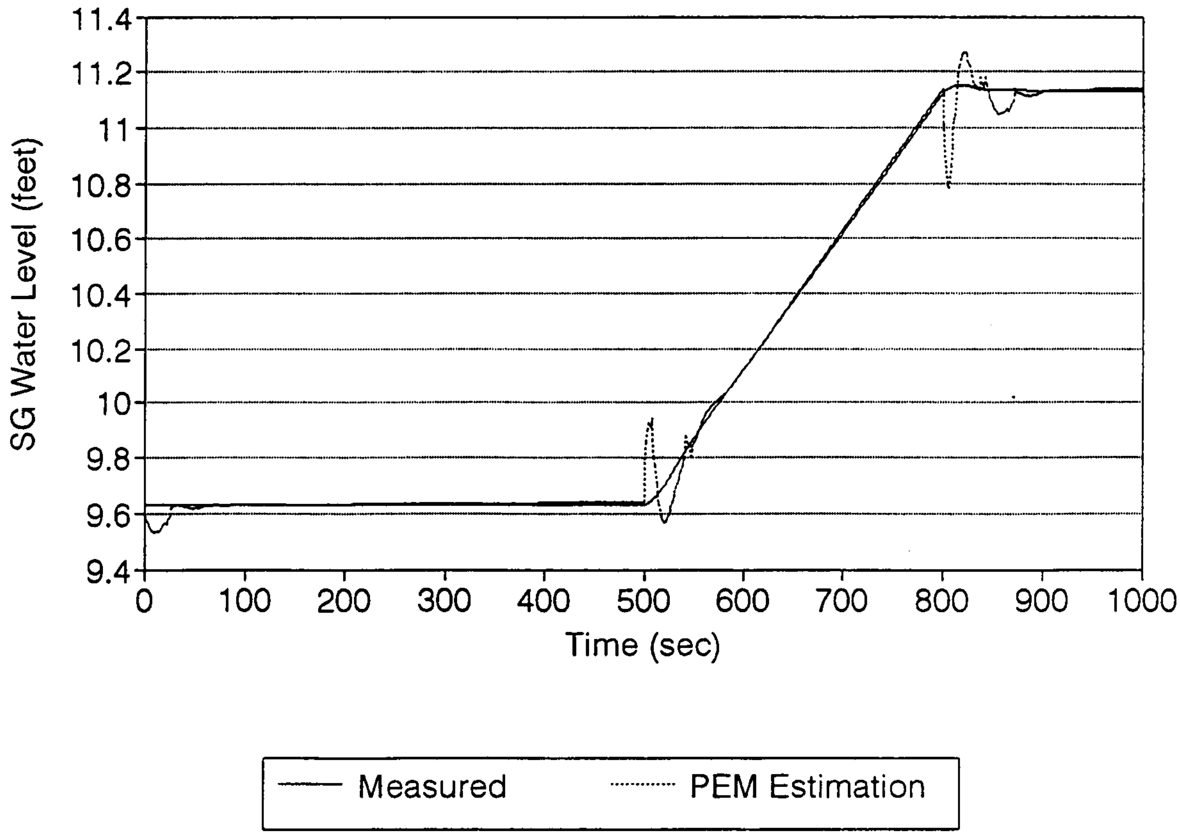

Figure 6.49: PEM Model Estimation of Steam Generator Water Level.

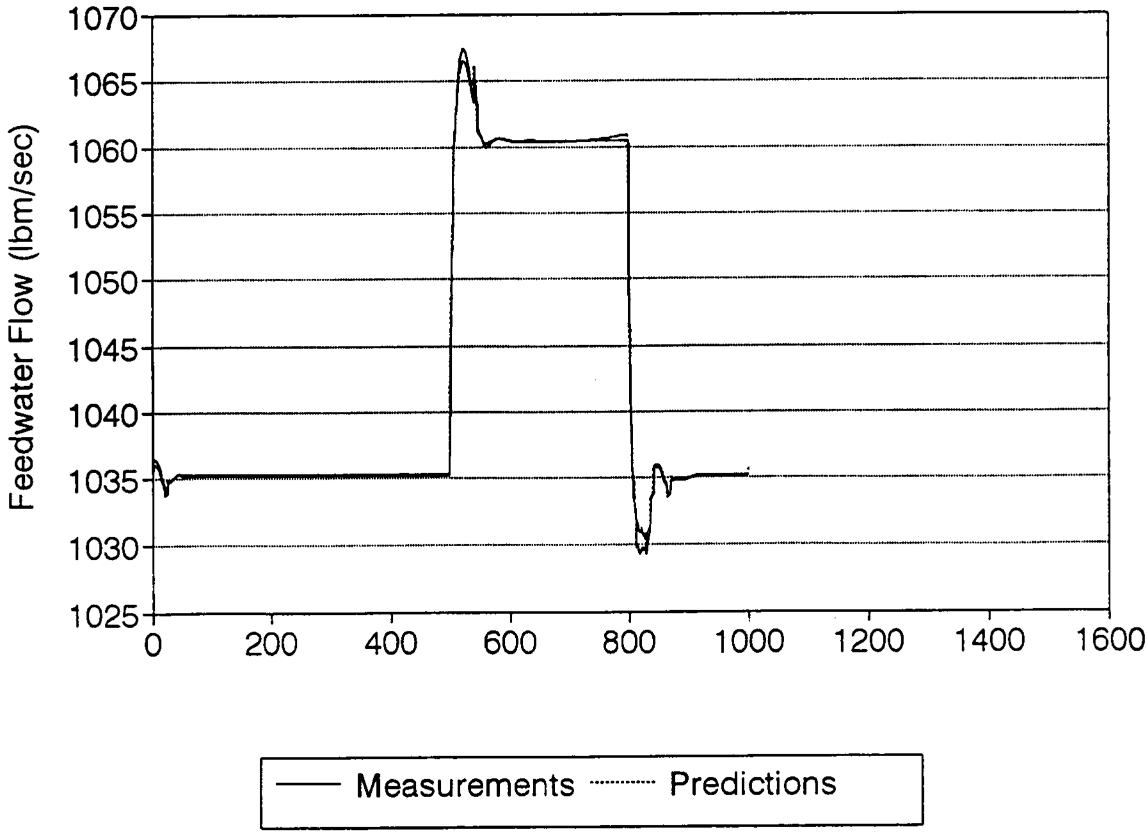

Figure 6.50: PEM Model Estimation of Feedwater Flow.

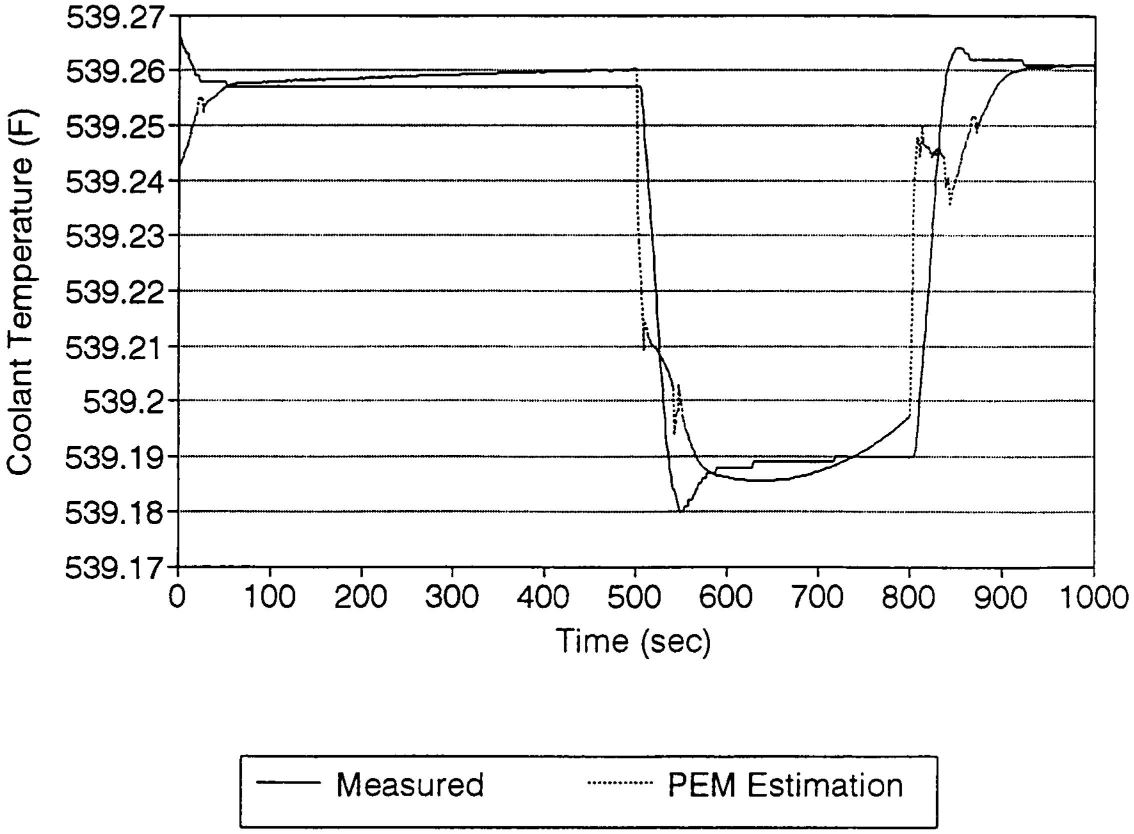

Figure 6.51: PEM Model Estimation of Coolant Temperature Signal.

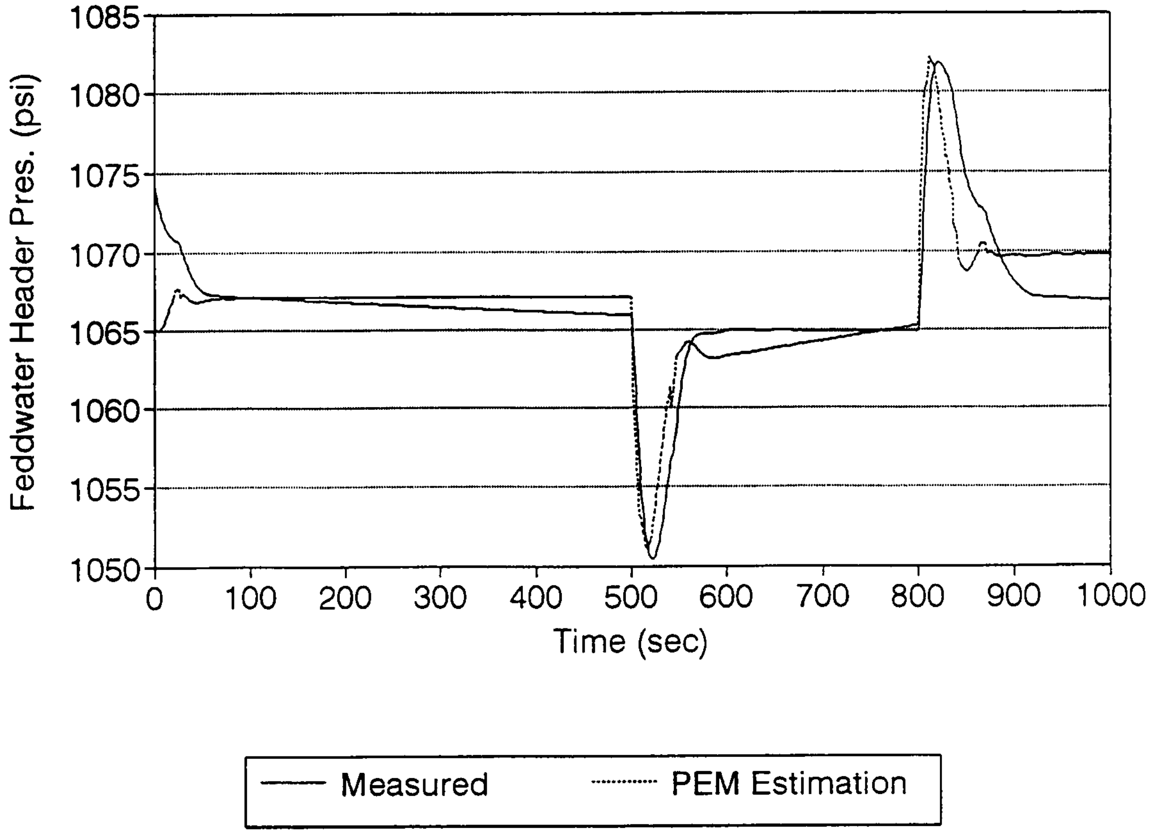

Figure 6.52: PEM Model Estimation of Feedwater Header Pressure Signal.

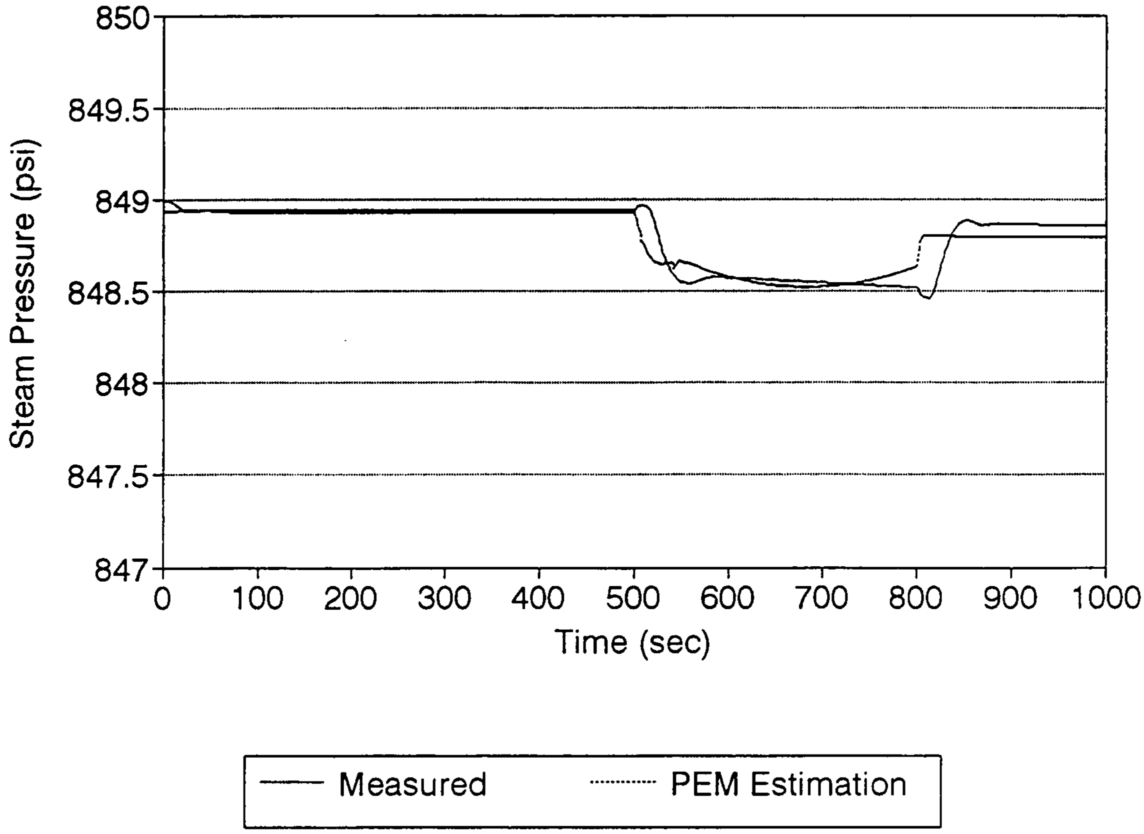

Figure 6.53: PEM Model Estimation of Steam Pressure Signal.

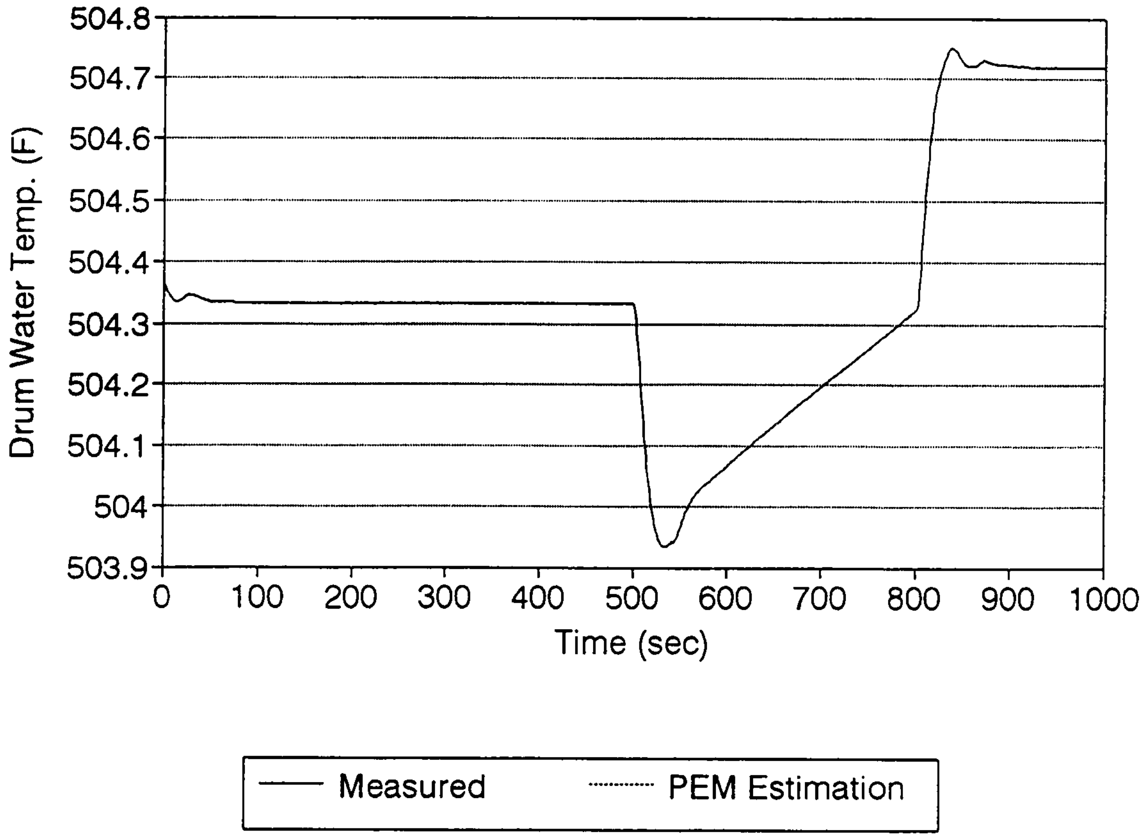

Figure 6.54: PEM Model Estimation of Drum Water Temperature Signal, Measurement and Estimation Results Exactly Match.

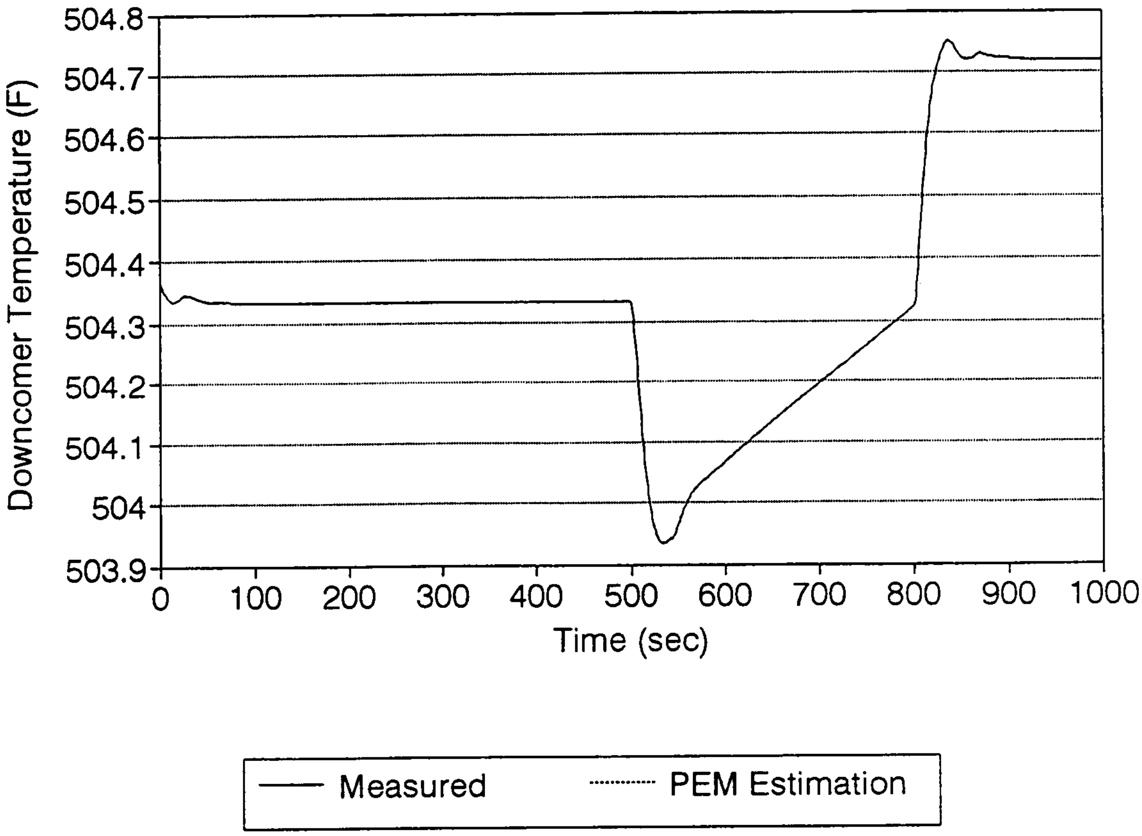

Figure 6.55: PEM Model Estimation of Downcomer Temperature Signal, Measurement and Estimation Results Exactly Match.

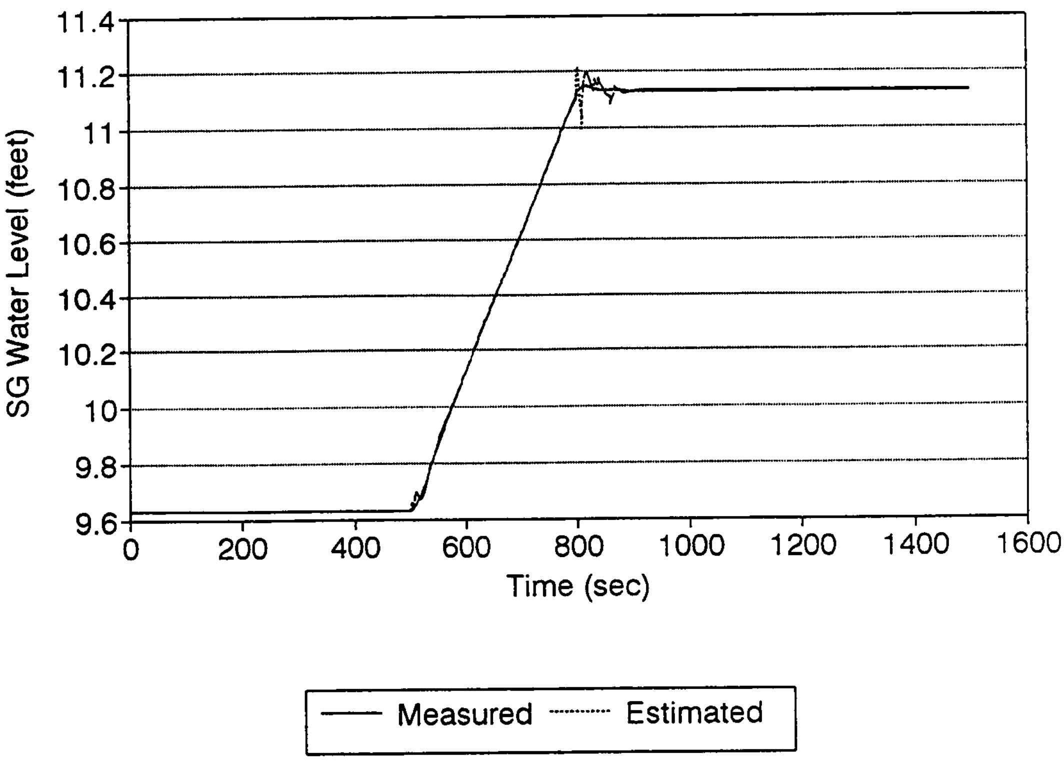

Figure 6.56: ANN Model Estimation of Steam Generator Water Level.

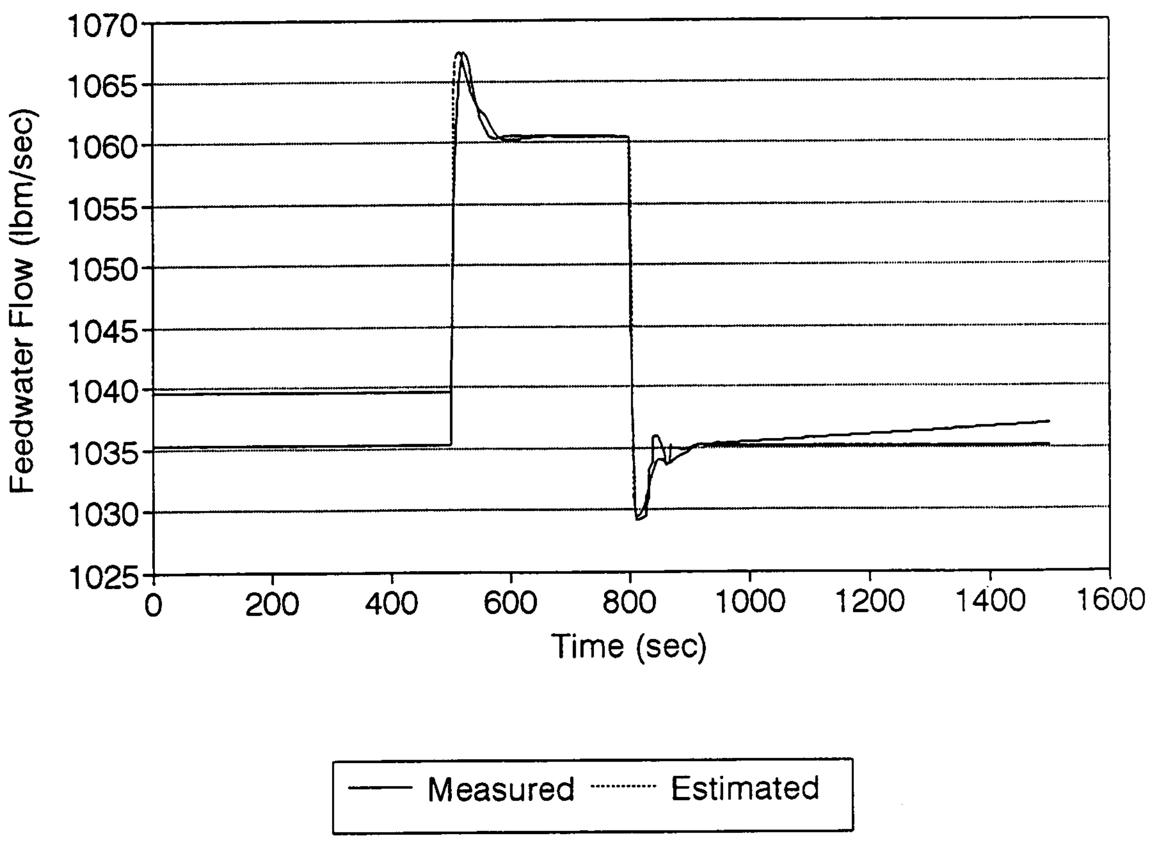

Figure 6.57: ANN Model Estimation of Feedwater Flow.

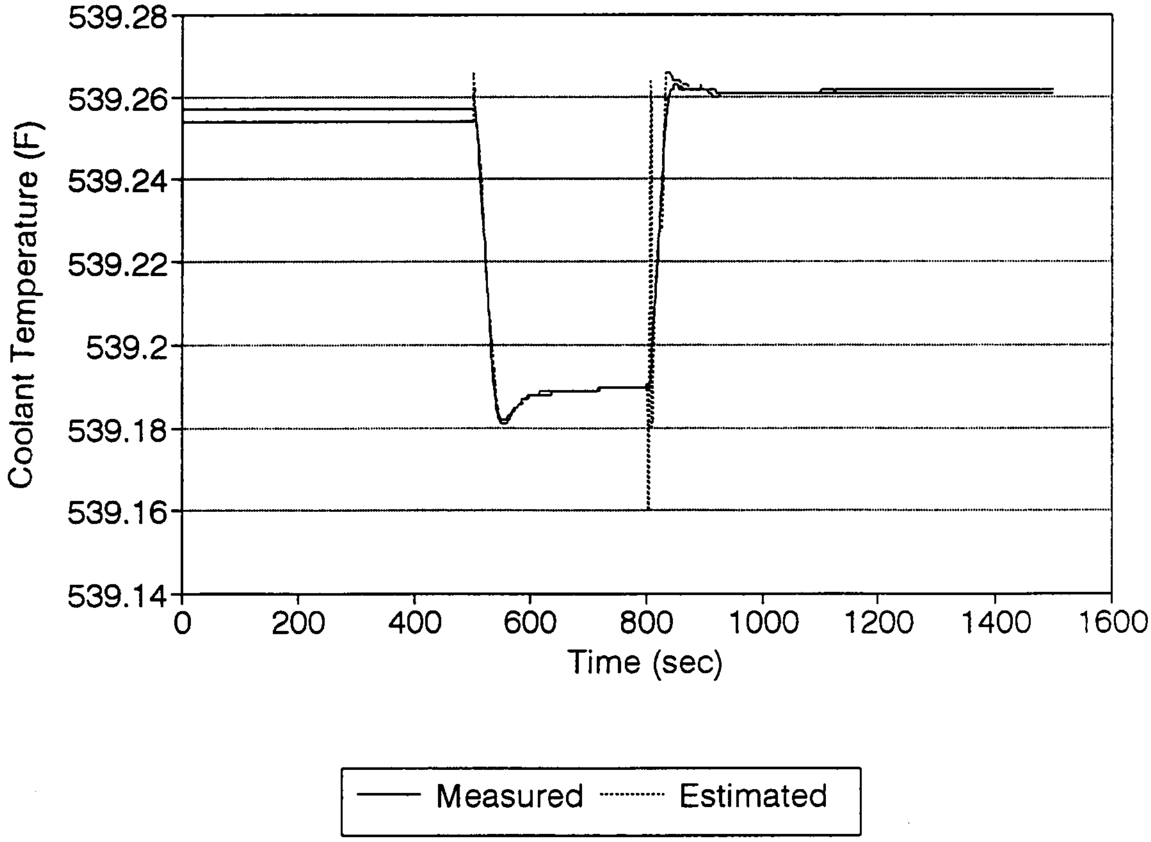

Figure 6.58: ANN Model Estimation of Coolant Temperature Signal.

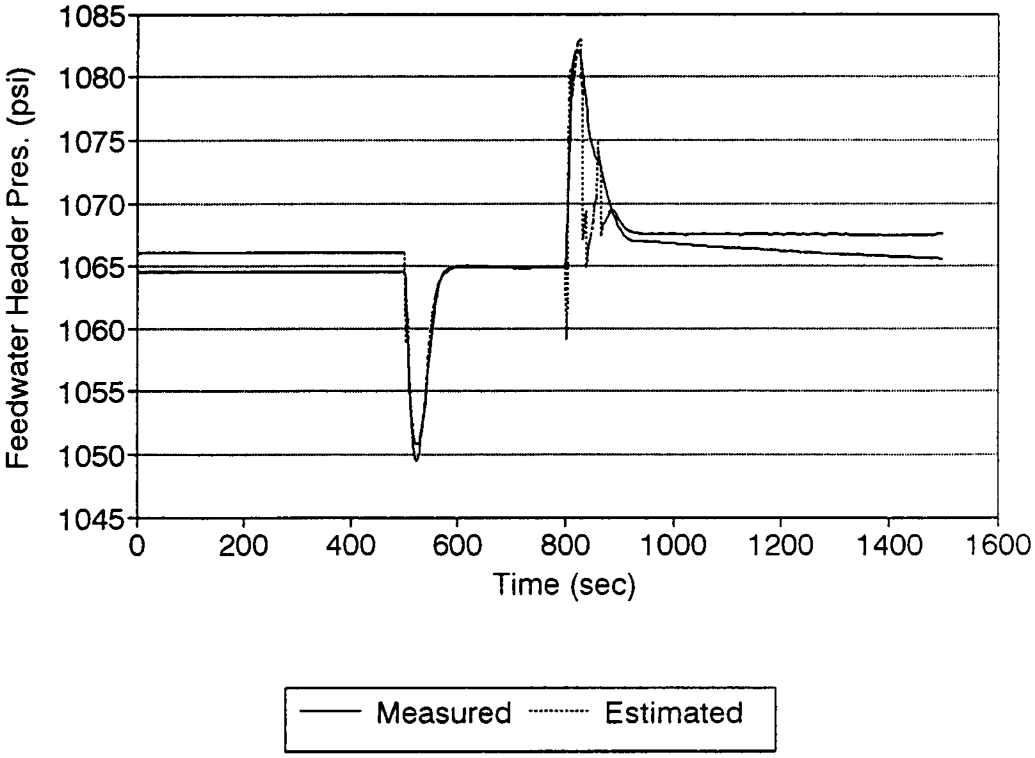

Figure 6.59: ANN Model Estimation of Feedwater Header Pressure Signal.

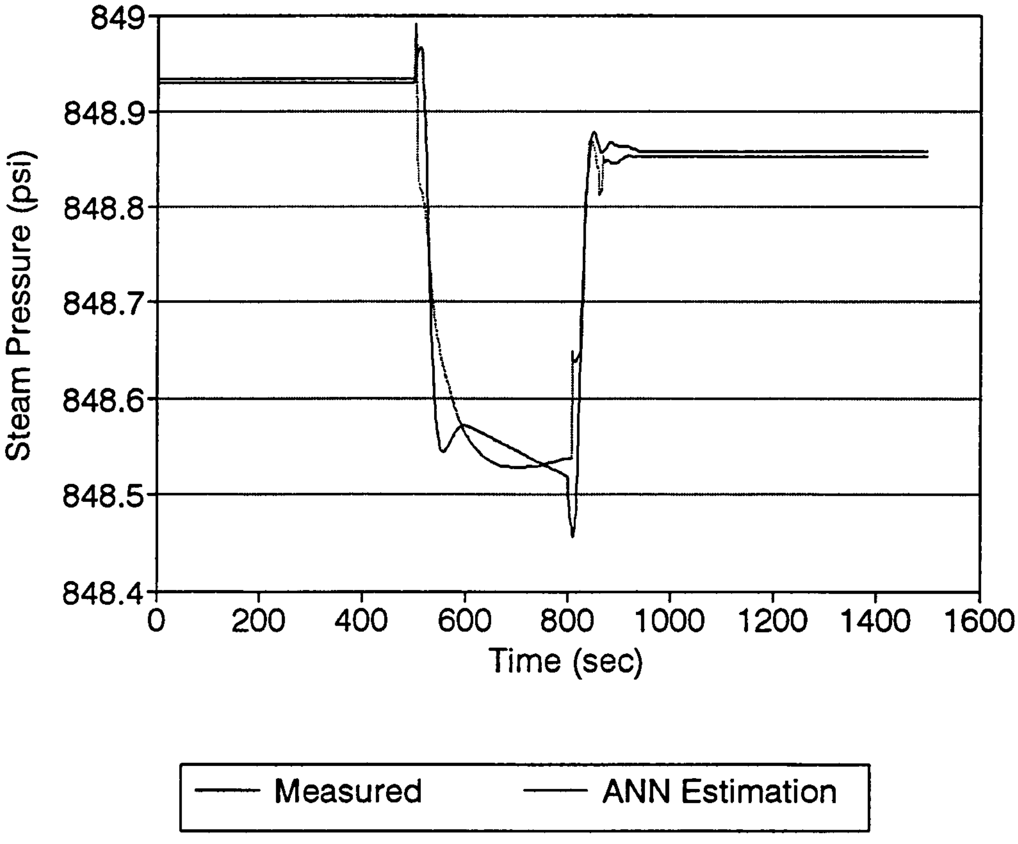

Figure 6.60: ANN Model Estimation of Steam Pressure Signal.

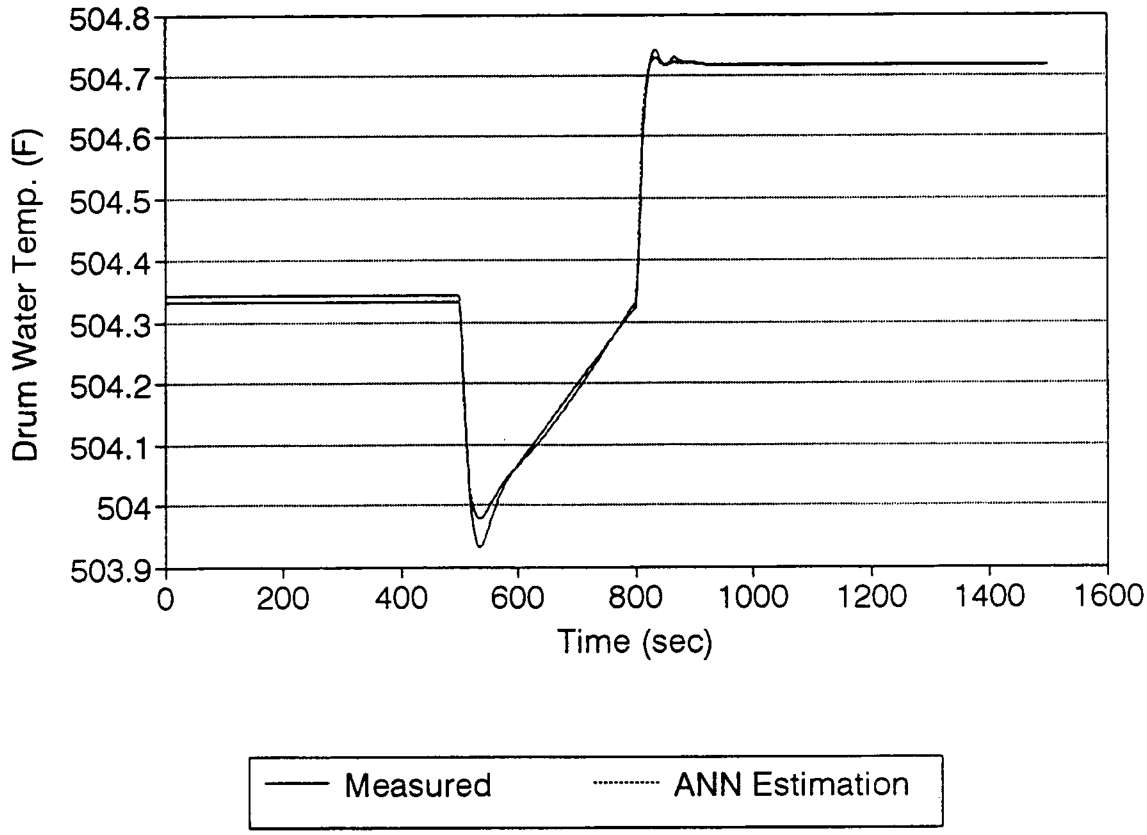

Figure 6.61: ANN Model Estimation of Drum Water Temperature Signal.

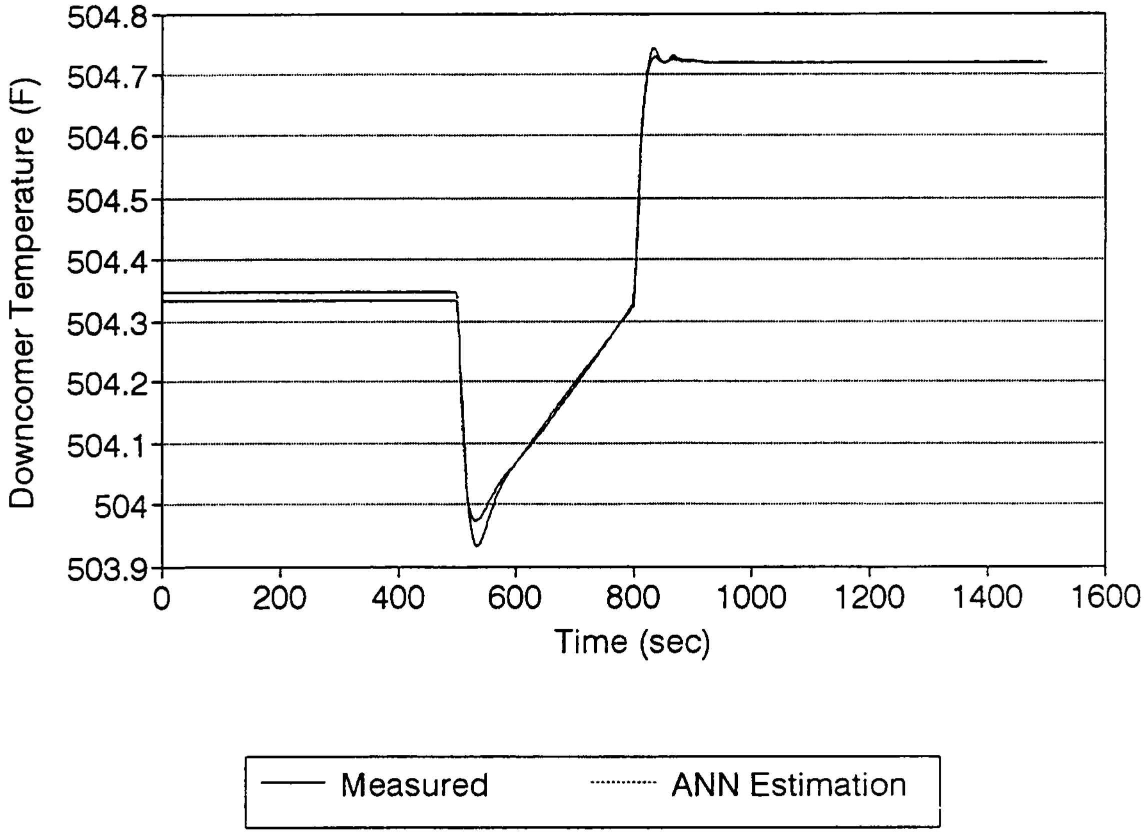

Figure 6.62: ANN Model Estimation of Downcomer Temperature Signal.

gies were developed as part of the feedwater flow regulation system: steam generator water level control and main feed pump speed control. Both of these control systems were utilized during the simulation tests.

Along with the control module results, command validation and decision-making module results were also discussed in this Chapter. A systematic way for selecting the most appropriate control strategy was developed and different tests were completed to demonstrate the feasibility of utilizing more than one control algorithm for the same task. The results of the signal validation module were also displayed in this chapter. A software parallelism was utilized within the signal validation module by developing two different models for the selected signals. Process empirical models and artificial neural network models were developed for estimating the process variables of interest.

Chapter 7

Summary, Conclusions, and Recommendations for Future Work

7.1 Summary

The application of digital technology to nuclear power plant monitoring, diagnostics, and control offers a number of advantages, the most important being improved availability and fault-tolerance. In this dissertation research the design and implementation of a control system that integrates various modules into one large computer-aided system was studied. The digital technology enables us to implement this new idea in the software domain.

The use of computational intelligence, such as fuzzy logic, neural networks, and adaptive control algorithms have broadened the relevance of developing robust and reliable control systems for nuclear power plants. Integrating these control algorithms with validation and monitoring modules will further enhance the availability and safety of these systems in the presence of degrading measurements, controller anomalies, and unanticipated transients.

The parallel control module was integrated with the signal validation and the command validation modules. The utilization of software parallelism was investigated and its applicability was demonstrated to feedwater flow regulation in PWRs. This application also indicates the feasibility of the approach to large-scale systems.

The FCDS provides two different means of fault-tolerance. First, by including a signal validation system, the possibility of sensor failures or computing inaccurate control actions due to degrading sensor readings can be eliminated. Second, the utilization of multiple control algorithms provides alternate approaches during the operation of the controlled process. Different control algorithms may be needed to avoid controller failure due to control input signal error, and the choice from multiple algorithms may provide better results for different operating regimes.

7.2 Conclusions

A fault-tolerant control and diagnostics system for enhancing nuclear reactor operations was developed in this dissertation. The research has demonstrated the integration of control, signal validation and command validation with application to large-scale systems. The concept of software-based fault-tolerance was developed and illustrated through a parallel design strategy. The new approach may be referred to as a "smart" controller.

Signal validation is a proven useful tool that establishes a systematic way to demonstrate the accuracy of sensor readings. The fault-tolerant control and diagnostics system (FCDS) presented here offers a signal validation approach in which two different methodologies were utilized to overcome their individual deficiencies. The signal validation module provides validation of some of the selected measurements which are important for the feedwater flow regulation of pressurized water reactors.

Steam generator water level, feedwater flow, feedwater header pressure and steam pressure signals were among the validated signals. Two models were developed for each of these selected signals to incorporate the software-based parallelism.

A process empirical modeling (PEM) technique and artificial neural networks (ANN) were utilized for developing the models for the signal validation module. Although the current signal validation module provides sufficient information about the measurements and gives accurate estimations for the modeled signals, a broader approach for the signal validation would improve the overall reliability and availability of the system.

The process empirical modeling approach usually gives accurate estimates if the system is operating in the domain where the models are developed. The accuracy of the model estimation becomes poor as the system leaves that domain, as well as in the event of inaccurate readings of the model input signals. In order to overcome these shortcomings of PEM models, another approach was utilized, namely, the artificial neural network modeling. ANN models are more robust against measurement degradation since the model structure is not rigid. They are not based on conventional mathematical relationships and provide good results when the signals fall outside their training domain. One major problem with the ANN models is their long training phase. If an ANN model needs to be updated for a new operational condition, the off-line training may take several hours. One solution for this problem is to use a system with an on-line training strategy. For better validation and monitoring, on-line, adaptive neural network modeling must be used in the signal validation module.

An improved version of the FCDS must be tested with redundant sensors and with real data collected from an operating power plant rather than the simulation data.

The current version of the FCDS covers only feedwater flow system signals in the signal validation module. A broader signal validation module must include more signals both from the primary side and the secondary side of a PWR. Including the Kalman filtering technique with accurate models enhances the signal validation results.

The FCDS incorporates two nonlinear control algorithms in addition to the conventional controller. One of the algorithms is a model-based adaptive controller which gives excellent results for trajectory following problems. The second control algorithm is based on fuzzy logic, and gives exceptionally accurate results during unanticipated transients of the controlled process. Two different fuzzy logic controllers were developed as part of the control module. The first fuzzy controller uses control input signals similar to those used in the conventional steam generator water level control system, namely, flow mismatch between steam flow and feedwater flow rates and the level error. The second controller was developed to offer control solution in the event of a feedwater/steam flow sensor failure or degradation. The level error signal and the change in the level signal are the two control input signals for this fuzzy controller. The FCDS utilizes these different algorithms to offer a better solution for the feedwater flow regulation problems of pressurized water reactors.

The Reconstructive Inverse Dynamics (RID) was used for both the steam generator water level control and the main feedwater pump speed control of the feedwater flow regulation system. The simulation tests had shown that the RID controller gives the best results when the operation was of a trajectory following nature. Both the RID controllers have given excellent results during water level set point changes and ΔP set point changes. Although the RID controller gives reasonable results during steam valve perturbations, the results are not as accurate as those obtained using the fuzzy logic controller. A simple explanation of this poor performance of the

RID level controller is that it is a model-based control algorithm and steam valve perturbation creates disturbances in the system which cause undefined level errors. Both the fuzzy logic controllers give considerably better results when compared to the RID results. The second fuzzy logic controller, developed for steam generator water level control, provides robust results since flow mismatch is not an input signal to the control algorithm. This once again demonstrates the importance of using different strategies with different algorithms for feedwater flow regulation system to overcome sensor/control problems. Fuzzy logic controllers have given exceptionally good results during both level set point changes and steam valve perturbations.

The command validation is the third module that was developed as part of the FCDS. This is a new concept as a validation scheme, and checks the quality of the control solutions and ensures the validity of the control actions. A decision making procedure was developed for the command validation module to select the best control signal based on the availability of the control input signals.

Various perturbation tests were performed to demonstrate the feasibility of applying the FCDS for feedwater flow regulation of a PWR. Level set point changes were introduced to test the system for trajectory following problems and excellent results were obtained from each of the individual control algorithms. Steam valve perturbations and actuator constraint problems were introduced during normal operation to test the quickness and robustness of the control system. Sensor problems were introduced to test the signal validation module and the feasibility of the software parallelism within the control system. The decision-making module along with the command validation system had given exceptionally accurate results while switching from one control algorithm to another (for example to avoid the failed sensor problem even during a level perturbation test).

The command validation module with a rule-based decision making system was developed for selecting the best controller, or the combination of controllers for feedwater flow regulation in PWRs. By integrating the various tasks into one system, the availability of the control system was increased during sensor failures, degrading control input signals and during fast transients. Current control designs generally cannot handle these conditions properly.

The current version of the decision-making process is a simple rule-based system, where the status of the operation is checked through the predefined parameters such as level error and flow error. The feasibility of utilizing the decision making system and command validation system was tested for several perturbations and the results were excellent. The decision-making block was specifically designed to handle the steam generator water level control without challenging the control systems. A-priori knowledge of the individual performances of the control algorithms were the basis for selecting control algorithms for different operating regimes. Tests showed that the decision-making block was able to switch between the controllers even during a transient without causing disturbances to the system. The decision-making block was developed to handle steady-state operation of a PWR.

The FCDS has introduced *software parallelism* to signal validation, command validation, and to the control system. This feature provides an additional fault-tolerance, and improves the availability of the overall system.

7.3 Recommendations for Future Work

The existing feedwater control system regulates the steam generator water level in each of the four steam generators using measurements of the steam generator narrow-range level, steam and feedwater flow rates, steam and feedwater header pressures, and the turbine impulse pressure. The ability of this system to control effectively is limited to some extent by sensor characteristics such as range, accuracy, and availability.

Automatic feedwater control using existing feedwater flow measurement techniques is not possible at low power levels due to range limitations. The venturi-type flow elements are sized for rated flow conditions and they are not usable except as trend information at less than 15-20 percent rated flow. Without accurate low-power flow measurements, automatic control of feedwater flow in the existing systems is reduced to a single-element control system using narrow-range steam generator level signal.

The feedwater flow elements are also subjected to measurement errors due to venturi fouling. Corrosion deposits on the venturi surface cause a shift in the differential pressure and cause bias errors in the measured flow. An alternative flow measurement system needs to be utilized to overcome the existing flow measurement problems.

Vulnerability to sensor failure imposes an additional limitation on the overall system availability. Although the FCDS introduces an integrated signal validation and control system, a single failure of the selected sensor channel will result in a spurious control system output and a possible reactor trip, since the existing systems in PWRs depend on a single input from the feedwater flow channels. A more complicated signal validation system needs to be part of the feedwater flow regulation of PWRs.

Automatic feedwater control at low-power levels can be significantly improved by utilizing feedforward inputs to replace the present feedwater flow measurement. Either wide-range steam generator water level or neutron flux measurements (depending on the control algorithm) can be used to improve system response at low-power levels. The existing systems are also subjected to steam flow measurement inaccuracies and sensor failure limitations similar to those discussed earlier in this section.

Steam generator narrow-range level is another critical measurement for the feedwater control system as well as for the reactor protection system. Level is measured by differential pressure transmitters with a constant reference leg. These measurements are subjected to instabilities due to "shrink" and "swell" effects and inaccuracies due to process temperature and pressure changes. The "shrink" and "swell" phenomenon is a problem at low power levels, and a major cause for low-low level reactor trips during startup. The FCDS includes a scheme to overcome the sensor problems of the steam generator water level readings. The FCDS was tested only for steady-state operations around 100 % power level; therefore it is important to extend the work to include low power level operations and the general startup phase.

The present feedwater flow regulation systems are also limited by dependence on a single-level channel input per steam generator. Although there are three channels available for each steam generator, only one is selected for feedwater flow control. A generalized consistency checking procedure must be part of the steam generator water level channel selection system, as it is recommended for feedwater flow measurement system to avoid single failures of the level channels.

The feedwater and steam header pressure measurements are important inputs to the main feed pump speed control system. The availability of this system is compromised in its existing configuration due to the lack of redundancy in these measurements. The FCDS provides two models for each of these measurements which provide accurate estimations in the event of failure of these sensors. A failure of a single transmitter will cause a transient which may result in a reactor trip, especially if the failure causes a decrease in the pump speed. This problem requires further study to overcome the deficiency due to limited sensors.

An alternative solution to the single-failure limitations imposed by feedwater and steam header pressure measurements must be developed. Control of feed pump speed on feedwater demand, rather than on steam/feedwater header differential pressure may eliminate the control system dependence on these two inputs.

This dissertation research has demonstrated the feasibility of integrating monitoring and diagnostics tasks with control systems in the software domain. This system also introduces "software parallelism" for validation and control by utilizing more than one software algorithm to avoid possible algorithm dependent flaws. The system may be transferred to the hardware domain, since the algorithms utilized in the FCDS are easy to implement on digital systems. The hardware implementation of artificial neural networks and fuzzy logic controllers has been demonstrated in Japan and in the United States. The utilization of an enhanced version of the FCDS for nuclear power plants would show significant improvements in their operation, and the fault-tolerant nature of the system would significantly reduce the cost of operation.

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APPENDICES

Appendix A

U-Tube Steam Generator Model Formulation

This section discusses the theoretical model of a U-tube steam generator. The study was first completed by Ali [31], and the model was generalized by Naghedolfeizi [30]. The modeling by Naghedolfeizi's was further investigated, modified and developed into a new code in FORTRAN. Following equations are the final form of the model equations first developed by Ali.

A.1 Governing Equations of the U-Tube Steam Generator

A.1.1 Primary Side Equations

Inlet Plenum

$$\frac{dT_{pi}}{dt} = \frac{W_{pi}}{M_{pi}} (\theta_i - T_{pi}) \tag{A.1}$$

U-Tube Primary Lump Equations

First node:

$$\frac{dT_{p1}}{dt} = \frac{W_{pi}}{\rho_{pi} A_p L_{s1}} (T_{pi} - T_{p1}) + \frac{U_{pm} S_{pm1}}{M_{p1} C_{p1}} (T_{m1} - T_{p1}) \tag{A.2}$$

Second node:

$$\frac{dT_{p2}}{dt} = \frac{W_{pi}}{\rho_{pi}\,A_p\,L_{s2}}(T_{p1}-T_{p2}) + \frac{U_{pm}\,S_{pm2}}{M_{p1}\,C_{p1}}(T_{m2}-T_{p2}) +$$

$$\frac{(T_{p2}\;-\;T_{p1})}{L_{s2}}\frac{dL_{s1}}{dt} \tag{A.3}$$

Third equation:

$$\frac{dT_{p3}}{dt} = \frac{W_{pi}}{\rho_{pi}\,A_p\,L_{s1}}(T_{p1}-T_{p2}) +$$

$$\frac{U_{pm}\,S_{pm2}}{M_{p1}\,C_{p1}}(T_{m3}-T_{p3}) \tag{A.4}$$

Fourth node:

$$\frac{dT_{p4}}{dt} = \frac{W_{pi}}{\rho_{pi}\,A_pL_{s2}}(T_{p1}-T_{p2}) + \frac{U_{pm}\,S_{pm1}}{M_{p1}\,C_{p1}}(T_{m4}-T_{p4}) +$$

$$\frac{T_{p3}-T_{p4}}{L_{s1}}\frac{dL_{s1}}{dt} \tag{A.5}$$

Outlet Plenum

$$\frac{dT_{po}}{dt} = \frac{W_{pi}}{M_{po}}(T_{p4}-T_{po}) \tag{A.6}$$

Metal Tube Equations

First node:

$$\frac{dT_{m1}}{dt} = \frac{U_{pm}\,S_{pm1}}{M_{m1}\,C_m}T_{p1} - \frac{U_{pm}\,S_{pm1}\,+\,U_{ms1}\,S_{ms1}}{M_{m1}\,C_m}T_{m1} +$$

$$\frac{U_{ms1}\,S_{ms1}}{M_{m1}\,C_m}\frac{(T_d+T_{sat})}{2} + \frac{(T_{m2}-T_{m1})}{2L_{s1}}\frac{dL_{s1}}{dt} \tag{A.7}$$

Second node:

$$\frac{dT_{m2}}{dt} = \frac{U_{pm}\,S_{pm2}}{M_{m2}\,C_m}T_{p2} - \frac{U_{pm}\,S_{pm2}+U_{ms2}\,S_{ms2}}{M_{m2}\,C_m}T_{m2} +$$

$$\frac{U_{ms2}\,S_{ms2}}{M_{m2}\,C_m}T_{sat} + \frac{(T_{m2}-T_{m1})}{2L_{s2}}\frac{dL_{s1}}{dt} \tag{A.8}$$

Third node:

$$\frac{dT_{m3}}{dt} = \frac{U_{pm}\,S_{pm2}}{M_{m2}\,C_m}T_{p3} - \frac{U_{pm}\,S_{pm2} + U_{ms2}\,S_{ms2}}{M_{m2}\,C_m}T_{m3} +$$

$$\frac{U_{ms2}\,S_{ms2}}{M_{m2}\,C_m}T_{sat} + \frac{(T_{m3} - T_{m4})}{2L_{s2}}\frac{dL_{s1}}{dt} \tag{A.9}$$

Fourth node:

$$\frac{dT_{m4}}{dt} = \frac{U_{pm}\,S_{pm1}}{M_{m1}\,C_m}T_{p4} - \frac{U_{pm}\,S_{pm1} + U_{ms1}\,S_{ms1}}{M_{m1}\,C_m}T_{m4} +$$

$$\frac{U_{ms1}\,S_{ms1}}{M_{m1}\,C_m}\frac{(T_d + T_{sat})}{2} + \frac{(T_{m3} - T_{m4})}{2L_{s1}}\frac{dL_{s1}}{dt} \tag{A.10}$$

A.1.2 Secondary Side Equations

Subcooled Region Equations

Mass Balance:

$$\frac{dL_{s1}}{dt} = \frac{(W_1 - W_2)}{\rho_{s1}\,A_{fs}} \tag{A.11}$$

Energy Balance:

$$\frac{d}{dt}[\rho_{s1}\,A_{fs}\,L_{s1}\,C_{p2}\frac{(T_d + T_{sat})}{2}] = U_{ms1}\,P_{r2}\,L_{s1}\,(T_{m1} + T_{m4} - T_d - T_{sat}) +$$

$$W_1\,C_{p2}\,T_d - W_2\,C_{p2}\,T_{sat} \tag{A.12}$$

Boiling Region Equations

Riser/Separator Volume

$$\frac{d}{dt}(V_r\,\rho_r) = W_3 - W_4 \tag{A.13}$$

$$\frac{d\rho_r}{dt} = -\frac{(K_1 + K_2\,X_e)}{V_f + X_e\,V_{fg})^2}\frac{Dp}{dt} - \frac{V_{fg}}{(V_f + X_e\,V_{fg})^2}\frac{dX_e}{dt} \tag{A.14}$$

Drum Water Volume

Mass balance:

$$\frac{d}{dt}(\rho_{dw}\, A_{dw}\, L_{dw}) = W_{fi} + (1 - X_e)\, W_4 - W_1 \tag{A.15}$$

Energy balance:

$$\frac{d}{dt}(\rho_{dw}\, A_{dw}\, L_{dw}\, T_{dw}) = W_{fi}\, T_{fi} + (1 - X_e)\, W_4\, T_{sat} - W_1\, T_{dw} \tag{A.16}$$

Drum Steam Volume:

$$(V_{dr} - A_{dw}\, L_{dw})\, \frac{d\rho_g}{dt} - (\rho_g\, A_{dw})\, \frac{dL_{dw}}{dt} = X_e\, W_4 - C_l\, P \tag{A.17}$$

A.1.3 Downcomer Region Equation

$$\frac{dT_d}{dt} = \frac{W_1}{M_d}(T_{dw} - T_d) \tag{A.18}$$

A.1.4 Constitutive Relations

Thermodynamic Properties of Water and Steam:

$$h_b = h_f + \frac{X_e}{2}\, h_{fg} \tag{A.19}$$

$$h_{ex} = h_f + \frac{X_e}{2}\, h_{fg} \tag{A.20}$$

$$h_f = X_3 + K_3\, P \tag{A.21}$$

$$h_{fg} = X_4 + K_4\, P \tag{A.22}$$

$$L_{s2} = L - L_{s1} \tag{A.23}$$

$$T_{sat} = X_5 + K_5\, P \tag{A.24}$$

$$V_f = X_1 + K_1\, P \tag{A.25}$$

$$V_{fg} = X_2 + K_2\, P \tag{A.26}$$

$$W_{st} = C_l\, P \tag{A.27}$$

$$\rho_b = \frac{1}{V_f + \frac{X_e}{2} V_{fg}} \tag{A.28}$$

$$\rho_g = X_6 + K_6\, P \tag{A.29}$$

A.1.5 Recirculation Loop Equation

$$W_1 = \frac{C_1}{12}\left[\rho_d\,(L_{dw} + L_d - L_{s1}) - L_r\,\rho_r\right]^{1/2} \tag{A.30}$$

Table A.1 and Table A.2 give the list of model variables and their descriptions.

Table A.1: Steam Generator Model Variables

No:	*Variable Name*	*Description*
1.	A_{fs}	Secondary flow area in the U-tube region
2.	A_{dw}	Effective area of the drum water section
3.	C_1	Effective pressure drop coefficient in the recirculating loop
4.	C_l	Steam valve coefficient
5.	C_m	Specific heat capacity of the metal tubes
6.	$C_{p1,2}$	Specific heat capacity of the primary fluid and subcooled region
7.	h_b	Average enthalpy of the boiling region
8.	$h_{f,fg}$	Saturated and latent enthalpies of the water
9.	h_{ex}	Exit enthalpy of the boiling region
10.	K_{1-6}	$\frac{\partial V_f}{\partial P}, \frac{\partial V_{fg}}{\partial P}, \frac{\partial h_f}{\partial P}, \frac{\partial h_{fg}}{\partial P}, \frac{\partial T_{sat}}{\partial P}, \frac{\partial \rho_g}{\partial P}$
11.	L	Effective height of U-tubes
12.	L_d	Downcomer length
13.	L_{dw}	Water level in the steam generator (drum section)
14.	$L_{s1,2}$	Subcooled ad boiling lengths
15.	$M_{m1,2}$	Metal mass in metal nodes (1,2)
16.	M_{pi}	Mass of water in the inlet plenum
18.	P	Steam generator pressure
19.	$P_{r1,2}$	Inside and outside perimeters of the U-tubes
20.	$S_{ms1,2}$	Heat transfer areas from the U-tubes to the secondary side in the subcooled and boiling regions respectively
21.	$S_{pm1,2}$	Heat transfer areas from the primary side to the U-tubes in nodes (1,2)

Table A.2: Steam Generator Model Variables (continued)

No:	*Variable Name*	*Description*
22.	T_d	Downcomer temperature
23.	T_{dw}	Drum water temperature
24.	T_{m1-4}	Metal tube temperatures in nodes (1-4)
25.	T_{p1-4}	Primary coolant temperatures in nodes (1-4)
26.	T_{pi}	Coolant temperature in the inlet plenum
27.	T_{po}	Coolant temperature in the outlet plenum
28.	T_{sat}	Saturated temperature of the water and steam in the UTSG
29.	U_{pm}	Heat transfer coefficient from the primary side to the metal side
30.	$U_{ms1,2}$	Heat transfer coefficient from the metal side to the subcooled boiling regions
31.	V_{dr}	Volume of the drum section
32.	$V_{f,g}$	Specific volume of the water and steam
33.	V_{fg}	V_g - V_f
34.	V_r	Volume of the riser region
35.	W_{st}	Steam flow rate
36.	X_{1-6}	Constant parameters of the water property equations
37.	X_e	Exit quality of the steam leaving the boiling region
38.	ρ_b	Average density of the fluid in the boiling region
39.	ρ_g	Density of the saturated steam
40.	ρ_r	Density of the fluid in the riser region

Appendix B

Signal Validation Models

B.1 Process Empirical Modeling (PEM)

A systematic effort was undertaken to create empirical models of selected parameters of a feedwater flow regulation system for a pressurized water reactor. The study involved the development of seven different process variables. Following sections discuss the process empirical modeling results for steam generator water level, feedwater flow rate, coolant temperature, feedwater header pressure, steam pressure, downcomer temperature, and drum water temperature signals.

B.1.1 Steam Generator Water Level Model

The following model is the developed using PEM. Four input signals were used for this model. These were feedwater flow, steam pressure, downcomer temperature, and feedwater header pressure,

$$Level = f(W_{feedwater}, P_{steam}, T_{downcomer}, P_{feedwater-header})$$

The formulation for the level model is given in Equation (B.1).

$$Level = a_0 + a_1 x + a_2 y + a_3 z + a_4 w \tag{B.1}$$

where,

$Level$ = Steam generator water level (feet)

x = Flow rate (lbm/sec)

y = Feedwater header pressure (psi)

z = Steam pressure (psi)

w = Downcomer temperature (^0F)

a_0 = -170.1369

a_1 = 3.108905

a_2 = -0.3681067

a_3 = -109.3382

a_4 = 90.00582

Modeling Error (%) = 3.674383E-01

B.1.2 Feedwater Flow Model

Three input signals, namely, steam generator water level, steam pressure, and feedwater header pressure, were used for this PEM model,

$$W_{feedwater} = f(level, P_{steam}, P_{feedwater-header})$$

Equation (B.2) gives the formulation for the model.

$$W_{feedwater} = a_0 + a_1x + a_2x^2 + a_3y^2 + a_4y + a_5z \tag{B.2}$$

where,

$W_{feedwater}$ = Feedwater flow rate (lbm/sec)

x = Steam pressure (psi)

y = Steam generator water level (feet)

z = Feedwater header pressure (psi)

a_0 = -0.1097219E+05

a_1 = 3580.130

a_2 = -188.2649

a_3 = -22.95189

a_4 = 425.8047

a_5 = -65.98013

Modeling Error (%) = 0.3046183

B.1.3 Coolant Temperature Model

Three input signals, namely, steam generator water level, feedwater flow rate, and feedwater header pressure, were used for this PEM model,

$$T_{coolant} = f(level, W_{feedwater}, P_{feedwater-header})$$

Equation (B.3) gives the formulation of the model.

$$T_{coolant} = a_0 + a_1 x + a_2 x^2 + a_3 y^2 + a_4 yx + a_5 z^2 \tag{B.3}$$

where,

$T_{coolant}$ = Coolant temperature (^0F)

x = Feedwater header pressure (psi)

y = Steam generator water level (feet)

z = Feedwater flow rate (lbm/sec)

a_0 = 571.5861

a_1 = -3.017898

a_2 = 0.7830303

a_3 = 0.2198355

a_4 = -0.2066177

a_5 = -0.06546272

Modeling Error (%) = 0.001606055

B.1.4 Feedwater Header Pressure Model

Three input signals, namely, steam generator water level, feedwater flow rate, and steam pressure, were used for this PEM model,

$$P_{feedwater-header} = f(level, W_{feedwater}, P_{steam})$$

Formulation of the model is given by Equation (B.4).

$$P_{feedwater-header} = a_0 + a_1 x + a_2 y + a_3 z \tag{B.4}$$

where,

$P_{feedwater-header}$ = Feedwater header pressure (psi)

x = Steam pressure (psi)

y = Feedwater flow rate (lbm/sec)

z = Steam generator water level (feet)

a_0 = 22150.48

a_1 = -1028.461

a_2 = -35.83885

a_3 = 0.6637346

Modeling Error (%) = 0.2026685

B.1.5 Steam Pressure Model

Two input signals were used to develop the PEM model for steam pressure signal, namely, steam generator water level and feedwater flow rate.

$$P_{steam} = f(level, W_{feedwater})$$

Formulation is given by Equation (B.5).

$$P_{steam} = a_0 + a_1 x + a_2 x^2 + a_3 y + a_4 y^3 \tag{B.5}$$

where,

P_{steam} = Steam pressure (psi)

x = Feedwater flow rate (lbm/sec)

y = Steam generator water level (feet)

a_0 = 684.2070

a_1 = 26.03851

a_2 = -0.8989868

a_3 = -3.818944

a_4 = 0.01424117

Modeling Error (%) = 7.936214E-03

B.1.6 Downcomer Temperature Model

Coolant temperature and drum water temperature signals were used to develop the PEM model for the downcomer temperature signal.

$$T_{downcomer} = f(T_{coolant}, T_{drum-water})$$

Equation (B.6) gives the formulation of the model.

$$T_{downcomer} = a_0 + a1x + a_2y \qquad \text{(B.6)}$$

where,

$T_{downcomer}$ = Downcomer temperature (^0F)

x = Coolant temperature (^0F)

y = Drum water temperature (^0F) a_0 = -2.560963

a_1 = 0.2834439

a_2 = 33.63156

Modeling Error (%) = 8.024223E-05

B.1.7 Drum Water Temperature Model

Coolant temperature and downcomer temperature signals were used for developing the drum water temperature PEM model.

$$T_{drum-water} = f(T_{coolant}, T_{downcomer})$$

Equation (B.7) gives the formulation of the model.

$$T_{drum-water} = a_0 + a_1 x + a_2 y \tag{B.7}$$

where,

$T_{drum-water}$ =Drum water temperature (^0F)

x = Coolant temperature (^0F)

y = Downcomer temperature (^0F)

a_0 = 2.63261

a_1 = -0.291588

a_2 = 33.66869

Modeling Error (%) = 8.024223E-05

B.2 Artificial Neural Networks (ANN)

Artificial neural network (ANN) models were developed using the Backpropagation Neural Network training algorithm. The algorithm was previously implemented [7] on a VAX workstation. The models were developed off-line using simulation data similar to those which were used to develop the PEM models. ANN models were developed for steam generator water level, feedwater flow, coolant temperature, feedwater header pressure, steam pressure, downcomer temperature, and drum water temperature signals. These models were utilized by the signal validation module

Table B.1: ANN Model for Steam Generator Water Level

Input Signals	*Feedwater Flow* *Steam Pressure* *Downcomer Temperature*
Number of Training Patterns	150
Number of Hidden Nodes	15
Training Standard Deviation	8.87×10^{-3}

Table B.2: ANN Model for Feedwater Flow

Input Signals	*SG Water Level* *Steam Pressure* *FW Header Pressure*
Number of Training Patterns	150
Number of Hidden Nodes	15
Training Standard Deviation	0.873

to cross-examine the signals before they were broadcast to the control module. Tables B.1 through B.7 summarize the information about the ANN models and their prediction errors.

Table B.3: ANN Model for Coolant Temperature

Input Signals	*SG Water Level* *Feedwater Flow* *FW Header Pressure*
Number of Training Patterns	150
Number of Hidden Nodes	15
Training Standard Deviation	1.24×10^{-3}

Table B.4: ANN Model for Feedwater Header Pressure

Input Signals	*SG Water Level* *Feedwater Flow* *Steam Pressure*
Number of Training Patterns	150
Number of Hidden Nodes	15
Training Standard Deviation	1.12

Table B.5: ANN Model for Steam Pressure

Input Signals	*SG Water Level* *Feedwater Flow*
Number of Training Patterns	150
Number of Hidden Nodes	15
Training Standard Deviation	6.58×10^{-2}

Table B.6: ANN Model for Downcomer Temperature

Input Signals	*Coolant Temperature* *Drum Water Temperature*
Number of Training Patterns	150
Number of Hidden Nodes	15
Training Standard Deviation	2.06×10^{-2}

Table B.7: ANN Model for Drum Water Temperature

Input Signals	*Coolant Temperature* *Downcomer Temperature*
Number of Training Patterns	150
Number of Hidden Nodes	15
Training Standard Deviation	1.27×10^{-2}

VITA

Evren Eryürek was born in Eskişehir, Turkiye on August 19, 1963. His parents are Mete and Şenay Eryürek, faculty member in a university in İstanbul. His sister, Bige, is a broker with a Bachelor of Science degree in Management and Business in İstanbul stock market, and married to Cumhur since 1992.

In September 1980, Evren entered Hacettepe University in Ankara, the capital city of Turkiye, to obtain a Bachelor of Science degree in Physics. After obtaining his degree, Evren worked at two industrial companies for nearly two years in Turkiye. In the fall of 1988, Evren entered the graduate school to obtain a Master of Science degree in Nuclear Engineering at the University of Tennessee, Knoxville.

In 1991, Evren began doctoral studies at the University of Tennessee, Knoxville, in the Nuclear Engineering Department where he was working since 1988 under the supervision of Dr. Belle R. Upadhyaya. He studied the applicability of advanced computing techniques including artificial neural networks, fuzzy logic, inverse dynamics to the control, monitoring and diagnostics of nuclear power plants. His research work has been documented in over thirty publications in professional journals and national and international conferences, and he has been invited to give numerous lectures at research laboratories and universities in the U.S. and abroad.

Evren is a member of the Institute of Electrical and Electronics Engineers, the American Nuclear Society, and the Instrumentation Society of America. He has been elected member of the Tau Beta Pi and the Sigma Xi Honorary Societies, and he has been selected for the 1994 edition of the Who's Who in Science and Engineering. His research interests include advanced control, fault-tolerant control, intelligent control, fuzzy logic, artificial intelligence, pattern recognition, signal processing, monitoring and diagnostics.