A Study on Modeling Nuclear Power Plant Operator's Cognitive Behaviors at Man-Machine Interface and Its Experimental Validation

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A STUDY ON MODELING NUCLEAR POWER PLANT OPERATOR'S COGNITIVE BEHAVIORS AT MAN-MACHINE INTERFACE AND ITS EXPERIMENTAL VALIDATION

Contents

Abstract

In recent years, great advancements have been achieved in the field of computer and automatic control technologies. For large-scale complicated systems such as a nuclear power plant (NPP), the advancements have changed the role of operators from the traditional role of manual controllers to the supervisory controllers of the automated system, which consists of multiple computer-controlled subsystems. The introduction of automation technologies into plant systems has been indeed reduced operators' physical workload and failure of machine system. On the other hand, the accidents or incidents resulted from human errors have been notable recently. As the results, human reliability has been recognized as an important issue with respect to the safety and reliability of the man-machine system as a whole.

In order to examine the reliability of operators' activities, the human system interactions (HSIs) in case of an emergency have been studied by conducting large-scale operator experiments, in which operators are asked to interact with the plant simulator through a mockup of the MMI in the central control room. The obtained experimental data have helped to improve MMI design and operator training, in order to minimize the human error. However, the approach requires a large amount of time and considerable cost to create the experimental environment and to analyze the experimental data. Moreover, the application of the experimental data is limited to the HSIs that have been examined by the large-scale operator experiments.

In this thesis study, a new methodology is proposed to supplement the existing large-scale experimental approach. The new methodology is based on a computer simulation system in which a human model of the operator is utilized together with the plant and MMI simulators. The human model is a computerized model of the operator's cognitive behaviors in case of an emergency, such as anomaly detection and diagnosis. Numerical experiments based on the computer simulation are conducted to simulate the complicated HSIs by utilizing the human model to interact with the plant simulator. The results show the validity of the human model. The findings of the study demonstrate the flexibility of the new methodology and the promising possibility of its application to human reliability analysis. The study has been conducted in three steps that are described in the three main parts of the thesis, respectively.

In the first part, a laboratory experiment is described. The laboratory experiment is carried out to examine how operators actually monitor the plant system, detect and diagnose the abnormal transients. The analysis results clarified the operator's cognitive information process and provided various concrete data for developing the human model at the next step.

The second part describes the development of the human model in detail. The study aims at developing a human model that can simulate operators' cognitive behaviors (anomaly detection and diagnosis) observed in the laboratory experiment and can be applied to human reliability analysis easily. The human model is developed at a real-time expert development platform in accordance with a general human modeling framework. The human model consists of a number of sub-models of the human memory mechanism: working memory element for the short-term memory (STM) and graphical network-structured knowledge database for the long-term memory (LTM). The details of operators' cognitive behaviors are modeled as the various kinds of information processing conducted in STM and LTM. The validity of the human model is demonstrated by conducting an inter-comparison between the simulation results by the human model and the laboratory experimental data.

The third part gives a description about an application study of the developed human model. The study aims at establishing a new approach for the human reliability analysis (HRA) practice. The application study attempts to estimate the "time-reliability curve" that describes human cognitive error probability required in HRA. The "time versus cognitive reliability" (TCR) curves are then derived from the laboratory experiment, in order to analyze the probabilistic factors influencing operator's performance of anomaly detection and diagnosis. The TCR based on the human model simulation of plant anomaly diagnosis (TCR/HUMOS-PAD) curves are estimated by modeling the probabilistic factors and conducting a number of numerical experiments. The validity of the application study is proven by the inter-comparison between TCR/HUMOS-PAD curves and the TCR curves derived from the laboratory experiment. Furthermore, the human model is incorporated into a real-scale man-machine interaction simulation system SEAMAID, in order to estimate TCR curves in the simulation environment of the real-scale central control room of NPP. The results demonstrate the promising possibility that the computer simulation could replace the large-scale experiments in the future.

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ABWR
: Advanced Boiling Water Reactor

AHHD
: Anomaly Hypothesis Hierarchy Diagram

AI
: Artificial Intelligence

BWR
: Boiling Water Reactor

CD
: Chronological Diagram

CRT
: Cathode-Ray Tube

CVCS
: Chemical Volume Control System

DNB
: Departure from Nucleate Boiling

DP
: Diagnosis Phase

EPRI
: Electric Power Research Institute

FSFH
First-Symptom-First-Hypothesis

FWM
Focal Working Memory

HCR
Human Cognitive Reliability

HCR/ORE
Human Cognitive Reliability based on Operator Reliability Experiment

HEP
Human Error Probability

HSI
Human System Interaction

HRA
Human Reliability Analysis

HUMOS-PAD
Human Model Simulation of Plant Anomaly Diagnosis

I&C
Instrument and Control

JACOS
JAERI Cognitive Simulation System

JAERI
Japan Atomic Energy Research Institute

KB
Knowledge Base

KDB
Knowledge database

LOCA
Loss of Coolant Accident

LTM
Long Term Memory

MFM
Multilevel Flow Modeling

MMI
Man Machine Interface

MMS
Man Machine System

MP
Monitoring Phase

NPP
Nuclear Power Plant

OAT
Operator Action Tree

OCCS
Operator Crew Cognitive Simulation

ORE
Operator Reliability Experiment

OSH
Operation Sequence History

PRZ
Pressurizer

PSA
Probabilistic Safety Assessment

PSE
: Peripheral Sight Effect

PSF
: Performance Shaping Factor

PWM
: Peripheral Working Memory

PWR
: Pressurized Water Reactor

SEAMAID
: Simulation-based Evaluation and Analysis support system for MAn-machine Interface Design

SEAMAID/HUMOUS-PAD
: SEAMAID combined with HUMOUS-PAD

SG
: Steam Generator

SGTR
: Steam Generator Tube Rupture

STM
: Short Term Memory

SYBORG
: Simulation System for the Behavior of an Operator Group

TCR
: Time versus Cognitive Reliability

TCR/HUMOS-PAD
: Time versus Cognitive Reliability based on Human Model Simulation of Plant Anomaly Diagnosis

THERP
: Technique for Human Error Rate Prediction

TRC
: Time Reliability Curve

WM
: Working Memory

WME
: Working Memory Element

Chapter 1

Introduction

1.1 Human Factors at Man-Machine Interface

Along with the great advancements of the modern information technology based on computers, not only in the field of the academic study on information science, but also in industrial systems, what is called as "information revolution" has taken place. It has been said that the 21st century will be the century of information.

The advancements of information technologies have changed not only the nature of controlled systems but also the role of operators of large-scale complicated industrial systems, such as nuclear power plants (NPP). Currently, the machine system can work automatically and safely in most time since the instrument and control (I&C) systems have been developed into an information system by utilizing the high-level automation and computer-based control technology. Consequently, operators have changed their role in the total system from the manual controllers to the supervisor of automated system that consists of multiple computer-controlled sub-systems [1].

Safety is the most important issue in large-scale complicated systems, especially in NPP systems. An NPP system consists of three important components: the machine system, operators, and the man-machine interface (MMI). Through the MMI, operators monitor and control the plant system. Consequently, all of the components have their contributions to the safety and reliability of the total system as a whole. Among the components, the safety and reliability of the machine system have been and will be further enhanced along the technology advancements. As the results, accidents/incidents occurring simply because of failures in machine systems have been decreased. However, the accidents resulted from human errors have become noteworthy recently, such as the nuclear accident occurred in Three Mile Island in 1979 and the Chernobyl disasters in 1986, where human failures have amplified the magnitude of the accidents. From a study on human error [2], the accidents caused by human error account for 80% of all accidents in the industries of airplanes and electrical power plants. Although the technology advancements can enhance the safety and reliability of machine system, it is very difficult to improve the reliability of human beings who are the designer, maker, and operator of the machine systems. Therefore, further efforts are necessary to study human factors in human system interactions (HSIs). Under the background, the human factors has been recognized as an important issue for enhancing the safety and reliability of the man-machine system as a whole [3, 4]. Studies on the human factors have been flourishing worldwide recently.

With respect to operators' errors in case of an emergency, two reasons were given by J. Rasmussen [5]. One reason is the difficulty of operators' decision-making tasks at the potentially risky situations. The other one is that the requirements for coping with the emergency may not be met by the skill developed during normal operating periods. In order to study operators' behaviors in case of an emergency, the conventional approach is to conduct large-scale operator experiments in which various accident situations are simulated to examine the HSIs. The plant simulator, real-size MMI simulator (called as mockup) and skilled operators are required in the experiments. The operators are asked to interact with the plant simulator through the MMI simulator. By observing and analyzing operators' behaviors in the experiments, efforts have been made to improve MMI design and operator training. The approach can provide valuable experimental data for analyzing the HSIs in case of an emergency. However, the approach has also drawbacks summarized as follows [6, 7].

- Large amount of time and considerable cost are required to create the environment for the large-scale experiments.
- Due to the considerable cost, the experiment cannot be conducted frequently, and the experimental scope has to be also limited to a small extent.
- The obtained experimental results can be applied only to the situations that have been examined by the large-scale experiments.

Hence the development of other methodologies has been required to supplement the large-scale experimental approach.

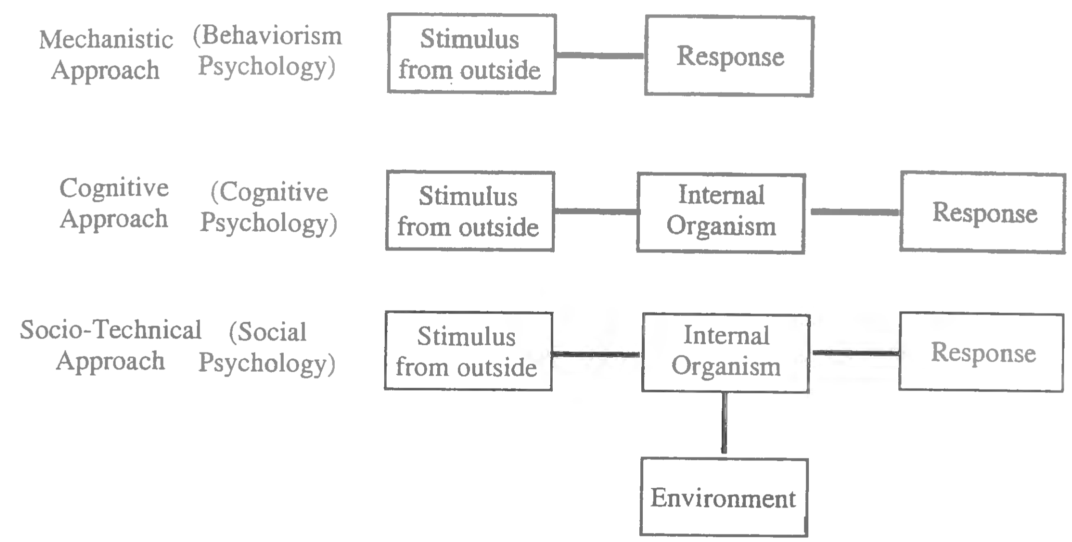

Figure 1.1: Three approaches of human model study

1.2 Human Model Researches

Under the background described above, researches on human model have been conducted as one of the hopeful methods to supplement the large-scale experimental approach. The human model approach has been developed on the basis of the achievements both in the experimental approach and in the field of psychology.

Historically, human model researches in NPP have been conducted by adopting three approaches categorized by their theoretical origins in the psychology [8]. They are mechanistic, cognitive and socio-technical approach. The fundamental concepts for the approaches are shown in Figure 1.1. The features and achievements of the approaches are listed as follows.

- Mechanistic approach
  The mechanistic approach is developed in accordance with the behaviorism psychology. Human behaviors are treated by the same way as hardware elements in the machine system. Based on the external observation, human behaviors are classified into two categories: "success" and "failure". Based on the mechanistic approach, technique for human error rate prediction (THERP) was developed by Swain [9] to evaluate the human errors of observable human behaviors quantitatively.
- Cognitive approach
  The cognitive approach is based on the cognitive psychology. It pays attentions to the

high-level human cognitive behaviors that are performed in the brain of human beings and are not observable directly from the external behaviors, e.g. decision-making, anomaly diagnosis and so on. The cognitive approach models the functioin of the brain of the human being as a kind of information processing devices. Thus, human behaviors are the outputs of the information-processing device. The human cognitive behaviors are divided into a number of basic processing parts in the approach. The total cognitive behaviors are then modeled by defining the interactions among the basic parts of information processing.

- Socio-technical approach
  The socio-technical approach is derived from the social psychology. It pays attention to the systematic and management factors of total MMS by studying the reliability of the crew activity. By examining the factors that exert influences on the crew performance, the researches have been devoted to improving the management of operator crew.

In recent years, along with the advancements in computer technologies, the human model researches have been progressed to study operators' behaviors by computer simulation, and normally what is called as artificial intelligence (AI) has been employed in this approach. AI approach applies the symbolic processing technology to model operators' behaviors. The symbolic processing on computers is based on the cognitive information processing models proposed by the cognitive psychology mentioned above. The human modeling based on AI has been expected to be the most hopeful method to supplement the conventional large-scale operator experiment, since the dynamic and complicated HSIs can be simulated and analyzed on computers by connecting the human model with the plant simulator and MMI simulator.

Currently, most of the human model researches based on AI approach are focused on clarifying the mechanism of human error or on supporting the improvement of the MMI design [10, 11, 12, 13, 14]. A brief review on the existing human modeling researches in Japan is given below.

With respect to supporting the design of the man-machine system by the human modeling approach, OCCS [10] (operator crew cognitive simulation) and SEAMAID [11] (simulation-based evaluation and analysis support system for man-machine interface design) have been developed. OCCS has been developed in accordance with the decision-making ladder model proposed by J. Rasmussen by utilizing the blackboard control model.

Various kinds of researches on HSI [15, 16] have been conducted by utilizing OCCS, such as the evaluation of the human mental workload, modeling of the operation crew's activity, validation of the human model. But, there are some drawbacks of the human model in OCCS with respect to apply it to HRA/PSA practice. The model did not consider the deductive and abductive reasoning required in high-level cognitive activities, and it did not give the explicit description about the computerized model of knowledge database. The model did not reflect the inherent diversity and variety in human behaviors, which are important with respect to evaluating human reliability.

On the other hand, SEAMAID is developed by MITSUBISHI Electric Corporation to support MMI design of NPP system. The human model in SEAMAID only simulate the response operation activities that are described in detail by the operation procedures in advance. The primary drawback of SEAMAID is that SEAMAID does not consider the operator's thinking process to diagnose abnormal transients where no prescribed operation procedures are available.

With respect to clarifying the mechanism of human errors by the human modeling approach, SYBORG [12, 13] (Simulation System for the Behavior of an Operator Group) and JACOS [14] (JAERI Cognitive Simulation System) are developed by Human Factors Research Center of CRIEPI (Central Research Institute for Electric Power Industry) and Human Factors Research Laboratory of JAERI (Japan Atomic Energy Research Institute), respectively. SYBORG focused on the thinking process of the individual opeartor and the formation of the operation crew's volition, in order to clarify human error mechanism. SYBORG has proposed various sub-models to achieve the objective, such as the human-human interface for crew communication behaviors, micro processing models and memory models for the thinking process of the individual operator. The validity of SYBORG has been verified by comparing the simulation results with the laboratory experiment using several students as the subjects [17]. However, SYBORG does not model the high-level decision-making behaviors in which the deductive and abductive reasoning are required.

The attention of JACOS is paid to the mechanism of short and long term memories of human information processing, where the blackboard architecture is utilized to model the short-term memory, while the long-term memory as two kinds of knowledge database consisting of "procedural knowledge" and "functional knowledge". The potential human errors in the cognitive information processing are considered from either the lack of necessary information, or the inappropriate information processing. Some scenarios have been utilized to verify whether or not JACOS's simulation would agree with the designed specification

[14]. However, the simulation results by JACOS have not been validated by conducting any operator experiment.

Based on these reviews, the subjects remaining in the human modeling approach are summarized as follows.

1. Modeling the inherent characteristics in human behaviors, such as the diversity and variety, learning-effect, forgetting-effect.
2. Modeling the knowledge-based behaviors such as decision-making, anomaly diagnosis before the response activities based on operation procedures.
3. Validation of the developed human mode.
4. Modeling of the operation crew's activities.
5. Application of the human model to the researches on human factors, such as supporting MMI design, human reliability analysis (HRA).

This thesis study is devoted to the researches on the all subjects listed above except for the subject 4 by modeling operator's high-level knowledge-based cognitive behaviors with highlighting the modeling mothods both for anomaly detection and diagnosis before the execution of the operation procedures.

1.3 Objective and Methodology

The objective of this thesis study is to develop a simulation system for analyzing and evaluating human high-level cognitive behaviors in case of an emergency in NPP. The objective can be divided into two sub-objectives; (i) develop and validate a human model to simulate operator's cognitive behaviors, and (ii) apply the human model to the practice of human reliability analysis (HRA).

The study therefore requires to resolve the following subjects.

- Modeling the operator's cognitive behaviors of detecting and diagnosing abnormal transients in case of an emergency.
- Modeling the inherent characteristics in human cognitive behaviors, such as diversity and variety.
- Conducting the simulation of the HSIs in real-time.

- Validating the human model
- Application of the human model to HRA practice

In order to achieve those subjects described above, the thesis study is conducted in three steps. Firstly, a small-scale laboratory experiment is conducted to examine how the operator behaves in case of an emergency in NPP. In the laboratory experiment, the operators are asked to detect and diagnose various abnormal transients. The common tendency and the individual characteristics of the cognitive behaviors would be examined by analyzing the experimental data. The experimental data and the analysis results would be utilized to develop and validate the human model in the succeeding steps of this study.

Next, a human model is developed to simulate the cognitive behaviors of detecting and diagnosing abnormal transients. A general human modeling framework [8] developed out of "fallible machine" model [18] is utilized to develop the human model. The framework is implemented into computers by applying the symbolic processing methods of AI technology. The analysis results of the laboratory experiment are applied to the framework. The human model will be validated by conducting inter-comparisons between the laboratory experimental data and the simulation results obtained from numerical experiments in which the developed human model is utilized.

As the third step of the thesis study, the developed human model is applied to HRA in NPP, in order to conduct a pilot study to estimate fundamental human error probability (HEP) parameters required for HRA not by large-scale experimental approach but by computer simulation. The current methodology for estimating the HEP parameters of human cognitive behaviors depends on the large-scale operator experiment having a number of problems described previously. The application of the human model is conducted to demonstrate the promising possibility that the computer simulation would be usable for obtaining the fundamental HEP parameters efficiently, in stead of conducting the large-scale experiment with the NPP training simulator.

The contents of this thesis study are constituted by five chapters and those of the subsequent chapters are summarized as follows.

Chapter 2 will describe the conduction of a small-scale laboratory experiment. The analysis results of the experimental data will show how the subjects actually monitor plant system, detect and diagnose abnormal transients.

Chapter 3 will describe the development of the human model. Based on a general human modeling framework, the human model will be developed to simulate the operators' behaviors of detecting and diagnosing abnormal transients in the laboratory experiment. Comparisons will be conducted between the simulation results and the experimental results to demonstrate the validity of the human model.

Chapter 4 will describe the application of the human model to estimate time reliability correlation required in HRA in NPP. The validity of the application will be demonstrated by inter-comparisons between the "time versus cognitive reliability" (TCR) curves obtained from the laboratory experiment and the ones derived by the means of conducting numerical experiments by the human model simulation.

In Chapter 5, the final chapter, the the findings of the thesis study will be summarized and the future subjects will be discussed.

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Chapter 2

A Laboratory Experiment on Studying Operator's Cognitive Behaviors at Man-Machine Interface and Its Data Analysis

In order to examine operators' behaviors in case of an emergency in NPP, a laboratory experiment is conducted. In this chapter, the detailed description of the experiments is given together with the analysis methods and analysis results of the experimental data.

2.1 Objective of the Experiment Study

In nuclear power plant (NPP), operators' activities include the routine monitoring tasks at regular situations, periodical maintenance, and decision-making and response operation in case of an emergency. Operators' activities in case of an emergency are very important with respect to the safety and reliability of the total NPP system. In the emergency, operators' activities can be divided into the following three steps.

- Step 1: Detect the abnormal transient.
- Step 2: Identify the root cause of the abnormal transient.
- Step 3: Operate appropriately based on the procedures to cope with the abnormal transient and to guarantee the safety of the system.

To analyze the operators' behaviors, step 1 and 2 are usually summarized together and called as "decision-making" phase. While, step 3 is called as "response operation" phase.

In "response operation" phase, operators' activities are required to follow the operation procedures. The response operation behaviors are therefore classified as rule-based behaviors by Rasmussen [1]. On the other hand, in "decision-making" phase, operators have to detect the anomaly, to collect various symptoms for judging what happened in the plant system, and to decide finally what operation procedures should be applied to the situation. Operators' behaviors in "decision-making" phase are cognitive behaviors that are more complicated compared with the rule-based behaviors in "response operation" phase. Moreover, since the appropriate response activities must be based on a correct decision made in "decision-making" phase, the operators' behaviors in "decision-making" phase are also very important with respect to the safety and reliability of the plant system.

2.1.1 Review on Operator Experiments

In order to examine operators' cognitive behaviors in case of an emergency in NPP, the conventional approach depends on large-scale operator experiments. The large-scale experiments require NPP simulator, real-size model of MMI (called as mockup) and skilled operators. One of the typical experimental studies is the operator reliability experiment (ORE) carried out by Electric Power Research Institute (EPRI) [2]. ORE was conducted for two objectives. One is to collect operator response and reliability data by using full-scale NPP simulators and actual operation crews. The other objective is to apply the experimental data to examine the validity of the human cognitive reliability correlation for use in human reliability analysis. The features of ORE are summarized as follows.

- The experimental data were collected from NPP simulators during routine operator re-qualification training sessions at two types of NPP systems (pressurized water reactor; PWR and boiling water reactor; BWR).
- The scenarios selected in ORE represent key sequences and important HSIs with respect to HRA studies.
- Trained observers collected the experimental data such as operation crew response time, errors, and various other human factors.
- Operators' feedback from post-session interviews was utilized to help understanding the causes of operators' actions.
- Statistical analysis of the experimental data was conducted to validate human cognitive reliability (HCR) correlation for operators' actions in control room.

The experimental results turned out that the human cognitive reliability (HCR) correlation is not fully supported by the experimental data. Consequently, a new correlation called as HCR/ORE is derived from the experimental data to describe the cognitive reliability of operators' actions classified by their cue-response characteristics.

In Japan, similar operator experiment studies were also conducted. Based on the collaboration of four electric power corporations [1], one corporation [2], and one national research institute [3], experimental data were collected from the performance of operation crews at the training center during the period of one and a half years. The experimental data were analyzed by statistical method to examine the affordable time before operators have to do response operation with respect to the safety of NPP [3]. The experimental results turn out that the maximum time taken to diagnose abnormal transients is within 5 minutes.

The major merit of the experimental approach is that it can provide valuable experimental data about the interactions between the operation crew and the plant system. In case of an emergency, the HSIs are very important with respect to the safety and reliability of plant system. Hence the analysis results of the experimental data could help to improve MMI design, to clarify the problems resulted from human factors, and to enhance the relability and safety of the plant system as a whole. However, as described in the preceding chapter, there are some problems by the large-scale experimental approach, with respect to the requirements for conducting the experiments and the limitation in the application of the experimental results.

2.1.2 Objective of Laboratory Experiment

In this thesis study, based on artificial intelligence (AI) and computer simulation technology, a new approach called as human modeling is proposed to simulate the interactions between the operators and the plant system at MMI. The total simulation system includes plant and MMI simulators, and a human model that can simulate the operators' behaviors in case of an emergency in NPP.

In case of an emergency, operators' behaviors can be categorized as "decision-making" and "response operation" phases, as described previously. The methodology is different for modeling operators' behaviors in the two phases because the characteristics of operators' be-

[1] Kansai, Shikoku, Hokkaido, and Kyushu Electric Power Corporation
[2] MITSUBISHI Heavy Industry
[3] Japan Atomic Research Institute

haviors in the two phases are different. Operators' behaviors in "response operations" phase are rule-based behaviors that are required to follow the operation procedures completely. Modeling the operation procedures properly can be therefore used to simulate operators' behaviors in "response operations". However, operators' activities in "decision-making" phase are cognitive behaviors that include detecting and diagnosing abnormal transients. It is quite difficult to model operators' cognitive behaviors because of the complex dynamic characteristics of plant system in the emergency and the versatile characteristics of human cognitive activities.

The attention of this thesis study is paid to the development of a human model that can simulate well operators' cognitive activities. A small-scale laboratory experiment was conducted to examine the cognitive behaviors and validate the human model. The objectives of the small-scale laboratory experiment are listed as follows.

- To examine how the operators actually monitor the plant system, detect and diagnose abnormal transients.
- To obtain necessary experimental data that reflect operators' cognitive behaviors for developing a human model in the next study step.

2.2 Laboratory Experiment and Data Processing

2.2.1 Methods of Laboratory Experiment

The experimental methods are described in this subsection. The conduction of the laboratory experiment is different from the conventional large-scale experiments since the development of a human model is the fundamental objective of the experiment.

In the experiments like ORE, the study focused on examining the performance of an operation crew consisting of three persons typically in Japan. One of them is the shift-supervisor who is responsible for activities of the operation crew. The other two operators are responsible for monitoring and operating the primary and secondary plant system, respectively. In case of an emergency, the shift-supervisor judges what has happened in the plant system and decides how to cope with the situation with the collaboration from the two other operators. Thus, the cognitive behaviors of the supervisor are very important in examining the activities of the operation crew. The attention in this thesis study is concentrated on modeling the cognitive activities of the shift-supervisor. The laboratory experiment was conducted to examine how a shift-supervisor detects and diagnoses abnormal transients.

The following things were considered with respect to conduct the laboratory experiment.

- To achieve the objective of developing a human model, the abnormal transients utilized in the laboratory experiments should be selected so that the scenarios represent the typical cognitive behaviors of the shift-supervisor.
- The laboratory experiments only examine shift-supervisor's activities in "decision-making" phase. The response operation is beyond the scope of the laboratory experiment.
- External activities of the operator should be recorded exactly for the later analysis, such as MMI operation.
- The interview approach should be applied to examine the causes of the external activities.
- The behaviors of a number of different subjects should be examined with respect to diagnosing the same abnormal transient, in order to study the inherent diversity in human behaviors.

Table 2.1: Participants

Subjects	Age	Work Experiences in PWR-type NPP	Experiences with PWR-type NPP Simulator
I	33	Basic design of PWR-type NPP and development of advanced MMI	Trained with full scale PWR-type NPP simulator
A	33	Same as Subject I	Same as Subject I
T	37	Design of central control board and development of computer system for PWR-type NPP	Design and construct full scale and simple PWR-type NPP simulator

- A number of experimental trials should be conducted for the same subject in order to study the inherent variety in human behaviors.
- A limitation should be put on the number of the experimental trials in which the identical subject diagnoses the same abnormal transient, in order to avoid the learning effect.
- Experimental results should be applied to the human modeling easily.

The laboratory experiment is conducted based on these standpoints. The detailed description about the experiment conduction and the experimental data processing will be given in the following subsections.

2.2.2 Contents and Subjects

In the laboratory experiment, a subject was asked to monitor the simulated status of a pressurized water reactor (PWR) type NPP by operating a MMI that presents plant status onto a computer display. After experimenters introduce an abnormal transient into the plant simulator, the subject was asked to detect the abnormal transient and then to find out its root cause based on the plant status information provided by the MMI.

Three subjects participated in this experiment and they are designated as "Subject I", "Subject A", and "Subject T" here. Table 2.1 gives the detailed descriptions about each subject. Most of the subjects are not real operators of NPP, but they either had engaged in designing the control system and the simulator of NPP for training, or had the

Table 2.2: Abnormal transients emulated in the laboratory experiment

Abbreviation	Abnormal Transient	Explanation
SGTR	Steam Generator Tube Rupture	Due to the rupture in heat-exchange tubes of Steam Generator, the radioactive water in primary system flows into the secondary system.
LOCA	Loss of Coolant Accident (small and middle scale)	Due to the leakage of coolant in primary system, the radioactive water flows into containment vessel.
FW.Fl.Sen.F	Feed Water Flow Sensor Failure	Because of a failure of the sensor instrument, the water level presented by feed water flow sensors is higher than actual one, automatic control systems start working to decrease the feed water level.
FW.Cont.V.F	Feed Water Control Valve Failure (stuck open)	Since the control valve of the feed water stuck in the position where the feed water flow is smaller than that in normal state, the water level of Steam Generator is decreasing.
PRZ.Prs.Cont.F.Low	Pressurizer Pressure Controller Failure (fail low)	Due to the failure in the pressurizer pressure control circuit, the input signal of pressure controller, called as the compensatory pressure, is smaller than normal one in steady state, automatic control systems start working to increase the pressurizer pressure.
PRZ.Prs.Cont.F.High	Pressurizer Pressure Controller Failure (fail high)	This is just the reverse case of the above abnormal transient.
PRZ.Spray.V.F	Pressurizer Spray Valve Failure (big and small scale)	Since the pressurizer spray valve opened unexpectedly, the pressurizer pressure is decreased.
NIS.F	Power range NIS failure	Since a failed sensor of neutron flux indicates a lower value than that in steady state, automatic control systems start working to pull out the control rod in order to keep power output of the reactor.
PRZ.Lvl.Cont.F.High	Pressurizer Water Level Controller Failure (fail high)	Because of a failure in the pressurizer water level control circuit, the input signal of water level controller is bigger than the normal one, automatic control systems start working to increase the water level into primary coolant system.
PRZ.Lvl.Cont.F.Low	Pressurizer Water Level Controller Failure (fail low)	This is just the reverse case of the above abnormal transient.

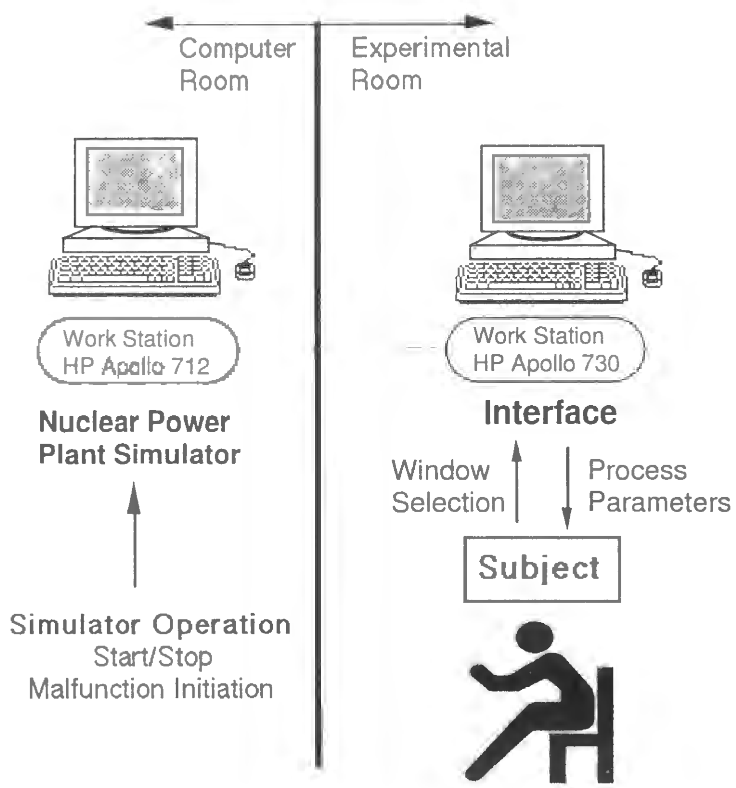


Figure 2.1: Configuration of laboratory experiment

experience of being an instructor in an operator-training center for PWR type NPP. Their behaviors in the experiment are therefore considered very similar to real operators of NPP. The activities of the three subjects observed in the laboratory experiment were analyzed in detail to study the internal cognitive behaviors of how they really monitor the plant system, and how they detect and diagnose abnormal transients.

In this laboratory experiment, twelve kinds of abnormal transients were selected as the diagnosis tasks to examine operators' internal cognitive behaviors. The abbreviations and detailed description of the abnormal transients are listed in Table 2.2. Among such abnormal transients, "SGTR" and "RCS leakage" are very important accidents with respect to the safety and reliability of a PWR-type NPP, the subjects have enough experiences in coping with them. It has expected that the subjects would find out the root cause of the two abnormal transients easily by applying the experiences. The rest abnormal transients are the transients caused by the failures in plant control system. To find out the root cause of the abnormal transients, the subjects have to apply his knowledge concerning the plant control system to examine the probability of various hypotheses. The final decision

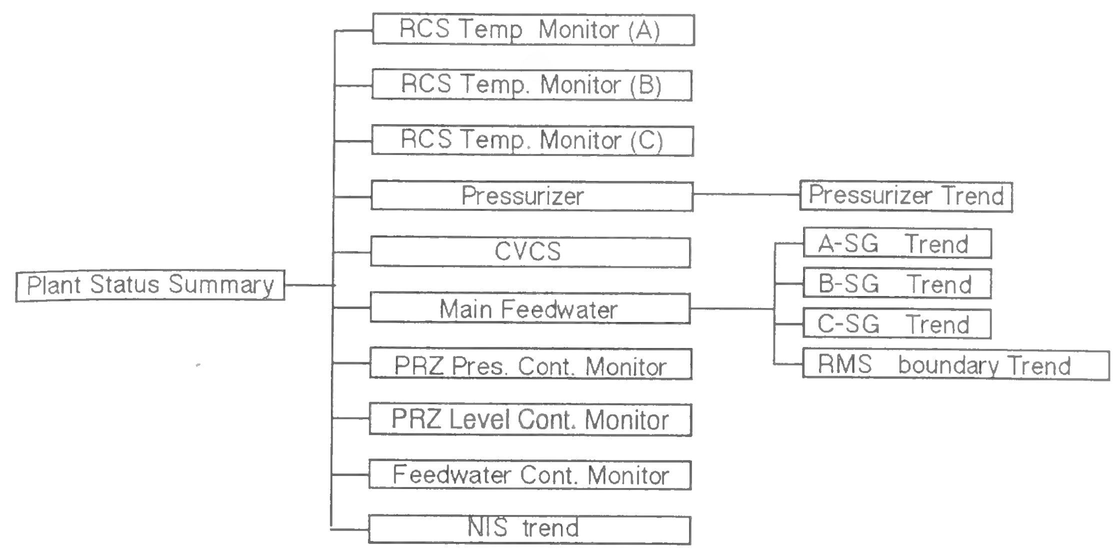


Figure 2.2: Hierarchical structure of man-machine interface

could be made on what had happened in the plant system by verifying and examining each hypothesis. The diagnosis tasks of finding the root cause of these abnormal transients are also selected intentionally since all of the activities are operators' internal cognitive behaviors.

2.2.3 Configuration of the Laboratory Experiment

Figure 2.1 shows the overall configuration of the laboratory experiment. Two engineering workstations were utilized in the experiment. On the workstation placed in the computer room, a real-time PWR type NPP simulator was utilized to simulate the status of NPP both at steady and anomaly situations. On the other workstation placed in the experimental room, a MMI of NPP is presented to subjects for providing the information about plant status that is obtained from the plant simulator.

The plant simulator utilized in the laboratory experiment is developed by MITSUBISHI Electric Corporation [4]. It has the ability to simulate the dynamic characteristics of a 3-loop PWR plant system in real time for both steady state and anomaly situations.

The MMI utilized in the laboratory experiment is a simple one designed by referring to the second generation MMI of NPP, in which cathode-ray tube (CRT) display is utilized as a subsidiary tool for providing information about plant prameters to operators. The MMI is called as CRT-based interface in this thesis. The configuration and features of the CRT-based interface are described in detail as follows.

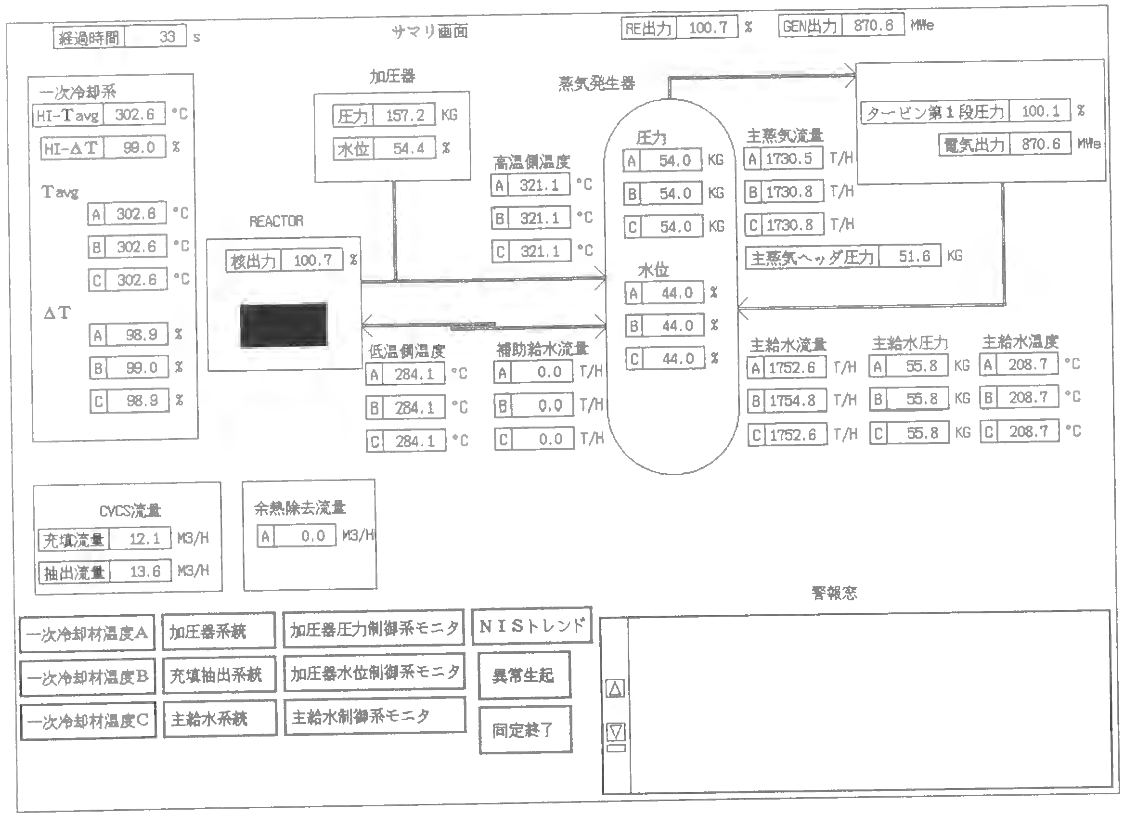


Figure 2.3: Plant status summary window

The CRT-based interface is developed as a graphical user interface in the X-window environment on the UNIX operation system. It consists of 16 interface windows and has a hierarchical organization as shown in Figure 2.2. The pictures of all interface windows are listed in Appendix A. As an example, the picture of "Plant Status Summary" window is shown in Figure 2.3 to give a simple mimic diagram of the overall plant configuration .

On the CRT-based interface, plant parameters' values are presented in a format of digital numbers. The numbers are shown in a frame around the mimic representation of the correspondent plant instrument. Besides "Plant Status Summary" window, there are 15 interface windows designed for showing the detailed information about sub-systems of plant, such as Pressurizer Pressure System, Pressurizer Water Level System, Feed Water System. On these interface windows, the mimic representation of the plant sub-system and/or trend graphs of a number of important parameters are shown in the same way as the CRT display utilized in the actual plant control room. Subjects can switch to these interface windows for obtaining detailed information by pushing the buttons that are located at the left-bottom of "Plant Status Summary" window.

Table 2.3: Alarm messages utilized in the laboratory experiment

Alarm Messages
"SG-Level < Steam Flow "
"SG-Level > Steam Flow "
SG-Level Big Deviation
Tavg Low
PRZ. Pressure High
PRZ. Compensation Pressure High
PRZ Pressure Low
PRZ Pressure Low First out alarm
PRZ Relief Valve Action
PRZ Level Low
PRZ Level High
A-Loop-Tavg Big Deviation
B-Loop-Tavg Big Deviation
C-Loop-Tavg Big Deviation
Neutron Flux Changing Rate(+) High
Neutron Flux Changing Rate(-) High

An alarm sub-window is designed for showing plant alarm messages at the right-bottom of all 16 interface windows. Rather than the large numbers of alarm messages in the actual NPP, only few alarm messages are utilized in the laboratory experiment as shown in Table 2.3. Moreover, no alarm sound and no alarm messages that guide subjects directly to find out the root cause of an abnormal transient were utilized intentionally in this laboratory experiment. All the settings for the alarm messages aimed at examining how the subjects detect the abnormal transient by themselves. It means that rather than depending on alarms in the actual NPP operation, subjects had to detect an abnormal transient almost by themselves through checking the changes in parameter values. By examining subjects' parameter reference activities and the personal biases about focused parameters, the efforts are made to obtain the experimental data concerning the judgement on the occurrence of abnormal transients.

In addition, the CRT-based interface has the capability to record the operation activities of subjects in real time during the experiments. Since subject's operation information demonstrates the procedures of how a subject detects and diagnoses an abnormal transient, the detailed information about the operation activities of the subject should be recorded for the later experimental data analysis, such as at what time, on which interface window and to what parameter a subject referred during each simulation trial. The feature of the CRT-based interface is that it can record the information automatically in real time. In another experimental study conducted by K.Furuta in 1996 [5], the methodology for recording subject's operation information was relied on video recording. The subjects' behaviors were estimated by tracking the mouse point movement recorded by a video recorder. The method is not accurate since the parameter focused on by the subject cannot be estimated exactly. The function of the CRT-based interface has been expanded so that subjects' MMI operation can be recorded automatically and exactly in real time. All of CRT-based interface operations are performed by moving or clicking the mouse input device in this laboratory experiment. Hence the best and simplest method to obtain the MMI operation information is to record the position of the mouse pointer. In accordance with the recording method, the subject was asked to move the mouse pointer onto the frame corresponding to the parameter he wants to check. The detailed description and discussion on the expanded function of the CRT-based interface are given in Appendix B for reference.

In addition, although the subjects can operate MMI to access parameter status information, they cannot make any active operations on the plant. The function for operating the plant is not implemented into the MMI, such as starting safety system or manipulating control system. Such settings are based on the simple consideration that the operator should not make active response operations before he finds out the root cause of the abnormal transient.

2.2.4 Procedures of the Laboratory Experiment

In the laboratory experiment, a simulation trial is conducted by the procedures shown below;

1. to initiate the plant simulator to simulate the normal steady status of NPP
2. to start up the CRT-based interface for presenting plant state to subject.
3. to ask the subject to monitor the NPP system through operating the CRT-based interface to find out whether or not there is an abnormal deviation from the steady state.
4. to introduce an abnormal transient into plant simulator within 100 seconds after starting.
5. when the subject recognizes an abnormal deviation from the steady state, he is asked to push "Anomaly Detected" button located on each interface window.

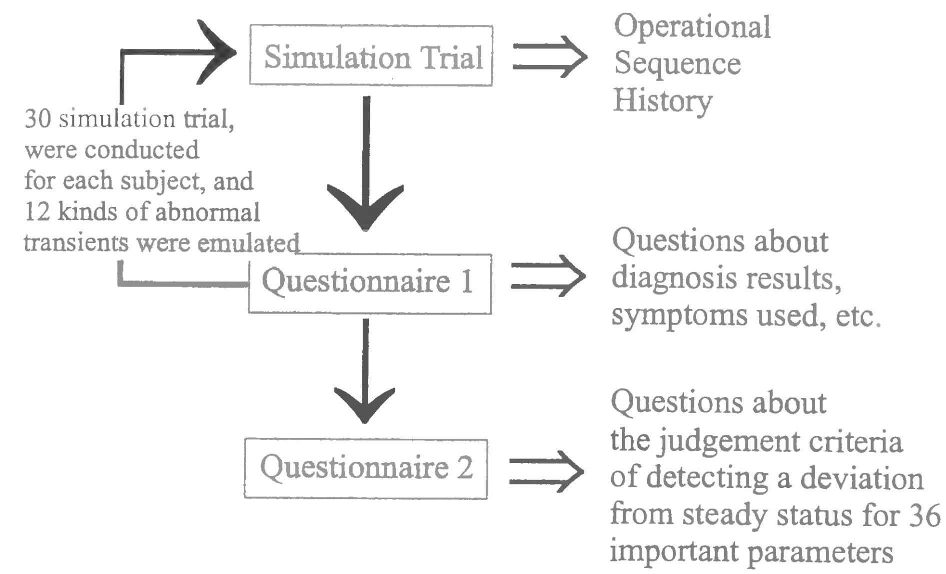


Figure 2.4: Experimental data collection

6. the subject is asked to find out the root cause of the abnormal transient by referring to various plant parameters through operating the CRT-based interface.
7. when the subject thinks that he find out the root cause, he is asked to push "Cause Identified " button located on each interface window.
8. a simulation trial ends when a subject pushes "Cause Identified " button or when 300 seconds of maximum allowed time for one simulation trial expire.

The simulation trial is conducted for each subject more than twice. Total 30 simulation trials were conducted for each of "Subject I", "Subject A" and "Subject T" across the period of two days.

2.2.5 Experimental Data and Data Processing

One objective of this laboratory experiment is to obtain the necessary data for developing a human model that can simulate operators' cognitive behaviors in an emergency in NPP. In this subsection, the data collection procedures, the obtained experimental data, and the data processing methodology are described.

The experimental data are collected by recording subjects' external activities (MMI operations) in the experiments and by interviewing with subjects for the causes of the

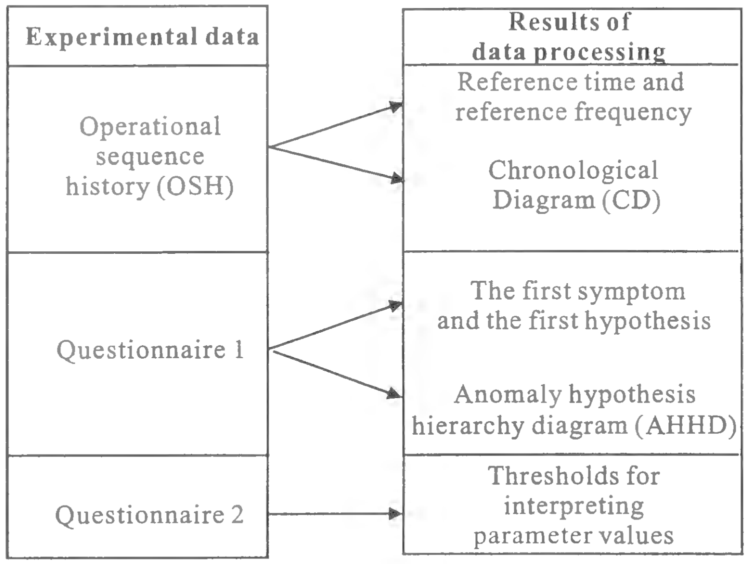


Figure 2.5: Experimental data processing

external activities. Figure 2.4 shows the procedure for collecting the experimental data. The data processing results are shown in Figure 2.5.

Data Collection Procedures

Two kinds of experimental data were collected from this laboratory experiment. One is the operation information of the CRT-based interface recorded automatically in each simulation trial. The other experimental data are the answers to the questions given to subjects in interviews, as shown in Figure 2.4.

For each abnormal transient, 30 simulation trials were conducted for each subject. In each simulation trial, the subjects' operation sequence history (OSH) was automatically recorded by the CRT-based interface. After each simulation trial, a questionnaire sheet was given to the subject for examining how he found out the root cause of the abnormal transient (see Figure 2.11). The questionnaire is called in this thesis as "Questionnaire 1". Questions about the just finished simulation trial are given to subjects in the questionnaire, such as the diagnosis result and the confidence on the result, the observed symptoms supporting the result and their relative important index, and other hypotheses considered in the trial. And after the total 30 trials were over, another questionnaire sheet was given to the subject for examining how he detected an abnormal transient (see Figure 2.13). The questionnaire is called in this thesis as "Questionnaire 2", in which subjects are asked to give the high-

Table 2.4: Operation sequence history

Time (sec.)	Operation Record	Explanation
24	C-Hot	
25	focused until now	
26	A-Hot	
27	focused until now	
29	A-FW	
29	focused until now	
33	B-Cold	
33	focused until now	
34	Reactor Output	
36	focused until now	
37	M143 Malfunction Start	FW.Fl.Sen.F was introduced into the simulator
39	B-FW	
39	focused until now	
40	A-FW	
40	focused until now	
44	detected	The abnormal transient was detected
70	A-FW	
72	focused until now	
73	A-SG-Lvl	
74	focused until now	
74	A-FW	
77	focused until now	
83	Main Feed Water Screen	
86	A-SG Trend Screen	
87	Trend Graph	
92	focused until now	
93	Trend Graph	
108	focused until now	
110	end	The root cause was found out

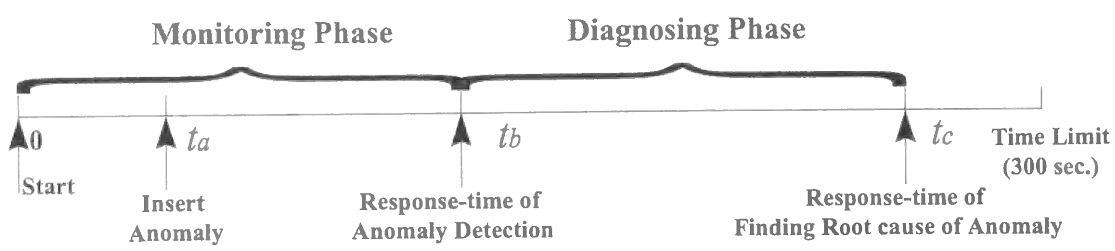


Figure 2.6: Monitoring phase and diagnosing phase

and low-thresholds of parameter values for judging an abnormal deviation.

The detailed contents, data processing methods and the results are described orderly with respect to the obtained experimental data; OSH, "Questionnaire 1" and "Questionnaire 2".

Operation Sequence History (OSH)

As an example of an original OSH recorded by the CRT-based interface, table 2.4 shows the operation history of "Subject I" in a simulation trial of diagnosing "RCS leakage". The left column of the table represents the timing when the subject operates the CRT-based interface by moving or clicking the mouse device. The corresponding interface operation is shown in the middle column.

Since OSH represents the history of the subjects' external activities, the analysis of the OSH is expected to obtain the information about how subjects were monitoring NPP system, by what symptom subjects detected the abnormal transient, how subjects identified the root cause of the abnormal transient and so on. The information is very useful with respect to developing a human model in the next study step.

With respect to the data processing of OSH, it is divided into two phases by the time when the subject pushed "Anomaly Detected" button, as shown in Figure 2.6.

- Monitoring phase (MP): Time span from the beginning of a simulation trial until the subject detected an abnormal transient.
- Diagnosing phase (DP): Time span after the detection of the abnormal transient until the subject found out the root cause.

In MP, subjects monitor the status of the plant system by checking the values of various plant parameters. On the other hand, subjects collect various symptoms actively for identifying the root cause of the abnormal transient in DP. The separation of the two phases is

therefore necessary to examine the different characteristics of subjects' cognitive behaviors in the two phases. In the experimental studies such as ORE, the exact separation of the two phases is difficult since it is made by the subjective judgement of trained observers. In this laboratory experiment, it can be made exactly and easily because the subjects push "Anomaly Detected" button by himself when he detects an abnormal symptom.

Corresponding to MP and DP, the data processing of OSH is then conducted separately. The OSH in MP is analyzed to clarify how subjects monitor the plant system by examining how long and how often subjects conduct the reference of plant parameters. The other data processing is made to help understanding subjects' diagnosis process in DP by transfiguring OSH into a chronological diagram (CD). These two methods of data processing are described in detail as follows.

Monitoring strategy: reference time and frequency

In the laboratory experiment, it has been assumed that parameter reference behaviors of each subject in MP have a certain unchanging tendency throughout all simulation trials. It is because subjects did not know in advance when and what transient would happen throughout all simulation trials where different abnormal transients were simulated by the plant simulator. The tendency of the monitoring activities represents subjects' knowledge and experiences with respect to monitoring tasks, such as which plant sub-system should be paid attention to more than others, which parameters should be checked more frequently than others. In this thesis study, the characteristics of subject's parameter reference activities are defined as his "monitoring strategy".

In order to clarify the "monitoring strategy", cumulative reference time (how long) and cumulative reference number of times (how often) are calculated for the individual plant parameters checked by each subject in MP throughout all simulation trials. The calculated results of "Subject I", "Subject A" and "Subject T" are shown in the figures 2.7, 2.8, and 2.9, respectively. Furthermore, the parameters checked by subjects in MP were classified into the following six groups in accordance with the sub-systems composing the plant system.

- parameters related to reactor
- parameters related to pressurizer (PRZ)
- parameters related to chemical volume control system (CVCS)

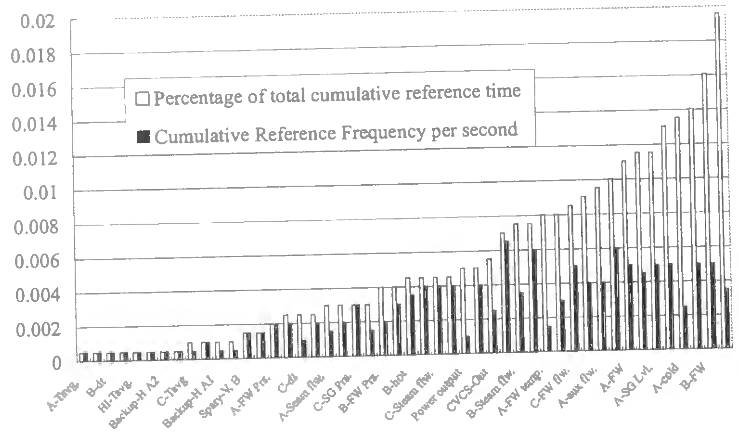


Figure 2.7: Reference time and reference frequency ("Subject I")

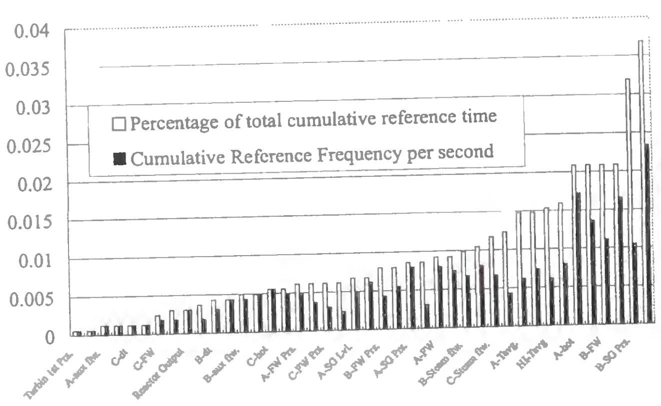


Figure 2.8: Reference time and reference frequency ("Subject A")

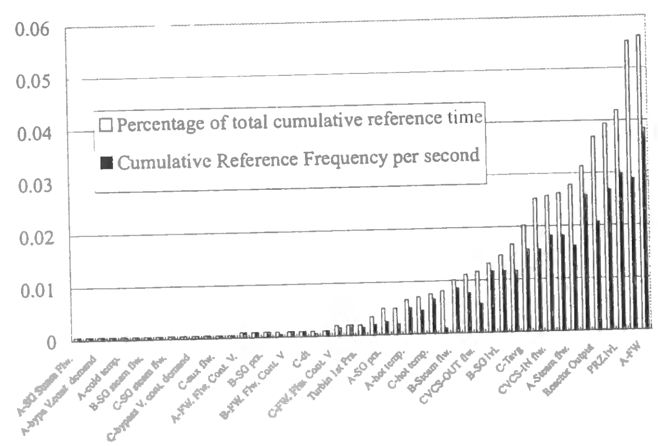


Figure 2.9: Reference time and reference frequency ("Subject T")

- parameters related to steam generator (SG)
- parameters related to turbine
- other parameters

Each subject's direction of attention on some specific plant subsystem can be then clarified by combining the classification of plant parameters with the analysis results of the reference time and frequency of individual plant parameters. The detailed analysis results are described in next section.

Chronological Diagram

The second data processing for OSH is to visualize it so that the subjects' behaviors, especially the behaviors in DP, can be understood and analyzed easily. For each simulation trial, one chronological diagram (CD) is drawn as shown in Figure 2.10. The horizontal axis of CD represents the elapsed time. The bottom part of CD shows the information about at what time, on which interface window, the subject monitored the status of the plant. The names of 16 interface windows are listed on the vertical axis in the bottom part of CD. On the other hand, the top part of CD shows the information about at what time, subject checked what concrete plant parameter. The names of the plant parameters checked by subjects are listed on the vertical axis in the top part of CD. The black or gray painted parts at both top and bottom of CD represent how long the subject continue looking at the plant parameter on the interface window.

Subjects' diagnostic process can be traced chronologically by the representation of CD. Combined with the answers to the questions in "Questionnaires 1" after each simulation trial, CD is utilized to clarify the detailed diagnosis process of each subject. A detailed analysis example is described in the next section.

Answers to "Questionnaires 1"

After each simulation trial, an interview with the subject was conducted to examine the just finished anomaly diagnosis. A questionnaires sheet is given to the subject in the interview. Figure 2.11 shows an example of the sheet. The questions given to subjects are listed as follows;

1. diagnosis result and the degree of subject's belief on it,

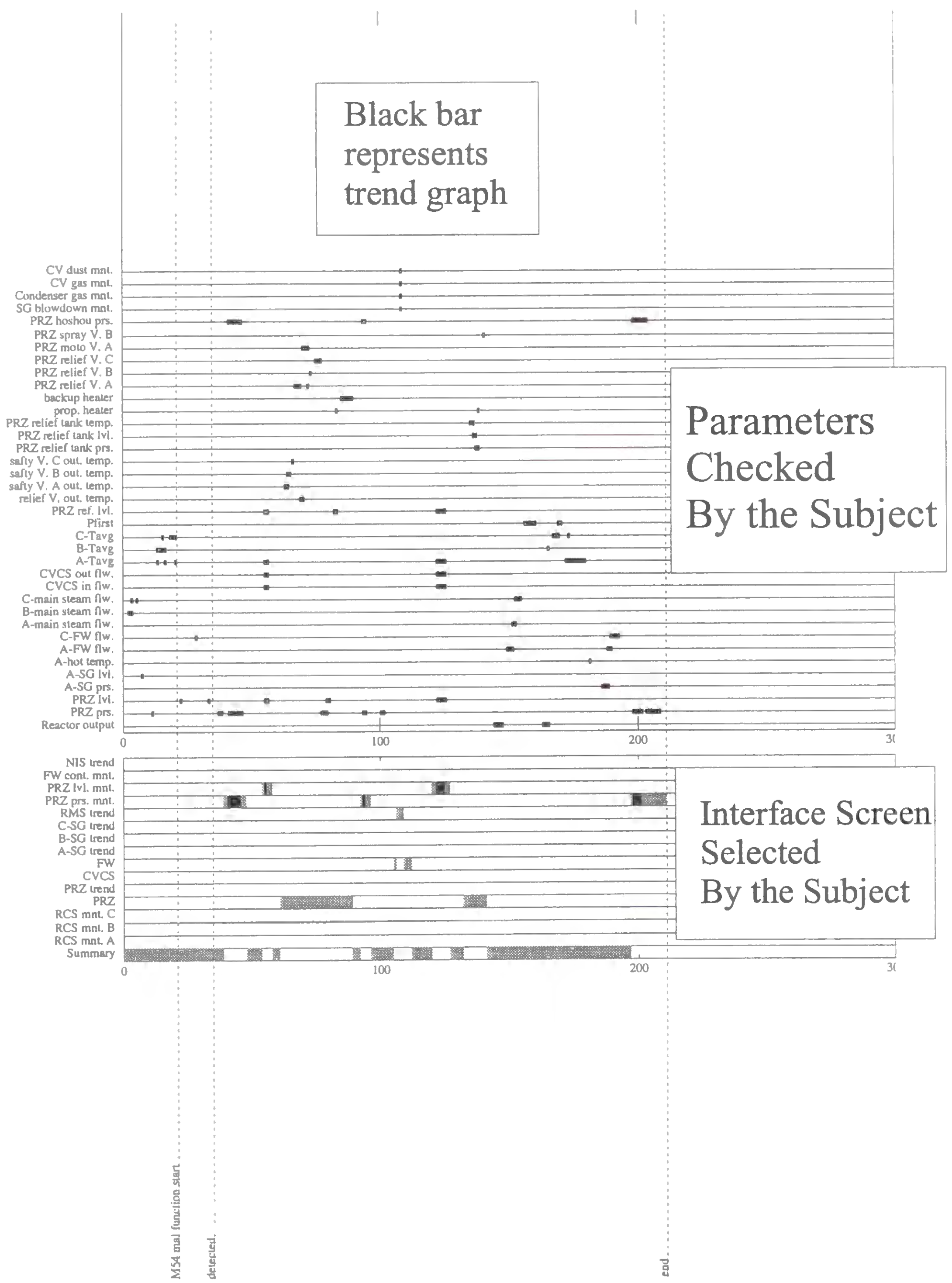
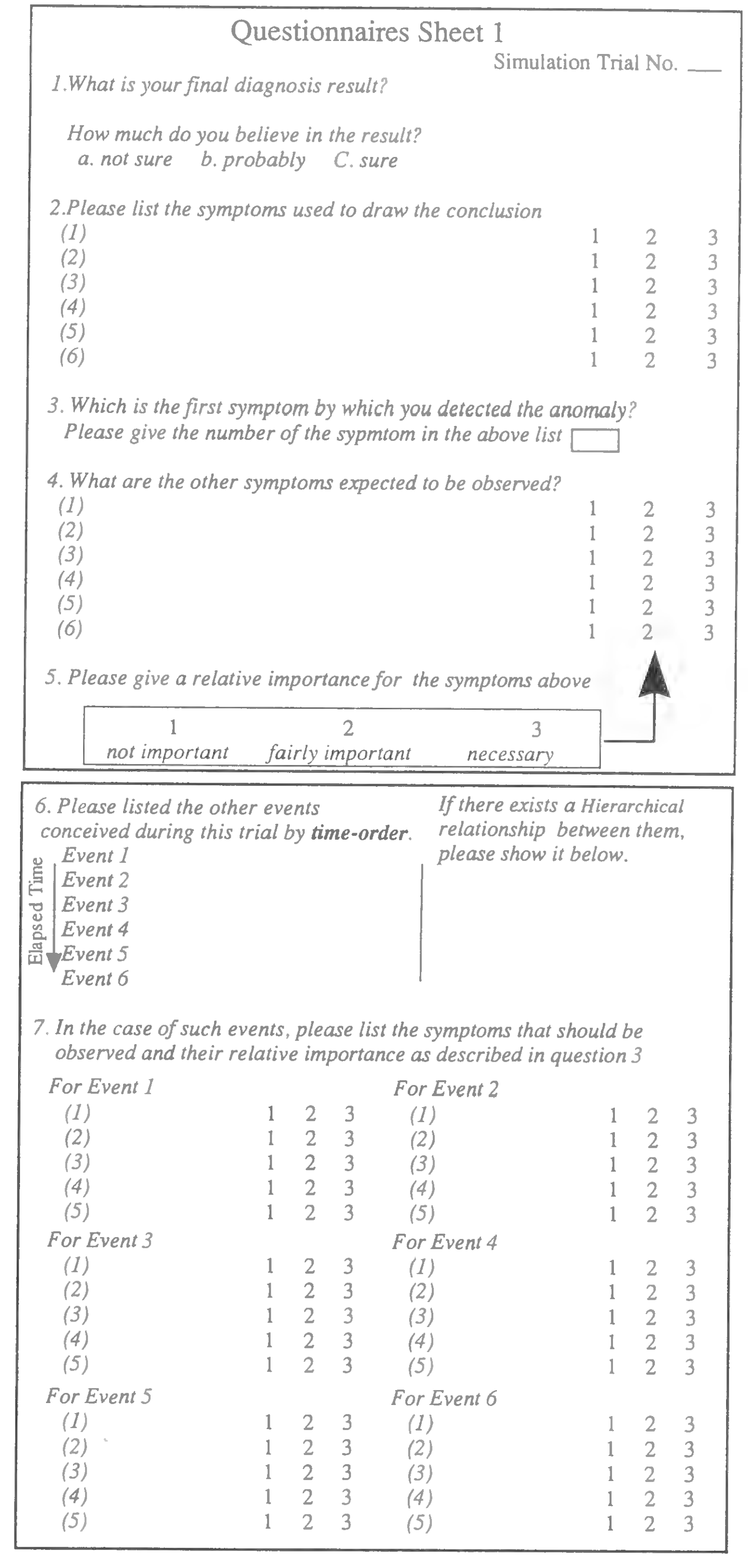


Figure 2.10: Chronological diagram (CD)



Questionnaires Sheet 1

Simulation Trial No. ___

1.What is your final diagnosis result?

How much do you believe in the result?
a. not sure b. probably C. sure

2.Please list the symptoms used to draw the conclusion

(1)	1	2	3
(2)	1	2	3
(3)	1	2	3
(4)	1	2	3
(5)	1	2	3
(6)	1	2	3

3. Which is the first symptom by which you detected the anomaly?
Please give the number of the sypmtom in the above list ☐

4. What are the other symptoms expected to be observed?

(1)	1	2	3
(2)	1	2	3
(3)	1	2	3
(4)	1	2	3
(5)	1	2	3
(6)	1	2	3

5. Please give a relative importance for the symptoms above

1	2	3
not important	*fairly important*	*necessary*

6. Please listed the other events conceived during this trial by ***time-order***.

Elapsed Time
Event 1
Event 2
Event 3
Event 4
Event 5
Event 6

If there exists a Hierarchical relationship between them, please show it below.

7. In the case of such events, please list the symptoms that should be observed and their relative importance as described in question 3

For Event 1				*For Event 2*			
(1)	1	2	3	(1)	1	2	3
(2)	1	2	3	(2)	1	2	3
(3)	1	2	3	(3)	1	2	3
(4)	1	2	3	(4)	1	2	3
(5)	1	2	3	(5)	1	2	3
For Event 3				*For Event 4*			
(1)	1	2	3	(1)	1	2	3
(2)	1	2	3	(2)	1	2	3
(3)	1	2	3	(3)	1	2	3
(4)	1	2	3	(4)	1	2	3
(5)	1	2	3	(5)	1	2	3
For Event 5				*For Event 6*			
(1)	1	2	3	(1)	1	2	3
(2)	1	2	3	(2)	1	2	3
(3)	1	2	3	(3)	1	2	3
(4)	1	2	3	(4)	1	2	3
(5)	1	2	3	(5)	1	2	3

Figure 2.11: Questionnaires sheet 1

2. observed symptoms that support his diagnosis result,
3. the symptom by which subject detected the anomaly first,
4. other symptoms that might have been observed if the above diagnosis would be assumed,
5. relative importance for each symptom in question 2 and 4 with respect to diagnosing the abnormal transients,
6. all hypotheses considered in time order during the simulation trial and the hierarchical relationship between them if there exists one, and
7. symptoms supporting hypotheses in the answers to question 6 and their relative importance.

Based on subjects' answers to the questions, the detailed information about the diagnosis process can be obtained for developing a human model that can simulate such human information processing. The necessary data for developing the human model are listed as follows.

- The first symptom, by which the subject detected the abnormal transient. It is substantially the answer to the question 3,
- The first hypothesis, by which the subject started the diagnosis tasks. It is contained in the answers to the question 6,
- The relationships among the hypotheses, by which subject considers new hypothesis after he rejects one. They are substantially the answers to the questions 5 and 6,
- The knowledge and experiences by which subjects examine each hypothesis. They are substantially the answers to the questions 2, 4, 5, and 7.

Based on CD and the answers to question 3 and 6, First-Symptom-First-Hypothesis patterns throughout all simulation trials are summarized in tables 2.5, 2.6, and 2.7 for each subject, respectively. The characteristics of initiating diagnosis tasks in the cases of each subject can be obtained by analyzing these tables.

With respect to the latter two kinds of necessary data for developing a human model, they are substantially the subjects' knowledge and experiences concerning plant operation

Table 2.5: First-Symptom-First-Hypothesis patterns of "Subject I"

Plant Parameters	First Symptom	First Hypothesis	Frequency	Samples
SG-LVL.	Big or Small	Feed Water System	4	No.8, No.26, No.4, No.19
PRZ.Prs.	Small	PRZ.Pressure control system	1	No.15
		RCS/SGTR	8	No.10, No.22, No.9, No.29, No.12, No.30, No.7, No.14
		Leakage in the Gas phase of PRZ.	1	No.21
	Big	Wrong pull of control rod	2	No.16, No.3
PRZ.Lvl.	Small	RCS	1	No.20
CVCS-IN	Big	RCS	5	No.1, No.23, No.25, No.11, No.24
	Small	PRZ.level control system	3	No.6, NO.17, No.28
Feed Water Level	Big	Feed Water Control System	2	No.2, No.18
Reactor Output	Big	NIS sensor error	1	No.5
		Wrong pull of control rod	2	No.13, No.27

Table 2.6: First-Symptom-First-Hypothesis patterns of "Subject A"

Plant Parameter	First Symptom	First Hypothesis	Frequency	Samples
PRZ.Prs.	Small/Big	PRZ.Pressure control system	14	No.1, No.3, No.5, , No.7, No9, No.10, No.12, No.14, No.16, No.21, No.25, No.26, No.29, No.30
Feed Water	Small	feed water system	1	No.4
CVCS-IN	Small/Big	PRZ.Level control system	7	No.6, No.8, No.11, No.17, No.20, No.24, No.28,
Main Steam Flow	Unbalance between 3-loop main steam flow	Failure of feed water sensor	1	No.18
	Big	Feed water control system	1	No.15
SG-Lvl.	Small	Feed water control system	1	No.19
PRZ.Lvl.	Big/Small	PRZ.Level control system	2	No.22, No.23,
Reactor output	Big	Wrong pull of control rod	2	No.13、No.27
Warning Messsage	Unbalance of feed water flow and steam flow	Feed water control system	1	No.2

Table 2.7: First-Symptom-First-Hypothesis patterns of "Subject T"

Plant Parameter	First Symptom	First Hypothesis	Frequency	Samples
CVCS-IN	Big	PRZ.level control system	2	No.26, NO.11
PRZ.Pressure	Big/Small	PRZ.pressure control system	15	NO.8, NO.15, No.10, No.22, No.20, No.25, No.14, No.7, No.30, No.21, No.12, No.23, No.29, No.3, No.16
	Small	RCS	1	No.9
	Big	Wrong pull of control rod	1	No.13
		PRZ.level control system	1	No.5
PRZ.Level	Big/Small	PRZ.level control system	5	No.1, No.28, No.17, No.24, No.6
Warning Message	Unbalance of feed water flow and	Feed Water system	2	No.2, No.18
Feed water flow	Small	Feed Water control system	2	No.4, No.19
Reactor output	Big	PRZ.pressure control system	1	No.27

and the natures of abnormal transients. A hierarchical structure is proposed to represent the organization of the knowledge and experiences in order to analyze subjects' anomaly diagnosis knowledge. The data processing for forming the hierarchical structure is described in detail as follows.

- First, for each subject and each abnormal transient, all of the hypotheses considered in the simulation trials were represented as a small hierarchical structure to describe their relationships in accordance with the answers to question 6.
- Then, for each subject, the diagnosis knowledge of all abnormal transients is obtained as a big hierarchical structure by summarizing the small hierarchical structures throughout all the abnormal transients.
- Finally, an integrated diagnosis knowledge of the three subjects is obtained by summarizing the diagnosis knowledge, as shown in Figure 2.12.

The structure is called here as anomaly hypothesis hierarchy diagram (AHHD) that represents the organization of subjects' knowledge and experiences for diagnosing abnormal transients. AHHD consists of two parts: knowledge about primary NPP system and knowledge about secondary NPP system, as shown in Figure 2.12. The former part is further divided into three knowledge branches shown below.

- knowledge branch for Primary System Coolant,
- knowledge branch for Primary System Control, and
- knowledge branch for Reactor Power Output.

In AHHD, the nodes in the upper level represent more abstract hypothesis such as "P.S. Controller Failure", while the nodes in lower level represent more concrete hypothesis such as "PRZ relief valve fails open", etc. Combined with CD, the hierarchical organization of subjects' knowledge and experiences is utilized to clarify the diagnosis process in detail for each subject in each simulation trial.

Answers to "Questionnaires 2"

In the laboratory experiment, subjects detect abnormal transients by noticing an abnormal deviation of parameter value from the steady status in most cases. However, the judgement

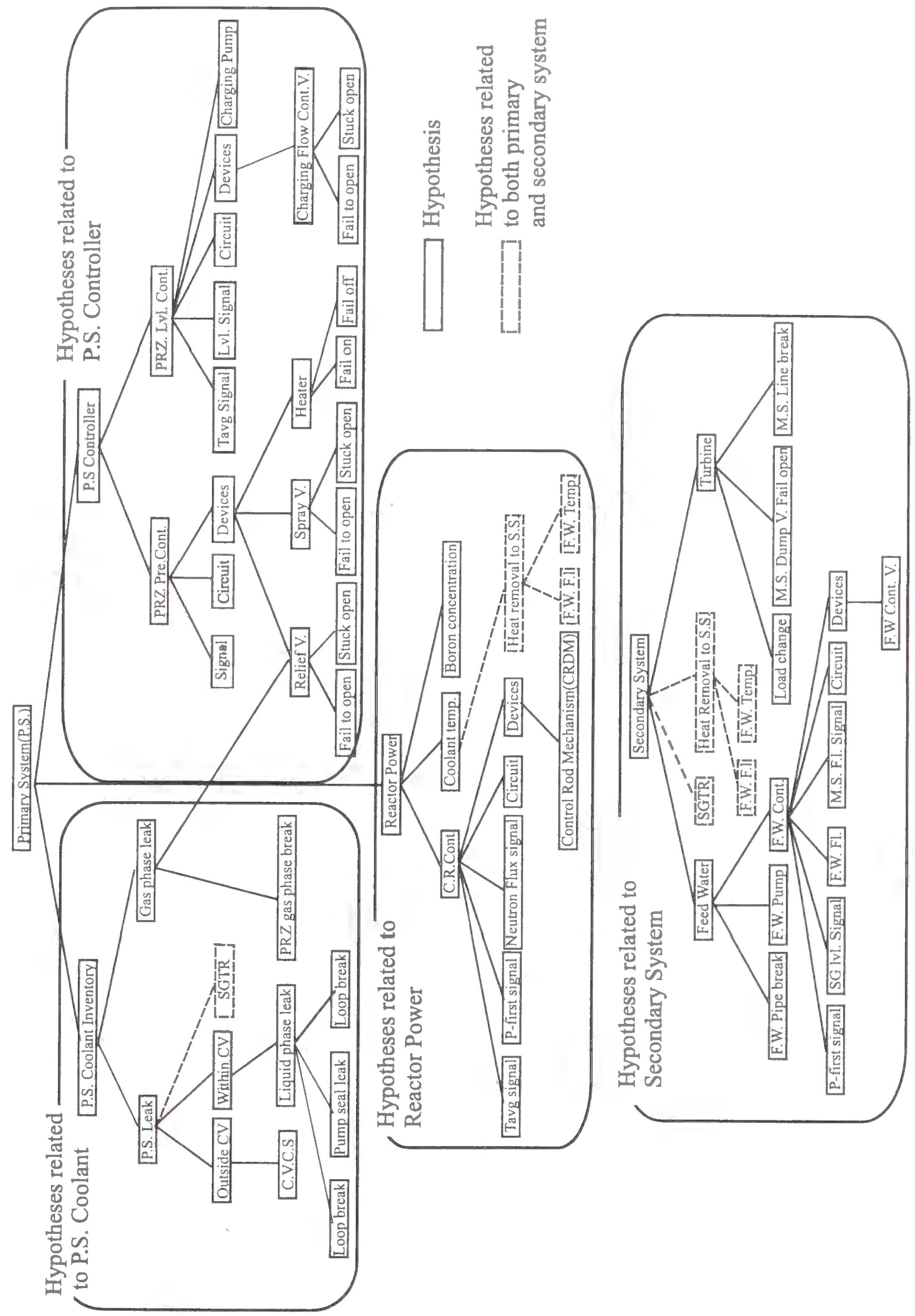


Figure 2.12: Anomaly hypothesis hierarchy diagram (AHHD)

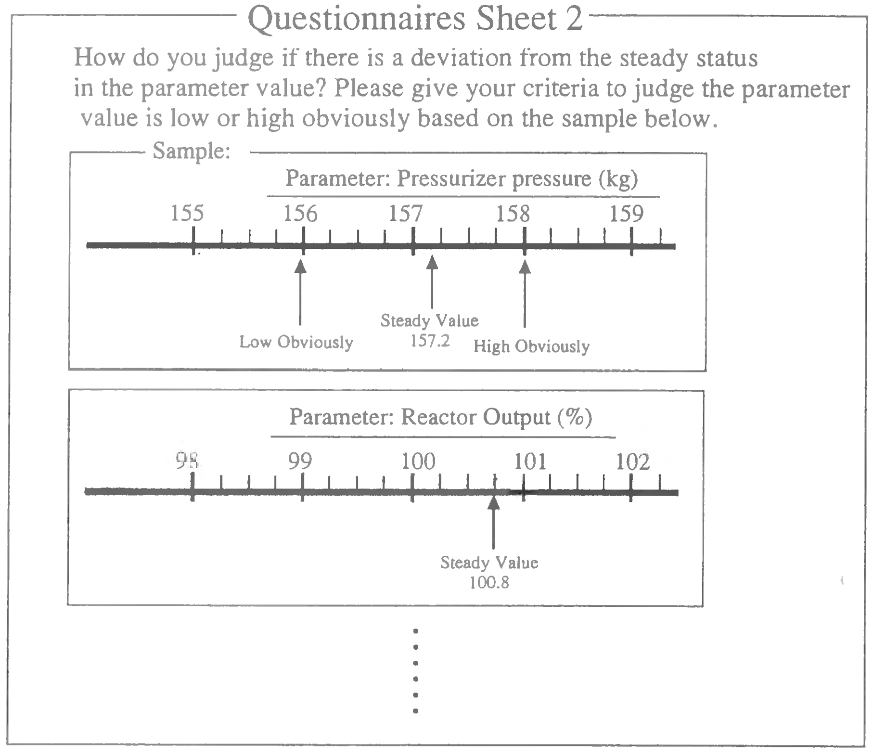


Figure 2.13: Questionnaires sheet 2

on the parameters' value is a kind of subjective behavior and is different from person to person since the parameter values fluctuate even in steady status of NPP system. The differences would exert influences on the anomaly detection time that directly influences the affordable time for diagnosing the abnormal transient. The subjective judgement is therefore important with respect to the human reliability and should be analyzed in detail.

Consequently, the "Questionnaires 2" is designed for the analysis. It was given to each subject after he finished the total 30 simulation trials. Figure 2.13 shows a part of "Questionnaires 2".

In the questionnaire sheet, total 36 parameters are selected as the indicators of the status of the five plant sub-systems (Pressurizer, Chemical Volume Control System, Reactor, Steam Generator, and Radioactive Monitoring System). For the 36 parameters, each subject was asked to give the high and low thresholds of the parameters value by which the subject feels the value is out of normal range and thus thinks something wrong in the system were required. These thresholds are subjective values for each subject and reflect individual characteristics of how strictly he monitors parameters' deviation.

Table 2.8: Threshold values to recognize deviation

+: Subject recognizes deviation less than 10% of steady state value
-: Subject recognizes deviation more than 50% of steady state value
*: Parameter not refered

	Subejct 1		Subject2		Subject3	
	Dec.	Inc.	Dec.	Inc	Dec.	Inc
PRZ pres.	+	+	+	+	+	+
PRZ level	-	+	+	+	+	
PRZ heater power						-
PRZ releif valve outlet temp.	*	-	*	-	-	-
PRZ spray valve open ratio	*		*	+	*	
PRZ relief tank temp.	*	-	Surge temp. used		-	-
PRZ relief tank level	*	-	Surge temp. used		-	-
PRZ relief tank pres.	*	-	Surge temp. used		-	-
Charging flow		+	+	+		
Letdown flow	+		PRZ Pres. used			
VCT level cont. valve open ratio	+		VCT level used			
VCT tank level	-	-	-	-	-	-
Charging flow cont.valve open ratio		+	Chargin flow used		+	+
Reproducible heat Ex.outlet temp.	+	+			+	+
Reactor Power	+	+	+	+	+	+
Generator output	+	+	+	+	+	+
Coldleg temp.	+	+	+	+	+	+
Hotleg temp.	+	+	+	+	+	+
Tavg.	+	+	+	+	+	+
HI-Tavg	+	+	+	+	+	+
HI-dT	+	+	*	*	+	+
dT	+	+	*	*	+	+
Power Range NIS	+	+	+	+	+	+
P first	+	+	+	+	+	+
Main steam flow		+	+	+	+	+
SG level	+	+	+	+	+	+
Main FW flow	+	+	+	+	+	+
SG pressure	+		+	+	+	+
Main FW temp.	+	+			+	+
Main FW pres.		+	*	*	+	+
Steam flow-FW deviation	-	-	-	-	-	-
Main steam header pres.	+	+	+	+	+	+
SG level deviation	+	+	SG level used		+	+
FW cont. valve open ratio		+	SG level used			
SG blowdown monitor	-	-	-	-	-	-
CV gas monitor	-	-	-	-	-	-

The answers obtained from "Questionnaires 2" are processed to clarify the criteria for judging the parameters' abnormal deviation. The data processing is made in two steps. Firstly, the 36 parameters were categorized into five groups to represent the five plant subsystems. Then, the threshold values of each plant parameter were analyzed by examining the deviation degree from the steady status. The analysis aims at examining how much severely the parameter was monitored by the subject.

Table 2.8 summarizes the thresholds of each parameter for three subjects. In the table, symbol "+" means that the subject recognizes anomaly at the deviation fewer than 10% of steady state value, symbol "-" means more than 50% of steady state value and no sign means in-between of those two criterions. Hence the parameters marked with "+" would be checked by the subject quite strictly. The detailed analysis results of each subject's characteristics are described in the next section.

2.3 Experimental Data Analyses

The experimental data analysis and the results are described in this section. With respect to developing a human model, the attentions of data analysis are concentrated on both the common tendency in the behaviors of all the subjects and the differences in the individual cases.

First of all, as the operators of NPP, there does exists a common tendency in their cognitive activities due to the standard education and training. The analysis of the common tendency could clarify the fundamental mechanism of the cognitive activities.

On the other hand, there are also individual characteristics in the cognitive behaviors due to the inherent diversity and variety in human activities. By analyzing the individual characteristics, the methods can be derived for modeling the diversity and the variety in the fundamental mechanism.

With respect to applying the analysis results to the development of the human model, the common tendency can be utilized to develop the modeling framework. The individual characteristics can be utilized to suggest how to adjust parameters in the modeling framework to simulate the diversity and variety.

From the foregoing viewpoints of data analysis, the following subsections give the description about the analysis of the subjects' behaviors in the experiments. The obtained analysis results are shown in Figure 2.14, together with their application to model the subjects' behaviors both in MP and DP.

2.3.1 Monitoring Strategy

As the results of the data processing of OSH in MP, the figures 2.7, 2.8, and 2.9 show the examination results of the reference time (how long) and reference number of times (how often). The "monitoring strategy" of each subject is then analyzed by classifying plant parameters into six groups and examining the reference time and reference frequency of each group. The analysis results are shown in the figures 2.15 and 2.16. For each subject, the reference time and the reference frequency for each parameter group are represented in the percentage to the total reference time and reference number of times in MP.

From the figures 2.15 and 2.16, one can find out that the scanning pattern of subjects has a common tendency that shows the first three ranks of reference time and frequency are "Steam Generator", "Reactor", "Pressurizer" with respect to the six parameters groups. There are two reasons for the tendency that parameters related to Steam Generator are

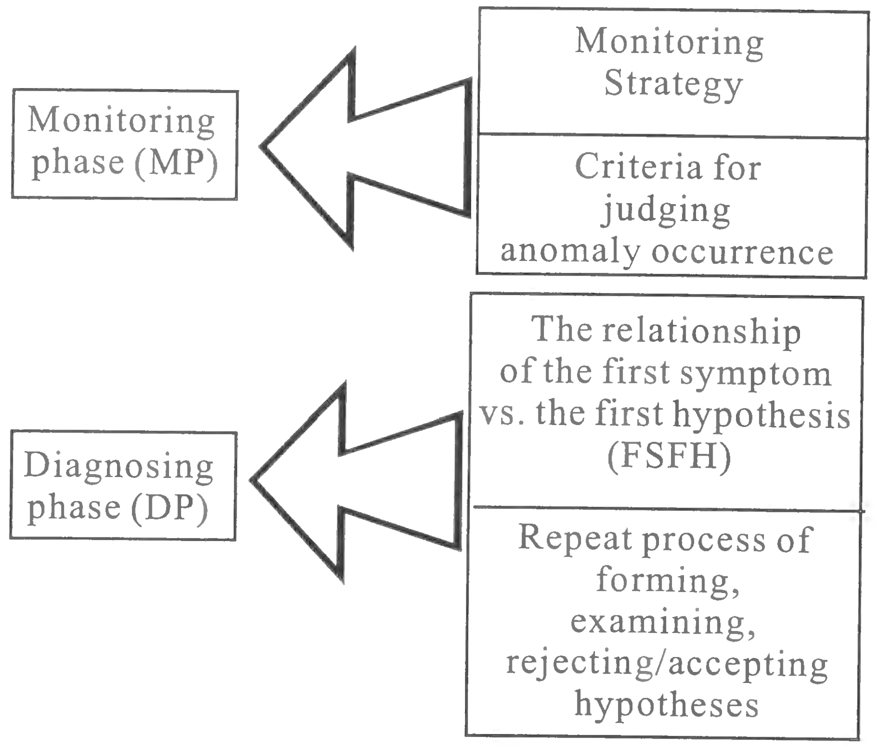


Figure 2.14: Experimental data analysis results

checked most frequently. One is because the anomalies resulted from the steam generator can evolve so quickly that reactor may reach a scram in a minute [4]. Therefore, the parameters in the parameter group of SG should be checked frequently. The other reason is because the steam generator is located between the primary and secondary system for exchanging heat. Thus, the anomaly resulted from SG will exert influence to both primary and secondary systems.

As for the differences of the individual "monitoring strategy", "Subject T" seems to check parameters most frequently, while "Subject I" least. "Subject A" paid more attention to the parameters related to reactor than other subjects. The tendency reflects that "Subject A" believed parameters related to "Reactor" are more important than others.

With respect to developing a human model that can simulate subjects' activities of monitoring plant system, the analysis results suggest that

- subjects' monitoring task can be modeled as a repeating process of checking param-

[4]Compared with the amount of the steam generated per unit time, there is no much affordable feed water. Therefore, if the feed water is stopped or decreased due to a certain anomaly, it will cause the reactor reaches a scram very quickly.

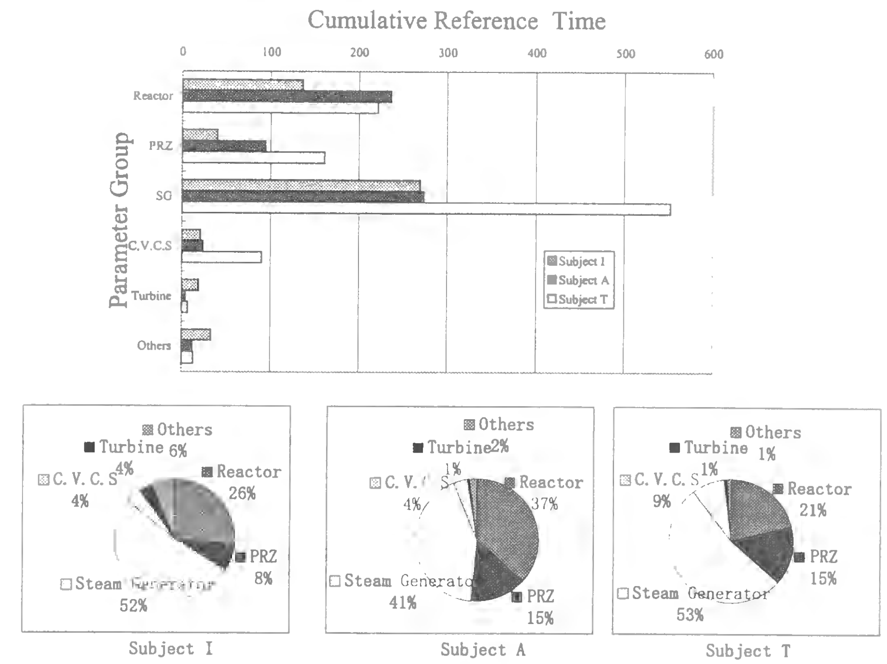


Figure 2.15: Reference time of each parameter group

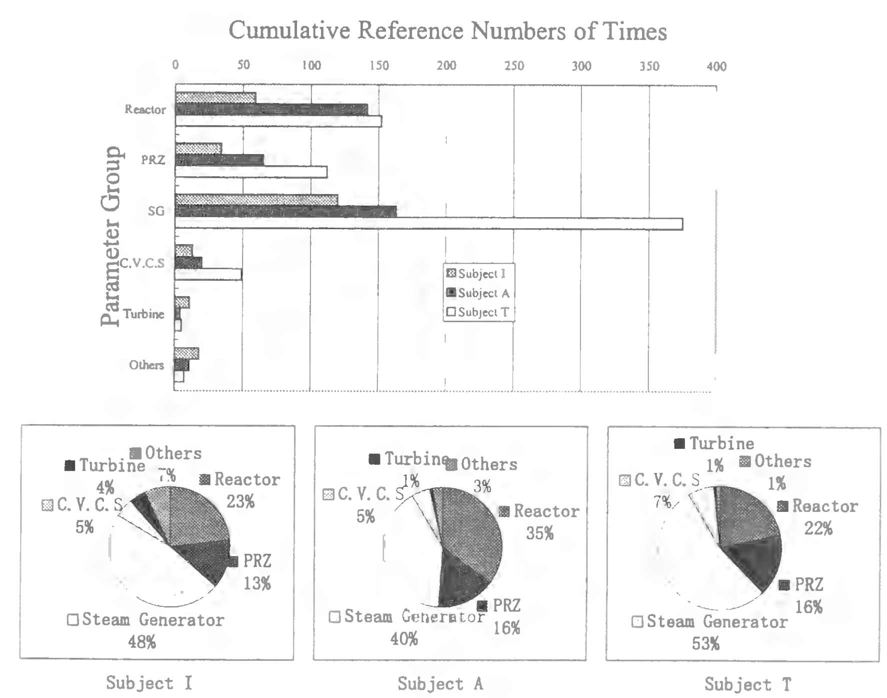


Figure 2.16: Reference frequency of each parameter group

eter value,

- what parameters should be checked can be selected from the 36 important plant parameters that represent the indicators of the status of the plant sub-systems,
- the classification of the parameters into groups can be utilized to model the "monitoring strategy",
- the individual characteristics in the "monitoring strategy" can be modeled by changing the checking frequency of each parameter group.

2.3.2 The Criteria for Judging Anomaly Occurrence

With respect to analyzing the deviation of parameter values shown in Table 2.8, the factors that could exert influences on the subjective judgement are listed as follows.

- The inherent variation of parameters' value. For an example, the parameters related to water level or steam flow always fluctuate even in the steady status. While, the parameters related to temperature are almost constant.
- The importance of parameters with respect to the safety of the plant system.

Based on the consideration, table 2.8 is analyzed to clarify the criteria for judging the occurrence of an abnormal transient.

The fact that parameters related to reactor were monitored most severely is found as a common tendency from the table. It is because reactor core is the most important part of all NPP system, and also because the values of the parameters in the group are almost constant at steady status. Thus, a minimal change of the parameters should be taken seriously.

As for the differences with respect to each subject, "Subject A" seems to check only a number of specific parameters instead of all 36 parameters. He checks the parameters more severely than other subjects do. Such characteristics are considered to reflect the level of subject's expertise that means he can monitor whole plant system by checking only few parameters.

Moreover, although subjects gave the thresholds for judging the abnormal deviation of parameter values, there did exist a common tendency that subjects would also make the judgement that a certain anomaly had happened even the absolute changes in parameter

value do not exceed the thresholds. In such cases, the subjects predict that the parameter value will exceed the thresholds soon by the observed variation tendency.

With respect to developing a human model that can simulate the subjective judgement on parameter values, the analysis results suggest that:

- it is necessary to set the high and low thresholds for the individual subject and such settings are parts of the individual "monitoring strategy",
- the subjective judgement to interpret parameter values can be modeled as a kind of fuzzy judgement in which the obtained thresholds can be utilized.

2.3.3 First Symptom and First Hypothesis

After the subject detects an abnormal transient, he will start anomaly diagnosis process. The symptom by which subjects detect an abnormal transient is called as "first symptom" in this thesis. In the experimental study conducted by K.Furuta (1996) [5], it has been found that the first symptom is very important because it almost decides the pattern of the following diagnosis process.

Various hypotheses may be considered in accordance with the first symptom. However, since human beings cannot deal with the possible hypotheses simultaneously, he will select one of them to start the diagnosis process. The hypothesis is called as "first hypothesis". In this thesis study, the attention is concentrated on the relationships between the first symptom and the first hypothesis. How subjects start the diagnosis process can be understood by examining the relationship.

Based on CD and the answers to question 3 and 6 in "Questionnaires 1", the first symptom and the first hypothesis are summarized in tables 2.5, 2.6, and 2.7. together with the frequency of the first-symptom-first-hypothesis (FSFH) pattern observed through out all simulation trials. By analyzing the table, the characteristics in the relationship of First-Symptom-First-Hypothesis are obtained as follows.

- The first symptoms detected by the three subjects are almost same. They are the abnormal deviation observed in the value of the following parameters: PRZ Pressure, PRZ Level, Charging Flow, Main FW Flow, Reactor Power, and SG Level or Main Steam Flow.
- The other common tendency is that the first symptom almost always leads the subject to diagnose the sub-system to which the plant parameter belongs. For example, the

big or small deviations observed in the values of "Main FW Flow", "SG Level", "Main Steam Flow" always lead to the hypotheses about "FW system". While the anomaly in "Reactor Power" almost always leads to the hypotheses about NIS system or Control Rod. Therefore, the tendency in the FSFH relationship can be explained by the characteristics of human reflex action.

- While, rather than the reflex action, one can also find out another feature from the FSFH relationship of "Subject I". In the case of "Subject I", the first symptoms observed in the values of PRZ Pressure, PRZ Level, and Charging Flow almost always lead to the hypotheses about "RCS leakage" or "SGTR". While, in the cases of "Subject A" and "Subject T", such symptoms lead to the hypotheses about control systems. Since "RCS leakage" and "SGTR" are very important accident with respect to the safety of NPP, the examination of the hypotheses first in the cased of "Subject I" can be considered as a kind of his diagnosis strategy.

With respect to developing a human model, the analysis results shown above suggest that a database should be devised for describing the FSFH relationship. The database should be also devised for each subject to reflect the individual characteristics.

2.3.4 Formation, Examination, and Rejection or Adoption of Hypotheses

So far, the analysis results have been shown to explain how subjects monitor the plant system, how they detect abnormal transients, and how they start the diagnosis process. In this subsection, a detailed analysis example of the diagnosis process is first conducted to examine how the subject finds out the root cause of the abnormal transients. Then, the characteristics of the diagnosis process are summarized. Finally, suggestions are given with respect to developing a human model to simulate the diagnosis process.

AHHD and CD are utilized to analyze the detail of subjects' diagnosis process. For the simulation trial No.12 of "Subject T", the figures 2.17 and 2.18 show the AHHD and CD, respectively. This is the case where "Subject T" failed to identify "PRZ spray valve fails open", but instead reached an erroneous conclusion of "PRZ gas phase break". In the simulation trial, a message is given to "Subject T" intentionally to inform him that the plant will scram in 100 second after introducing an abnormal transient into the plant simulator. It is to examine how subjects behave under time pressure. The time pressure is considered as one of the factors that lead "Subject T" to the wrong diagnosis result.

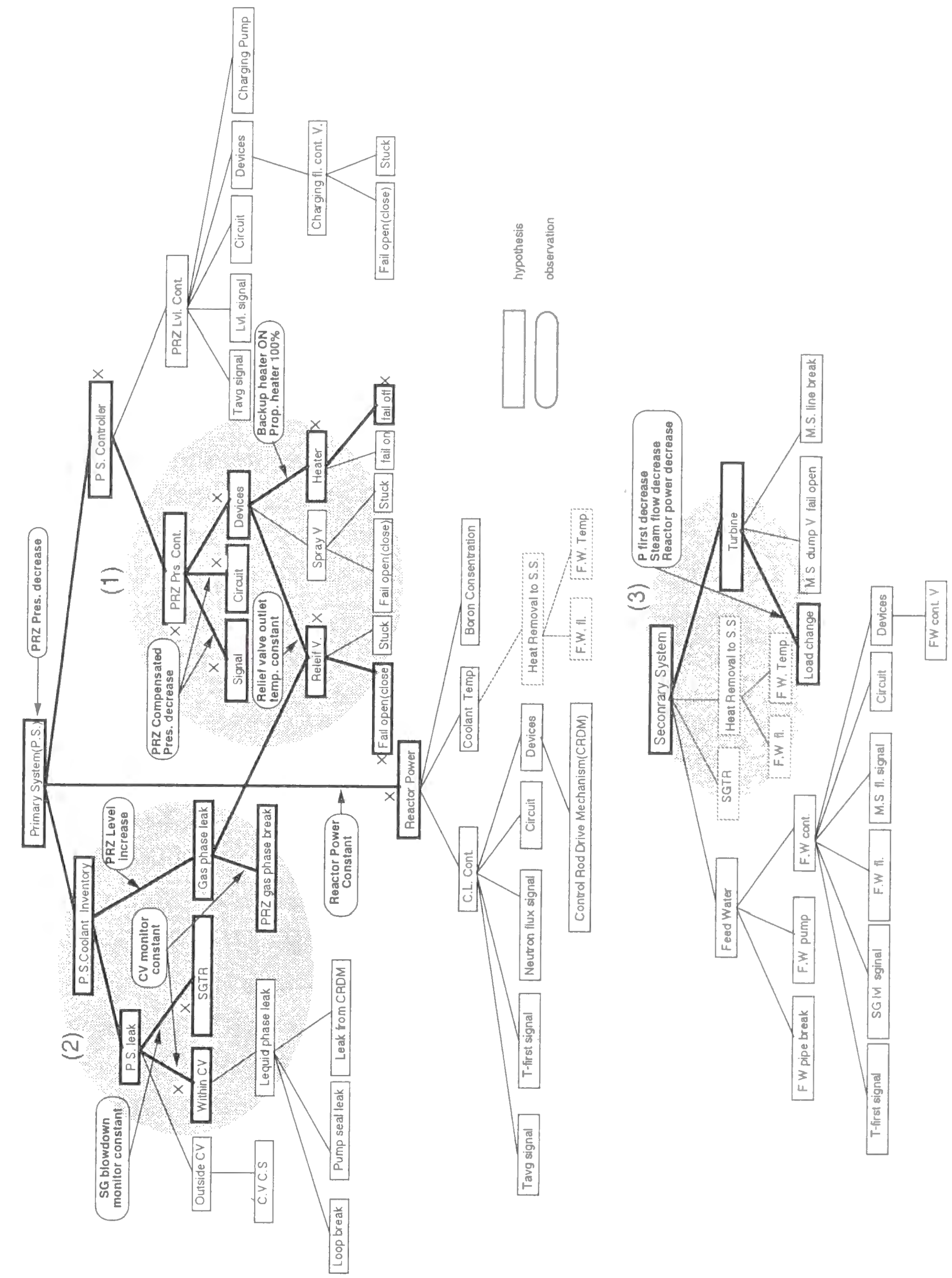


Figure 2.17: Analysis the diagnosis process by AHHD ("Subject T" simulation trial No.12)

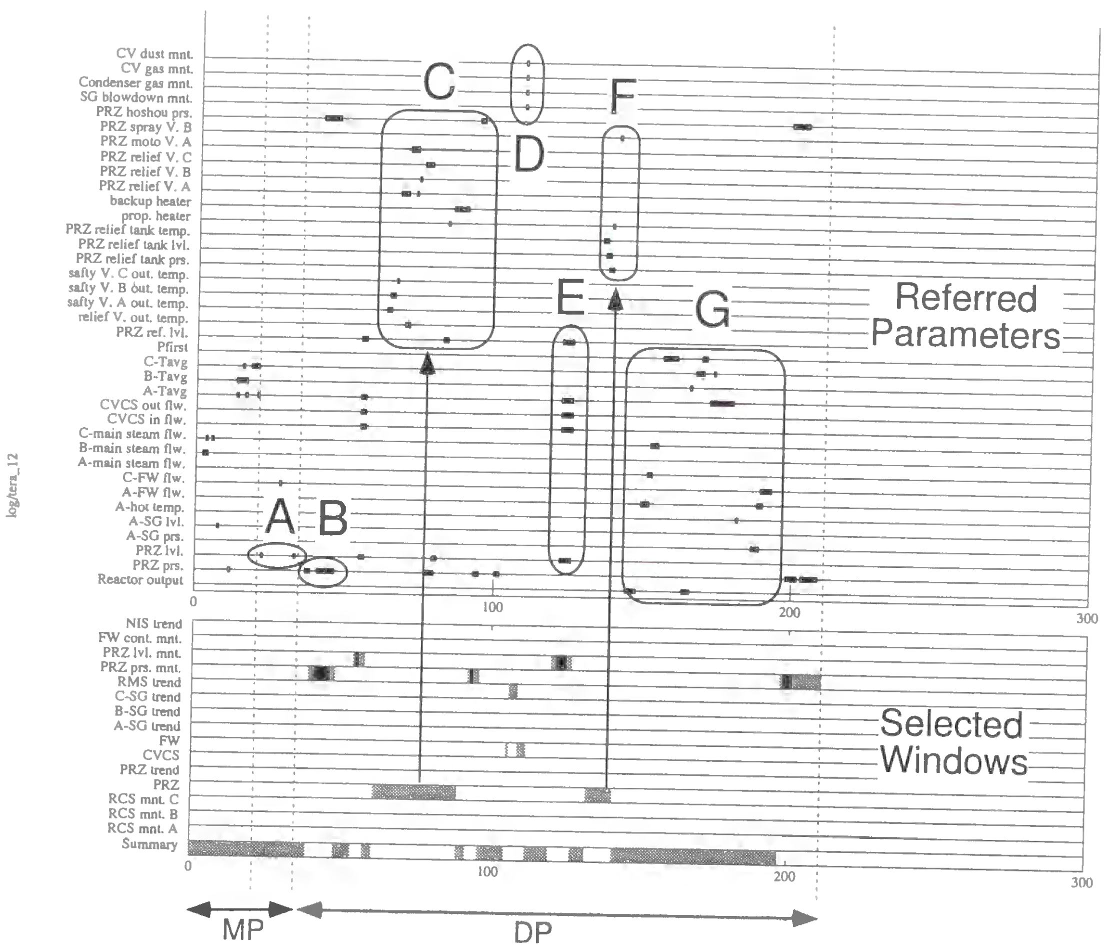


Figure 2.18: Analysis the diagnosis process by CD ("Subject T" simulation trial No.12)

From the answers to "Questionnaire 1", "Subject T" noticed the decrease of PRZ pressure as the first symptom. Although the reference to PRZ pressure is not explicitly recorded on CD (as shown in (A) in Figure 2.18), it is assumed that "Subject T" noticed the first symptom by the peripheral sight effect (PSE). PSE is such an effect of perception that the distinctive change will be noticed if it occurs in the peripheral sight. In this case, the subject would notice the changes in PRZ pressure when he checked the PRZ level because PRZ pressure is located near to PRZ level in the interface, as shown in (A) of Figure 2.18.

At this point, the hypotheses of "PRZ control system", "RCS leakage" and "SGTR" may be considered by "Subject T". He first considered the hypothesis of "PRZ control system" as shown in the shade part (1) of Figure 2.17. The selection of the first hypothesis reflects the characteristics of his FSFH relationship as summarized in Table 2.7.

Based on the hypothesis, there are two possibilities for the root cause: the wrong control signal output by the control circuit and the wrong action of the control devices in PRZ system. "Subject T" first switched to "PRZ Prs. Control Window" as indicated in (B) of Figure 2.18, in order to check the former possibility. In the inteface window, he confirmed that the pressure was decreasing in primary loop and also noticed that "PRZ Comp. Prs" was decreasing as well. [5] These symptoms indicate that the control circuit performed well.

Then, in order to examine the latter possibility, "Subject T" switched to "PRZ System Monitor Window" to check the states of the various devices related with PRZ pressure controller such as "PRZ relief valve", "PRZ safety valve" and "PRZ heater". He found that they were all functioning correctly (as shown in (C) of Figure 2.18). But, "Subject T" made an oversight that he failed to check the status of "PRZ spray valve", which was the root cause of this abnormal transient.

Since "Subject T" felt ambiguously that there may be no anomaly in PRZ control system, his attention turned to the possibility of "RCS leakage" or "SGTR" as shown in the shade part (2) of Figure 2.17. However, the hypotheses of "RCS leakage" and "SGTR" were denied by the observed facts showing that all radiation monitors retained normal status (as shown in (D) of Figure 2.18). In order to confirm the rejection of hypotheses of "RCS leakage" and "SGTR", "Subject T" checked the trend graph of "PRZ level" in the

[5] "PRZ. Comp. Prs" is the output of the PRZ control circuit and is the control signal of the devices in PRZ system, such as "PRZ. Spray V", "Heater". Based on the design of the control circuit, the input of a decreasing "PRZ Prs." should generate a decreasing "PRZ. Comp. Prs".

"PRZ level Controller Monitor window" (as shown in (E) Figure 2.18). In the interface window, he noticed a minimal increase of the PRZ water level that denied the possibility of the leakage accidents again and supported another hypothesis of "PRZ gas phase leakage" weakly.

At this point, since "Subject T" still doubted PRZ control system, he visited the "PRZ System Monitor Window" again. In that window, he checked the status of "PRZ relief tank temperature", tank level, and tank pressure and found they were all in correct status (as shown in (F) of Figure 2.18). Before returning back to "Plant Status Summary" window, "Subject T" made a very brief reference (under 1 second) to "PRZ Spray Valve B", which was malfunctioning and was the root cause of the abnormal transient. However, he was unable to notice the wrong status of "PRZ Spray Valve B". The oversight failure is considered as the effect of the time pressure.

In the meantime, what is call as "Turbine Run Back" [6] occurred and it made various changes in the secondary system. The attention of "Subject T" was then turned to the secondary system (as shown in (G) of CD and the shade part (3) of AHHD). However, "Subject T" could not understand such subsequent plant behaviors because he lacks the knowledge about "Turbine Run Back". In the end, due to the time pressure effect and incapability of understanding the plant behavior, "Subject T" gave the uncertain conclusion that the root cause of the abnormal transient was "PRZ gas phase leakage".

Based on the detailed analysis, the characteristics of diagnosis process can be summarized as follows.

- Not a single hypothesis, ordinarily, a number of hypotheses are recalled by subjects in accordance with the first symptom.
- The diagnosis process is not a parallel process. The hypotheses recalled by subjects are examined in sequence.
- It is also not a process of tracing the hierarchy map from the abstract upper hypothesis downward to the concrete lower hypothesis shown in AHHD. AHHD just represents the organization of subjects' diagnosis knowledge.

[6] Due to the rapid decrease of "PRZ.Prs" in primary system, a phenomenon called as Departure from Nucleate Boiling (DNB) will occur. If DNB occurs, the heat exchange between the fuel and the coolant will become so worse that the nuclear fuel will be damaged due to extreme high fuel temperature. Therefore, to avoid such situation, the turbine output is decreased by an automatic operation called as "Turbine Run Back" to reduce the reactor output.

- With respect to examining the recalled hypothesis, sets of knowledge elements or experiences are utilized rather than the individual knowledge element in AHHD. They describe either the function of plant sub-systems or the natures of specific accidents/incidents.
- The diagnosis process is a recursive process of forming, examining, and rejecting or adopting hypotheses until the root cause is identified.

Besides the above features, there is also another common tendency that when the subject is not completely sure about his diagnosis results, he will re-confirm other related hypotheses in order to convince himself. The tendency is not shown in the above detailed analysis due to the time pressure effect. Figure 2.19 describes the total diagnosis process summarized from the analysis results of all 30 experimental trials for the three subjects. The detailed steps of the information processing are described as follows.

1. Subjects recall a hypothesis based on the first symptom.
2. Based on the hypothesis, they predict the status of the plant parameters whose status would support the hypothesis.
3. Subjects would obtain the actual status of the related parameters by performing active MMI operations.
4. Subjects would then compare the actual status with the prediction made previously and therefore, change the confidence degree on the hypothesis.
5. Subject would make a judgement on the next action based on the current confidence degree on the hypothesis.
   - If the confidence degree is high enough, the hypothesis will be adopted as the diagnosis results.
   - Conversely, the hypothesis will be rejected if the confidence degree is too low. In this case, subject will recall a new hypothesis based on the first symptom and repeat the step 1 to 4.
   - One of the rest two alternatives is to refer to the other un-checked plant parameters related to the current hypothesis so that the confidence degree will be further increased or decreased.

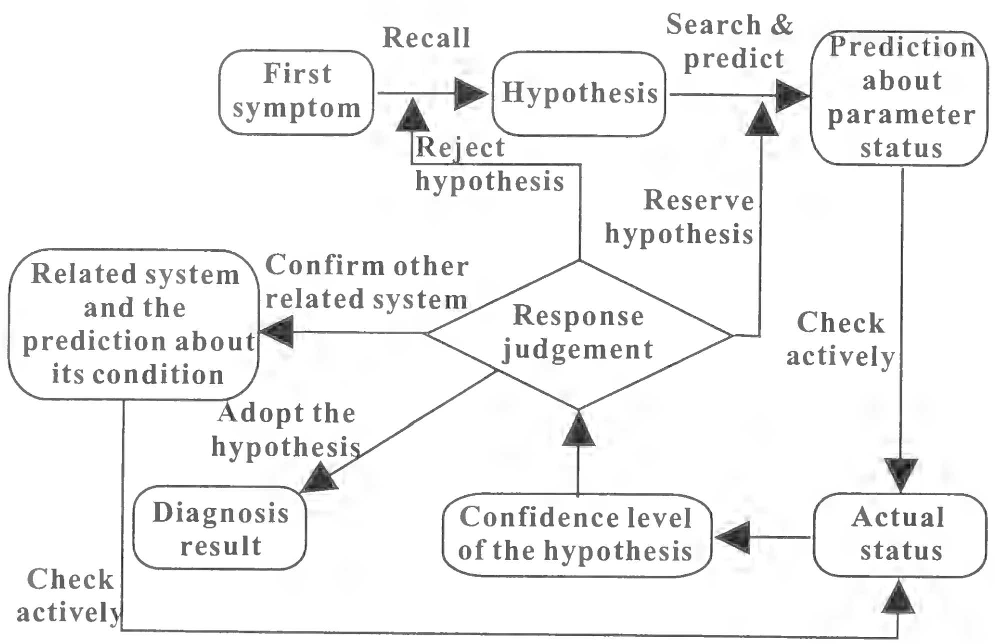


Figure 2.19: Diagnosis process summarized from all experimental trials

- If a subject is so cautious that he does not accept the hypothesis even all the plant parameters related to it have been checked, the last alternative is designed for describing the re-confirmation activities of other related system. The re-confirmation activities will change the confidence degree further.

Finally, with respect to developing a human model that can simulate the diagnosis process, the above analysis results give the following suggestions.

- The hypothesis formation can be modeled as a selection of hypotheses from a database that summarizes the recalled hypotheses in accordance with the first symptom.
- The hypothesis examination can be modeled as an accumulation process of collecting various symptoms that should be observed in accordance with the knowledge about the hypothesis.
- The hypothesis adoption or rejection can be modeled as the results of a decision on the hypothesis by using the accumulated symptoms.
- The total diagnosis process can be modeled as the repeating process of such hypothesis selection, symptoms accumulation and the decision on adoption or rejection of hypotheses until the root cause is identified.

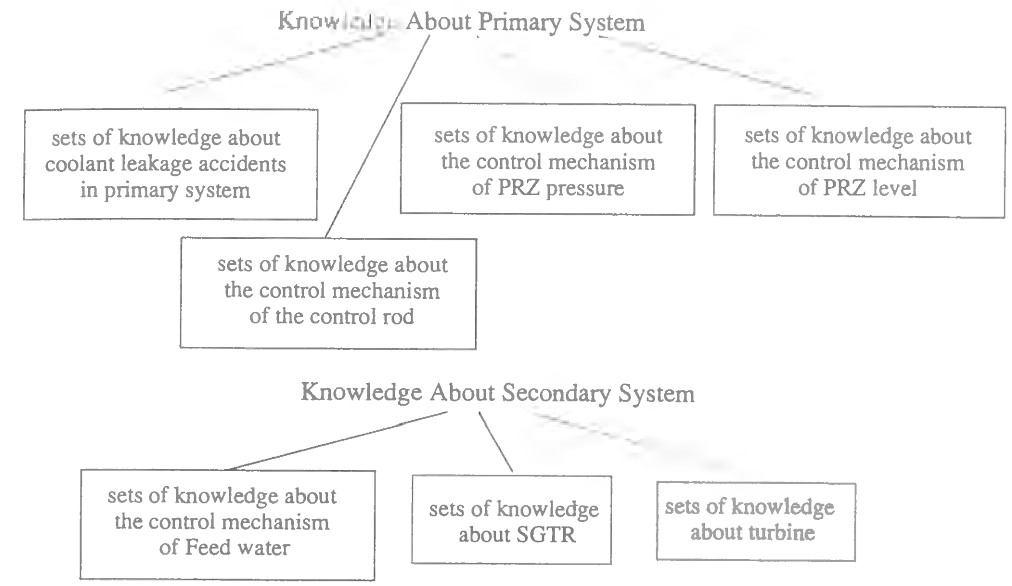


Figure 2.20: Sets of knowledge for diagnosing abnormal transients based on AHHD

2.3.5 Sets of Knowledge for Diagnosing Abnormal Transients

As described in the analysis results of the diagnosis process, sets of knowledge elements are utilized to examine the recalled hypothesis, rather than the individual knowledge element. Therefore, in order to simplify and to represent the sets of knowledge explicitly, the AHHD is modified as shown in Figure 2.20. There are seven sets of diagnosis knowledge:

- sets of knowledge about coolant leakage accidents in primary system
- sets of knowledge about the control mechanism of the control rod
- sets of knowledge about the control mechanism of PRZ pressure
- sets of knowledge about the control mechanism of PRZ level
- sets of knowledge about the control mechanism of Feed water
- sets of knowledge about SGTR
- sets of knowledge about turbine

The re-arrangement of the diagnosis knowledge organization helps to model the sets of knowledge as a knowledge module. Based on knowledge modules, the human long-term memory will be modeled as an integrated knowledge network in the next chapter.

So far, the laboratory experiment has been analyzed with respect to how the subjects detect and diagnose the abnormal transients. All the analysis results described in the above subsections are applied to develop a human model to simulate subjects' cognitive behaviors of diagnosing abnormal transients in Chapter 3.

2.4 Concluding Remarks

A laboratory experiment is described in this chapter, in order to examine the operator's cognitive behaviors in case of an emergency for developing a human model. The cognitive behaviors of the three subjects are examined to show how they monitor the plant system, detect and diagnose abnormal transients. Subjects' activities in the laboratory experiment are divided into two phases: monitoring phase and diagnosing phase in accordance with the experimental procedures. The obtained analysis results are summarized below for the two phases, respectively.

For the monitoring phase,

1. The monitoring task is a repeating process of checking the value of plant parameters until the first symptom is noticed.
2. The tendency of the monitoring task is summarized as the "monitoring strategy" that reflect the subjects' attention on a specific plant sub-system.
3. The criteria utilized to interpret parameter values are obtained by conducting an interview with the subjects.

For the diagnosing phase,

1. The diagnosis task is a repeat process of forming, examining, and rejecting or adopting hypotheses until the root cause of the abnormal transient is identified.
2. The diagnosis task is initiated by the first symptom. The relationship between the first symptom and the first hypothesis is summarized for each subject.
3. The knowledge for diagnosing the abnormal transients is obtained by conducting another interview with the subjects. The organization of the knowledge is represented as the anomaly hypothesis hierarchy diagram.

These results can be utilized to describe the process of subjects' cognitive behaviors. All the results obtained in this chapter are applied to develop a human model in the next chapter. The laboratory experiment provides an experimental basis for developing and validating the human model.

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Chapter 3

Development of Human Model for Operator's Cognitive Behaviors at Man-Machine Interface and Its Validation

In the preceding chapter, a laboratory experiment is described in detail to show how the author examined the operator's cognitive behaviors at MMI in case of an emergency in NPP. The experimental data had been analyzed with respect to developing a human model for simulating subjects' behaviors. This chapter describes the development and validation of the human model.

3.1 Objective of Human Modeling Study

Prior to describing how the human model is developed, it is necessary to discuss what kind of human model should be developed in this thesis study. In this section, the study motivation is first explained for the human modeling in the field of NPP system. Then, some of the existing human modeling studies in NPP system are reviewed to clarify the subjects for the further development of the studies on human modeling. At the end of this section, the objective of the human modeling study is specified for this thesis study.

3.1.1 Human Modeling Studies Based on Artificial Intelligence

As described in Chapter 1, human model researches have been conducted by three approaches categorized by their theoretical origin in the psychology [1]. They are mechanistic, cognitive and socio-technical approach. Among them, the cognitive approach is closely related to the human modeling approach developed later by applying artificial intelligence.

Rather than the observable external human activities focused in the mechanistic approach, the cognitive approach pays attentions to the high-level internal cognitive behaviors such as decision-making, anomaly diagnosis. The internal cognitive activities are described as the cognitive information-processing model. A number of models have been proposed by the information processing approach. J. Rasmussen proposed SRK (skill, rule, knowledge) model [2, 3] to categorize human behaviors into three types, and decision-making ladder model [2, 4] describes how the cognitive information processing is conducted. S.K. Card gave "Human Processor Model" [5] based on experiments to describe the characteristics of human cognitive behaviors such as the required time for various information processing. J. Reason proposed "fallible machine" model [6] to describe the memory mechanism within which various kinds of cognitive information processing are conducted. These human models are all qualitative and conceptual models. Although they cannot be utilized to examine operators' activities quantitatively, these qualitative and conceptual models established the foundation for the following artificial intelligence approach.

In recent years, a new approach based on artificial intelligence and symbolic processing methods of AI technology has been proposed [7, 8] to develop the above information processing approach into a further concrete shape. By applying the symbolic processing methods of AI technology, various symbols are devised on computers to represent various kinds of information elements consisting of the human model proposed by the information processing approach. Thus, the high-level internal cognitive behaviors are then modeled as the manipulation of the structured symbols on computers. The manipulation of the structured symbols is similar to computer programming. Consequently, rather than the qualitative and conceptual models proposed by the information processing approach, models developed by the artificial intelligence approach are generally implemented into computers as computerized programs. Based on the computerized human model, the operators' behaviors at various situations can be examined quantitatively by conducting computer simulation. Currently, the computerized human models based on the artificial intelligence approaches are the predominant methodology of human model study [9]. It is because engineers of human-machine systems have found that these computerized structures are very powerful for modeling the dynamic and complex interactions between operators and the machine system.

Human model researches based on AI approach have made a great progress in Japan

in recent years. Currently, most of the human model researches based on AI approach are focused on examining the mechanism of human errors and on supporting the improvement of MMI design [10, 11, 12, 13, 14].

With respect to supporting the design of the man-machine system, OCCS [10] (Operator Crew Cognitive Simulation) and SEAMAID [11] (Simulation-based Evaluation and Analysis Support System for Man-machine Interface Design) have been developed by Tokyo University and MITSUBISHI Electric Corporation, respectively.

- OCCS has been developed by K. Furuta by applying the decision-making ladder model proposed by J. Rasmussen. The ladder model has been developed into a computerized model by utilizing the blackboard control model. Various researches [15, 16] have been conducted by utilizing the human model, such as the evaluation of the human mental workload, modeling of the operation crew's activity, and validation of the human model.

- SEAMAID has been developed to support MMI design of NPP system. The human model utilized in SEAMAID is developed by applying the framework of "fallible machine" model proposed by J. Reason [6]. The human model in SEAMAID only simulate the response operation activities that are described in detail by the operation procedures in advance.

  The given designs of MMI can be therefore evaluated comparatively by simulating and analyzing the man-machine interaction where the operator's response operation is utilized as a kind of standard of MMI evaluatioin. The application of MMI evaluation by SEAMAID has been confirmed usable in the maintenance field of NPP system [17].

On the other hand, with respect to examining the mechanism of human errors by the human modeling approach, SYBORG [12, 13] (simulation system for the behavior of an operator group) and JACOS [14] (JAERI Cognitive Simulation System) are developed by Human Factors Research Center of CRIEPI (Central Research Institute for Electric Power Industry) and Human Factors Research Laboratory of Japan Atomic Energy Research Institute (JAERI), respectively.

- SYBORG
  SYBORG focused on the individual thinking process and the communication between the members of crew. It proposed a modeling framework for the individual thinking process and the concept of human-human interface for the communication between

members of the crew. The validity of SYBORG has been confirmed by comparing the simulation results with the manned experiment [18].

- JACOS
  JACOS also selected the decision-making ladder model as the modeling framework. However, JACOS expanded the modeling framework so that the memory mechanism proposed by J. Reason can be incorporated within it. The blackboard is utilized to model the short-term memory. While the long-term memory is modeled as knowledge database consisting of "procedural knowledge" and "functional knowledge". Subsequently, the potential human errors in the cognitive information processing can be simulated either by modifying the knowledge database, or by changing the parameter values from plant simulator, or by modeling the characteristics of human information processing such as notice bias, characteristics of searching knowledge database, and the limitation of short-term memory. The validity of SYBORG has been verified by comparing the simulation results with the laboratory experiment using several students as the subjects [18].

3.1.2 Objective of Human Modeling

Although the above studies on human modeling have contributed to supporting the MMI design and examining human error mechanism, there are still subjects remaining in human modeling studies.

Modeling Knowledge-based Behaviors

With respect to modeling operators' behaviors in the two phases described in Chapter 2, the development of human model for "response operation" phase is relatively easy compared with the one for "decision-making" phase. The operators' tasks in "decision-making" phase are substantially high-level cognitive behaviors including perception, prediction, judgement, reasoning and decision-making. Modeling operators' such cognitive behaviors is quite difficult. In this case, the complexity of the man-machine interaction will be further multiplied by the dynamic characteristics of plant system and the inherent diversity and variety in human behaviors.

However, the existing human modeling researches either avoid developing the model for the operator's behaviors in "decision-making" phase, e.g., SEAMAID, or only deal with simple cases where the complicated cognitive information processing can be omitted. In the

case of OCCS, it did not consider reasoning required in the cognitive information processing for anomaly diagnosis. Rather than utilizing the reasoning rules, the anomaly identification in OCCS is conducted by checking the similarity between the observed symptoms and the symptomatic patterns defined in advance. In the case of SYBORG, the primary attention is paid to the simulation of team behaviors taking consideration of the communication between the members of a crew. JACOS indeed gave a detailed consideration to modeling anomaly diagnosis. However, the human model did not consider the situations where the first hypothesis does not relate directly to the root cause of the abnormal transient.

Therefore, further efforts are required to model the knowledge-based behaviors in "decision-making" phase. In this thesis study, we have focused on operator's cognitive information processing in case of an emergency: anomaly detection and diagnosis. In the preceding chapter, the detection and diagnosis of abnormal transients had been examined by conducting the laboratory experiment. Hence the human model will be developed in accordance with the obtained analysis results of the experimental data.

Inherent Characteristics in Cognitive Information Processing

The mechanism of cognitive information processing should be modeled in order to develop a model to simulate operator's knowledge-based behaviors. The cognitive approaches of human modeling have proposed various kinds of conceptual model to describe the mechanism. Among them, "fallible machine" model proposed by J. Reason described the characteristics of working memory and the mechanism of information retrieval from the knowledge database. The model provided a fundamental framework for describing and modeling the memory mechanisms such as working memory, the basic knowledge database retrieval mechanisms of "similarity-matching" and "frequency gambling". One cannotice that the concepts proposed by J. Reason in the "fallible machine" model have been referred by lots of existing human modeling researches. For example, the human model in SEAMAID has been developed on the basis of the "fallible machine" model. On the other hand, based on the concepts about the memory mechanism, new models are proposed in SYBORG, and the decision-making ladder model has been expanded in JACOS so that the concepts of both short- and long-term memory can be incorporated into the framework.

In case of an emergency, the inherent diversity and variety in human behaviors will multiply the complexity of the man-machine interaction. The diversity and the variety are substantially the external appearances of the internal cognitive information processing. However, little efforts have been made to examine how the diversity and the variety of human behaviors derive from the internal cognitive information processing. Moreover, these inherent characteristics are important factors in the human reliability analysis where the statistical methods are applied to examine the influence of the diversity and variety with respect to the safety and reliability of plant system. Further efforts are therefore necessary to model the inherent diversity and variety in the cognitive information.

In this thesis study, a general human modeling framework developed out of "fallible machine" by H.Yoshikawa [1] will be utilized to model the inherent characteristics of the cognitive information processing. The diversity and variety will be examined to clarify how they are generated in the internal cognitive information processing.

Validation of Human Model

The confirmation of the validity of the developed human model is necessary to examine how well the model can simulate the cognitive information processing of real operators. However, it had been pointed out by the H.Yoshikawa and K.Furuta [1] that the scientific validation in the conventional meaning is extremely difficult for the human modeling approach. Under the background, a small-scale validation in a specific field has been focused as the efficient method both for validate the developed human model and for further improvements of human model.

Currently, the most applied validation method is to compare the simulation results with the operator experiment, e.g., OCCS and SYBORG. However, there are also such cases, e.g., JACOS, where only the verification of the human model has been conducted to check whether the model is developed in accordance with the designed specifications.

In this thesis study, prior to developing the human model, the laboratory experiment was conducted to examine the cognitive information processing. Therefore, the validation of the human model will be conducted by comparing the obtained experimental data with the simulation results.

Application of Human Model

Along with the progress made in the human modeling researches, it has been point out by Kirwan [8] that human modeling would become a useful tool for HRA/PSA of NPP, if the modeling capability could be expanded so that it could represent well versatile human behaviors on monitoring and controlling the process plant, with various environmental effects surrounding human tasks taken into consideration.

Currently, the purpose of most human modeling studies is either to support MMI design or to examine the human error mechanism. Little efforts have been made to estimate quantitatively human errors in cognitive information processing by means of the human modeling approach. In this thesis study, another objective of human modeling is therefore to develop a human model so that it can be applied to the practice of HRA/PSA in NPP.

Modeling Crew's Activities

In NPP, the plant system is monitored and controlled by a group of operators called as operation crew. The modeling of the operation crew's activities is therefore necessary to examine the human factors in the team behaviors. In this aspect, SYBORG has the lead in modeling the crew' activities by focusing on the voice-communication between members of a crew. On the other hand, the researches on a single operator have been conducted by considering the organization of an operation crew in the central control room in Japan: one shift-supervisor responsible for the activity of the total operation crew, and two assistant operators responsible for the reactor and turbine, respectively. As described in Chapter 2, the cognitive behaviors of the shift-supervisor are important in examining the activities of the operation crew. Therefore, the modeling of the cognitive behaviors of the shift-supervisor is conducted as the first step of the studies on modeling total crew's activities. In this thesis study, the human model will be developed to simulate the cognitive behaviors of the shift-supervisor.

Summary of the Objectives

Based on the above discussion, the objectives of the human modeling are then summarized as follows.

- Develop a human model based on the observation, i.e., on the analysis results of the experimental data so that the model can well simulate the subjects' cognitive behaviors of detecting and diagnosing abnormal transients.
- Develop and validate the human model that can simulate the inherent diversity and variety in human cognitive behaviors.
- Apply the developed human model to the practice of HRA/PSA.

The study to achieve the former two objectives is described in this chapter. The latter one will be the subject of the next chapter.

3.2 General Human Modeling Framework

The human modeling approach based on AI could be conducted in two steps as follows.

- To select or propose a human modeling framework to describe the mechanism of cognitive information processing.
- To implement the modeling framework into computers by applying the symbolic processing methods of AI technology.

In this section, a general human modeling framework is described for modeling operators' cognitive behaviors at MMI in NPP system. The framework is developed by H. Yoshikawa mainly based on the "fallible machine" model proposed by J. Reason [6]. A general description is given first to explain the modeling framework briefly. Then, the components and the interactions between them are described in detail to show how the framework explains human cognitive information processing.

In the following sections, we will explain how to apply the symbolic processing methods of AI technology to implement the modeling framework into computers in order to develop a computerized human model.

3.2.1 A General Human Modeling Framework

J. Reason proposed "fallible machine" model in his book "Human Error" [6]. The model paid attention to describing the mechanism of human memory. The fundamental concepts of the model are shown in Figure 3.1.

"Fallible machine" model has two kinds of memory components. One is the short-term memory called as working memory (WM) and the other is the long-term memory called as knowledge base (KB). WM is further subdivided into two parts: focal WM (FWM) and peripheral WM (PWM). Figure 3.1 shows the inter-connections between these components. As for the communication with the outside world, the two kinds of memory components utilize the input and output functions. The input function comprises an array of specialized sensors whose activity is fed into PWM. While the output function consists of sets of effectors that transform the instructions stored in KB into speech or motor action, and direct the orientation of the sensors. There are also feedback loops connecting the output and input functions.

Since "fallible machine" model is too conceptual and primitive to be implemented into computers, H. Yoshikawa [1] had developed it into a general human modeling framework

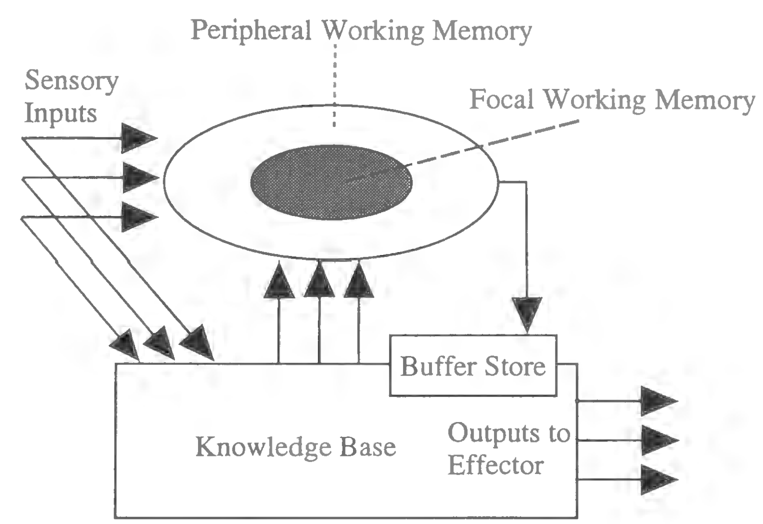

Figure 3.1: Fallible machine Model (by J.Reason [6])

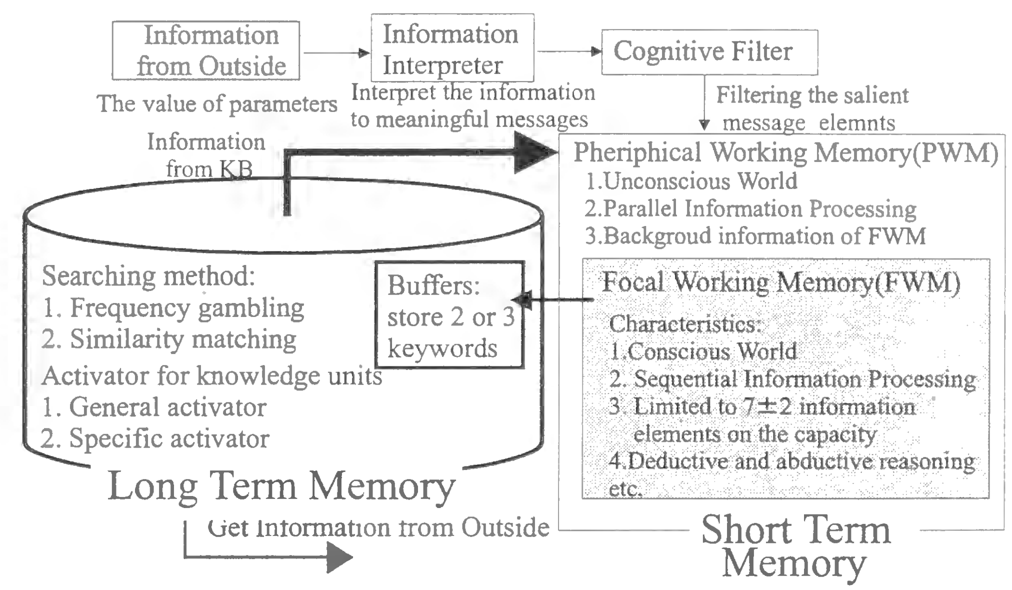

Figure 3.2: The general human modeling framework (by H.Yoshikawa [1])

for modeling operators' cognitive behaviors at MMI of a plant system. As shown in Figure 3.2, the framework incorporates other cognitive study achievements on operators' cognitive activities, such as the perception information processing, the concept of information chunking, the deductive and abductive reasoning utilized to diagnose abnormal transients. There are mainly three components in the general human modeling framework: the information interpreter together with the cognitive filter, the short-term memory (STM) consisting of FWM and PWM, and the long-term memory (LTM).

From next subsection, we will describe these components in detail to explain the characteristics of human cognitive information processing.

3.2.2 Perception Information Processing

In NPP system, various kinds of plant information are presented to operators through the MMI, such as indicators of instruments and values of plant parameters. The information can be perceived through the five organs of sense. The model of such information perception is simplified as the function of the information interpreter in the modeling framework. The information interpreter will convert the various kinds of information into meaningful messages.

However, human beings do not aware all the information entering the five organs of sense. Only such information attracts a person's attention that relates to the current context of information processing. The effect is modeled as the function of a cognitive filter. Only the salient message elements will be passed into PWM through the cognitive filter.

3.2.3 Peripheral Working Memory

PWM is an unconscious world and the information processing within it is conducted in parallel. Two kinds of information enter into PWM: one is from the cognitive filter and the other one is from the knowledge database. They are the background information relating to the information processing in FWM. The function of PWM is to govern the access to FWM. It is decided in accordance with a number of principles as listed below.

- Visual information dominance principle
  That is to say visual information has priority access to FWM at any time. With respect to the plant operation, it implies that the information about the status of the plant parameter within operator's view has a privileged access to FWM.

- Change detection dominance principle
  This means that the information indicating a striking change in the outside world has a privileged access to FWM. Such principle gives the explanation of peripheral sight effect (PSE), which was observed in the laboratory experiment . [1]

- Coherence principle
  Access to FWM is biased to favor information that relates to the current contexts of information processing in FWM. This principle preserves the consistency of successive FWM elements.

- Activation principle
  As for the information elements from the knowledge database, the access to FWM through PWM is determined by the level of an activation (described later in detail) of the knowledge units from which they originate. The higher the level of activation, the greater the chances of admission to FWM.

3.2.4 Focal Working Memory

FWM is a conscious world and is the workspace for the information processing. The capacity of the workspace is limited to about seven information chunks, as described in the "human processor model" proposed by Card [5]. FWM receives information elements continuously from both the outside world and the knowledge database through PWM. It has a cycle time of a few milliseconds and processes two or three discrete information elements in each cycle. During a run of consecutive cycles, these elements may be transformed, extended or recombined as the result of the information processing. The cognitive information processing is conducted attentively in sequence. J. Reason had given a useful image for the function of FWM: "slicer". By "slicer", the information consisting of information elements is cut into "slices". As shown in Figure 3.2, the "slices" are then dropped into a buffer as the keywords to search knowledge database. The "width" of these "slices" may vary in accordance with the type of "work". In the context of anomaly diagnosis, these concepts of "slice", "width", "work" will be explained concretely in the following sections where the modeling of FWM is described in detail.

[1] PSE means that if there is striking change in a parameter value and the parameter is within operator's peripheral view, he will detect the change. Also refer to subsection 2.3.4

3.2.5 Long-term Memory: Knowledge Database

Long-term memory is a vast database of knowledge units. There are neither capacity limits on the knowledge database, nor time limits on the conservation of the knowledge units stored in the knowledge database.

As for the organization of the knowledge database, the following two points had been argued by J. Reason [6].

- No any hierarchical structure or modularity exists originally in the knowledge base itself.
- The outward appearance of the structured organization is formed by the way with which the information is retrieved from the database [19].

The organization of the knowledge database is therefore not fixed and will be changed by the information retrieval method. On the other hand, the structured organization can be formed by continuing a consistent information retrieval method. In other words, if the keywords from FWM are dropped repeatedly into the buffer of the knowledge database in consistent sequences (e.g., routine actions, rithmetical procedures, and so on), the knowledge units activated by he keywords tend to be organized into a certain structure. Considering the repeat of education and training in the case of operators in NPP, it could be assumed that a certain kind of structured organization has been formed for the knowledge concerning the plant system and the operation experiences. Based on the assumption, a certain structure is generally utilized to model the organization of operator's knowledge database, such as the hierarchy and graphical network.

As for the retrieval mechanism of knowledge database units, the concept of activation is proposed to describe the retrieval processing. For each knowledge unit within the knowledge database, it is assumed that there is a modifiable level of activation. When the activation level exceeds a given threshold, the knowledge unit will produce a product. The products may be instructions for action, words or images, depending on the characteristics of the knowledge unit. The products are then delivered either to PWM or to the outside world through the output function. Knowledge units receive their activation charge from two principal sources labeled as specific and general activators. Corresponding to these two kinds of activators, there are two retrieval mechanisms of the knowledge database called as similarity matching and frequency gambling.

In the case of the specific activator, the retrieval mechanism is very simple. After one cycle information processing in FWM, the FWM "slices" are dropped into the knowledge

database and are held briefly in a buffer as the keywords for retrieving knowledge units. With respect to searching the database by the keywords, only the knowledge units possessing attributes that correspond to the keywords held in the buffer will increase their activation level in accordance with the goodness of the match. The closer the match, the greater charge will be obtained. The retrieval mechanism is therefore called as "similarity matching". It guarantees the consistent of the information processing in FWM.

On the other hand, in the case of the general activator, knowledge units are allowed to receive the activation charge without continuous direct relationship with the "slices" dropped from FWM. At such situation, the most important general activator derives from the frequency of prior use. It means that the more often a particular knowledge unit has been applied in the past, the greater is its activation level. As the result of the activation principle, the well-used knowledge units will have the advantage to be retrieved in the competition. The retrieval mechanism is therefore called as "frequency gambling".

With respect to developing a computerized human model, the similarity matching and frequency gambling give the primitive information retrieval mechanism of the knowledge database. In the following sections, the concrete methods of developing a computerized human model based on the human modeling framework are described in detail, with respect to the context of modeling operator's behaviors of detecting and diagnosing abnormal transients in NPP system.

3.3 Modeling Operator's Cognitive Behaviors in Monitoring Phase

As stated in Chapter 2, the characteristics of operator's behaviors are different in monitoring phase and diagnosis phase. The human modeling has been conducted separately for the two phases. The computerized model is developed on a real-time object-oriented expert system development environment called as G2 developed by GenSym Ltd [20]. In this and the next section, the development of the human model is described with respect to the operator's behaviors in the monitoring and diagnosing phase, respectively.

Based on the analysis results of the experimental data in Chapter 2 and the foregoing general human modeling framework, operators' cognitive behaviors are modeled in the following two steps.

- Devising a fundamental configuration to model the common cognitive behaviors observed in the laboratory experiment.
- Adjusting specific parameters in the fundamental configuration to model the individual characteristics of operators' cognitive behaviors.

With the modeling methods, the human model should be able to simulate both the common and individual characteristics observed in the laboratory experiment.

3.3.1 Modeling of Monitoring Phase

With respect to modeling the subject's behaviors in monitoring phase, the following modeling methods have been suggested by the analysis results of the experimental data summarized in Chapter 2.

- Subjects' monitoring task can be modeled as a periodical activity of checking parameter value.
- The common tendency of "monitoring strategy" can be modeled by classifying the parameters checked by subjects into five groups in accordance with the configuration of the plant sub-systems.
- The characteristics of the individual "monitoring strategy" can be modeled by adjusting the reference frequency of the parameter group.

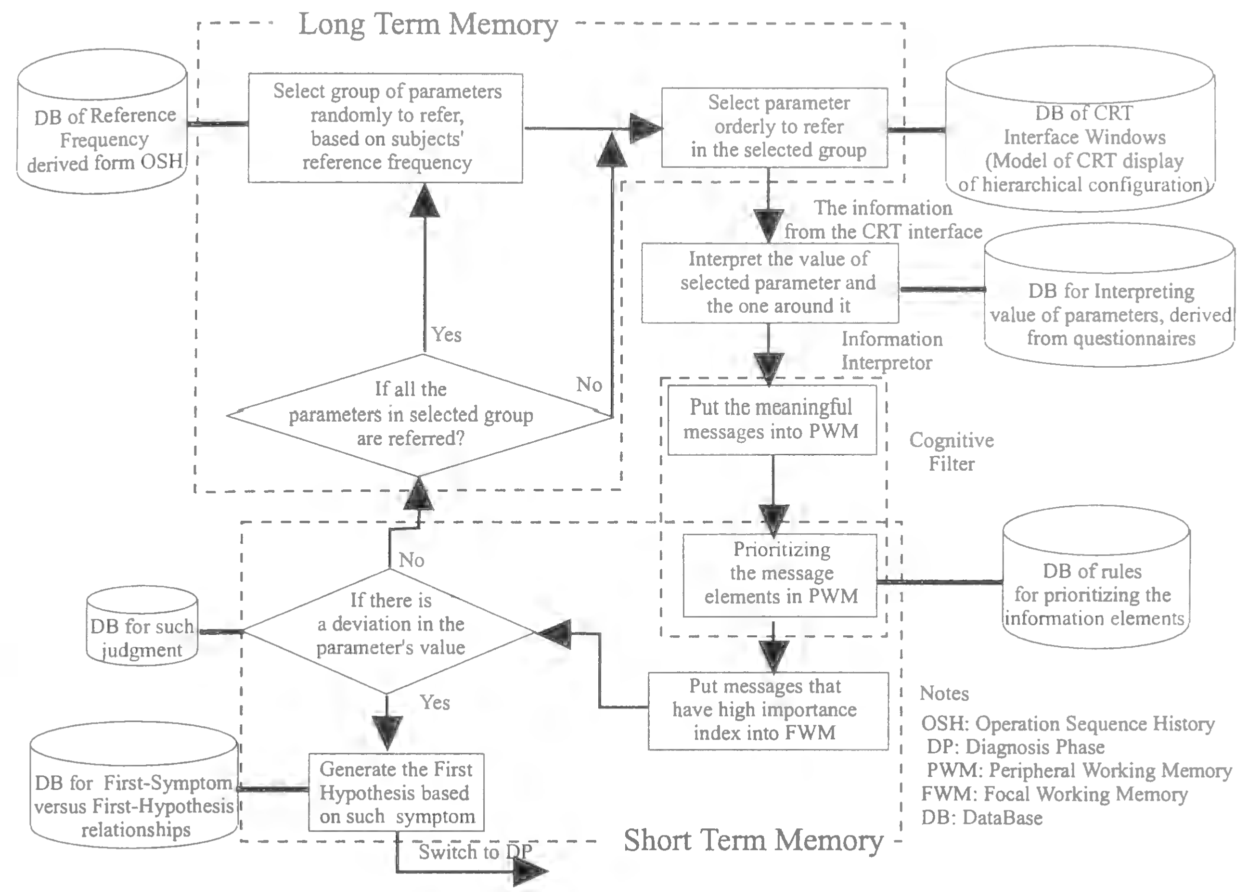

Figure 3.3: Modeling of operators' cognitive behaviors in monitoring phase

- The interpretation of parameter values can be modeled by applying the fuzzy membership function to model the individual characteristics.

By combining these modeling methods with the general human modeling framework, the cognitive behaviors of operators in the monitoring phase can be described as the repeated three kinds of information processing; (i) the information perception, (ii) the interpretation of parameter values, and (iii) the judgement on the occurrence of an abnormal transient. The repeted informatioin processing will continue until a deviation from steady parameter value is detected as the intimation of an abnormal transient. Figure 3.3 shows the information processing flow in the monitoring phase in accordance with the human modeling framework. The sub-models of the three kinds of information processing are described in detail as follows, together with the necessary databases required in the information processing.

Perception Process

The modeling of the perception process is substantially the modeling of subjects' "monitoring strategy". Based on the analysis results [2] of "monitoring strategy", plant parameters checked by the subjects are classified into five groups corresponding to the configuration of the plant system. Then, the perception information processing is conducted in following two steps.

1. In the first step, a parameter group will be selected from the total five groups. The selection is based on the reference frequency of each parameter group summarized in Figure 2.16. In order to model the characteristics of individual "monitoring strategy", a database is made for each subject to describe the reference frequency of each parameter group.

2. In the second step, a plant parameter will be selected from the parameter group chosen in the first step, as the parameter to be check next. This selection is made in a sequence defined in advance.

These two selections are substantially two kinds of searching task to find out which plant parameter should be checked next. As explained previously, there are two methods for searching database: frequency gambling and similarity matching. The selection of parameter group corresponds to the frequency gambling because it is based on the reference frequency that reflects the frequency of parameter groups checked in the past.

On the other hand, the parameter selection within the group corresponds to the similarity matching. In this case, the status of the plant sub-system is the specific activator for conducting the similarity matching. The specific activator is derived from the parameter group selected by the frequency gambling. In the meaning of indicating the status of the plant sub-system, the parameters in the same group are similar.

Interpretation Process

The function of the interpretation processing is the translation of the value of parameters into meaningful messages. The analysis results of the answers to "Questionnaire Sheet 2" are utilized to model the translation processing. The analysis results [3] have suggested that the interpretation of parameter value can be modeled as a kind of fuzzy judgement.

[2] Refer to subsection 2.3.1

[3] Refer to subsection 2.3.2

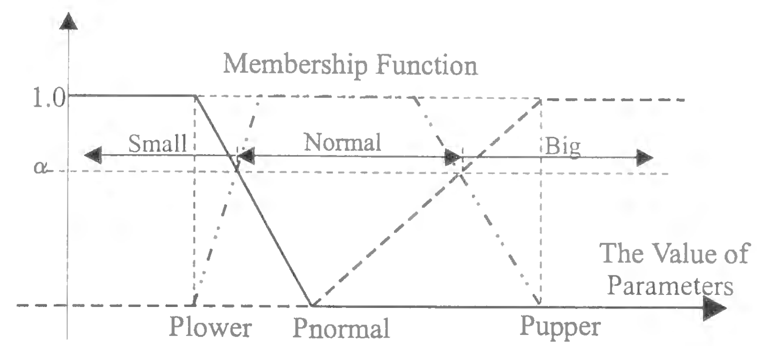

Figure 3.4: Fuzzy membership function for interpreting parameters' value

Table 3.1: The rules for assigning the priority of information elements

High

Priority

Low

Importance Index	Parameter Status
0	Warning Information
1	Deviation from normal value range of the parameter being focused
2	Normal state of the parameter being focused
2	Deviation from normal value range of the parameter located near the parameter being focused
3	Normal state of the parameters located near the parameter being focused

The obtained criteria can be applied to judge the occurrence of an abnormal transient. A fuzzy membership function is devised as the interpretation model. The criteria for judging anomaly occurrence are modeled for each subject. Figure 3.4 shows the membership function for interpreting a parameter value. The inherent individual characteristics of interpreting parameter value can be modeled by setting the lower and upper thresholds of the parameter value.

After the parameter values are interpreted into meaningful messages, the meaningful information elements are transferred into PWM where the access priority to FWM is assigned for each element. The rules for prioritizing the information elements are summarized in Table 3.1. The elements having high importance index (0-2) are then transferred into FWM for judgement process.

Judgement Process

Based on the information element about the status of parameter values, the judgment is made on whether or not there is a symptom indicating the occurrence of a certain abnormal transient. If there are no abnormal symptoms, the next parameter to be checked will be found out by searching the database of "monitoring strategy" modeled at LTM with the two searching methods. In this case, the monitoring behaviors will continue. On the other hand, if an abnormal symptom is detected, the symptom will be stored in PWM. The symptom is called as the first symptom that is the important background information for the following anomaly diagnosis. Then, the monitoring task will be terminated and the activities of the human model will be switched to the simulation of the anomaly diagnosis phase.

3.3.2 Human Model Adjustment Factors for Monitoring Phase

Inherent Diversity and Variety

The diversity and variety are inherent characteristics of human behaviors. The diversity means here that the different persons would response differently to the identical situation. On the other hand, the variety means here that the same person may be response differently to the same situation. The diversity and variety are derived from the characteristics of internal cognitive processing: frequency gambling and similarity matching.

In the conventional human modeling studies, little attention had been paid to the modeling of these inherent characteristics, especially to modeling the variety. The simulation by these conventional models always results in the same pattern, rather than the various patterns observed in human behaviors. In the study field of human reliability analysis, these inherent diversity and variety are important factors to evaluate the reliability of human behaviors. In order to apply the human model to the practice of the human reliability analysis in thenext chapter, the human model developed in this chapter should have the capability to simulate the diversity and variety.

In this thesis study, the concept of human model adjustment factor is proposed to model the diversity and variety. Adjustment factors are substantially parameters in the developed human model. By adjusting the parameters, the simulation result by the human model will be changed so that it can reflect the individual characteristics of human behaviors. Subsequently, the inherent characteristics of diversity and variety would be simulated by the human model with the different adjust factors.

Modeling Individual Characteristics in MP

In the context of monitoring tasks in case of an emergency, the interest of analyzing operator's behaviors centers on when and by what symptom operators detect the occurrence of the abnormal transients. In other words, the detection time and the first symptom are the chief interests. However, the inherent diversity and variety in operators' monitoring tasks would influence the detection time and the first symptom. In this subsection, the attention is paid to modeling the characteristics by applying the concept of human model adjustment factor, based on the analysis results of the laboratory experiment.

- Reference frequency of parameter group
  As stated previously in Chapter 2, the "monitoring strategy" of each subject is different and it would influence the detection time and the first symptom. With respect to modeling the individual characteristics of monitoring tasks, the reference frequency of the five parameter groups is focused as one of the human model adjustment factors.

- Criteria for judging the occurrence of abnormal transient
  The abnormal transient will be detected quickly if the operator consider a slight deviation in parameter values as the abnormal indication. In other words, the criteria of judging parameter values play an important role in anomaly detection. Therefore, the fuzzy membership factor α shown in Figure 3.4 is focused as another human model adjustment factor to model the individual characteristic in interpreting the parameter value.

- Peripheral sight effect (PSE)
  PSE is observed in subjects' OSH in the laboratory experiment and it is considered to reflect the characteristics of the individual attention. The modeling of PSE is based on the observed PSE samples in the laboratory experiment. PSE samples are collected by focusing on the parameters checked by subject immediately after and before he detected the abnormal transient. Based on the samples, rules are incorporated into the database of "monitoring strategy" for the perception processing. The rules define for what parameter PSE will occur. If a deviation from normal value range is detected by PSE, the priority of the information element is assigned as "2" and therefore, will be processed by the judgment sub-model. Thus, the individual characteristics in detecting the anomaly can be modeled by modifying these rules.

So far, the methods have been described for modeling the subject's cognitive behaviors in monitoring phase. In the next section, the modeling of anomaly diagnosis will be explained in detail.

3.4 Modeling Operator's Cognitive Behaviors in Diagnosing Phase

In the anomaly diagnosis phase, the information processing is more complicated since both the formation and examinations of various hypotheses are required besides the perception and the interpretation,.

In this section, a description is first given to explain characteristics of the cognitive information processing in diagnosing abnormal transients. Then, models of STM and LTM are described in detail to show how they are implemented into computers by applying the symbolic processing methods of AI technology. In the end, the various kinds of information processing taken place at STM and LTM are modeled as the manipulation of the symbols.

3.4.1 Cognitive Information Processing in Diagnosing Phase

As the analysis results summarized in the conclusion of chapter 2, the diagnosis task is a repeat process of forming, examining, and rejecting or adopting hypotheses until the root cause is identified for the abnormal transient.

The detailed analysis results of the simulation trial No.12 of "Subject T" [4] suggests following hints for modeling the diagnosis process,

- The hypothesis formation can be modeled as a selection from a database of hypotheses recalled by the first symptom.
- Since the hypothesis cannot be adopted or rejected by checking only one parameter, the hypothesis examination can be modeled as an accumulation process of the confidence variation by checking various symptoms which should be observed in accordance with the knowledge on the anomaly hypothesis.
- The judgement of hypothesis adoption or rejection can be modeled as the results of the accumulation process of the confidence variation.
- The whole diagnosis process can be modeled as the repeated process of hypothesis selection, confidence accumulation and the decision on adoption or rejection until the final decision on the root cause is made.

[4] Refer to subsection 2.3.4

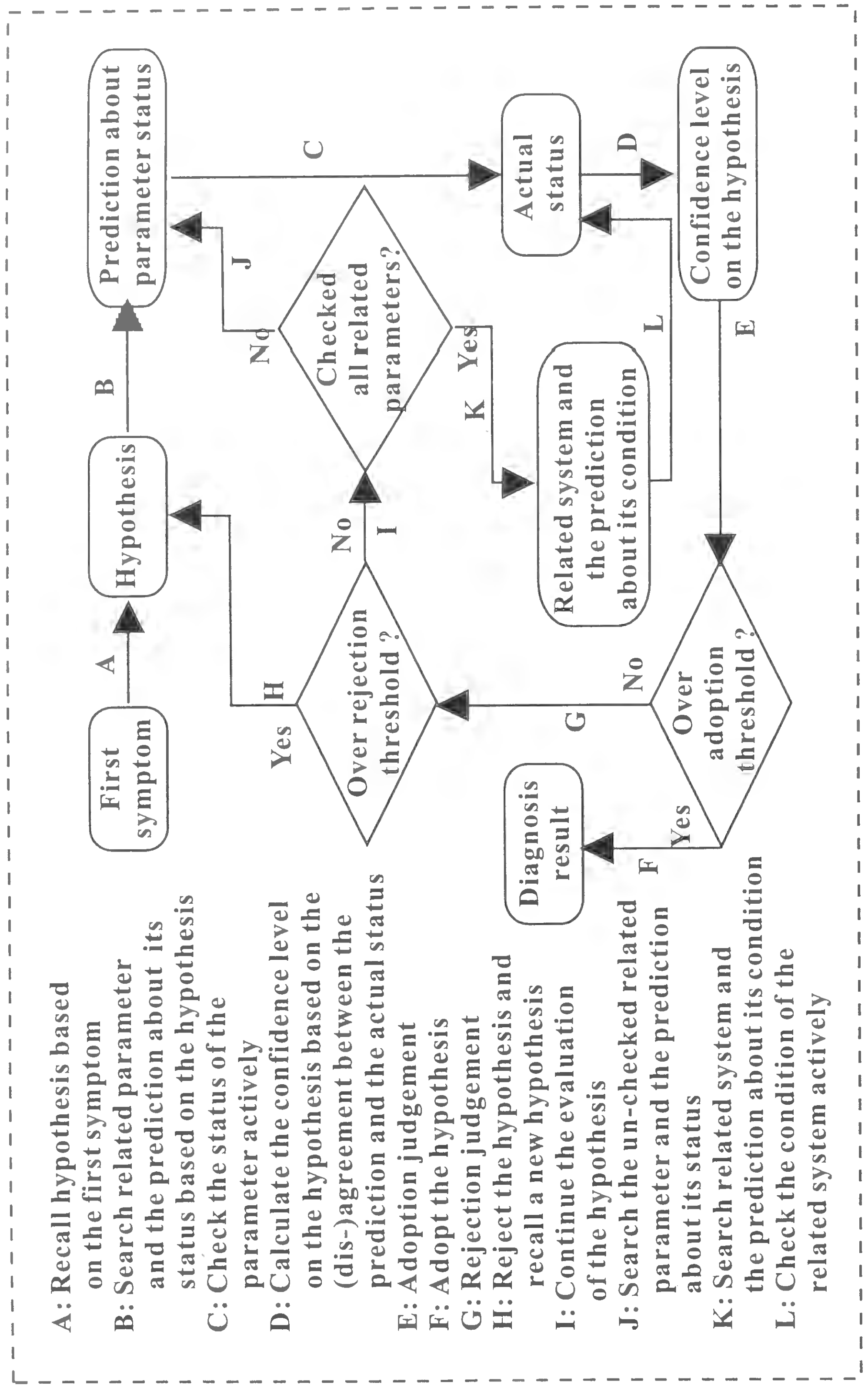

Figure 3.5: Modeling of information processing in anomaly diagnosis

Based on the above suggestions, the detailed information processing flow is devised for the internal cognitive processing during diagnosis phase, as shown in Figure 3.5. The detailed processes indicated as $A, B, C, \cdots, L$ in the figure are explained as follows.

A: Recall the first hypothesis based on the first symptom.

B: Search related parameter and the prediction about its status based on the hypothesis.

C: Check the status of the parameter actively.

D: Calculate the confidence level of the hypothesis based on the agreement or the disagreement between the prediction and the actual status.

E: Hypothesis adoption judgement.

F: Adopt the hypothesis as the diagnosis result and terminate diagnosis.

G: Hypothesis rejection judgement.

H: Reject the hypothesis and recall a new hypothesis.

I: Reserve the hypothesis and continue to find out more symptoms to examine the hypothesis.

J: Search the un-checked related parameter and the prediction about its status.

K: Search related system and the prediction about its condition.

L: Check the condition of the related system actively.

The cognitive behaviors in the anomaly diagnosis phase are implemented into the computer as the cycles of the information processing until a hypothesis is adopted as the root cause of the abnormal transient. In the following subsections, the detailed descriptions are given for the modeling methods of STM, LTM, and the various information processing taken place in them.

3.4.2 Model of STM: Working Memory Element

In this and the next subsection, the methods are explained for modeling the objects that would be handled by the information processing at STM and LTM. The information elements processed at STM are modeled by a frame called here as "working memory element (WME)". As for LTM, knowledge database (KDB) has been constructed to model operator's knowledge and experiences about diagnosing abnormal transients. The knowledge and experiences are represented by graphical network structure in KDB.

As described previously in this chapter, the function of FWM can be imagining as a "slicer" that cut the incoming information into various kinds of "slices". WME is devised for modeling the incoming information. Then, the information processing at FWM (the function of "slicer") can be converted into the symbolic processing of WME.

The data structure of WME is shown in Table 3.2. The explanation is given below for each attribute defined in the data structure.

- Category
  It defines the type of WME. The category is substantially the model of the type of "work" described previously in the "slicer" image of FWM function. Therefore, the category indicates the cognitive processing context to which the WME belongs. Several types of the cognitive processing have been defined as in Table 3.2 to describe different contexts of the cognitive information processing for diagnosing abnormal transient. Such category information is used to retain the coherence of the information processing.

- Content
  It describes the information carried by the WME. The concrete content depends on the category of WME and the detailed explanation is shown in Table 3.3. For example, if the category of WME is "alarm", the content will be the name of alarm. While if the category of WME is "hypothesis", the content will be the combination of the name of hypothesis and the current confidence level of the hypothesis. The content of WME will be processed in FWM to abstract keywords for searching knowledge database. The keywords can be imagined as the "slice" that is the product of the information processing at FWM. The concrete keywords then can be imagined as the "width" of "slice". Since the different type "slice" has different "width" as described previously, the keywords abstracted from the content of WME are different.

Table 3.2: Data structure of working memory element

Attribute	Explanation
Category	alarm, hypothesis, value prediction, trend prediction, value symptom, trend symptom, loop-decision, diagnosing result
Content	defined according to the category
Processing State	yes, no, reserved, verifying, rejected
Processing Priority	the number from 0 to 2
Holding time	initial value= 7, if "processing state" = yes then minus 1 per second

Table 3.3: Contents of WME

Category	Content	Examples
Alarm	alarm message	"PRZ.Prs. is low"
Hypothesis	name of the hypothesis + the current confidence level of it	SGTR+50
Prediction	name of the parameter + the prediction about it status	PRZ.PRS+small, PRZ.Lvl.trend+decreasing
Symptom	name of the parameter + its actual status	PRZ.PRS+big, PRZ.Lvl.trend+decreasing
Loop-decision	name of the parameter + its actual status + the deviation	A.SG.Lvl+high+14.3
Diagnosis result	name of the root cause + the final confidence level of it	SGTR+110

- Processing State
  It is the flag indicating the processing state of WME. There are four types of flags. "No" will be assigned to the WME that is the new incoming information and is waiting to be processed. "Yes" will be assigned to the WME that had been processed at FWM and will not be used in the later information processing. "Reserved" will be assigned to the WME that had been processed at FWM and will be utilized in later cognitive processing tasks. The "reserved" WME is substantially the model of the background information stored in PWM as the FMW information processing. "Verifying" and "rejected" will be assigned to the "hypothesis" WME to indicate whether the hypothesis is under current examination or had been rejected.

- Processing Priority
  It defines the processing sequence of WME. In other words, it defines the priority of the access to FWM. Similar to the case of modeling information processing in monitoring phase, "0" indicates the highest priority assigned to alarm WME. "1" is assigned to the WME generated by the cognitive processing conducted immediately before. The assignments reflect the "change detection dominance principle" and the "coherence principle" in the previous description about the principles governing the priority of access to FWM [5]. The latter principle retains the coherent of the information processing. "2" is reserved for the future improvement of the human model and is not assigned to any WME at present.

- Holding time
  It represents how long the WME will be retained at STM. From the characteristics of human cognitive information processing examined by Card [5], the holding time of WME at STM is about 7 (5~226) seconds. Currently, 7 seconds have been set as the longest holding time if the processing state of WME is "Yes" or "rejected ". As for the rest WME whose processing state is "no" or "reserved" or "verifying", it is assumed to be remembered until its processing state is changed to "Yes".

3.4.3 Model of LTM: Network Structured Database

The model of the network-structured organization of the knowledge database is described in this subsection to show how the diagnosis knowledge obtained from the laboratory experiment is implemented into computers as a computerized form.

Lots of models of knowledge database of NPP operators have been proposed. K. Furuta have proposed recently a generic model of an operator's knowledge on plant systems and the operation tasks [21]. The model consists of four cognitive subspaces of fundamental knowledge: plant configuration, parameter causality relationship, parameter state and task goal spaces. These four subspaces are interrelated with each other to represent the relationships of the knowledge entities. The feature of this model is the clear discrimination of various different kinds of knowledge. On the other hand, M. Lind have proposed another model called as "Multilevel Flow Modeling (MFM)" [22], which is adopted by JACOS [14] to represent the knowledge of NPP operators. The system behavior is represented as the

[5] Refer to subsection 3.2.3

flows of mass, energy and information in MFM. The multilevel flows are represented by a network structure in JACOS.

In this study, a graphical network-structured organization is proposed to represent the knowledge database by taking a reference of the above modeling methods. The differences of the model with the above models are listed below.

- Only the anomaly diagnosis knowledge is modeled by the graphical network structured organization. The modeling of the response operation is beyond the scope of this thesis study.

- The anomaly diagnosis knowledge is obtained from the interviews with the three subjects in the laboratory experiment, rather that the ideal, very detailed textbook knowledge utilized in JACOS.

This subsection gives the detailed modeling methods of the knowledge database to show how the diagnosis knowledge obtained from the laboratory experiment is implemented into computers as a computerized form.

With respect to modeling operators' cognitive behaviors in case of an emergency, the knowledge and experiences are divided into two groups: the knowledge about the control systems of NPP, and the experiences or knowledge about the nature of accidents in NPP. For each type, the knowledge is further divided into knowledge modules based on the analysis results of the experimental data, as summarized in the subsection 2.3.5. There are totally seven knowledge modules corresponding to the seven sets of knowledge listed below.

- knowledge module of coolant leakage accidents in primary system
- knowledge module of the control mechanism of the control rod
- knowledge module of the control mechanism of PRZ pressure
- knowledge module of the control mechanism of PRZ level
- knowledge module of the control mechanism of Feed water
- knowledge module of SGTR
- knowledge module of turbine

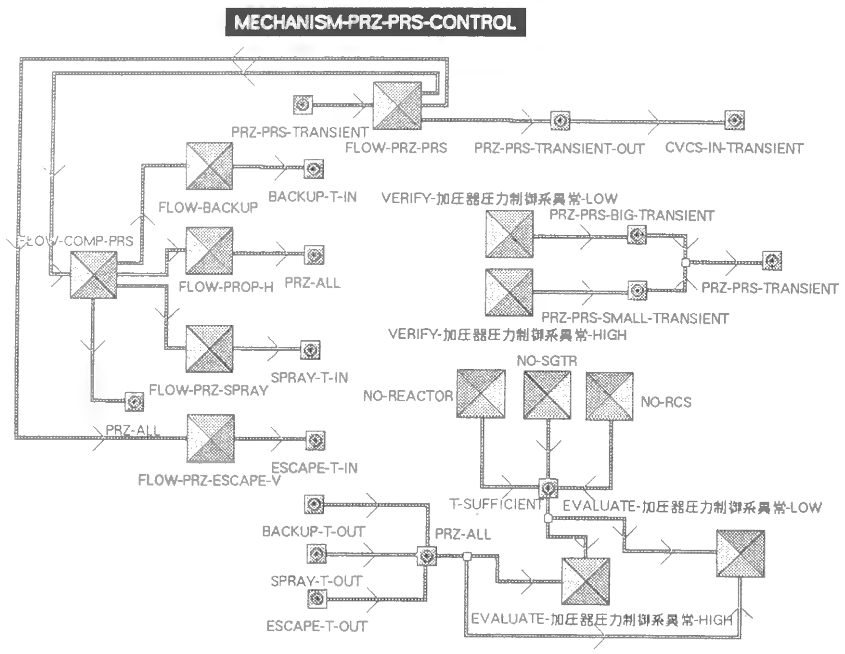

Figure 3.6: Knowledge module of "PRZ.Prs Control System"

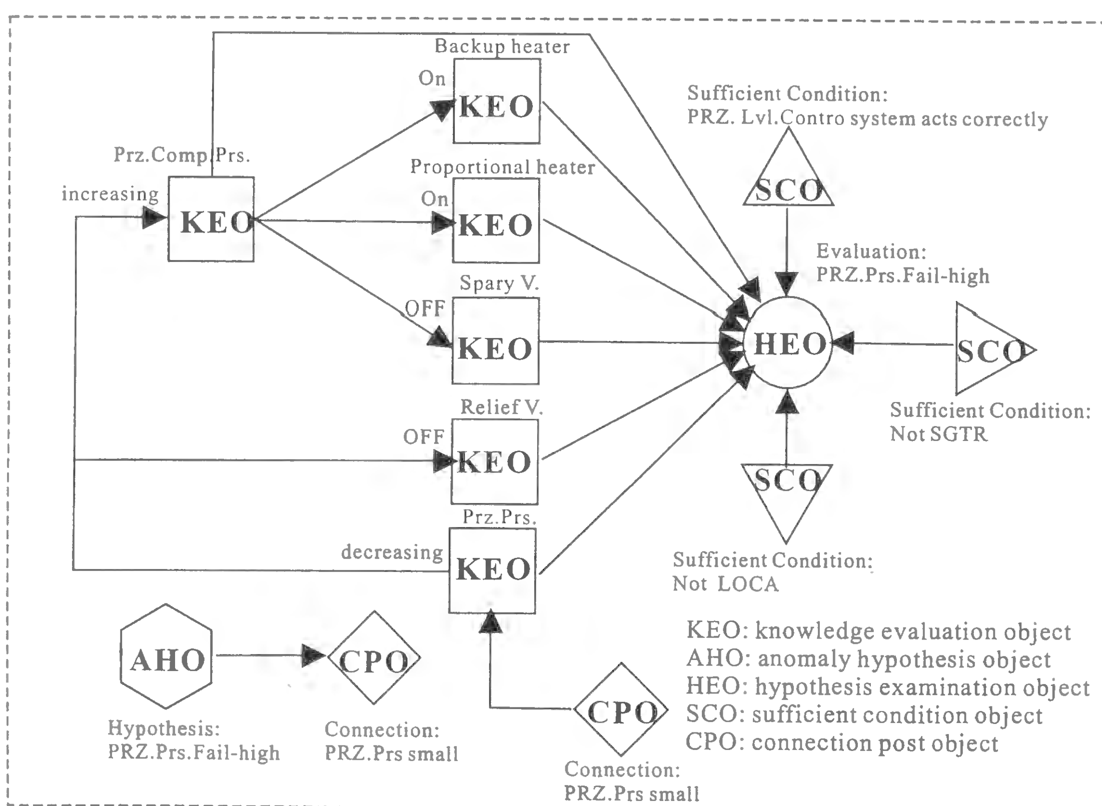

Figure 3.7: Modeling methods of the knowledge about "PRZ.Prs Control System"

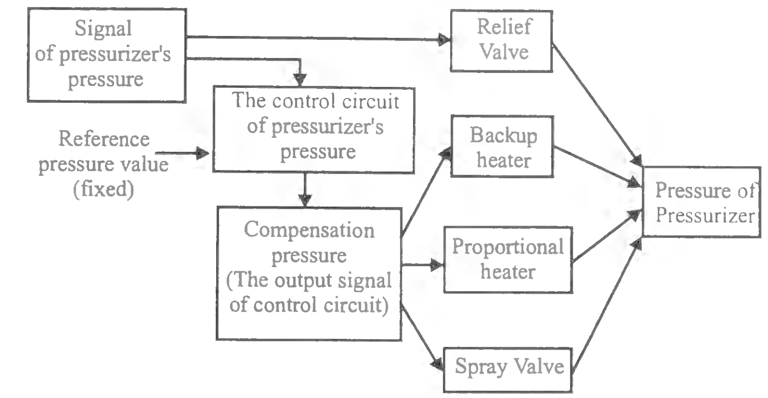

Figure 3.8: Logical mechanism of the pressurizer pressure control system

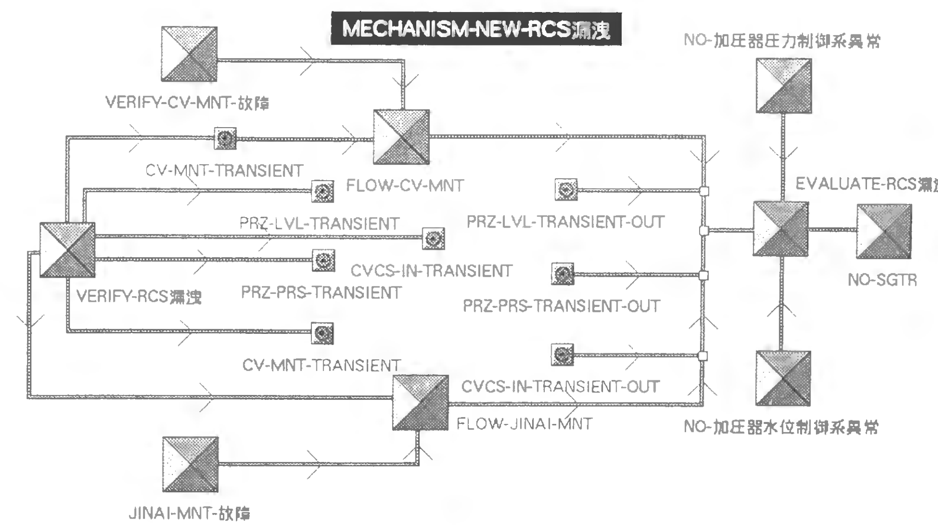

Figure 3.9: Knowledge module of "RCS leakage" accident

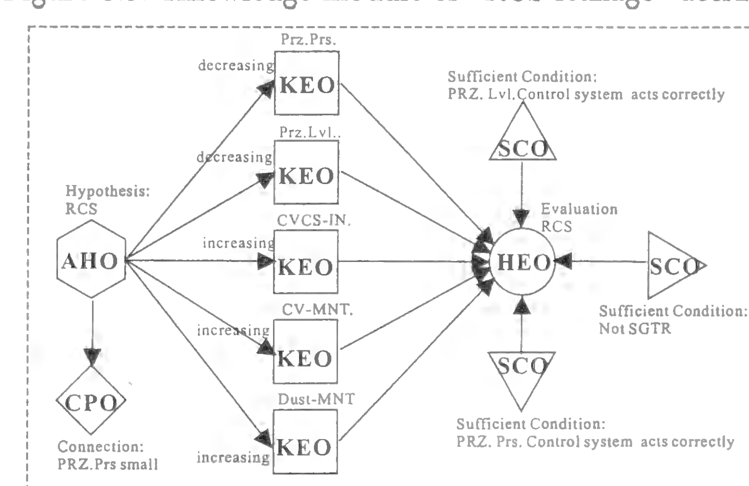

Figure 3.10: Modeling methods of the knowledge about "RCS leakage"

Table 3.4: Five types of knowledge objects

Knowledge Object	Abbreviation and symbol	Naming of the object in G2	Samples
knowledge element object	KEO □	Flow-XXX	Flow-PRZ-PRS
anomaly hypothesis object	AHO ⬡	Verify-XXX	Verify-RCS
hypothesis examination object	HEO ○	Evaluate-XXX	Evaluate-RCS
sufficient condition object	SCO △	NO-XXX	NO-SGTR
connection post object	CPO ◇	XXX-transient	PRZ-PRS-Small-transient

By utilizing a graphical network structure, these knowledge modules are modeled separately. Figure 3.6 shows the implemented knowledge module of the pressurizer pressure control system in the expert development system G2, as an example of modeling the knowledge about control systems. Figure 3.7 simplify Figure 3.6 so that it can be understood easily. The model of the knowledge about the pressurizer pressure control system is constructed in accordance with the control mechanism depicted by Figure 3.8. Figure 3.8 shows the logical relationships between the components of the pressurizer pressure control system, such as "compensation pressure", "relief valve", "backup heater". These components are modeled as "knowledge element objects" indicated as "KEO" (explained in detail later) in Figure 3.7. Besides "KEO", the other objects are devised to model the related knowledge about the anomaly diagnosis.

As an example of modeling the experiences or knowledge about the nature of accidents, Figure 3.9 shows the implemented knowledge module of coolant leakage accidents in primary system called as "RCS leakage". Similarly, Figure 3.10 gives a simplified representation of Figure 3.9 for understanding it easily. These two examples will be utilized to explain the modeling methods of the knowledge database as follows.

All objects in the two figures are called as "knowledge object". As seen in the figures 3.7 and 3.10, the graphical network-structured knowledge database consists of five types of knowledge objects and the pointing arrows between them. The pointing arrows represent the cause-effect relationships among the objects. The concrete contents of the relationships are defined in the format of IF-THEN rules within each object. The five types of knowledge objects are summarized in Table 3.4 and the detailed function of each object is explained below.

Knowledge Element Object

KEO is represented by the square mark. It is the fundamental element for constructing the network-structured knowledge database. Basically, one KEO corresponds to one plant parameter. KEOs store three kinds of information about the plant parameter, summarized as follows.

- The steady values of the parameter, and the upper- and lower thresholds for judging the deviation in the parameter value.
- The location information describing where the instrument corresponding to the parameter is located on MMI.
- Rules describing the cause-effect relationship between KEOs.

The first one will be utilized for the interpretation process. The second one will be utilized in an active parameter reference, described in detail later. The last one will be utilized in the reasoning of verifying and examining an anomaly hypothesis.

Anomaly Hypothesis Object

AHO is represented by the hexagon mark. It is the model of the hypothesis formed by operators based on the practical experiences and knowledge about the abnormal transients. Basically, one hypothesis corresponds to one AHO. With respect to the abnormal transient, the predictions about the status of plant parameters are described in the format of "declare type" rules within the AHO. These predictions are described in the left side of the KEOs, as shown in the figures 3.7 and 3.10.

Hypothesis Examination Object

HEO is represented by the circle mark. It is the model of knowledge that is utilized to examine the hypothesis represented by AHO. Basically, one HEO corresponds to one AHO. Based on the analysis results summarized in the subsection 2.3.4, the hypothesis examination can be modeled as an accumulation process of the confidence on the hypothesis. In order to model the hypothesis examination, the concept of confidence level is devised for describing how much the operator is confident that the hypothesis is correct. The detailed modeling methods are described as follows.

- With respect to examining a hypothesis, scores are assigned to the plant parameters whose conditions are predicted in accordance with the hypothesis. Such plant parameters are called as the "necessary plant parameters". The score is called as confidence score. The "necessary plant parameters" are selected from the analysis results of "questionnaire sheet 1" where the questions were given to subjects for examining the symptoms supporting various hypothesis. Table 3.5 shows an assignment example of the confidence score for the "necessary plant parameters" with respect to diagnosing "RCS leakage".

- The confidence scores of the "necessary plant parameters" are set so that the whole sum of them comes to 100 points. The confidence level "100 points" of an anomaly hypothesis means that all the major symptoms supporting the hypothesis are confirme and therefore, it is quite possible that the root cause is the hypothesis. The accumulation of the confidence score represents the current confidence level of the hypothesis.

- The confidence level will be increased if the actual condition of the parameters agrees with the prediction made in accordance with the hypothesis. On the other hand, The confidence level will be decreased if the actual condition of the parameters disagrees with the prediction. Therefore, the confidence level will be accumulated in either plus or minus direction in accordance with the observed symptoms.

The assignment of the confidence score is based on the relative importance of the "necessary parameters" with respect to diagnosing the abnormal transient. The relative importance can be abstracted from the analysis results of "questionnaire sheet 1" where the questions were given to subjects for examining the relative importance index of parameters with respect to diagnosing abnormal transients.

Sufficient Condition Object

With respect to adopting a hypothesis, the reference to the status of the necessary plant parameters is substantially the verification of the necessary conditions. The hypothesis cannot be adopted only by checking the necessary conditions. After all necessary conditions are confirmed, the sufficient conditions should be also checked. SCOs represented by the triangle mark are devised for the sufficient conditions as shown in the figures 3.7 and 3.10. SCO is utilized to model the re-confirmation activities in the cognitive behaviors of

Table 3.5: Example of confidence score assignment

Necessary Parameters	Predicted Status	Confidence Score for agreement	Confidence Score for disagreement
PRZ.PRS.	small	+8	-7
PRZ.PRS. Trend	decreasing	+7	-7
PRZ.LVL	small	+15	-7
PRZ.LVL Trend	decreasing	+15	-7
Radioactive gas within CV.	big	+7	-15
Radioactive gas within CV. Trend	increasing	+13	-15
Radioactive dust within CV.	big	+7	-15
Radioactive dust within CV. Trend	increasing	+13	-15
CVCS-IN	big	+8	-7
CVCS-IN Trend	increasing	+7	-7

anomaly diagnosis. The re-confirmation activity means that if the operator is not quite sure about his diagnosis results, he will consider other related hypotheses and will check the related systems to confirm whether the systems are in correct conditions or not. Then, the diagnosis result will be further examined by the re-confirmation activity. This re-confirmation activity corresponds to the information processing flow of "K $\rightarrow$ L $\rightarrow$ D $\rightarrow$ E $\rightarrow$ G $\rightarrow$ I $\rightarrow$ K", as shown in Figure 3.5. The previous subsection 3.4.1 has described the meanings of those alphabets in detail. The modeling methods of SCOs are described as follows.

- The plant parameters indicating the condition of the related systems are called here as "sufficient parameters" with respect to re-confirming the diagnosis result.

- The related systems are assumed in correct condition in accordance with the diagnosis result. Therefore, the status of the "sufficient parameters" is predicted on the assumption.

- The confidence scores are also assigned to those "sufficient parameters" to feed the effect of the re-confirmation back to the confidence level of the diagnosis result. The assignment of the confidence scores to the "sufficient parameters" is modeled as a table-type database stored in the corresponding SCO. Table 3.6 shows an example of the assignment with respect to the SCO of "PRZ.Prs.Cont system" in the case of the diagnosis result of "RCS leakage", as shown in Figure 3.10.

- The confidence scores are assigned to the "sufficient parameters" whose states indicate the condition of the pressure control system. The status of the "sufficient parameters" is predicted on the assumption that the control system will act correctly in the accident of "RCS leakage". If the actual status agrees with the prediction, the increase of the confidence level of "RCS leakage" is set to 5 points. However, in the case of disagreement, it means that the diagnosis result of "RCS leakage" is wrong and there may be a failure in the control system. Therefore, the diagnosis result of "RCS leakage" will be rejected immediately and a new hypothesis about the failure of the control system will be recalled.

- There will be several SCOs for one HEO, as shown in the figures 3.7 and 3.10. They are classified into two groups called as "must-examination" and "option-examination" SCOs, respectively. The "must-examination" means that the related systems represented by the SCOs must be confirmed with respect to adopting the diagnosis result. It models the subject's most important re-confirmation activities to adopt the diagnosis result. For an example, "not-SGTR" is defined as the "must-examination" SCO of the hypothesis "RCS leakage". "SGTR" is similar to "RCS leakage" in the observable symptoms of the primary plant system. Therefore, the confirmation that "SGTR" does not occur is important in adopting the root cause of the abnormal transient is "RCS leakage". On the other hand, the SCOs classified into "option-examination" group would be checked optionally to re-confirm the diagnosis result. For an example, the re-confirmation of the control system is defined as "option-examination" SCOs of the hypothesis "RCS leakage".

Connection Post Object

Finally, as for CPO represented by the diamond mark in the figures, it is just the "connection post" object defined originally in G2 [20]. The characteristic of CPO is that the CPOs having same name would be treated as identical objects. The characteristic of CPO is utilized in the following ways to model the knowledge database.

- Modeling the first symptom
  The first symptom is modeled by CPO, e.g., "PRZ.Prs Small" as shown in the figures

Table 3.6: Confidence score assignment for confirming sufficient condition

Sufficient Parameters	Predicted Status	Confidence Score for agreement	In the case of disagreement
PRZ.Comp.PRS.	small	+5	Reject the hypothesis immediately
PRZ.Comp.PRS. Trend	decreasing	+5	
Proportional heater	on	+5	
Backup heater	on	+5	
Spray valve	off	+5	
Relief valve	off	+5	

  3.7 and 3.10. The first symptoms are connected at the downstream position of all possible hypotheses recalled by it.

- Modeling the relationship of the knowledge modules
  As described previously, totally seven knowledge modules are utilized to model the knowledge database. The relationships of the knowledge modules are the common symptoms. For an example, the abnormal transients "RCS leakage" and "PRZ.Prs. Control failure-high" have the common symptoms "PRZ.Prs Small". CPOs are utilized to model the relationship between the knowledge modules. As the result, CPOs would help to model the transition of the thinking focus from one knowledge module to another one in diagnosing an abnormal transient.

- Modeling the scope of the hypotheses recalled by the first symptom
  The scope of the hypotheses recalled by the first symptom is the different aspect of the relationship of the knowledge modules. The scope is defined as all AHOs connected at the upper stream of the first symptom.

Other Knowledge Database

Besides the graphical network-structured representation of the knowledge database, table-type databases are devised to represent the following knowledge.

- The correspondence relation between alarm messages and the variation of parameter value.

- The relationship of the first symptom and the first hypothesis.

Table 3.7: Interpretation of alarm messages

Alarm Messages	Interpretation
"SG-Level < Steam Flow "	SG-Level small
"SG-Level > Steam Flow "	SG-Level big
SG-Level Big Deviation	SG-Level big
Tavg Low	Tavg small
PRZ. Pressure High	PRZ.prs big
PRZ. Compensation Pressure High	Comp.prs big
PRZ Pressure Low	PRZ.prs small
PRZ Pressure Low First out alarm	PRZ.prs small
PRZ Relief Valve Action	Relief-V. On
PRZ Level Low	PRZ.lvl. small
PRZ Level High	PRZ.lvl. big
A-Loop-Tavg Big Deviation	A-Tavg big
B-Loop-Tavg Big Deviation	B-Tavg big
C-Loop-Tavg Big Deviation	C-Tavg big
Neutron Flux Changing Rate(+) High	NIS big
Neutron Flux Changing Rate(-) High	NIS small

The former one will be utilized to interpret the meaning of alarm messages. Table 3.7 shows the interpretation of the alarm messages utilized in the laboratory experiment.

The latter one is devised for each subject to represent the individual characteristics summarized previously in tables 2.5, 2.6, and 2.7 in Chapter 2. The model of the relationship in the case of "Subject I" is shown in Table 3.8 as an example. The models of the relationship of the other subjects are shown in Appendix D. At present, the table is devised so that one first-symptom corresponds to one first-hypothesis. In the cases where multiple first-hypotheses are recalled by subjects in the laboratory experiment, only the first-hypothesis recalled most frequently will be selected as the first hypothesis corresponding to the first symptom.

So far, the implementation of knowledge database into computers as computerized forms are explained by describing modeling methods of knowledge modules and the connection relationships between them. Such methods have much flexibility to enrich the knowledge database only by adding more knowledge module and connecting them with the existing ones.

Table 3.8: Modeling of recalling the first hypothesis in the case of "Subject I"

First Symptom	First hypothesis of Subject I	Settings in Model of Subject I
SG-Lvl	FW related (100%)	FW related
PRZ-prs Small	PRZ.Cont.F (10%), RCS/SGTR(80%), Leakge in Gas phase of PRZ.(10%)	RCS
PRZ-prs Big	Reactor related (100%)	Reactor related
PRZ-lvl small.	RCS (100%)	RCS
CVCS-in Big	RCS (100%)	RCS
CVCS-in Small	PRZ. Lvl. Cont. F. (100%)	PRZ. Lvl. Cont. F.
FW. Lvl. Big	FW related (100%)	FW related
Reactor Output	Reactor related (100%)	Reactor related

3.4.4 Modeling of Information Processing in Diagnosing Phase

In the beginning of this section, it has been suggested that the information processing of anomaly diagnosis can be modeled as the processing flow shown in Figure 3.5. The information itself processed at STM and LTM has been modeled as WME and network-structured knowledge database in the preceding subsection. In this subsection, we will describe how to implement the information processing at STM and LTM into computers as the manipulation of the WME and the network-structured knowledge database. The modeling is based on the discussion about the functions of PWM, FWM and LTM described in the general human modeling framework.

Information Processing in PWM

As described previously, PWM stores the background information related to the information processed in FWM. Its function is to govern the access to FWM. To model the information processing on computers, two types of symbol manipulation are devised as shown in Figure 3.11. One is for the new incoming information and the other one is for setting the holding time of the old information. The details of them are explained as follows.

In accordance with where the new information comes from, there are three types of information entering into PWM:

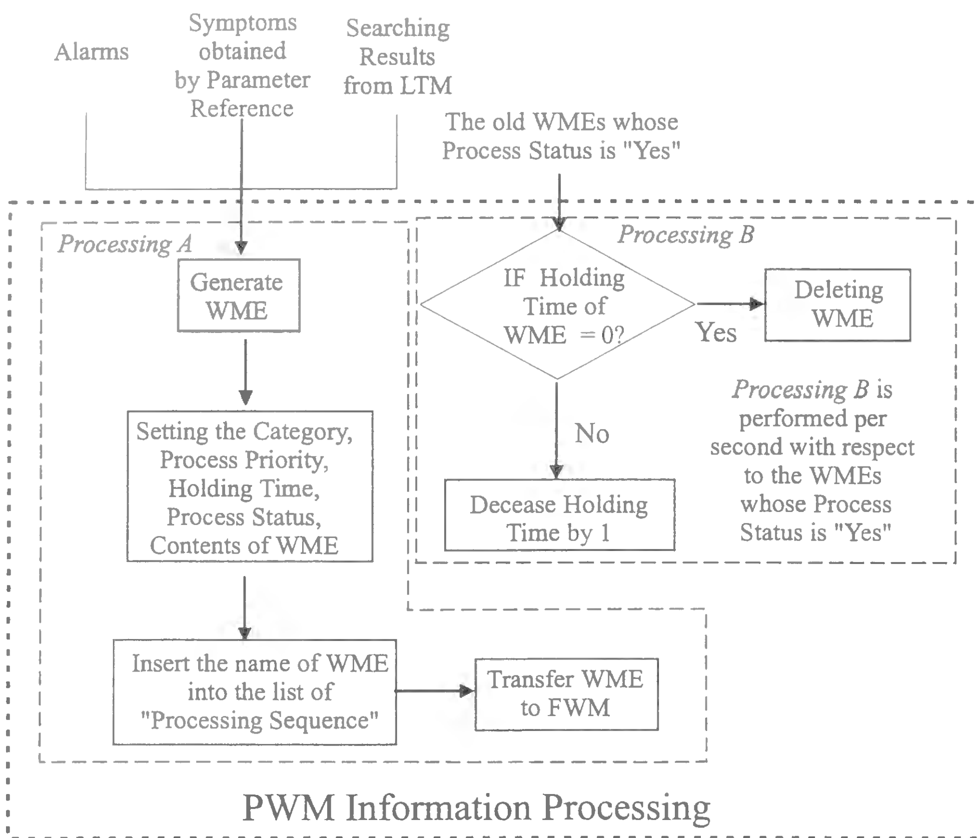

Figure 3.11: Information processing in PWM

- warning information from outside world unexpectedly
- symptoms by the active parameter reference from outside world expectedly
- searching results of knowledge database from LTM

As shown in Figure 3.11, *Processing A* is devised to model how the new incoming information is processed at PWM. Since all incoming information into FWM will pass through PWM, the formation of WME is considered as one of the unconscious information processing taken place at PWM. *Processing A* models the formation of WME. That is to say, *Processing A* converts the new incoming information into WME and sets the attributes of WME such as *Category*, *Processing Priority*, *Processing Status*, *Holding Time*. The function of governing the privilege access to FWM is modeled as the settings of the *Processing Priority* for WMEs. As described in the data structure of WME, the priority of $0-2$ is assigned to WMEs. As the result of the *Processing A*, the new WME is generated and is then transferred into FWM.

Table 3.9: Keywords abstracted form the content of WME

Category	Content	Abstracted Keywords	Examples
Alarm	alarm message	same as the content	"PRZ.Prs. is low"
Hypothesis	name of the hypothesis + the current confidence level of it	name of the hypothesis	SGTR
Prediction	name of the parameter + the prediction about it status	name of the parameter	PRZ.PRS, PRZ.Lvl.trend
Symptom	name of the parameter + its actual status	same as the content	PRZ.PRS+big, PRZ.Lvl.trend+decreasing

On the other hand, there is also information from FWM besides the new incoming information. The information had been processed in FWM and is transferred back to PWM as the background information. Therefore, such information had been converted into WME. Comparing with new WME whose *Processing Status* is set as "No" by *Processing A* at PWM, *Processing Status* of the WME from FWM would be set as "reserved" or "Yes" by FWM processing in accordance with whether the background information will be utilized in the future processing or not. The setting of "Yes" means the WME is no longer useful. In this case, *Processing B* is devised to model the forgetting effect of the WME that will be not refreshed by FWM processing, as shown in Figure 3.11. *Processing B* decreases the *Impression Index* of the WME by 1 per second. As the result of the *Processing B*, the WME will be deleted when the *Holding Time* is decreased to "0".

Information Processing in FWM

As described previously, the function of the information processing in FWM is abstracting keywords to search database in the "fallible machine" model. Besides that, the examination of hypothesis based on reasoning is also conducted in FWM in the context of anomaly diagnosis in the general human modeling framework. The modeling of these two kinds of information processing at FWM is described here in detail.

First of all, since the information processing in FWM is conducted consciously in sequence, a stack is devised to define the processing sequence of WMEs transferred from PWM. The stack is called as "Processing Sequence". The processing sequence of WMEs is set in accordance with the *Processing Priority* of WMEs.

As for the keyword abstraction from WMEs, FWM processing is conducted in accor-

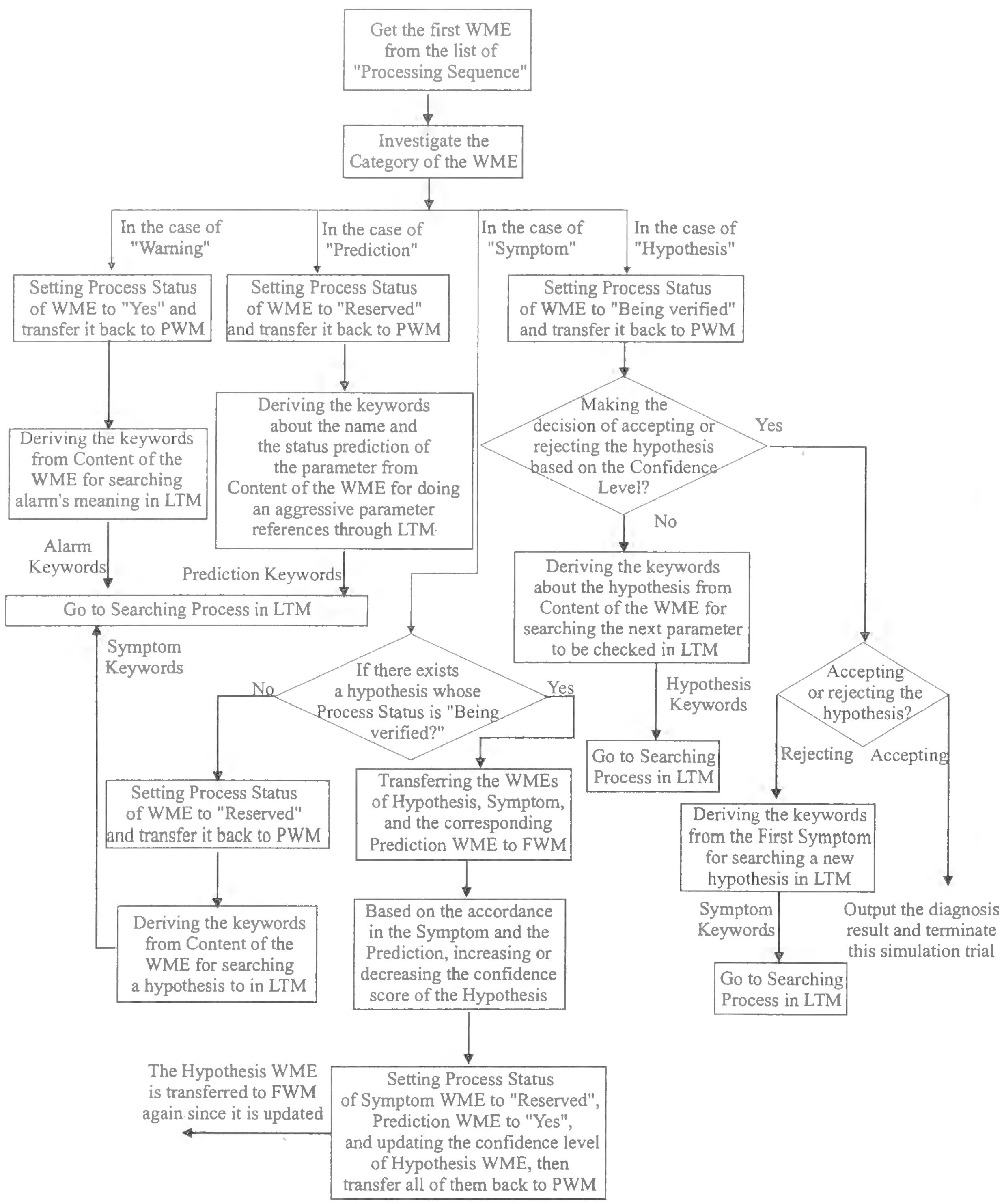

Figure 3.12: Information processing in FWM

dance with the category of the WME picked up from the stack. Table 3.9 summarizes the keywords abstracted from the content of WME. The details of the information processing conducted in FWM are described as follows, as shown in Figure 3.12.

- "Alarm"

  The alarm messages are abstracted from the content of the alarm WME as the keywords. The keywords will be utilized to search the knowledge database by the information processing in LTM to find out the parameter and the prediction about its status corresponding to the alarm so that the meaning of the alarm can be understood. The *Processing Status* of the alarm WME is set to "Yes". The processed alarm WME is then transferred back to PWM.

- "Prediction"

  The name of the parameter is abstracted from the content of the prediction WME as the keyword. The keywords will be utilized by the information processing in LTM to search the knowledge database to find out where the parameter is located on the man-machine interface in order to make an active parameter reference. After this abstracting processing, the prediction WME (symbolized here temporarily as "$P - WME$") is transferred back to PWM and its *Processing Status* is set to "reserved" for the later information processing of the hypothesis examination.

- "Symptom"

  In this case, the processing is different with respect to whether PWM stores a hypothesis WME (symbolized here temporarily as "$H - WME$") to be examined or not.

  - No hypothesis to be examined

    If the hypothesis does not exist, the content of the symptom WME is abstracted as the keywords utilized by the information processing in LTM to search the knowledge database to find out a hypothesis. In this case, the *Processing Status* of the symptom WME is then set to "reserved" as the model of the "first symptom" that is the important background information for the later processing of recalling a new hypothesis. The processed symptom WME is then transferred back to PWM.

  - Exists a hypothesis to be examined

    In this case, the corresponding "$P-WME$" reserved in PWM will be transferred again into FWM, together with "$H - WME$" representing the hypothesis, in order to examine the hypothesis. The examination is conducted by comparing the content of the symptom WME with the content of "$P - WME$". If the contents agree with each other, it means that the hypothesis is supported by the symptom. Subsequently, the confidence level of the hypothesis is increased. On the other hand, if the contents disagree with each other, the confidence level of the hypothesis is decreased. How much the confidence level is increased or decreased is decided by the rules defined in the "hypothesis examination object" (HEO) described previously as one of the objects consisting of knowledge database. After the information processing of the hypothesis examination, the *Processing Status* of both the symptom WME and "$H - WME$" is set to "reserved", and that of "$P - WME$" is set to "Yes" since it is no longer useful. The content of "$H - WME$" is updated to reflect the new confidence level of the hypothesis. All the WMEs are transferred back to PWM. The updated hypothesis WME is transferred again into FWM to continue the information processing of anomaly diagnosis.

- "Hypothesis"

  Three kinds of different data processing would be conducted in accordance with the confidence level of the hypothesis WME; (i) adopting, (ii) rejecting the hypothesis, (iii) and continuing to collect more symptoms to examine the hypothesis further.

  - Adopting

    The hypothesis would be adopted as the root cause of the abnormal transient if the confidence level were high enough to over an upper threshold set in advance. The anomaly diagnosis will be terminated in this case.

  - Rejecting

    On the other hand, the hypothesis would be rejected if the confidence level were low enough. In this case, *Processing Status* of the hypothesis WME will be set to "Rejected" and the WME will be dropped into PWM as the background information. Moreover, the first symptom reserved in PWM will be then dropped into LTM again to search a new hypothesis.

  - Continuing examination

    As for the third case, it means that the decision of adopting or rejecting the

Table 3.10: Inputs and outputs of the information processing in LTM

Input	Output	Concrete Output Contents
Keywords abstracted from alarm WME	Prediction information	the corresponding parameter and the prediction about its status
Keywords abstracted from prediction WME	Active parameter reference	the location information of the parameter on man-machine interface, and then conducting an active reference to obtain the status of the parameter
Keywords abstracted from symptom WME	Hypothesis information	a hypothesis recalled in accordance with the symptom
Keywords abstracted from hypothesis WME	Prediction information	a related parameter and the prediction about its status in accordance with the hypothesis

hypothesis cannot be made because the confidence level is not so high or low. In other words, the situation is not so clear to make a decision. It is necessary to collect more symptoms in this case. Hence the name of hypothesis WME would be abstracted as the keywords utilized to search the knowledge database for a new plant parameter whose status would support or deny the hypothesis.

Information Processing at LTM

With respect the LTM processing, the main task is to search the knowledge database modeled as the graphical network-structured database. The searching tasks are fundamentally conducted by two methods: "similarity matching" and "frequency gambling", as explained in the general human modeling framework.

Table 3.10 summarizes the inputs and outputs of the information processing in LTM. The inputs are the four kinds of keywords. Three kinds of outputs are generated by the processing in LTM; (i) prediction information, (ii) hypothesis information and (iii) conduction of an active parameter reference. The first two kinds of outputs will be transferred into PWM where they will be registered as the new prediction and hypothesis WME, respectively. The third output will generate the symptom information that is also transferred into PWM. The detailed information processing in LTM is conducted in accordance with the keywords dropped from FWM shown in Table 3.9.

- Prediction information in accordance with the alarm keywords

The plant parameter together with the prediction about its status will be generated as the prediction information by searching LTM in accordance with the keywords abstracted from the alarm WME. This searching task is a kind of "similarity matching".

- Symptom information by conducting an active parameter reference
  With respect to conducting the active parameter reference, the location information will be first obtained from the "knowledge element object" corresponding to the plant parameter indicated by the keywords. The MMI operation will be then conducted to obtain the status of the parameter. The result of the parameter reference will be transferred into PWM as the new symptom information. Moreover, the rules of increasing or decreasing the confidence level of the hypothesis, as described in the "hypothesis examination object", will be also transferred into FWM through PWM, in order to conduct the examination of the hypothesis in FWM. This task is also a kind of "similarity matching".

- Hypothesis information recalled by the first symptom
  Based on the keywords abstracted from the first symptom, a new hypothesis will be suggested in two steps of database processing. The first step is to collect all possible hypotheses recalled by the first symptom. It is a kind of "similarity matching" since the searching task collects only the hypotheses related to the first symptom. The second step is to select one of them as the hypothesis to be examined next. This step is a kind of "frequency gambling" that gives the reason of the diversity in the cognitive information processing of anomaly diagnosis.

- Prediction information in accordance with the hypothesis
  A prediction information will be generated by searching the knowledge database in accordance with the hypothesis indicated by the keywords. The contents of the prediction information include the name of a plant parameter and its status prediction based on the hypothesis. The searching task is also conducted in two steps. The first step is to activate all the KEOs that represent the plant parameters related to the hypothesis. This step is a kind of "similarity matching". The second step is to select one of the plant parameters whose status has not been checked, and to predict the prediction about its status based on the assumption that the hypothesis is correct. This step is a kind of "frequency gambling" that gives the reason of the variety of the parameter reference sequence in examining a hypothesis.

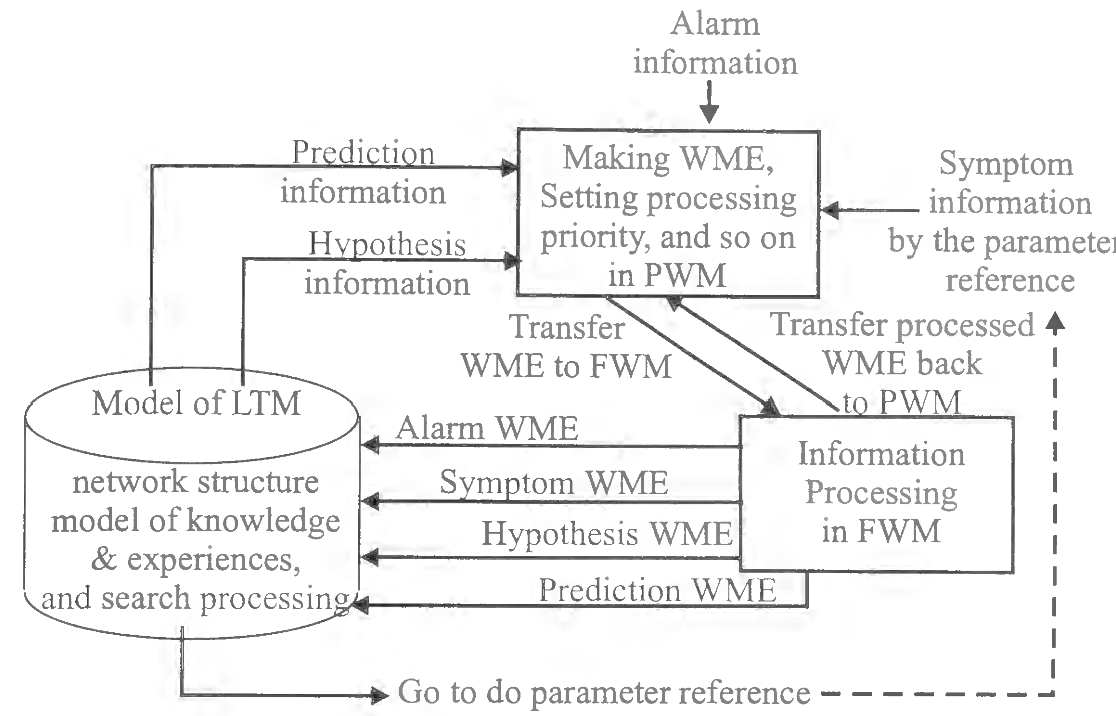

Figure 3.13: Internal cognitive information processing flow

So far, the modeling methods of the internal information processing are explained with respect to diagnosing an abnormal transient. Figure 3.13 gives the summary of the information processing flow.

3.4.5 Human Model Adjustment Factors for Diagnosing Phase

In the context of diagnosing the root cause of the abnormal transients, the following factors are considered as the adjustment factors by which the individual characteristics in the information processing can be modeled.

- First-Symptom-First-Hypothesis relationship
  As described previously in Chapter 2, the first symptom by which subject detects abnormal transient did influence almost the pattern of the following anomaly diagnosis. Moreover, the first-symptom-first-hypothesis relationship is different from person to person. First-Symptom-First-Hypothesis database has been devised to define the examination priority and the scope of the anomaly hypotheses corresponding to the first symptom. Therefore, the individual characteristics in recalling hypothesis can be simulated by modifying the database.

- Thresholds of confidence level for rejecting or adopting a hypothesis

  The another human adjustment factor is the thresholds of confidence level by which a hypothesis is rejected or adopted. In previous description about the concept of confidence score and confidence level, it can be understood that the thresholds of the confidence level represent the degree of subjects' caution regarding the adoption or rejection of an anomaly hypothesis. The caution is one of the individual characteristics that will exert an influence on the time taken to find out the root cause of an abnormal transient. A subject may reject a wrong hypothesis too late because of the over adherence on it. He may also adopt a correct hypothesis too late because of the over deep deliberation. With respect to modeling the effect of over adherence, a low confidence level can be set as the threshold of rejecting a hypothesis so that more time would be taken before a hypothesis is rejected. Similarly, a high confidence level can be set as the threshold of adopting a hypothesis. Thus, the adjustment of the thresholds of the confidence level can simulate the effects of the individual caution regarding adoption or rejection of the hypothesis.

3.5 Human Model Simulation and Its Validation

3.5.1 Viewpoints of Human Model Validation and Method

Viewpoints of the human model validation

So far, the human model has been developed to simulate the cognitive information processing in the anomaly detection and diagnosis. In this section, we will confirm whether the human model achieve the objectives set forth in the beginning of this chapter or not. Two objectives of the total three should be achieved in this chapter, as listed below.

- Develop a human model so that it can simulate well the subjects' cognitive activities observed in the laboratory experiment.
- Develop the human model so that it can simulate the inherent diversity and variety characteristics in the cognitive activities of detecting and diagnosing abnormal transients.

With respect to validate the human model, the former objective means that the developed human model should be able to simulate the general characteristics of the subjects' cognitive information processing observed in the laboratory experiment. On the other hand, the latter objective means that the individual characteristics of each subject's cognitive information processing should be also simulated well by the developed human model. Therefore, the validation of the human model will be conducted in this section with respect to confirming these two viewpoints.

Methods of the human model validation

Since the validation of the human model is to verify whether the model can simulate the subjects' behaviors well or not, the simulation results by the human model should be compared with subjects' data obtained in the laboratory experiment. Therefore, the validation of the human model is conducted in two steps.

- Step 1: Conducting numerical experiments in which the human model will detect and diagnose abnormal transients.
- Step 2: Comparing the simulation data with the subjects' data obtained in the laboratory experiment.

With respect to conducting the numerical experiments, the human model is connected to the identical NPP simulator utilized in the laboratory experiment. But, instead of passing through the CRT-based interface, the human model is connected directly to the plant simulator. The time taken to operate the CRT-based interface by the subjects (e.g., switching interface windows, referring to plant parameters' value or trend variation) is modeled as the time delay in the direct retrieval of the parameter value by the human model. Based on the reference time and frequency summarized as experimental data in Chapter 2, the time taken to check one parameter is calculated. Table 3.11 shows the time delay settings utilized in the numerical experiments in accordance with the calculation results.

Detecting and diagnosing the same 12 abnormal transients utilized in the laboratory experiment are the content of the numerical experiments based on the human model simulation. Also, total 30 trials were conducted for each model of the subjects. The experimental procedures are also same with the one described in subsection 2.2.4.

Contents of the human model validation

Since the human model is developed separately for the monitoring and diagnosing phase, the contents of the human model validation are devised for both of the phases.

With respect to the monitoring phase, the primary interests centered on when and by what symptom the subjects detect the occurrence of an abnormal transient. Therefore, the first symptom and the time taken to detect an abnormal transient are selected as verification items for the monitoring phase. On the other hand, the detailed diagnosis procedure plays an important role with respect to analyzing operators' cognitive behaviors. Therefore, the operation sequence history is selected for validating the human model simulation of the diagnosing phase.

In the following subsections, the details of the human model validation are described with respect to verifying the agreement between the simulation results and the experimental data.

Table 3.11: Time delay settings

MMI Operation	Time Delay
Parameter Value Reference	2 sec.
Parameter Trend Reference	4 sec.
Switch MMI screen	1 sec.

3.5.2 Comparison of First Symptom

With respect to 12 kinds of abnormal transients, the first symptoms detected by the subjects in the laboratory experiments are compared with the ones detected by the corresponding human model in the numerical experiments.

Tables 3.12, 3.13 and 3.14 show the first symptoms detected by three subjects and the corresponding human model. In the right-end column of the tables, the degree of the agreement between the first symptoms is represented by three kinds of marks. The double circle marks mean that the first symptoms detected by the human model in the numerical experiments agree with the subjects' data completely. The crisscross marks means the first symptoms are different completely. The normal circle marks are for the cases where the first symptoms detected by the human model are "similar" to the ones detected by subjects in the laboratory experiment. The word of "similar" has three meanings explained as follows.

- The first symptom detected by the human model is included in the ones detected by the corresponding subject in the laboratory experiment.
- The converse situation of the above case.
- Although the first symptoms detected by the human model and the corresponding subject are different, they indicate the anomaly of the same sub-system of the plant system.

From these tables, we can conclude that the first symptoms detected by the models agree well with the ones detected by the subjects in the laboratory experiments. Moreover, which respect to modeling the inherent diversity and variety of human behaviors, the following conclusion can be obtained.

- As described previously in Chapter 2, the first symptoms detected by the subjects are different even in the case of the same abnormal transient. It reflects the diversity of the human behaviors. From the tables, one cannotice that different first symptoms have been detected by the three models, even in the case of the same abnormal transient. Therefore, we can conclude that the models simulate the diversity well.
- On the other hand, the variety is another inherent characteristics of human behaviors. With respect to detecting anomaly, the variety means that even in the case of same abnormal transient, the same person would detect the different first symptoms. From the tables, one can also notice that such variety is also simulated well by the models.

Table 3.12: The comparison of first symptom in the case of "Subject A"

Abnormal Transients	Model of Subject A	Subject A	Agreement
SGTR	PRZ-prs small CVCS-in big	Steam flow big CVCS-in big PRZ.prs small	○
RCS big	CVCS-in big PRZ-prs small	PRZ-lvl. small PRZ-prs small	○
RCS small	PRZ-prs small	CVCS-in big PRZ-prs small	○
FW lvl sensor failure	Warning message	Warning message	◎
FW flow cont. V. F	FW small SG-LVL small	FW small SG-LVL small	◎
PRZ. Prs.cont. F.H	CVCS-in big PRZ prs small	PRZ-lvl. big PRZ prs small	○
PRZ Prs.cont. F.L	PRZ prs big	PRZ prs big	◎
PRZ. Spray V. F. S	CVCS-in big PRZ prs small	PRZ prs small	○
PRZ. Spray V. F. B	CVCS-in big PRZ prs small	PRZ prs small	○
PRZ lvl.cont fail low	CVCS-in small	CVCS-in small	◎
PRZ lvl.cont fail high	CVCS-in big	CVCS-in Big	◎
NIS	PRZ prs big Reactor output big	PRZ prs big Reactor output big	◎

Table 3.13: The comparison of first symptom in the case of "Subject I"

Abnormal Transients	Model of Subject I	Subject I	Agreement
SGTR	PRZ-prs small CVCS-in big	SG-Lvl. big FW. Flow small PRZ.prs small	○
RCS big	CVCS-in big PRZ-prs small	CVCS-in big PRZ-prs small	◎
RCS small	CVCS-in big PRZ-prs small	PRZ-lvl. small PRZ-prs small	○
FW lvl sensor failure	Warning message	Warning message	◎
FW flow cont. V. F	SG-LVL small	SG-LVL small	◎
PRZ. Prs.cont. F.H	CVCS-in big PRZ prs small	CVCS-in big PRZ prs small	◎
PRZ Prs.cont. F.L	PRZ prs big	PRZ prs big	◎
PRZ. Spray V. F. S	PRZ prs small	CVCS-in big PRZ prs small	○
PRZ. Spray V. F. B	PRZ prs small	PRZ prs small	◎
PRZ lvl.cont fail low	CVCS-in small	CVCS-in small	◎
PRZ lvl.cont fail high	CVCS-in big	CVCS-in big	◎
NIS	PRZ prs big	Reactor output big	×

Table 3.14: The comparison of first symptom in the case of "Subject T"

Abnormal Transients	Model of Subject T	Subject T	Agreement
SGTR	PRZ-prs small SG-Lvl. big PRZ-lvl. small	CVCS-in big PRZ.prs small	○
RCS big	PRZ-lvl. small	PRZ-lvl. small PRZ-prs small	○
RCS small	PRZ-lvl. small	PRZ-prs small	○
FW lvl sensor failure	Warning message	Warning message	◎
FW flow cont. V. F	SG-LVL small	FW flow small	○
PRZ. Prs.cont. F.H	PRZ prs small	PRZ prs small	◎
PRZ Prs.cont. F.L	PRZ prs big	PRZ prs big	◎
PRZ. Spray V. F. S	PRZ prs small	PRZ prs small	◎
PRZ. Spray V. F. B	PRZ prs small	PRZ prs small	◎
PRZ lvl.cont fail low	PRZ-lvl. small CVCS-in small	PRZ-lvl. small	○
PRZ lvl.cont fail high	PRZ-lvl. big	CVCS-in big PRZ-lvl. big	○
NIS	PRZ prs big Reactor output big	PRZ prs big Reactor output big	◎

The agreement of the first symptoms and the simulation of the diversity and variety suggest that the "monitoring strategy", criteria of judging the occurrence of abnormal transient and the peripheral sight effect were modeled successfully for each subject.

3.5.3 Comparison of Detection Time

By conducting the numerical experiments, the data about the time taken to detect the occurrence of abnormal transients were collected for the 12 kinds of abnormal transients. Same as the laboratory experiments, the multiple trials were conducted for same abnormal transient. The data about the detection time by the human model are collected from each trial. The detailed data of the detection time are summarized in tables C.2 and C.1 in appendix C. From the tables, one would notice the followings:

- The human model can detect same abnormal transient at different time. It reflects the modeling of the variety of human behaviors.
- The average detection time of the different model will be also different. It reflects the modeling of the diversity of human behaviors.

With respect to validating the appropriateness of the modeling of the variety and diversity, the comparison of the average detection time should be conducted.

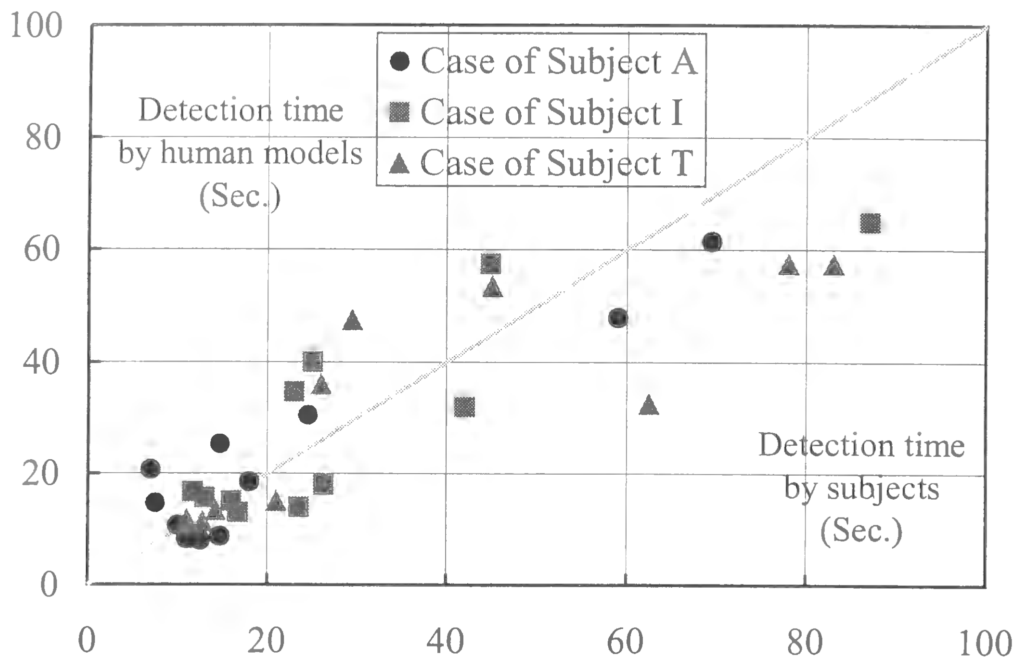

Figure 3.14: Comparison of detection time between subjects and the models

Table 3.15: Evaluation index of the agreement shown in the above figure

Subjects	Coefficient of the correlation (ideal: 1.0)	Slope of the best-fit regression line (ideal: 1.0)	Y-axis intersects of the best-fit regression line (Ideal: 0.0 sec.)
Case of "Subject A"	0.935	1.14	-3.8
Case of "Subject I"	0.851	1.01	0.5
Case of "Subject T"	0.836	1.15	-0.3

Based on the data shown in Table C.1, the comparison of the average detection time between the subjects and the corresponding models is represented by Figure 3.14. In the figure, X-axis (the horizontal axis) represents the detection time by the subjects and Y-axis (the vertical axis) represents the detection time by the human models. The circle marks represent the pair of the detection times of "subject A" and the corresponding model. In the same way, the square and triangle marks are devised for the cases of "Subject I" and "Subject T", respectively. The line in the figure is the diagonal. Therefore, the distribution of the plot points around the diagonal represents the agreement of the detection time between subjects and the corresponding models. In order to examine the agreement quantitatively, the data processing is made in two steps described below.

- Step 1: coefficient of the correlation

  The coefficients of the correlation are calculated to check whether a linear correlation exists between the detection time data of the subjects and the corresponding models. If the models simulate well the characteristics of subjects' behaviors, the coefficients will approximate to 1.0. The calculation results are shown in Table 3.15. The results demonstrate that the detection time data of the subjects and models have a strong linear correlation.

- Step 2: best-fit regression line

  Then, based on the conclusion of Step 1, the best-fit regression line is formed for each case to check how much the best-fit line approximates to the diagonal. Both the slope and the Y-axis intersects of the best-fit regression line are shown in Table 3.15. The results turn out that both the slope and the Y-axis intersects approximate closely to the ones of the diagonal.

Based the above discussion, we could conclude that the detection time of the human model agrees well with the one of the corresponding subjects. The agreement demonstrates that the "monitoring strategy", criteria of judging the occurrence of abnormal transient, and the peripheral sight effect were modeled successfully for each subject. It also proves that the time delay settings are appropriate.

So far, the validation of the human model had been conducted with respect to comparing the first symptoms and the detection time in monitoring phase. In the following subsection, the validation will be conducted by comparing the operation sequence history of the human model in diagnosing phase.

3.5.4 Comparison of Operation Sequence History

In order to verify the validity of the human model simulation, the most direct method is to compare the OSH between simulation results and the experimental data. It is because the OSH reflects the overall performance of the various sub-models. In this subsection, the methods are shown to explain the simulation of the anomaly diagnosis process observed in the laboratory experiment. The validity of the developed human model will be verified by comparing the simulated anomaly diagnosis process with the operation sequence history obtained from the laboratory experiment.

The simulation of the diagnosis process of "Subject A" in diagnosing "RCS leakage small" is compared with the correspondent operation sequence history, as an example of the validity of the human model. The comparison is shown in the tables 3.16 and 3.17. The left side of Table 3.16 is the operation sequence history of "Subject A" in the experimental trial No.10 where "RCS leakage small" was the abnormal transient. The right side of the table is the simulated diagnosis process by utilizing the developed human model. The monitoring activities are omitted in the table. The diagnosis process is divided into several phases indicated as $A, B, \cdots, G$. The operation activities in each phase are explained in Table 3.17.

In the rest of this subsection, we will first describe the characteristics of the diagnosis process of "Subject A" in this case. Then, the simulation settings for reflecting the characteristics are explained. In the end, the validity of the human model will be proven by the comparison of the diagnosis process.

Characteristics of the diagnosis process of "Subject A"

With respect to diagnosing "RCS leakage small" in this case, the characteristics of "Subject A" can be summarized as follows.

- First symptom
  "Subject A" detected the occurrence of the abnormal transient by noticing the variation in the value of "PRZ.Prs.", as shown in phase A in left side of table 3.16.

- First hypothesis
  As summarized in Table 2.6 in Chapter 2, the first symptom of "PRZ.Prs" is always leading to the first hypothesis of the anomaly in "PRZ.Prs. Control System". As

Table 3.16: The comparison of operation sequence history

Operation Sequency of Subject A in Simulation Trial No.10

Time (sec.)	Action	Correspondent Relation
82	check "PRZ. Prs." and detected the anomaly	A
86	switch to "PRZ. Prs. Control System" screen	A
88	watch trend graph of "PRZ.Prs." and "PRZ. Comp-Pres."	B
102	switch back to "Summary" screen	B
108	switch to "FW system" , and then to "RMS"	C
110	watch radiation monitor of CV-Gas-MNT, CV-Dust-MNT, SG-Blowdown-MNT, and	C
114	switch back to "FW system" , then to "Summary" screen	C
119	check "PRZ. Prs." and check "PRZ. Lvl."	C
125	switch to "PRZ. Lvl. Control System" screen	F
126	watch trend graph "PRZ.lvl." and "CVCS-IN Flw."	F
130	switch back to "Summary" screen, and then to "PRZ. Prs. Control System" screen	E
136	watch trend graphof "PRZ.Prs." and "PRZ. Comp-Pres."	E
140	check "PRZ. Comp-Pres."	E
141	check "PRZ. Prs."	E
147	switch back to "Summary" screen, then to "PRZ. System" screen	E
155	check "Prop-heater" and "Backup-heater A1"	E
162	switch back to "Summary" screen	E
163	check "CVCS-In flw." and "CVCS-out flw."	F
174	Check A- B- C-SG Lvl and Prz.	D
186	switch back to "FW system" screen, then to "RMS" screen	D
190	watch radiation monitors	D
191	push "Identified" Button	G

Human Model Simulation

Correspondent Relation	Time (sec.)	Action
A	119	check "PRZ. Prs."
A	125	detected the abnorml transient
B	129	watch the variation-trend of "PRZ.Prs."
B	137	watch the variation-trend of "PRZ. Comp-Pres."
B	142	check "Prop-heater"
B	146	check "Backup-heater A1" and "Backup-heater A2"
C	159	watch the variation-trend of "CV-Gas-MNT"
C	165	watch the variation-trend of "CV-Dust-MNT"
C	173	check "PRZ. Lvl."
C	176	watch the variation-trend of "PRZ.Prs."
C	182	watch the variation-trend of "PRZ.Lvl."
D	193	watch the variation-trend of "SG-Blowdown-MNT"
D	199	watch the variation-trend of "Condener-Gas-MNT"
D	206	check "A-SG Lvl."
D	208	check "FW flw."
D	211	watch the variation-trend of "FW flw."
E	231	watch the variation-trend of "PRZ. Comp-Pres."
F	253	check "CVCS-In flw."
F		Warning "PRZ. Lvl. Low!!"
F	255	check "PRZ. Lvl."
F	259	check "CVCS-IN Cont. V"
G	273	Output diagnosis result andd terminate simulation

Table 3.17: The actions in the phases shown in the above table

Phases	Operation Activities in the Phases
A	Detected the occurrence of the abnormal transients by checking PRZ.Prs.
B	Examining "PRZ.Prs Control System fail-high"
C	Examining "RCS"
D	Confirming not "SGTR"
E	Confirming "PRZ.Prs Control System"
F	Confirming "PRZ.Lvl. Control System"
G	Terminating diangosis process

the result, "Subject A" examine the possibility of "PRZ.Prs. Control System Fail-high" in this case, as shown in phases B in the left side of table 3.16. After rejecting the hypothesis by noticing the correct response of "PRZ.Prs Control System", he switched his attention to the anomaly hypothesis of "RCS leakage", as shown in phases C in the left side of table 3.16.

- Related diagnosis knowledge
  After identifying the root cause of the abnormal transient, "Subject A" confirmed the related plant sub-system such as "PRZ.Prs. Control System" and "PRZ.Lvl. Control System" to verify the correct response of the control system, as shown in phases E and F in the left side of table 3.16. Moreover, before he terminated the diagnosis process, "Subject A" checked the SG-related plant parameters such as "SG-Lvl" to assure himself that the anomaly is not "SGTR" since the two kinds of abnormal transients are very similar to each other, as shown in phases D in the left side of table 3.16.

Settings in human model simulation

With respect to simulating the above characteristics, the following settings are made in the human model.

- The relationship of the first symptom and the first hypothesis
  As described previously in the modeling of the knowledge database, the relationship of the first symptom and the first hypothesis is modeled as table-type database for each subject, as shown in Appendix D. In the case of "Subject A", "PRZ.Prs. Control System failure" is the first hypothesis corresponding to the first symptom of "PRZ.Prs". Such relationship is implemented as one of the settings in the human model simulation.

- The scope of the hypotheses and the sufficient conditions
  Besides "PRZ.Prs. Control System fail-high", the scope of the hypotheses recalled by the first symptom "PRZ.Prs. small" includes "RCS leakage", "SGTR" and "PRZ.Prs.Spray Valve failure". The probability is set same as 1/3 for examining these hypotheses after the rejection of the first hypothesis. That means the rest three hypotheses have a fair chance to be examined.

- The settings of the sufficient conditions
  The confirmation of the correct response of "PRZ.Prs. Control System", "PRZ.Lvl. Control System" is defined as the "option-examination" sufficient conditions of adopting "RCS leakage". In addition, the verification of "not-SGTR" is defined as the "must-examination" sufficient condition since "SGTR" is similar to "RCS leakage" in the observable symptoms of the primary system.

- The thresholds for adopting and rejecting a hypothesis
  In accordance with the initial confidence score (20 points) assigned to the active hypothesis, the threshold for rejecting a hypothesis is assumed as 10 points. As described above, "Subject A" confirmed all the sufficient conditions for adopting "RCS leakage". Therefore, the thresholds for adopting a hypothesis in the human model is set enough big (200 points) so that all the sufficient conditions can be confirmed.

Simulation results

The simulation results are shown in the right side of Table 3.16, based on the above settings in the human model. The model detected "PRZ.Prs small" as the first symptom, as shown in phase A. The hypothesis "PRZ.Prs Control System fail-high" was recalled first in accordance with the settings in table-type database describing the relationship of the first symptom and the first hypothesis.

The model predicted the conditions of the plant parameters in accordance with the hypothesis and then checked the conditions of the parameters such as "PRZ.Comp-Prs", "Prop-heater". The results turned out that the actual conditions of the parameters did not agree with the predictions. Subsequently, the confidence level of the hypothesis was decreased in accordance with the results of the parameter reference, as shown in the phase B. In the end, the confidence level of "PRZ.Prs. Control System fail-high" was decreased below "10 points" that was the threshold for rejecting a hypothesis. Therefore, the model rejected the hypothesis.

After that, the model selected "RCS leakage" as the second hypothesis from the scope of the hypotheses recalled by the first symptom. The model predicted the conditions of the parameters related to "RCS leakage" in the same way as in the case of the first hypothesis. The model then conducted parameter references to check the conditions of the parameters such as "CV-Gas-MNT", "PRZ.Lvl". The hypothesis was confirmed since the all the

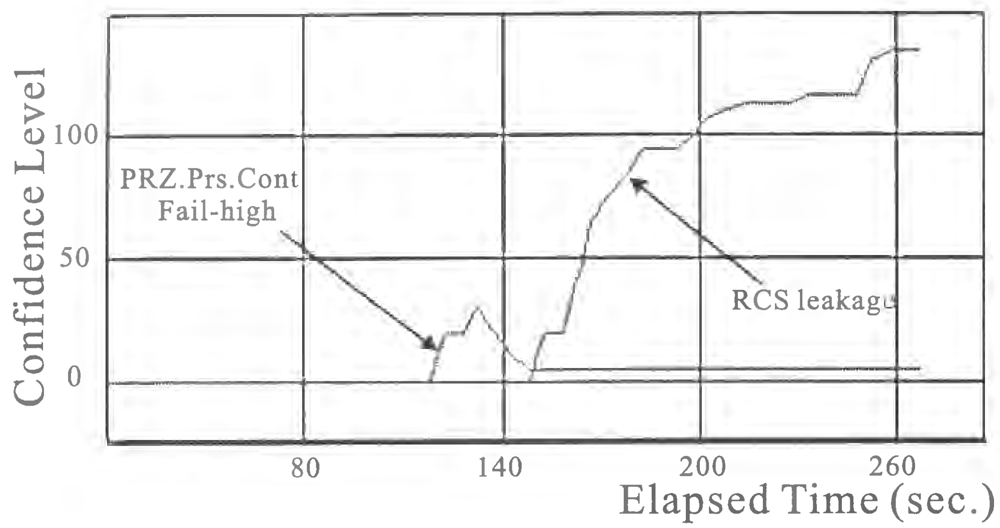

Figure 3.15: The confidence-score changes during the simulation

conditions of the parameters agreed with the predictions, as shown in the phase C. At this point, the confidence level of the hypothesis had been increased near to "100 points". But, the model did not terminate the diagnosing process by adopting "RCS leakage" as the root cause of the abnormal transient. It is because the threshold of the confidence level for adopting a hypothesis was set big enough (200 points) so that the model can simulate the re-confirmation activities observed in the experimental trial No.10 of the "Subject A".

As shown in phase D, the model first verified the "must-examination" sufficient condition: "not-SGTR" by checking the states of the SG-related plant parameters, such as "Blowdown-MNT", "SG-Lvl". The states of those parameters indicated that "SGTR" did not occur. Next, "PRZ.Prs. Control System" and the "PRZ.Lvl. Control System" are checked as the re-confirmation of the "option-examination" sufficient conditions, as shown in phases E and F. The results turned out the control systems responded correctly. In the end, the diagnosis process is terminated since all the necessary and the sufficient conditions had been confirmed.

So far, the conduction of human model simulation is described for the diagnosis process of "Subject A" in the experimental trial No.10. The confidence level variation during the human model simulation is depicted in Figure 3.15. The horizontal and the vertical axis represent the elapsed time and the confidence level of the hypothesis, respectively. There are two curves to represent the confidence level variation of the two hypotheses considered by the human model in the simulation of the diagnosis process. One is for "PRZ.Prs.

Control System fail-high" and the other one is for "RCS leakage". Corresponding to the operation sequence history of the human model, "PRZ.Prs Control System fail-high" was considered at 130 seconds after the simulation was started. The hypothesis received "20 points" as the initial confidence level. Then, the confidence level of the hypothesis was decreased in accordance with the results of the parameter references in phase B of Figure 3.16. At about 160 second, the confidence level of the hypothesis was decrease below 10 points. Therefore, "PRZ.Prs Control System fail-high" was rejected and "RCS leakage" was considered at that time. After that, the confidence level of "RCS leakage" was increasing constantly corresponding to the results of the parameter references in the phases C,D,E, and F. The diagnosis process can be understood easily by utilizing the operation sequence history and the confidence level variation of the anomaly hypotheses.

The above descriptions about the simulation results demonstrate that the human model simulation can explain the details of the diagnosis process of "Subject A" in the experimental trial No.10. The agreements between the simulation and the experimental data show the validity of the total performance of the individual sub-models that consist of the developed human model, such as model of knowledge database, model of the diagnosis processing flow.

3.6 Concluding Remarks

In this chapter, we described in detail the methods of developing a human model to simulate operator's cognitive behaviors of anomaly detection and diagnosis. The development of the human model is based on the analysis results of the cognitive behaviors, as described in detail in the preceding chapter.

The reviews are first made on the human modeling approaches and on the existing human modeling researches in NPP field, in order to clarify the objective of the human modeling in this thesis study. The objectives are summarized as follows.

- Develop a human model so that it can well simulate well the subjects' cognitive behaviors of detecting and diagnosing abnormal transients.
- Develop the human model that can simulate the inherent diversity and variety in human cognitive behaviors.
- Develop the human model so that it can be applied to the practice of HRA/PSA.

The former two ones are the objectives of this chapter.

The human model is then developed in accordance with a general human modeling framework. The fundamental concepts related to the human cognitive information processing are described by using the general human modeling framework, such as perception information processing, PWM, FWM and the knowledge database.

In accordance with the framework, the concept of "working memory element" has been proposed to model the knowledge elements processed in PWM and FWM. A graphical network structured organization is adopted to model the knowledge database. Furthermore, the various kinds of cognitive information processing are modeled as the manipulation of the WME and the knowledge database.

Based on these modeling methods, the anomaly detection and diagnosis are modeled separately. The modeling of anomaly detection are summarized as follows.

- The monitoring behaviors of subjects are modeled as the random parameter reference, in which the individual "monitoring strategy" is reflected.
- The anomaly detection is modeled as the process of parameter status verification by checking whether or not the parameters' value is deviated form the steady status. The interpretation of parameter values utilized the criteria of judging anomaly occurrence obtained in the preceding chapter.

The anomaly diagnosis process is modeled as a repeated procedure of recalling hypothesis, collecting symptoms, examining the hypothesis, rejecting the hypothesis until a hypothesis is adopted as the root cause of the abnormal transient. The modeling methods of each step are summarized as follows.

- The relationship of the first symptom and the first hypothesis is utilized to simulate the hypothesis recollection.
- The concepts of "confidence score" and "confidence level" are introduced to model the degree of operator's belief on a hypothesis. The confidence level of a hypothesis will be increased or decreased by comparing the parameter's status with the prediction in accordance with the hypothesis.
- The rejection and the adoption of hypotheses are modeled as the judgment if the current confidence level is beyond a certain threshold defined in advance.
- The threshold is modeled so that it could be changed to model the individual characteristics in the decision-making.

Furthermore, the concept of human modeling adjustment factor is introduced to model the individual characteristics of the cognitive behaviors to detect and diagnose an abnormal transient. The introduced adjustment factors are (i) the reference frequency of parameter group, (ii) the criteria for judging the occurrence of abnormal transient, (iii) the peripheral sight effect for the anomaly detection; and (i) the First-Symptom-First-Hypothesis relationship, (ii) the thresholds of confidence level for rejecting or adopting a hypothesis for the anomaly diagnosis.

Finally, numerical experiments are conducted to validate the human model by connecting the human model to the NPP simulator utilized in the laboratory experiments. The inter-comparison between the simulation results and the laboratory experimental data are conducted in three aspects: (i) first symptoms, (ii) average anomaly detection time and (iii) the detailed diagnosis procedures. The results demonstrate that the human model could simulate well both the general and the individual characteristics in the operator's cognitive behaviors of the anomaly detection and diagnosis. As the third step of this thesis study, an application study of the developed human model will be described in the next chapter.

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Chapter 4

Application of Human Model for the Human Reliability Analysis in Probabilistic Safety Assessment

In the preceding chapter, the development of the human model had been described in detail to show the modeling methods of operator's cognitive behaviors in case of an emergency of NPP. An application study of the developed human model is described in this chapter, aiming at estimating fundamental human cognitive error parameters needed for the human reliability analysis (HRA) which is made for probability safety assessment (PSA) of NPP. The developed human model in the preceding chapter is called as "human model simulation of plant anomaly diagnosis" (HUMOS-PAD) from this chapter for the convenience.

4.1 Objective of the Application Study

In this chapter, a new approach is proposed to apply HUMOS-PAD to HRA/PSA practice of NPP. As described previously, the importance of the human system interactions (HSIs) at MMI has been recognized with respect to the safety and reliability of the plant system as a whole. But, the study on the HSIs has been difficult since the HSIs would be influenced both by the complicated dynamic plant process and by the versatile, variable characteristics of the human behaviors.

In the study field of the HSIs in NPP, the examination of the operators' behaviors depends on the conduction of the large-scale operator experiment that requires skilled operators, mock-up of the real-scale man-machine interface, and the real-scale plant simulator. The typical example of the large-scale experiment is the operator reliability experiment (ORE) conducted by Electric Power Research Institute (EPRI) in order to examine the validity of the human cognitive reliability correlation used in HRA by utilizing the experimental data. In ORE, a NPP simulator is utilized, and the skilled operators are requested to interact with the simulator for coping with various simulated anomaly situations. Although the large-scale experiments like ORE can provide valuable experimental data about the interactions between operator-crew and plant system, not only the large amount of time and considerable costs are required for conducting and analyzing the large-scale experiments, but also the applicability of the obtained experimental results would be only limited within the tested condition [1]. The development of other methodologies has been required to supplement the large-scale experimental approach.

The studies on the model of operators' cognitive behaviors have been conducted as one of the hopeful methods to supplement the conventional approach. The computer simulation has been expected to replace the large-scale experiment by utilizing the model that can simulate operators' behaviors in case of an emergency. Compared with the large-scale experiments, the computer simulation requires almost no costs. Moreover, it has much flexibility to cope with various situations in the human machine interactions. With respect to the application of the human model to HRA/PSA practice in NPP, Kirwan had pointed out that human modeling would become a useful tool. The application requires that the human model should be able to represent well the versatile human behaviors on monitoring and controlling the process plant, with various environmental effects surrounding human tasks being taken into consideration [2].

The objective of the study in this chapter is to conduct a pilot study to estimate the fundamental parameters needed in the HRA/PSA practice of NPP by applying HUMOS-PAD developed in the preceding chapter. In the following sections, the methodology of HRA/PSA of NPP is first described to summarize the required fundamental human error parameters. Then, a new simulation-based approach is proposed to estimated "time versus cognitive reliability (TCR)" curves that represent the trade-off relationship of the affordable time and the human cognitive reliability. The probabilistic factors influencing the relationship are clarified by analyzing the TCRs obtained from the laboratory experimental data. Next, the modeling method of the probabilistic factors is explained to show the implementation of the effects of the factors into the framework of HUMOS-PAD. In the end, the validity of the application of HUMOS-PAD is confirmed by comparing the TCRs estimated by HUMOS-PAD and the ones obtained from the experimental data.

4.2 Probabilistic Safety Assessment and Human Reliability Analysis

In this chapter, the methodology of probabilistic safety assessment and the human reliability analysis is described briefly to show how they evaluate quantitatively the reliability of the man-machine system as a whole. In the end, a framework is proposed to summarize the fundamental human error parameters needed in PSA/HRA.

4.2.1 Probabilistic Safety Assessment

Probabilistic Safety Assessment (PSA) had been also called as Probability Risk Assessment historically. It has been developed to identify potential significant risk areas and to quantify the overall risk from a potentially hazardous plant.

The core contents of PSA analysis are the logical tree models of the plant and its functions. There are two basic trees, "fault tree" and "event tree", as described below.

- Fault tree is to address the question: how can a given plant failure occur? The starting point of a fault tree is usually a gross system failure (called as top event). The possible causes are then traced back through a series of logical AND/OR gates to the independent root failures as shown in Figure 4.1.

- Event tree is to address the question: what could happen if a given fault or event occurs? An event tree begins with an initiating fault or event and works forward in time considering the probabilities of failure of each of the safety systems that stand between the initial malfunction and some unacceptable outcome shown as in Figure 4.2.

The whole procedure of PSA was first established in 1975 as U.S. Reactor Safety Study, which was described as WASH-1400: *An Assessment of Accident Risks in U.S. Commercial Nuclear Power Plants* [3].

The development of a standardized PSA was a major step forward in reliability engineering although PSA has been criticized on a number of aspects [4]. But, PSA has a major drawback that was its inability to accommodate adequately the substantial contribution made by human failures to the accident risk. In Figure 4.1, human errors can result in a fault event besides the hardware failure as well. In other words, the human error can be one of the independent root failures of a fault event. Therefore, the quantity of the

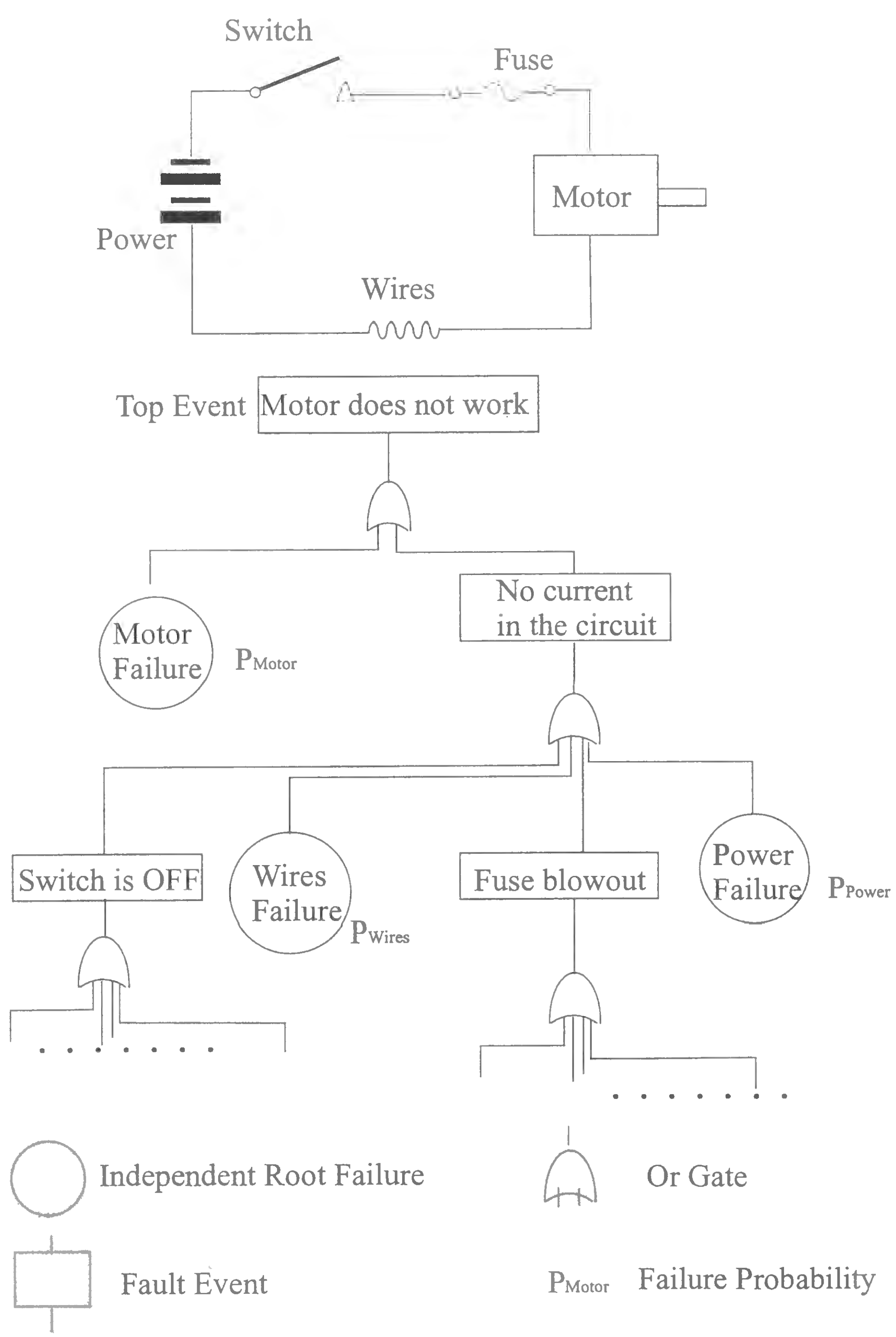


Figure 4.1: An example of fault tree

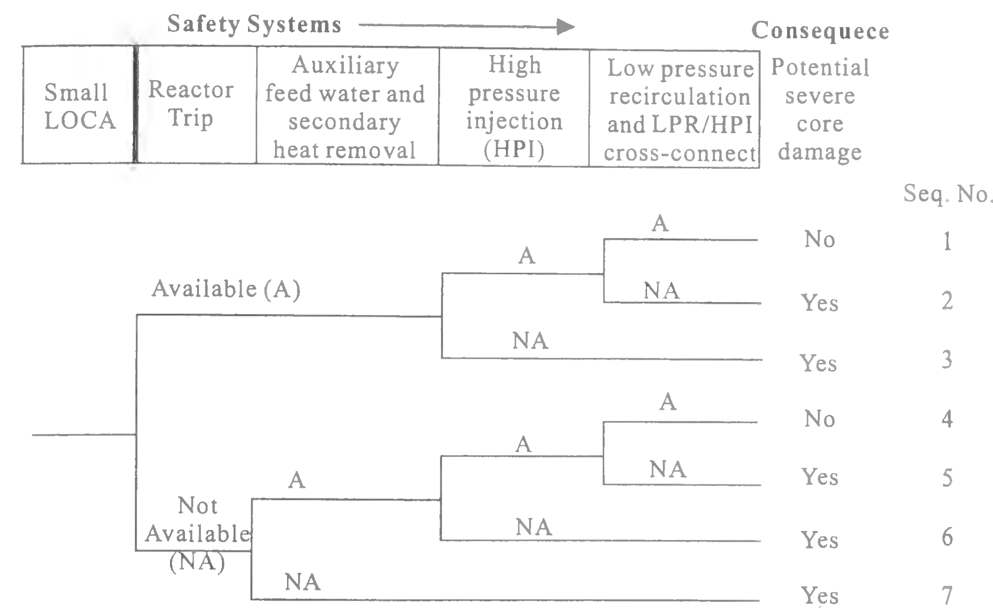


Figure 4.2: An example of event tree for a small LOCA in PWR

human error rates is necessary to calculate the failure probability of the top event shown in Figure 4.1. But, the human errors were not considered in PSA. The problem had been the stimulus of the efforts to analyze the human errors and to convert human error rates into quantity needed by PSA. The efforts are summarized as the studies on human reliability analysis (HRA) described in the next subsection.

4.2.2 Human Reliability Analysis

The objectives of Human reliability analysis (HRA) are as follows;

- to point out the human errors that can influence the system safety,
- to evaluate such influences quantitatively, and
- to suggest improvements to prevent from such human errors.

The subject of HRA is to study various aspects of human behaviors (called as human factors) with respect to PSA. HRA evaluates quantitatively the probability of the deviation of the human actions or human action sequences from the standard procedures. THERP and TRC approaches are the notable ones to quantify human error rates for PSA practice. The former one has paid attention on the human errors in the external observable human actions. The latter one has focused on the human errors in the high-level cognitive information processing.

Technique for Human Error Rate Prediction(THERP)

THERP [5] is probably the best known and most widely used means to provide human reliability data to PSA studies. The basic assumption of THERP is that the operator's actions can be regarded in the same way as the success or failure of given equipment such as a pump or a valve. Subsequently, the human reliability can be assessed essentially in the same way utilized in the case of the hardware equipment items. The objective of THERP is "to predict human error probabilities and to evaluate the degradation of a man-machine system likely to be caused by human errors alone or in connection with equipment functioning, operation procedures and practices, or other system and human characteristics that influence system behavior". [5]

The attention of THERP is paid to the human errors that are observable from the external appearance of human actions. These human errors are further divided into the following two groups.

- Omission Error: Omit the necessary operations prescribed by the operation procedures.
- Commission Error: Conduct uncalled-for operations beyond the ones prescribed by the operation procedures.

The basic analytical tool is a form of event tree termed as probability tree diagram in THERP, as shown in Figure 4.3. The branches represent the binary decision points where correct or incorrect behavior is the only available choices. Each branch represents a combination of human activities and the presumed influences upon these activities, what is termed as performance shaping factors (PSFs). The event tree starts from some convenient point in the system and works forward in time. With the possible exception of the first branching, all the human task elements depicted by the tree branches are conditional probabilities.

PSFs are the major concession made by THERP to consider the humanity of the operators. They are utilized to modify the nominal human error probabilities (HEPs) in accordance with the analyst's subjective judgement of various factors that likely influence the operator's reliability, such as the work environment, the quality of the man-machine interface, the skills, experience, motivation and the expectations of the individual operator.

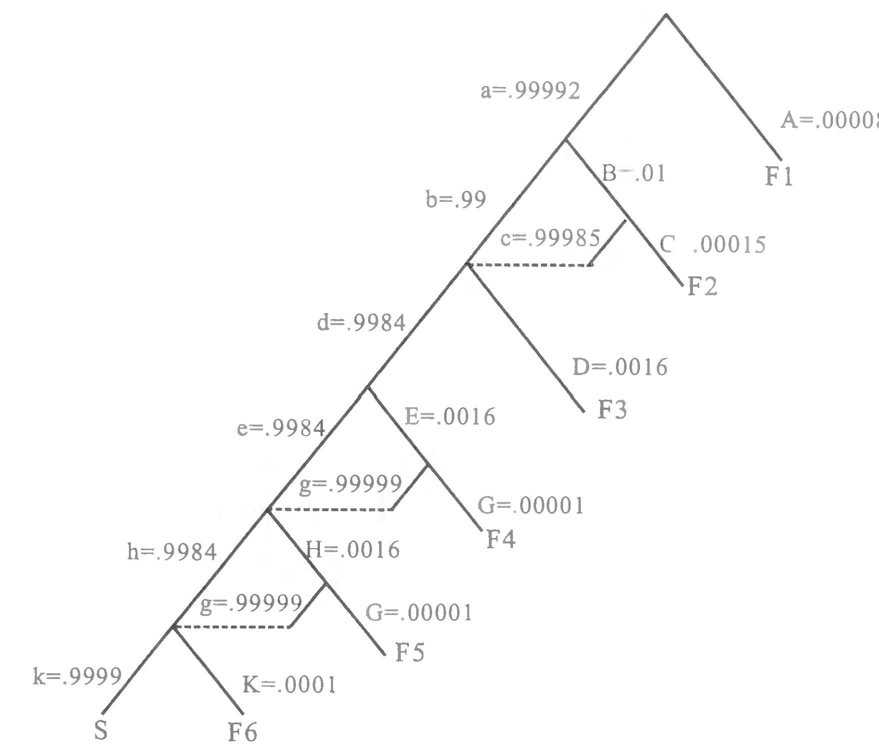


Figure 4.3: An example of event tree utilized in THERP

Thus, the operational failure probabilities can be evaluated quantitatively and provided to PSA studies in a relative easy way by the approach of THERP. However, THERP was unable to cope with the human errors resulted from the internal cognitive information processing since the internal activities are not observable externally, such as the anomaly diagnosis in case of an emergency. With respect to the cognitive human errors, TRC approach was proposed and THERP had introduced the concept to evaluate quantitatively the human cognitive reliability in anomaly diagnosis.

Time-Reliability Curve Techniques

Time reliability curve (TRC) techniques are concerned with quantifying post-accident human errors. The model of operator action trees (OATs) was the first TRC technique developed in the early 1980s [6, 7]. OAT technique deals with the human errors occurring after an accident sequence has been initiated. The errors are called as cognitive errors because they involved mistakes in higher-level human cognitive information processing, such as reasoning, diagnosis and strategy selection. Therefore, the objective of OAT is to deal with operator errors during accident and abnormal transients and to provide error types and their probabilities to PSA studies.

The fundamental assumptions of OAT are described as follows.

- Operator's behaviors after an accident can be divided into three phases called as the perception of the accident, the diagnosis, and the response operation.

- The human error rates in the situation can be evaluated in quantity by applying an analytical tool called as the time-reliability curve, which describes the probability of failure as a function of the affordable time interval to perform the required tasks.

Based on the concept of TRC, THERP proposed a nominal diagnosis model providing probabilities of failure to correctly diagnose an abnormal event within a given time T. The model gave three TRC curves: the median curve, its upper and lower bound curve [5]. The utilization of the three TRC curves is committed to the subjective judgement of the experts in HRA.

Late in 1984, human cognitive reliability (HCR) model was proposed by Hannaman and his co-authors [8] by relating TRCs to the three human cognitive behavior modes (skill-, rule-, and knowledge-based behaviors) [9]. HCR model assumed that the conduction of the different kinds of cognitive activities would take different time. HCR model provides sets of curves, each one relating to a different kind of cognitive processing (Skill-based, Rule-based, or Knowledge-based) for a specific situation (e.g., "SGTR"). The mathematical representation of HCR model was approximated by three-parameter Weibull distributions (one distribution for each category: skill, rule, and knowledge as shown in Figure 4.4), as shown below.

$$P(t) = exp\left[-\left(\frac{t/T_{1/2} - C_{\gamma_i}}{C_{\eta_i}}\right)^{\beta_i}\right] \qquad t/T_{1/2} \geq C_{\gamma_i} \tag{4.1}$$

Where

$P(t)$	:	the probability that operator crew cannot complete the correct tasks successfully before t, termed as crew non-response probability at time t
$T_{1/2}$	:	the median time taken to complete a task (for the normalization)
t	:	The actual time taken by operator crew to complete a task successfully
$C_{\gamma_i}, \beta_i, C_{\eta_i}$	:	location, scale and shape parameters associated with the category of cognitive behavior.

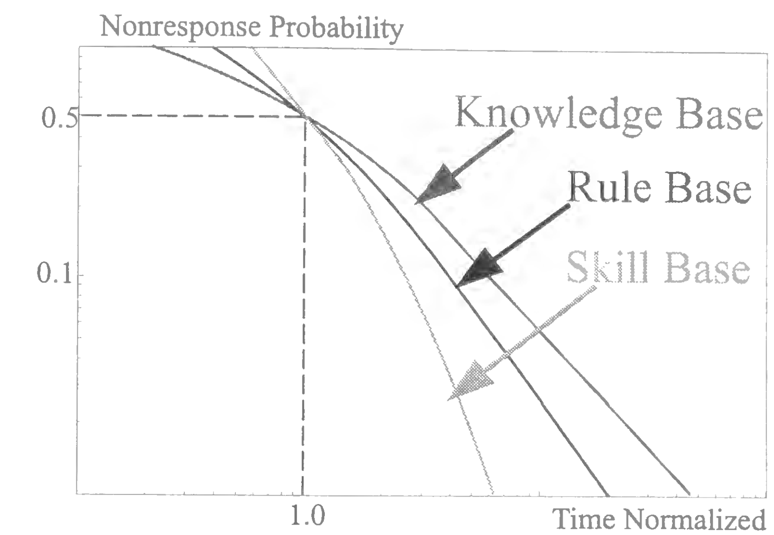


Figure 4.4: Human cognitive reliability curves

Later in 1990, Operator Reliability Experiment (ORE) [1] was carried out to validate the HCR model. Five hypotheses made in the HCR model were the validation objects, as listed below.

1. Operator crew response, which is measured by the time taken to respond, is variable.

2. A normalized (unitless) measure of crew response time removes or reduces the influence of the intrinsic time characteristic of the scenario, which is hardware or plant dependent.

3. Operation-crew's behavior in response to given interactions can be described by categories (imply the category: skill, rule, knowledge) that are useful for predicting expected response time variability.

4. The time taken by Operation-crew to response can be represented using a standard probability distribution.

5. PSFs affect the average response time but not response variability; and multiple PSFs have a multiplication effect on the average response time.

As the results of the validation, not all of them were supported by the experimental data. Especially, the experimental results did not support the category of skill, rule and knowledge. Subsequently, a new model was proposed and is called as "human cognitive reliability based on operator reliability experiment (HCR/ORE)". HCR/ORE model is

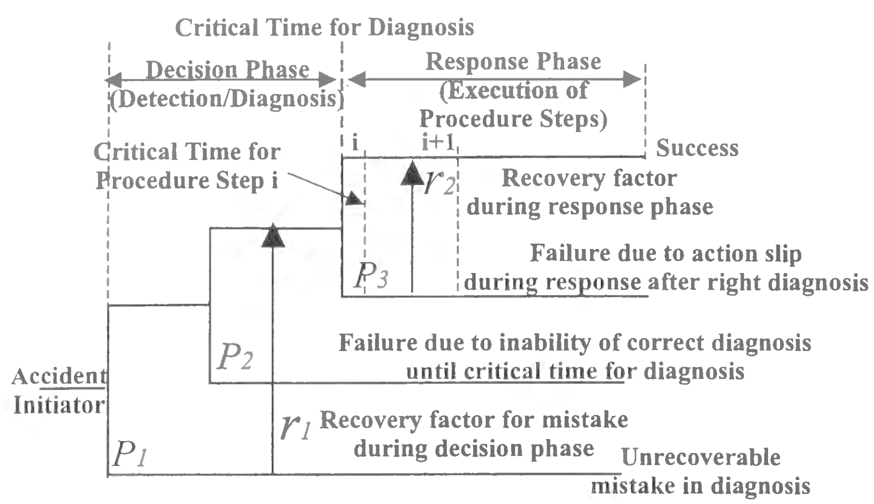


Figure 4.5: Human error probability required in PSA/HRA

characterized by two parameters: $T_{1/2}$ (median response time of operation-crew) and σ (logarithmic standard deviation of normalized time). With these two parameters, the probability (indicated as P_{NR}) of the non-response of the operation-crew within a given time T_w can be calculated by using the following equation:

$$P_{NR} = 1 - \Phi\left[\frac{ln(T_w/T_{1/2})}{\sigma}\right] \tag{4.2}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution. The distribution is based on the ORE data and is summarized into databases for various human machine interactions.

Subjects of Human Reliability Analysis

In view of the human modeling application for HRA/PSA, literature surveys had been made on the existing methodologies of HRA/PSA for NPPs [1, 5, 10, 11, 12] to clarify the necessary "Human Error Probability" (HEP) parameters required in HRA/PSA of NPPs.

In the present PSA/HRA practice for NPP, there are mainly two kinds of HEP: (1) Pre-initiator HEP (Type A), and (2) Post-initiator HEP for various Human System Interactions (HSI) factors (Type C) [1]. The word "initiator" indicates the occurrence of an abnormal event that gives rise to incident/accident in NPP. Because the Type C HEP is related to complex HSI factors at MMI, it is more important but more difficult to estimate than the Type A HEP. As the results of the literature survey, a comprehensive framework of Type C HEP parameters as related with the PSA/HRA is illustrated in Figure 4.5.

There are five HEP parameters in the framework.

- two parameters for unrecoverable failure rate in the decision-making phase indicated by P_1 and P_2, respectively
- one parameter for unrecoverable action slip in the response phase indicated by P_3
- two recovery rates indicated as r_1 and r_2, respectively, for both phases of early decision-making phase and later response phase

In the decision-making phase, P_1 gives the probability of cognitive mistakes such as mistaken diagnosis. P_2 gives the probability of failure to respond to the initiator until a certain crucial time. It means that operators have to finish their decision-making prior to that time, otherwise the plant system will fall into unrecoverable accident condition. In the response phase, P_3 gives the probability of non-recoverable action slips during response after correct diagnosis.

Therefore, by focusing mainly on the unrecoverable human error probabilities, the total Type C HEP during HSI can be calculated as the sum of P_1, P_2 and P_3. Since the parameter P_1 is related with "commission error" by the definition in THERP, it is very difficult to estimate it even from the real field data, and therefore, in the current practice, human reliability analysts subjectively estimate it. For the parameter P_3 in the response phase where human error will take the form of action slip or "omission error" that can be normally evaluated by THERP. Finally, parameter P_2 giving the non-response probability until the crucial time is very much time dependent. P_2 is, therefore, normally represented by TRC.

The typical example of P_2 is given by the HCR model described previously. HCR model has been widely used in HRA/PSA to estimate HEP for operators' diagnostic actions since its advantage of taking the simple Weibull function and taking into account of operators' cognitive modes of skill, rule, and knowledge based action. However, as described previously, the validity of the HCR model has been not confirmed by the experimental data obtained from ORE. HCR/ORE model is then proposed to describe the cognitive reliability of operators' actions classified by their cue-response characteristics [1, 10]. But, there are drawbacks in HCR/ORE that depends on the large-scale experimental approach, such as the requirements for conducting the experiments and the limitation of the application of the experimental results. Hence new approaches to estimate P_2 are required to supplement the existing methodologies.

4.2.3 Time Cognitive Reliability based on HUMOS-PAD

A new TRC approach is proposed to estimate P_2 in this section. The feature of the approach is to estimate TRC by HUMOS-PAD developed in this thesis study. It is called as "Time versus Cognitive Reliability curves based on human model simulation of plant anomaly diagnosis (TCR/HUMOS-PAD)". The comparisons between the new TRC approach and the existing TRC techniques are conducted to show the features of TCR/HUMOS-PAD.

The reviews on the existing HRA approaches represented by THERP, TRC, HCR, and HCR/ORE give the following conclusions.

- The fundamental human error probabilities required in current HRA/PSA practice in NPP can be summarized in the framework shown in Figure 4.5.
- The human error probability P_2 in the framework has been the research subject of various TRC techniques such as HCR and HCR/ORE.
- But, there are still problems with these existing TRC techniques such as the validation of the model for HCR, the enormous cost and the limited application of HCR/ORE.

Based on the background, we propose a new TRC technique by utilizing HUMOS-PAD to estimate P_2. The new approach pays attention on how to estimate P_2 by conducting the computer simulation of the dynamic human machine interaction, in which the operator's anomaly diagnosis behaviors is simulated by HUMOS-PAD. Table 4.1 shows the features of TCR/HUMOS-PAD and its relationship with the existing TRC techniques: TRC in THERP, HCR, HCR/ORE, in order to discriminate the new TRC approach with the existing ones.

The existing TRC techniques and the TCR/HUMOS-PAD are compared in the following aspects.

- Methods to obtaining TRC
  In THERP, TRC for a given anomaly diagnosis is selected from the three curves by the subjective judgment of experts in HRA. In case of HCR, the estimation of TRC is just the calculation of the equation 4.1. In the case of HCR/ORE, it is required to conduct large-scale operator experiment to get the experimental data for the given anomaly diagnosis. The new approach of TCR/HUMOS-PAD is another version of HCR/ORE because only the difference between them lies in that HUMOS-PAD replaces the role of real operator in the case of HCR/ORE. Therefore, rather than

Table 4.1: Features of TRC techniques

TRC techniques	Features	Methods to obtain TRC
THERP	Three curves: the median one, its lower and upper bound	Subjective judgement by HRA expterts
HCR	1. Take the mathematical representation of three-parameter Weibull distribution 2. Each distribution corresponds to one of the skill-, rule-, and knowledge-based cognitive process	By calculating the equation of Weibull distribution
HCR/ORE	1. Take the mathematical representation of two-parameter standard normal cumulative distribution, 2. The two parameters are median response time and logarithmic standard deviation of normalized time 3. Do not separate the time taken to detect and diagnose abnormal transients	By conducting large-scale operator experiments and by analyzing the obtained experimental data with statistical analysis
TCR/HUMOS-PAD	1. Utilizing human model for simulating operator cognitive behaviors 2. Mathematical formulation has not yet been proposed to represent the curves 3. Analyze the curves by focusing on the shape of the curves and the median response time 4. Separate the time taken to detect and diagnose abnormal transients	By conducting computer simulation of the required human machine interactions and by analyzing the simulation results with the same method utilized in HCR/ORE

conducting the large-scale operator experiment, the necessary TRC data related to a given anomaly diagnosis can be obtained by conducting numerical experiments based on computer simulation of the man-machine interaction.

- Representation and application of TRC
  There is no mathematical representation for three TRCs in THERP. The application of the TRCs to a given anomaly diagnosis is committed to the subjective judgement of HRA experts by taking account of the related PSF like the training (exercises) with respect to the abnormal transient. The three-parameter Weibull distribution is utilized to represent the three HCR curves, as shown in the equation 4.1. For a given anomaly diagnosis, the three parameters are adjusted to shape one of the three curves classified by the skill-, rule-, and knowledge-based operator's behaviors. In the case of HCR/ORE, a two-parameter standard normal cumulative distribution is utilized to represent the HCR/ORE curve for a given anomaly diagnosis, as shown in the equation 4.2. The application of the HCR/ORE curve depends either on adjustment the two parameters of the existing HCR/ORE curves to cope with a new anomaly diagnosis, or on the conduction of the large-scale operator experiment to obtain the two parameters that define the HCR/ORE curve. While, there is also no mathematical representation yet for TCR/HUMOS-PAD proposed in this thesis study. But, the time cognitive reliability curves can be derived easily by conducting the computer simulation of the human machine interaction at a given anomaly diagnosis. The new situation of the anomaly diagnosis can be easily coped with by modifying the human model and the MMI model utilized in the computer simulation.

- Separation of detection and diagnosis
  TCR/HUMOS-PAD can separate easily the time taken to detect and diagnose abnormal transients. The feature cannot be realized easily by the other TRC techniques. The separation of detection and diagnosis is important with respect to HRA in the following aspects.

  1. The operators' actions after an abnormal transient can be separated into anomaly detection and anomaly diagnosis phases.
  2. The characteristics of the human machine interaction are quite different in the two phases, as described in Chapter 2. Therefore, the detection and diagnosis are different human cognitive behaviors in view of HRA.

  3. The affordable time before the response operation is the time limit for both anomaly detection and diagnosis. The quick anomaly detection will save time for the anomaly diagnosis, and therefore, will enhance the cognitive reliability of operators' decision-making.
  4. The separation can also help to specify the problems of the operators' response in both phases with respect to enhancing the quality of MMI for the quick anomaly detection, or exercising the skill of operators for a certain abnormal events.

So far, the approach of TCR/HUMOS-PAD is described by compared with the existing TCR techniques. In one sentence, TCR/HUMOS-PAD is the computer simulation version of HCR/ORE. Therefore, the probabilistic factors shaping the different TCR curves should be modeled in the human modeling framework developed in the preceding chapter.

4.3 TCR Curves Derived from Laboratory Experiment

In order to clarify the probability factors influencing the characteristics of TCR curves, TCR curves were first derived from the laboratory experiment described in Chapter 2. The data processing method and the analysis of the TCR curves are described in detail in this section.

4.3.1 Data Processing Method for Deriving TCR Curves

Two kinds of TCR curves were obtained from the experimental data, as shown in Figure 4.6. One is related to the subjects' anomaly detection, in the time span from t_a to t_b, while, the other one is related to the subjects' anomaly diagnosis, in the time span from t_b to t_c of Figure 4.6, respectively. In the laboratory experiment, since the subjects were asked to push "Anomaly Detected" button to indicate the explicit timing that they had detected the occurrence of an abnormal transient, the subjects' behaviors can be easily divided into two phase (Anomaly Detection in MP and Anomaly Diagnosis in DP).

The analysis of the operation sequence history can give those experimental data: detection time $t_b - t_a$ and diagnosis time $t_c - t_b$ needed for deriving the two kinds of TCR curves. The data processing procedure is listed below.

1. Sort of response time
   The experimental data about the detection time and diagnosis time were sorted with ascending order of time.

2. Calculation of non-response probability
   The probability of the failed response to the detection and diagnosis is then calculated

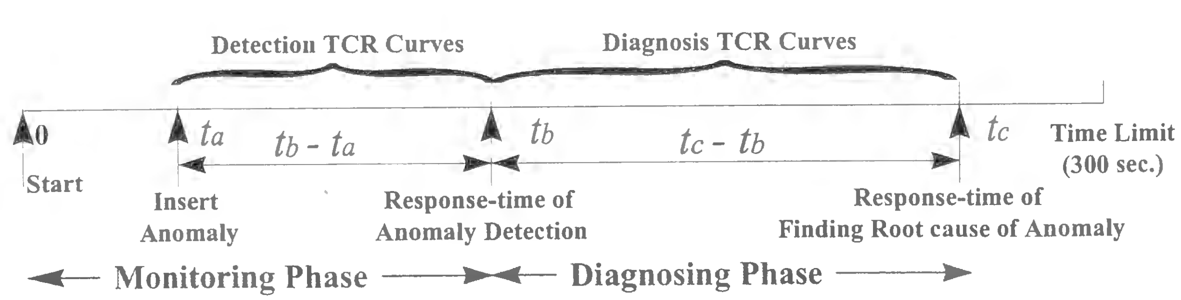


Figure 4.6: Two kinds of TCR curves from the laboratory experiment

by the equation shown below. The equation is given by the technical report of HCR/OER [1]. The detailed explanation of the equation is described in Appendix E.

$$\begin{aligned} P_i(non-response) &= P_r(response\ time > t_i) \\ &\approx 1 - \frac{i}{N+1} \\ & i = 1, 2, ..., N \end{aligned} \tag{4.3}$$

where P_i is the non-response probability by the time t_i, P_r is the response probability for the case where response time is over t_i, i is the i'th data point, t_i is the i'th response time in the ascending sequences of response time, and N is the total number of samples.

3. TCR curves before normalization
   TCR curves were then plotted as shown in Figure 4.7. In accordance with the equation, the non-response probability would be 0.5 at the median data ($(N+1)/2$) of the ascending response time sequence, as indicated by $T_{1/2}$ in Figure 4.7. The median time therefore means that 50% operators have responded successfully to the required tasks (anomaly detection or diagnosis) by that time, while the other 50% operators do not respond yet.

4. Normalized TCR curves
   If all the time data points t_i are divided by $T_{1/2}$, then TCR curves normalized to $T_{1/2}$ will be obtained, as shown in Figure 4.7. The slope is focused to analyze the characteristics of the obtained TCR curves, Hence the best-fit regression line is made to estimate the slope of the TCR curves, as shown in Figure 4.7. In accordance with the gradient of the best-fit regression line, two patterns of normalized TCR curves are shown in the right side of Figure 4.7. They are TCR curves with steep slope and gentle slope, respectively.

Two points are noticed from above data processing to derive TCR curves. One point is that deriving TCR curves is necessary to take into account of only the successful response of subjects in the experiments. Other cases were omitted, such as mistaken diagnosis and the experimental trial where the subject was helped by experimenter during experiment.

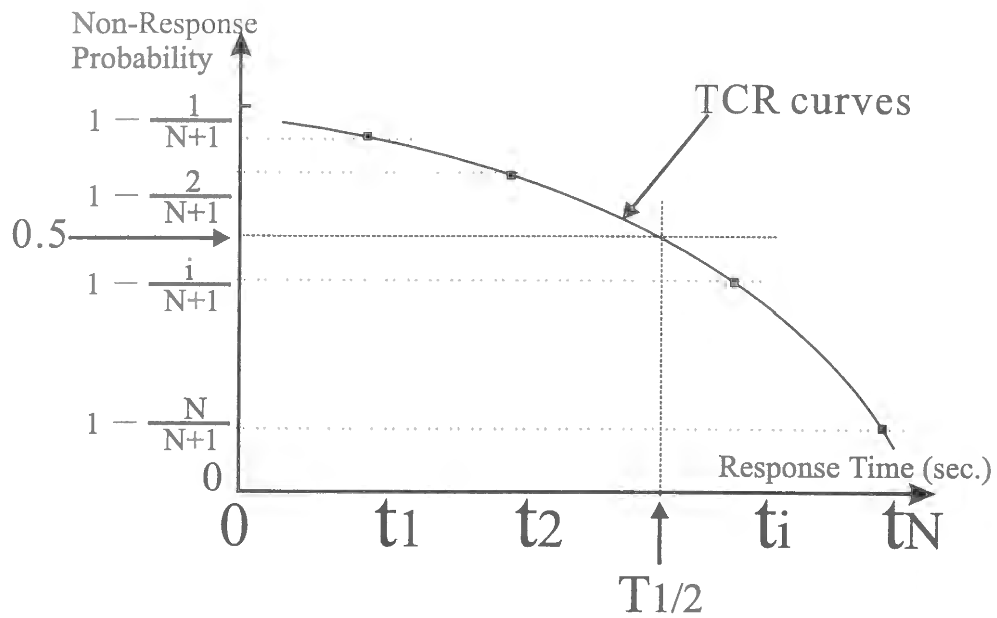


Figure 4.7: TCR curve before normalization

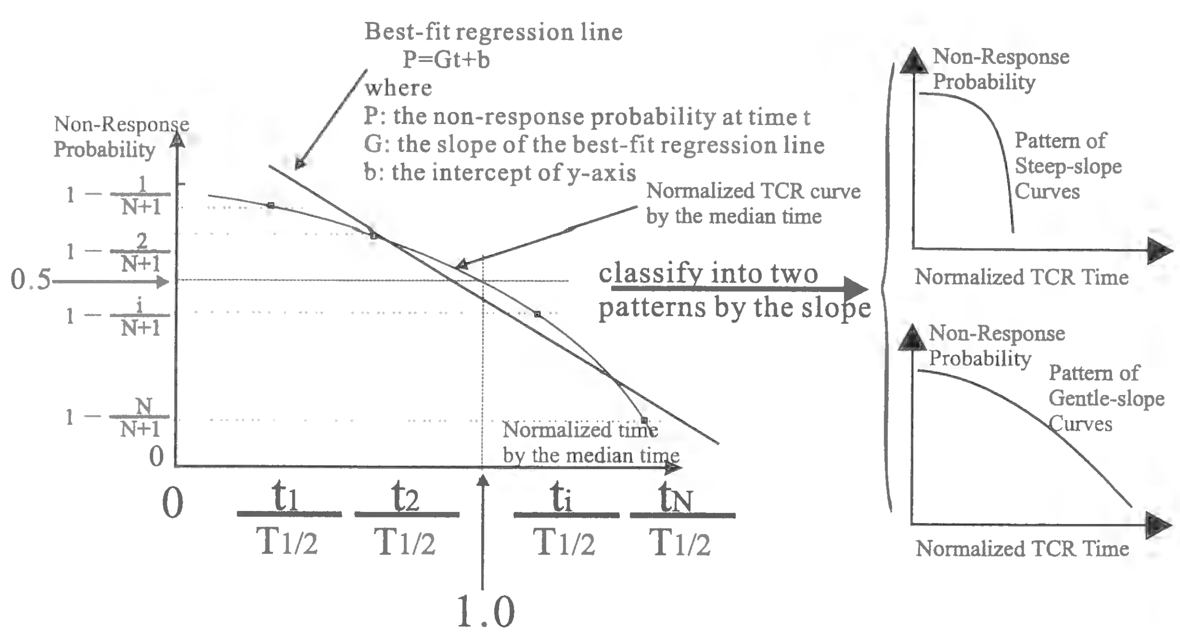


Figure 4.8: Normalization of TCR curves by the median time

The other one point is that the total number of successful experimental data were needed to satisfy the condition $N \gg 1$ (practically $N \geq 10$) because of the assumption that the response probability in each time section is the same as $1/(N+1)$.

Based on the data processing methods, all TCR curves derived from the laboratory experiment are summarized in Appendix F for both anomaly detection and diagnosis. For each abnormal transient, the tables 4.2 and 4.3 summarize the valid sampling numbers, the estimated slope and the median time of the anomaly detection TCR curves by sorting the slope and median time in the right-end of the tables, respectively. Those data of anomaly diagnosis TCR curves are summarized in the tables 4.4 and 4.5.

The slopes of the TCR curves are represented by the value of the gradient of the best-fit regression line. The bigger value means the steeper slope. The detailed analysis of the TCR curves is described in the following subsection with respect to examining the probabilistic factors that influence the characteristics of TCR curves.

4.3.2 Analysis of Different Slope of TCR Curves

In order to apply HUMOS-PAD to estimate the TCR curves, the factors forming the TCR curves should be analyzed so that those factors could be modeled in the modeling framework of HUMOS-PAD. The characteristics of TCR curves can be described by the slope and the median response time from the viewpoint of the above data processing. Hence the analysis of the TCR curves is conducted from the two aspects. In this and the next subsection, the slope and the median response time will be analyzed respectively for both the anomaly detection and diagnosis TCR curves.

First of all, the different slope of TCR curves means that there do exist some probabilistic factors influencing operators' performance of detecting and diagnosing abnormal transients. The figures 4.9 and 4.10 show the typical cases of steep and gentle slopes of the TCR curves both for anomaly detection and anomaly diagnosis. The difference of the slope of TCR curve can be explained as follows:

> "In the case of steep slope TCR curves, the anomaly can be detected or identified by any operator at any trial of the same transient at a certain time after transient was initiated. In the case of gentle slope TCR curve, there are probabilistic nature for detecting or identifying the anomaly which stems from either the human side or the abnormal transient itself."

Table 4.2: Anomaly sorted by the slope of the detection TCR curves

Types of Abnormal Transients	Valid Sample Numbers	Median time (sec.)	Degree of the slope
RCS_M	9	46	-1.733254
RCS_S	10	66.5	-1.148825
NIS	11	17	-0.939669
SGTR	12	10	-0.789474
FW.FL.Sen.F	14	11	-0.780628
PRZ.Spary.V.B	12	9.5	-0.682869
PRZ.Spary.V.S	12	15	-0.654327
PRZ.Prs.H	10	9.5	-0.568763
PRZ.Lvl.H	8	23.5	-0.565773
FW.FL.Cont.V.	12	16.5	-0.533789
PRZ.Prs.L	10	35	-0.397916
PRZ.Lvl.L	8	21.5	-0.168108

Table 4.3: Anomaly sorted by the median time of the detection TCR curves

Types of Abnormal Transients	Valid Sample Numbers	Degree of the slope	Median time (sec.)
PRZ.Spary.V.B	12	-0.6828688	9.5
PRZ.Prs.H	10	-0.5687631	9.5
SGTR	12	-0.7894737	10
FW.FL.Sen.F	14	-0.7806278	11
PRZ.Spary.V.S	12	-0.6543274	15
FW.FL.Cont.V.	12	-0.5337886	16.5
NIS	11	-0.9396692	17
PRZ.Lvl.L	8	-0.1681075	21.5
PRZ.Lvl.H	8	-0.5657729	23.5
PRZ.Prs.L	10	-0.3979163	33
RCS_M	9	-1.7332536	46
RCS_S	10	-1.1488247	66.5

Table 4.4: Anomaly sorted by the slope of the diagnosis TCR curves

Types of Abnormal Trasients	Valid Sample Numbers	Median Time (sec.)	Degree of the slope
FW flow Cont.V.F.	10	106	-0.91609941
SGTR	9	67	-0.64402581
PRZ Spray S	11	76	-0.55004614
PRZ Prs high	10	89.5	-0.51434982
FW lvl sensor failure	15	110	-0.48584182
RCS small	8	60	-0.40937997
PRZ Prs Low	9	38	-0.37381607
RCS big	8	59	-0.30962251
PRZ Spray B	11	64	-0.29085322

Table 4.5: Anomaly sorted by the median time of the diagnosis TCR curves

Types of Abnormal Trasients	Valid Sample Numbers	Degree of the slope	Median Time (sec.)
PRZ Prs Low	9	-0.3738161	38
RCS big	8	-0.3096225	59
RCS small	8	-0.40938	60
PRZ Spray B	11	-0.2908532	64
SGTR	9	-0.6440258	67
PRZ Spray S	11	-0.5500461	76
PRZ Prs high	10	-0.5143498	89.5
FW flow Cont.V.F.	10	-0.9160994	106
FW lvl sensor failure	15	-0.4858418	110

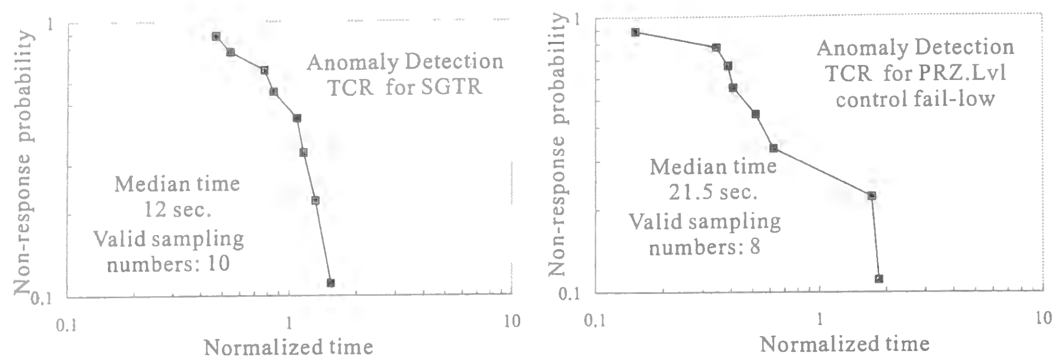


Figure 4.9: Anomaly detection TCR curves derived from the laboratory experiment

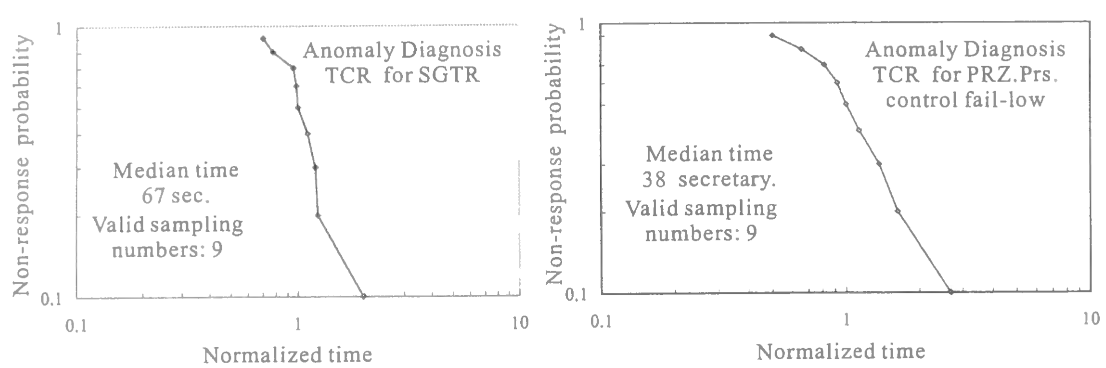


Figure 4.10: Anomaly diagnosis TCR curves derived from the laboratory experiment

The probabilistic factors in subjects' cognitive behaviors of detecting and diagnosing abnormal transients are clarified by analyzing the different slope of TCR curves, as summarized in Table 4.6.

As for detecting the occurrence of an abnormal transient, there are mainly three probabilistic factors in subjects' cognitive behaviors:

1. variation degree of parameters to which subjects feel something wrong in the system,
2. reference frequency of parameters, and
3. reference sequence of parameters.

These three factors would result in different time taken to detect an anomaly. The first factor reflects the different thresholds of parameter value to judge whether the variation in parameter value is beyond the normal status or not. The rest two factors reflect the differences in subjects' "monitoring strategy".

Table 4.6: Probabilistic factors in detection and diagnosis phases

Anomaly Detection	Anomaly Diagnosis
Variation degree of parameters for judging something wrong	Hypotheses recalled
Reference Frequency	Examination sequence of the recalled hypotheses
Reference Sequence	Different display type (digital number & trend graph)
	Belief level thresholds on which subjects make a final decision

As for the probabilistic factors in diagnosing the root cause of an abnormal transient, there are mainly four factors.

1. Hypothesis recall
2. Hypothesis examination sequence
3. Display type
4. Belief level

These probabilistic factors are analyzed in detail to show how they shape different anomaly diagnosis TCR curve.

Probabilistic Factors in Anomaly Diagnosis

With respect to analyzing the effects of these factors, the time taken to diagnose the root cause of an abnormal transient should be examined carefully because TCR curves describe the trade-off relationship between the affordable time and cognitive reliability.

The diagnosis time is defined in Figure 4.6 as the time span from t_b (the occurrence of an abnormal transient had been detected) to t_c (the root cause of the abnormal transient is found out). Therefore, the diagnosis time is the total amount of time taken to conduct various cognitive tasks to reach final conclusion of diagnosis. The total necessary time is different since the subjects would take different diagnosis methods and conduct different tasks to find out the root cause. The detailed diagnosis process described in the preceding chapter should help to understand how these factors work.

- Hypothesis Recall Factor
  After the detection of an abnormal transient, subjects would recall one or more hypotheses into their mind. The task is called here as "hypothesis recall". The task of "hypothesis recall" is conducted in accordance with the first symptom detected by the subject. The hypotheses recalled by subjects would be different from person to person because of the diversity of human cognitive behaviors (even in the case that the subjects detected identical first symptom). The difference in the span of the recalled hypotheses would require different time to examine them, and therefore would result in different time taken to identify the root cause of an abnormal transient.

- Hypothesis Examination Sequence Factor
  Next, subjects will examine the recalled hypotheses by collecting symptoms supporting or denying the hypotheses. The matter would be simple if the subject recalls only a single hypothesis. But, usually a number of hypotheses are recalled. Therefore, there exists "hypothesis verification sequence" because it is impossible for human to do thing in parallel. The "hypothesis examination sequence" would be different from person to person since the diversity of human cognitive behaviors. For an example, "Subject A" and "Subject T" prefer to verify the hypothesis about control system firstly, compared with "Subject I". Since the root cause may exist in the recalled hypotheses, "hypothesis examination sequence" would result in different diagnosis time.

- Display Type Factor
  To examine the recalled hypothesis, subject would conduct MMI operation to collect the information about plant parameters' status, which are the symptoms supporting or denying the hypothesis. In the laboratory experiment, both the digital numbers showing parameters' value and the trend graph showing parameter value changes with time are utilized to present plant parameters' status to subjects. The reference time of two types of display is different since the trend graph provides not only the information about the current status of parameters, but also the past trend until current status. The reference of trend graph usually takes more time than that in

  the case of digital number. The selection of the display type would exert an influence on the time taken in each step of parameter reference, and therefore, would result in different total diagnosis time.

- Belief Level Factor
  During subject's collecting symptoms, it has been considered that subject's belief on the correctness of a hypothesis would be changed in the direction of either conviction or negation. In other words, the belief level on the correctness of a hypothesis would be increased or decreased in accordance with the observed symptoms. When the belief level of a hypothesis is increased or decreased to a certain level, subject would adopt or reject the hypothesis. The level is called here as the threshold of the belief level, which would be different for person to person. For an example, the threshold may be a high for adopting the hypothesis in the case of a cautious person, while it may be low for others. When the belief level does not reach the threshold, operators will get more symptoms related to the hypothesis for increasing or decreasing the belief level until it reach the threshold. Therefore, the total diagnosis time will be changed.

As a conclusion, all these probabilistic factors in subjects' behaviors would result in the different slope of anomaly diagnosis TCR curves.

Analysis of the Obtained TCR Curves

The reasons for the different slope of TCR curves for both phases of anomaly detection are analyzed by considering both the natures of abnormal transients and the above-mentioned human information processing characters. The analytical results are shown in Table 4.7 and the detailed discussions are given below for both phases.

- Anomaly detection phase
  One reason for steep slope TCR curves is that there are so many anomaly symptoms in many groups of plant parameters that any operator can recognize the changes in parameter value very easily (e.g., in the case of "RCS leakage") . But even if not so many symptoms, the occurrence of anomaly is easily noticed by the peripheral sight effect because of the striking variation in certain parameters (e.g., in the case of pressurizer spray valve failure-big). The other reason would be that the operators would not miss a slight variation of the important parameters in a certain specific

Table 4.7: Analysis of the slope of TCR curves for both detection and diagnosis

Slope of HCR Curves Pattern	Anomaly Detection	Diagnosing Root Cause
Steep Slope	1. Many anomaly symptoms 2. Or Peripheral Sight Effect(PSE) 3. Or check parameters severely or frequently	Only a limited hypothesis can be assumed due to only few anomaly symptoms appeared in specific system
Gentle Slope	1. Difficult for PSE 2. And symptoms appear only in specific system 3. And the system is not checked severely or frequently by operators	Many hypothesis are assumed due to appearance of many anomaly symptoms. So probabilistic character of human behavior would appear in diagnosis phase

plant subsystem monitored very severely or very frequently by the operator (e.g., Power range NIS failure, Feed-water flow sensor failure). The cases of gentle slope TCR curves are those where the situation does not correspond to anyone mentioned above.

- Anomaly diagnosis phase

  The gentle-sloped TCR curves will be brought about when lots of anomaly symptoms appear in different plant sub-systems (e.g., in the case of "pressurizer spray valve failure-big" and "RCS leakage"). As the result, operators would recall lots of hypotheses, and therefore, the time required to find out the correct root cause of the abnormal transient would vary from case to case. On the contrary, the steep slope TCR cases will be generated by the situation where only a limited hypothesis can be considered because of the limited symptoms appearing in plant parameters (e.g., in the case of pressurizer pressure controller failure). In the case, the time taken to identify the root cause would be not so different as that in the case of the gentle TCR curves.

4.3.3 Analysis of Median Time of TCR Curves

The median time $T_{1/2}$ is defined as the time until when 50% operators respond to the required task (e.g., anomaly detection or diagnosis) while the rest 50% operators do not yet respond. $T_{1/2}$ is considered to reflect the effects of performance shaping factors (PSFs) in HCR/ORE model [1]. PSFs are defined as the environmental factors affecting operator's performance. Three types of factors are analyzed generally as PSFs:

Table 4.8: Median time of detection and diagnosis TCR curves

Median Time	Anomaly Detection	Anomaly Diagnosis
Large	1. Few distinct abnormal symptoms 2. Small-scale disturbance of abnormal transients	1. Unfamiliar with MMI 2. Harder to be identified at the complex degree of abnormal transients
Small	1. Lots of distinct abnormal symptoms 2. Large-scale disturbance of abnormal transients	1. Large-scale disturbance of abnormal transients 2. Easier to be identified at the complex degree of abnormal transients 3. Speedy propagation of abnormal transients 4. Well experienced abnormal transients

- internal factors such as the degree of operation skill, operators' human character, etc.,
- external factors such as the quality of MMI, the nature of the required task, etc., and
- stress factors such as operators' psychological stress and physiological stress.

In the laboratory experiment, we would like to focus on one of the external factors: the nature of the required task, i.e., the nature of the abnormal transient to be detected or diagnosed. The experimental data of median times $T_{1/2}$ for detecting and diagnosing each abnormal transients were already sorted, as shown in the tables 4.3 and 4.5, respectively. The analytical results for $T_{1/2}$ of both detect and diagnosis TCR curves is summarized in Table 4.8 with respect to the reason why $T_{1/2}$ becomes large or small, and the detailed discussion for both cases are given below.

Anomaly Detection Phase

The median time $T_{1/2}$ ranges from 9.5 to 66.5 seconds. In the laboratory experiment, the detection of the occurrence of abnormal transients depends largely on the awareness of the abnormal variation in parameter value since only very limited alarm tiles were presented onto the MMI. Three types of abnormal transient would be detected quickly, as described below.

- The abnormal transient causing *lots* of abnormal symptoms would be detected quickly (e.g., "SGTR").
- The *distinct symptoms* in specific sub-systems monitored frequently or severely by subjects would also give small $T_{1/2}$ (e.g., in the case "NIS.F").
- The large-scale disturbance of identical abnormal transients would be detected more quickly than the small-scale one (e.g., in the case of "PRZ.Spray.V.F" big and its small one).

Compared with the small-scale disturbance, the abnormal symptoms are more *distinct* and propagated more quickly to the other sub-systems in the case of large-scale disturbance. Therefore, *lots of distinct symptoms* would appear in various plant sub-systems. In conclusion, small $T_{1/2}$ is due to the emergence of *lots of distinct abnormal symptoms.* While, the large $T_{1/2}$ is due to relative lack of distinct abnormal symptoms in any sub-systems.

Anomaly Diagnosis Phase

The diagnosis time turned out almost same for the identical abnormal transients with different scale disturbance (e.g., in the case of "RCS leakage median" and its small on). It means that, the disturbance scale of the abnormal transient is not the major factor that determines the total diagnosis time since the diagnosis methodology is almost the same. However, the time taken to diagnose the big-scale disturbance of the identical abnormal transients is a little less than the small-scale one. It is considered because of the emotional pressure of speedy propagation of abnormal transients. The emotional pressure would make the subject not hesitate too much to make a final decision among alternatives of root cause.

The median time is also considered to reflect the relative complexity of the abnormal transients. Simplicity or complexity may be defined as the possible recalled hypotheses. The simplicity means that the possible hypotheses is limited, while, the complexity is the contrary.

Based on the above discussions about the slope and the median time of both detection and diagnosis TCR curves, now let us consider what the analysis results mean for the safety and reliability of total NPP. As for the safety of total NPP, it is appreciated to detect and diagnose the abnormal transients quickly as much as possible. In other words, the steep TCR curves having a small $T_{1/2}$ are most appreciated. Since TCR curve represents the trade-off relationship between the affordable time and the human cognitive reliability, it

can be utilized as the operator performance measurement both for the evaluation of the MMI design and for improving the efficiency of the operator training.

Furthermore, very limited alarm tiles and no alarm sound were utilized in the laboratory experiment so that the detection of the occurrence of abnormal transients depended mainly on subjects' active monitoring activities. The analysis results show that detecting the occurrence of the abnormal transients was not an easy job in some cases due to abnormal transients' natures and human inherent probabilistic natures. Therefore, the laboratory experiment results can help to suggesting the alarm designing methodology and furthermore, the design of the operator supporting system.

4.4 Modeling Probabilistic Factors in Operator's Cognitive Behaviors

In the preceding section, TCR curves for both anomaly detection and diagnosis have been derived from laboratory experimental data. The analysis of the different slope of the TCR curves turned out that the different TCR curves are the result of the combination effects of the probabilistic factors in human cognitive information processing and the dynamic natures of the abnormal transients.

As described previously, the new approach TCR/HUMOS-PAD proposed in this thesis study is the computer simulation version of HCR/ORE. HUMOS-PAD replaces the role of operators in HCR/ORE. In order to derive TCR curves by the computer simulation, the probabilistic factors in operator cognitive information processing should be modeled in the human modeling framework utilized in the preceding chapter. This section gives the description about the method of modeling the probabilistic factors that would generate different TCR curves.

4.4.1 Modeling Methods of Probabilistic Factors

In the preceding chapter, three models have been developed, corresponding to the three subjects in the laboratory experiment. Although the three models were developed in the same modeling framework, the individual characteristics of the three subjects were simulated well by applying the concept of the human model adjustment factors proposed in subsection 3.3.2 to model the inherent diversity and variety in human behaviors.

On the other hand, TCR curves describe the statistical characteristics of operators' the cognitive information processing in detecting and diagnosing abnormal transients. In the preceding section, the probabilistic factors influencing the statistical characteristics had been clarified by analyzing the TCR curves derived from the laboratory experiment. Therefore, the subject of the application of HUMOS-PAD to HRA/PSA is substantially the subject of modeling those probabilistic factors with the human model adjustment factors.

A concept of "unified model" is proposed to estimate TCR curves by computer simulation, rather than the three models developed in the preceding chapter. The unified model is really the prototype of the three models corresponding to the three subjects. In other words, the three models are just specific cases of the unified model. Besides those models, various other individual models would be also derived from the unified model by modifying the human model adjustment factors.

The procedure steps can be summarized as follows for the estimation of TCR curves by HUMOS-PAD.

- Decide how to model the effects of the probabilistic factors in human cognitive behaviors and to select human model adjustment factors.
- Decide the plausible span of the variation of selected human model adjustment factors.
- Conduct a numerical experiments by setting a set of human model adjustment factors in HUMOS-PAD to obtain the response time of diangosing abnormal transient.
- Repeat the same simulaiton with changing human model adjustment factors
- Finally, the anomaly diagnosis TCR curves could be derived from the numerical experimental data on the response time of a large number of simulation.

Since the application of HUMOS-PAD to derived TCR curves will be validated by comparing to the TCR curves derived from the laboratory experiment with the TCR/HUMOS-PAD, the settings throughout all the above steps will take a reference to the analytical results of the laboratory experiment, as described in detail in Chapter 2.

The first two steps are described in the following subsections. The conduction of the numerical experiments and the derived TCR/HUMOS-PAD will be explained in the next section.

4.4.2 Modeling Probabilistic Factors in Anomaly Detection Phase

There are mainly three probabilistic factors in accordance with the analysis results of anomaly detection TCR curves derived from the experimental data.

1. The variation degree of parameters to which subjects feel something wrong in the system,
2. The reference frequency of parameters, and
3. The reference sequence of parameters in the display.

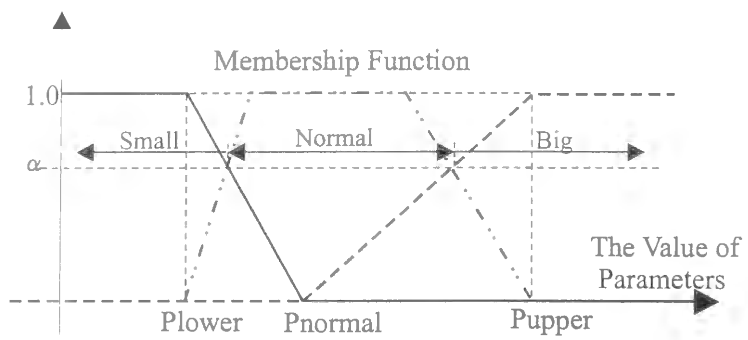


Figure 4.11: Fuzzy membership function for interpreting parameters' value

Fuzzy Membership Function of Interpretation

The effects of the first factor have been modeled by the fuzzy membership function in the preceding chapter, as shown here again in Figure 4.11. The settings of the fuzzy membership function were made for each subject in accordance with the characteristics of interpreting parameter value, such as the membership factor α, the upper and lower thresholds of parameter variation in the figure.

With respect to deriving TCR/HUMOS-PAD, the settings of the fuzzy membership function in the unified model should be made so that it can reflect all the characteristics of interpreting parameter values. Therefore, the upper and lower thresholds of parameter values are set as the maximum and the minimum thresholds of the three subjects, respectively. Furthermore, the membership factor α is set so that it would fluctuate from 0.1 to 0.9 in the computer simulation. The setting is based on the assumption that the variation of the cognitive behaviors of interpreting parameter value should be within the scope defined by the upper and lower thresholds.

Monitoring Strategy

As for the rest two factors, they are substantially operator's "monitoring strategy". The "monitoring strategy" has been modeled in two steps, as described in detail in the preceding chapter. First step is to classify plant parameters into five groups in accordance with the plant sub-systems ("Reactor","PRZ", "Steam Generator", "Turbine", "CVCS"). The next step is to set the reference frequency for each group in accordance with the analytical results of subject's monitoring behaviors recorded in OSH, as shown in Figure 2.16. The parameter reference is then modeled by two kinds of selection: (i) random selection of the parameter group based on the reference frequency (ii) sequent selection of a specific parameter in the

selected parameter group.

With respect to deriving TCR/HUMOS-PAD curves, the reference frequency of each group in the unified model is set to the average values of the reference frequency of the three subjects. The settings are based on the consideration that the characteristics of the reference frequency of the three subjects are similar with each other.

4.4.3 Modeling Probabilistic Factors in Anomaly Diagnosis Phase

Four probabilistic factors would influence the characteristics of anomaly diagnosis TCR curves, as listed again below.

1. Hypothesis recall
2. Hypothesis examination sequence
3. Display type
4. Belief level

The detailed settings of these factors are described in follows.

Hypothesis Recall

Two types of settings are made to model the probabilistic effects generated by "Hypothesis Recall".

- The scope of the recalled hypotheses
  We had summarized the relationships between the first hypothesis and the first symptom in the preceding chapter. The recalled hypotheses are different from person to person even the subjects detect the identical first symptom. The settings of the relationship in the unified human model are shown in Table 4.9 that summarizes the first symptoms and all corresponding possible hypotheses. The possible hypotheses is the set of the hypotheses considered by subjects in their anomaly diagnosis process.

- The first hypothesis
  One of the hypotheses is then selected as the first hypothesis from the scope of the recalled hypothesizes. The uniform distribution is used to set the selection probability of each hypothesis since all the hypotheses have a chance to be the first hypothesis.

Table 4.9: All possible hypotheses by the first symptom

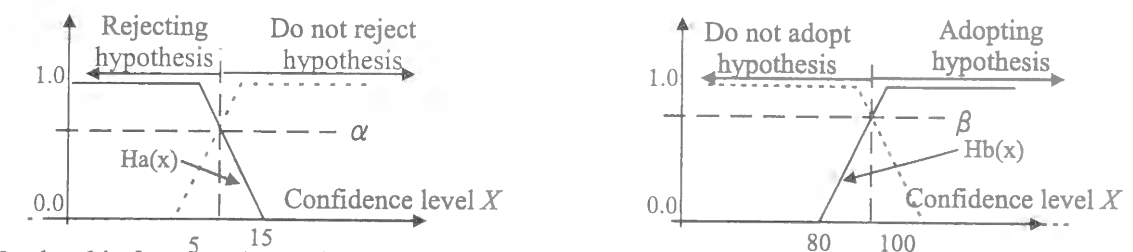
First Symptom	Scope of the Possible Hypothese
SG-Lvl big	SGTR
	FW control failure
SG-Lvl small	FW control failure
FW. Flow small	SGTR
	FW control failure
Steam-flow big	FW control failure
PRZ-prs big	PRZ. Prs. Control fail-low
	Reactor related
PRZ-prs small	PRZ. Prs. Control fail-high
	RCS
	SGTR
	PRZ.Spary.V fail
PRZ-lvl big	PRZ. Lvl. Control fail-high
PRZ-lvl small	RCS
	SGTR
	PRZ. Lvl. Control fail-low
CVCS-in big	RCS
	SGTR
	PRZ. Lvl. Control fail-low
	PRZ. Prs. Control fail-high
CVCS-in small	PRZ. Prs. Control fail-low
	PRZ. Lvl. Control fail-low
Reactor-output big	Reactor related

Hypothesis Examination Sequence

The selection of the hypothesis to be examined next would be made if a hypothesis were rejected. In this case, the probability of the selection is also set in accordance with uniform distribution. The settings are based on the assumption that the chance to be selected as the next hypothesis is equal for all the un-examined hypotheses in the scope defined by Table 4.9.

Display Type

The two types of display (digital number and trend graph) give the operator a chance to select one of them to check the status of plant parameter. The reference proportion of digital numbers type display vs. the trend graph type display are assumed to be 40% vs. 60% since there was a tendency that the three subjects would like to refer to the trend graph for the detailed information about the parameter variation presented in the trend graph.



(a.) Membership function about rejecting hypothesis (b.) Membership function about adopting hypothesis

Figure 4.12: Fuzzy membership function for decision-making of a hypothesis

Belief Level

There are two types of belief level corresponding to adopting and rejecting a hypothesis, respectively. The belief level had been modeled by the concept of confidence score and confidence level defined in the description of "Hypothesis Examination Object" in the section 3.4.3. The confidence scores are assigned to the plant parameters whose status is predicted in accordance with the hypothesis under the examination. The confidence level is the result of the accumulation of the confidence scores. It will be increased if the actual condition of the parameters agrees with the prediction made in accordance with the hypothesis. On the other hand, The confidence level will be decreased if the actual condition of the parameters disagrees with the prediction. The degrees of increase or decrease are defined by the confidence score of the plant parameter with respect to examining the hypothesis. The hypothesis will be adopted if the confidence level is increased/decreased over/below a certain threshold. The thresholds would be different from person to person since the diversity of human cognitive behaviors.

Fuzzy membership functions are devised to model the diversity in the decision-making of adopting or rejecting a hypothesis, as shown in Figure 4.12. There are two membership functions in the figure for rejecting and adopting a hypothesis, respectively. In the membership functions, the following assumptions are made.

- A hypothesis would be adopted/rejected by all operators if its confidence level is bigger/smaller than 100/5 points.
- The anomaly diagnosis would be continued by all operators if the confidence level is between 15 and 80 points.
- The diversity in the hypothesis adoption and rejection is then modeled by the membership factors α and β defining the decision-making thresholds that would vary in

the scopes of 80~100 points and 5~15 points, respectively.

- The variation of those thresholds is assumed as the uniform distribution in the corresponding variation scopes.

4.5 TCR/HUMOS-PAD Curves and Validation

Numerical experiments are conducted by utilizing the human model for simulating the subjects' behaviors of diagnosis, in order to validate the application of human model simulation application for the HRA/PSA practice. TCR/HUMOS-PAD curves for diagnosing an abnormal transient are derived from the calculated data of diagnosis time obtained by human model simulation. These curves are then compared with the TCR curves derived from the laboratory experiment.

4.5.1 Conduction of Human Model Simulation

Like the previous laboratory experiment, where PWR-type NPP simulator, MMI simulator and subjects were utilized, the same PWR-type NPP simulator is also used in the numerical experiments. But, the human model with interaction models to MMI is connected to the plant simulator directly. The time taken to operate the MMI simulator used in the laboratory experiment, e.g., switching interface screens, referring to plant parameters' value or trend graph, is estimated from the experimental data, and utilized in HUMOS-PAD as the time delay effects. Table 4.10 shows the settings of time delay effects used in the human model.

Anomaly Detection TCR/HUMOS-PAD Curves

Two cases of "SGTR" and "PRZ.Lvl.F.High" are selected as the abnormal transients to be detected by HUMOS-PAD, because they are the typical cases where the anomaly detection TCR/HUMOS-PAD curves would exhibit either steep or gentle slope. By the same way in the laboratory experiments, the data of anomaly detection time were obtained by conducting 20 cases of numerical experiments for each abnormal transient, and by the same data processing methods as shown in the figure 4.6 and the equation 4.3. Two anomaly detection

Table 4.10: Settings of time taken to operate MMI in HUMOS-PAD

MMI Operation	Time Delay
Parameter Value Reference	2 sec.
Parameter Trend Reference	4 sec.
Switch MMI screen	1 sec.

TCR/HUMOS-PAD curves were obtained for the cases of "SGTR" and "PRZ.Lvl.F.High", as shown in Figure 4.13, where the TCR curves derived from the laboratory experiment are also depicted for an inter-comparison.

Anomaly Diagnosis TCR/HUMOS-PAD Curves

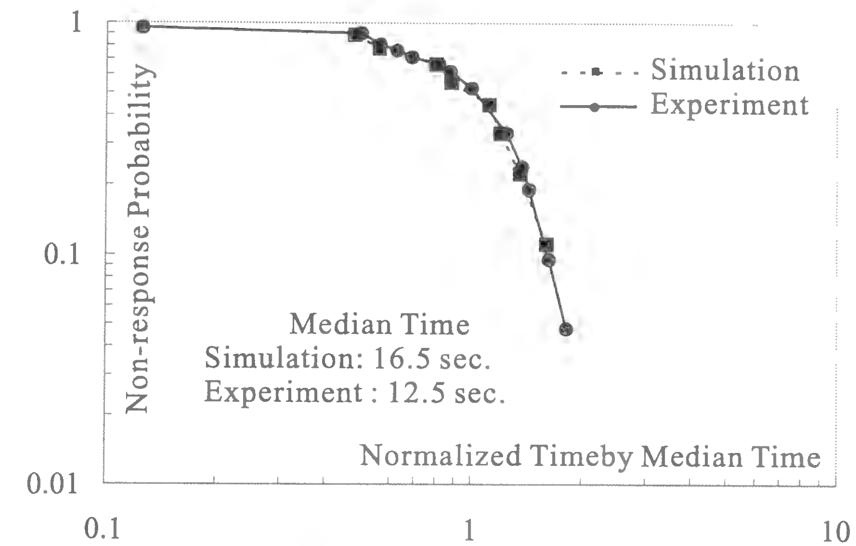
In the case of the human model simulation for diagnosis phase, the settings of the thresholds of confidence level are necessary, besides the time delay effects in the detection phase. With respect to deriving the TCR/HUMOS-PAD, the initial confidence level (20 points) would be assigned to the hypothesis recalled by the first symptom. The confidence level would be increased or decreased in accordance with the results of the hypothesis examination. Three thresholds (80,90,100 points) are devised to simulate the cognitive diversity in adopting a hypothesis. The hypothesis rejection threshold is assumed as "10 points".

"SGTR" and "RCS leakage" are diagnosed by HUMOS-PAD to estimate the anomaly diagnosis TCR curves. Ten numerical experiments were conducted for each of the three thresholds of confidence level. The obtained anomaly diagnosis TCR/HUMOS-PAD curves are shown in the figures 4.14 and 4.15, together with the corresponding diagnosis TCR curves derived from the laboratory experiment.

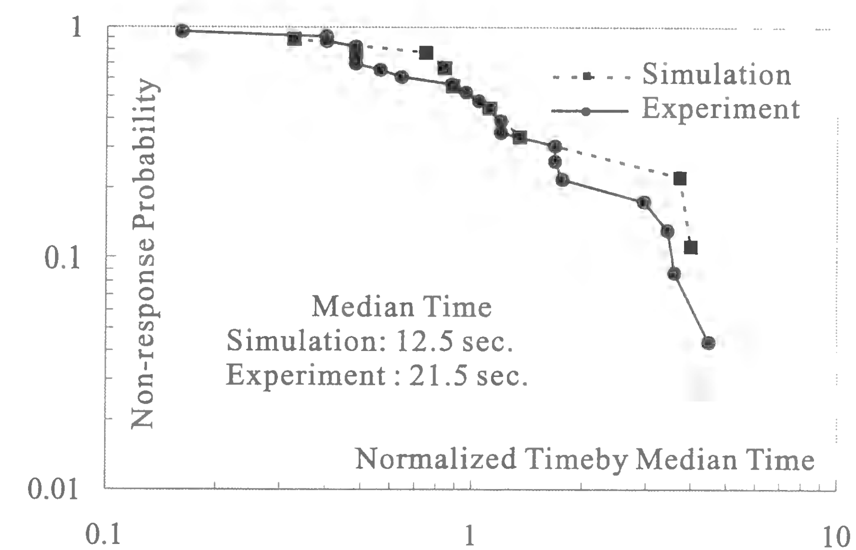
From the inter-comparisons shown in the figures 4.13, 4.14 and 4.15, the detection and diagnosis TCR curves by HUMOD-PAD agree well with the ones derived from the experimental data well. The detailed discussions about the inter-comparison are given in the next section.

4.5.2 Validation of Human Model Simulation

As shown in Figure 4.13, the slope of the TCR/HUMOS-PAD curves agree well with the two typical anomaly detection TCR curves derived from the laboratory experiment. It suggests that the appropriateness of the settings of the "monitoring strategy" and the fuzzy membership function for interpreting parameter values. On the other hand, some differences can be noticed from the inter-comparison of the median time. The median time of the simulation results is a little bigger than that of laboratory experiment in case of the detection of "SGTR", while the converse situation is found in the case of the detection of "PRZ.Lvl.Cont. fail-high". We consider that the differences are normal since the median time is defined as the median data in the ascending response time sequence. In other words, the median time may vary along with the increase of the sampling numbers. Hence



(a.) Normalized TCR Curves of detecting SGTR



(b.) Normalized TCR Curves of detecting PRZ.Lvl.Cont.F.H

Figure 4.13: Anomaly detection TCR/HUMOS-PAD curves after normalization

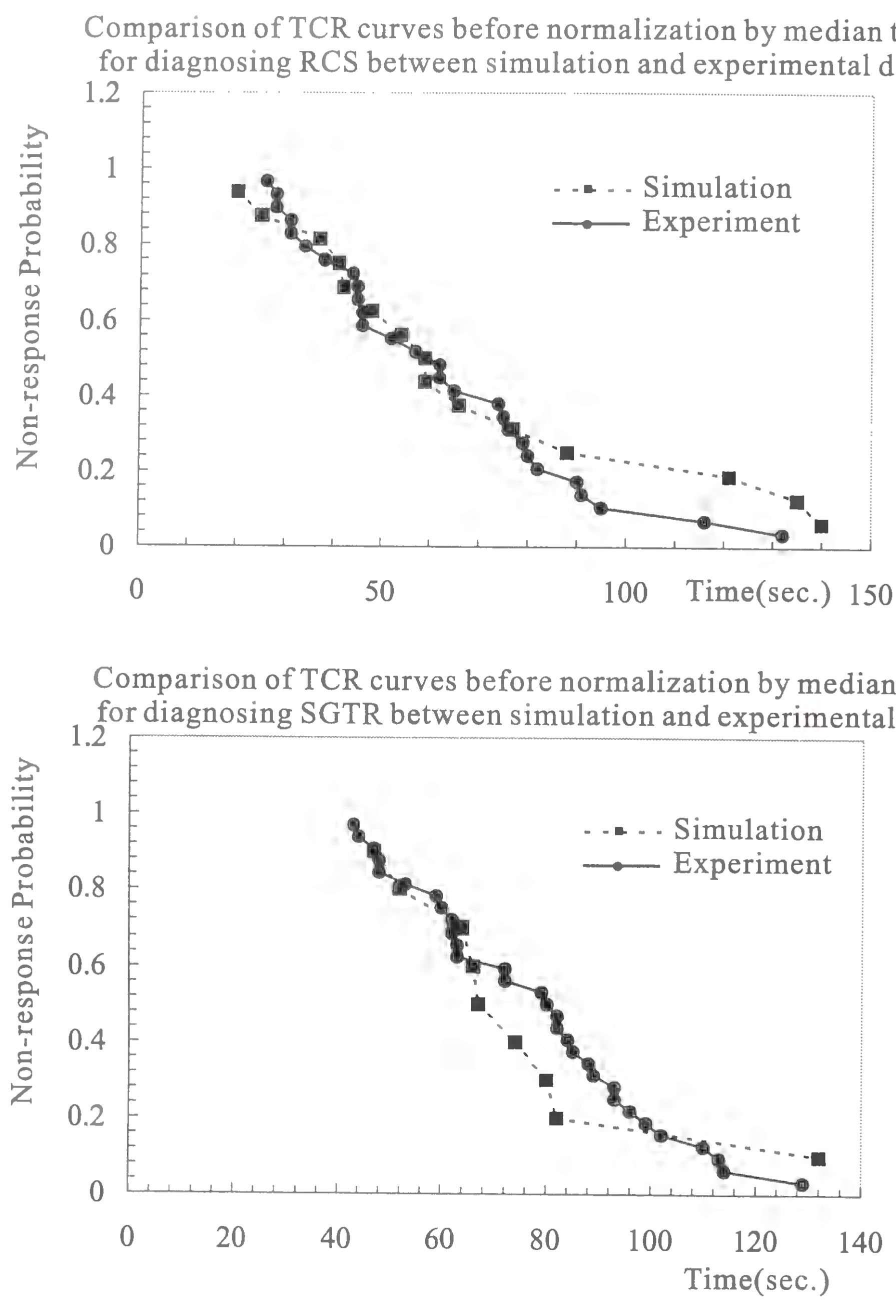


Figure 4.14: Anomaly diagnosis TCR/HUMOS-PAD curves before normalization

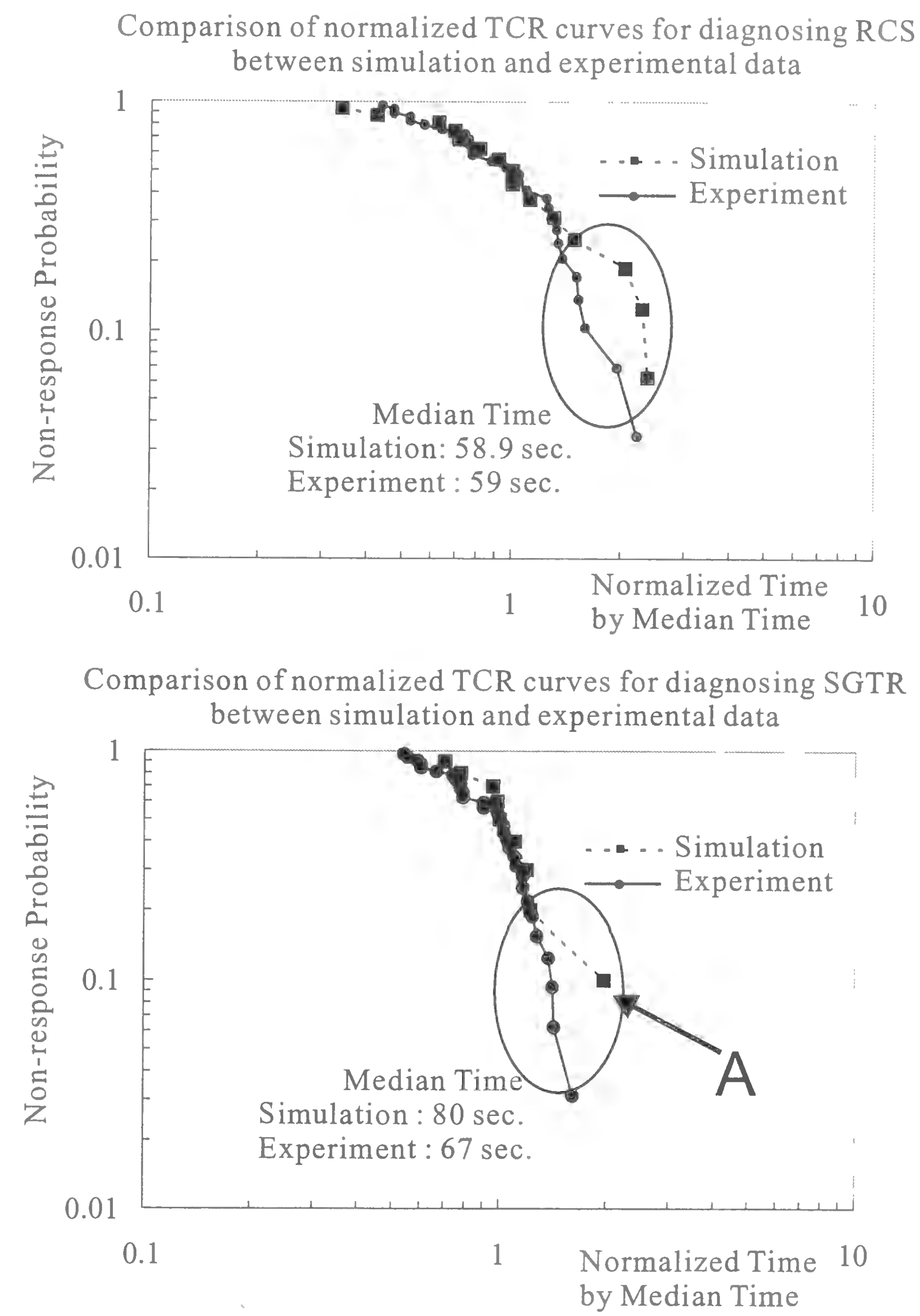


Figure 4.15: Anomaly diagnosis TCR/HUMOS-PAD curves after normalization

the similar results of the median time demonstrate the appropriateness of the time delay setting for modeling the MMI operation.

The figures 4.14 and 4.15 show the inter-comparisons of the anomaly diagnosis TCR curves before and after the normalization data processing, respectively. The results shown in Figure 4.14 demonstrate that the tendency of the curves agrees well with each other. It suggests that the anomlay diagnosis has been modeled properly. Moreover, the probabilistic factors and their variation characteristics are also modeled well in HUMOS-PAD. The data of the median time confirms the conclusion as well. However, there is common problem that the differences are shown in the tail end of the normalized TCR curves, as shown in 4.15.

The experimental trial represented by the point "A" in Figure 4.15 has been re-analyzed to explain these differences by focusing on the operation history sequence and the interview records of this case. The results turn out that the differences are generated because of an adherence effect, as explained in detail below by utilizing the operation history sequence shown in Figure 4.16.

In this experimental trial, the subject doubted "FW cont. system failure" after he noticed the parameter variation in the secondary system of NPP. The parameter 'Feed Water Flow" was checked repeatedly since he insisted that the root cause should be "FW cont. system failure". The examination of the hypothesis took about 50 seconds (the third of the total time taken to identify the real root cause). After that, the subject changed his mind and took a reference to "RMS monitor". The reference made him find the real root cause in a short time (about 30 seconds).

The characteristics of the adherence effect can be described as the repeat reference to same or similar plant parameters. The modeling of the adherence effect would be one of the subjects of the further study.

So far, we have described the application of HUMOS-PAD to estimate TCR curves. The following subsection will give a further study on estimating the anomaly diagnosis TCR curves in a real-scale simulation environment of NPP where a real-scale MMI simulator of the central control room is used rather than the simple CRT-based used in the laboratory experiment.

4.5.3 Estimating TCR Curves by SEAMAID/HUMOS-PAD

In order to estimate the anomaly diagnosis TCR curves in the environment of real central control room of NPP, HUMOS-PAD had been incorporated into a real-scale man-machine

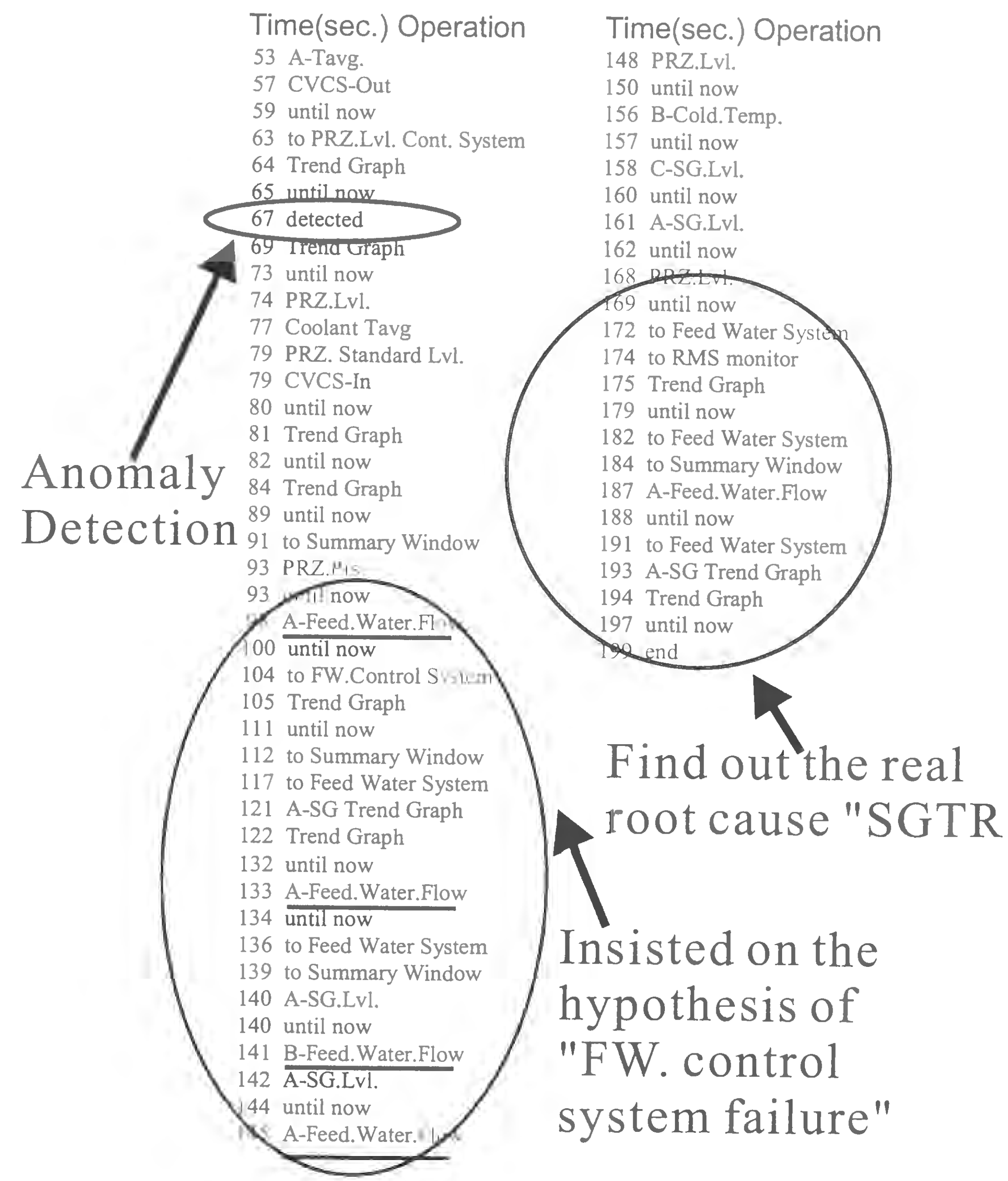


Figure 4.16: Adherence effect in anomlay diagnosis of "SGTR"

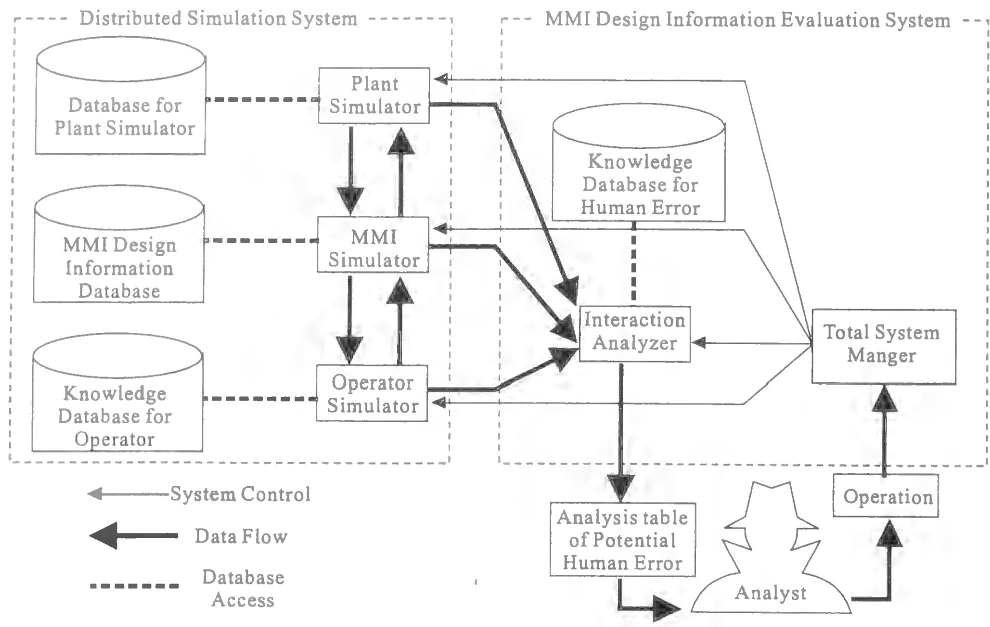


Figure 4.17: Configuration of SEAMAID

interaction simulation system SEAMAID which has been developed by MITSUBISHI Electric Corporation under the sponsorship of Ministry International Trade and Industry and Nuclear Engineering Corporation [13].

SEAMAID

Simulation based Evaluation and Analysis Support System for Man-Machine Interface Design (SEAMAID) is composed of two sub-systems, as shown in Figure 4.17, distributed simulation system and MMI design evaluation system. The functions of the two sub-systems are summarized as follows.

- The distributed simulation system includes three simulator that simulate the behaviors of NPP, MMI, and operator in case of an emergency, respectively. The man-machine interactions are then simulated by the interactions between the three simulation systems in real time. Therefore, SEAMAID can simulate not only the individual behavior of the components of NPP but also the interactions between them.

- MMI design evaluation system is an analysis support system for evaluating a given MMI design from the viewpoints of human factors. With SEMAID, an analyst can set various abnormal transient situations for the evaluation of the MMI design by utilizing "Total System Manager" shown in Figure 4.17 to communicate with the three simulators. The evaluation of the MMI design can be then conducted by utilizing "Interaction Analyzer" to analyze the recorded interactions between the MMI and operators.

To compare different given MMI designs for a NPP, a standard for evaluating the MMIs is necessary. The operator's standard operations following the operation procedures are selected as the evaluation standard in SEAMAID. But, operator's behaviors of the anomaly diagnosis are not considered in detail by the operator simulator in SEAMAID since there is no operation procedures guiding operator's behaviors. Therefore, it is necessary to implement HUMOS-PAD into SEAMAID as a diagnosis engine, in order to estimate the TCR curves by SEAMAID.

Incorporation of HUMOS-PAD into SEAMAID

Figure 4.18 shows the system architecture of the operator simulator in SEAMAID, together with the incorporated HUMOS-PAD. Prior to explain the methods of the incorporating HUMOS-PAD into SEMAID, the original operator simulator in SEAMAID should be described.

The operator simulator in SEAMAID has been developed in accordance with the general human modeling framework described in the preceding chapter. The functions of main units shown in Figure 4.18 are summarized as follows.

- **Shared Memory 1**: the communication area from "MMI Simulator" to "Operator Simulator". There are two types of information; (i) alarm information , (ii) the focused MMI information.

- **Shared Memory 2**: the communication area form "Operator Simulator" to "MMI Simulator". There are two types of information; (i) information on how the operator manipulates; (ii) MMI information on which the operator is focusing.

- **Perception Process**: this process receives all the information from around the operator through "Shared Memory 1", transforms it into information elements, and further sends each èlement to PWM.

- **PWM**: it is a temporary area holding information elements from "MMI Simulator" or the knowledge base (KB) database. The information in PWM is processed unconsciously.

- **FWM Process**: this process conducts four types of data processing; (i) transporting information elements from PWM to FWM, (ii) prioritizing information elements in FWM, by assigning an "Important Index" which is calculated from a "saliency" or index of similarity with focal information, (iii) chunking function of the information elements in FWM, and (iv) inference function at FWM with interaction to KB database to maintain the context.
- **FWM**: it is a limited space where the information is processed consciously.
- **KB Retrieval Process**: it retrieves information elements from the KB database using keywords coinciding with the information having highest "Important Index".
- **KB Database**: it corresponds to the long-term memory. A Petri-net model is utilized to model the KB database that stores the real-scale MMI information and the detailed operation procedures.

The further detailed information about the operator simulator is given by the developers of SEAMAID [13]. From the above brief description, one would notice that the modeling methods have lots of similarities to the methods used in HUMOS-PAD since both models are developed in accordance with the general human modeling framework.

By incorporating HUMOS-PAD into SEAMAID, operator's rule-based behaviors are simulated by SEAMAID, such as the response operation based on the operation procedures, and the knowledge-based behaviors, i.e., anomaly diagnosis, will be simulated by HUMOS-PAD. The new version of SEAMAID is called here as SEAMAID combined with HUMOS-PAD (SEAMAID/HUMOUS-PAD).

The detailed simulation procedures of SEAMAID/HUMOS-PAD are summarized as follows, with respect to simulating operator's behaviors in case of an emergency.

1. SEAMAID will detect the occurrence of an abnormal transient by the alarm information received from "Share Memory 1" just after the abnormal. Through the processing conducted in PWM and FWM, SEAMAID will transfer the alarm information to HUMOS-PAD for diagnosing the anomaly, as indicated by the arrow "A" in Figure 4.18.
2. HUMOS-PAD will then diagnose the abnormal transient by applying the anomaly diagnosis knowledge summarized as the knowledge database, which has been described in detail in the preceding chapter.

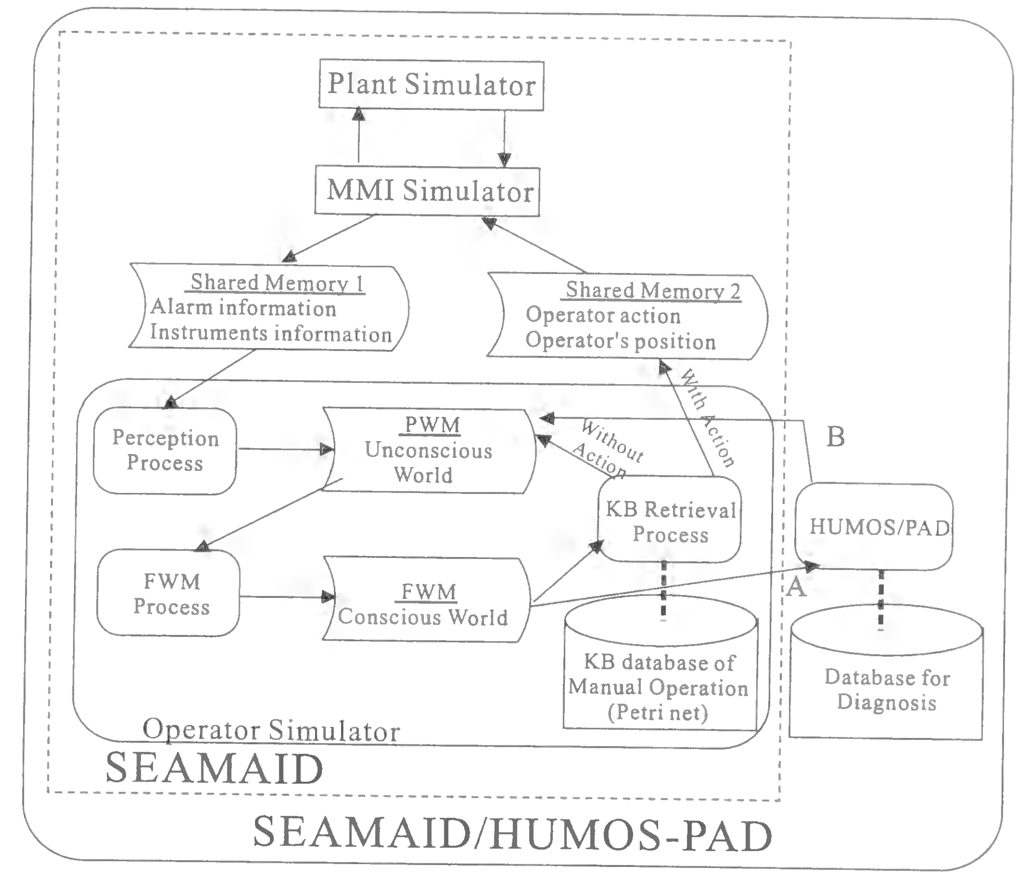


Figure 4.18: Modeling architecture of operator simulator in SEAMAID/HUMOS-PAD

3. HUMOS-PAD will request to SEAMAID for the symptoms supporting or denying the hypotheses recalled in the process of diagnosing abnormal transients, in order to examine the hypotheses. The request will be written in PWM and will be transferred into FWM afterwards, as indicated by the arrow "B" in Figure 4.18.
4. As the processing results of the request came from HUMOS-PAD, "KB Retrieval Process" will write necessary information to "Share Memory 2" for conducting a parameter reference. The necessary information will be retrieved from "KB Database" that stores the real-scale MMI information and the operation procedures represented by Petri-net.
5. The results of the parameter reference will be then written to "Shared Memory 1" as the symptoms required by the anomaly diagnosis in HUMOS-PAD. Through the data processing in PWM and FWM, the symptoms will be transferred into HUMOS-PAD

for the anomaly diagnosis, as indicated by the arrow "A" in Figure 4.18. So far, one processing cycle is completed for the anomaly diagnosis.

6. After a numbers of processing cycles of anomaly diagnosis, HUMOS-PAD will give the diagnosis result to SEAMAID by writing the result to PWM, as indicated by the arrow B in Figure 4.18. SEAMAID will then simulate operator's appropriate response operation in accordance with the operation procedures modeled by the Petri-net model.

Anomaly Diagnosis TCR Curves by SEAMAID/HUMOS-PAD

Five hypotheses have been made by HCR models as described previously. One of them states that the technique of normalization will remove the influence of the intrinsic time characteristic of the experimental scenario, which is hardware or plant dependent. Furthermore, it is said that the normalization of HCR/ORE curves by the median response time had demonstrated the validity of the hypothesis in ORE technical report [1]. Therefore, the hypothesis suggests that operator's same cognitive behaviors would generate same pattern of normalized TCR curves even in the different MMI environment, and all the differences in the MMI environment would be reflected by the median response time.

The methods are derived from the hypothesis to estimate and validate the anomaly diagnosis TCR curves by utilizing SEAMAID/HUMOS-PAD, as described in follows.

- Conducting numerical experiments in which SEAMAID/HUMOS-PAD will simulate operator's cognitive behaviors of anomaly diagnosis.
- Deriving the anomaly diagnosis TCR curves from the simulation results of the above numerical experiments.
- Comparing the anomaly diagnosis TCR curves obtained by SEAMAID/HUMOS-PAD with the ones derived from the laboratory experiment.

To explain the above validation method of the application of SEAMAID/HUMOS-PAD to estimate TCR curves, we give a discussion on the among the three experiments: the laboratory experiment, the numerical experiments by HUMOS-PAD and the numerical experiments by SEAMAID/HUMOS-PAD, as summarized in Table 4.11.

First of all, the laboratory experiment is a subject experiment in which the human is the examination subject. The rest two experiments are numerical experiments conducted

Table 4.11: Differences between the three experiments

Experiments	Laboratory Experiments	Numerical Experiments by Human Model Simulation	Numerical Experiments by New Version SEAMAID Simulation
Nature of the Experiments	Subject Experiments	Numerical Experiments	Numerical Experiments
Subject of the Behaviors	Human beings	Human Model	Diagnosis Engine (the left one introduced into SEAMAID)
Utilized MMI	Simple one based on real-scale MMI, and has a configuration of 16 screen displays	Model of the left 16-screen-configuration MMI	Mmodel of real-scale MMI in SEAMAID
Characteristics of the MMI	1.Making parameter eference and switching screen display by mouse operation, 2. Do not involve physical movements such as walking	1.Database of information about parameter location in the MMI 2.Setting the delay time to simulate MMI operation such as parameter reference or screen display switch	1.Database of information about parameter location in the real-scale MMI 2. Require physical action such as walking and set the walk speed to "1m/sec."
Utilized NPP Simulator	PWR-type training NPP simulator	Same as left	Same as left

by computer simulation. The examination subject of the numerical experiments is the performance of the human models developed to simulate operator's behaviors.

Next, the most important differences are in the MMI used in those experiments, with respect to validate the application of SEAMAID/HUMOS-PAD. A simple 16-window-configured CRT-based MMI was used in the laboratory experiment. The mouse operation is the characteristics of the CRT-based MMI. Therefore, the CRT-based MMI almost does not require the physical actions such as working. The model of the simple CRT-based MMI is used in the numerical experiment by HUMOS-PAD. The time delay settings are used to model the mouse operation time. The MMI design information is modeled as a database storing the location information of parameters. On the other hand, SEAMAID provides a MMI model of the real-scale first generation central control room where CRT is not utilized. The Petri-net KB database is devised to storing the real-scale MMI design information and the operation procedures. Moreover, the working is required to conduct a parameter reference in the MMI model used in SEAMAID. The walking speed is set to "1 meter/sec." as a standard.

In the end, all the experiments utilize the same PWR-type NPP simulator to simulate the dynamic characteristics of the plant in case of an emergency.

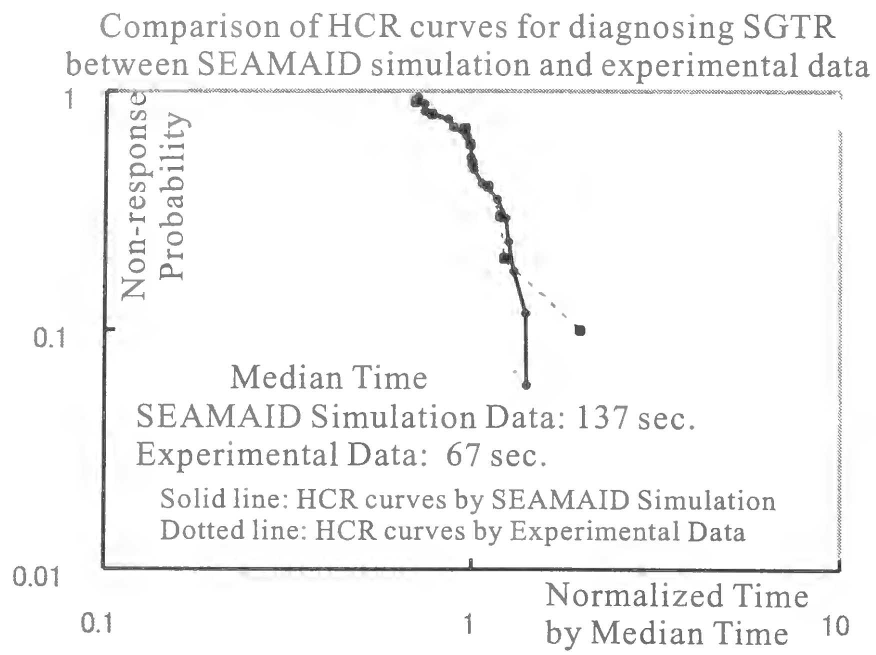


Figure 4.19: Validation of human model by SEAMAID simulation

The following assumption can be then derived by combining the above comparison of the three experiments with the hypothesis about the normalization effect of TCR curves.

- The normalized TCR curves derived from the three experiments should have the same characteristic in the slope of TCR curves, with respect to diagnosing the same abnormal transient.
- The median response time given by SEAMAID/HUMOS-PAD should be longer than the one given by the two other experiments, since the parameter reference requires more time in the MMI of SEAMAID than the one in the CRT-based MMI.

The preceding subsection has conducted the comparisons between the TCR/HUMOS-PAD and the TCR curves derived from the laboratory experiment, as the validation of the application of HUMOS-PAD to HRA/PSA practice. In the rest of this section, the discussions are made to clarify the application of SEAMAID/HUMOS-PAD to estimate TCR curves in the real-scale simulation environment of NPP.

Discussions about TCR curves by SEAMAID/HUMOS-PAD

TCR curve about diagnosing "SGTR" was estimated from the numerical experiments by SEAMIAD/HUMOS-PAD, as shown in Figure 4.19 where the corresponding TCR curves

derived from the laboratory experiment are also depicted to show the inter-comparison between them. From the inter-comparison, one cannotice that the slope of the normalized TCR curves of diagnosing "SGTR" agrees well with each other. The results confirmed the normalization effect hypothesis of HCR model. Consequently, the validation of the application of the human model approach to the HRA/PSA practice is further confirmed in the real-scale simulation environment of NPP.

On the other hand, the median response time reflects the effects of the different MMI used in the experiments. One cannotice that the median time in the case of the laboratory experiment is almost half of that in the case of SEAMAID/HUMOS-PAD. The difference suggests that the CRT-based MMI would give a better response time than the first generation MMI where one parameter corresponds to one instrument. In fact, the most advanced MMIs in the NPP industry have reflected the above conclusion, such as the MMI used in Advanced Boiling Water Reactor (ABWR) [14] where large display is utilized in the central control room, together with the CRT terminals for each operators.

Suggestions of the future HRA/PSA methods

The future PSA/HRA methods could be suggested from the application study of HUMOS-PAD in this chapter, as summarized in Figure 4.20 and explained below.

1. First to specify the abnormal transient to be analyzed.
2. If there exists a validated HUMOS-PAD coping with the abnormal transient in the HUMOS-PAD database, proceed to step 8.
3. Conducting small-scale laboratory experiments to analyze the cognitive behaviors of the skilled operators of NPP in diagnosing the abnormal transient. The MMI used in the laboratory can be a simple CRT-based interface.
4. Analyzing the experimental data to find out the probabilistic factors and the variation distribution.
5. Modeling those probabilistic factors in the modeling framework so that HUMOS-PAD could simulate well the characteristics of the operators' cognitive activities in diagnosing the abnormal transient.
6. Applying modified HUMOS-PAD to simulate operators' cognitive activities in the small-scale experiments and comparing the simulation results with the experimental

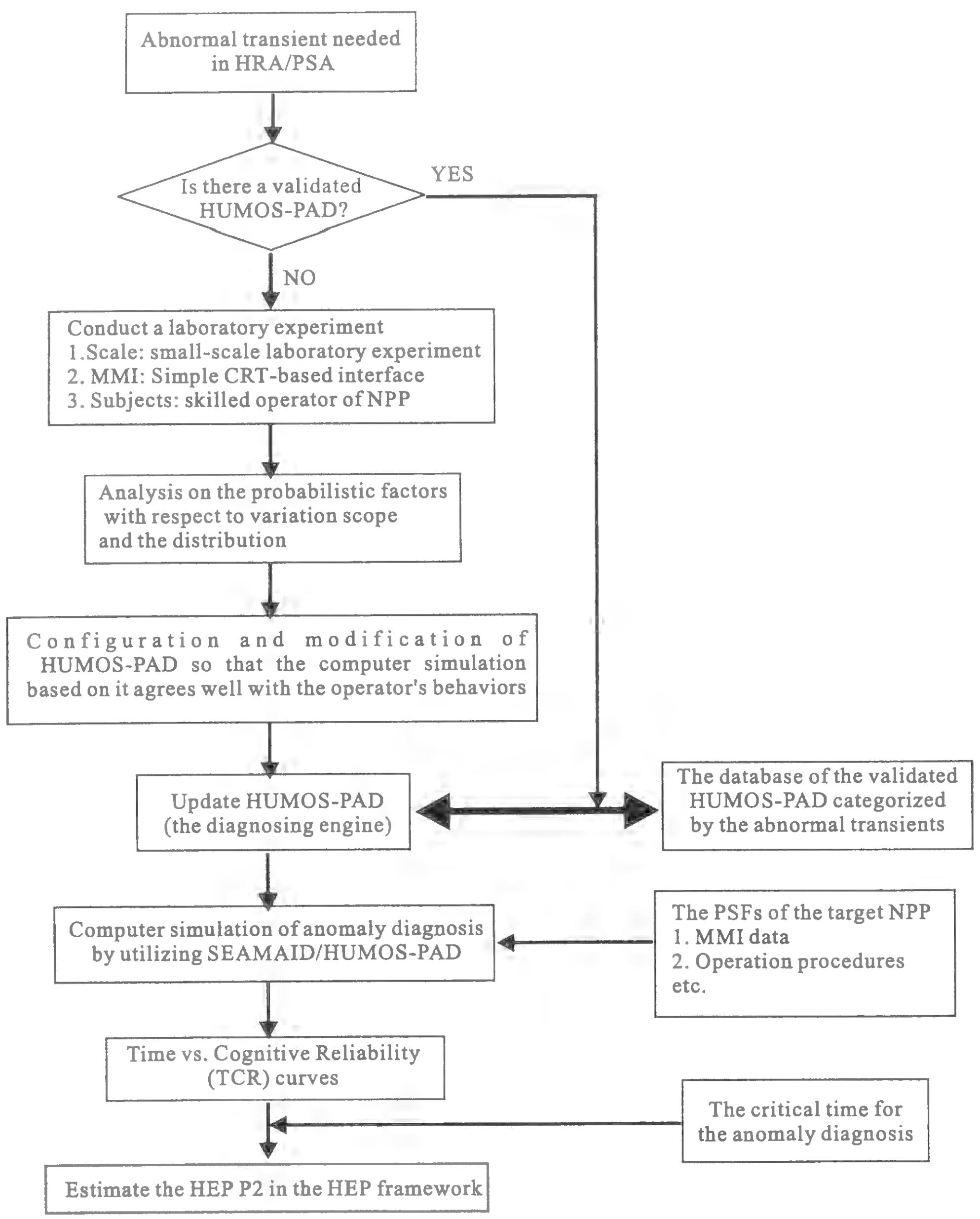


Figure 4.20: Future HRA methods by HUMOS-PAD

results. If the simulation results do not agree well with the experimental data, repeat step 4 to step 5 until the HUMOS-PAD could reflect well the characteristics of the cognitive behaviors of the skilled operators.

7. Storing the validated HUMOS-PAD in the database of validated HUMOS-PAD categorized by the type of the abnormal transients.

8. Utilizing the validated HUMOS-PAD as the diagnosis engine of SEAMAID to conduct the real-scale simulation of the man-machine interaction in diagnosing the abnormal transient. The MMI design data and operation procedures of a specific given NPP can be also modeled by modifying the Petri-net database in SEAMAID.

9. TCR curves could be then derived from the large numbers of numerical experiments by SEAMAID/HOMUS-PAD. The human error probability P_2 could be then estimated.

4.6 Concluding Remarks

In this chapter, a new approach is proposed for PSA/HRA in NPP by applying the human model simulation methodology. A description about PSA and HRA is given first to explain the existing human reliability quantification techniques, such as THERP and TRCs (Time Reliability Curves). As the results of the review on the methods of HRA, a framework is proposed to describe fundamental human error probability parameters required in HRA/PSA. The attention of the study in this chapter is then paid to the human cognitive reliability probability in the framework. The probability is represented generally by TRCs which have been estimated by conducting large-scale operator experiments, which have some drawbacks such as the necessary large amount of time and considerable cost, the limitation in the application of the experimental data. Hence the objective of the study in this chapter is set as to estimate the "time versus cognitive reliability (TCR)" curves for anomaly detectioin and diagnosis by conducting computer simulations based on HUMOS-PAD, called as TCR/HUMOS-PAD.

Two types of TCR curves have been first derived from the laboratory experiment to clarify the probabilistic factors influencing operator's performance of anomlay detection and diagnosis, respectively. The probabilistic factors in the anomaly detection are summarized as (i) the variation degree of parameters to which subjects feel something wrong and (ii) the reference frequency and sequency. Four probabilistic factors are summarized concerning the anomaly diagnosis; (i) hypothesis recall, (ii) hypothesis examination sequence, (iii) display type of parameter values, and (iv) belief level for decision-making. The effects of the probabilistic factors are modeled by the human model adjustment factors in the modeling framework of HUMOS-PAD. TCR/HUMOS-PAD curves were then derived in following two cases.

1. TCR/HUMOS-PAD curves for anomaly detection and diagnosis corresponding to the ones derived in the laboratory experiment.

2. TCR curves for anomaly diagnosis in the simulation environment of real-scale central control room of NPP by incorporating HUMOS-PAD into SEAMAID as a diagnosing engine.

The validity of the application study of HUMOS-PAD to HRA/PSA is confirmed by conducting inter-comparisons between the former TCR curves (TCR/HUMOS-PAD) curves derived by computer simulation and the ones derived from the laboratory experiment.

Furthermore, the inter-comparison is also conducted between the TCR curves derived from the laboratory experiment and the TCR curves derived from the computer simulation based on the SEAMAID combined with HUMOS-PAD. The agreement in the slope of the two curves suggests the promising possibility that the computer simulation utilizing HUMOS-PAD would be usable for obtaining TCR curves, efficiently, in stead of conducting the large-scale experiment with the NPP training simulator. In the end, a procedure is suggested to derive TCR curves by the computer simulation based on SEAMAID/HUMOS-PAD in the future HRA/PSA approach in NPP.

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Chapter 5

Conclusion

In this thesis study, a basic research was conducted on modeling operators' cognitive behaviors of detecting and diagnosing abnormal transients in case of an emergency in NPP, aiming at contributing to improve the safety and reliability of the total man machine system.

The thesis study was conducted in three steps, as described below.

In Chapter 2, a laboratory experiment was conducted to examine operators' cognitive behaviors of detecting and diagnosing abnormal transients. The obtained experimental data from the subjects participated in the laboratory experiment were analyzed to derive the following characteristics of human cognitive behaviors at man-machine interface to detect and diagnose plant anomalies.

- Monitoring Strategy
- Criteria for judging anomaly occurrence
- Relationship of the first symptom and the first hypothesis
- The way of recalling, diagnosing, accepting and rejecting a hypothesis during the diagnosis process
- Sets of knowledge for diagnosing abnormal transients

All these results were applied to develop a human model for simulating subjects' cognitive behaviors in this laboratory experiment.

In Chapter 3, the modeling methods were described in detail for developing the human model. The human model was developed in accordance with a general human modeling framework where the anomaly detection and diagnosis were modeled separately.

The anomaly detection was modeled as the parameter status reference verifying whether or not the parameters' value would deviate from the steady status. The employed parameter reference model is in accordance with the "monitoring strategy" by grouping plant parameters and by setting the reference frequency of the parameter groups.

The anomaly diagnosis process was modeled as a repeating procedure of recalling hypothesis, collecting symptoms, examining the hypothesis, rejecting the hypothesis until a hypothesis would be adopted as the root cause of the abnormal transient. The modeling methods of each above step are summarized as follows.

- The relationship of the first symptom and the first hypothesis is utilized to simulate the hypothesis recollection.
- The concepts of "confidence score" and "confidence level" are introduced to model the degree of operator's belief on a hypothesis. The confidence level of a hypothesis will be increased or decreased by comparing the parameter's status with the prediction whether or not it is in accordance with the hypothesis.
- The rejection and the adoption of hypotheses will depend on the judgment whether or not the current confidence level is beyond a certain threshold defined in advance.
- The threshold is modeled so that it could be changed to reflect the individual variation of human decision-making.

Furthermore, the concept of human modeling adjustment factor is introduced to model the individual characteristics of the cognitive behaviors to detect and diagnose an abnormal transient. The introduced adjustment factors are (i) the reference frequency of parameter group, (ii) the criteria for judging the occurrence of abnormal transient, (iii) the peripheral sight effect for the anomaly detection; and (i) the First-Symptom-First-Hypothesis relationship, (ii) the thresholds of confidence level for rejecting or adopting a hypothesis for the anomaly diagnosis.

Finally, numerical experiments were conducted to validate the human model by connecting the human model to the NPP simulator utilized in the laboratory experiments. The inter-comparison between the simulation results and the laboratory experimental data were made from three aspects: (i) first symptoms, (ii) average anomaly detection time and (iii) the detailed diagnosis procedures. The results demonstrated that the human model could simulate well both the general and the individual characteristics in the anomaly detection and diagnosis.

In Chapter 4, an application of the human model for HRA/PSA was conducted. The developed human model (named as HUMOS-PAD) was utilized to estimate the "time versus cognitive reliability (TCR)" curves which is one of the important HEPs required in HRA/PSA.

TCR curves were firstly derived from the laboratory experiment to clarify the probabilistic factors influencing the performance of anomaly detection and diagnosis, respectively. The effects of the probabilistic factors were modeled by the human model adjustment factors in the modeling framework of HUMOS-PAD. TCR/HUMOS-PAD curves were then derived for the following two cases:

1. TCR/HUMOS-PAD curves for anomaly detection and diagnosis corresponding to the ones derived in the laboratory experiment.
2. TCR curves for anomaly diagnosis in the simulation environment of real-scale central control room of NPP by incorporating HUMOS-PAD into SEAMAID as a diagnosing engine.

The validity of the HUMOS-PAD application to HRA/PSA was confirmed by conducting inter-comparisons between the TCR curves (TCR/HUMOS-PAD) derived from the computer simulation and the ones derived from the laboratory experiment.

Furthermore, the inter-comparison was also conducted between the TCR curves derived from the laboratory experiment and the TCR curves derived from the computer simulation based on SEAMAID/HUMOS-PAD. The good agreement of both curves suggested a plausible possibility that the computer simulation utilizing HUMOS-PAD would be usable for obtaining TCR curves efficiently, in stead of conducting the large-scale experiment with the NPP training simulator. In the end of chapter 4, a procedure was also suggested to derive TCR curves by the computer simulation based on SEAMAID/HUMOS-PAD in the future HRA/PSA approach in NPP.

So far, the findings are summarized for the three study steps. The conclusions of the thesis study can be then summrized as follows;

- With respect to the human modeling approach, the thesis study showed the methods to model the inherent variety and diversity in the human cognitive behaviors by computer simulation technology.
- With respect to the application of the human modeling approach, the thesis study demonstrated the promising prospect for applying the computer simulation technol-

ogy to estimate the fundamental human cognitive reliability parameters needed in HRA/PSA.

- The thesis study established an innovative methodology for improving and designing the man machine interface for the central control room of NPP.

Moreover, with respect to the general researches on human behaviors in other study fields, the thesis study suggested a new methodology to anlayze human behaviors by following the three study steps of small-scale experiments, human model developement and application.

Finally, the following subjects of HUMOS-PAD are remaining for the further study.

- Improvement of HUMOS-PAD
  The improvements are necessary with respect to applying HUMOS-PAD to estimate various anomaly diagnosis TCR curves, in order to establish a new methodology to replace the large-scale experiment.

- Modeling of Operation Crew
  As described previously in Chapter 3, the modeling of operation crew is one of the subjects remaining in the human model study. The human-human communication function is necessary to model the behaviors of the operation crew, especially the verbal communication. In fact, the study on visualization of the diagnosis process of HUMOS-PAD by synthesis voice has been started [1] as the first step of the human-human communication.

- Contribution to the next generation MMI
  As one of the application of HUMOS-PAD, it has been utilized as the brain of a virtual collaborator: an innovative interface agent system between human and plant [2, 3, 4]. The virtual collaborator is proposed as the next generation MMI of NPP. As the collaborator of human beings, the various aspects of human behaviors are required to model, such as emotion, verbal communication, learning effects.

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Finally, I would like contributing the thesis work to my dear parents. The study life abroad in Japan would be impossible without the their supports. Especially, the constant encouragement from my dear mother in various aspects has helped me to continue and finish the thesis study. Thanks are also due to my dear brother for his assistance in writing this thesis.

Appendix A

All Snapshots of the CRT-based Interface

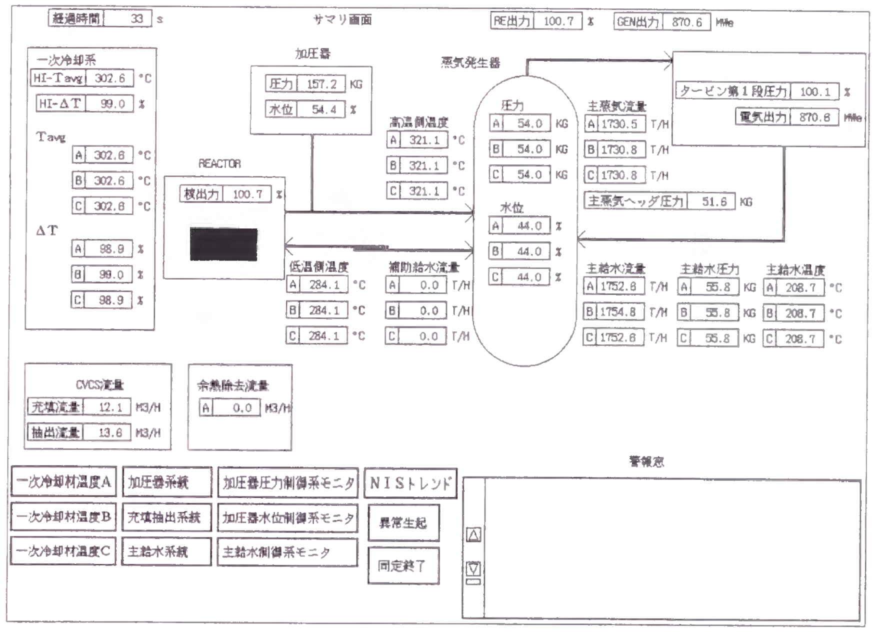

Figure A.1: Summary screen

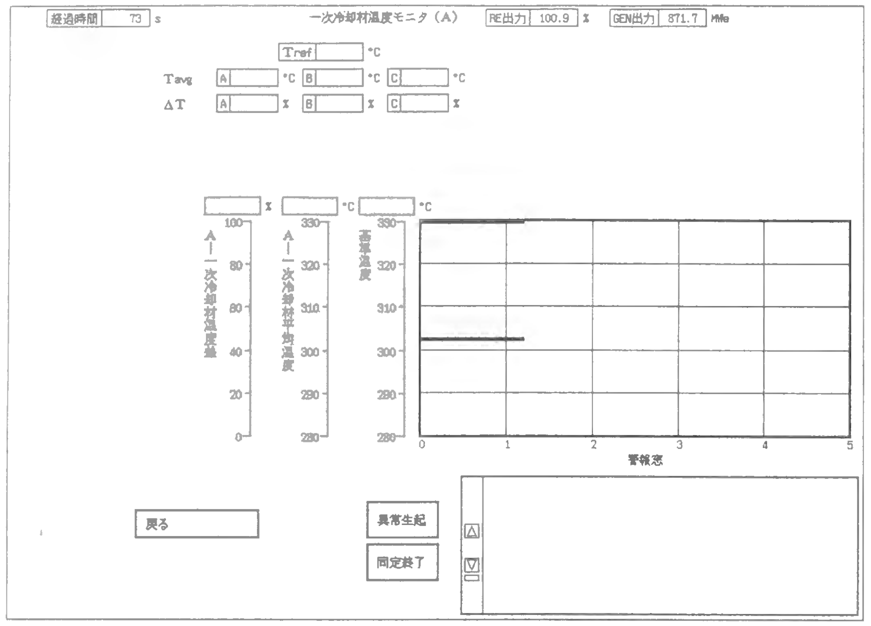

Figure A.2: Loop-A coolant temperature monitor

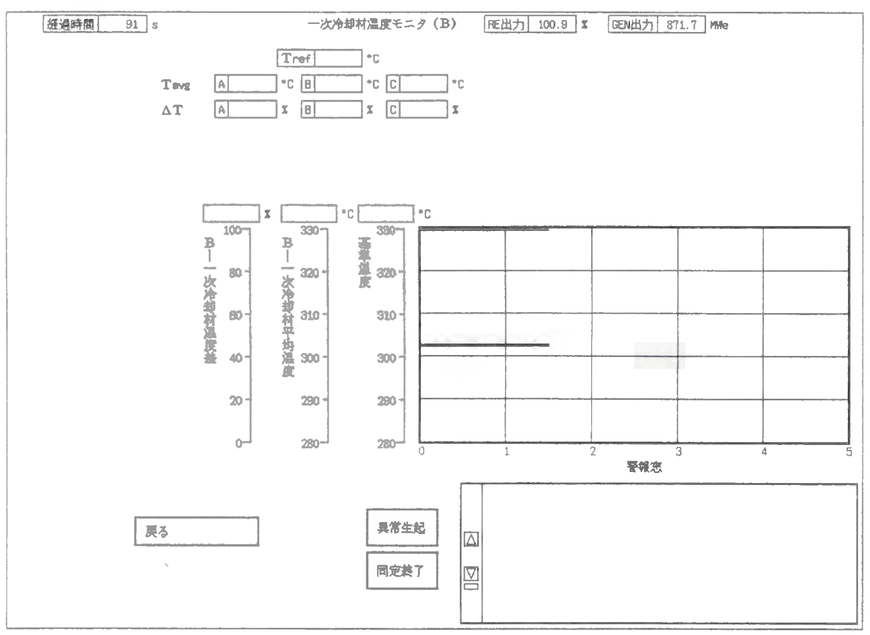

Figure A.3: Loop-B coolant temperature monitor

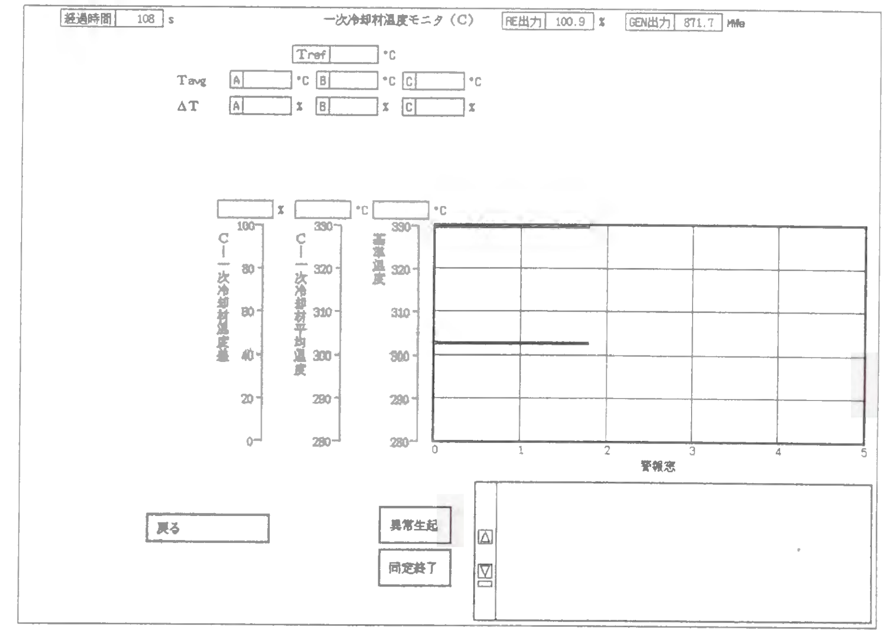

Figure A.4: Loop-C coolant temperature monitor

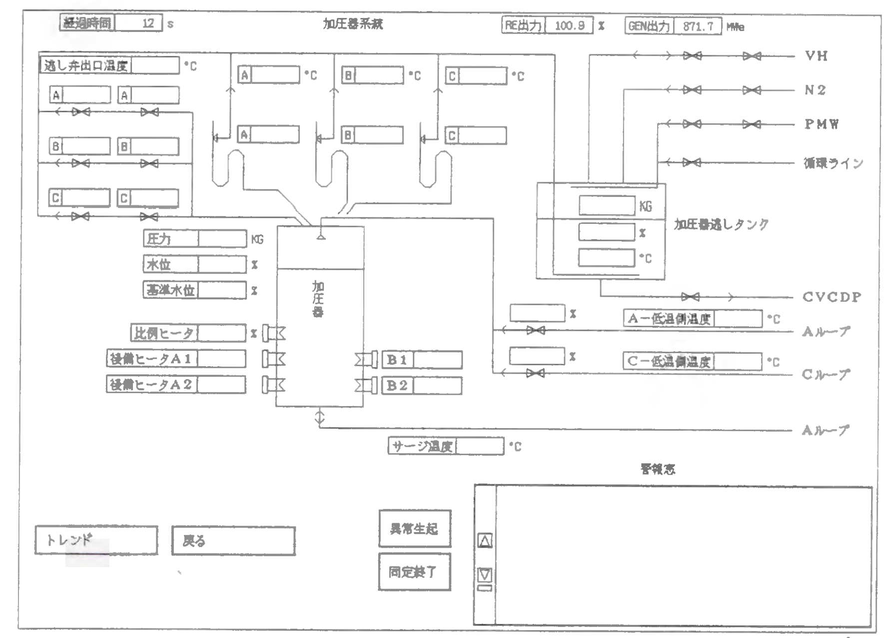

Figure A.5: Pressurizer system

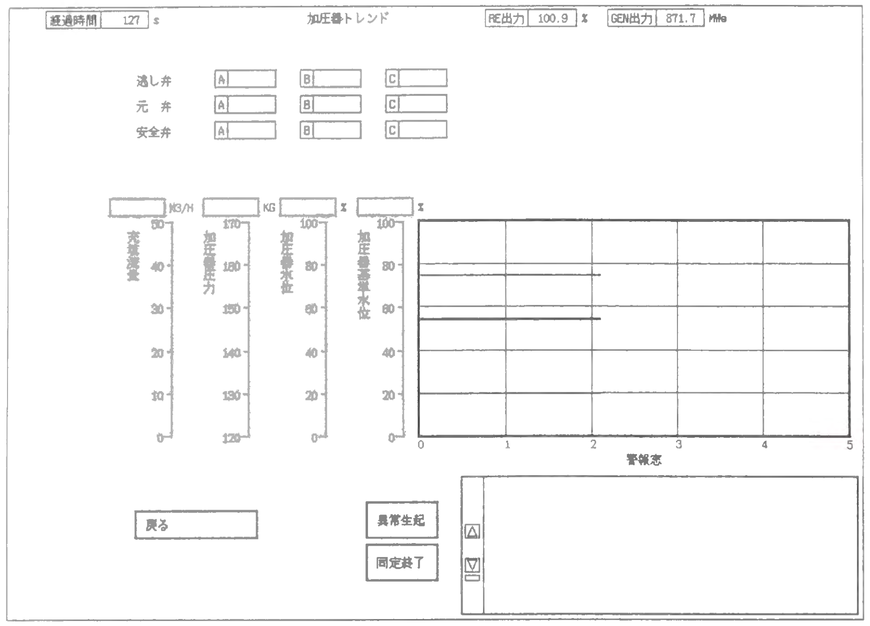

Figure A.6: Trend graph of pressurizer system

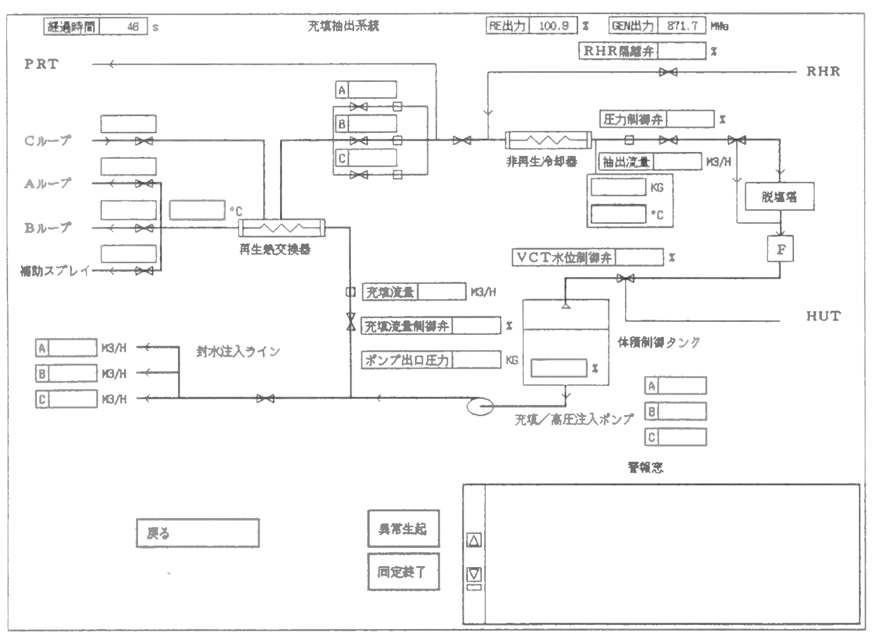

Figure A.7: CVCS system

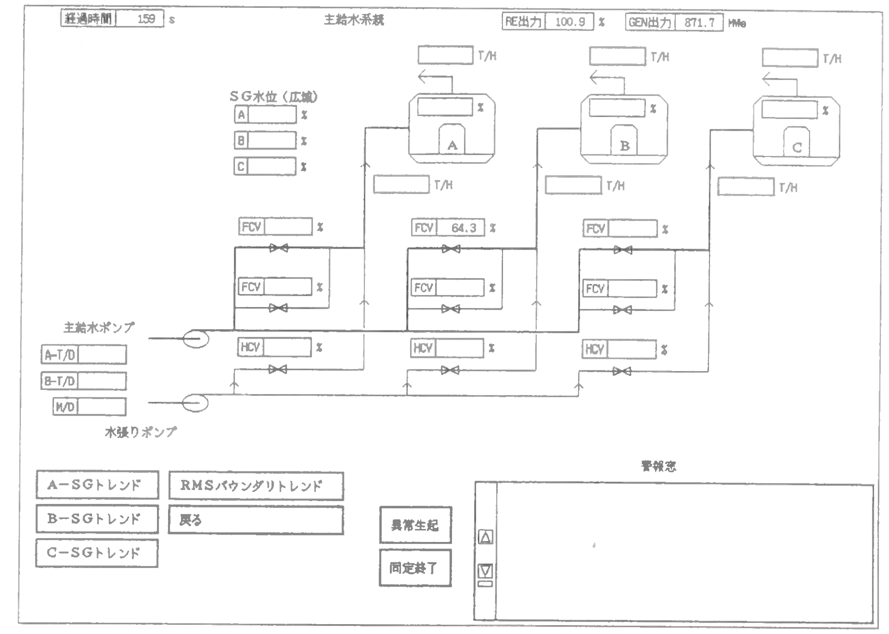

Figure A.8: Main feed water system

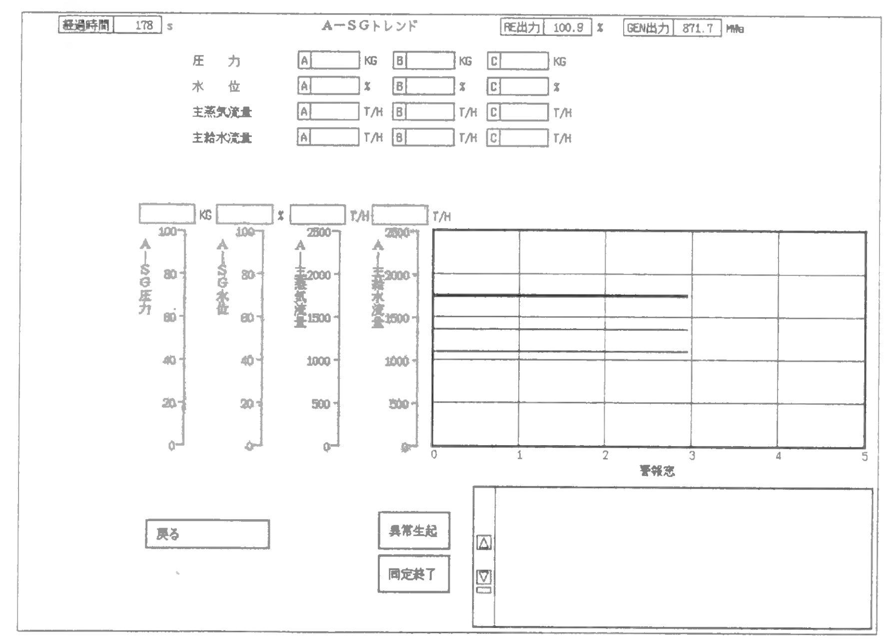

Figure A.9: Trend graph of loop-A steam generator

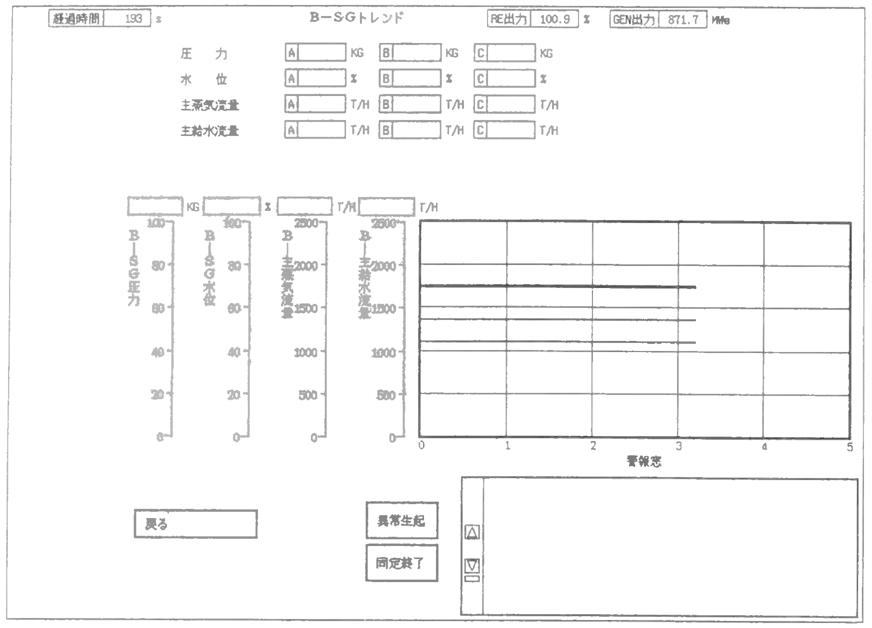

Figure A.10: Trend graph of loop-B steam generator

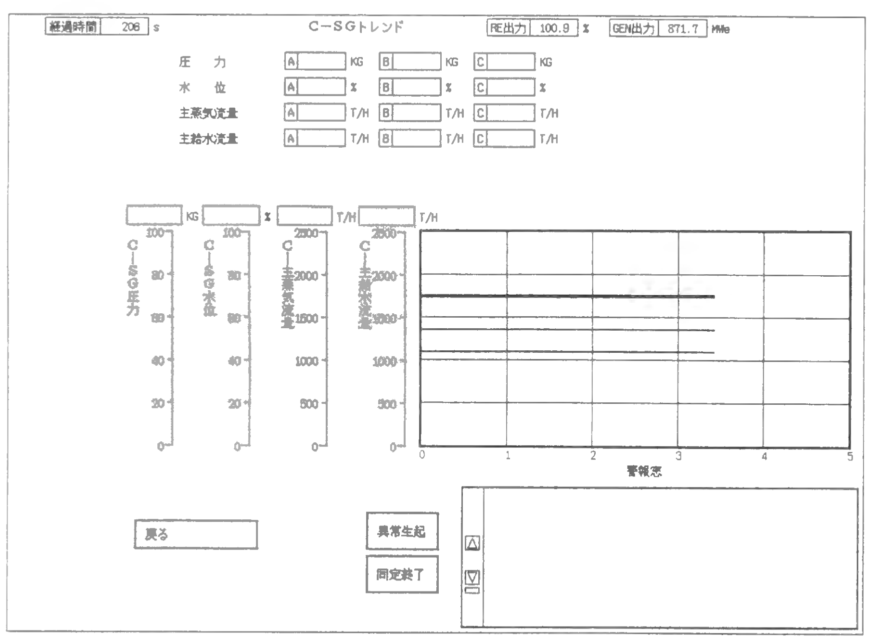

Figure A.11: Trend graph of loop-C steam generator

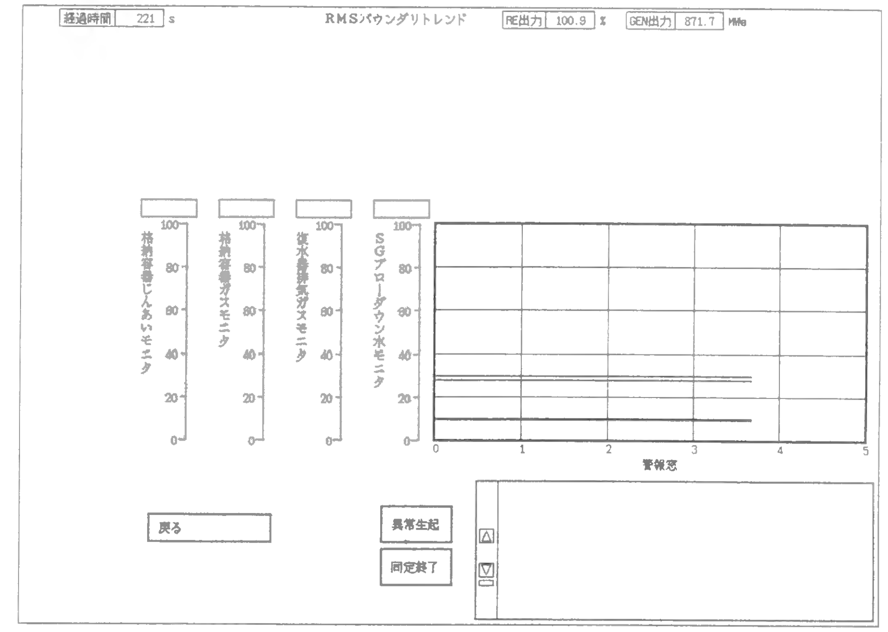

Figure A.12: Trend graph of radiation monitor system

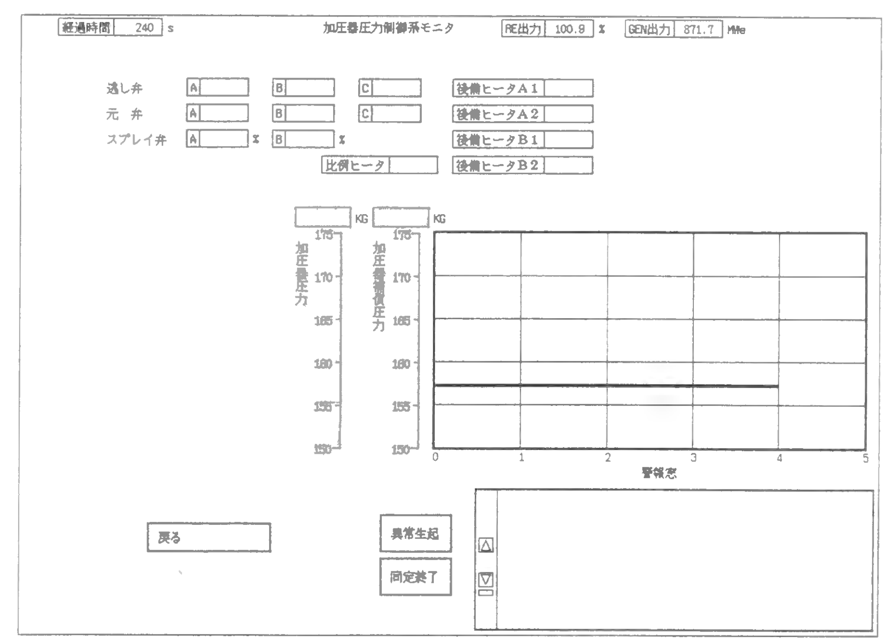

Figure A.13: Pressurizer pressure control monitor system

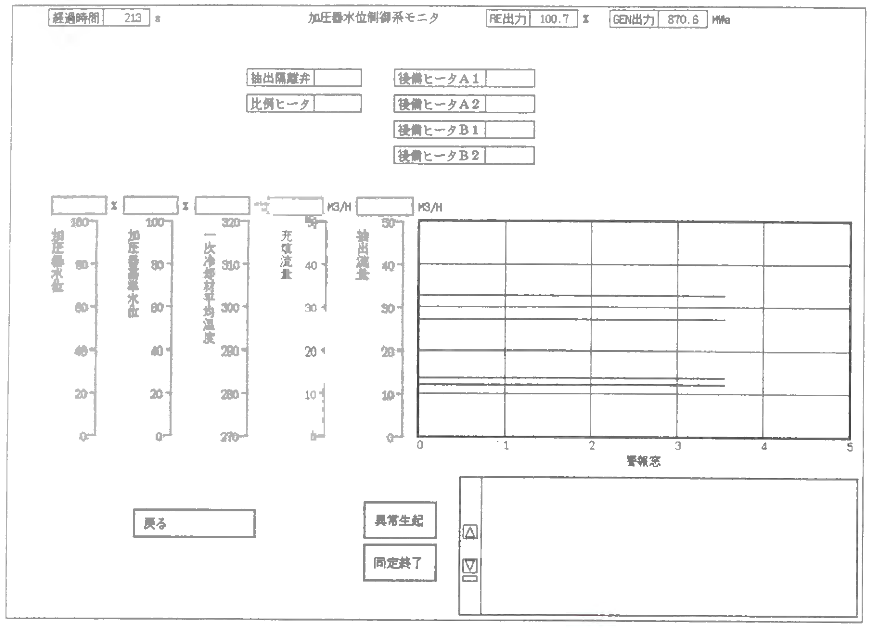

Figure A.14: Pressurizer level control monitor system

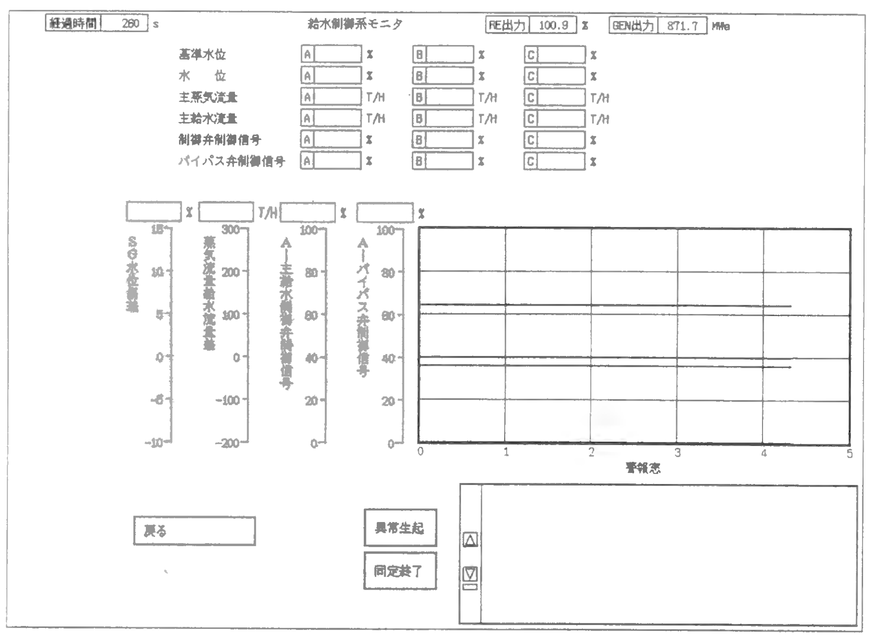

Figure A.15: Feed water control monitor system

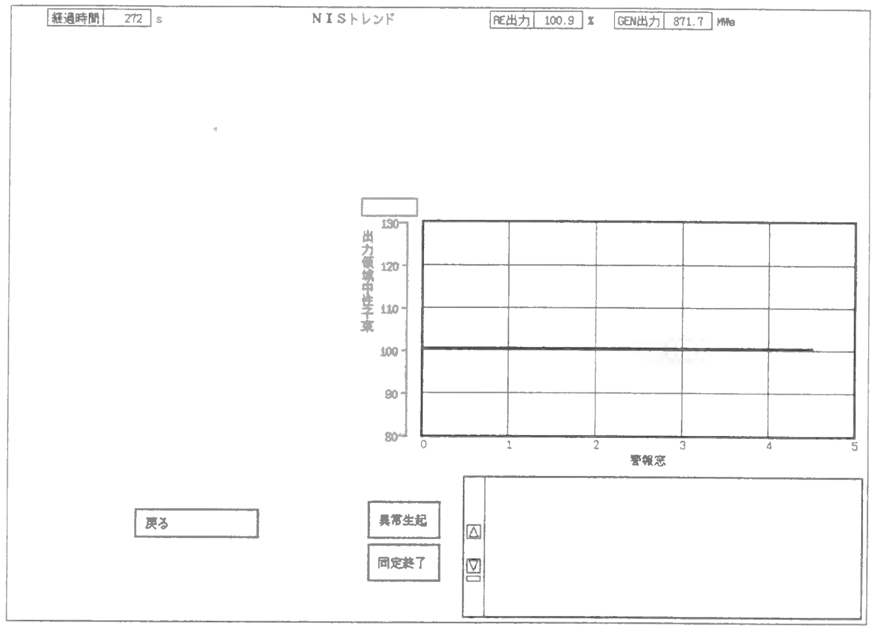

Figure A.16: Trend graph of NIS

Appendix B

Discussion on the OSH-Auto-Recording Function

In order to record the subjects' operation information more exactly, the function of the MMI simulator utilized in this laboratory experiment is expanded so that it can record subject's operation automatically. Since the most of the subjects' MMI operation in the laboratory experiment is through moving or clicking the mouse input device, the recording method is fundamentally based on recording subjects' mouse operation.

By recording the mouse operation of clicking buttons shown on the CRT-based interface, switching interface window and detecting/identifying an abnormal transient can recorded easily. However, the method cannot record subject's parameter reference since the parameter reference may not involve a mouse operation. Therefore, to record subject's behaviors of parameter reference exactly, a solution is proposed. The solution requires subjects to move the mouse point when he makes a parameter reference. The detail description is given by Figure B.1 and is discussed as follows.

- First of all, such solution is derived from the conventional researches. It had been confirmed by the conventional study that when the subjects make a parameter reference, they are likely to move the mouse pointer to the region around the target parameter.

- As described previously, the subjects' behaviors can be divided into monitoring phase and diagnosing phase. In MP, since the information on "Summary" window gives a general overview of the total plant system, the subjects' monitoring operation is concentrated in "Summary" window. In "Summary" window, all parameter values are shown in the correspondent "parameter frame", as shown in Figure B.1. In

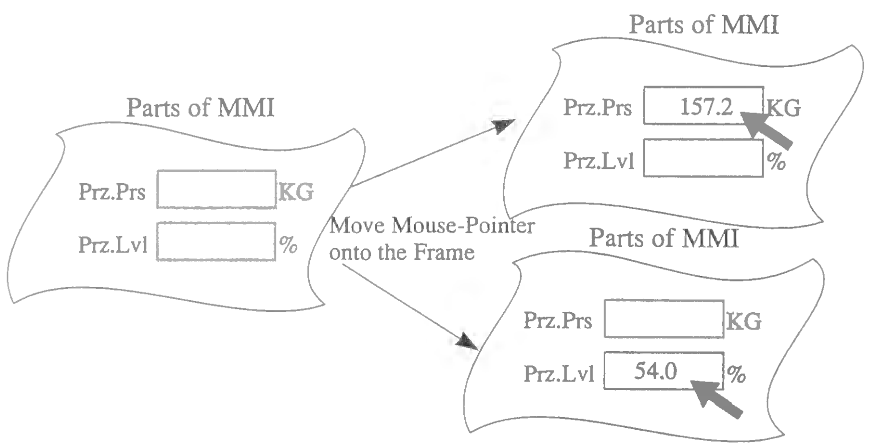

Figure B.1: Show and hide parameter value by movement of mouse pointer

order to record subjects' monitoring operation, they *wereasked* explicitly to move the mouse pointer onto the frame corresponding to the parameter he want to check.

- After the detection of an abnormal transient, that is in the diagnosis phase, not only the "summary" window, the subjects also switch to the sub-windows to get more detail information about the plant sub-systems. In such sub-windows, as shown in Figure B.1, the value of parameters and the trend graphs demonstrating parameters' value variation will not be shown in the correspondent frame unless the mouse pointer is moved onto the frame. Thus, the subjects "have to" move the mouse pointer.

- The reason why make such restriction to subjects' operation is that the operators' behaviors in DP are considered as a kind of "target-parameter-driven" behaviors. "Target-parameter-driven" means here that before the reference activities, what parameters should be checked are specified by the subject based on the anomaly hypothesis recalled into his mind. It is the main difference between the parameter reference activities in MP and DP. Such features can be also considered as one of the differences between experts (e.g. skilled operators) and amateurs (e.g. students). Rather than randomly searching abnormal symptoms in the case of students, skilled operators tend to check parameters' status based on a hypothesis. Therefore, hiding out parameters' value or trend curves from subjects' view will not disturb subjects' diagnosis task.

However, by such recording method, it is possible to get wrong information when the subject moves the mouse pointer just to pass through a parameter frame. Therefore, in

order to avoid such wrong record, only if the mouse pointer is put on the corespondent frame more than 0.3 seconds, the correspondent parameter value will be shown in the frame.

Appendix C

Detailed Data on Detection Time by Human Models

Table C.1: The comparison of the average detection time

Type of Abnormal Transient	Subject A (sec.)	Model A (sec.)	Subject I (sec.)	Model I (sec.)	Subject T (sec.)	Model T (sec.)
SGTR	11	8.25	11.67	16.7	12.8	11.3
RCS_BIG	59	48	44.8	57.5	62.5	32.5
RCS_SMALL	69.5	61.5	87	65	78	57.5
FW_Cnt_V	18	18.5	23.5	14	21	15
PRZ.Prs_H	7.5	14.7	16.7	13	11	11
PRZ.Prs_L	24.5	30.5	42	32	45	53.5
Spary_S	14.7	25.3	26.25	18	26	36
Spary_B	7	20.7	13	15.7	11	11.7
PRZ.Lvl_L	14.7	8.7	23	34.7	83	57.5
PRZ.Lvl_H	12.5	8	25	40	29.5	47.5
NIS	10	10.7	16	15	14.25	13.3

Table C.2: The detailed data about the detection time by human models

Type of Abnormal transient	Time by Model of "Subject A" (sec.)	Average Time (sec.)	Time by Model of "Subject I" (sec.)	Average Time (sec.)	Time by Model of "Subject T" (sec.)	Average Time (sec.)
SGTR	8.0 14.0 5.0 6.0	8.3	19.0 20.0 10.0	16.3	16.0 12.0 4.0 13.0	11.3
RCS Middle	45.0 51.0	48.0	46.0 69.0	57.5	39.0 26.0	32.5
RCS Small	56.0 67.0	61.5	62.0 68.0	65.0	37.0 78.0	57.5
FW_Cnt_V	32.0 5.0	18.5	17.0 11.0	14.0	10.0 20.0	15.0
PRZ.Prs_H	27.0 10.0 7.0	14.7	17.0 17.0 5.0	13.0	19.0 6.0 8.0	11.0
PRZ.Prs_L	19.0 42.0	30.5	42.0 22.0	32.0	63.0 44.0	53.5
Spary_S	25.0 23.0 28.0	25.3	27.0 17.0 10.0	18.0	28.0 72.0 8.0	36.0
Spary_B	15.0 24.0 23.0	20.7	21.0 16.0 10.0	15.7	14.0 15.0 6.0	11.7
PRZ.Lvl_L	4.0 5.0 17.0	8.7	51.0 21.0 32.0	34.7	29.0 56.0 10.0 14.0 85.0 151.0	57.5
PRZ.Lvl_H	5.0 12.0 7.0	8.0	54.0 20.0 46.0	40.0	36.0 59.0	47.5
NIS	6.0 15.0 11.0	10.7	12.0 9.0 24.0	15.0	17.0 14.0 9.0	13.3

Appendix D

Modeling of First Hypothesis Recalled by Subjects

Table D.1: Modeling of recalling the first hypothesis in the case of "Subject I"

First Symptom	First hypothesis of Subject I	Settings in Model of Subject I
SG-Lvl	FW related (100%)	FW related
PRZ-prs Small	PRZ.Cont.F (10%), RCS/SGTR(80%), Leakge in Gas phase of PRZ.(10%)	RCS
PRZ-prs Big	Reactor related (100%)	Reactor related
PRZ-lvl small.	RCS (100%)	RCS
CVCS-in Big	RCS (100%)	RCS
CVCS-in Small	PRZ. Lvl. Cont. F. (100%)	PRZ. Lvl. Cont. F.
FW. Lvl. Big	FW related (100%)	FW related
Reactor Output	Reactor related (100%)	Reactor related

Table D.2: Modeling of recalling the first hypothesis in the case of "Subject A"

First Symptom	First hypothesis of Subject A	Settings in Model of Subject A
SG-Lvl small	FW control failure(100%)	FW control failure
PRZ-prs big or small	PRZ. Prs. Control failure(100%)	PRZ. Prs. Control failure
PRZ-lvl small.	PRZ. Lvl. Control failure(100%)	PRZ. Lvl. Control failure
CVCS-in big or small	PRZ. Lvl. Control failure(100%)	PRZ. Lvl. Control failure
FW small	FW control failure(100%)	FW control failure
Reactor-output big	Reactor related(100%)	Reactor related
Steam-flow big	FW control failure(100%)	FW control failure

Table D.3: Modeling of recalling the first hypothesis in the case of "Subject T"

First Symptom	First hypothesis of Subject T	Settings in Model of Subject T
FW. Flow small	FW control system failure (100%)	FW control system failure
PRZ-prs Small	PRZ.Cont.F (93%) RCS(7%)	PRz. Prs.control system failure
PRZ-prs Big	PRZ.prs control system failure(75%) Reactor related (25%)	PRz. Prs.control system failure
PRZ-lvl big or small	PRZ. Lvl. Control system failure (100%)	PRZ. Lvl. Control system failure
CVCS-in big	RCS(50%)	RCS
	PRZ. Prs control system failure(50%)	
Reactor output	Reactor related(100%)	PRz. Prs.control system failure

Appendix E

Methods to Derive TCR Curves in HCR/ORE

Figure E.1 illustrates the procedure to derive time cognitive reliability in HCR/ORE. TCR curves were derived by the methods as well from the laboratory experimental data.

In the upper graph of Figure E.1, the horizontal axis represents the time taken to response to the required event, and the vertical axis represents the number of experimental trials in which operator had successfully responded to the event until the required time. In other words, if an abnormal transient occurs at t_0, then it means that until t_1 including t_1, the number of the experimental trials in which operator successfully detected/diagnosed the abnormal transient is 1, until t_2 including t_2 the number is 2, ..., and until t_i including t_1 the number is i. From the upper graph, it is demonstrated that when an abnormal transient occurs, since the incapability of understanding the situation well, only few operators can respond to the event immediately just after the initiation of the event. However, as time goes by, the number of trials in which operators can respond to the event successfully will increase.

As the experiment data processing, the whole time span after the beginning of the even is divided into $(N+1)$ time sections, which are $t_0 \sim t_1, \ldots, t_{N-1} \sim t_N, t_N \sim \infty$. t_0 represents the time when an abnormal transient occurs. Provided the simulation trials are independent and do not exert any influence to each other, the response probability in each time section could be assumed same as $\frac{1}{N+1}$. Hence the response probability by the time t_i would be given by $[i \times (\frac{1}{N+1})]$ and the response probability will be 1 by the time ∞. Finally, by $[1 - i \times (\frac{1}{N+1})]$, the non-response probability at time i will be obtained. Until now, the data processing can be summarized by the following equation.

$$P_i(non - response) \quad = P_r(response\ time > t_i)$$

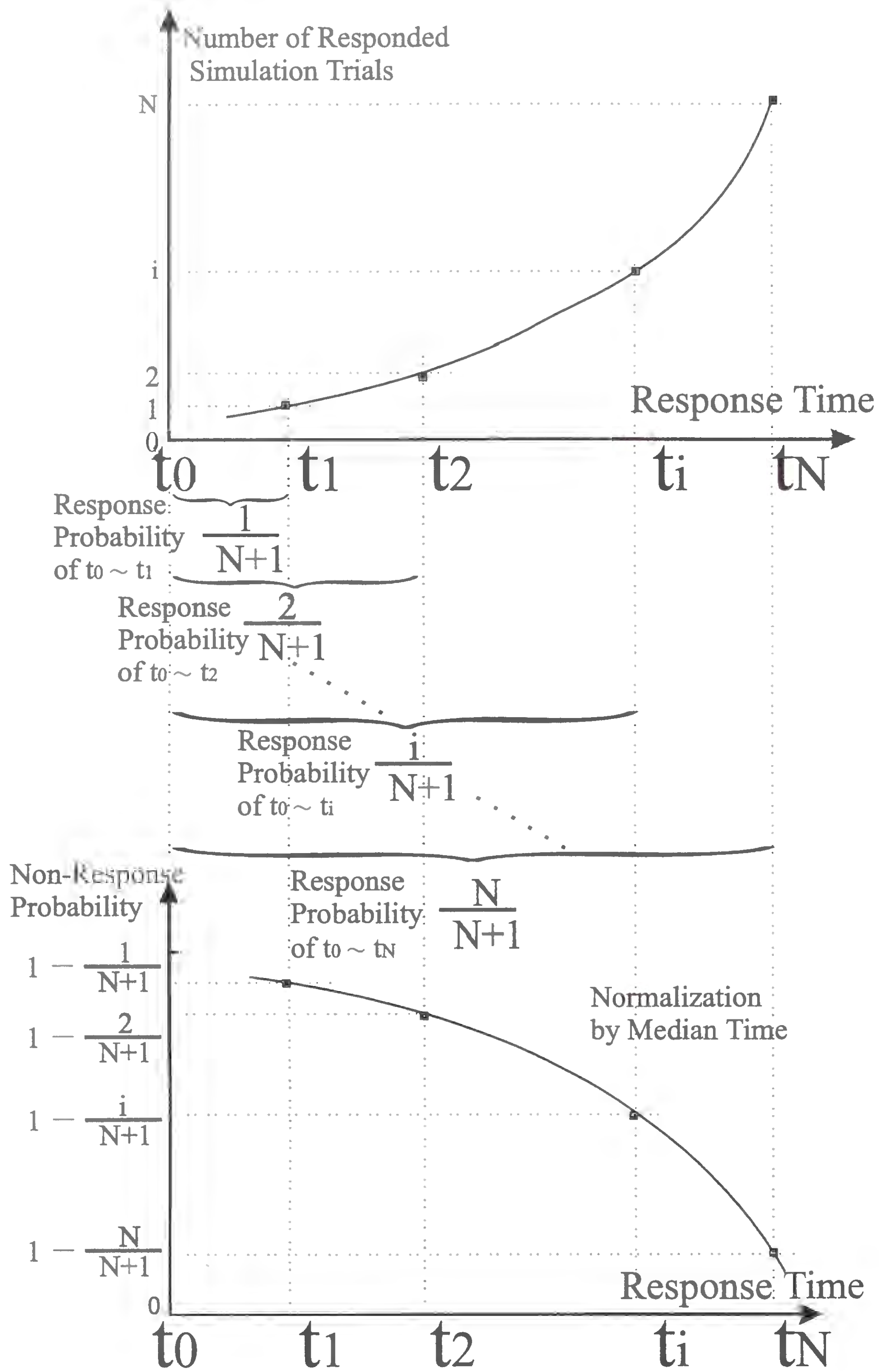

Figure E.1: Method of calculating non-response probability

$$\approx 1 - \frac{i}{N+1}$$
$$i = 1, 2, ..., N \tag{E.1}$$

where P_i is the non-response probability by the time t_i, P_r is the response probability for the case where response time is over t_i, i is the i'th data point, t_i is the i'th response time in the ascending sequences of response time, and N is the total number of samples.

Based on the equation, the curve describing the relationship of non-responsibility and time is shown in the lower graph of Figure E.1.

Appendix F

All TCR Curves Derived from Laboratory Experiment

Anomaly Detection TCR Curves

Total 12 types of anomlay diagnosis TCR curves derived from the laboratory, as shown in the figures F.1 ~ F.12 from next page. The figures show the normalized TCR curves together with the valid sampling numbers and the median time.

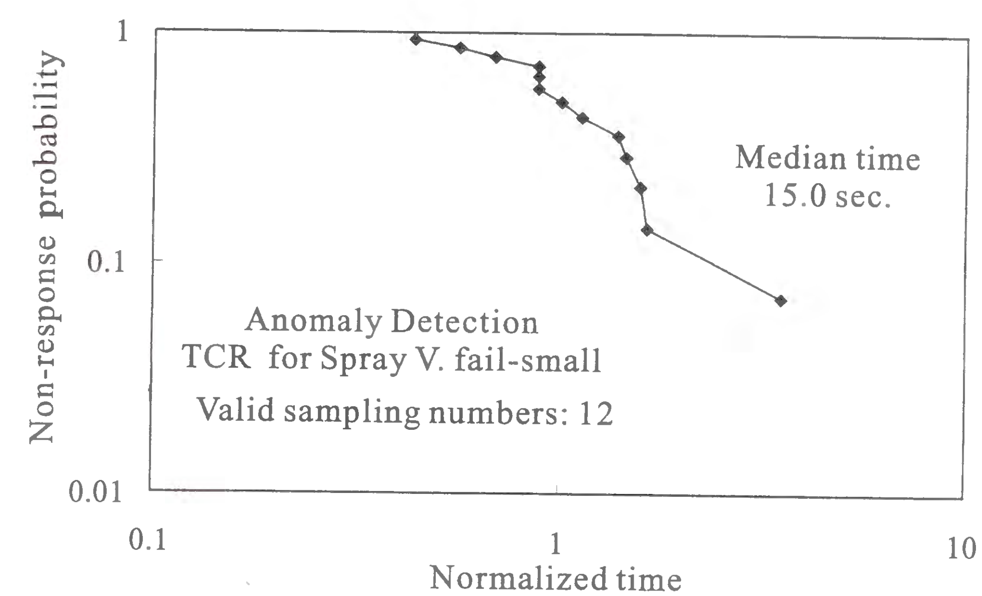

Figure F.1: TCR curves for detecting "PRZ.Spray V. Fail small"

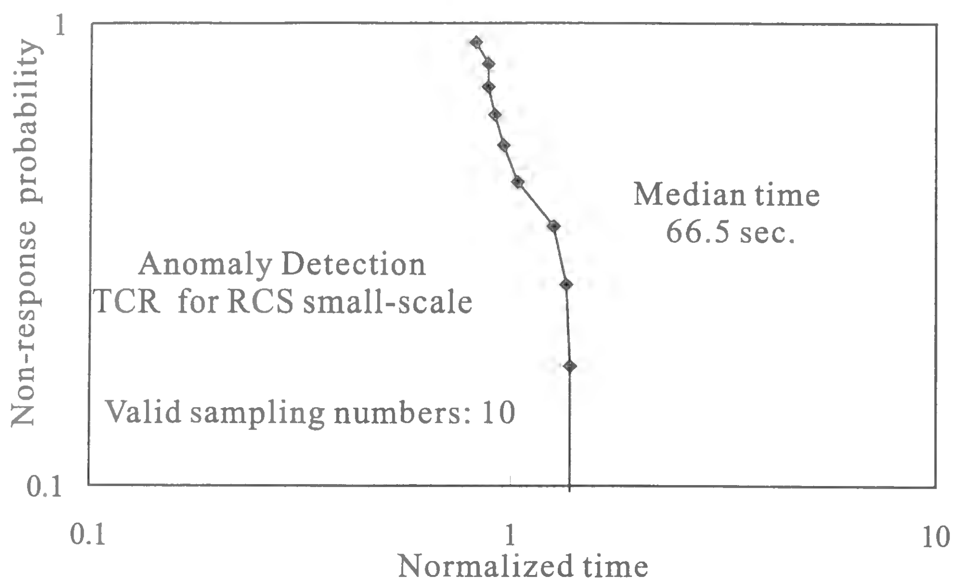

Figure F.2: TCR curves for detecting "RCS leakage small-scale"

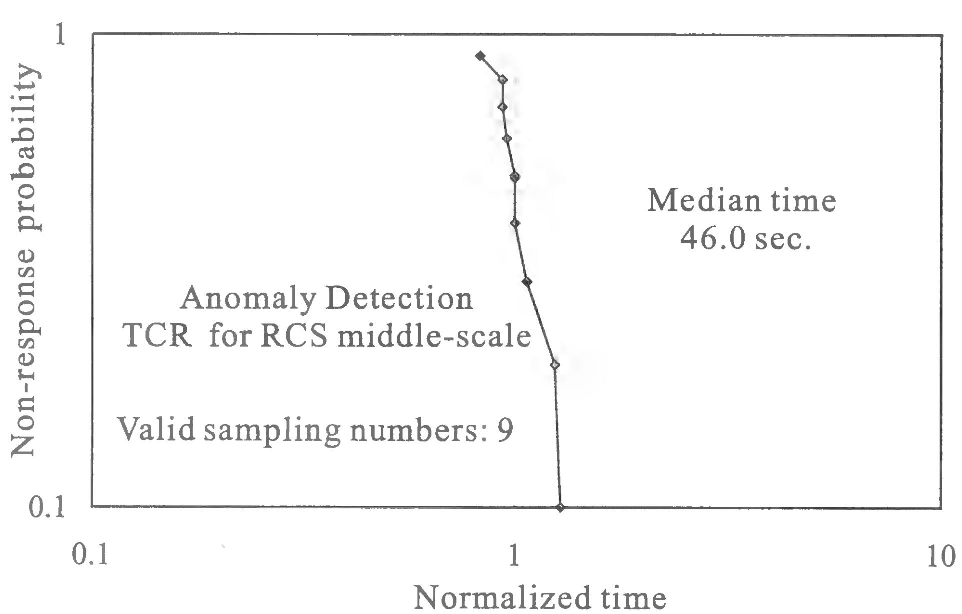

Figure F.3: TCR curves for detecting "RCS leakage middle-scale"

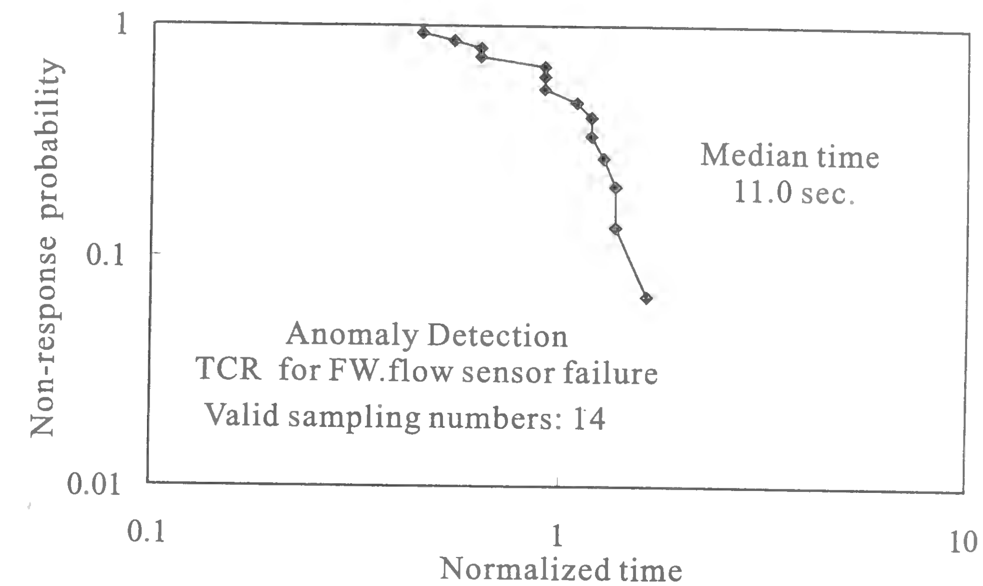

Figure F.4: TCR curves for detecting "FW. flow sensor failure"

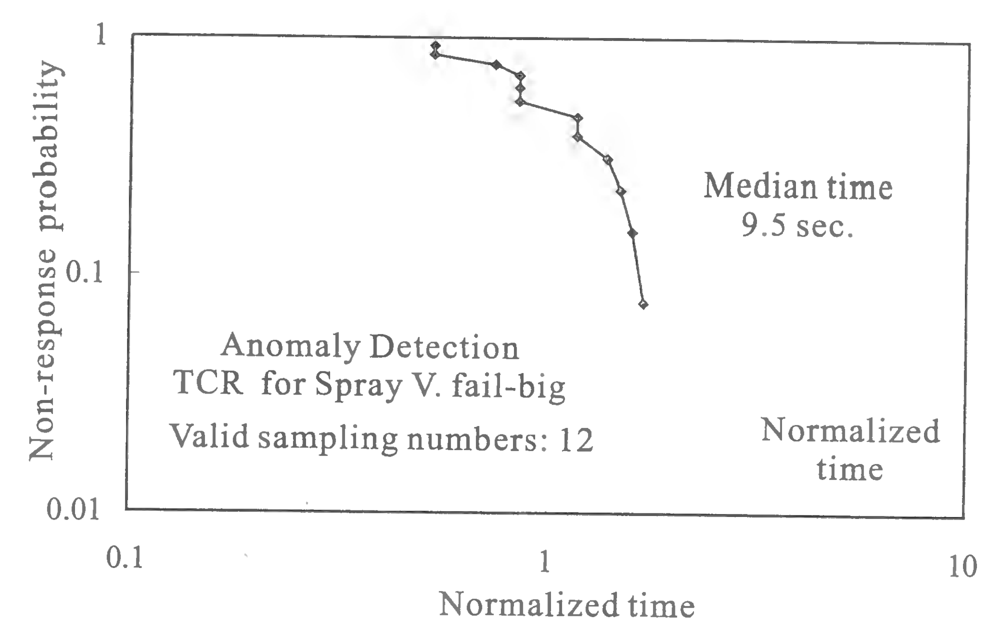

Figure F.5: TCR curves for detecting "PRZ. Spray V. Fail big"

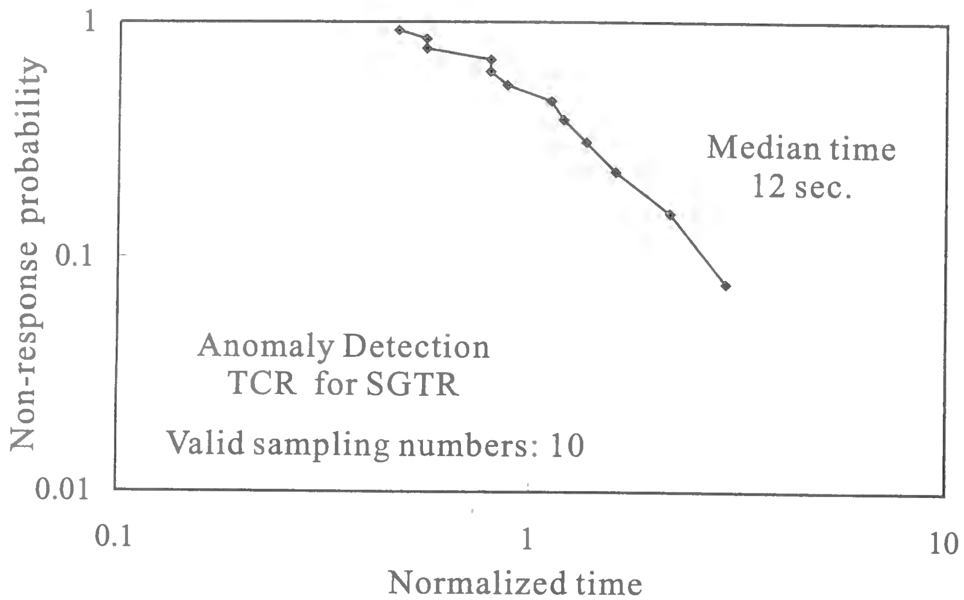

Figure F.6: TCR curves for detecting "SGTR"

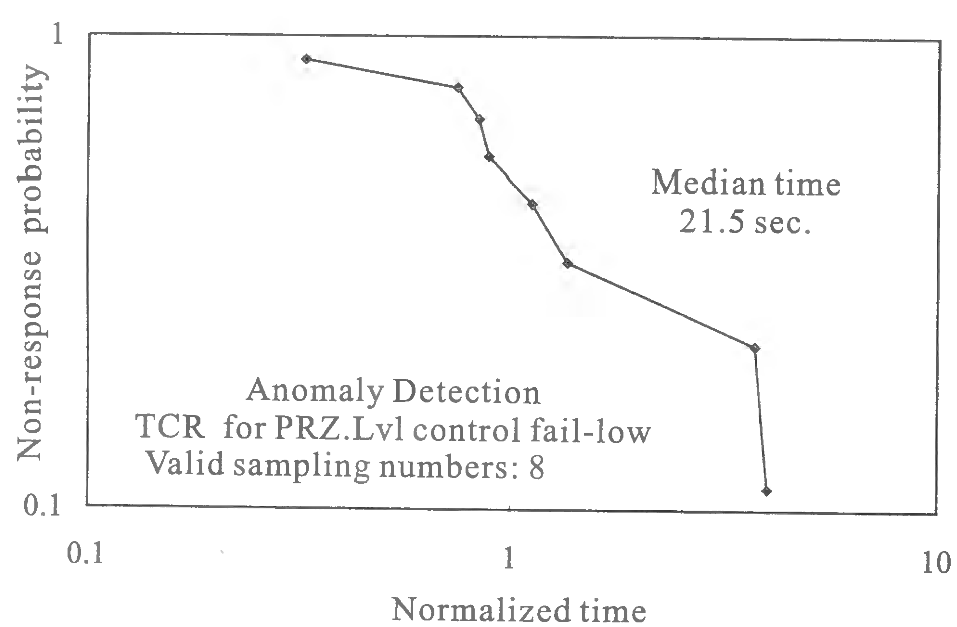

Figure F.7: TCR curves for detecting "PRZ.Lvl. Cont. Fail-low"

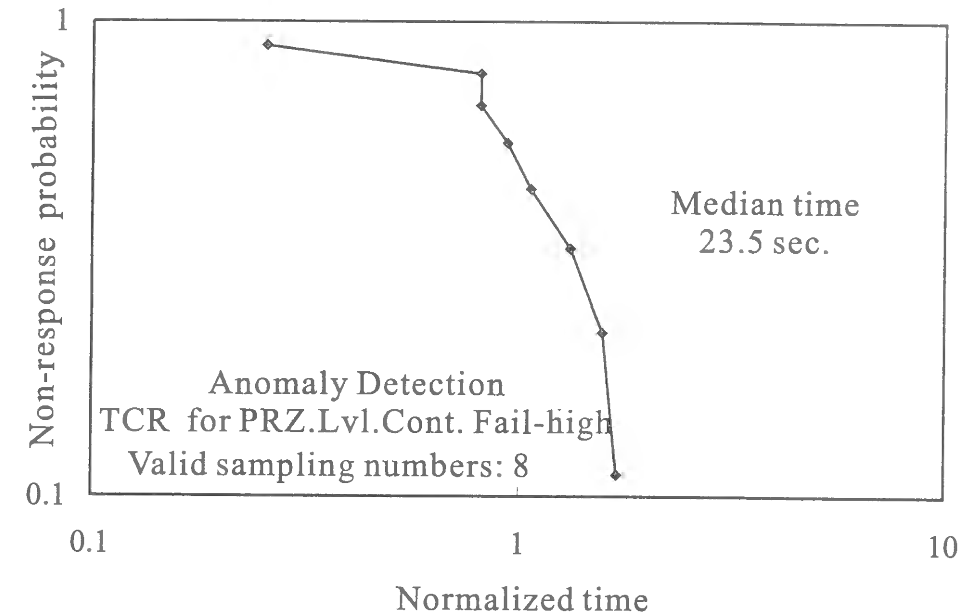

Figure F.8: TCR curves for detecting "PRZ.Lvl. Cont. Fail-high"

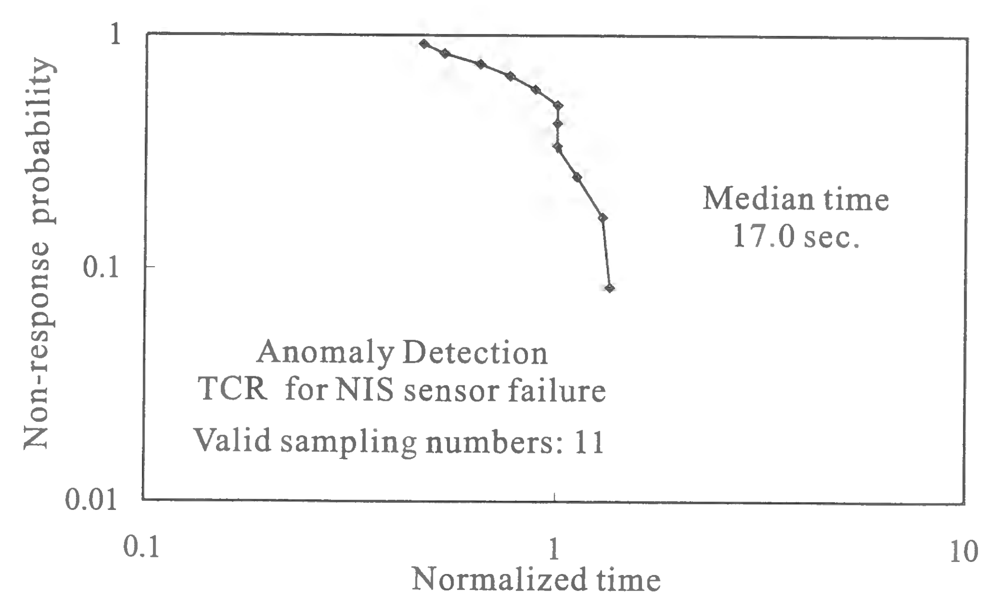

Figure F.9: TCR curves for detecting "NIS sensor failure"

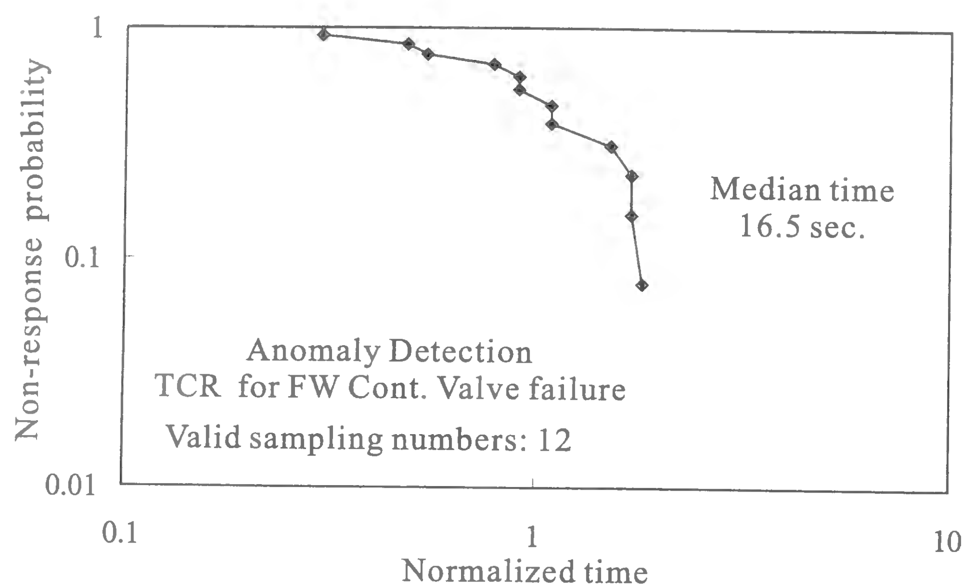

Figure F.10: TCR curves for detecting "FW. Cont. V. failure"

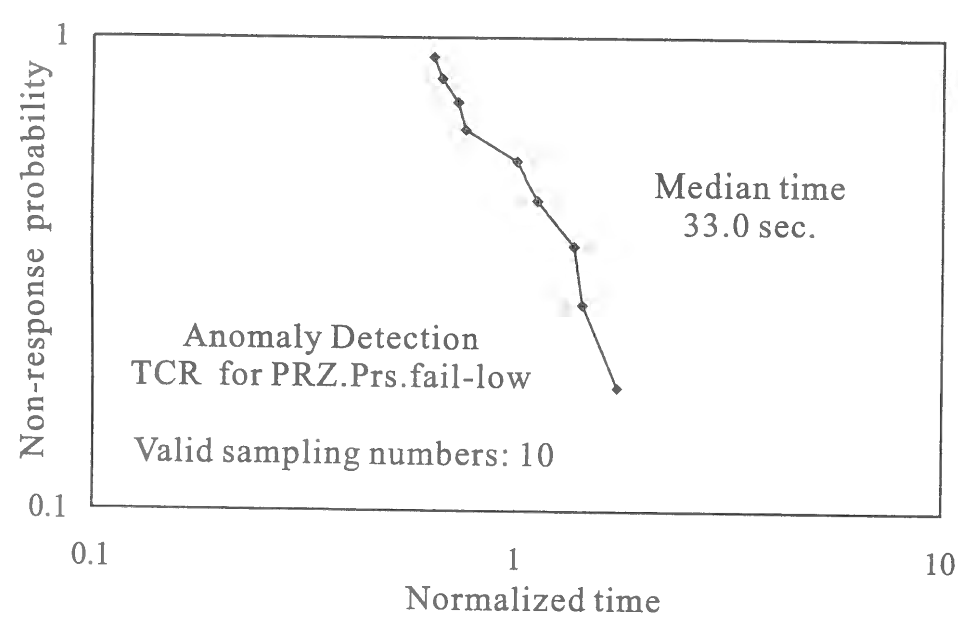

Figure F.11: TCR curves for detecting "PRZ.Prs. Cont. fail-low"

Appedix F: All TCR Curves Derived from Laboratory Experiment

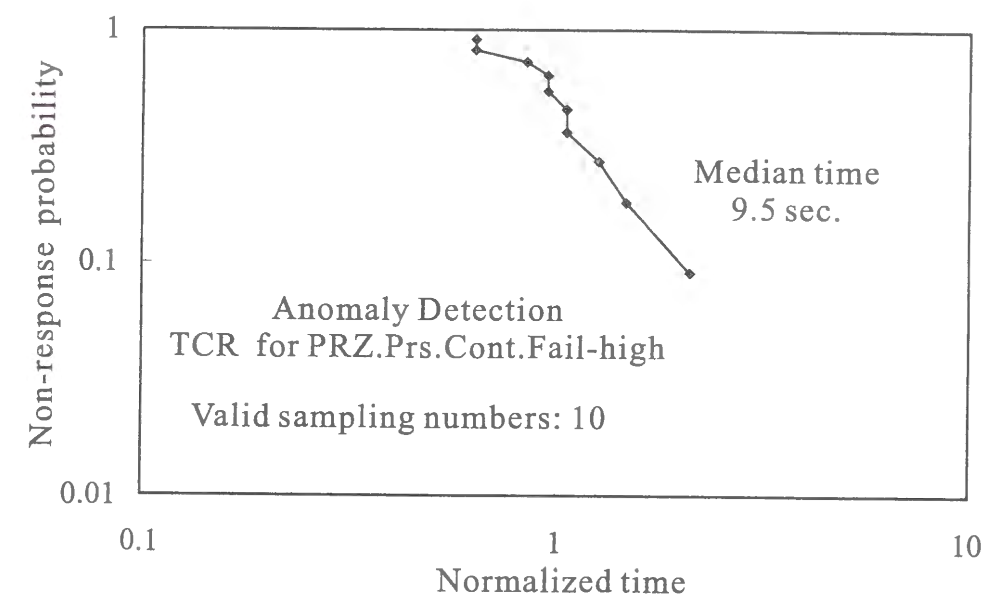

Figure F.12: TCR curves for detecting "PRZ.Prs. Cont. fail-high"

Anomaly Diagnosis TCR Curves

Total 9 types of anomlay diagnosis TCR curves derived from the laboratory, as shown in the figures F.13 ~ F.21 from next page. The figures show the normalized TCR curves together with the valid sampling numbers and the median time.

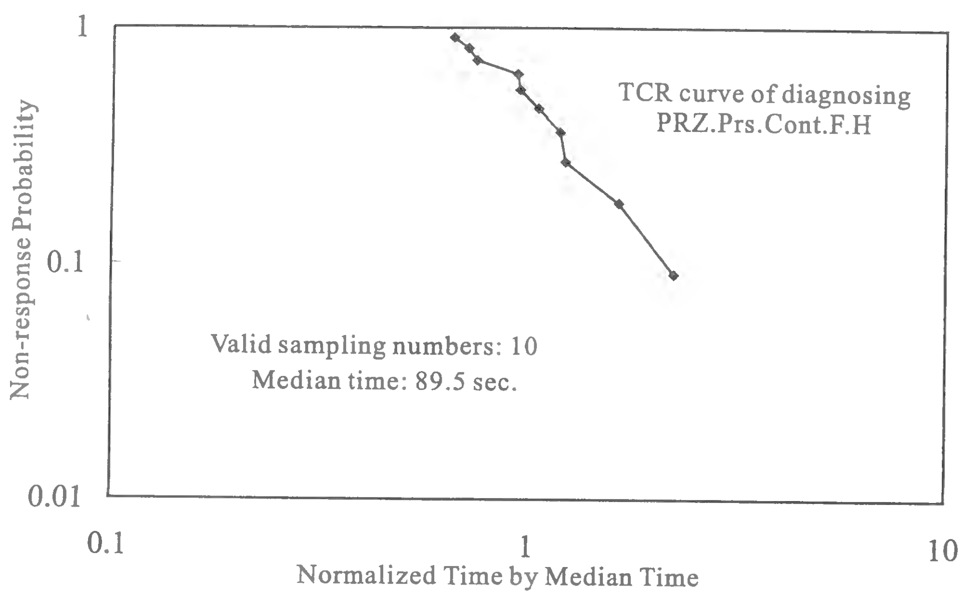

Figure F.13: TCR curves for diagnosing "PRZ.Prs. Cont. fail-high"

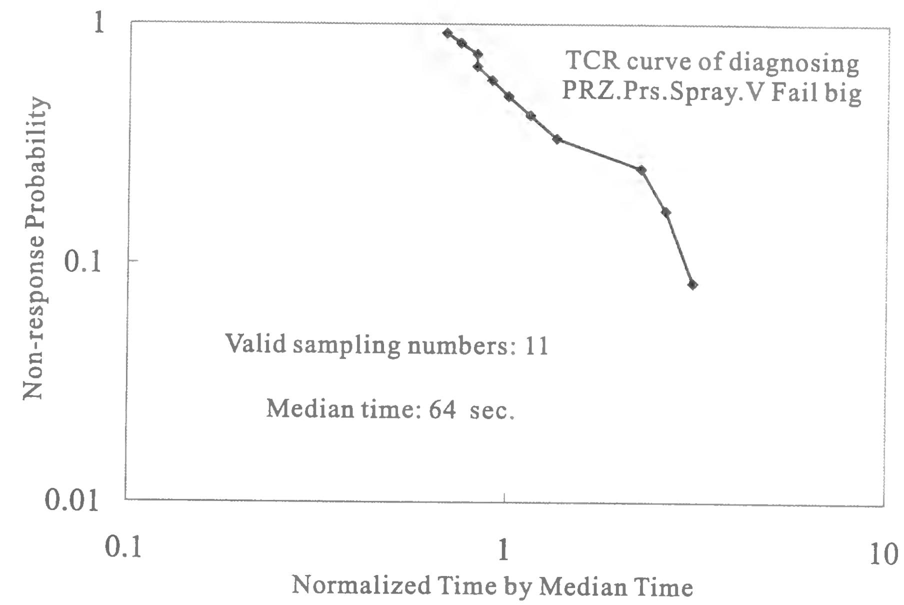

Figure F.14: TCR curves for diagnosing "PRZ. Spray V. Fail big"

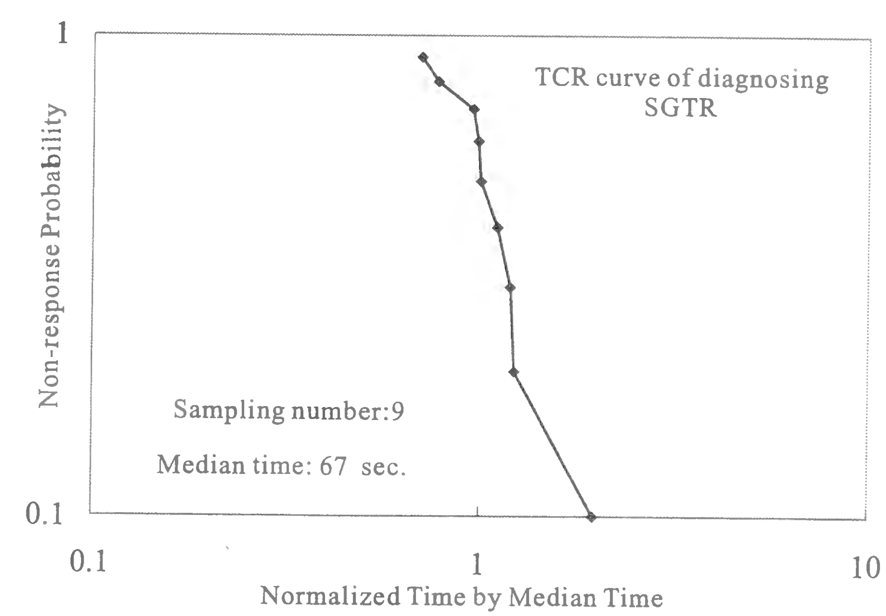

Figure F.15: TCR curves for diagnosing "SGTR"

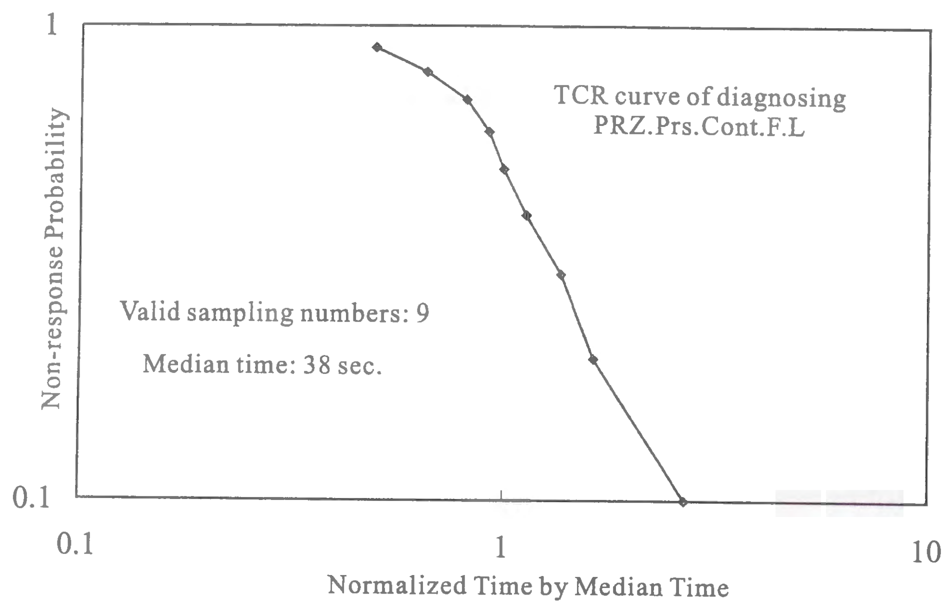

Figure F.16: TCR curves for diagnosing "PRZ.Lvl. Cont. Fail-low"

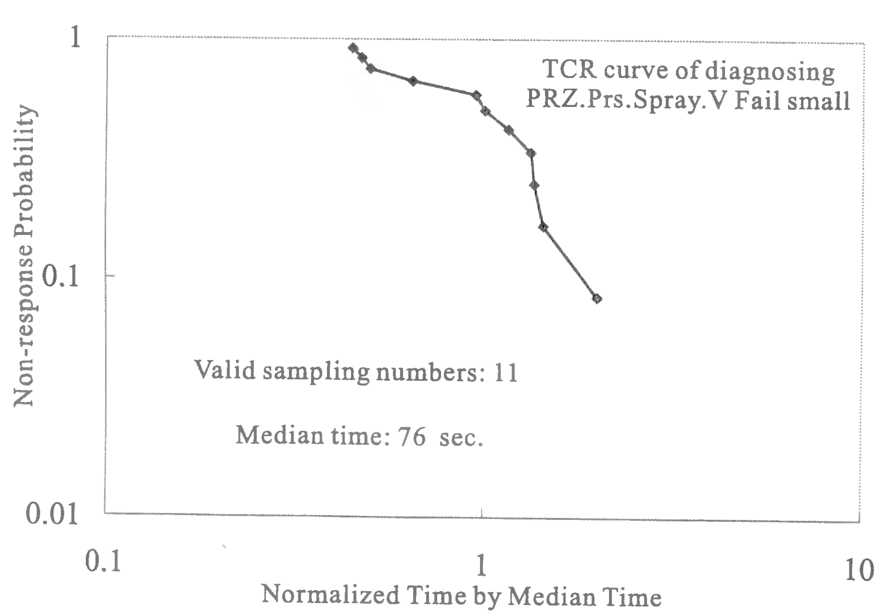

Figure F.17: TCR curves for diagnosing "PRZ. Spray V. Fail small"

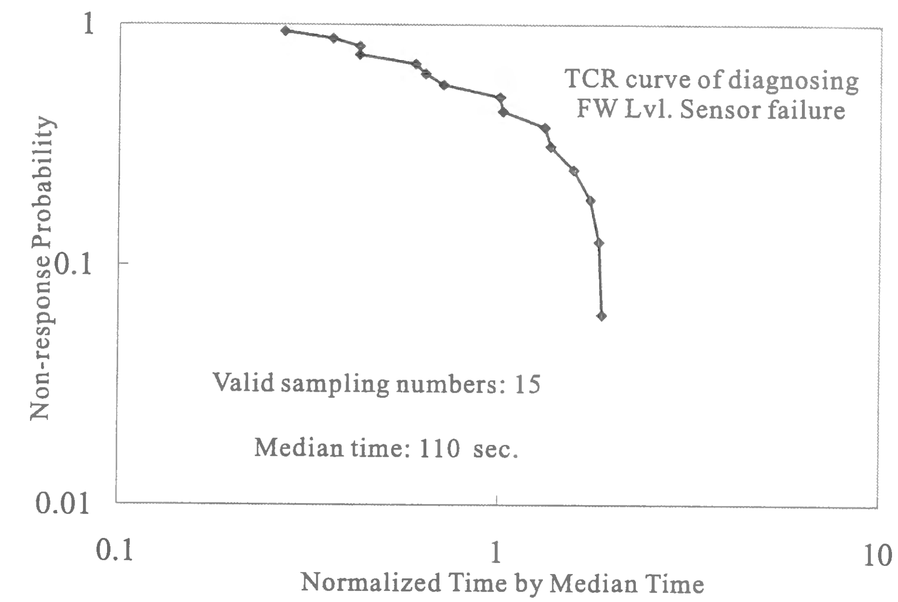

Figure F.18: TCR curves for diagnosing "FW. flow sensor failure"

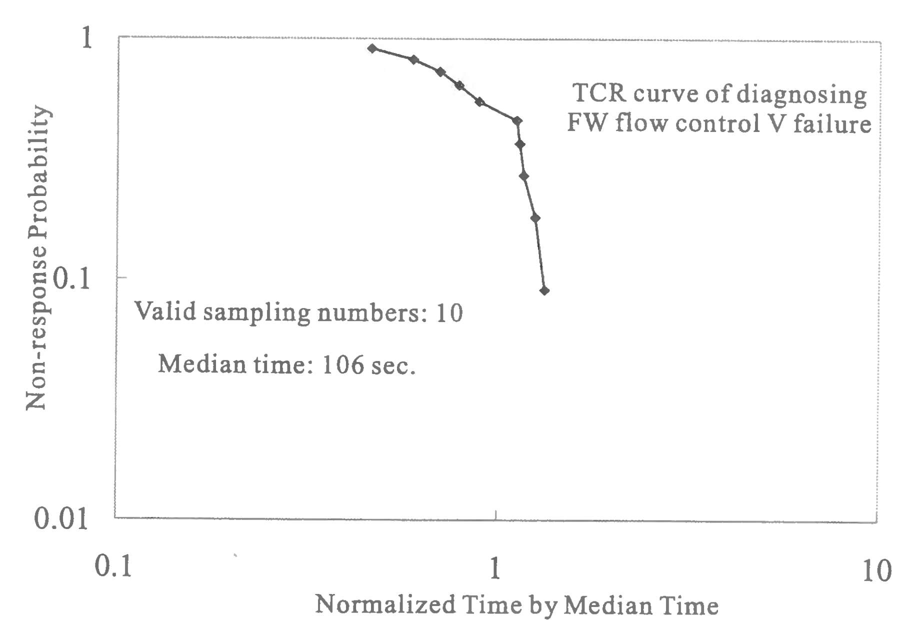

Figure F.19: TCR curves for diagnosing "FW. Cont. V. failure"

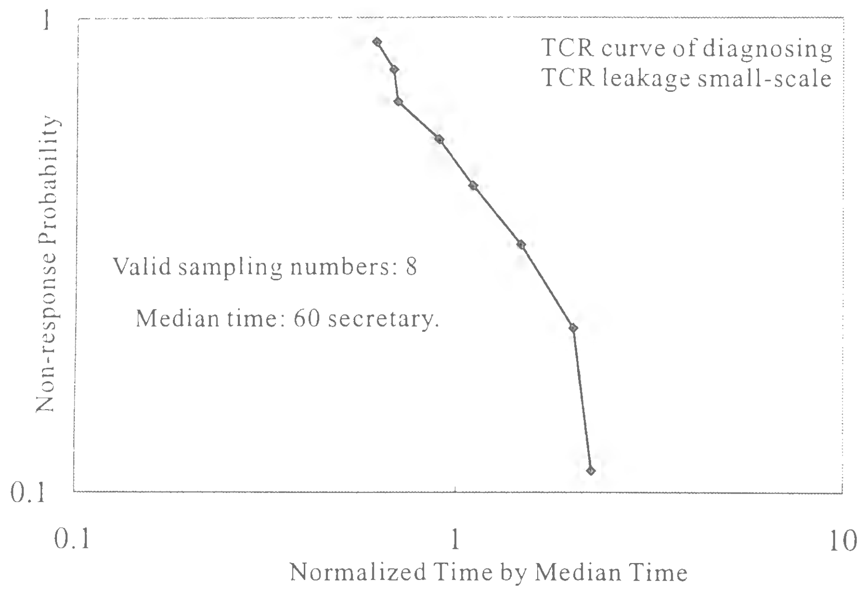

Figure F.20: TCR curves for diagnosing "RCS leakage small-scale"

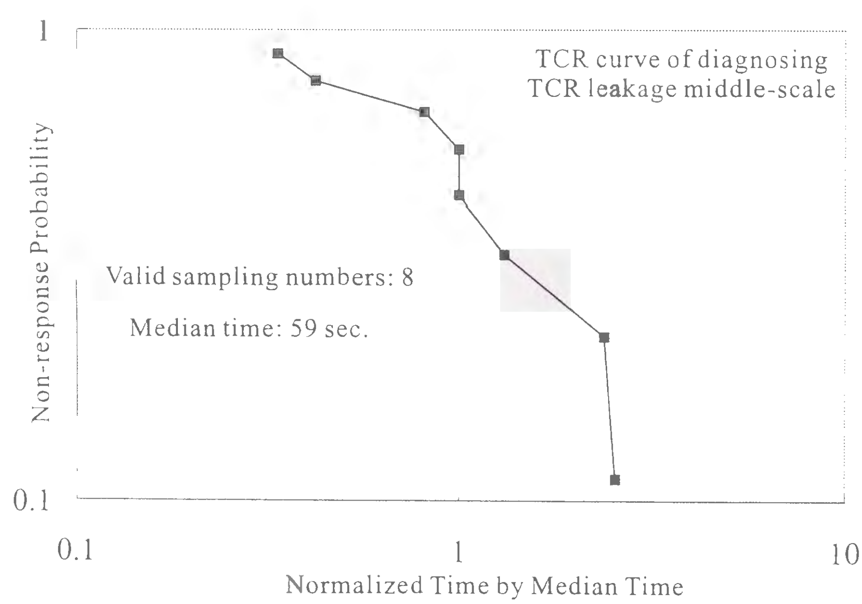

Figure F.21: TCR curves for diagnosing "RCS leakage middle-scale"

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