ADVANCED MONITORING AND ADVICE INTEGRATING A COMPREHENSIVE SENSOR NETWORK FOR IMPROVED OPERATIONAL AVAILABILITY

by

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Abstract

This research broadens the prime concern of nuclear power plant operations from safe performance to both economic and safe performance through monitoring and advice. First, rotating machines such as turbine generators and reactor coolant pumps are identified as main contributors for the lost availability through the review of pressurized water reactor (PWR) forced outage records. The integrated architecture utilizes comprehensive sensor networks incorporating modern signal processing systems, advisory systems for sensor validation, and advisory systems for the intelligent diagnosis and maintenance (D&M).

For the development of comprehensive sensor networks for complex target systems, an integrated method incorporating a structural system hierarchy and a functional system hierarchy, a fault-symptom matrix, sensor selection criteria, a sensor installation feasibility study, and advanced instrumentation techniques is formulated. Such advanced instrumentation techniques reflect the state of the art in advancement of data acquisition, data processing, and data integration techniques. Once the sensor types and locations are selected definitively, they are incorporated into drawings using a computer aided design tool (e.g. AutoCAD) program in order to make sure that it would be possible to install the comprehensive set of recommended sensors on each specific component studied.

The second major part of this study is the development of an intelligent D&M advisory system integrating a comprehensive sensor network. This advisory system employs a Bayesian Belief Network (BBN) as a high level reasoning tool for incorporating inherent uncertainty for use in probabilistic inference. It is demonstrated that a rule-based knowledge representation is simply a special case of a general BBN by showing how the general BBN can be reduced to a rule-based representation. The presented major steps for constructing the BBN based generic inference algorithms are applied to systematic elicitation and synthesis of various levels of experts' knowledge. Prototype D&M algorithms are represented explicitly through topological symbols and links between them in a causal direction.

This D&M advisory system is set up with an easy-to-learn, user-friendly, man-machine interface and modern graphics for efficient operator interactions. As new pieces of evidence from sensor networks developed are entered into this system, it provides operational advice concerning both availability and safety so that the operator is able to determine the likely failure modes, diagnose the system state, locate root causes, and take the most advantageous action. Thereby, the comprehensive monitoring supported advice improves operational availability.

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my parents **Kang, Yun-Won** and **Lee, Young-Lee**,
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TABLE OF CONTENTS

List of Figures

List of Tables

Nomenclature

ACC	Accelerometer
A/D	Analog-to-Digital
API	Advanced Program Interface
AS	Air-Side
BBN	Bayesian Belief Network
BID	Bayesian Influence Diagram
BSD	Bearing Ball Sphere Defect
CAD	Computer Aided Design
CBM	Condition Based Maintenance
CCWS	Component Cooling Water System
CF	Certainty Factor
CM	Condition Monitoring
CPT	Conditional Probability Table
D&M	Diagnosis and Maintenance
DCS	Data Communication System
EFMDAS	Electrical Fault Monitoring Data Acquisition System
EHC	Electro-Hydraulic Control
EM	Electro Magnetic
ERTS	Electronic Rotor Temperature Sensor
ES	Expert System
FD	Bearing Train Defect
FFT	Fast Fourier Transform
FMEA	Failure Mode and Effect Analysis
FOT	Forced Outage Time
FSH	Functional System Hierarchy
FT	Fault Tree
GCCM	Generator Core Condition Monitor
HP	High Pressure
HPM	Hydrogen Purity Meter
HS	Hydrogen-Side
HUGIN	Handling Uncertainty in General Inference Network
HX	Heat Exchanger
I&C	Instrumentation and Control
INEL	Idaho National Engineering Laboratory
INPO	Institute of Nuclear Plant Operations

IRD	Bearing Inner Race Defect
KNGR	Korean Next Generation Reactor
KP	Keyphasor (Phase Reference Probe)
LAN	Local Area Network
LFM	Logic Flowgraph Methodology
LOCA	Loss of Coolant Accident
LP	Low Pressure
MFP	Main Feedwater Pump
MTBF	Mean Time between Failures
MTTR	Mean Time to Repair
NPP	Nuclear Power Plant
NPRDS	Nuclear Plant Reliability Data System
NRC	Nuclear Regulatory Commission
ORD	Bearing Outer Race Defect
PDA	Partial Discharge Analysis
PP	Proximity Probe
PWR	Pressurized Water Reactor
RCP	Reactor Coolant Pump
RF	Radio Frequency
RTD	Resistance Temperature Detector
RXD	Rotor Expansion Detector
SCCW	Stator Coil Cooling Water Auxiliary System
SOA	Spectrometric Oil Analysis
SOT	Scheduled Operating Time
SSH	Structural System Hierarchy
SW	Service Water
TBWD	Thrust Bearing Wear Detector
TC	Thermocouple
TG	Turbine Generator
TSD	Turbine Stress Detector
TVMDAS	Torsion Vibration Monitoring Data Acquisition System
WDA	Wear Debris Analysis

Chapter 1. Introduction

1.1 Motivation

As increased productivity is necessary to remain competitive in all areas of machinery process operation, attaining a high level of power plant operational availability is one of the most importance issues facing the nuclear power industry. The nuclear power industry must be willing to expand the goal of each plant from safe performance to both safe and economic performance. This is due to the fact that forced outages or power reduction constitute significant financial losses and possible degradation of power system reliability to unacceptable levels. For example, the financial loss caused by one day of forced outage amounts to about $ 0.7 million for a 1300 MW nuclear power plant. In addition, the degradation of system integrity due to forced outages may increase even further financial losses.

Consequently, it is of vital importance to reduce the probability of forced outages and improve the maintenance schedule and procedure. There is a strong interest in the implementation of modern condition monitoring and intelligent maintenance. The capability to provide early detection and diagnosis of component deterioration is an essential part of any effective maintenance program.

Therefore, the work reported here is concerned with use of on-line monitoring and advice to improve nuclear power plant operational availability. It is focused upon new pressurized water reactors (PWRs), such as is envisioned for the Korean Next Generation Reactor (KNGR).

1.2 Objectives

The work reported here examines operational availability improvements through monitoring and advice. The key objectives are categorized in this section. They are aimed at constituting the entire form of a comprehensive sensor network integrated advisory system at the design stage in a systematic way. It is in this context that we examine the techniques now available and movement of the state of the art toward on-line intelligent condition based monitoring, diagnosis, and maintenance.

1.2.1 Method Formulation for Developing Sensor Networks

The rapid advancement of powerful monitoring devices and computers permits us to configure an advanced on-line sensor network as a foundation for efficient plant monitoring and diagnosis. This technical trend and increasing competition motivates an interest in plant operations for both increased safety and operational availability.

In designing a monitoring system a study should reveal which components make dominant contributions to lost operational availability of the PWRs. Those components with high failure rates and those failures causing long duration outages are the prime culprits for causing the plant's unavailability. When designing equipment, it is desirable to consider condition monitoring in conjunction with failure mode studies. Thus, for any important component each failure mode should be identified and a number of possible methods for detecting the onset of failure should be considered. However, most of the equipment in a nuclear power plant have very complex functions and interrelationships with other subordinate components. As the complexity and interrelationship of subordinate components increases, it becomes more difficult to employ a proper set of sensors and advanced data processing techniques in a systematic way. To that point, there has been no well-established systematic method in common use for developing comprehensive sensor networks considering all steps of modern data processing techniques for complex systems. That situation motivates the work reported here to develop a systematic approach for analyzing failure modes and determining associated sensor sets incorporating modern data processing equipment.

1.2.2 Comprehensive Sensor Network Development at the Design Stage

These days, special instrumentation and powerful computer supported maintenance systems are finding their ways into nuclear power plants. The cumulative effect of using a monitoring and diagnostic system is expected to be a significantly improved operational availability of the power plant in addition to detailed understanding of system conditions by the plant operation staff. Thus, an integrated architecture for systematically performing on-line condition monitoring and intelligent diagnostic maintenance should be configured.

As prerequisite work, we should perform a state of the art review on modern sensor processing technologies used in other industries such as aerospace, chemical process and automated manufacturing for evaluating the feasibility that may also be imbedded useful for the nuclear power industry. Moreover, special instrumentation and powerful computer supported maintenance systems are finding their ways into nuclear power plants. Currently, there are many newly developed proprietary devices on the market that may be used for advanced condition monitoring. Most of these devices are usually applied after a plant component has been installed. It very difficult and expensive to add instrumentation to a plant once it has been built. Rarely is equipment supplied which has been designed with the presence of condition monitoring devices as a basic design consideration. A designer has incentives to install an abundant sensor network into the initially constructed plant. Thus, this study places a great emphasis upon the value of inclusion of modern condition monitoring into the requirement of design equipment, and it expands a concern for the development of intelligent systems in order to integrate process and control with condition-based maintenance (CBM). A modern condition monitoring can ensure that all actions and decisions are made based upon substantial and corroborated diagnostic information, thereby eventually leading to financial gains.

1.2.3 Sensor Network Supported Advisory System Development

Even though a comprehensive monitoring system is configured through this study, effective maintenance and troubleshooting of complex mechanical equipment is still a formidable task. Considerable diagnostic information available from this monitoring system is not always correlated or otherwise analyzed and presented in a form which can be well suited for aiding the operator's judgement. Technical staff should interpret a large amount of available information, such as data from sensors or data processing equipment, promptly and efficiently. In practice, it is very difficult to establish cause and effect relationships because of the non-linear nature of complex mechanical systems. In this situation, operators must use subjective judgement, based upon their experience and training, in prioritizing alarms and analyzing diagnostic conditions.

Expert systems (ES) are known to be computer-based systems employing human knowledge to solve problems that are thought to require human expertise. Applications of expert systems in many fields of study have grown very rapidly during the last decade or so. Automating some of the decision making tasks to be performed on a regular basis, thereby relieving the operator to do more demanding tasks can reduce the burden of the operator. A knowledge-based advisory system incorporated into a modern condition monitoring system is recommended for capturing the decision logic of diagnosis and maintenance. This advisory system transforms information from comprehensive sensor networks into the operational advice that is useful to safe and economic operation.

However, most of the knowledge-based systems employed in the area of diagnosis have used a shallow knowledge of the system, which link an observed phenomenon to an individual system fault itself. In the nuclear power industry existing monitoring systems have been designed mainly from the safety standpoint. In the diagnostic advisory system their corresponding safety related operational procedures are usually represented by a set of production rules that express deterministic problem solving domains or straightforward stochastic problem solving domains supplemented with an uncertainty factor. This is usually done with shallow understanding or heuristics of the causal evolution of system faults.

In most practical applications, however, uncertainty is inherent factor to be considered, not an exception. There are various sources of uncertainty. The observations may be uncertain, the information may be incomplete, and the relations in the domain may be of a non-deterministic type. Thus, there is a need for expert systems that deal with uncertain situations. Moreover, in a complex, sophisticated problem solving domain, the use of deterministic rules often forces the domain expertise descriptions into an inappropriate representation because they are characterized by a large collection of rules based upon empirical associations. Trouble shooting in a rule-based system typically involves simple retrievals of stored candidate lists indexed by failure symptoms. The availability-driven diagnosis involves an inherently increasing uncertain due to greater system complexity than is associated with safety-related monitoring.

Although this can result in fast efficient diagnoses for deterministic fault identification, it is not suitable for representing structural and functional domain knowledge in a complex system, which represents the interconnection and the behavior among subordinate components in a complex system. A complex mechanical system mechanism involves complicated cause-effect interactions between many subordinate components. Skilled management is required in order to achieve efficient performance. This requires considerable experience and a sound understanding of the cause-effect relationships governing the complex processes of interest. Finally, this broadened concern motivates the work reported here to employ high level reasoning tools for incorporating inherent uncertainty for analysis of complex problems.

1.3 Overview

The work reported here broadens the prime concern of nuclear power plant operations from safe performance to both economic and safe performance. We examine improvements in terms of the instrumentation and control area. The framework of an integrated architecture for performing modern on-line condition monitoring and intelligent maintenance for operational availability improvement is configured in this work. This integrated architecture is composed of comprehensive sensor networks incorporating modern signal processing systems, advisory systems for sensor validation, and advisory systems for intelligent diagnosis and maintenance. Because the degree of validity of sensor readings proves to be a major factor in determining the accuracy of information which will be provided for diagnosis and maintenance advice, this advisory system is required to perform sensor validation and data file configuration for every diagnostic advisory system input. In an advisory system for intelligent diagnosis and maintenance, the information from the sensor validation advisory system is correlated, analyzed, and presented in a form that can be well suited for aiding the operator's decisions. We conclude that many of these efforts, use of a condition monitoring system, intelligent sensor validation advisory system, and intelligent diagnosis and maintenance advisory system are directed at perfecting on-line capabilities for improved availability and efficiency of the power plant.

The work reported here includes two major parts for plant availability improvement: 1) A modern on-line condition monitoring system is developed for early fault detection in complex machines. 2) Assuming that there are valid sensor readings available through sensor validation advisory systems, an advisory system for intelligent diagnosis and maintenance is developed.

First, it is shown which components have had dominant influences upon major lost availability in the recent operation of PWRs in United States. Complex rotating machines such as turbine generators and reactor coolant pumps are identified as main contributors for the lost availability through the review of plant forced outage records. They are known to be very complex systems composed of various mechanical and electrical components. Insufficient understanding of system characteristics, for example, due to its complexities, usually renders development of an efficient monitoring condition more difficult. Demands for improving availability facilitated by instrumentation and control (I&C) make the development of a sensor network subject to a requirement for profound understanding of system features and functionality. The sensor network development in the complex system should be based upon sufficient understanding of essential system attributes such as structure, function, and interrelationships. However, a conventional analytical method called Failure Modes and Effect Analysis (FMEA) for sensor network development has proven to be inadequate as system complexities, interrelationship of subordinate components and the number of the utilized sensor sets grow.

For the development of the comprehensive sensor networks for complex target systems, an integrated method incorporating a structural system hierarchy and a functional system hierarchy, a fault-symptom matrix, sensor selection criteria, a sensor installation feasibility study, and advanced instrumentation techniques is formulated. The design method suggested here also describes the rationale for the allocation of sensors for a particular monitored component. The nature of this abstraction is dictated by the needs for determination of the needed sensor types. It emphasizes an approach using structural and functional system abstraction for developing sensor networks that are capable of reflecting the aspects of the system's performance and structure. Such advanced instrumentation reflects the state of the art in advancement of data acquisition, data processing, and data integration techniques incorporated in order to extend the systematic monitoring coverage. The application of this method to reactor coolant pumps and turbine generators has been judged to be systematic and appropriate as the result of discussions with system experts. Once the sensor types and locations have been selected definitively, they are incorporated into drawings using a computer aided design (e.g. AutoCAD) program to make sure that it would be possible to install the comprehensive set of recommended sensors on each specific component studied.

The second major part of the work reported here is the development of intelligent D&M advisory system. Its intent is not to replace the plant operators, but rather, to assist the operator during plant operations in order to improve operational availability. Proper maintenance and troubleshooting of complex mechanical equipment is performed by an intelligent diagnosis and maintenance advisory system, which is supported by the comprehensive network developed in this work. This is done assuming that a sensor validation advisory system configures validated data files for use in the D&M advisory system, which employs a Bayesian Belief Network (BBN) as a high level reasoning tool for incorporating inherent uncertainty for use in probabilistic inference. The BBN is a relatively new discipline in the area of knowledge based system application. Bayes' Theorem, Bayesian updating and influence diagrams for decision-makings provide theoretically sound foundations. It has proven successful in complex decision making problems with uncertainty by graphically representing the diagnostic problem domain through simple topological symbols and links between them (PEAR 88).

We demonstrated that a rule-based knowledge representation is a part of and a special case of the general BBN by showing how the general BBN is reduced to be a rule-based representation. The work reported here shows that the BBN-based system is superior to the rule-based system in its ability for complexity and uncertainty management, systematic decision-making, and model modification and refinement.

Thus, the work reported here explores an application of Bayesian Belief Networks (BBNs) using the HUGIN (HUGI 94) expert system shell for modeling the uncertainty within the content of intelligent diagnosis and maintenance of complex mechanical systems. It has excellent features in the structure for system use, which facilitate operator interactions with an easy-to-learn user-friendly, man-machine interface and modern graphics.

The work reported here presents the process by which the BBN based generic inference algorithm is created. The presented major steps for constructing BBN based generic inference algorithms are applied to systematic elicitation and synthesis of various levels of experts' knowledge. The major steps suggested in the work reported here are a structural system hierarchy and a functional system hierarchy, refined causal networks, Bayesian belief networks (BBNs) with inference engine, and Bayesian influence diagrams (BIDs) with inference engine. These four levels of model construction are supported by required expertise, which is composed of expert model review, expert's conditional probability table, library of corrective actions, and library of utility value.

The prototype D&M network for example target systems is formulated explicitly through topological symbols and links between them in a causal direction. The output of the influence diagram is a diagnostic mapping from the symptoms or sensor readings to a determination of likely failure modes, directed by information flow. As new pieces of evidence from sensor networks developed are entered into this system, it provides operational advice concerning both availability and safety so that the operator is able to determine the likely failure modes, diagnose the system state, locate root causes, and take the most advantageous action. Thereby, the comprehensive monitoring well-grounded advice improves operational availability.

For a successive adjustment a diagnostic algorithm should be subject to a series of test cases and its prediction compared with the expected outcomes and the expert should check how the available knowledge may be applied to solving real diagnostic examples. Finally, the testing and validation strategy suggested in this research is aimed at ensuring that newly acquired knowledge and further refinement result in a more sophisticated model.

1.4 Organization

There are eleven remaining chapters in this dissertation. They sequentially address the target system selection, an integrated method for sensor network development, sensor network implementation, and D&M advisory system development.

These main objects constitute the integrated structure for a sensor network integrated advisory system for improved operational availability.

Chapter 2 reviews a Nuclear Regulatory Commission (NRC) database (INEL 96) in order to reveal which components make great contributions for the lost availability of PWR power plants in the United States. For this evaluation, the relationships among availability, reliability, and maintainability are stated. These are concepts, closely related to each other, in terms of machine performance. The characteristics of target systems selected are described.

Chapter 3 presents an integrated method for sensor network development including advanced instrumentation techniques and compares it with conventional methods. The overall procedure of the method presented in this chapter illustrates how several steps composed of a structural system hierarchy and a functional system hierarchy, fault-symptom matrix, sensor selection criteria, installation feasibility study and advanced instrumentation techniques are utilized in designing a comprehensive sensor network. In this chapter, after the turbine generator lubrication oil systems is used to explain the application of this method in order to verify its adaptability, the same approach is applied concerning complete target systems.

Chapter 4 outlines the current trend and scope of modern on-line monitoring and suggests advanced condition monitoring techniques that can be applied to rotating machinery such as the reactor coolant pump and the turbine generator. The details of each new utilized technique in vibration analysis, wear debris analysis, partial discharge analysis, motor current analysis, rotor flux monitor, shaft voltage detector, generator core condition monitor, fiber optic end-turn vibration monitor, torsional vibration monitor, hydrogen gas purity sensor, hydrogen dew point monitor, hydrogen leakage detector, and water conductivity detector are described.

In Chapter 5, the overall architecture of a plant-wide condition monitoring system network is configured. The sensor types for important components of the turbine generator and the reactor coolant pump are listed. The determined sensor types and locations on each specific component studied are incorporated into drawings using the AutoCAD program (AUTO 96). Finally, the sensors suggested for the target plant components addressed in the work reported here are presented in order of preference priority as recommended in measuring a specific parameter with several candidates of sensors.

Chapter 6 proposes the formalism of Bayesian Belief Networks for modeling the uncertainty inherent in the diagnostic problem and systematic decision making of interest. First, the characteristics of our problem solving situation are examined and its concept and fundamental theory are briefly stated. The details of their main features and comparison of them to rule-based expert systems are described. The BBN based expert systems are critically examined in terms of their treatments of rule-based expert systems, uncertainty management, knowledge representation, decision-making, ease of modification, and systematic root cause tracking. The basic principle and structure of prototype diagnostic networks are outlined and illustrated by means of a simple network.

In Chapter 7, selection of a proper expert system shell is performed for a problem solving tool. Commercially available shells for rule-based approach and BBN-based approach are reviewed briefly based upon the selection criteria defined in the work reported here. This chapter also demonstrates features of the HUGIN expert system shell, the tool for developing the advisory system.

Chapter 8 outlines a framework for configuring an integrated architecture for constituting a modern condition monitoring, sensor validation, and diagnosis and maintenance system. It explains a modeling strategy in terms of system causality and the concept of utility employed in the diagnostic inference algorithm embedded within the advisory system. Then, the presented major steps for constructing BBN-based generic inference algorithms are applied to systematic elicitation and synthesis of various levels of experts' knowledge. Finally, the prototype simple network, which will be applied to the entire network for target systems, is computerized using the HUGIN expert system shell.

Chapter 9 specifically addresses the implementation of the intelligent diagnosis and maintenance advisory system by showing how our representative models work. Task execution accompanied by an operator's interactions with the operator interface module and results are obtained through the advanced graphical user interface. We explain the diagnostic model structure and present its required knowledge base, which is obtained through elicitation of experts' knowledge. Furthermore, the actual deterministic abnormal operational procedures of a nuclear power plant are computerized using the HUGIN expert system shell.

Chapter 10 suggests the testing and validation process. The strategy for the validation of methods is presented for future work. Each step is summarized in order to validate this advisory system in the actual environment by comparing it against the reasoning of the experts in the real field.

Chapter 11 serves as the summary of this dissertation and the direction of future research. Here, the major findings are stated, conclusions are drawn and recommendations for future work are presented.

Chapter 2. Target Systems

2.1 Selection Criteria

There is a wide scope of monitoring coverage, which may range from a few critical components to the complete power plant. Once we identify which systems are the most responsible for the financial loss of the power plant, this study focuses upon the development of a sensor networks and intelligent diagnosis and maintenance (D&M) advisory system centering on those selected key systems. Target systems/components are those having high failure rates and whose failures will cause long duration outages and thus, greatly leading to financial losses. Forced outage time durations caused by these systems are directly related to significant financial losses and can degrade power system to an acceptable level.

The needs for identifying which components have been significantly responsible for lost availability call for systematic criteria. These criteria should provide ways to quantify machine characteristics into statistical measures that can then be used in mathematical calculations. Since reliability, maintainability, and availability are concepts related to each other, their relationships are illustrated in Figure 2.1. The legend shows

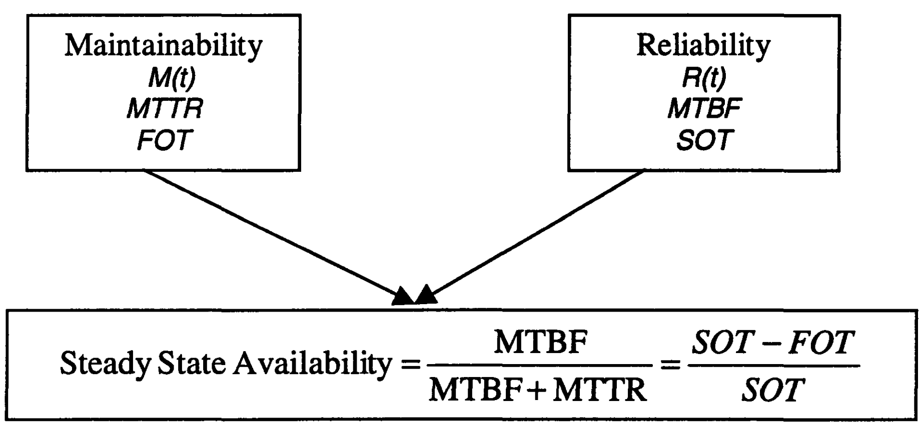


Figure 2.1 Relationships of Availability, Maintainability, and Reliability

(MTTR: mean time to repair, MTBF: mean time between failures,
SOT: scheduled operating time, FOT: forced outage time)

that reliability R(t) is the probability that an item will remain in service until time t, maintainability M(t) is the probability that repair will be accomplished in time interval [0,t], MTBF is a mean time between failures, and MTTR is mean time to repair. The MTTR can be defined as a function of the frequency of forced outages and total forced outage time caused by them. SOT is scheduled operating time and FOT is forced outage time. The steady state equipment availability is defined as the ratio of the actual operating time and the scheduled operating time.

From the mathematical relationship defined in the availability it is seen that an increase in MTBF, or a decrease in MTTR, will result in an improvement in system availability. As the MTBF relates to the reliability of the system through its failure rate, so does the MTTR its maintainability via the maintenance action rate, i.e. how quick it is to repair. Thus the importance of considering both factors during system specification and design can not be overemphasized. We focus upon the goals of increasing the MTBF and decreasing the MTTR through monitoring and advice.

In other words, Figure 2.1 shows that the availability depends importantly upon the forced outage time (FOT) because the scheduled operating time (SOT) is a fixed value. The fact that the financial loss by one day of forced outage amounts to $0.7 million for a 1300 MW plant explains the forced outage time as a key parameter for the selection of target systems.

2.2 Lost Availability Contribution of Plant Equipment

There are wide ranges of available monitoring techniques, which generally range from a few critical components to the complete power plant. This study focuses upon the key machines as target systems. These target systems (or components) are selected on the basis of past failure record review. Then, their advanced sensor networks for operational availability improvement of selected target systems are explored.

In a previous section, the forced outage time is selected as a criterion that is the most important factor to determine the operational availability. In order to identify the power plant components most responsible for lost availability, we looked into the NRC plant performance database containing failure records of components that cause forced outages of operating pressurized water reactors (PWRs) in the United States (INEL 96). This database is maintained by the Idaho National Engineering Laboratory. From 1990 to 1995, the economic importance of each component in the PWRs has been ranked in terms of total forced outage time caused by each specific component.

The information about the total outage time, contribution of total forced outage, number of failures, and MTTR are also listed for each specific component which is ranked within top twenty five. Table 2.1 shows that the main rotating machines such as

Table 2.1 Lost Availability Contribution Ranking of US PWR Plant Systems/Components (1990-1995) (INEL 96)

Rank	System/Component	Outage Time (hr)	Fraction of Total Forced Outage(%)	Number of Failures	MTTR (hr)
1	Transformer	14,442.2	10.64	39	370.3
2	Main Generator	10,955.3	8.07	70	156.5
3	Turbine	10,654.1	7.85	115	92.6
4	Steam Generator	10,597.6	7.81	46	230.4
5	Reactor Coolant Pump	10,004.1	7.37	47	212.9
6	Service Water System	6,369.5	4.69	6	1,061.6
7	Steam Extraction Piping	6,362.8	4.69	4	1,590.7
8	Diesel Generator	5,828.1	4.29	12	485.7
9	Control Rod System	4,194.6	3.09	51	82.2
10	Main Feedwater Valve	4,147.4	3.06	60	69.1
11	Pressurizer	4,073.4	3.00	20	203.7
12	Safety Injection System	3,899.4	2.87	8	487.4
13	Reactor Coolant System	3,327.2	2.45	22	151.2
14	Main Steam Valve	3,319.7	2.45	33	100.6
15	Circuit Breaker	3,067.1	2.26	14	219.1
16	Steam Generator Feedpump	2,854.5	2.10	18	158.6
17	Auxiliary Feedwater Pump	2,776.4	2.05	4	694.1
18	Moisture Separator Reheater	2,413.6	1.78	19	127.0
19	Inverter	2,399.8	1.77	12	200.0
20	Condenser	2,185.1	1.61	19	115.0
21	Main Feedwater Pump	1,983.5	1.46	37	53.6
22	Main Steam System	1,225.8	0.90	15	81.7
23	Relay	1,183.7	0.87	12	98.6
24	Intake System	1,142.2	0.84	2	571.1
25	Circulating Water	955.4	0.70	8	119.4

the main generator, the turbine, the reactor coolant pump are ranked within the top five components in terms of contributing to the total outage time. Unlike the power transformer as a passive component and the diesel generator as a standby component, the turbine generator and the reactor coolant pump are very important active systems. If the total forced outage time caused by main generators and turbines is added, turbine generators are identified as the most important equipment whose failures are associated with significant financial loss. The fraction of forced outage caused by turbine generators amounts to 16% and the fraction caused by reactor coolant pumps is shown to be 7%. These important rotating machines, turbine generators and reactor coolant pumps, are selected as the target systems being investigated here. The detailed lost availability loss contribution caused by turbine generators and reactor coolant pumps are evaluated in the following Section 2.3.1.

Consequently, it is of vital importance to reduce the forced outages and the associated financial losses caused by turbine generators and reactor coolant pumps. These aims can be initially explored by implementing comprehensive condition monitoring systems with sensor networks for these target components, which consolidate the foundation for efficient diagnosis.

2.3 Characteristics of Target Systems

The turbine generator and the reactor coolant pump are chosen as target systems for the development of the condition monitoring system and the intelligent D&M advisory system for their improved availability and efficiency. Both of them have critical rotating machines for the operation of the power plant and are composed of various mechanical and electrical components. Each of them is one of the somewhat unreliable equipment whose failure will result in a reactor trip, shutdown or power reduction, as no redundancy exists during operations at rated power. Thus, they have been involved in significant forced outage time and corresponding financial losses.

After their functions during the operation of power plant are reviewed, the following subordinate sections describe their main failure modes, failure causes, and forced outage contribution by specific subordinate components in order to look for newly developing monitoring and diagnostic techniques for use in supervising their performance. The current forced outage records by the chosen systems are evaluated by analyzing the Nuclear Plant Reliability Data System (NPRDS) (INPO 96) and the NRC plant performance database (INEL 96).

2.3.1 Turbine Generator

2.3.1.1 System Characteristics

In pressurized water reactors, the turbine generator converts the energy of the steam produced in the steam generators into mechanical shaft power and then into electrical energy. The larger PWRs typically have only one turbine generator per plant. It consists of a double-flow, high-pressure(HP) turbine and three double-flow low-pressure(LP) turbines driving a direct-coupled generator. It also requires numerous ancillary systems as well as the electrohydraulic control (EHC) system to support its operation. These are composed of a great number of mechanical and electrical components. These systems are normally supplied with the units. The major turbine generator subsystems are classified into stator winding systems, bearing systems, exciter systems, gland seal systems, and electrical grounding, excluding EHC systems. The function and scope of important subordinate systems in terms of availability are described in the following subordinate sections. Their diagrams are shown in Figure 2.2.

2.3.1.1.1 Stator Windings with Auxiliary Cooling Systems

The stator winding provides the generator output voltage and current, composed of stationary high voltage coils arranged in slots in the stator core to form a three-phase winding that is usually wye-connected. These coils are arranged in the phase groups spaced at intervals of 120 degrees. Two stator coils are arranged in each stator slot. Each coil consists of mica-insulated strands of copper plus ventilation tubes surrounded by insulation. The ventilation tubes are open at each end of the coil, allowing a blower to circulate gas through the tubes to cool the windings. The coils are held firmly in place by a system of high strength wedge filler and prestressed driving strips. The ends of the coils that extend beyond the core are mechanically braced to withstand vibration and abnormal forces.

Heat is produced in a generator as a result of resistive losses caused by current flow in the stator and field windings, stator core magnetic losses, and windage losses. Because the largest source of heat is the stator winding, the heat is removed by through convection by a flow of hydrogen cooling gas over the bars. This choice is made because the thermal properties of hydrogen are superior to those of other gases. Nevertheless, as the generator ratings are growing larger, the additional cooling system called Stator Coil Cooling Water Auxiliary System (SCCW) is usually employed. Demineralized water is pumped through hollow strands interspersed through the bar cross section. Their schematic diagrams of the SCCW and hydrogen cooling auxiliary systems are shown in Figures 5.4 and 5.5, respectively (GONZ 95), (BLAC 96).

2.3.1.1.2 Bearings with Lubrication Oil System

The TG bearings are designed to support and control the motion of rotating shafts, while providing very low frictions and must be lubricated whenever the rotor is turning at any speed. Oil is required to form the dynamic action that supports the rotating shaft on a thin film of oil. Adequate supply of this oil at the proper pressure and temperature will ensure that no damage is incurred either on the shaft journal or the bearing. Loss of oil to the bearing while the rotor is turning can result in loss of wiped babbitt, scored bearings, and damage to the rotor journals as well as to the gland seals.

The bearing lubrication oil provides a clean and temperature-controlled supply of oil to serve purposes described above. A diagram of a typical lubrication oil system is shown in Figure 5.3. The complete system includes pumps, coolers, oil tank, purification devices and associated piping, valves, and controls. During the normal operation, the lubrication oil is driven by a shaft-mounted oil pump. Electric motor-driven pumps are used to supply the oil as backups when the main oil pump fails (GONZ 95), (BLAC 96).

2.3.1.1.3 Gland Seal System

The hydrogen cooling gas described in the previous section must be tightly sealed within the generator frame. Because the generator shaft is driven by an external source of power, the shaft must extend through the gas-tight frame. The two major components of the hydrogen sealing system are the gland seal rings used to seal the frame and the seal oil supply system used to provide the oil flow to the rings allowing the rings to perform their functions.

Gland seals, supplied with oil under pressure, are used to prevent the leakage of hydrogen through the clearance between the shaft and the frame. A gland seal assembly consists of housings that are supported from the outer end-shield at each end of the generator. The seal oil supply system is designed to furnish the oil required by the gland seal ring in order to maintain a gas seal. It is the function of seal oil supply system to lubricate the seals, prevent hydrogen from escaping through the seals, and to do so without introducing excessive amounts of contaminants into the hydrogen (GONZ 95), (BLAC 96).

2.3.1.1.4 Generator Grounding

There is a difference between a power system ground and the system neutral. Electrically both points should be at the same potential and are normally connected to the earth. However, a system ground is not expected to carry a constant current. The generator experiences some phase unbalance in its normal load, therefore must be solidly grounded to the system.

2.3.1.1.5 Exciter System

The purpose of the excitation system is to provide direct current to the rotating electromagnetic field. It must be capable of supplying the required field current for all permissible load conditions and must be able to be controlled either manually or automatically by a control mechanism. The control system for the field current is referred to as an automatic voltage regulator, but modern excitation control systems include many features over and above the function of maintaining a constant generator terminal voltage.

2.3.1.2 System Failure Mechanism

The main generator ranks the second and the turbine ranks the third from the lost availability standpoint. The total sum of outage time caused by both the main generator and the turbine exceeds that caused by the transformer. Consequently, unplanned outages of turbine generators have caused a massive loss of financial earnings as the most dominant contributor.

The causes of turbine generator failures leading to forced outages form the search of NRC data from 1990 to 1995 are shown in Figure 2.2. Note that the definition of failures in Figure 2.3 considers only failures which have lead to plant outages.

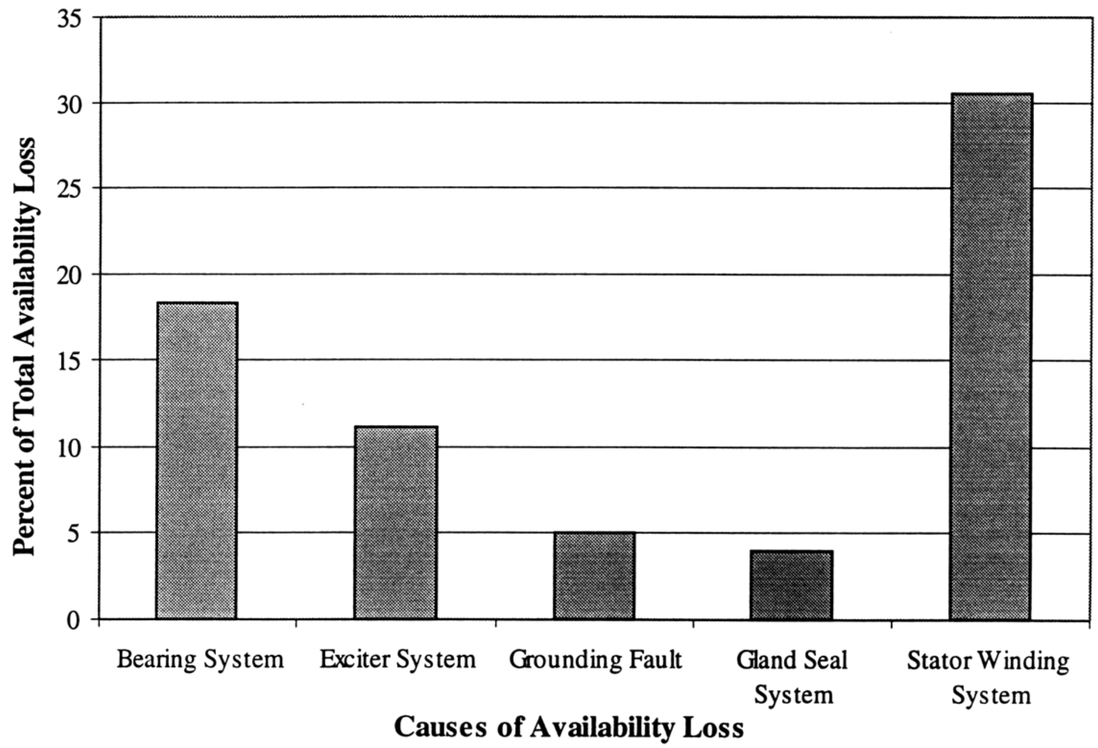


Figure 2.2 Leading Causes of Turbine Generator Availability Loss (from NRC Database)

It shows that the stator winding related systems are the most dominant contributors responsible for 30.5 percent lost availability. These systems include the stator winding itself, the hydrogen auxiliary system, and the stator coil cooling water auxiliary system. 18.3% of forced outages have been caused by the bearing related components, which are the bearing itself and lubrication oil systems. We note that 87.7 percentage of forced outages have been caused by turbine bearings.

Thus, the work reported here focuses upon the development of a comprehensive sensor network integrated diagnosis and maintenance advisory system, centering upon important components described in this section. These are bearings with the lubrication oil system, and stator windings with auxiliary cooling systems.

2.3.2 Reactor Coolant Pump

2.3.2.1 System Characteristics

In PWRs, reactor coolant pumps (PCPs) circulate water through the primary coolant systems in order to transport energy from the core to the steam generator. The larger PWRs typically use four RCPs per plant. They develop the necessary pressure to overcome the friction loss that the fluid suffers in flowing through the core plena, piping and steam generator tubes. As components of the primary coolant system, operating under high temperature, pressure, radiation and performing the critical function of providing circulating water to cool the core, the RCP must be designed and manufactured subject to stringent criteria. They are classified as Safety Class[1)] I and must obey the provisions of Section III of the ASME code.

Each RCP is about 10 m high with vertical orientation and are single stage, requiring an electric motor of about 10,000 horsepower. As a drive device, a three-phase alternating current induction motor designed to operate at constant speed is mounted vertically on the top of the pump. The inlet is at the bottom and the discharge is on the side.

Since the water circulated by the pumps is somewhat radioactive and seal failures can increase the likelihood of a loss-of-coolant accident (LOCA) during normal operations, the shaft should be equipped with properly designed seals in order to prevent leakage of the radioactive coolant.

[1)] As USNRC (Nuclear Regulatory Commission of the United States) design criteria, the quality requirements for each system and component of the nuclear power plant (NPP) have been categorized into safety classes I, II, III, and IV in terms of the safety importance. Class I is applied to the design of systems or system parts directly pressurized from the reactor.

2.3.2.2 System Failure Mechanism

The RCP ranks as the fifth greatest contributor whose failures have resulted in significant lost availability. Compared to the main feedwater pumps (MFPs) based upon data in Table 2.1, RCPs have somewhat lower failure rates in causing forced outages, but they have much longer contributors to the value of the MTTR due to the harsh environment described in Section 2.3.2.1. Additionally this is because access to the RCP for repair almost always requires shutting down the plant and creating the conditions necessary for access the pump.

From 1989 to 1995 the leading causes of availability loss contribution by specific components of the RCP to the total RCP failures are shown in Figure 2.3. The major RCP components leading to forced outages are classified into bearings, bus, motor, and seals. This bearing related components includes the bearings themselves, bearing lubrication oil system and bearing related vibration failures in shaft. Seal related components include the seal flow injection system as well as the seals themselves. Even though the bus is an electrical component, which is connected between the transformers and RCPs, its failure included within the set of RCP failure contributors. The failure of the motor includes the motor induced grounding failure as well as failure of the motor failure itself. A diagram of a typical motor is shown in Figure 5.9

We note that the definition of failures in the Figure 2.3 considers only failures that can lead to plant outages. Figure 2.3 shows that the bearing-related components are the most dominant contributors, providing 33.4 percent of lost availability, and the seal related failures are the second greatest contributors responsible for 30.0 percent lost availability. Actually, bearing related components have lower failure rates, compared with the failure rate of seal related components. Thus, the greater MTTR value of bearing related components overwhelms their lower failure rate, leading to a higher contribution to the availability loss than from the seal related component. Also, 15.3 percent of forced outages were caused by motor related failures. The rest of failures excluded in Figure 2.3 were caused by impeller, diffuser, casing, etc. and unknown failures.

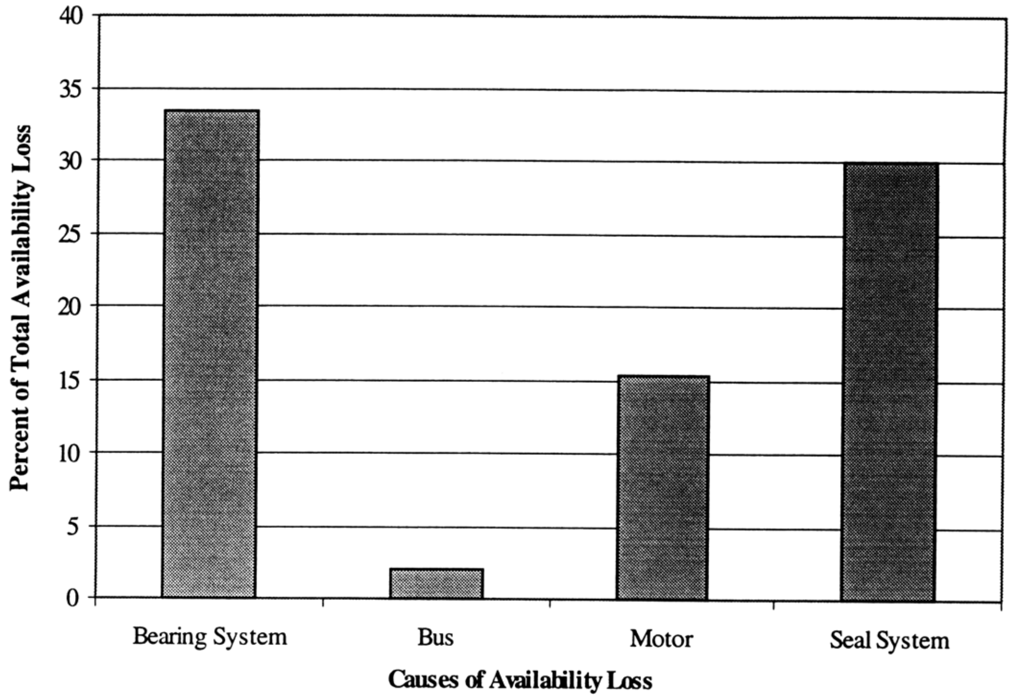


Figure 2.3 Leading Causes of Reactor Coolant Pump Availability Loss (from NRC Database)

Thus, the work reported here focuses upon the development of a comprehensive sensor network integrated diagnosis and maintenance advisory system, centering around important components described in this section, being bearings and a shaft with lubrication oil system, seals with seal flow injection system, and a motor.

Chapter 3. Integrated Method for Comprehensive Sensor Network Development

3.1 Introduction

The rapid advancement of powerful monitoring devices and computers permits us to design comprehensive sensor networks as the foundation of a system for efficient plant condition monitoring and diagnosis. In order for sensor networks to be effective in improving system operational availability, they should detect incipient system failures.

However, there has been no well-established systematic method in common use for developing sensor networks for complex systems such as turbine generators (TGs) and reactor coolant pump (RCPs). They are composed of various mechanical and electrical components. Sensor networks for monitoring such components should be designed subject to an understanding of complex system characteristics. Insufficient understanding of the system characteristics, for example, due to its complexity, usually renders an efficient condition monitoring difficult to realize.

In understanding the detailed system characteristics, it is convenient to distinguish between a system abstraction-based approach and a mathematical model-based approach. The mathematical model based approach utilizes a mathematical process model that reflects the physics of the process in terms of a set of algebraic and differential equations. Although it provides a detailed quantitative description, most of the current mathematical models are cumbersome, impractical to apply for uses of either monitoring parameter development or diagnosis. By contrast, a system abstraction-based approach utilizes an abstract concept of essential attributes such as structures, functions, and the interrelationships subject to the complexity of the systems under consideration. The nature of the abstraction made is dictated by the needs of either the diagnostic problem to be solved or the sensor network development. The work reported here emphasizes an approach using structural and functional system abstractions for developing comprehensive sensor networks that can reflect the aspects of complex system's performance and features.

Therefore, the aim of an integrated method incorporating system oriented hierarchies and advanced instrumentation techniques is to enable us to build advanced, real-time, condition monitoring systems applied to complex target systems. Moreover, as a prelude to system diagnosis in addition to efficient condition monitoring, the structural and functional system hierarchies for sensor network development can serve as a general frame for describing the knowledge that will be embedded into the diagnostic reasoning of an advisory system.

This method is defined in general terms here, and then implemented, using the example of monitoring aspects of complex rotating machines such as the turbine generator system and the reactor coolant system. The application of this method to reactor coolant pumps and turbine generators has been judged to be systematic and appropriate through following discussions with system experts.

3.2 Conventional Methods for Determination of Sensor Networks

Most of the sets of existing sensors in a nuclear power plant have been incorporated into the plant due to safety concerns. Their associated monitoring parameters indicate some important process behaviors. The straightforward determination of monitoring parameters and sensors are usually associated with a shallow understanding of or a heuristic treatment of system faults. Conventionally, Failure Modes and Effect Analysis (FMEA) has provided a conventional tool for depicting our problem solutions within a fixed frame. Basically, it tabulates answers to the questions 'what if' as dictated by our concern. It is concerned in the manner of failure, the effect of such failures, and other required information requested by specific concerns. Once major failure modes of interest are listed in a table concerning the development of sensor sets, then we try to tabulate associated monitoring parameters, corresponding sensors, and other information, such as costs, by incorporating associated knowledge. This approach is useful either for straightforward reasoning process for safety related sensor determination or for problem solving in well understood, simple systems

However, as system complexity, the interrelationships of subordinate components and the number of utilized sensor sets grow, FMEA has proven to be inadequate in dealing with complexity and high level reasoning required for sophisticated system features. This is why it offers little insight concerning complex system features and performance. Consequently, FMEA cannot reduce the system complexities in a systematic way and explain the complex interrelationships inherent among numerous subordinate components without overlooking important system features associated with specific concerns of this work, either. In particular, it is very difficult to represent cause and effect relationships because of its synergistic nature of complex systems. It is also poor in systematically incorporating advanced signal processing techniques, which can provide more detailed information on system performance based upon deep understanding of system features.

Thus, the work reported here requires a new integrated method, which can reflect entire tasks from system abstraction dictated by determination of sensors to advanced data processing techniques.

3.3 System Oriented Hierarchy Based Approach Integrating Advanced Instrumentation Techniques

The wok reported here formulates an integrated method incorporating a structural system hierarchy (SSH) and a functional system hierarchy (FSH), a fault-symptom matrix, sensor selection criteria, advanced instrumentation, and study of sensor installation feasibility.

The abstract failure modes of each hierarchical level in the FSH generate the corresponding monitoring parameters by using a fault-symptom matrix. The monitoring parameters of interests are listed under the primitive components in the SSH for deciding upon the monitoring locations. The corresponding sensor sets are chosen for observing the system parameters by use of sensor selection criteria. Then, we perform sensor installation feasibility studies with technical staff in the power plant with sensor manufacturing companies, and target system manufacturing companies and we coordinate their opinions to drawing work. Finally, the advanced instrumentation techniques reflect the state of the art in terms advancement in data acquisition, data processing, and data integration techniques incorporated into sensor networks developed in order to extend the systematic diagnostic coverage.

Assuming that the comprehensive sensor networks are developed based upon the presented procedures, the identification of the causes and locations of system fault initiation can be tracked properly by considering systematically the interrelationships between components and the combinations of various signal measurements. System diagnosis can be integrated by means of a set of suitable sensors at the subassembly or even the complete system level.

Figure 3.1 shows a process diagram representing these major steps sensor network development. Each box represents a module dedicated to the completion of our systematic development.

3.3.1 Structural System Hierarchy and Functional System Hierarchy

We employ a method for abstracting system features in order to determine the needed proper sensor types in a systematic way. It should be noted that this abstraction method describes causal relationships in terms of system structure and malfunctions dictated by the needs of systematically determining the system parameters and locations to be monitored. Abstracting a mechanical system structure and function is generally a formidable undertaking using the hierarchical approach of 'divide and conquer'. This process of subsequent division and refinement is repeatedly applied until the needed level of detail and completeness is achieved. This abstraction procedure will reduce the probability of overlooking possible failures.

The structural and functional system hierarchies are presented for decomposing the effective complexity of a system without overlooking the major features of the system's behavior and composition and then for determining the parameters and locations being monitored. This method is based upon a hierarchical decomposition of the complex systems under consideration. Each system is modeled by viewing it both as a structural hierarchy and a functional hierarchy. This is why the determination of monitoring locations is directly associated with system structure and the determination of monitoring parameters is associated with system malfunction.

In the first abstraction step, the hierarchical level of the system is defined in terms of its relationship to a lower level of systems in the structural system hierarchy (SSH). This hierarchical technique is primarily based upon consideration the system as a hierarchical tree of components. Figure 3.2 illustrates a generic decomposition for systems having four levels of description: device, modules, component and monitoring parameters or sensors. The node representing the system itself lies at the top of a hierarchy. This system itself at the top serves as the root of the system functional hierarchy. It is then decomposed into modules, which are in turn decomposed into primitive individual components listed at the bottom level of the nodes. These bottom nodes stand for specific monitoring locations.

Then, below the bottom nodes of the SSH the proper set of corresponding monitoring parameters are listed through the analysis of the FSH, which depends upon specific definitions of failures as violations of expected plant behavior or certain functional constraints. System malfunction modes formulated in terms of a functional system hierarchy (FSH) are decomposed into primitive nodes, from which monitoring parameters are extracted at each level of failure abstraction by means of a fault-symptom matrix as treated in Section 3.3.2. Creation of a functional hierarchy usually requires a more complex set of reasoning and additional knowledge because it should analyze the system performance and failure modes and then provide an accurate sensor set. Then, each level of the malfunction nodes of the FSH has one or more objects such as a device, module, or component. This system itself at the top of the SSH serves as the root object of the FSH. Decomposing the functional entity of a system into successive subordinate levels of functional complexity permits us to partition the malfunction process into concrete determination of monitoring parameters corresponding to the objects of SSH. These extracted parameters are finally assigned to the individual components listed at the bottom level of the SSH. The FSH forms the foundation for system diagnosis.

As example applications of the method presented, Figure 3.3 illustrates the elements of the SSH for the turbine generator lubrication oil system and Figures 3.4-1 to 3.4-4 illustrate how the FSH is configured. Thus, it is shown how this abstraction methodology is applied in the process monitoring of the turbine generator lubrication oil system as a module of the turbine generator. It is modeled by viewing it both in terms of a functional and compositional decomposition of the system, forming the SSH and the FSH. A top level functional abstraction, the lubrication oil system failure is shown to be decomposed in terms of the various primitive failure modes, which extract monitoring parameters. Also, at the top level structural abstraction, the lubrication oil system is shown to be broken down in terms of its primitive components, each of which has its required monitoring parameters.

Based upon the presented method, we configure the SSH and FSH of stator winding, stator core, rotor, gland seal system, auxiliary water cooling system, and auxiliary hydrogen system in the turbine generator as well as entire subordinate systems of reactor coolant pumps. As reference materials for above work, fault trees, the NRC database (INEL 96), NPRDS (INPO 97), and other power plant engineering references have been used for aiding such abstraction. They are shown in Section 3.4.

It is concluded that this structural and functional system abstraction applied to complex engineering systems can provide the framework of architectures and tools for sensor network development. Eventually, it will be explored how this abstraction method can pave the way for knowledge acquisition for an abnormal system state identification, root cause fault location and signal processing and integration imbedded in advisory systems.

3.3.2 Fault-Symptom Matrix

The each level of failure modes in the FSH has its own characteristics, which are indicated by the variations of process parameters and system status parameters. The accumulated expertise from operational experience and manufacturing process makes it possible to select a proper set of monitoring parameters for each failure mode.

In this work, the fault-symptom matrix shown in Table 3.1 is introduced for the ease of monitoring parameter determination for the primitive failure modes listed at the bottom level of the FSH. This matrix is intended to address the needs for monitoring parameters corresponding to specific failure modes extracted from each level of the FBH. The boxes of this matrix are marked with the symbol "Y" if there exists a need for sensing a specific failure mode by means of a specific parameter, or a number of listed parameters in the first row. They are composed of system process parameters (temperature, pressure, etc.) and system status parameters (vibration, partial discharge, etc). By doing this repeatedly, the required parameters are listed for the primitive components of the SSH where finally a set of sensors will be installed.

Table 3.1 illustrates how the fault-symptom matrix is applied for the determination of monitoring parameters for the turbine generator bearing lubrication oil systems. The failure modes listed in the column are taken from the failure modes of the FBH for bearing lubricating oil system. These parameters are determined in the fault-symptom matrix and are used to determine the corresponding sensor types, selected using the sensor selection criteria introduced in Section 3.3.3.

3.3.3 Sensor Selection Criteria

The monitoring locations and parameters obtained from the system abstraction and the fault-symptom matrix should be realized with the practically utilized sensor sets of the sensor network for availability improvement. Table 3.2 shows the current status of sensors available for specific parameter condition monitoring, and is the basis for selecting the proper sensor sets. For example, there are various kinds of available sensors for vibration measurement such as the proximity probe, tachometer, accelerometer, and phase reference probe. These sensor selection criteria provide some references for selecting the most proper sensor for the measurement of the specific parameter in the expected location.

In this context of sensor selection criteria, predictive monitoring, on-line monitoring, technical status identification, sophisticated program requirements and data processing equipment need to be considered when formulating the design of a sensor network. In the "Sensor Type" column, currently available sets of sensor types for each parameter are listed. The capabilities of these sensors are evaluated in terms of whether they can be employed for uses of predictive monitoring and whether they can provide information concerning the system status and process parameter values in an on-line fashion. The criterion, "Technical Status" indicates the current application feasibility, which is labeled "A", "D", and "R", which stand for the maturation states of advancement, development, and research, respectively. The criterion, "Program Requirement" deals with the needs for software to interpret the measurements from sensors. Some sensors, which need data processing equipment, are marked in the last criterion for "Data Processing Equipment".

3.3.4 Sensor Installation Feasibility Study

For new plants, more attention needs to be given to sensor locations as well as to the specific design for sensor installation should they be used in the future. Once the corresponding sensor sets are chosen for these parameters by use of sensor selection criteria, a sensor installation feasibility study is performed. Through meetings with technical staffs in power plants, sensor manufacturing companies, and target system manufacturing companies, their expertise is taken into account. After we coordinate such opinions into the final determination of sensor locations through installation feasibility confirmation or design specification modification, sensors are incorporated into drawings using computer aided design software (e.g., AutoCAD) to make sure that we could install the comprehensive set of recommended sensors on each specific component studied.

3.3.5 Advanced Instrumentation Techniques

The rapid development of currently available instrumentation technology has made it possible to perform efficient gathering and processing of information from various sensors, and motivates us to move to a new concept of monitoring for improved operation of the system. Recent developments have progressed to the point where the fusion of various sensor signals in a single unit has been achieved. The falling costs of advanced instrumentation and accumulation of plant operational experience may make these technologies more attractive in the future.

This advanced instrumentation step has been defined as three activities in our design procedure, which is composed of data acquisition, data processing, and data integration. Each step should be employed in order to elaborate the sensor network configuration most effectively. The first activity is to acquire data determined by the physical system status or the system performance process variables. Even though the same parameter is extracted in the preceding steps, the various sensors can be placed on a plant component according to its monitoring sensitivity range and engineering constraints. For example, both the shaft fault and the bearing fault are usually listed at the primitive nodes in FSH, leading to vibration as a monitoring parameters, but with different types of vibration sensors being used for vibration sensing such as proximity probes and accelerometers matched to each component, respectively. The data acquired by the sensors can be a set of measurements for system diagnostics and root cause identifications. With the availability of powerful computers, the advanced data processing techniques such as Fast Fourier Techniques (FFT) and waterfall diagrams enable us to further decompose the primitive malfunctions into more detailed failure modes.

Figures 3.5 and 3.6 show how the second step plays an important role in sensor network configuration and system diagnostics. The shaft vibration listed at the bottom level of the FBH are itemized into detailed failure modes represented by misalignment, bent shaft, unbalance, looseness, and oil whirl[1]. These failure modes are classified by the amplitude changes at their specific operational frequency and harmonics and by phase changes. Bearing damage is also broken down into more detailed failure modes such as inner race failure, outer race failure, ball damage failure, and shock pulse generation. They also classified with the amplitude change of specific frequency. Their detailed information is described in Section 4.3.1.

Finally, the third activity known as integration is very important in multiple sensor arrays relating to complex systems. Effective component diagnosis requires using a set of various signal fusions and the causal relationships describing the connections between the fault locations. Various signal combinations should reveal the failure root causes. For example, a situation requiring a precise signal interpretation can justify the autocorrelation and crosscorrelation of sensors. Those correlation techniques are good applications of signal integration techniques, which determine the time delay between signals coming from different channels. An averaging process is widely applied to separate repetitive signals from random noises and thus improves the ratio of signal to noise. When the same two channels are utilized, this technique is called an autocorrelation technique. Signal integration using two different sensors such as the

[1] Oil whirl: The occurrence of oil whirl is more likely in higher speed machines such as the turbine generator, which cause a precessing wedge of oil to be formed around the bearing, thus causing the shaft deflect.

electrical partial discharge signal and the acoustic signal is called crosscorrelation technique.

Shaft vibrations categorized in terms of misalignment, bent shaft, and unbalance are all indicated by the signal at the shaft rotational frequency "1x". The difficulty of distinguishing these failure modes can be overcome by use of additional measurements of orbit and phase. These measurements of some critical parameters can be elaborated using the concepts of signal redundancy, diversity and complementarity in order to increase the efficiency of condition monitoring and system diagnostics.

As a new monitoring concept motivated by recent development in integrated circuit technology, these measurements from multiple sensors may be combined within the instrumentation package to form what is termed an 'intelligent sensor" (WILL 94). This sensor combined with associated software convert combinations of input signals into a meaningful quantity. So, the output of this intelligent sensor, processing several signals such as specific frequency harmonics, phase, orbit frequency or temperature can provide information regarding detailed failure mode progress among the alternatives of misalignment, bent shaft and unbalance. This local processing concept, using intelligent sensors, will provide fast and efficient monitoring and reduce the diagnostic burden caused by increasing the amount of information obtained from increasing the number of sensors.

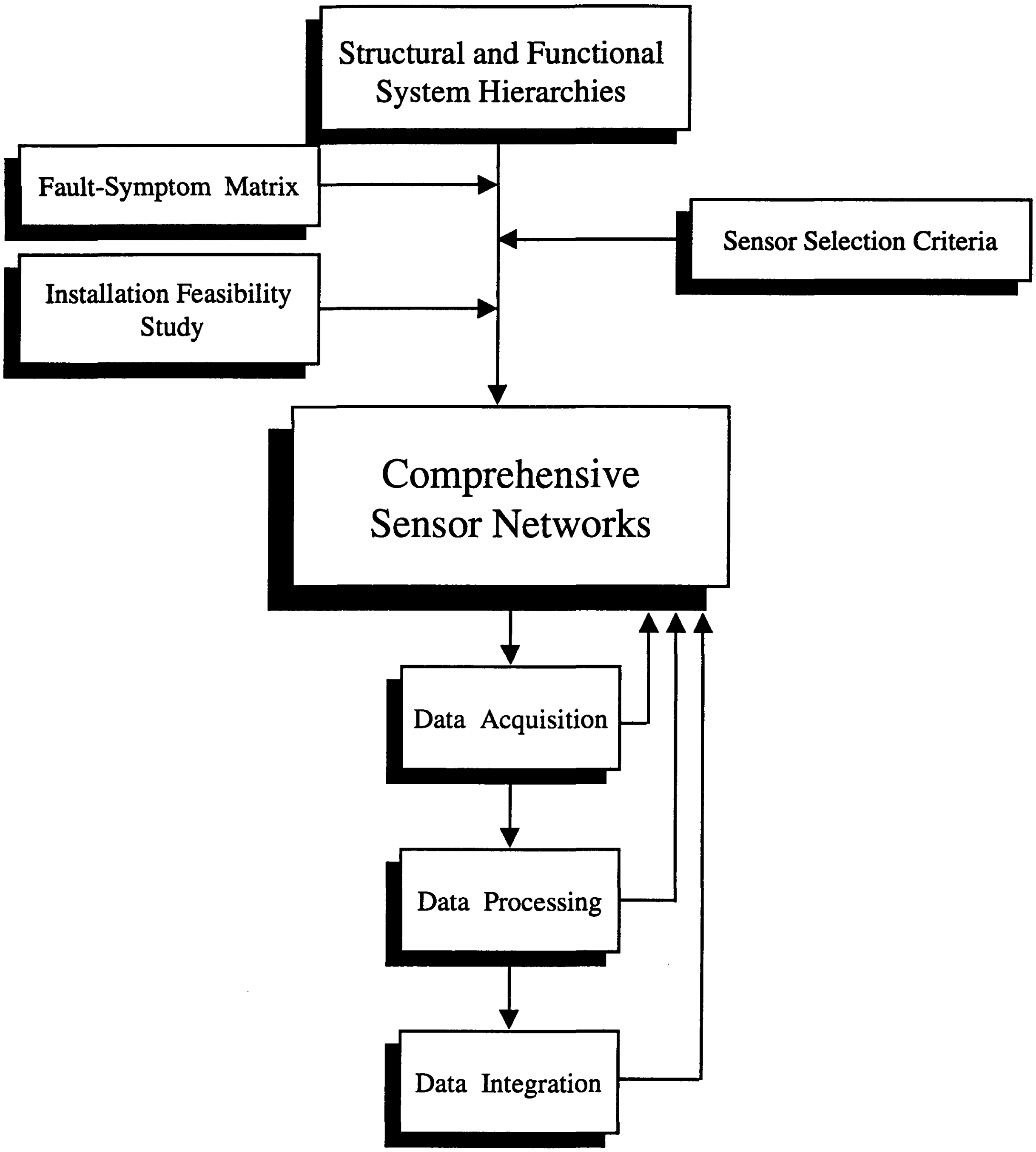


Figure 3.1 Process Diagram for Sensor Network Development

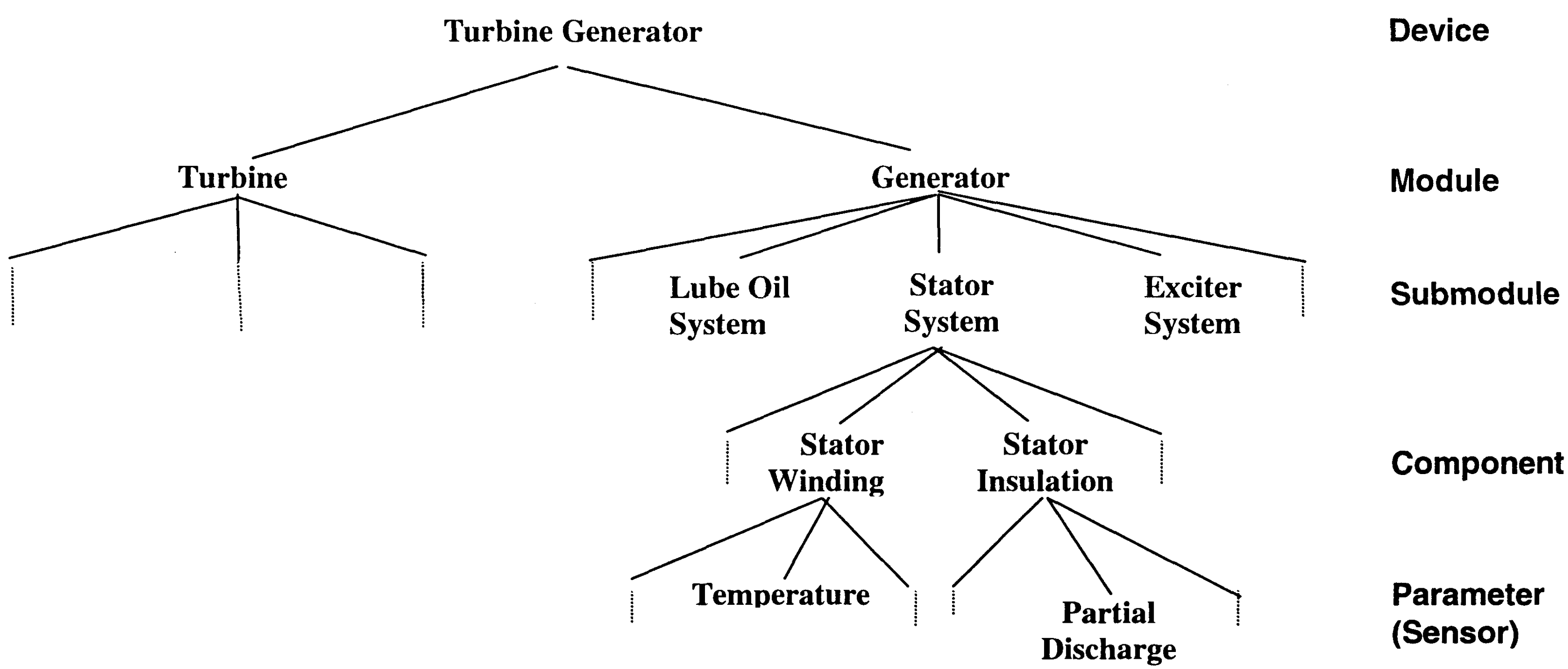
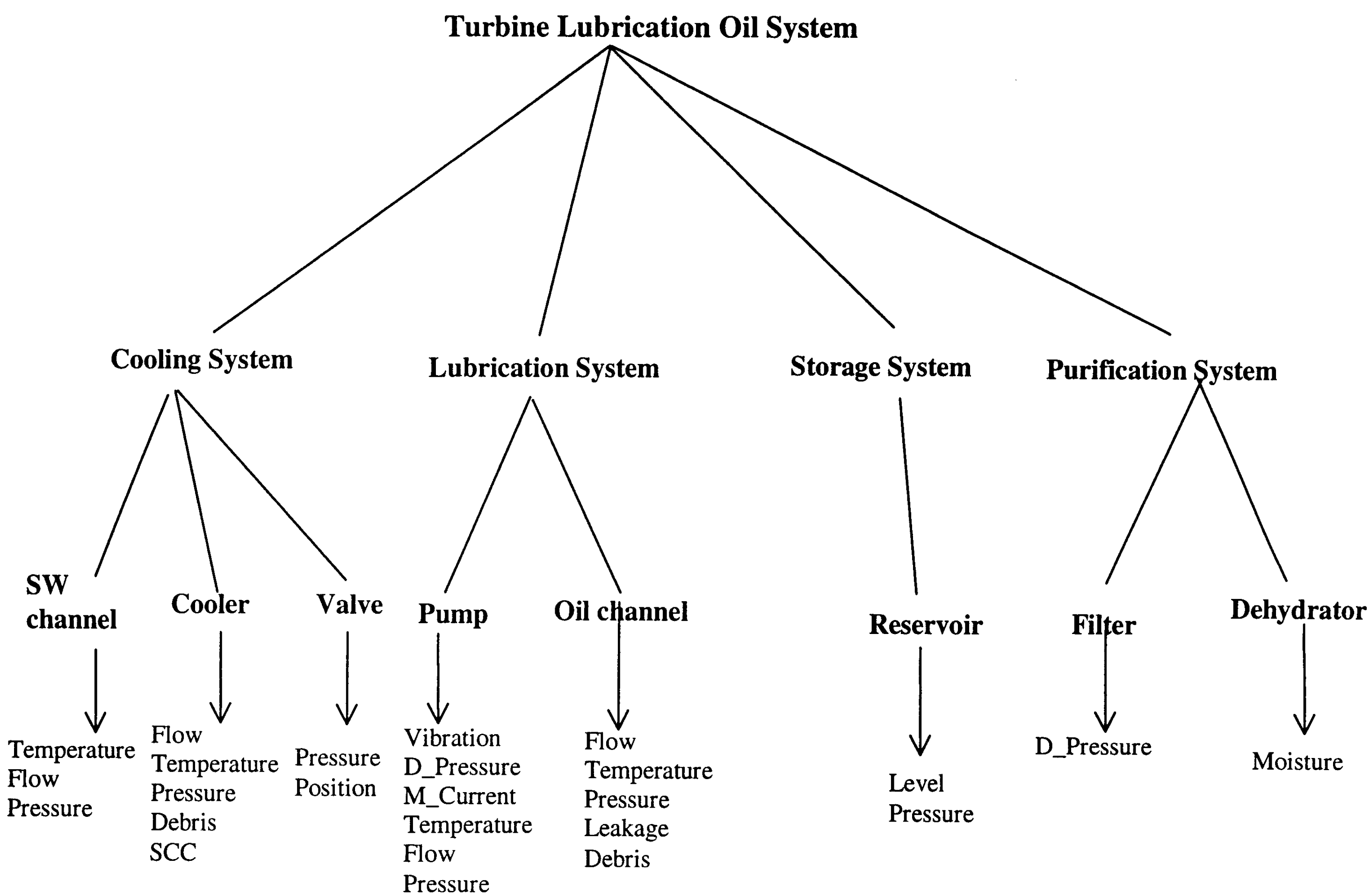
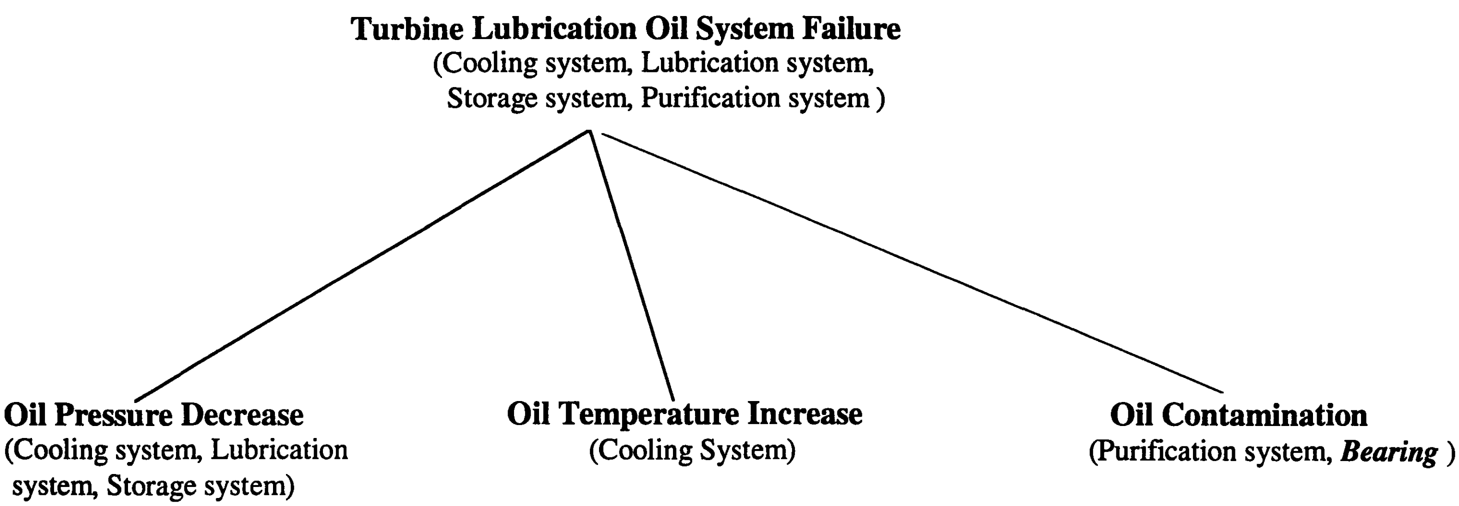


Figure 3.2 Elements of a Structural System Hierarchy in the Turbine Generator



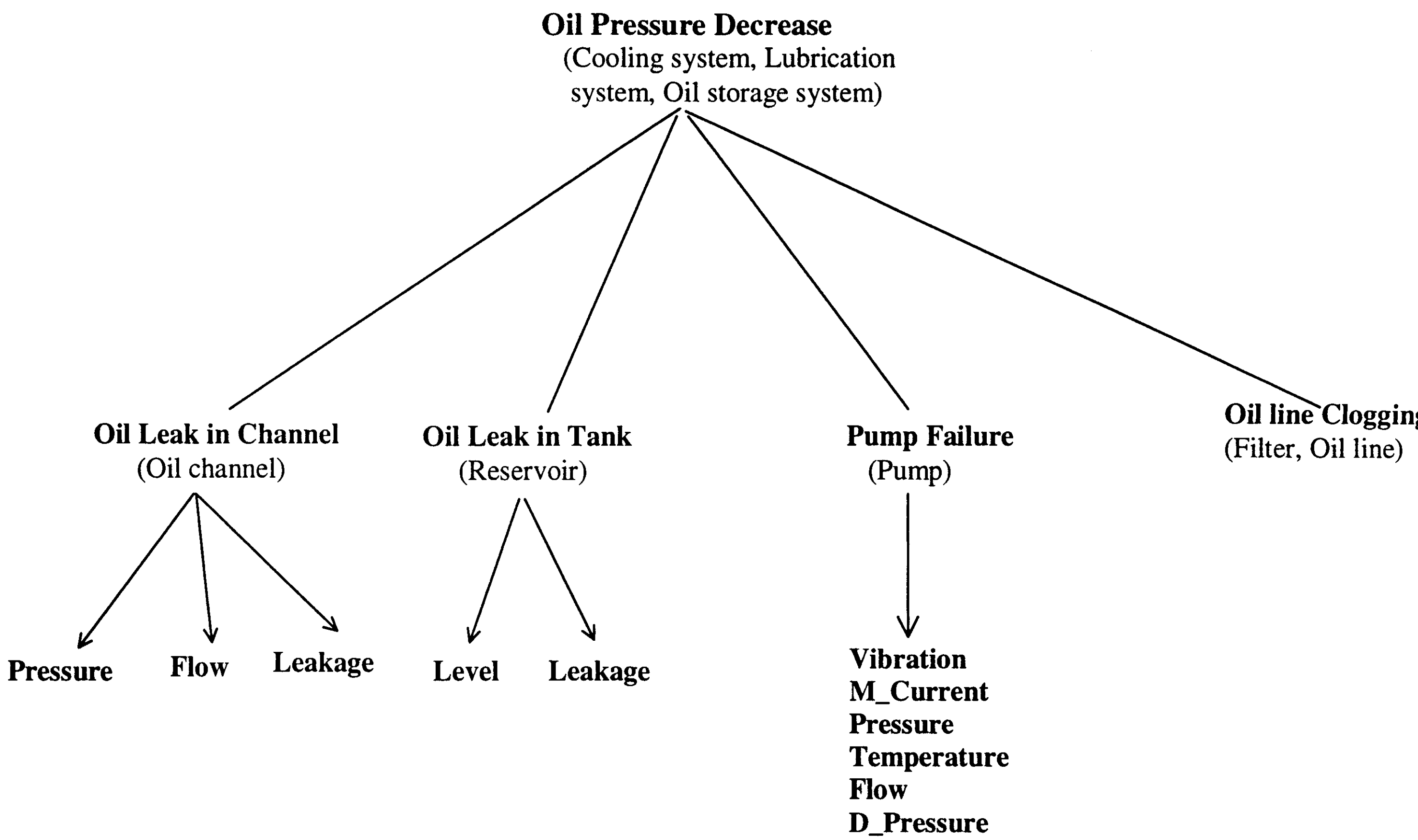
Legend,
SCC: Stress Corrosion Cracking
M_Current: Motor Current
D_Pressure: Differential Pressure

Figure 3.3 Structural System Hierarchy for the Turbine Lubrication Oil System



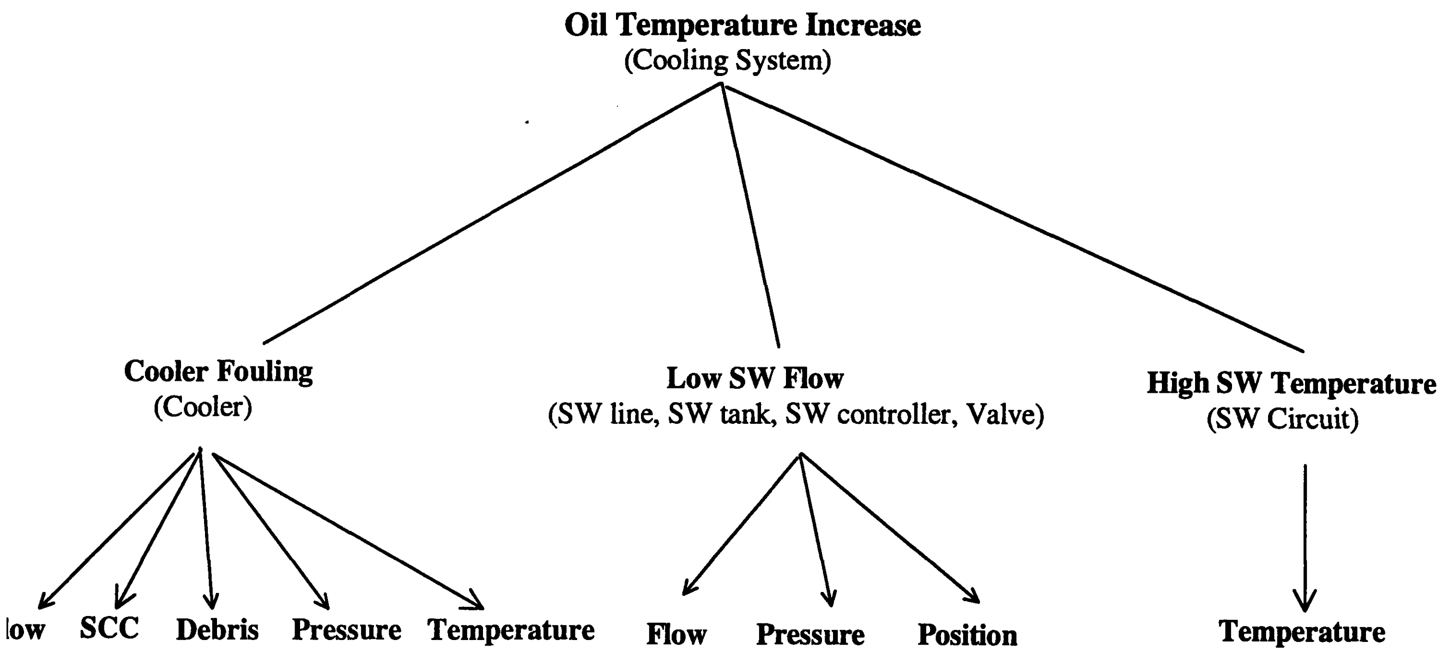
Note: An italic letter "*Bearing*" listed at the bottom level of this hierarchy indicates that the detailed information concerning that system is listed in another hierarchy.

Figure 3.4-1 Functional System Hierarchy for the Turbine Lubrication Oil System



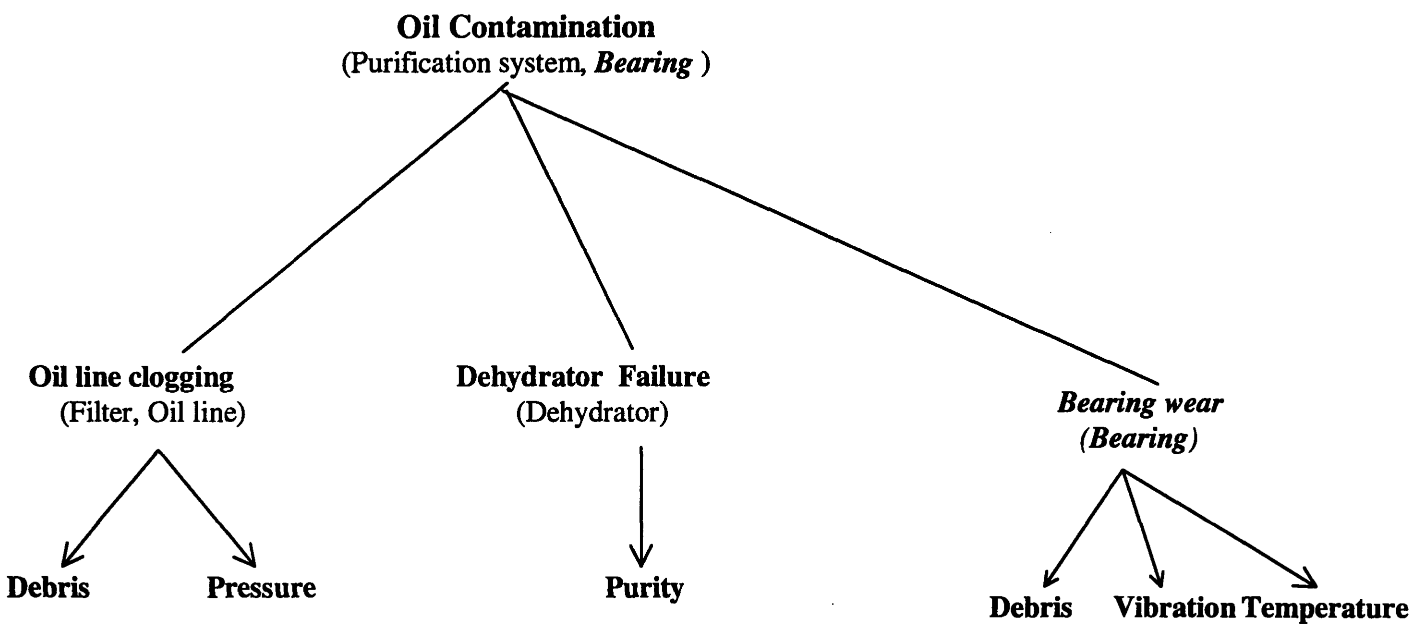
Legend,
M_Current: Motor Current
D_Pressure: Differential Pressure

Figure 3.4-2 Functional System Hierarchy for the Turbine Lubrication Oil System



Legend,
SCC: Stress Corrosion Cracking

Figure 3.4-3 Functional System Hierarchy for the Turbine Lubrication Oil System



Note: An italic letter "*Bearing*" listed at the bottom level of this hierarchy indicates that the detailed information concerning that system is listed in another hierarchy.

Figure 3.4-4 Functional System Hierarchy for the Turbine Lubrication Oil System

Table 3.1 Fault-Symptom Matrix for Bearing, Shaft and Lubrication Oil System

Fault	Temp	Flow	Leak	Purity	Debris	Vibration	Pressure	Humidity	Position
A-1						Y			
B- 1	Y	Y	Y		Y	Y			
C-1, C-2		Y					Y		
C-3	Y	Y	Y			Y	Y		
C-4	Y	Y			Y		Y		
C-5	Y	Y					Y		
C-6	Y								
C-7		Y		Y	Y		Y		
C-8				Y				Y	
C-9							Y		Y
D-1							Y		
D-2	Y								
D-3				Y	Y			Y	

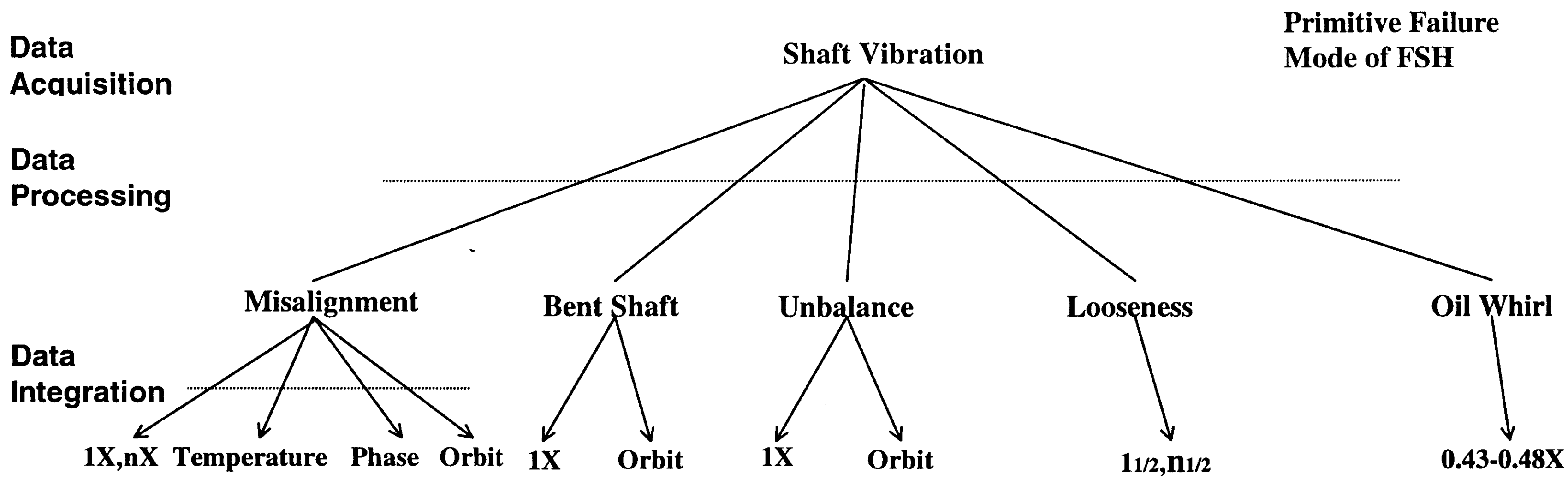
A-1: Shaft vibration
B-1: Bearing damage
C-1: Oil leak in oil path
C-2: Oil leak in tank
C-3 : Oil pump failure
C-4: Cooler fouling
C-5: Low service water flow
C-6: High service water temperature
C-7: Oil line clogging
C-8: Dehydrator failure
C-9: Valve Failure
D-1:Oil Pressure Decrease
D-2: Oil Temp Increase
D-3: Oil Contamination
Y: Yes

Table 3.2 Sensor Selection Criteria

Monitoring Parameter	Sensor Type	Predictive Monitoring	On-line Monitoring	Technical Status	Program Requirement	Data Processing Equipment
Temperature	RTD	Y	Y	D		
	Thermocouple	Y	Y	D		
	Fiber optic sensor	Y	Y	D		
Flow	Flow meter	Y	Y	D		
Humidity	Dew point monitor	Y	Y	D		
Purity	Purity sensor	Y	Y	D		
Leakage	Leakage detector	Y	Y	D		
Pressure	Pressure sensor	Y	Y	D		
Pyrolysis	GCCM	Y	Y	D		
Debris	Ferrography	Y	N	D		
	On-line wear debris sensor	Y	N	R	Y	
Partial discharge	Current transformer	Y	Y	D	Y	Y
	Capacitive coupling	Y	N	D	Y	Y
	Rogowski coil	Y	Y	D	Y	Y
RF	RF monitor	Y	Y	D		
Flux	Measuring coil	Y	Y	D		
Level	Level sensor	Y	Y	D		
Conductivity	Conductivity cell	Y	Y	D		
Valve position	Position sensor	Y	Y	D		
Vibration	Accelerometer	Y	Y	A	Y	Y
	Proximity probe	Y	Y	A	Y	Y
	Fiber optic sensor	Y	Y	R		
Phase	Keyphasor	Y	Y	A		
Motor current	Rogowski coil	Y	Y	R	Y	Y

(RTD : Resistance Temperature Detector, RF : Radio Frequency, GCCM : Generator Core Condition Monitor
Y : Yes, N: No, D: Development , R: Research, A: Advancement)

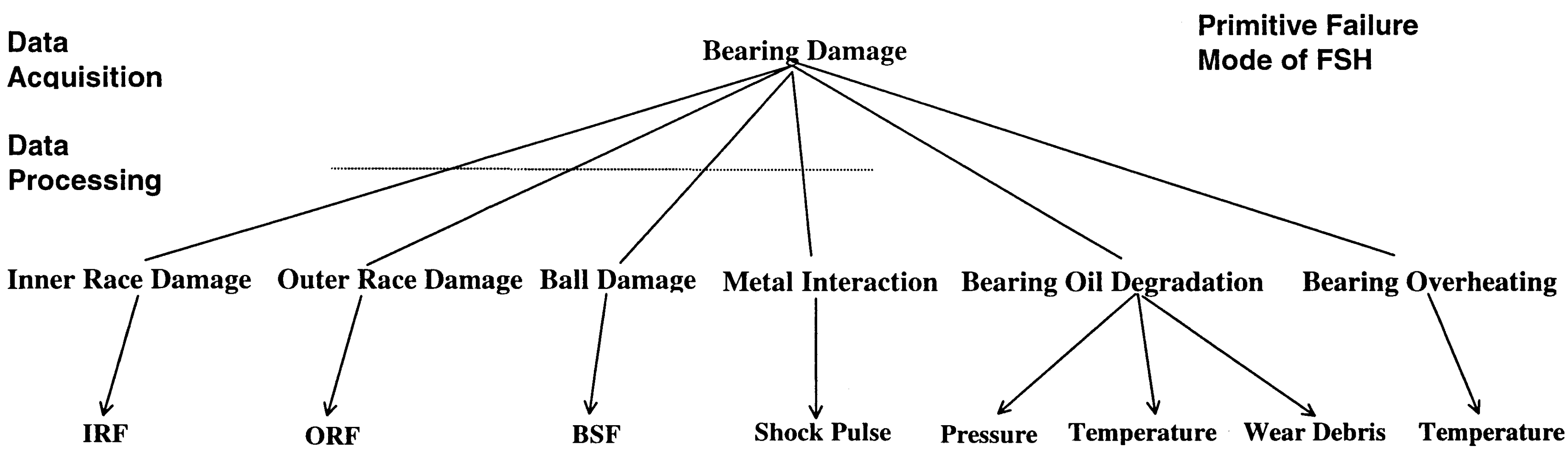
Sensors: Proximity Probe, Keyphasor



Legend,
nx: Multiplier of shaft rotational frequency
FSH: Functional system hierarchy

Figure 3.5 FSH and Further Breakdown of by Use of Advanced Instrumentation Techniques in Shaft Vibration Analysis

Sensor: Accelerometer



(IRF : Inner race defect frequency , ORF : Outer race defect frequency ,
BSF : Ball sphere defect frequency, FSH: Functional system hierarchy)

Figure 3.6 FSH and Further Breakdown of by Use of Advanced Instrumentation Techniques in Bearing Damage Analysis

3.4 Application of a Structural System Hierarchy and a Functional System Hierarchy into Sensor Network Development for Target System

3.4.1 Application into the Turbine Generator

Structural system hierarchies (SSHs) and Functional system hierarchies (FSHs) of stator winding, stator core, rotor, gland seal system, auxiliary water cooling system, and auxiliary hydrogen system in the turbine generator as well as entire subordinate systems of reactor coolant pumps have been configured as a prelude for the development of comprehensive sensor networks. As reference materials for this work, fault trees, NRC database, NPRDS (INPO 97), and other power plant engineering references have been used for helping to deriving such abstraction methods. The application of this method to target systems has been judged to be systematic and appropriate, reflecting discussions with system experts. We note that the listed monitoring parameters shown at the bottom level of SSHs and FSHs are obtained from the corresponding fault-symptom matrix, an example of which is shown in Section 3.3.2. The final developments regarding sensor type selection and location are shown in Chapter 5.

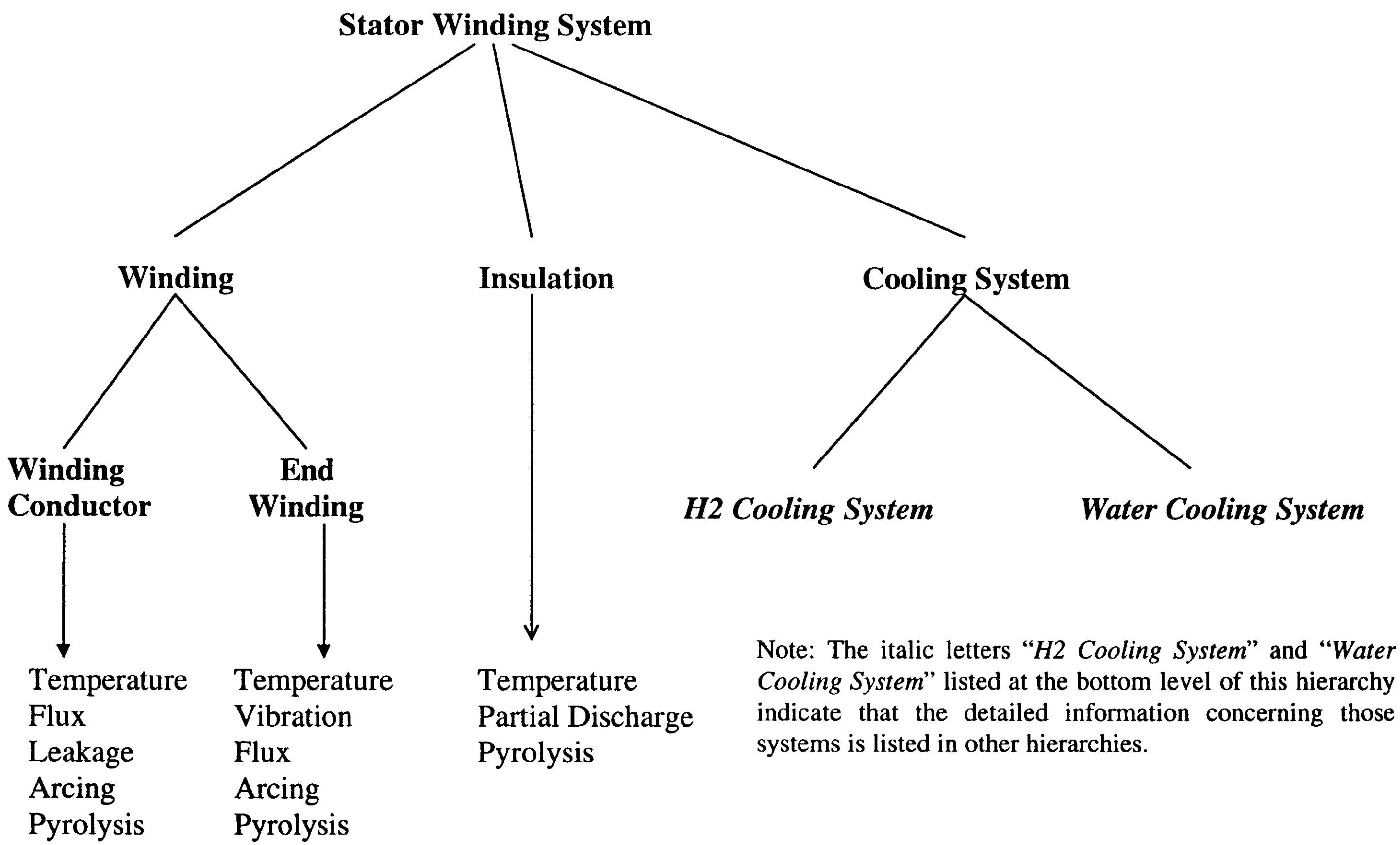
All hierarchies relating to the TG are shown in Figures 3.7 to 3.17. Figure 3.7 represent the SSH of the generator stator winding system. The italic letters "*H2 Cooling System*" and "*Water Cooling System*" listed at the bottom level of this hierarchy indicate that the detailed information concerning those systems is listed in other corresponding Figures 3.9 and 3.16, respectively.

Figure 3.8 illustrates the FSH for the generator stator winding system. The SSH for the hydrogen auxiliary system is illustrated in Figure 3.9. Figures 3.10-1, 3.10-2 and 3.10-3 show the FSHs for the hydrogen auxiliary system. An italic letter "*Gland Seal*" in Figure 3.10-1 depicts how this approach reflects the interrelationships among various components. That information is decomposed in Figure 3.11, which provides the SSH of the gland seal system. Figures 3.12-1 and 3.12-2 illustrate FSHs for the gland seal system.

Figures 3.13 and 3.14 shows the SSH and the FSH for the generator rotor system, respectively. Both of the SSH and the FSH of the generator stator core frame are shown in Figure 3.15. Figures 3.16 and 3.17 illustrate the SSH and the FSH for the SCCW.

3.4.2 Application into the Reactor Coolant Pump

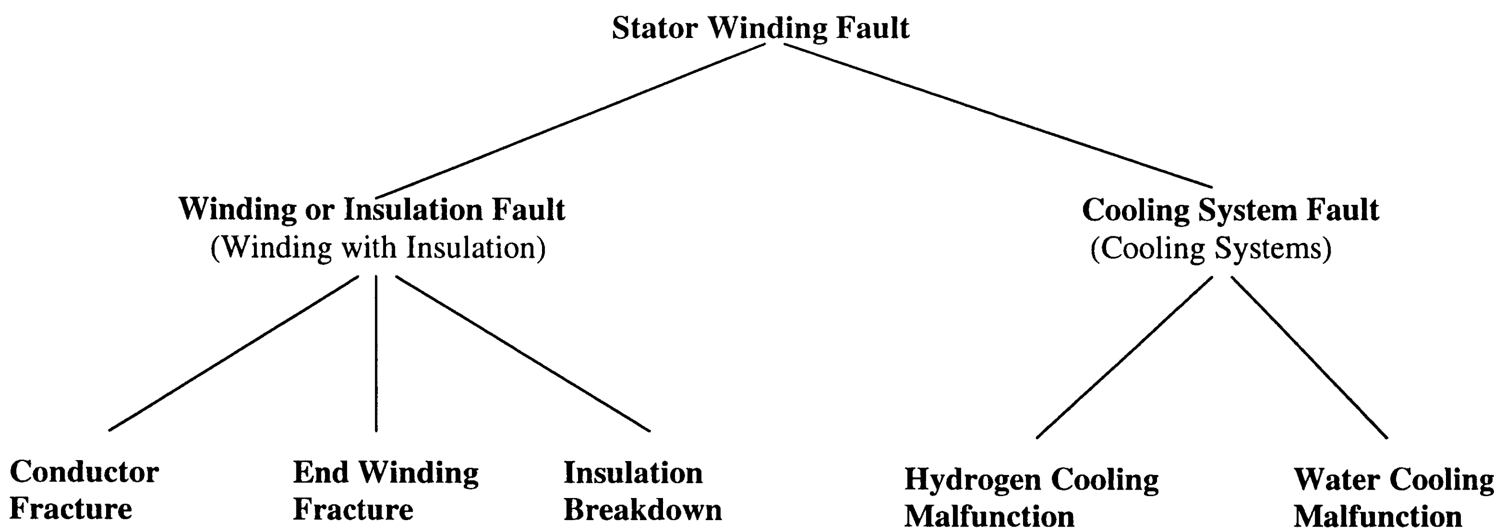
All hierarchies relating to the RCP are shown in Figures 3.18 to 3.24. Figure 3.18 shows the SSH of the motor, which is broken down to stator core, stator windings, rotor, airgap, and bearing. Figures 3.19 and 3.20 illustrate the FSHs for these subordinate motor components listed in Figure 3.18. Figures 3.20 includes the decomposition of failure modes by advanced instrumentation steps in the bearing. Figure 3.21 shows the SSH of bearing components and lubrication oil subordinate system. Figure 3.22-1, 3.22-2, 3.22-3, and 3.22-4 illustrate the FSHs of the bearing lubrication oil system. Figures 3.23 and 3.24 show the SSH and FSH of the seal component with the seal injection system, respectively. Note that italic letters indicate interrelationships among these hierarchies.



Note: The italic letters "*H2 Cooling System*" and "*Water Cooling System*" listed at the bottom level of this hierarchy indicate that the detailed information concerning those systems is listed in other hierarchies.

Legend, H2: Hydrogen
SSH: Structural System Hierarchy

Figure 3.7 SSH of the Generator Stator Winding System



FSH: Functional System Hierarchy

Figure 3.8 FSH of the Generator Stator Winding System

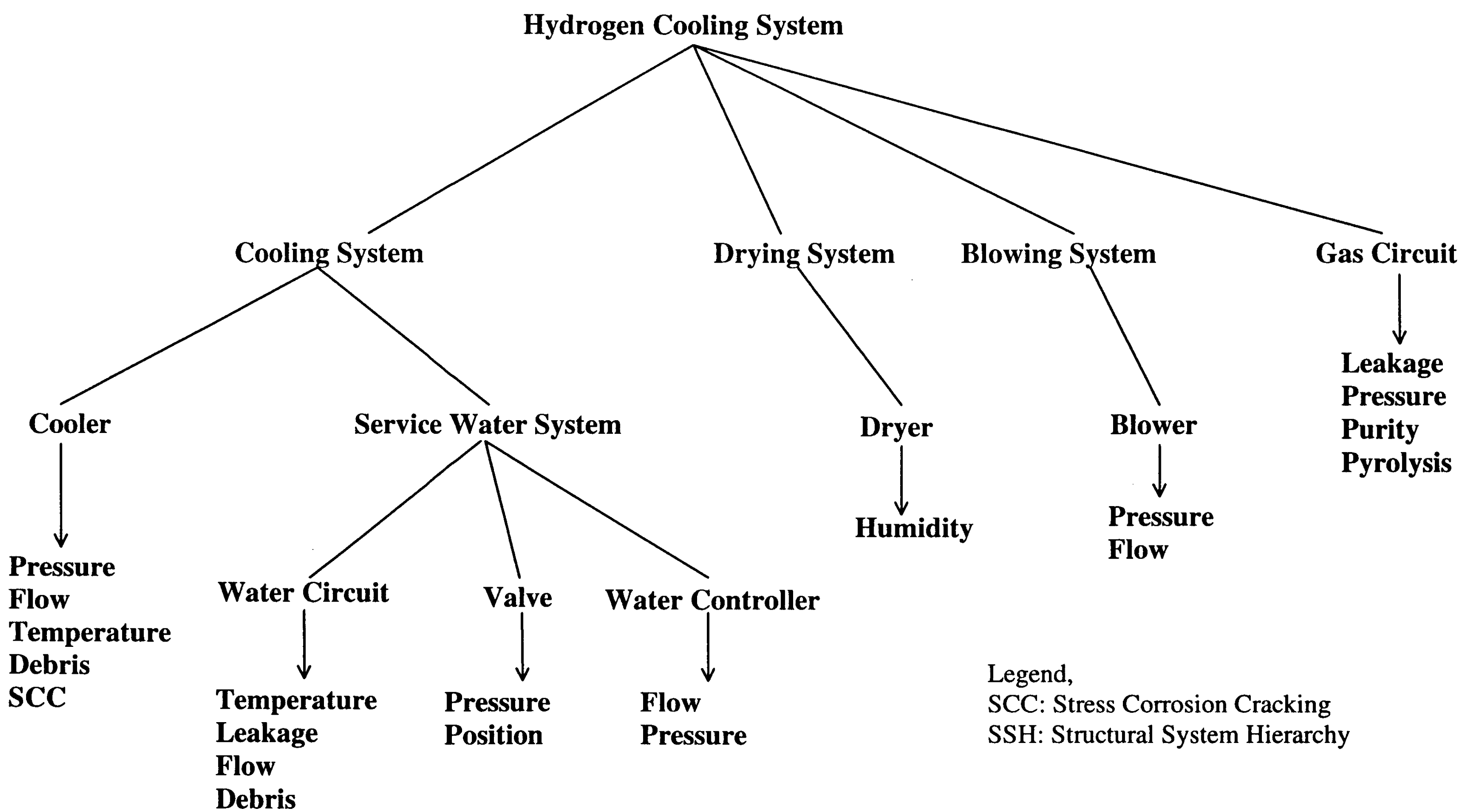


Figure 3.9 SSH of the Generator Auxiliary Hydrogen Cooling System

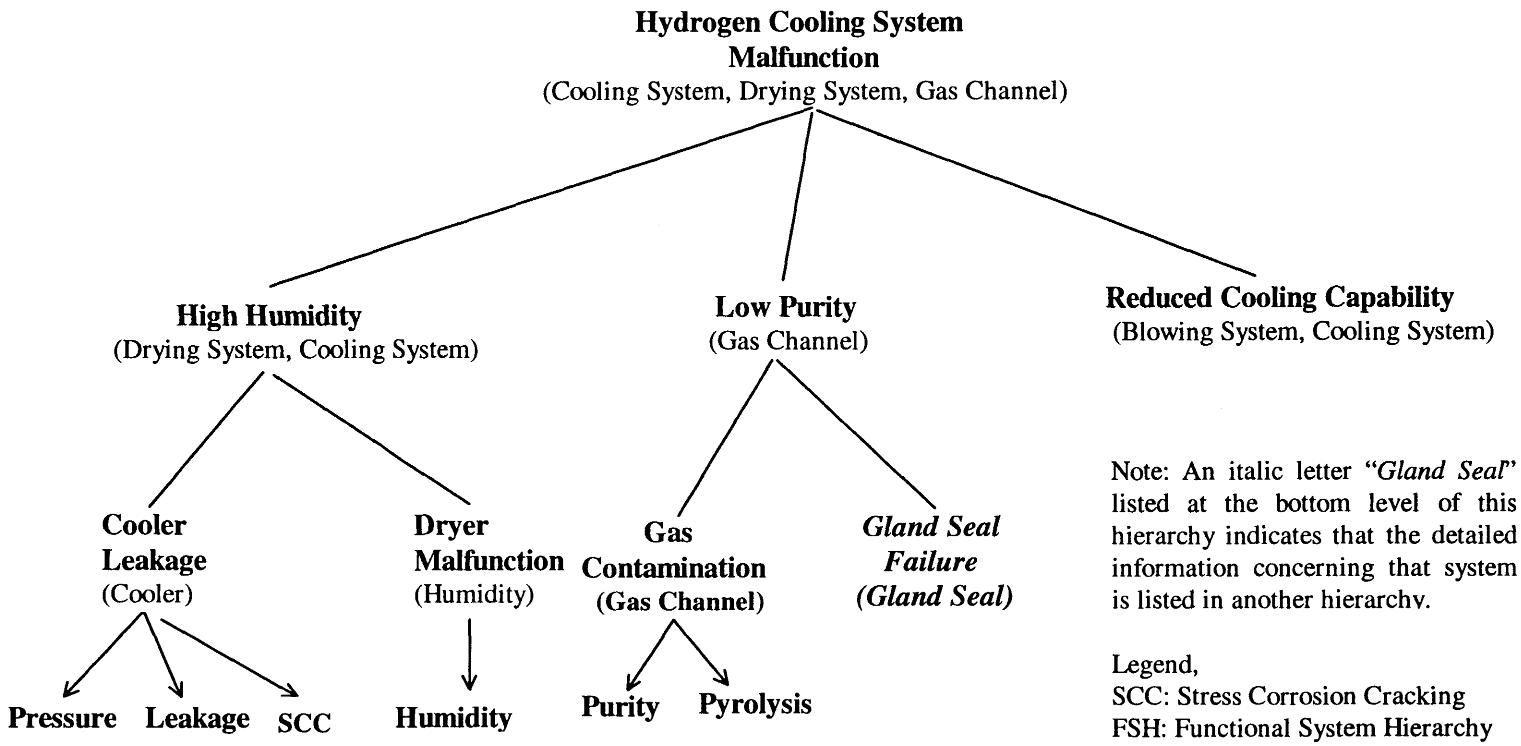
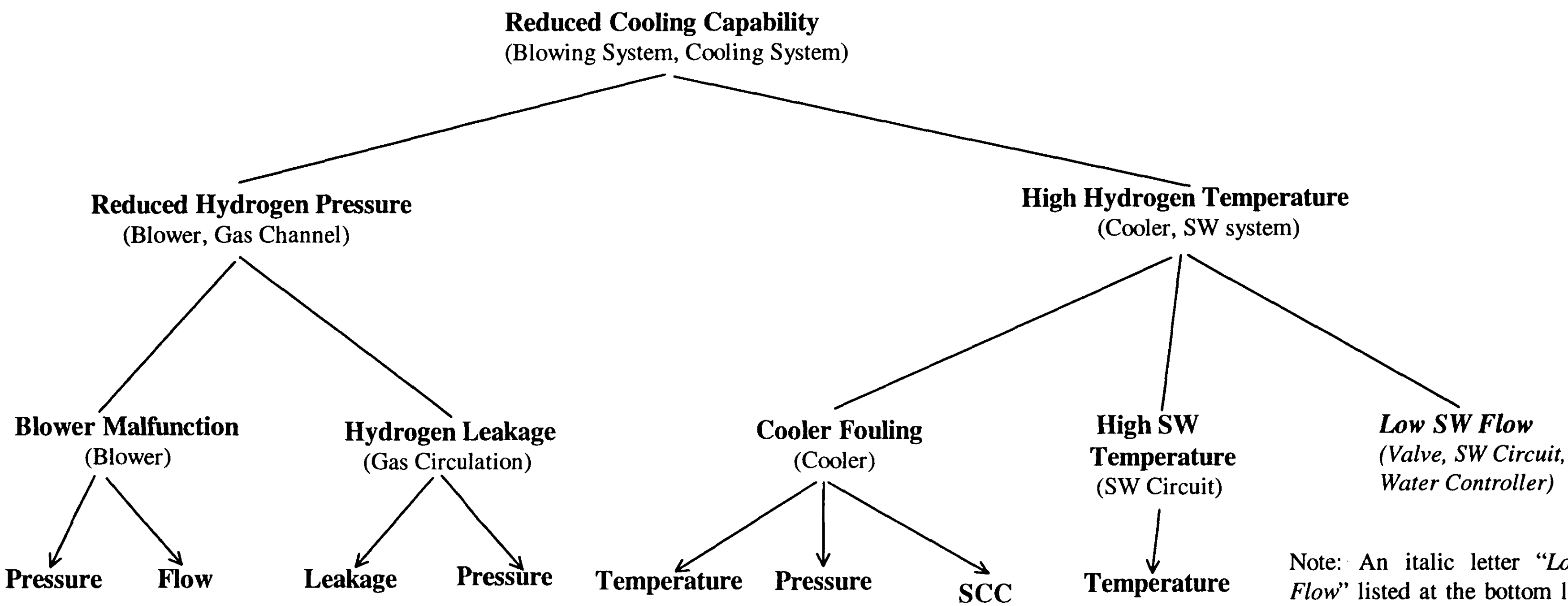


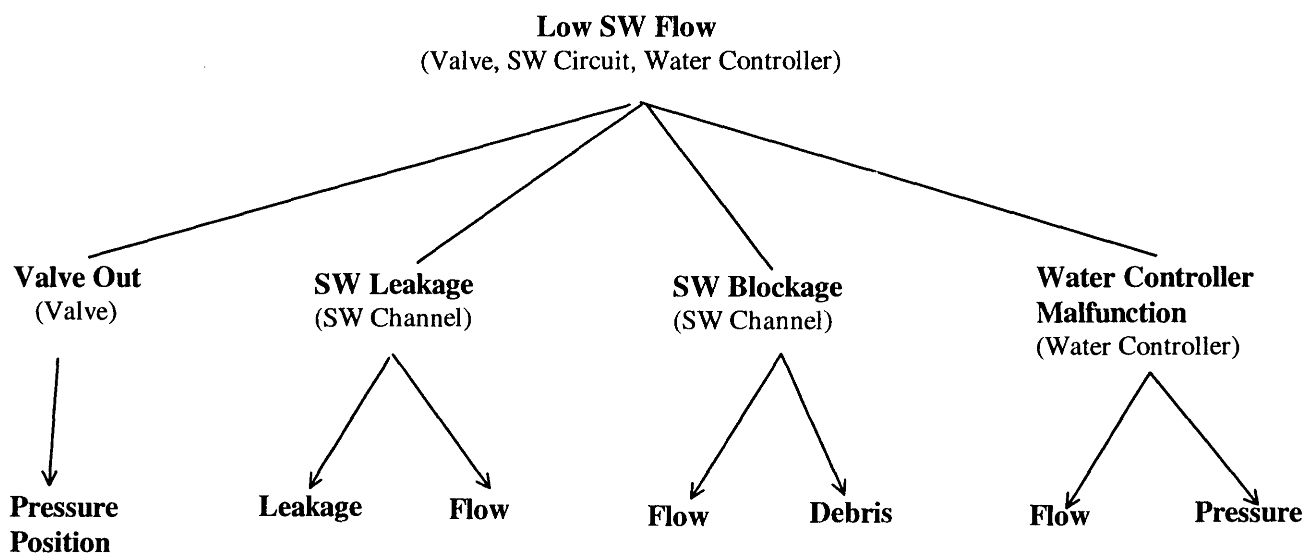
Figure 3.10-1 FSH of the Generator Auxiliary Hydrogen Cooling System



Note: An italic letter "*Low SW Flow*" listed at the bottom level of this hierarchy indicates that its detailed information is listed in other hierarchies.

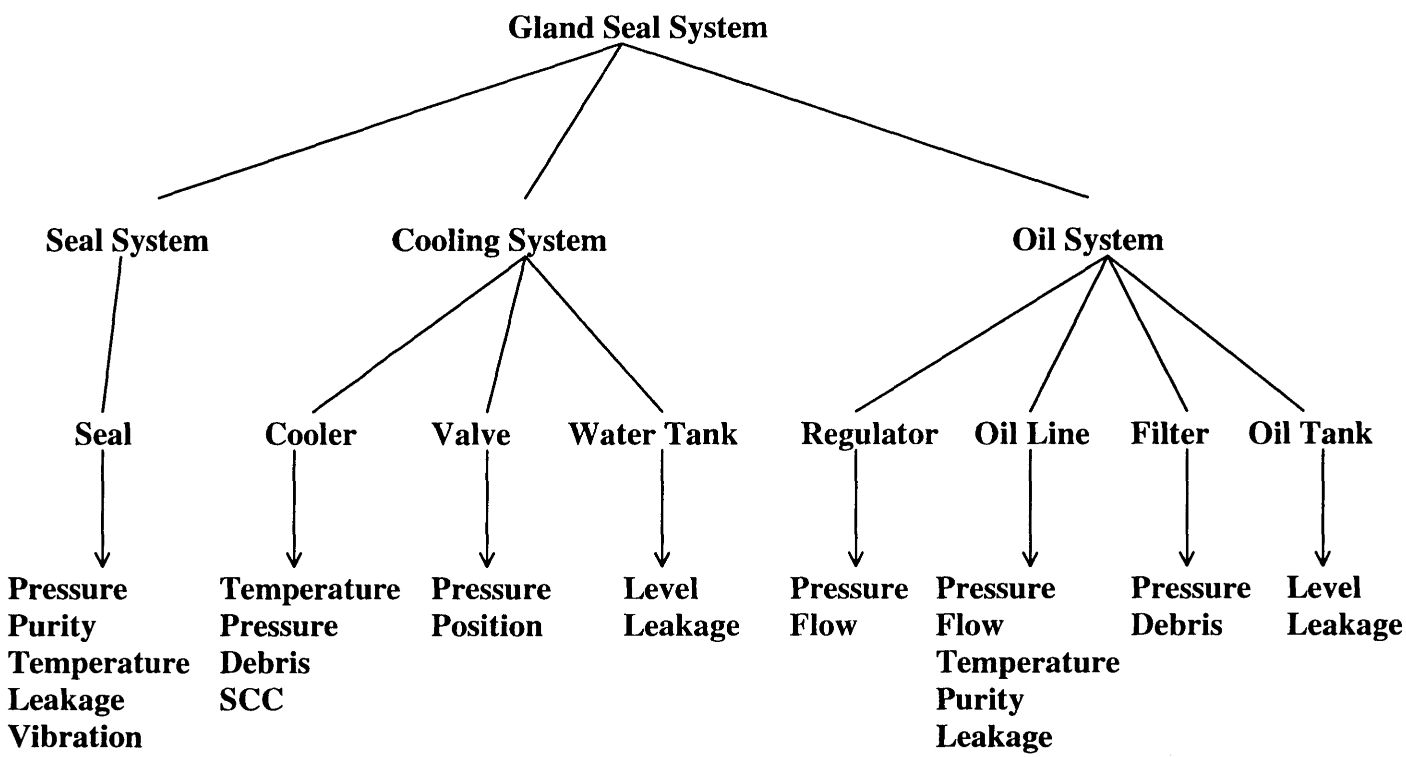
Legend,
SCC: Stress Corrosion Cracking
SW: Service Water

Figure 3.10-2 FSH of the Generator Auxiliary Hydrogen Cooling System



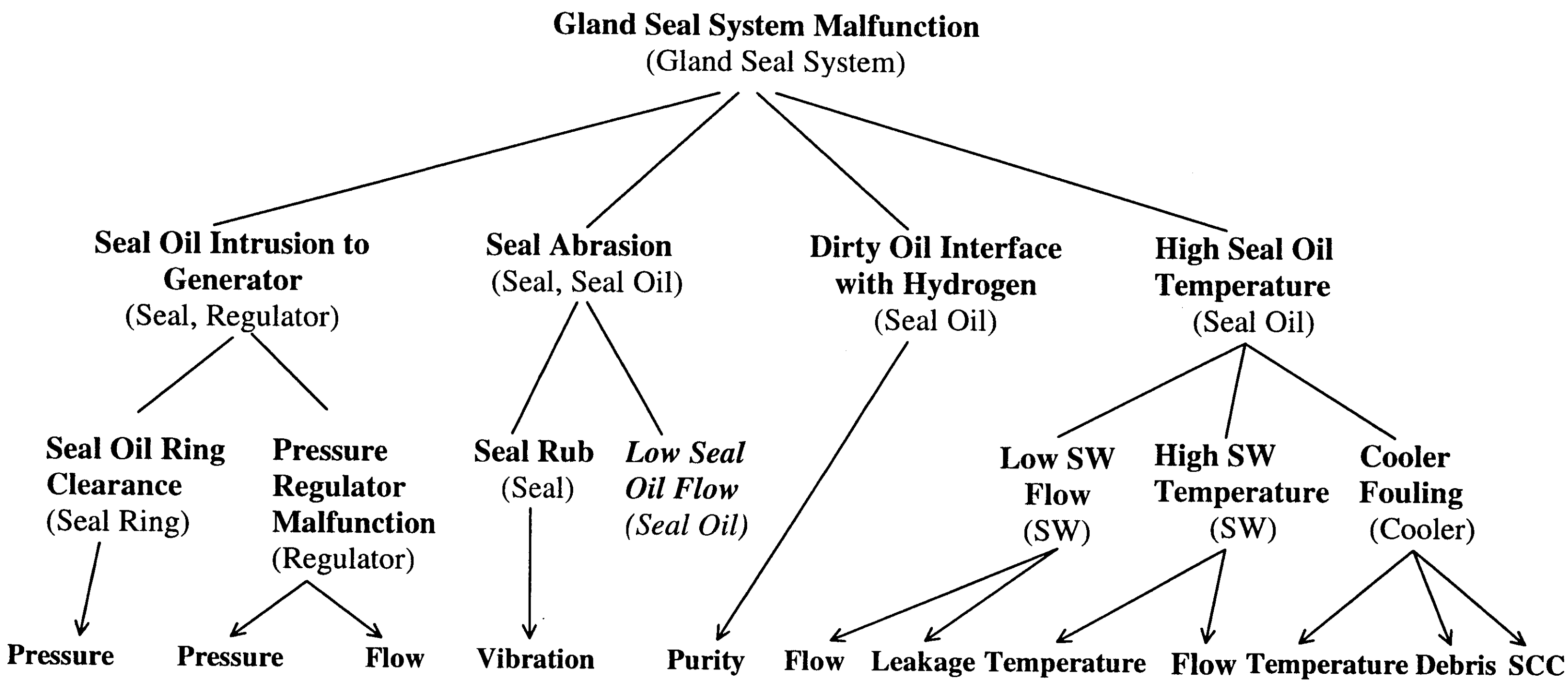
Legend,
SW: Service Water
FSH: Functional System Hierarchy

Figure 3.10-3 FSH of the Generator Auxiliary Hydrogen Cooling System



Legend,
SCC: Stress Corrosion Cracking
SSH: Structural System Hierarchy

Figure 3.11 SSH of the Turbine Gland Seal System



Legend,
SCC: Stress Corrosion Cracking
SW: Service Water
FSH: Functional System Hierarchy

Note: An italic letter "*Low Seal Oil Flow*" depicts how this approach reflects the interrelationships among various components.

Figure 3.12-1 FSH of the Turbine Gland Seal System

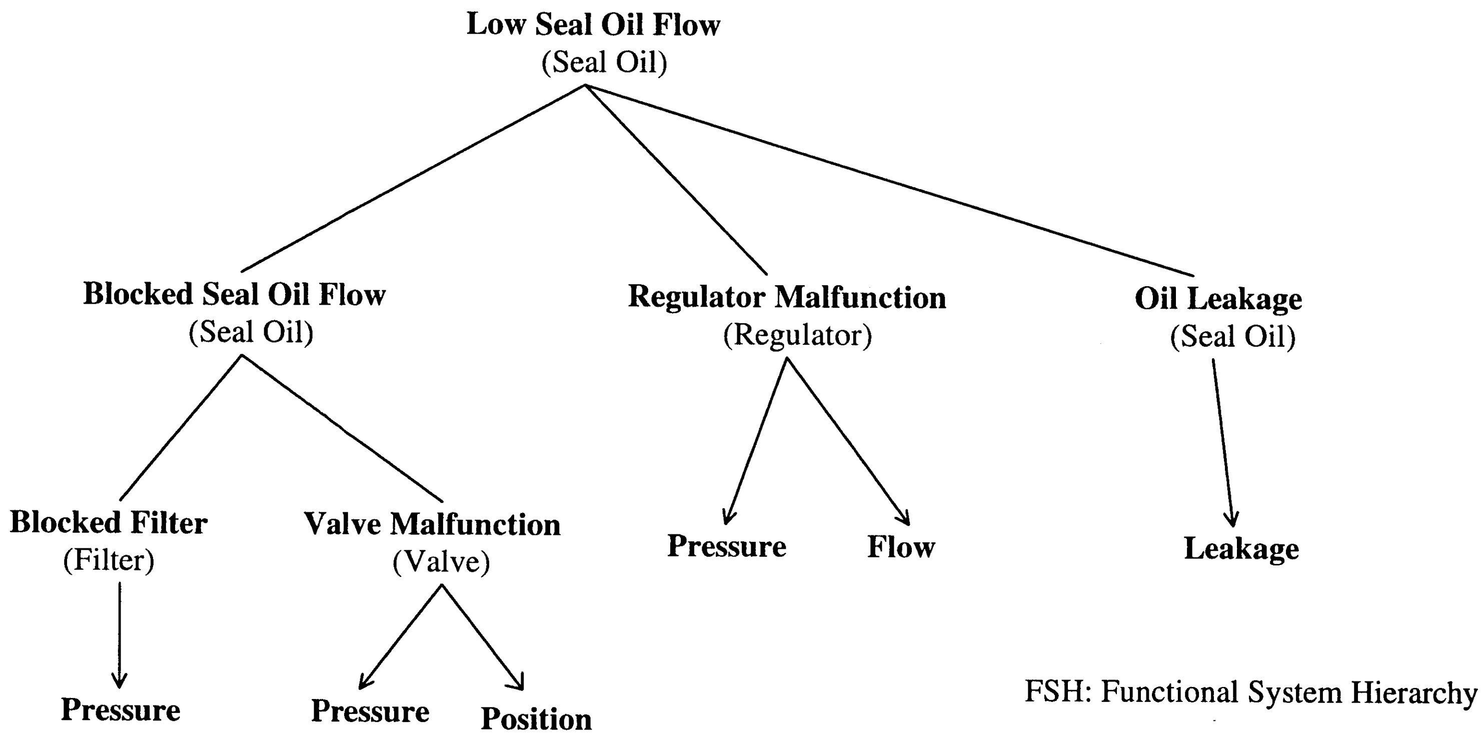
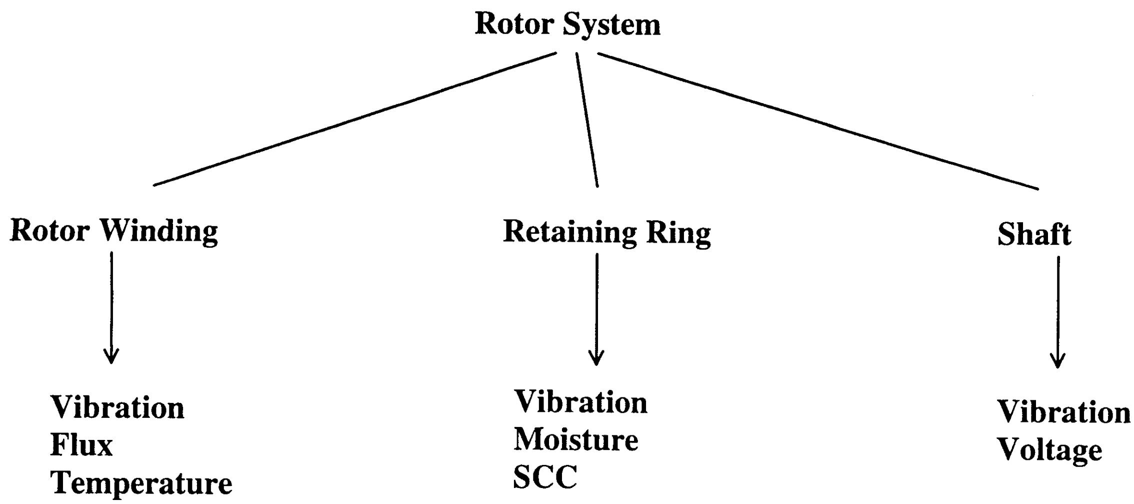
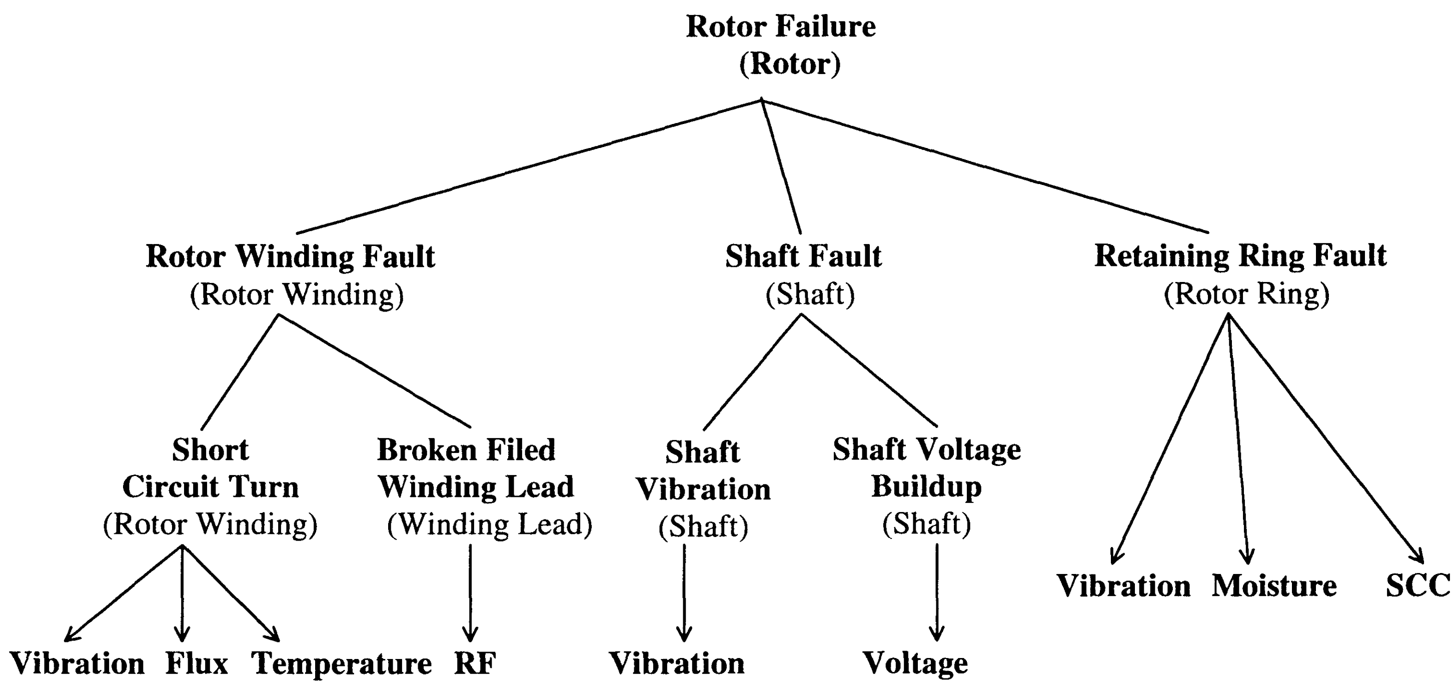


Figure 3.12-2 FSH of the Turbine Gland Seal System



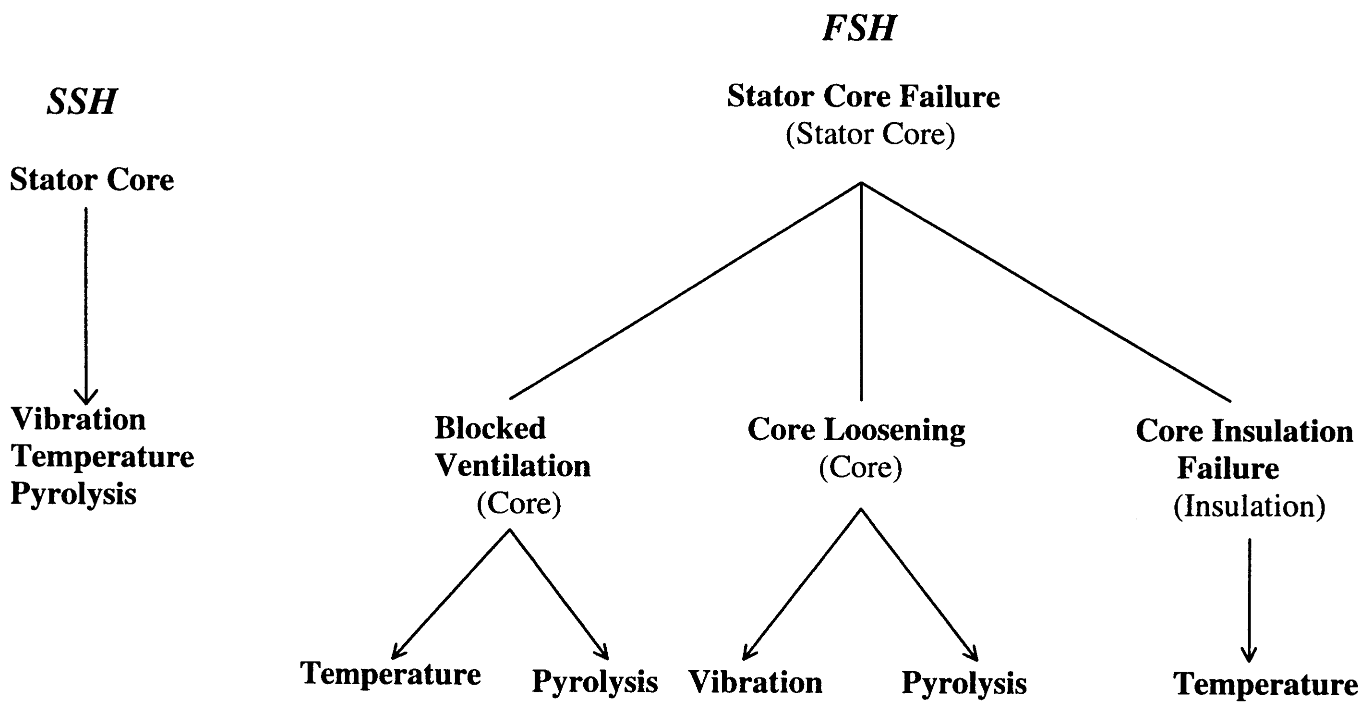
Legend,
SCC: Stress Corrosion Cracking
SSH: Structural System Hierarchy

Figure 3.13 SSH of the Generator Rotor System



Legend,
FSH: Functional System Hierarchy
RF: Radio Frequency
SCC: Stress Corrosion Cracking

Figure 3.14 FSH of the Generator Rotor System



SSH: Structural System Hierarchy
FSH: Functional System Hierarchy

Figure 3.15 SSH and FSH of the Generator Stator Core Frame

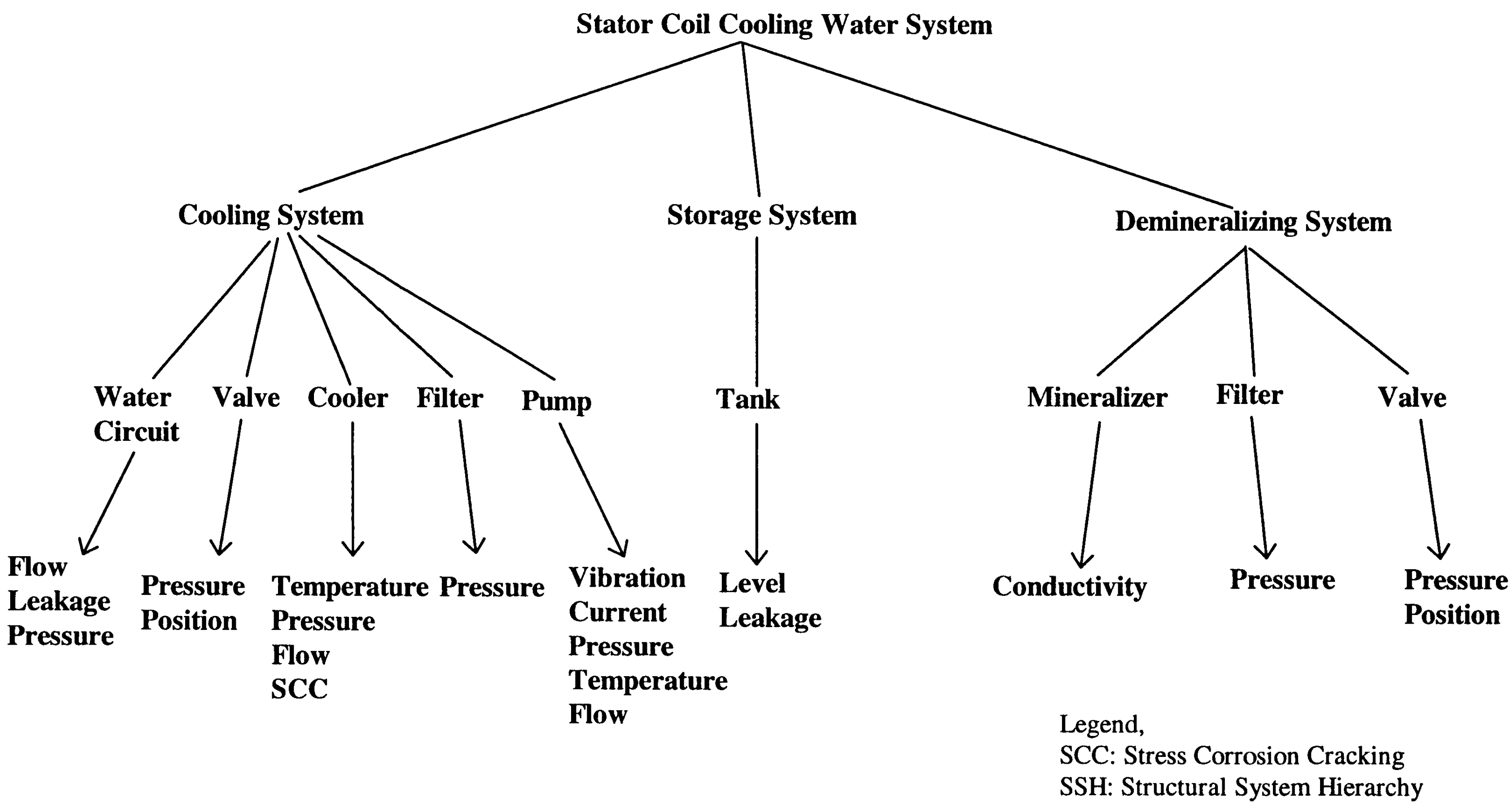
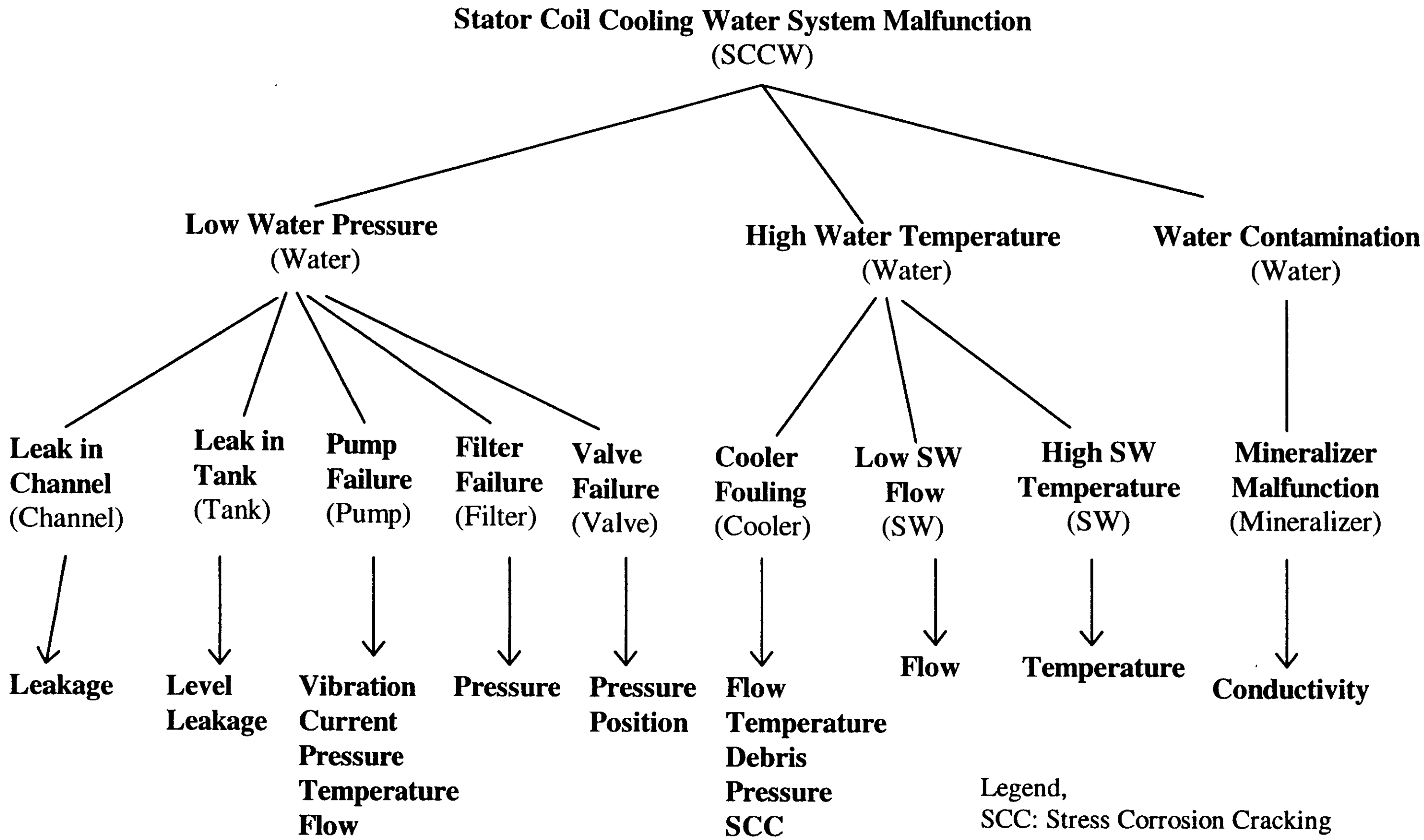


Figure 3.16 SSH of the Generator Stator Coil Cooling Water Auxiliary System



Legend,
SCC: Stress Corrosion Cracking
SCCW: Stator Coil Cooling Water System
SW: Service Water
FSH: Functional System Hierarchy

Figure 3.17 FSH of the Generator Stator Cooling Water Auxiliary System

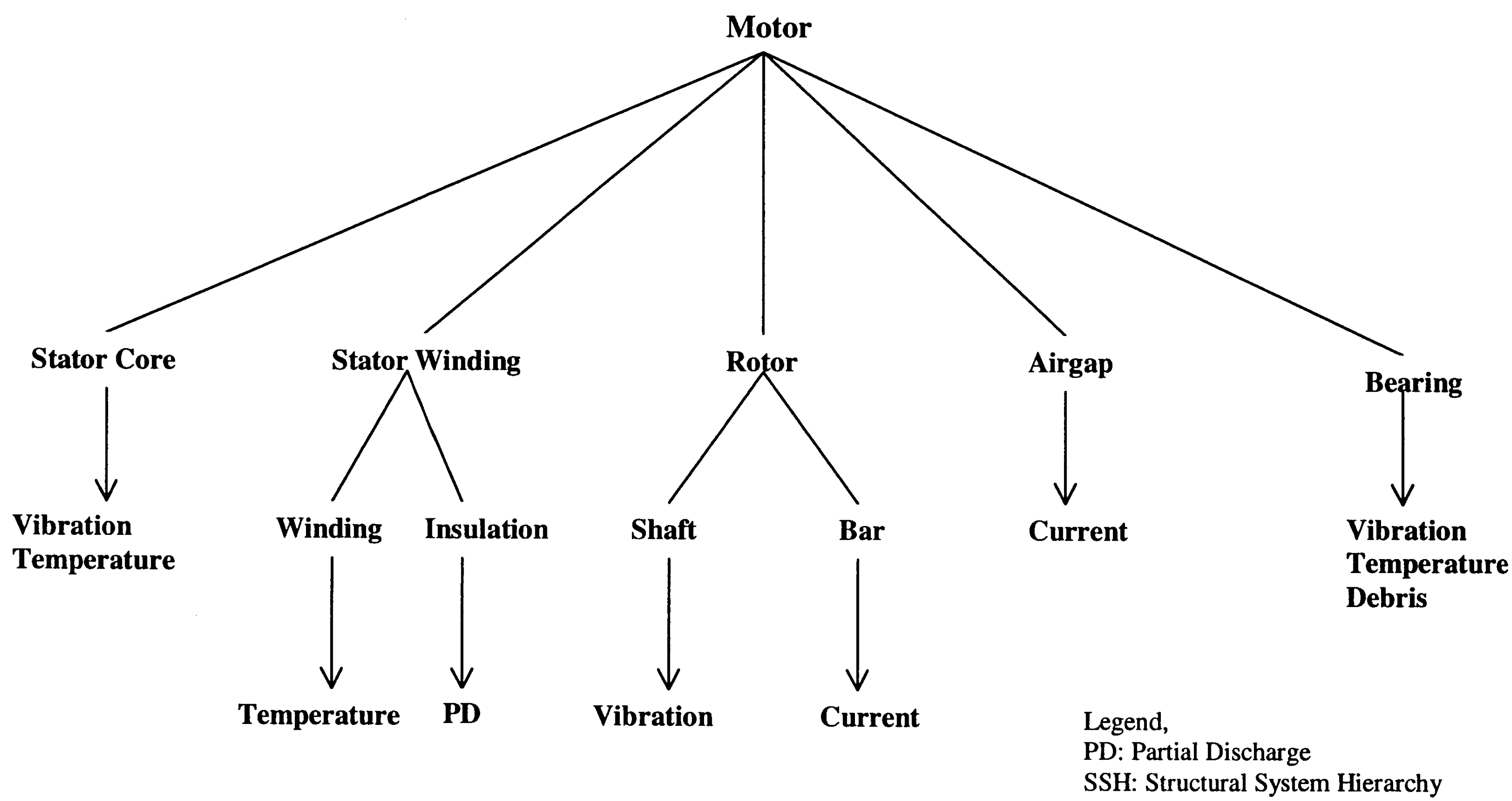


Figure 3.18 SSH of the Motor in the Reactor Coolant Pump

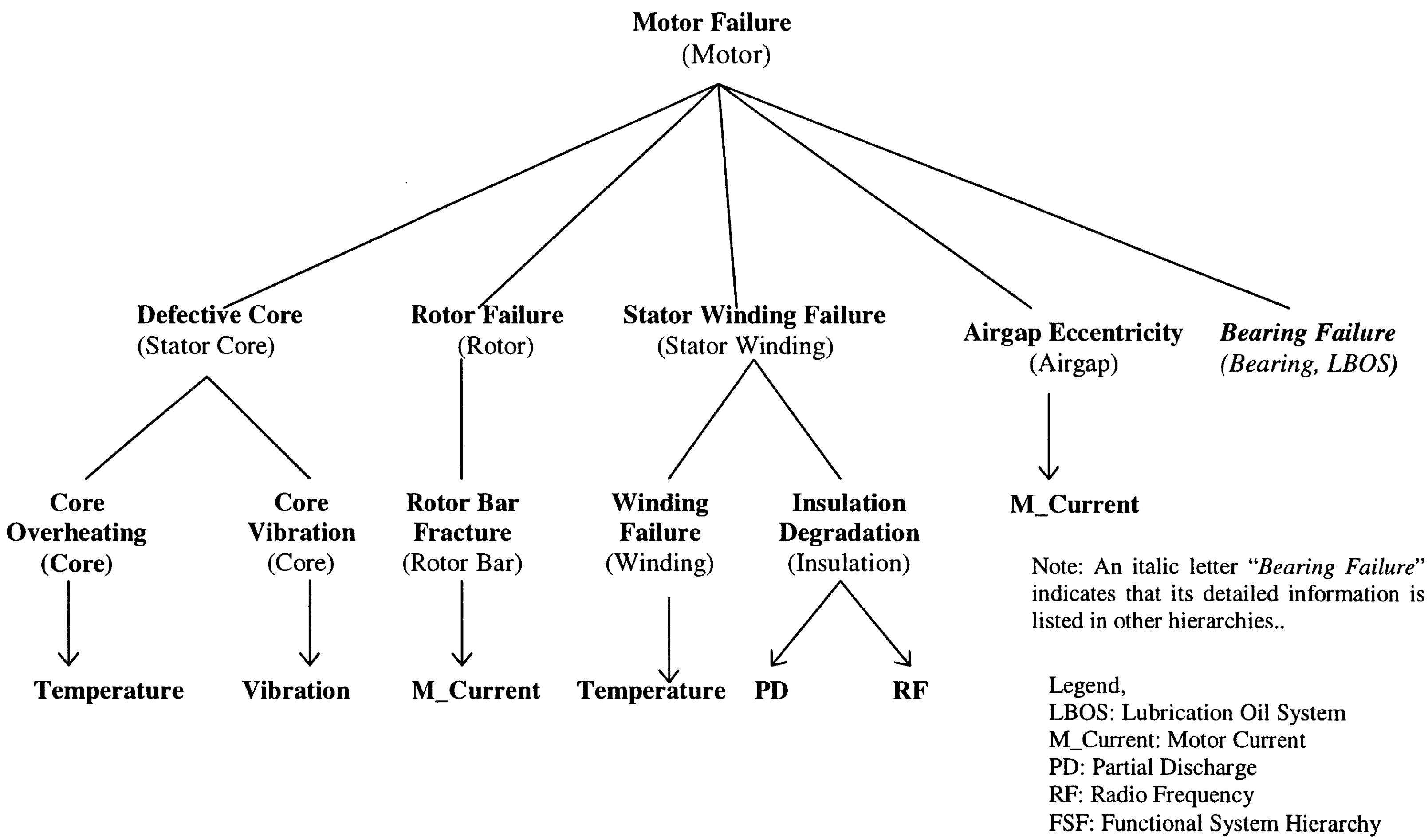
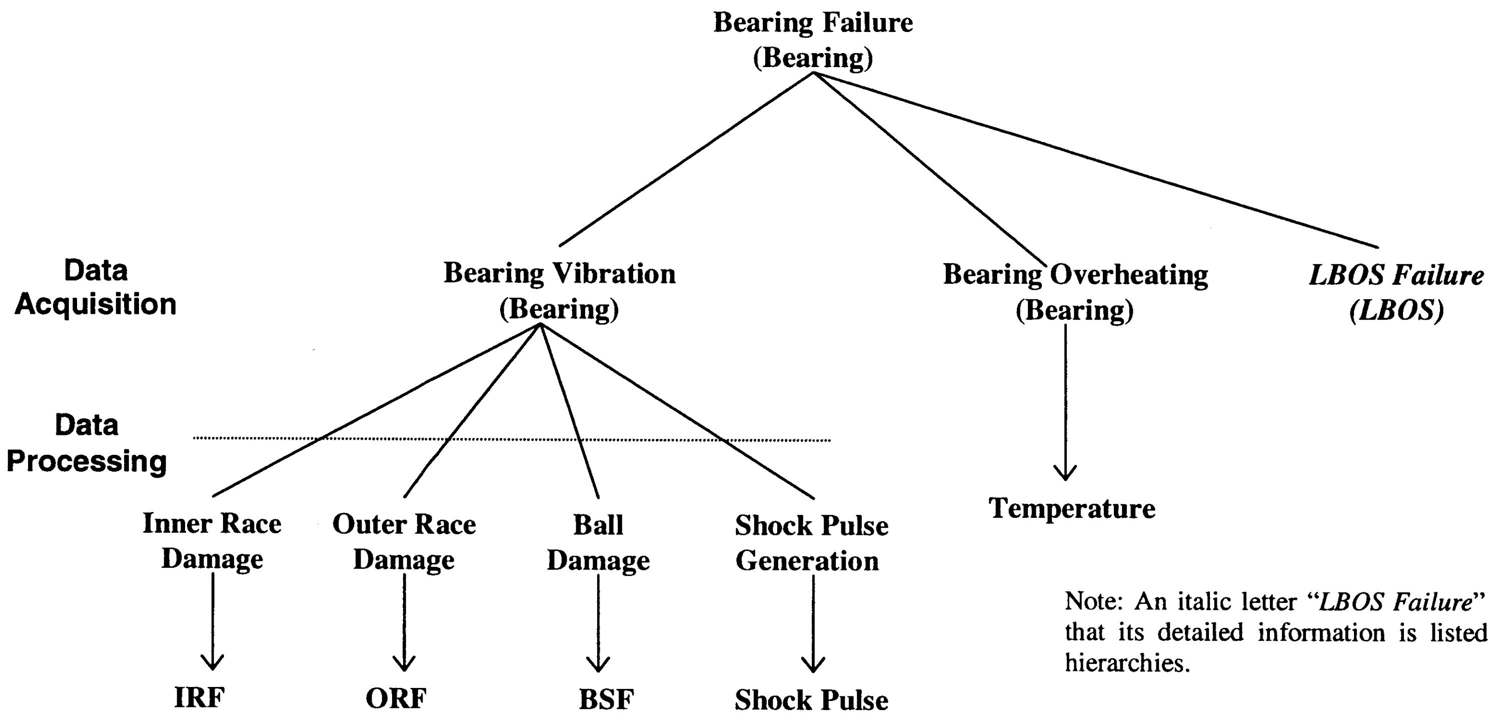


Figure 3.19 FSH of Motor in the Reactor Coolant Pump



Note: An italic letter "*LBOS Failure*" indicates that its detailed information is listed in other hierarchies.

Legend,
BSF: Ball Sphere Defect Frequency
IRF: Inner Race Defect Frequency
ORF: Outer Race Defect Frequency
LBOS: Lubrication Oil System
FSH: Functional System Hierarchy

Figure 3.20 FSH and Further Breakdown by Use of Advanced Instrumentation in RCP Bearing Analysis

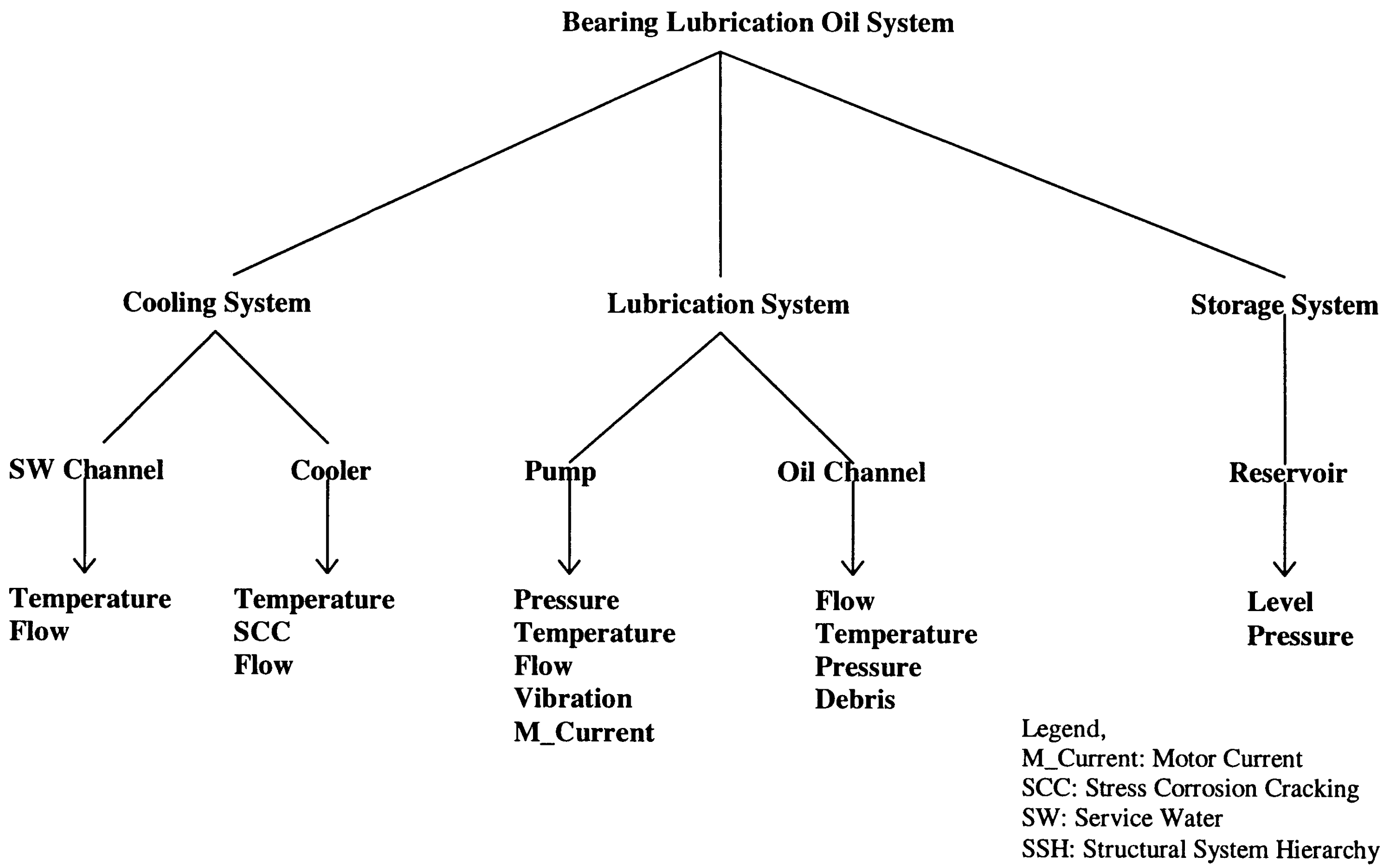
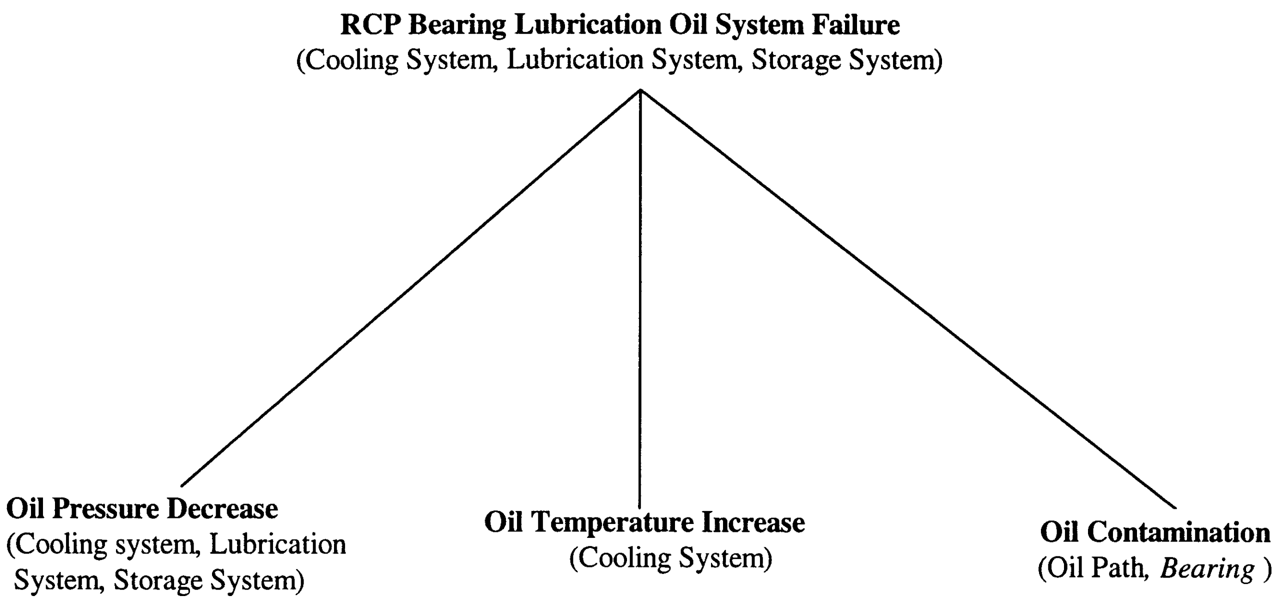


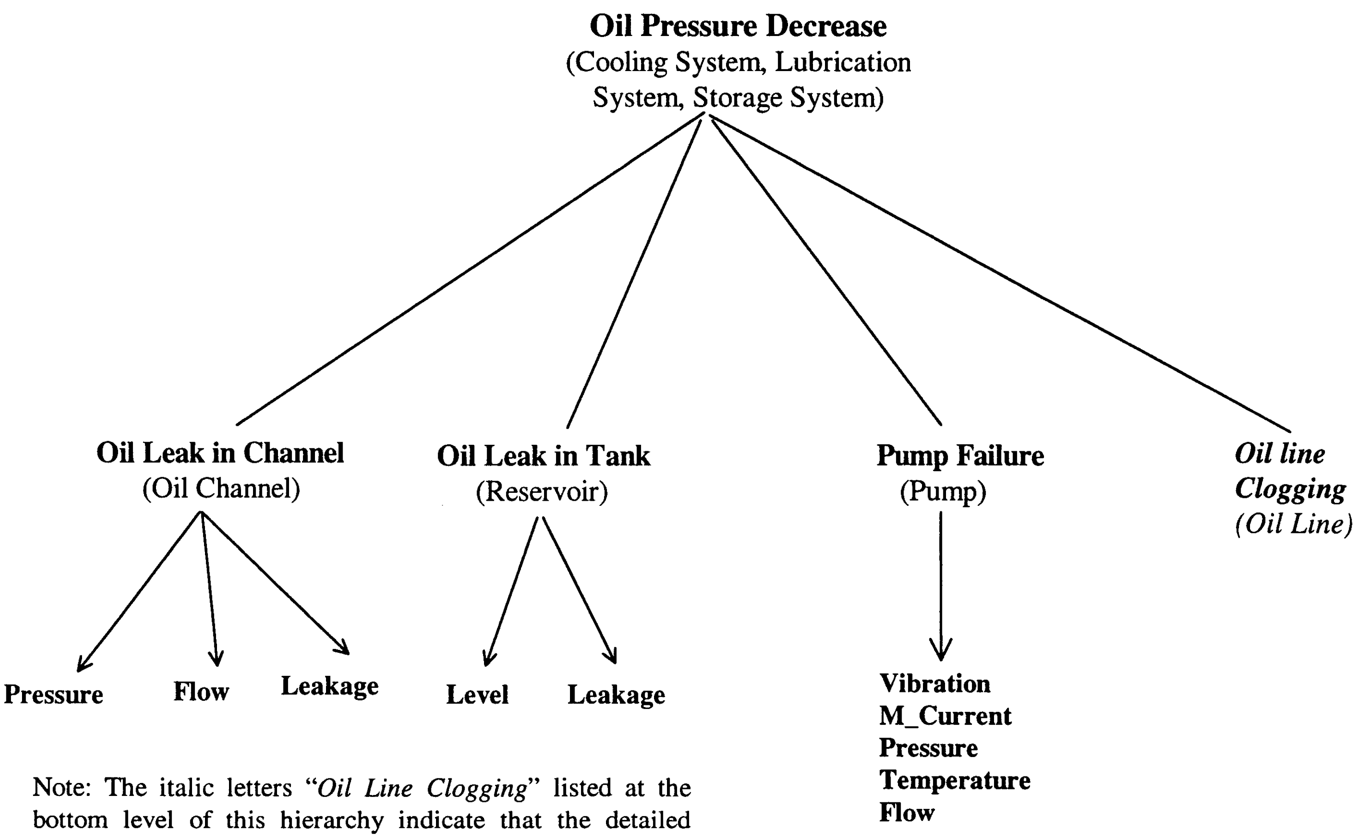
Figure 3.21 SSH of the Reactor Coolant Pump Bearing Lubrication Oil System



Legend,
RCP: Reactor Coolant Pump
FSH: Functional System Hierarchy

Note: An italic letter "*Bearing*" depicts how this approach reflects the interrelationships among various components.

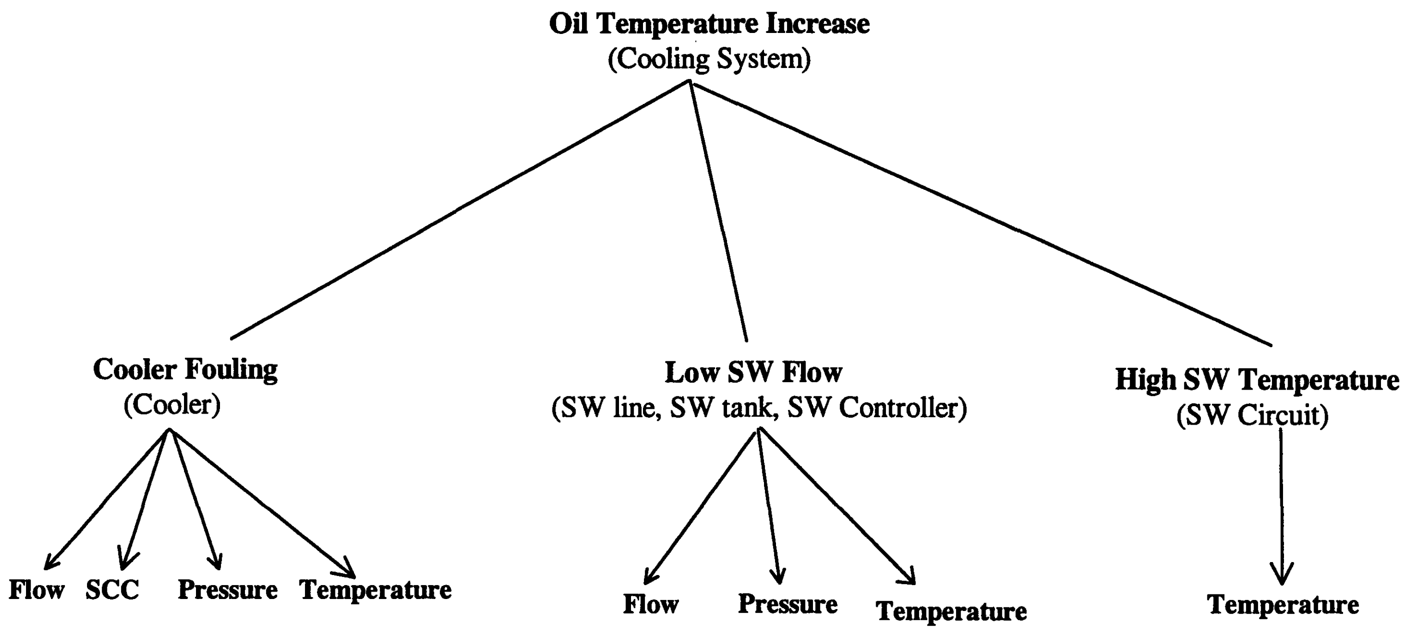
Figure 3.22-1 FSH of the RCP Bearing Lubrication Oil System



Note: The italic letters "*Oil Line Clogging*" listed at the bottom level of this hierarchy indicate that the detailed information concerning those systems is listed in other hierarchy.

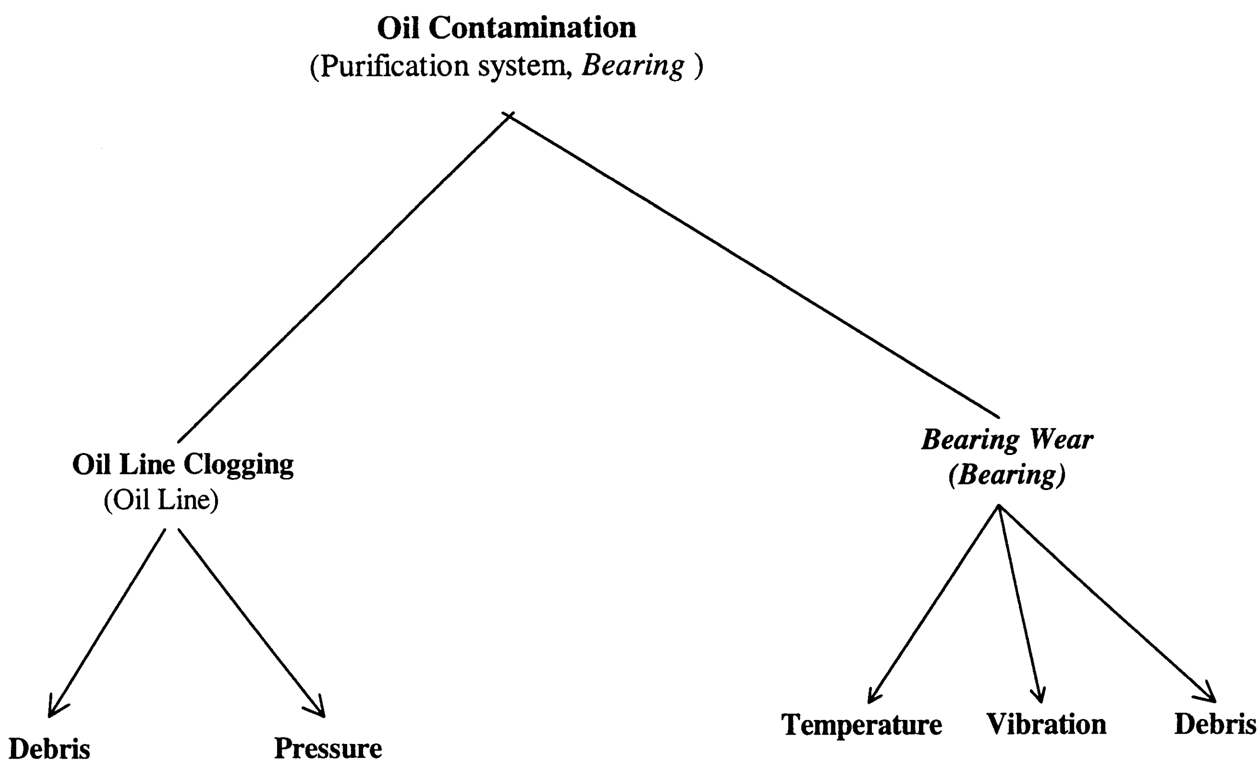
Legend,
M_Current: Motor Current
FSH: Functional System Hierarchy
RCP: Reactor Coolant Pump

Figure 3.22-2 FSH of the RCP Bearing Lubrication Oil System



Legend,
SCC: Stress Corrosion Cracking
SW: Service Water
FSH: Functional System Hierarchy
RCP: Reactor Coolant Pump

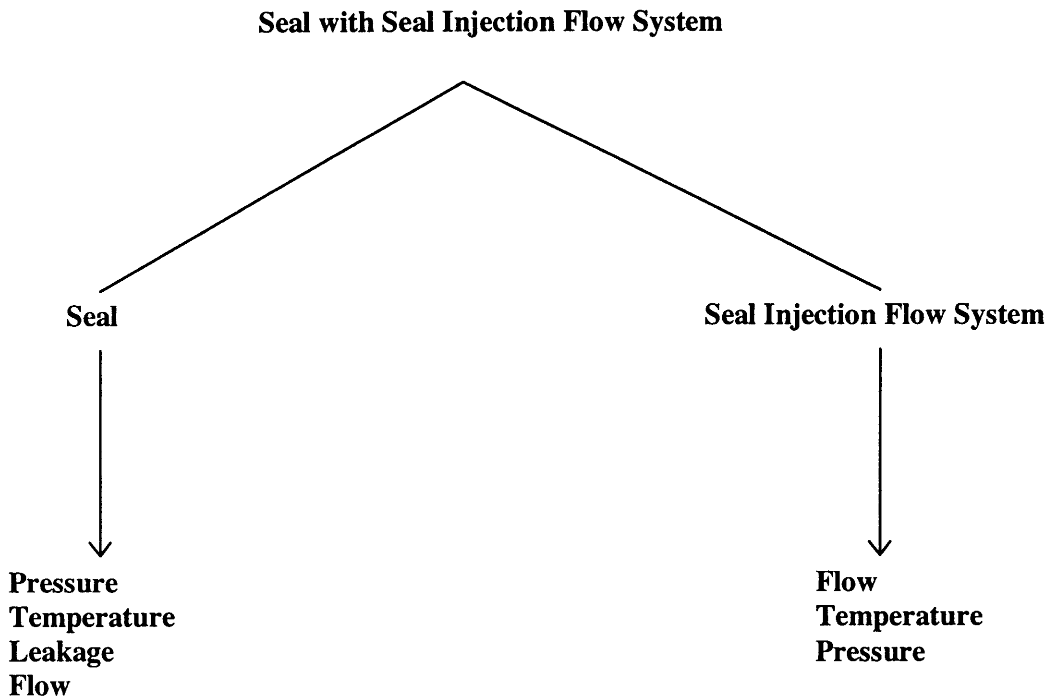
Figure 3.22-3 FSH of the RCP Bearing Lubrication Oil System



Note: An italic letter "*Bearing*" depicts how this approach reflects the interrelationships among various components.

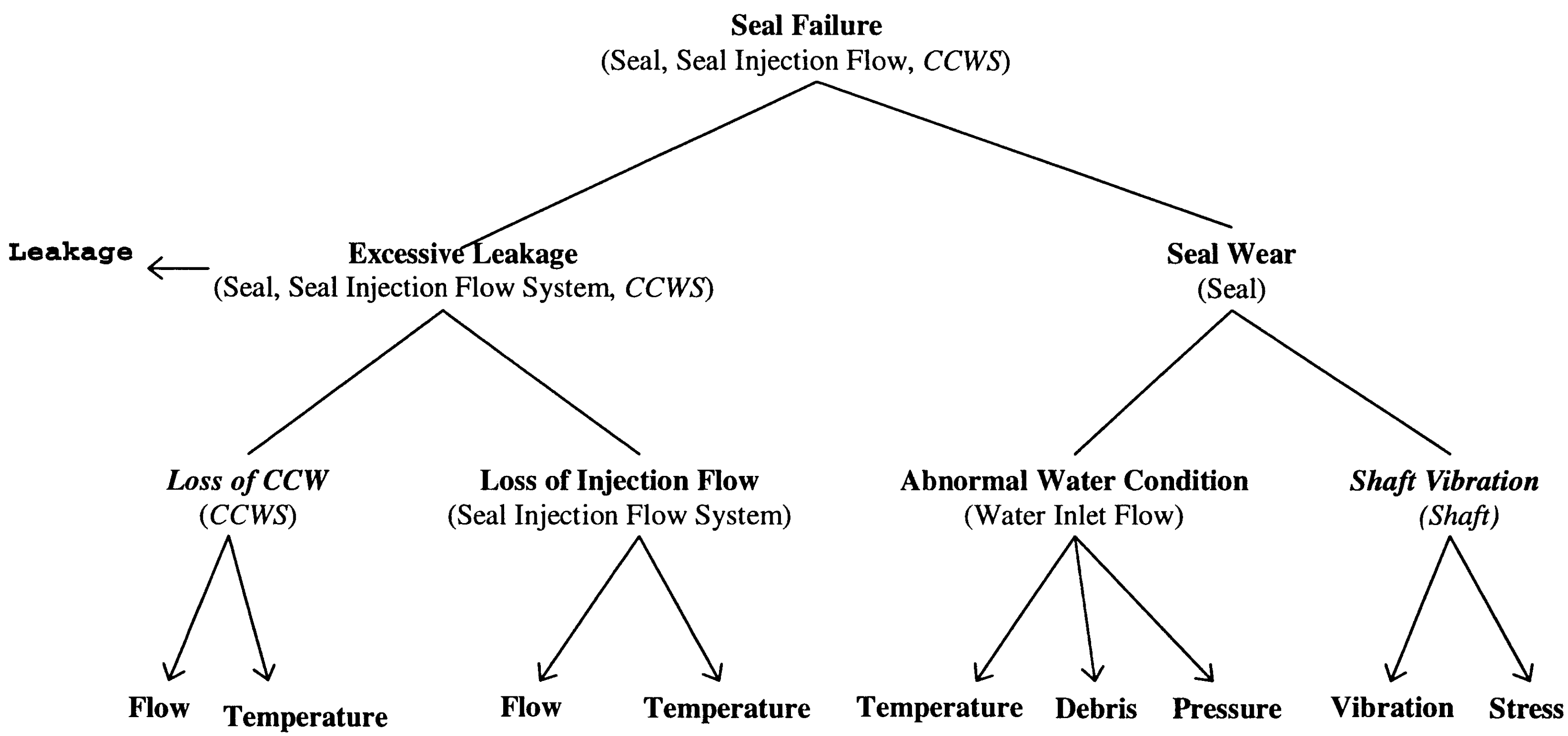
FSH: Functional System Hierarchy
RCP: Reactor Coolant Pump

Figure 3.22-4 FSH of the RCP Bearing Lubrication Oil System



SSH: Structural System Hierarchy

Figure 3.23 SSH of the Seal with Seal Injection Flow System



Legend,
CCW: Component Cooling Water
CCWS: Component Cooling Water System
FSH: Functional System Hierarchy

Note: The italic letters *"Shaft Vibration" and "Loss of CCW"* listed at the bottom level of this hierarchy indicate that the detailed information concerning those systems is listed in other hierarchies.

Figure 3.24 FSH of Seal with Seal Injection Flow System

Chapter 4. Modern Sensor Based Condition Monitoring Techniques for Target Systems

4.1 Scope of Condition Monitoring

Monitoring is the process of observing the real world and noticing when something unexpected, unusual, or potentially disastrous occurs. It is becoming increasingly important to use comprehensive monitoring schemes for the continuous assessment of the condition of critical systems that are essential for operational availability or safety in a complex power plant. By using the concept of condition monitoring (CM), it is possible to monitor the performance of the system of interest using trend analyses such that a change in system condition can indicate incipient faults that can be detected and their root causes located quickly. It can also provide adequate warning of imminent failures, and can aid in scheduling future preventive maintenance and repair work. This can lead to the improved operational availability by means of reducing downtime as well as preventing forced outages. Formally, these attractive points are classified as follow (DAVI 90):

> *1. An early knowledge of impending failure, through the use of trend analysis techniques or qualitative inspection: Preventive maintenance put in hand as a consequence of this information reduces the system/component failure rate and so increase equipment reliability.*
>
> *2. Actual condition knowledge and accurate failure prediction: This allows sufficient flexibility for the plant to be shutdown for repairs at a point in time convenient to the manufacturing schedule thereby improving system availability and minimizing random failure.*
>
> *3. Diagnostic potential: This is present in a condition based maintenance (CBM) and can pinpoint impending component failure together with the cause of that failure. The use of diagnostic routines also permits system modification, to remove identified failure modes and thereby improve inherent design reliability. In addition, through the rapid identification of an impending failure, system maintainability is improved together with workload planning and spare part stockholding.*
>
> *4. Flexibility: If used in conjunction with an adaptive control system, the monitoring aspect of CBM can extend the useful life of plant and equipment, by*

limiting the effect of a dynamic mechanism within the system. This reduces the likelihood of early failure and thus improves system reliability.

There are very many proprietary devices on the market that may be used for CM. At the present time, many new CM sensors and data processing equipment are backfitted for use with plant components in order to improve monitoring coverage. This process has been expensive because it sometimes requires some system modifications. The monitoring system specification and its development approach are intertwined, indeed considerable information of use in drawing up the specification regarding target components, imbedded sensors and equipment for data processing and integration can be obtained by investigating the development approach and evaluating currently available commercial products. Therefore, increased attention to monitoring at the design stage would be valuable so that CM equipment needs can be considered as essential design requirements.

When designing CM equipment, it is desirable to match the characteristics of currently available sensors to the failure modes to be monitored. The rapid advancement of powerful sensors and data processing equipment should be anticipated in the study of instrumentation design review. This means that each step of advanced instrumentation system development, namely data acquisition, data processing, and data integration should be incorporated in order to extend monitoring coverage in a systematic way.

Eventually, through the use of modern powerful monitoring devices and computers as a foundation of efficient plant diagnosis, CM can ensure that all decisions are made on substantial and corroborated diagnostic information, thereby yielding many technical, financial advantages.

The study in this chapter begins with the review of the current state of the art for monitoring techniques for use with target rotating machines, such as the reactor coolant pump and the turbine generator. The monitoring parameters on the target systems that are suitable for CM using available techniques are investigated. There are basically two distinct categories of monitoring parameters used in this work:

1) Process Parameters : e.g., temperature, pressure, flow

2) System Status Parameters : e.g., vibration, motor current, partial discharge, wear debris, flux, leakage, pyrolysis

Process monitoring, as its name implies, is concerned with monitoring of the machine process monitoring of the appropriate functions of all subordinate systems. Status monitoring is concerned with the physical health status of the machine. Generally, the monitoring of status parameters provides a longer time to enable corrective actions to be taken. However, it sometimes needs to use sophisticated local data processing equipment for interpreting complicated patterns of each signal and enhancing the ratio of signal to noise.

The following Sections, 4.2 and 4.3, outline the current scope of modern condition monitoring techniques for selected monitoring parameters, described above, that can be applied to target systems.

4.2 Modern Process Parameter Condition Monitoring Techniques

Process monitoring, as its name implies, is concerned with monitoring of machine process parameters such as temperature, flow and pressure. Temperature is a widely monitored parameter related to the process in electrical drives such as turbine generators or reactor coolant pumps. For example, it is quite common to find temperature sensing used to monitor the cooling fluids of Turbine Generators (TGs) and Reactor Coolant Pumps (RCPs), and specific area of the stator core. Bearing temperature is measured in order to provide complementary information for the assessment of its conditions. Here we have three widely used temperature sensors: thermocouple, resistance temperature detector (RTD), and thermistors.

The RTD is basically an electrical wire whose resistance varies in accordance with its temperature, a well-known concept in electricity. The RTD is simply a thin-film or wire-wound device that has a reasonably large, positive temperature coefficient of resistance value. The RTD exhibits the high linearity and is recommended as the most reliable and accurate temperature sensor for general temperature measurement.

Thermocouples are basically two wires of different material joined together at one end. The difference in materials will generate a small voltage proportional to the temperature at the joint. By measuring the voltage accurately, the temperature at the joint can be determined. Thermocouples are true point measurements, and they can come in dual elements. However, they are typically not accurate as RTDs

The final type of sensors is the thermistor. It operates in a like manner to the RTD but, because it is made from a ceramic semiconductor, it shows a large change in resistance as a function of temperature. It is inexpensive. However, its use is generally limited up to below 300 °C. Alternatively the thermistor may be used as a switching device to operate an alarm when the temperature exceeds a preset limit.

The choice of sensor location requires careful consideration during the specification stage of the machine design. Especially, use of an embedded temperature detector is recommended for the stator winding because the space in the stator end winding is very long and narrow. In some parts of the generator, the most likely hotspot is difficult to predict because of the great length of the potentially overheating elements. For example, temperature detectors embedded in the stator winding need to be located close to its hottest part, which my be in the slot portion or end winding portion depending upon the thermal design of the machine. Whereas this imbedded temperature detector using slot RTDs can be effective in determining a number of bar overheating conditions, they suffer from the inherent lack of discrimination between problems in the top or bottom bars. Sometimes, if the hot spot is localized and it does not coincide with the location of the RTD, the hot spot may never be detected. Also, this imbedded temperature detector indicates a temperature that is substantially lower than the hottest copper temperature at the same axial location (TAVN 87).

In an effort to address this problem, the development of a continuous temperature monitor using fiber optics makes it possible to detect a hot spot regardless of where it is. The fiber optic temperature sensor was developed to address this situation.

The lack of precise temperature data is a major shortcoming in assessing the condition of rotor winding insulation. Operation at high temperature causes many types of insulation to lose electrical and mechanical integrity, eventually resulting in catastrophic failures. As well, thermal cycling can induce aging by causing relative movement between insulation system components. The phenomena known as "*ratcheting*" whereby the rotor slot wedges loosen is a direct result of thermal cycling.

One system is introduced in this work to obtain accurate rotor temperature data. Sedding introduced that the Electronic Rotor Temperature Sensor (ERTS) measures the temperature of the rotor at a specific location (SEDD 89). The active components of the device are mounted in a modified rotor balancing plug that is installed in the balance hole in the winding face of the rotor. Temperatures are measured and transmitted across the airgap to receiving antennae located in the stator bore and end regions. A specially built receiver decodes the radio frequency (RF) transmissions. Packaging of the ERTS electronics is critical since the device is mounted at a point which experiences elevated temperatures and the presence of high magnetic fields. For these reasons the mechanical design of the plug and selection of a suitable potting compound are crucial in ensuring the integrity of the design.

The sensors for measurements of pressure and flow have been widely used for a long time. Usually, pressure transmitters are used for the measurement of pressure. Flowmeters are normally used for measurement of flow.

4.3 Modern Status Parameter Condition Monitoring Techniques

Status monitoring is concerned with the physical health status of the machine. System status parameters include vibration, motor current, partial discharge, and wear debris, etc. Their spectral analysis usually uses sophisticated data processing equipment for interpreting the complicated pattern of each signal and enhancing the ratio of signal to noise.

4.3.1 Vibration Analysis

Vibration analysis in rotating machinery such as the turbine generator and reactor coolant pumps is an extremely effective means for diagnosing incipient malfunctions that might have catastrophic results if not discovered in time. Vibration is an important sensitive parameter indicating the operating state of a rotating assembly. Every rotating machine has its own characteristic vibration signature, which can be obtained from frequency spectra of the monitored vibration signals.

Typically the primary vibration source is estimated by using vibration amplitude and frequency data. The changes of individual frequency components in the spectrum can give the earlier indications of faults in the pump elements. This spectrum analysis requires advanced data processing equipment with associated ancillary devices, which are illustrated in Figure 4.1. Moreover, in order to increase the accuracy of diagnosis, the combination of one sensor output with other measurement parameters should be performed.

4.3.1.1 Sensor Type

Vibration monitoring systems for RCPs employs three kinds of transducers. The measurement made by proximity probes is for relative displacement of the shaft. It provides a voltage output as a function of the probe-to-shaft gap. These transducers are the most sensitive to very low amplitude and low frequency vibrations of the rotating shafts in a RCP and a turbine generator. The second sensor type has been used to measure the shaft rotational velocity. These tachometer signals are necessary in order to provide the rotating speed of the turbine generator and to allow shaft torque measurements to be performed. The third sensor type, called an accelerometer, effectively measures the acceleration of rotating components such as bearings, the impeller and rotor because it has high frequency sensitivity.

Table 4.1 Comparison of Vibration Sensors

Type	Frequency Range	Measurement	Advantage	Disadvantage
Proximity Probe	0- 1500 Hz	Relative Displacement	Noncontact	Conductive parts Mounting difficulty Frequency limit
Tachometer	8-1500 Hz	Velocity	Self-generating Seismic	Moving part Massive EM sensitivity
Accelerometer	1-20,000 Hz	Acceleration	High frequency Small size Seismic	Temperature limit

(EM: Electromagnetic)

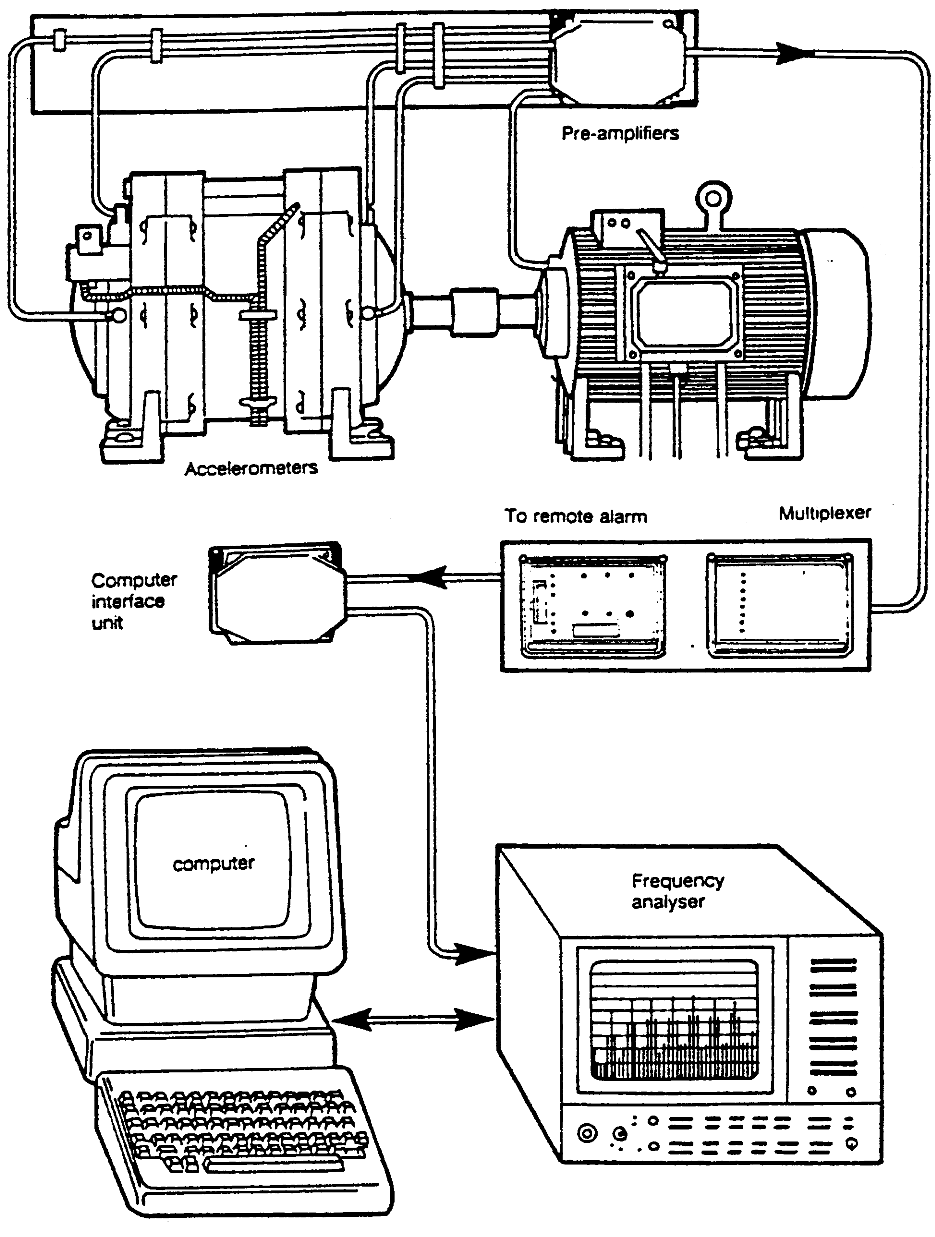


Figure 4.1 Data Processing Equipment for Advanced Vibration Spectrum Analysis (BOVI 89)

4.3.1.2 Major Failure Modes and Diagnosis

1) Imbalance

Imbalance is a condition where the center of mass is not coincident with the center of rotation. This usually stems from a nonuniform mass distribution about the center of rotation. So, imbalance shows up as a vibration signal with a frequency exactly equal to the shaft rotational speed, and with amplitude proportional to the amount of imbalance.

2) Misalignment

Coupling misalignment is a condition where the shafts of the motor and the pump are not on the same centerline. When coupled and rotated together, the two shafts are cyclically strained at the running speed. A deflection is created. The bearings affected by the force leading to this deflection create the reactionary forces that prevent the shafts from moving as much as it would in achieving its full amplitude excursion. This strain of the shaft generates higher frequency harmonics of vibration signal. So, misalignment shows up in the frequency domain as a series of harmonics of the running speed. Misalignment also has temperature dependency related to thermal fatigue. In the RCPs, the presence of a significant temperature difference in the vicinity of the shaft between the coolant water and seal cooling/injection water is another common factor. Therefore, the change of harmonics during temperature changes is a strong indication of temperature induced misalignment.

3) Looseness

Mechanical looseness shows up in the frequency domain as a 1/2 harmonic, as 1-1/2, 2-1/2, etc. These harmonics show up because of clipping of the waveform when the loose parts hit against their limits of movement. Generally, the presence of 1/2 harmonics indicates a more severe condition of looseness (WOWK 90).

4) Oil Whirl

The oil whirl is a condition, which causes a precessing wedge of oil to be formed around the bearing, thus causing the shaft vibration. The occurrence of oil whirl is more likely in higher speed machines. It manifests itself as a vibration signal of less than one-half of the rotational speed. This speed comes from the average oil velocity with some slippage (WOWK 90).

5) Bearing Damage

All roller bearings give off signals at four distinct specific frequencies, related to the bearing outer race defect (ORD), bearing inner race defect (IRD), bearing ball sphere defect (BSD) and train defect (TD) at specific vibration frequencies. Their relative amplitude is an indication of their condition. These fundamental frequencies of a rolling bearing can be obtained by simple calculations (ALLE 88) as

$$\begin{aligned} f_{ORD} &= (N/2) f_r [1 - b_d \cos(\beta)/d_p], \\ f_{IRD} &= (N/2) f_r [1 + b_d \cos(\beta)/d_p], \\ f_{BSD} &= d_p f_r / d_b \{1 - [b_d \cos(\beta)/d_p]^2\}, \\ f_{TD} &= (f_r/2)[1 - b_d \cos(\beta)/d_p]. \end{aligned} \tag{4.1}$$

Here, f_r is the shaft rotational frequency, N is the number of balls, b_d and d_p are the ball diameter and ball pitch diameter respectively, and β is the contact angle of the ball with the races.

It should be noted that the very first indications of bearing wear are metal-to-metal shocks. They show up as shock pulses in the time domain due to the short duration transient nature with a frequency between 1000 Hz and 10,000 Hz (BRAU 86). Therefore, the earliest detection of bearing degradation is these high frequency shock pulses in the time domain as measured by accelerometers.

6) Electrical Device Induced Vibration

Related by electrical device induced vibration, every electrical machine powered by 60Hz line frequency gives off a mechanical vibration at 120 Hz because of the magnetic field expanding and collapsing in the iron laminations of motors (VAS 93).

4.3.1.3 Vibration Diagnostic Chart

Diagnostic charts can be drawn to relate the RCP faults to vibration frequencies. These cause and effect relationships were derived by some detailed mathematical analysis (BRAU 86) or by observing the effects of real rotating machine faults.

Table 4.2 Vibration Diagnostic Chart

Fault	Frequency	Amplitude/ Other Parameters
Imbalance	1X	No Phase change
Misalignment	1X , 2X, 3X, nX	Orbit, Phase change
Bearing	BSF, IRF, ORF, TDF	High frequency shock in time domain
Looseness	1/2, 11/2, 21/2, $n_{1/2}$	Amplitude decrease with load
Bent shaft	1X	Orbit, Phase
Oil Whirl	0.43-0.48X	Oil temperature change
Cracking	Unexplained drop in higher harmonics	Phase change is more significant No definite single indicator
Motor Vibration	2 times synchronous frequency	Motor current

Legend,

nx: Multiplier of shaft rotational frequency
BSF: Ball sphere defect frequency
IRF: Inner race defect frequency
ORF: Outer race defect frequency
TDF: Train defect frequency

4.3.2 Wear Debris Analysis

Analysis of wear debris carried in the oil stream can provide an insight into the operating condition of the oil-wetted components of a machine. While wear debris analysis can be successful as the sole condition monitoring technique, it is better applied as part of suite of analysis techniques. It combines very well with vibration analysis and provides complementary information about faults where insufficient data exist to identify a fault using vibration analysis, and vice versa (YARR 91).

4.3.2.1 Off-line Wear Debris Analysis

Practically all wear debris analysis techniques rely upon sampling the oil. The types of representative off-line wear debris techniques are the following.

1) Spectrometric Oil Analysis (SOA)

A sample of oil taken from the machine lubrication system is analyzed for concentrations of metals. The concentrations of each metal in the oil are compared to preset limits, or used to calculate the machine's wear rate. SOA is usually performed by emission spectroscopy, X-ray fluorescence, and atomic absorption spectroscopy (YARR 91).

2) Wear Particle Analyzer

More recently ferrographic methods have come to be used. Analytical ferrography is an off-line technique that uses an intense magnetic field to extract ferrous wear particles. The wear particles are deposited in order of size, with the larger particles being deposited first at the entry, with progressively smaller debris coming down as the oil flows across the ferrogram. High power optical or scanning electron microscopy is used to study the size distribution of collected wear particles.

Direct reading ferrography is similar to analytical ferrography as described above, using the same magnet to collect the wear particles. Light sensors are used to determine the density of the wear debris deposited in the glass tube in two positions, thereby giving a numerical value for the concentration and an indication of the size distribution of the ferrous particles.

4.3.2.2 On-line Wear Debris Analysis

On-line wear debris detection sensors built into a machine's lubrication system are aimed to indicate continuously the occurrence of any wear particles. However, there are few commercially available wear debris monitors. Those that are in use have typically been design for the aircraft industry and as such are designed for too low an oil flow for industrial application. In this work, we introduce the state of the art available on-line wear debris analysis techniques. We describe their current capabilities and limitations, and provide a groundwork concerning feasibility of what activities in this area employed upon rotating machines in the power plants. In the near future, on-line wear debris monitor may show promise for use in rotating machines in the power plants. The types of on-line wear debris monitor available are the following.

1) Through-Flow Inductive Debris Monitor

Lubricating oil flows through a transducer coil, causing small changes in the inductance of the coil as any metallic particles pass. The direction of the frequency shift allows discrimination between ferrous and non-ferrous particles and the signal amplitude gives a measure of debris size and concentration. This type of sensor has the advantage of not disrupting the oil flow, but also has the disadvantage that this through flow coil suffers from electrical interference (WHIT 92).

2) Electrical Gap Bridging Detector

The Electrical Gap Bridging Detector uses a magnet to capture ferrous debris and bridge the electrical contacts. A sufficient build-up of fine debris or a single large particle can bridge the gap, thus completing the circuit and triggering a warning indication. This type of sensor is fitted to many aircraft engines and transmissions. In some installations the electrical gap type sensors can be a problem often being triggered by normal wear products and giving rise to false 'nuisance' warnings (YARR 91).

3) Instrumented Magnetic Chip Detector

The Instrumented Magnetic Chip Detector uses a magnet to capture ferrous wear particles. The magnet is equipped with inductive coils or magnetoresistive sensors that indicate the mass of ferrous material accumulated or the instantaneous disruption of the magnetic field as a particle arrives. These systems have an advantage over the simple gap system in that they continuously measure the accumulation of wear particles, and are not limited to a single detection (YARR 91).

4) Optical Oil Debris Monitor

The Optical Oil Debris Monitor is based upon illumination of the oil lubrication column with a diode laser, followed by imaging in transmission of suspended particles and identification of the particles by analysis or classifier. The optical monitor is capable of recognizing metallic and ferrous particles, such as those from metal bearings and gears, as well as non-ferrous particles, such as ingested sand and debris from composite bearings. Objects suspended in the oil flow are imaged by light transmission onto the array of detectors, appearing as dark shadows against a bright background (REIN 94).

5) Filter Blockage Technique

Within the Filter Blockage Technique a sample of fluid is passed through a filter screen and the pressure drop across the screen is monitored. As the filter becomes blocked, the pressure builds up giving an indication of the number of particles in the fluid. This technique has the disadvantage that it cannot distinguish between metallic and non-metallic debris (HUNT 91).

4.3.3 Motor Current Analysis

4.3.3.1 Motor Failure Mechanism

As a drive device, a large three-phase alternating current induction motor designed to operate at constant speed is mounted vertically on the top of the pump. When evaluating the reactor coolant pump performance, it is necessary that the condition of the motor should be considered, in addition to the coupling between pump and motor. To prevent the sudden failure of a motor, it is essential that failure modes should be identified and then corresponding on-line monitoring equipment to detect incipient failure signature should be set up.

The magnetic field produced in stator induces a flow of electrical current in the rotor windings. Typical failure modes in large-phase induction motors are rotor bar fracture, airgap eccentricity, bearing wear and insulation degradation as shown in Figure 4.2. During the mechanical transients, rotor bars are likely to be exposed to thermal and mechanical stresses coupling vibration. The incidence of cracking in the region of bars and end ring can cause serious damage to the stator winding and insulation failure. Speed and torque oscillations also occur as well as arcing and heating in the vicinity of a fault. Airgap eccentricity and unbalanced magnetic pull as a result of a bent shaft, bearing wear and misalignment can lead to a rubbing between rotor and stator and consequent damage to the stator windings. Moreover, bearing failures are caused by mechanical misalignment, abnormal rotor unbalance and shaft whirl. Finally heat generated in the stator windings, coupled with vibration, transients and airborne contaminants can disintegrate the organic insulation material.

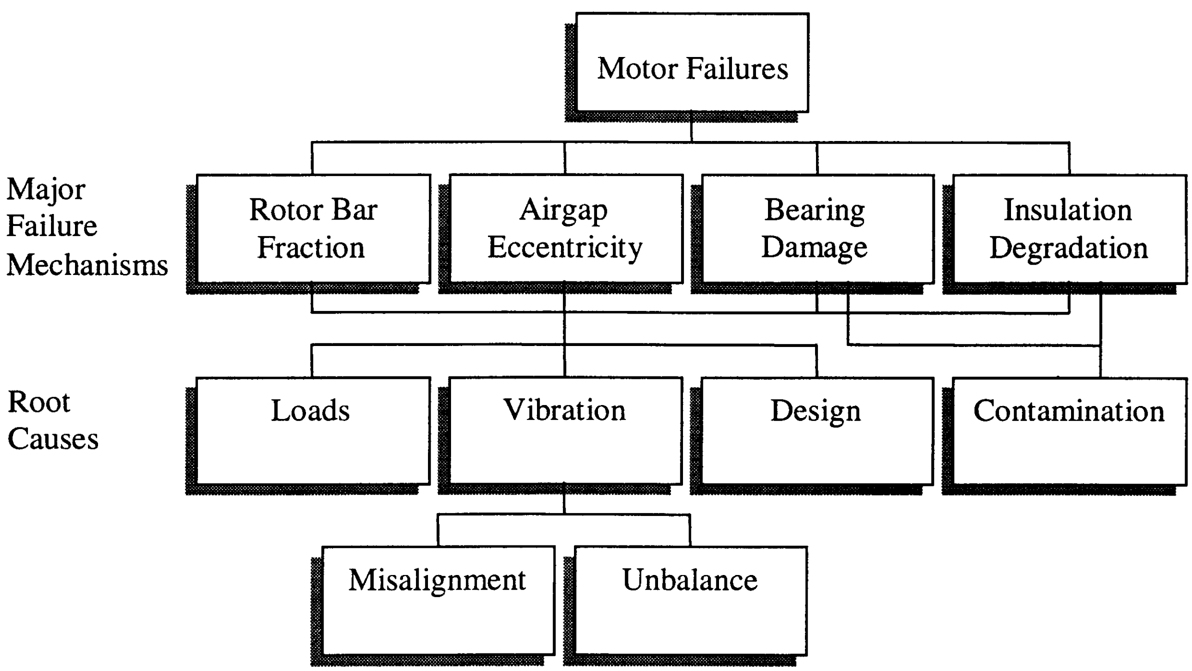


Figure 4.2 Motor Failure Diagram

4.3.3.2 Motor Current Monitoring Techniques

The identification of mechanical problems such as rotor bar fracture, airgap eccentricity and bearing wear via on-line analysis of the current is common. It can indicate an early stage of failure. Like vibration monitoring, it primarily relies upon the amplitude of specific frequency components in the current spectrum. The supply current is normally monitored very easily, without interfering with the machine, simply by fitting a clip-on current transformer around the supply cable to the motor, see Figure 4.3 (TAVN 87). Using an Analog-to-Digital (A/D) converter digitizes the monitored line current signal and using Fast Fourier Transform (FFT) can perform the spectrum analysis.

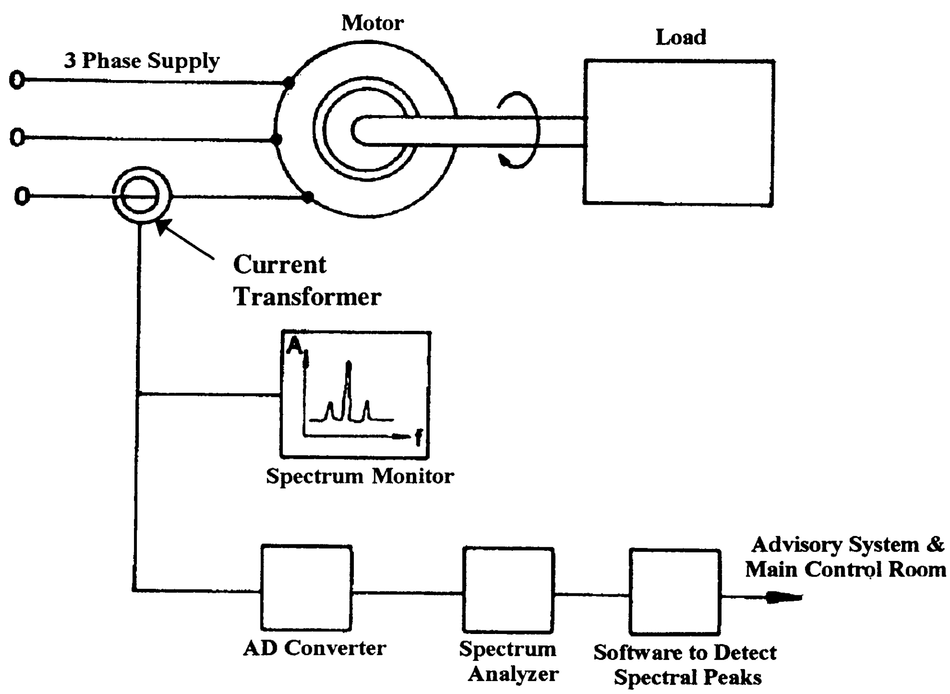


Figure 4.3 Current Transformer Installation for Motor Current Monitoring (TAVN 87)

Previous research (JONE 72), (WILL 82) shows that the speed and torque oscillations occurring due to asymmetry of broken rotor bars induce a twice the slip frequency sideband signal ($\pm 2sf_1$). The definitions used in this work are as follows:

$$s = (n_s - n)/ n_s, \qquad (4.2)$$

where, s : slip (dimensionless)

n_s : synchronous speed (rpm)

n : actual speed (rpm)

f_1 : supply frequency (60Hz) .

The Fast Fourier Transform technique (FFT) has made it possible to identify this unique pattern in the current spectrum in the frequency domain. A progressive increase in the amplitude of the slip frequency sideband signals is one of the most dominant indicatives of broken rotor bars.

Static eccentricity which can be caused by the incorrect position of the stator or rotor, will generate signals which also contain signals at twice the slip related frequency in addition to the slot harmonic components governed by the Equation 4.3 (YANG 81). In the presence of dynamic eccentricity ,caused by a bent rotor, there will also be a signal at twice the slip frequency sideband in addition to slot harmonic components, as

$$f_e = f_1 \, [\, (kZ_2 \pm n_d)(1-s)/P \pm v \,], \qquad (4.3)$$

where,

k : any integer

Z_2 : number of rotor slots

n_d : 0 for static eccentricity, 1 for dynamic eccentricity

P; number of pole pairs

v: 0, 2, 4, 8, ...

Early indications can be detected by measuring the increase in the levels of these specific frequency components. The diagnostic algorithms should contain the amplitude for normal state of the spectral component in order to quantify these malfunction modes.

4.3.4 Partial Discharge Analysis

Partial discharges are sparks involving the flow of electrons and ions when the electrical insulation of small volume of gas beaks down. This can occur in voids within the electrical insulation system itself or in regions adjacent to the insulation of high voltage stators. The term partial is used since there is a solid insulation, such as epoxy-mica, in series with the void, which prevents a complete breakdown.

Insulation of rotating machines is subjected to electrical, thermal, and mechanical stresses during the operation. The acquisition, storage, and processing of partial discharge signals in the rotating machines such as the turbine generator and the reactor coolant pump are important condition monitoring tools because the partial discharges not only degrade the electric insulation but also provide the symptoms of the incipient defects.

As deterioration of the stator windings continues to be one of the predominant causes of partial discharge, this degradation can be characterized by the changes in discharge activity as a major symptom of insulation failure. It is normally the result of progressive degradation that may typically be due to physical movement, contamination, or thermal effects. Several concrete conditions that can generate partial discharge activity are stator bar vibration, end winding contamination, damage to the end winding voltage suppresser system, broken conductor, insulation degradation, and collector brush sparking. In practice, it is often difficult to establish cause and effect relationships because of the synergistic nature of insulation deterioration mechanisms. In this case, we highly recommend use of a suite of sensors, which can provide correlated signals for the detection of complex degradation mechanisms (GEPS 94).

Capacitive couplings and Rogowski coil are available as transducers for on-line partial discharge monitoring. They have a good sensitivity and wide bandwidth, and can be easily installed. The capacitive coupling housed between the high voltage terminal and the monitoring instrument is generally not suitable for on-line monitoring of discharge activity. The Rogowski coil can be suggested. It is located around the high voltage terminals of the stator winding as a non-invasive current transducer for measurement of high frequency current pulses in the stator windings, as generated by partial discharge activity in the insulation structure. It looks similar to a conventional current transformer but there is no ferrous material in its construction because it is designed to respond to low level high frequency discharge signals of the order of picocoulombs (EDWA 92).

A partial discharge event at a point in the winding structure gives rise to a pulse of electric current that travels away from the point of origin as a wave. The most important features from a diagnostic viewpoint are repetitive peak discharge magnitude over a period of time. This is because the discharge magnitude, based upon signal pattern analysis, is related to the energy released at the point of discharge and the degree of significant insulation degradation. For on-line measurements, a spectrum analyzer for signal processing is recommended. It is tuned to specific frequencies and the levels of these frequencies are analyzed in a time sequence. The continuous increase of the specific magnitude indicates that insulation is being degraded. This instrument with Rogowski coil and data processing equipment is known in Figure 4.4.

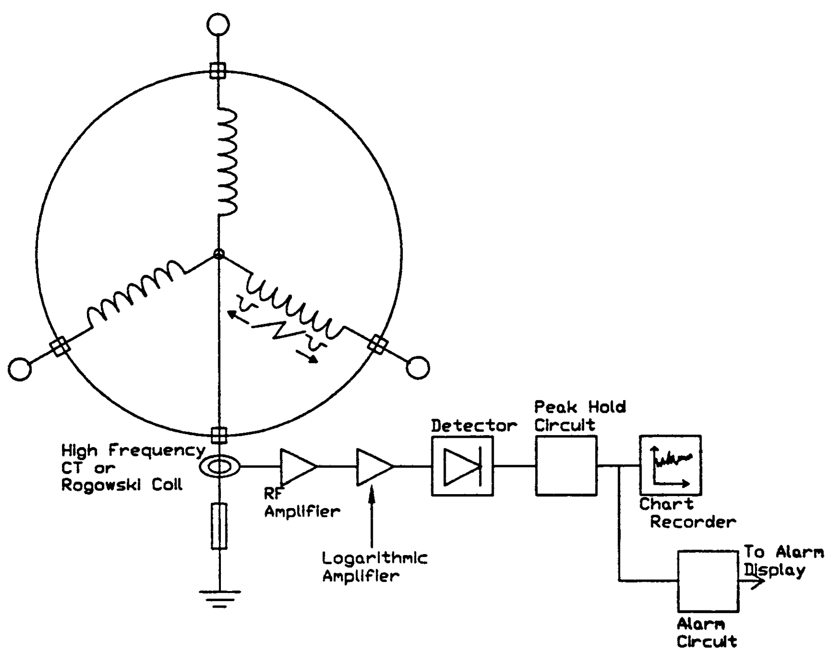


Figure 4.4 Schematic Diagram of On-line Partial Discharge Monitoring System (TAVN 87)

Therefore, the information about discharge signal pattern may provide important indications of the degradation process that has given rise to the discharge activity. It can provide complementary information correlated with other signals such as those from the stator winding temperature, and vibration, etc. Then, the partial discharge analysis can assist maintenance engineers to form a clear picture of the problem and to assess the urgency of any remedial action that may be required.

4.3.5 Rotor Flux Monitor

Shorted turns in the rotor winding change the airgap flux of the synchronous machine. Due to the interturn faults, an asymmetrical temperature distribution of the rotor can arise. This can cause abnormal operating conditions, which cause rotor vibration problems and decrease efficiency. With a larger number of shorted turns, the rotor may not even be able to achieve full load at any power factor. Furthermore, local overheating can also occur due to the shorted rotor winding. Shorted rotor turns can also lead to increased shaft voltages. This work introduces two sensors developed to obtain accurate information about abnormal flux distributions. These are known as the airgap search coil and the flux probe. Shorted rotor turns in a generator can be detected by using a small airgap search coil installed in the stator in the air-gap of the generator as shown in Figure 4.5. The search coil is situated near the rotor surface.

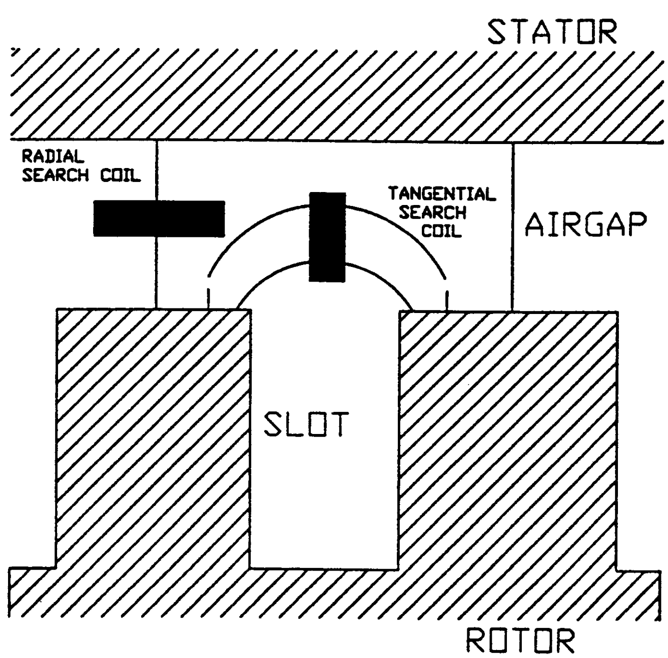


Figure 4.5 Generator Airgap Search Coil Installation (HIRV 91)

The search coil can be either cylindrical or rectangular in shape. As the rotor rotates, a voltage is induced in the search coil, which is proportional to the rate of change of the rotor flux associated with each rotor coil. The amplitude of the induced voltage is directly proportional to the ampere-turns in the rotor slot that passes under the search coil, and thus a reduced voltage is induced in the presence of a shorted coil. It should be noted that it is possible to detect the radial or circumferential component of the rotor flux by installing radially- or circumferentially- aligned search coils in the air-gap. Parallel half-phases of stator winding can also be used to measure variations in the airgap flux. By measurement of voltage and its spectrum in the airgap search coils and of the circulating currents in stator winding, it is possible to obtain information about the rotor winding faults of the electrical machine during its operation (HIRV 91), (VAS 93).

The presence of shorted turns is also determined by examining test data acquired through a sensor called a flux probe. Figure 4.6 shows flux probe installation. The flux probe is installed in the generator airgap where it senses the field winding slot leakage flux. The probe tip is a full 5 cm from the rotor surface, thus avoiding any interference with the retaining rings during assembly and disassembly. The probe is wired to the instrument terminal gland, which is mounted on the outer diameter of the generator frame. The wire routing is similar to that of the stator bar resistance temperature detector

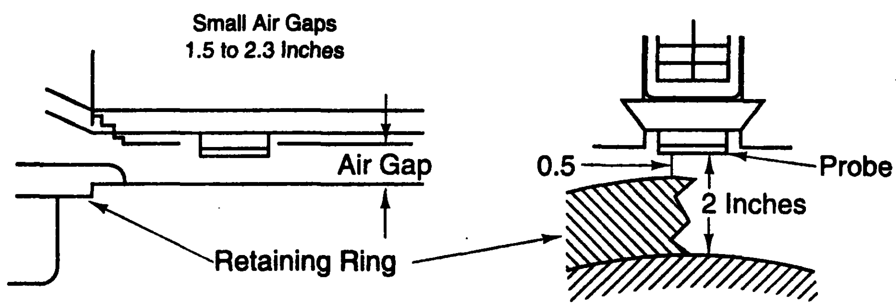


Figure 4.6 Generator Flux Probe Installation (GONZ 95)

(RTD) wiring. The probe produces a voltage proportional to the rate of change of flux as the rotor turns. This pattern of flux variation near the field is a signature unique to each field winding. A digital oscilloscope can also be utilized to capture and analyze data (GONZ 95), (GEPS 97).

4.3.6 Shaft Voltage Detector

With an increase of the size of generators, the magnitudes of shaft voltages and associated damaging circulating currents in the short-circuit path to the induced shaft voltage have significantly increased. Thus it is important to understand the mechanism of the generation of the shaft voltages and to take protective measures against them.

A net alternating flux is produced which links with the circuit consisting of the shaft, bearing and frame due to many reasons such as magnetic asymmetries, static excitation systems, electrostatic charges, etc. Thus, a potential difference is induced between the extremities of the shaft. This induced shaft voltages between the shaft and the bearing will stress the oil film of the bearings and in case of breakdown, electric discharge will occur and pitting will damage the surfaces of the bearings and the seals.

Shaft voltages due to axial shaft fluxes can be partially avoided by demagnetization of the magnetized parts. It is also useful to insert thick layers of material with low permeability in all flux paths. Shaft voltages due to static exciters can be reduced by keeping the common mode voltage and the rise of the voltage steps in the common mode voltage as small as possible. Also, the circulating current on the surface of bearing can be limited by the capacitive reactance of the bearing insulation (VAS 93).

4.3.7 Generator Core Condition Monitor (GCCM)

Excessive heat buildup in the insulated conductors in the generator field or armature can result in thermal decomposition of the winding's groundwall insulation. The thermal decomposition of winding or lamination insulation causes the formation of byproducts in the form of small particles, which are captured by the hydrogen stream on the outer surface of the conductor or lamination and blown through the generator.

The detection of overheating inside a large turbine generator before it reaches catastrophic levels in known to be difficult. This work introduces the generator core condition monitor (GCCM) to detect such overheating on-line. The primary objective of the GCCM is to identify such excessive buildups of heat in either the windings or core insulation by monitoring the thermal decomposition byproducts of the hotspot insulation before they result in catastrophic failures of the insulation, and thus of the generator itself.

Figure 4.7 illustrates the schematic diagram of one particular design of a GCCM. A small of sample of the gas is diverted continuously to the GCCM, which is typically located outside of the generator. When decomposition particles are present in the hydrogen stream, the electrons will stick to the particulate. The increased mass of the charged particulate means that it is not influenced by as much by the driving potential difference as are the free electrons, and is thus removed from the electron current. The GCCM measures this current flow and produces an analog signal directly proportional to the electron current level. A threshold point can be set to alarm when the current flow decreases to a preset level (GONZ 95), (SEDD 89).

4.3.8 Fiber Optic End-Turn Vibration Monitor

As the vibration amplitudes increase, the stator coil end-turns are progressively more fatigued from a mechanical standpoint. Common vibration sensors such as accelerometers are very susceptible to strong electromagnetic field near the generator stator windings. On the other hand, the fiber optic vibration sensor has the one significant advantage that the sensor and all cabling to and from it are nonconducting. Thus, use of fiber optic vibration monitor can enable on-line early detection and identification of developing end winding loosening through the measurement of coil end vibration levels and the trending of vibration levels of over time. This eliminates the need to insulate them from the high voltages inherent within the generator.

Figure 4.8 illustrates the operating principle of the fiber optic vibration sensor. A grid of evenly spaced slots is mounted at the end of a flexible reed. The increases fatigue may move the natural frequencies of the end region closer to a value near the 120 Hz, thereby worsening the situation through the resonance amplification mode. The reed is

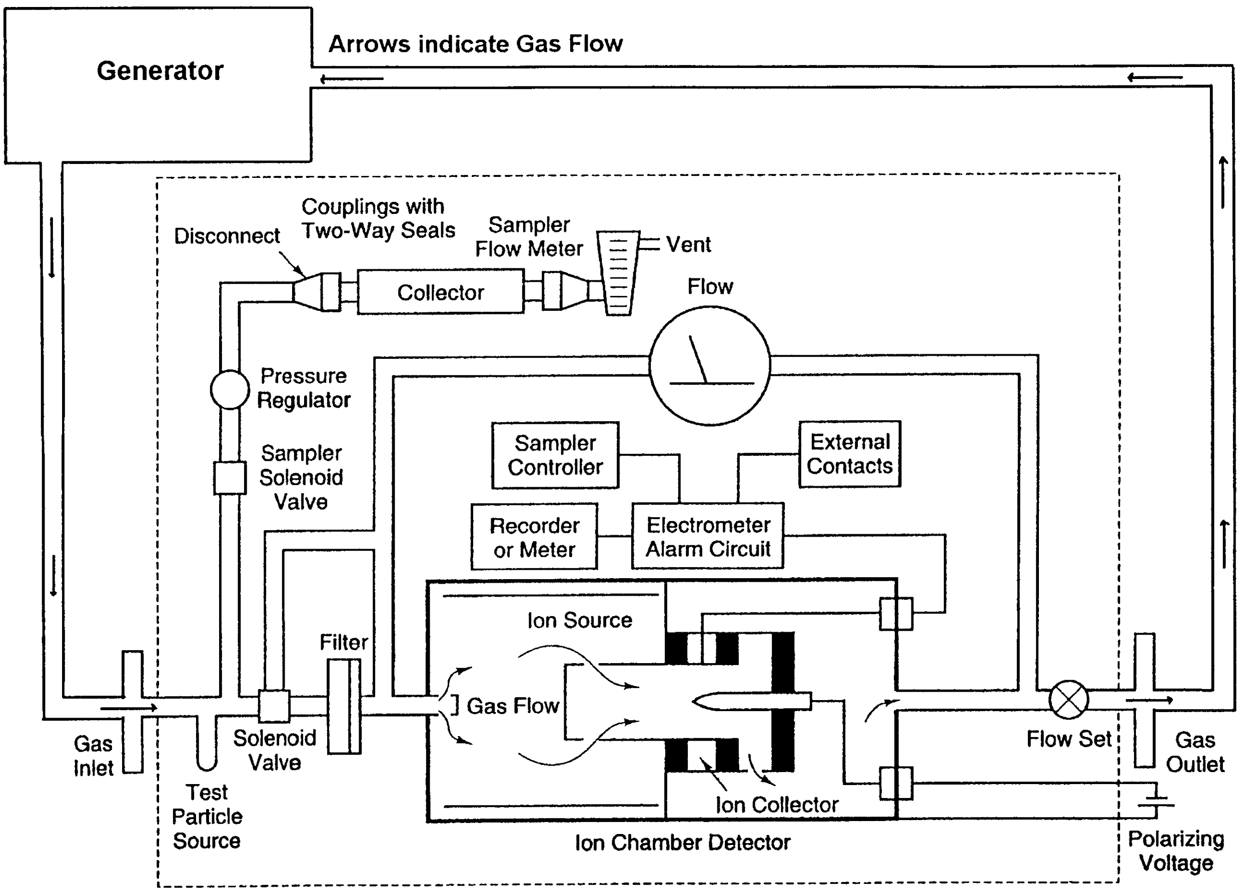


Figure 4.7 Schematic Diagram of Generator Core Condition Monitor (GCCM) (GONZ 95)

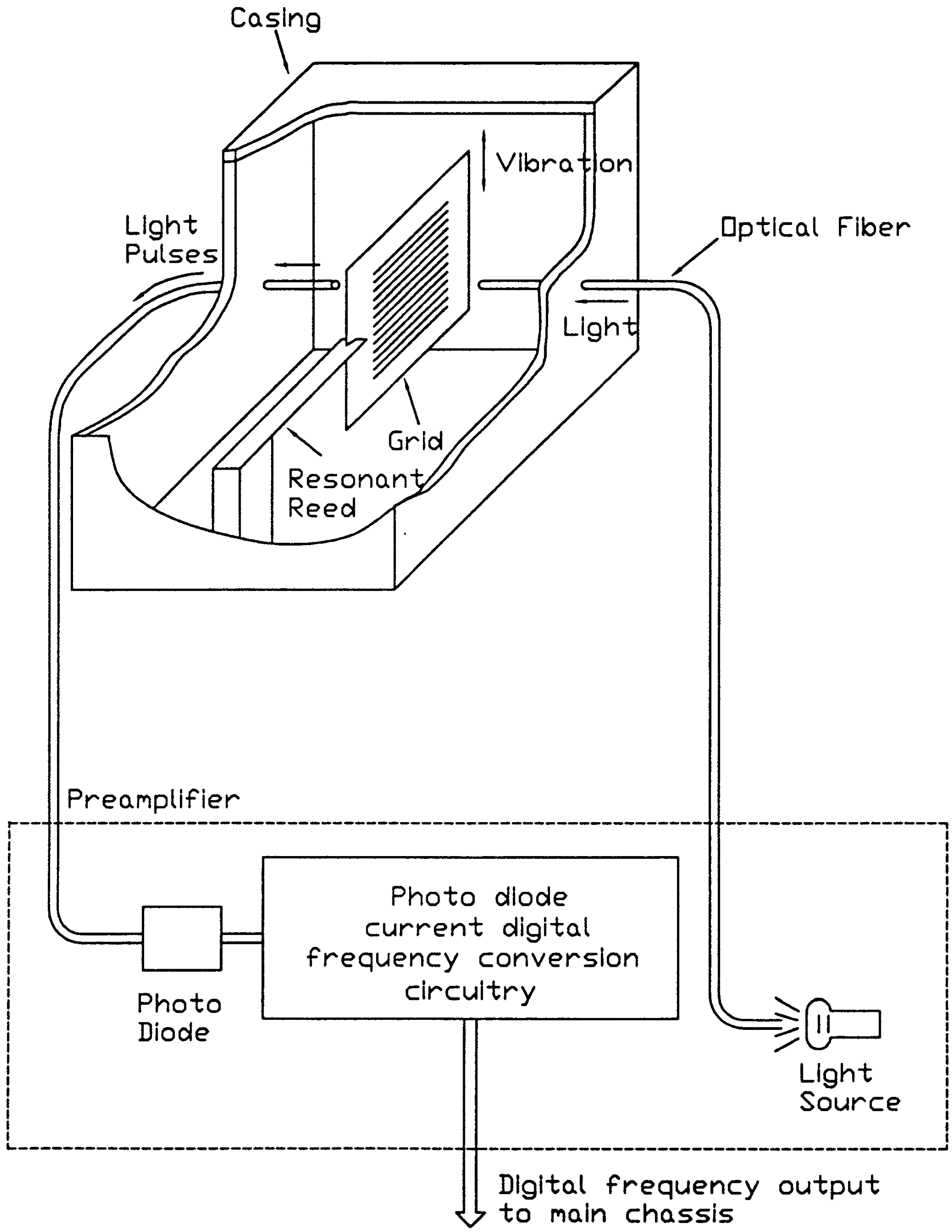


Figure 4.8 Operating Principle of Fiber Optic Vibration Sensor (GONZ 95)

tuned to be resonant at a natural frequency slightly above 120Hz (or 100Hz). A continuous beam of light is directed the grid at right angles to the vibratory motion. As each slot in the grid moves through the beam of light, a pulse of light enters the optical cable on the other side of the grid. The number of light pulses in a given period of time is proportional to the amplitude of vibration. The microprocessor-based monitor employs signal processing algorithms that detect the resonance vibration frequencies for all sensors directly from the output signal during TG operation. It increases the accuracy of the monitor by continuously updating the sensor's calibration. Furthermore, it eliminates erroneous vibration level readings by identifying possible sensor malfunctions.

The fiber optic vibration monitor provides measurements at various locations (usually six) on each end of the generator. Figure 4.9 shows the construction and installation locations of the sensor. The system is composed of vibration sensors, internally routed optical fibers, fiber optic hermetic pressure seals, fiber optic cable bundles, preamplifiers, and a readout box which permits the stator end winding vibration amplitude signals to be displayed within the control room and interfaced with a computer (GONZ 95), (HENS 93).

4.3.9 Torsional Vibration Monitoring

A wide variety of electrical disturbances on the transmission system, such as electrical faults and high-speed reclosing of circuit breakers, can cause TG shaft fatigue damage. A better understanding of the interactions between the electrical transmission system and the TG would provide an opportunity for early detection of shaft problems that can occur and to develop new operating procedures.

A torsional vibration system mentioned in this work consists of three modules: a torsion vibration monitoring data acquisition system (TVMDAS); an electrical fault monitoring data acquisition system (EFMDAS); and a data communication system (DCS). The TVMDAS monitors the electrical airgap torque applied on the generator rotor and the oscillatory changes in the shaft speed at two locations. The EFMDAS monitors the three generator terminal currents and voltages. The TVMDAS and the EFMDAS store data when an event occurs and transmit them via the DCS to the central computer (GORZ 86), (GONZ 95).

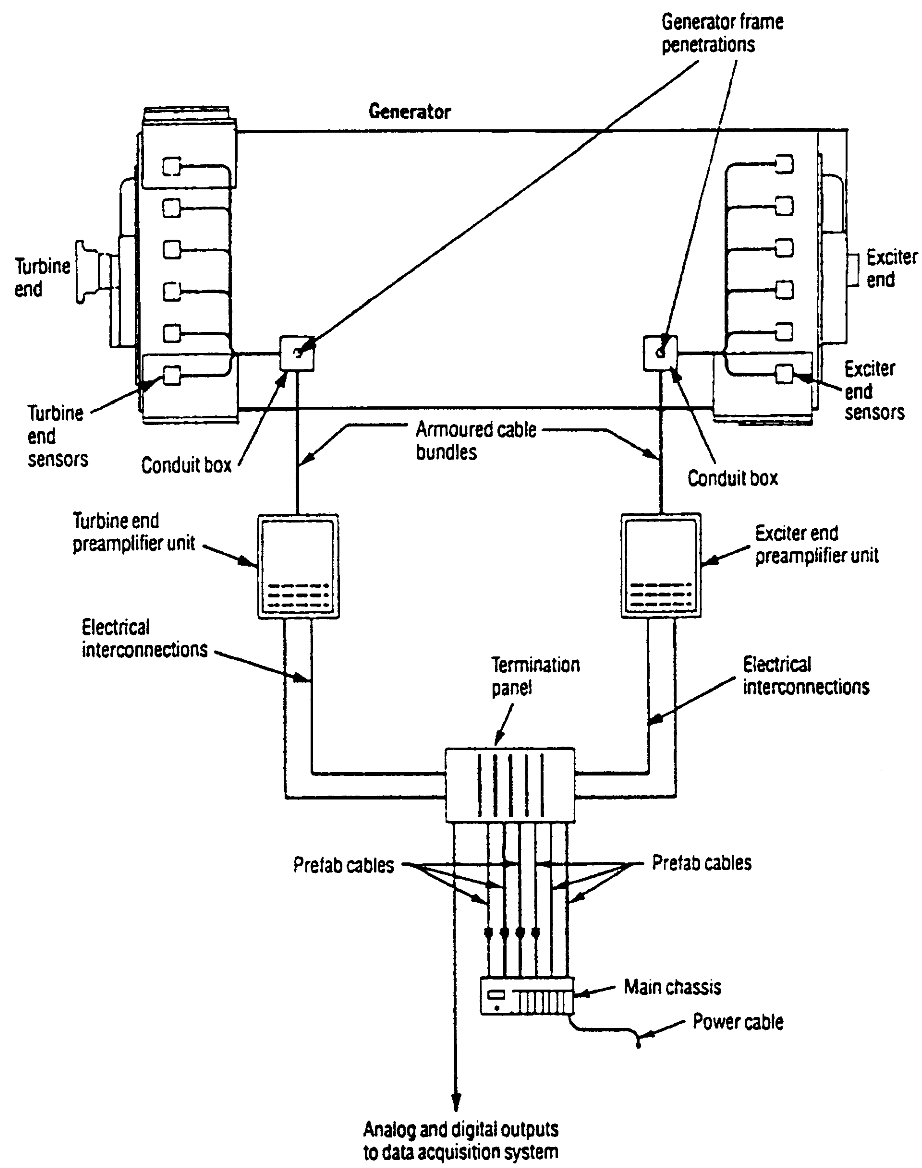


Figure 4.9 Construction and Installation Locations of Fiber Optic Vibration Sensor (HENS 93)

4.3.10 Hydrogen Gas Purity Sensor

The generator rotor moves within a hydrogen-filled cavity. Pure hydrogen gas has very low density, thus minimizing the windage losses of the machine. As the hydrogen becomes less pure as it mixes with water vapor, oil vapor, or even air, its density rises significantly, as do the windage losses. Hydrogen purity should be held at the level recommended by the manufacturer, or higher, in order to minimize windage losses.

The hydrogen purity meter (HPM) monitors the purity of the hydrogen gas inside the generator frame during operating conditions. There are various means to measure the purity. One is through conductivity measurements, and another popular one is through density measurement technique.

This work introduces the density measurement technique. The HPM uses measurements of the hydrogen density to calculate its purity. The method utilizes the differential pressure produced by a small, constant speed fan called the purity blower. This differential pressure is proportional to the gas density, which is proportional to the gas purity. The highly accurate microprocessor based design provides sophisticated information and can be incorporated into entire plant condition based maintenance (GONZ 95).

4.3.11 Hydrogen Dew Point Monitor

Determining the amount of moisture in the hydrogen gas in an important monitoring function. It is important to minimize the moisture content of the hydrogen gas. The ability of any gas to absorb water vapor is a direct function of its temperature. Therefore, at higher temperature, hydrogen can absorb a greater amount of moisture than at lower temperature. The hydrogen gas in the generator will very rarely be saturated because of the high temperatures involved during normal operation, even at less than full load levels. The danger from excessive moisture in a generator arises from the fact that even though the general environment may be relatively hot, the temperatures are unevenly distributed. Specifically, the temperature of the gas at the outlet of the hydrogen coolers will naturally be significantly lower than at its inlet. These localized lower temperatures cause a decreased moisture-absorbing capacity in the gas around the area of decreased temperatures and thus possible condensation in some sensitive elements of the generator internals.

The work reported here introduces two methods to determine the humidity of gases. The chilled mirror method uses a rather simple concept, which says that the reflectivity of the mirror is a function of the amount of condensation that has settled on its surface. The temperature of the mirror can be changed to determine the dew point. The problem with this method is that its reliability can be composed if the gas stream is contaminated with dirt, dust, or oil vapor.

Another method is the use of thin film aluminum oxide to detect the moisture content. This sensor consists of an aluminum strip, anodized by a special process to produce a porous oxide layer. This, in effect, forms an aluminum oxide capacitor, with the aluminum surface forming one electrode and the gold coating forming the other electrode. The porous aluminum oxide layer acts as a dielectric. The electrical impedance of the porous material is proportionally related to the amount of water vapor that forms on it. Thus, the absolute humidity is calculated by relating it to the impedance between the electrodes (GONZ 95).

4.3.12 Hydrogen Leakage Detector

The hydrogen pressure in a water cooled generator is commonly designed to be higher than the water pressure. Any cracks in the hollow water-carrying conductors or other small leaks will tend to result in a hydrogen leakage into the water system, rather than a water leak inside the generator frame. The types of failure that have been experienced include failure of the armature groundwall insulation because of permeation by water when the insulation is not water resistant. Monitoring the hydrogen leakage into the water system can serve to detect such cracks in the hollow conductors and other small leaks.

A water tank is used to collect the water as it exits the stator and to act as a source of cooling water for the pumps. In some designs, the tank is covered by blanket of clean hydrogen to control the oxygen content of the water at a proper level to minimize oxidation of the hollow strands in the coils. The water pressure is always maintained lower than the hydrogen pressure so that any perforations or cracks in the water-carrying hollow conductors will cause hydrogen gas to leak into the water system, and not vice versa. Therefore, any introduction of gas into the water system will register as an increase in pressure of the hydrogen blanket, if one is used. This is a key parameter to monitor when trying to detect the presence of such perforations or cracks. It should be noted that the manufacturer should be consulted to determine what amounts to normal leakage. This detector applies only to those designs that maintain a hydrogen blanket over the water tank (GONZ 95).

4.3.13 Water Conductivity Detector

Conductivity cells are used throughout the stator coil cooling water (SCCW) system to monitor the conductivity of the stator cooling water and ensure that its electrical conductivity is within limits. Because conductivity is such a critical parameter, cells should be placed at several locations in the system.

One such cell is typically placed at the outlet of the demineralizers to monitor their effectiveness in reducing the conductivity of the water routed through the demineralizer plant. A second conductivity cell is placed in the water tank to measure the overall conductivity of the water that will be pumped into the stator coils. It is recommended that a third cell is installed near the inlet to the generator to measure the water conductivity closer to the point where its value is most significant.

Chapter 5. Development of Comprehensive Sensor Networks

5.1 Introduction

Chapter 3 presents an integrated methodology for developing comprehensive sensor network involving modern data processing techniques and Chapter 4 introduces modern condition monitoring techniques. They provide the foundation for deciding what types of sensors to use and where to put them. This chapter explains recommendations of the sensors for use in on-line monitoring for operational availability improvement.

In addition, this chapter presents the overall architecture of plant wide condition monitoring system networks, reflecting modern features of data processing techniques, and then explains how the comprehensive sensor networks developed for the turbine generator (TG) and the reactor coolant pump (RCP) can be elaborated into comprehensive plant wide networks.

The studies of sensor installation feasibility have been performed several times with the technical staffs in the power plants such as Seabrook Nuclear Power Station, South Texas Nuclear Power Station, and Pilgrim Nuclear Power Station, and with the sensor manufacturers. The focus of this feasibility study is upon confirmation of design specifications for new types of sensors and their placement. Then, their opinions and suggestions on newly developed sensors have been coordinated into the final design work using computer aided design software (e.g. AutoCAD (AUTO 96)). The reason why we have gone through this design work is to make sure that we could install these sensors on specific components.

Through these studies, it is emphasized that for new plants more attention needs to be given to sensor locations as well as specific design for sensor installation should they be used in the future. The falling costs of advanced instrumentation and accumulation of plant operation may make these technologies more attractive in the future. Therefore, final decisions should be made by each utility considering its own specific situations for the needs of new monitoring systems and economic status.

In the end of this chapter, the order of sensor preference priority is presented in order to help the technical staff to choose the proper set of sensors in case that there are several candidates of sensors in measuring a specific parameter.

5.2 Architecture of Plant Wide Condition Monitoring System Networks

The work reported here suggests use of dedicated networks that link individual system (or component) monitoring systems into a plant wide data base system housed in the main diagnostic center. It can control overall monitoring and diagnosis work. This interconnection of the individual systems for the purpose of shared resources and common database is achieved though the implementation of local area networks (LAN). The main center LAN connects all of the major components together on a high speed data network. This center should diagnose the integrated system state throughout the plant, manage this information, display data in a use-friendly environment, and transfer configured information to the plant control room.

In this architecture, rather than requiring that all information from all sensors be brought to the centralized main diagnosis center, the use of remote data processing equipment is recommended for transferring more sophisticated, integrated data to the main center. These remote processors can communicate to the main center over high speed communication link utilizing the Ethernet standard for protocol and reduce the amount of cabling to the main center.

These networks should be designed to be easily integrated to other component instrumentation and control (I&C) equipment and the plant control room. This means that the diagnostic center can provide a communication interface, database management, knowledge based processing, and man-machine interface. This task can be supported via computer workstations that access and process data from the plant data highway.

5.3 Sensor Arrangements for Advanced Condition Monitoring in the Turbine Generator

The sensor network development methodology presented in Chapter 3 is employed to determine monitoring parameters and locations in stator winding, stator core, rotor, bearing lubrication oil system, stator coil cooling water auxiliary system, hydrogen auxiliary system, and gland seal system, etc. This design work has been performed in order to make sure of sensor locations and sensor types as shown on drawings and schematic diagrams that are feasible in the opinions of experts. Table 5.1 indicates the nomenclature for each sensor name.

Table 5.1 Nomenclature for Sensor Names

Nomenclature	Sensor Name
ACC	Accelerometer
ASC	Airgap search coil
CM	Conductivity meter
CT	Current transformer
DP	Differential pressure sensor
DXD	Differential expansion detector
FOTS	Fiber optic temperature sensor
FOVS	Fiber optic vibration sensor
FP	Flux probe
GCCM	Generator core condition monitor
HLD	Hydrogen leakage detector
HS	Humidity sensor
KP	Keyphasor
LKD	Leakage detector
LVS	Level sensor
MC	Motor current sensor
PDS	Partial discharge sensor
PP	Proximity probe
PS	Pressure sensor
PT	Position sensor
PuS	Purity sensor
RGC	Rogowski coil
RTD	Resistance temperature sensor
RXD	Rotor expansion detector
SRTD	Slot embedded RTD
SVD	Shaft voltage detector
SXD	Shell expansion detector
TBWD	Thrust bearing wear detector
TC	Thermocouple
TS	Temperature sensor (RTD, TC)
TSD	Turbine stress detector
VS	Voltage sensor
VT	Voltage transformer
WDA	Wear Debris Analysis

(RTD: Resistance Temperature Detector, TC: Thermocouple)

5.3.1 Sensor Arrangement for the Turbine Generator Exterior

Figure 5.1 illustrates what type of sensors to put and where to put them on the turbine generator exterior. Table 5.2 shows detailed sensor types corresponding to sensor location numbers. The detailed descriptions of individual sensors are mostly introduced in Chapter 4.

Table 5.2 Sensor Locations and Types in the Turbine Generator Exterior

Sensor Location Number	Sensor Type
1	HP differential detector
2	Turbine speed detector
3, 5, 7, 9, 11, 12, 14, 15, 17, 18	Bearing vibration sensor: ACC Bearing temperature sensor (RTD)
8, 22	Turbine metal temperature sensor(RTD)
6, 10, 13, 16	Shaft vibration sensor: PP, KP Shaft torsional stress sensor (TSD)
4	Shell expansion detector
19	LP rotor expansion detector (RXD)
20, 23	Turbine stress detector (TSD)
21	Thrust bearing wear detector (TBWD)

(ACC: Accelerometer, PP: Proximity Probe, KP: Keyphasor)

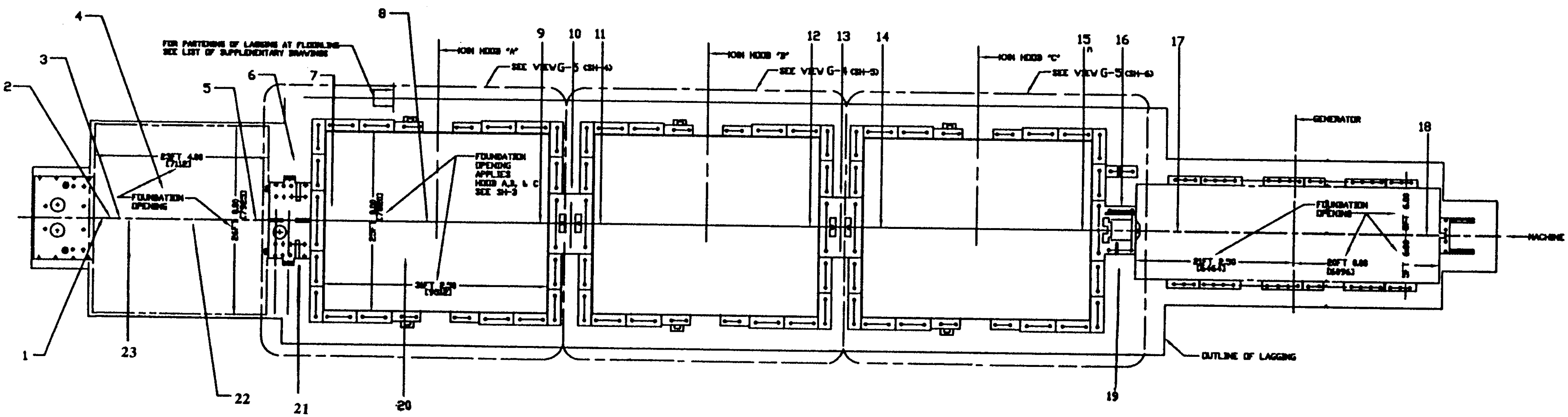


Figure 5.1 Schematic Diagram of the Sensor Network for Condition Monitoring on the Turbine Generator Exterior (KEPC 96)

5.3.2 Sensor Network for the Main Generator

Figure 5.2 illustrates sensor locations and types on the schematic diagram of generator interior. Table 5.3 shows the sensor types and corresponding installation locations. The bearing metal temperature and vibration measurements provide more correlated indications of the condition of the bearing.

Table 5.3 Sensor Locations and Types inside the Generator

Number	Component	Sensor Type
1,6,14,20	Stator end winding	FOVS (or ACC)
	Stator end winding slots	FOTS (or SRTD)
2, 5	Gland seal	RTD
	Gland seal oil path	RTD, PS, FS
3,16	Hydrogen path	RTD, PS, PuS, HS, GCCM
4,17	Stator core	RTD
7,13,21,23	Stator coil cooling water path	RTD, CM
8	Cooler water inlet path	RTD, PS
9	Cooler water outlet path	RTD, PS
10	Hydrogen blower	PS
11	Rotor	SVD, PP, KP
12,22	Bearing	ACC, RTD
	Bearing oil path	RTD, FS, PS
15	Stator winding terminal	CT, VT, RGC
18	Stator inside plate	LKD, ACC
19	Rotor airgap	FP (or ASC)

Accelerometers for vibration measurement and RTDs for temperature measurement are typically used for this task. The on-line partial discharge sensor such as Rogowski coil is recommended at the high voltage terminal and neutral terminal of the generator. For general temperature measurements except for those of the stator winding, RTDs are the first preference and then thermocouples are recommended. Fiber optic temperature sensors are favored for the stator winding temperature measurement. For the vibration measurement in the stator end winding, the fiber optic sensor is preferred and accelerometers are recommended as the second choice. In the rotor airgap, either flux probes or airgap search coils are recommended for detection of the flux variation caused

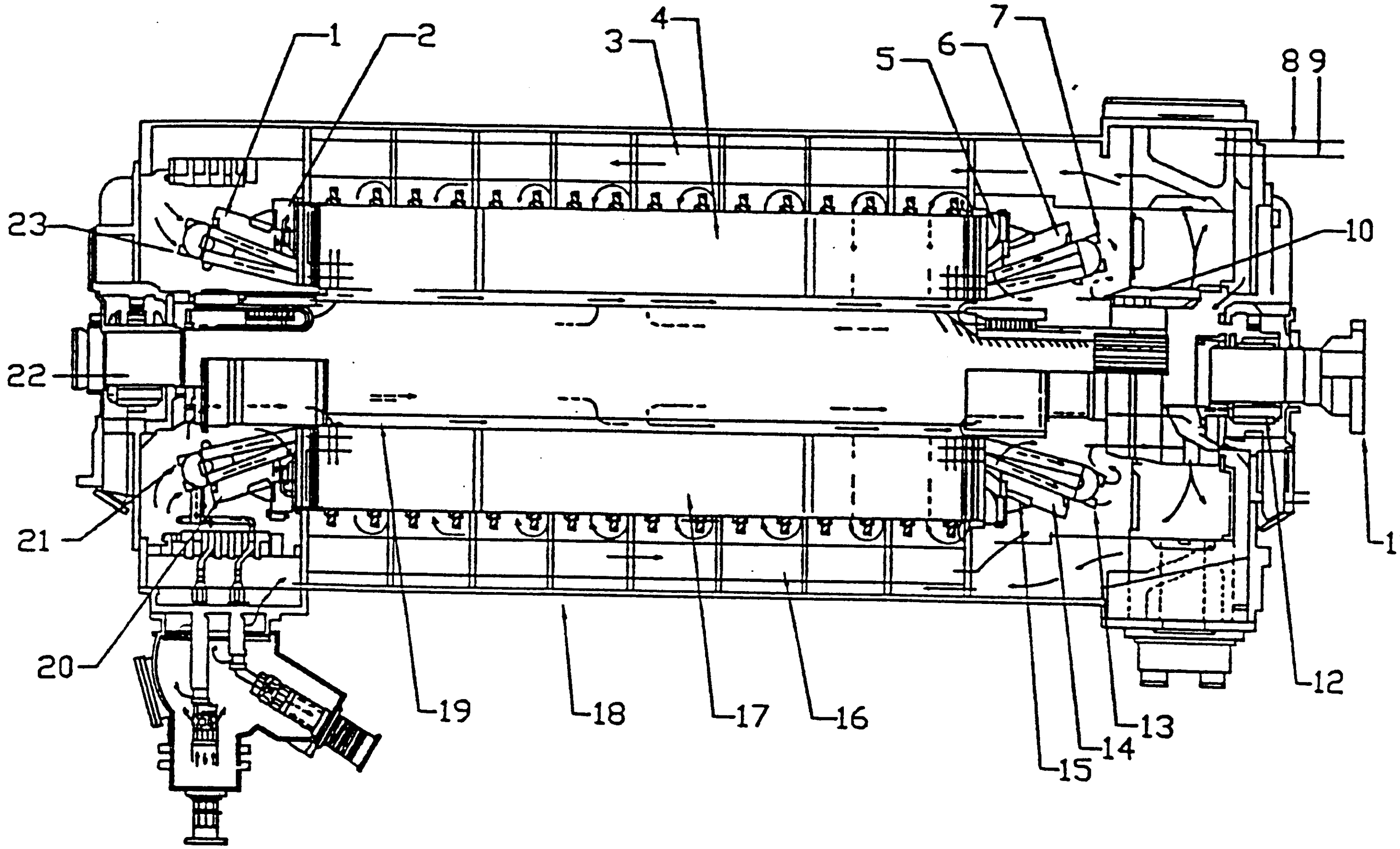


Figure 5.2 Schematic Diagram of the Sensor Network for Condition Monitoring in the Main Generator (JERV 93)

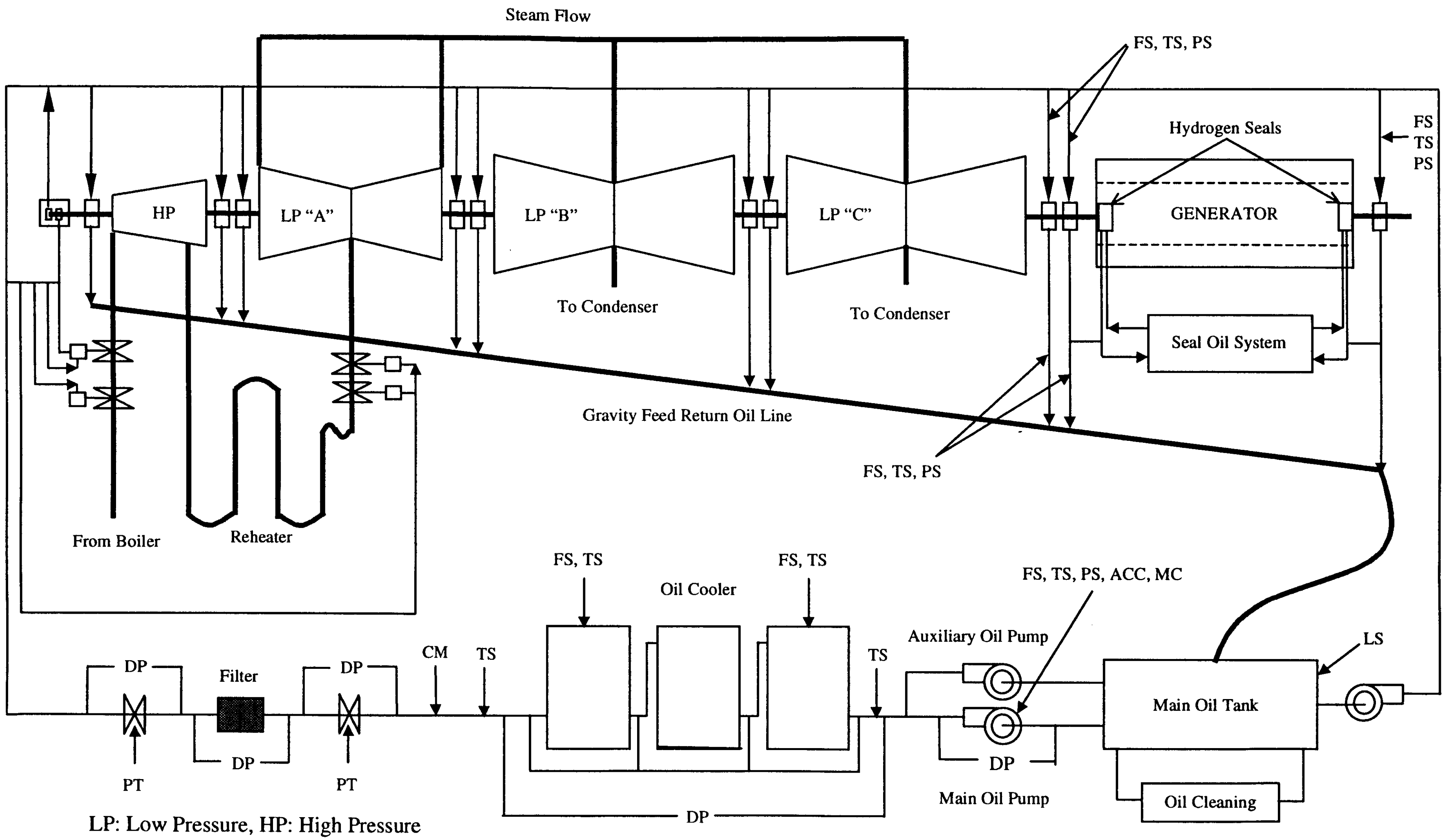
by short-circuited turns. This is why the uneven heating of the rotor may result in uneven thermal expansion of the conductor.

The detailed reasons why some specific sensors are preferred for the measurement of specific parameter monitoring at some locations are described in Chapter 4. The final decision on choice of specific sensors requires careful consideration based upon the specification stage of the machine and a cost-benefit analysis.

5.3.3 Sensor Network for the Turbine Generator Lubrication Oil System

Figure 5.3 shows sensor locations and sensor types in the turbine generator bearing lubrication oil system. We suggest that comprehensive sensors such as temperature sensors, flow sensors, pressure sensors, vibration sensors, motor current sensors, and partial discharge sensors to be used for the monitoring of lubrication oil pumps. Their exact locations and detailed explanation of sensor selection preference are shown in Chapter 4.

Foreign materials in the oil can result in a bearing wipe or in journal scoring. Furthermore, water entrained in the oil can be a cause of rusting in the ferrous metal parts with which it comes into contact. Thus, off-line wear debris analysis is recommended for assessing the debris contents and debris type in lubrication oil. The level of the oil tank is monitored closely for high and low levels. Level switches are typically used for this measurement. The temperature at the inlet of the coolers must be monitored. One major reason is that cooling water in the cooler secondary is not tuned on until the temperature of the oil reaches a certain level. We typically recommend using RTDs for this function. Moreover, monitoring of the lubrication oil cooler differential pressure can indicate whether there is flow in the coolers. Monitoring of inlet and outlet oil temperatures should be performed in order to detect the degradation in the cooling capability.



(Note: The legend is given in Table 5.1)

Figure 5.3 Schematic Diagram of Sensor Network for Condition Monitoring in the Turbine Generator Lubrication Oil System (BISS 95)

5.3.4 Sensor Network for the Stator Coil Cooling Water System

Figure 5.4 shows sensor locations and types in the stator coil cooling water system. In the turbine generator, the stator winding and coil cooling system usually are the most responsible for lost availability. This design work suggests what type of sensors to use and what locations to consider for comprehensive condition monitoring.

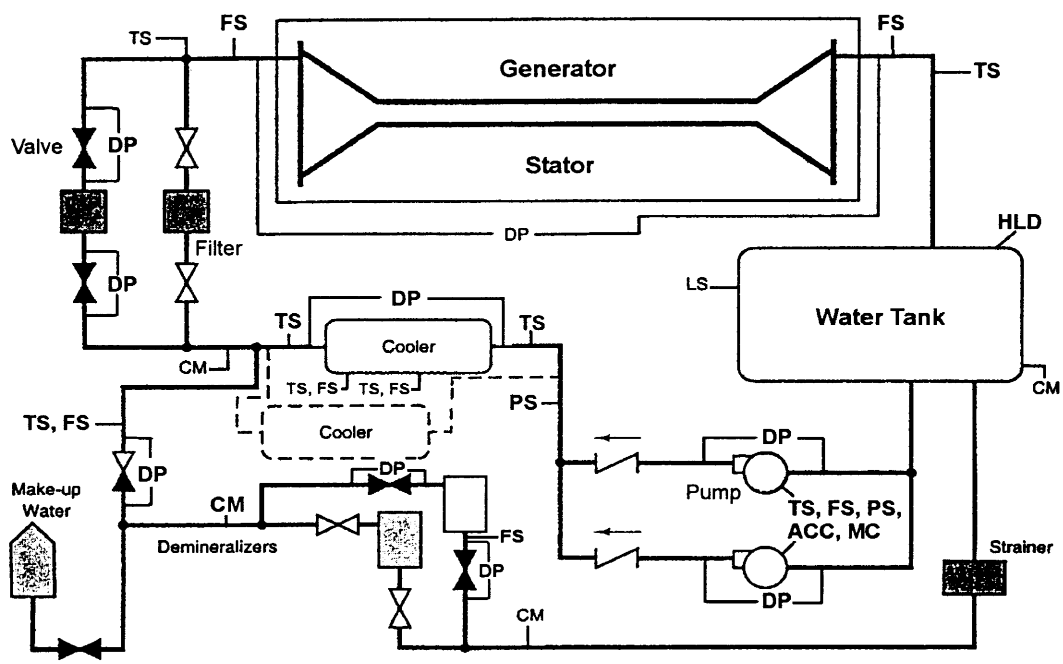


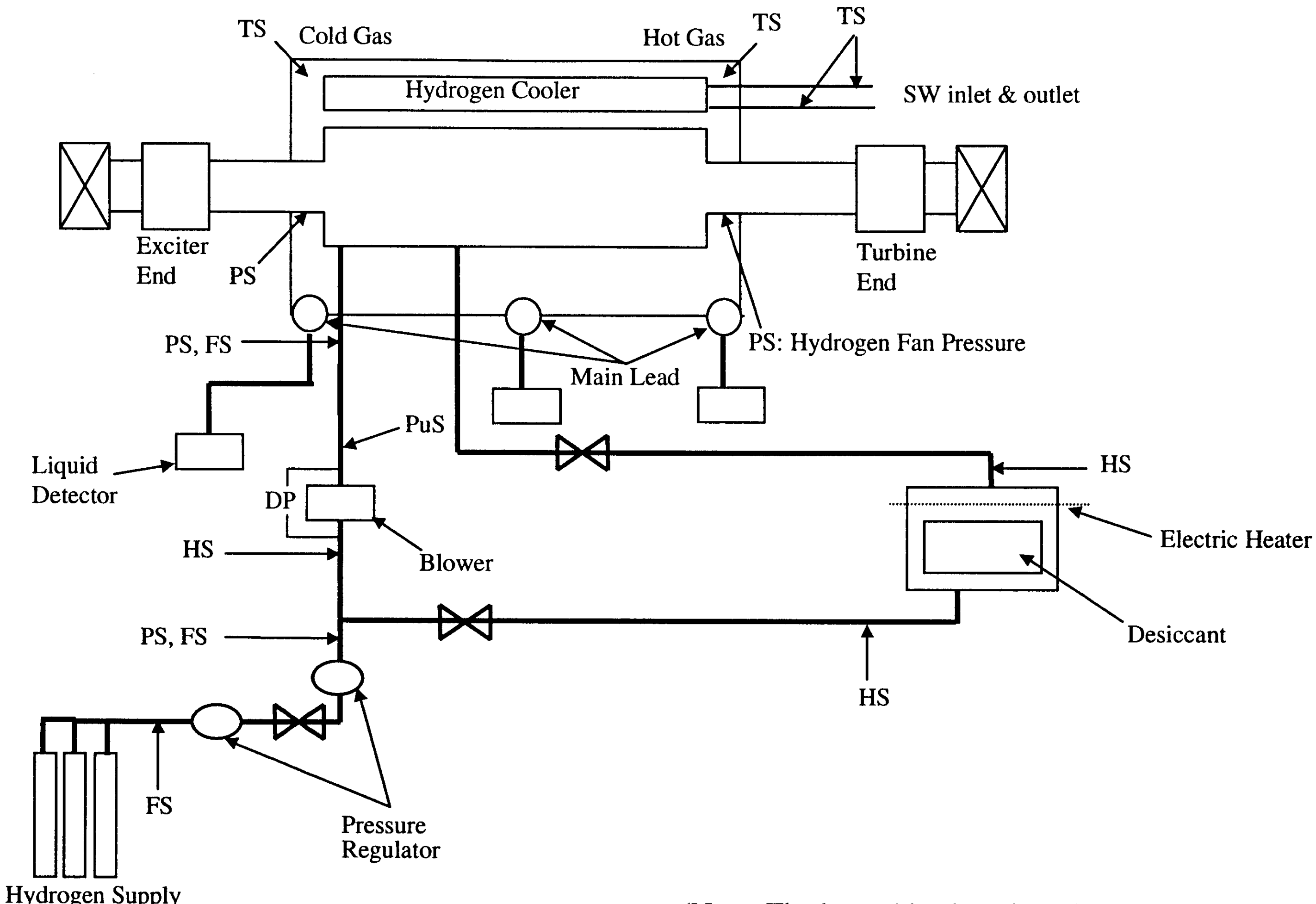
Figure 5.4 Schematic Diagram of Sensor Network for Condition Monitoring in the Stator Coil Cooling Water System (Note: The legend is shown is Table 5.1)

This study emphasizes on the needs of modern hydrogen leakage detector, which is installed inside the water tank. Its detailed mechanism and functions are described in Section 4.3.12. The water tank level can also indicate some problems with the system flow loss such as leaks. Conductivity cells are used through the SCCW system in order to monitor the conductivity of the stator cooling water and to ensure that its electrical conductivity is within acceptable limits. The outlet of the mineralizer, the tank interior, and water path after the strainer are recommended as sensor installation locations. The filter differential pressure is a good indicator that should be measured in order to determine the internal state of the filtering element. If it is excessively clogged with filtered material, the element will resist the flow of water, resulting in an abnormally large pressure drop across it. The differential pressure of the stator cooling water across the cooler can be used to detect the flow across the cooler in order to assess the cooler state as well as water cooling capability. Also, the temperatures of the cooling water should be measured at the inlet and outlet of the stator to check if the temperature is getting higher. For comprehensive monitoring of the cooling water pump, temperature, pressure, flow, vibration, partial discharge, and motor current should be measured with the corresponding sensors that are recommended in this study. Further analysis on the cost and benefit are recommended in deciding how comprehensively it is monitored.

5.3.5 Sensor Networks for Hydrogen Cooling Auxiliary System

In Figure 5.5, we recommend what types of sensors to put in the hydrogen auxiliary system. One of the most important parameters in the hydrogen system is its pressure because its directly affects the performance of the generator stator. We recommend using various monitoring points in the hydrogen supply system. The differential pressure measurement determines the integrity of the hydrogen blower and ventilation system. The problems caused by abnormal hydrogen pressure are directly related to the flow of hydrogen through the generator.

The temperature of the hydrogen is the second important parameter measured because the heat transfer capability of the system depends upon the temperature difference between hydrogen and stator windings. Inlet and outlet hydrogen temperature across the coolers should be measured in order to determine the effectiveness of the coolers. The humidity detector measures the moisture content of the hydrogen. High humidity levels can also be result in serious corrosion cracking of various critical components, such as retaining rings. Liquid detectors are liquid level switches located at the turbine end, the exciter end, the lead box, and underneath the hydrogen coolers. They collect water or oil that is leaking and condensing from the various sources in the generator. Especially, leaks in the hydrogen coolers may lead to critical problems such as moisture ingress into the hydrogen. The humidity measurement of hydrogen at inlet and outlet of the cooler, liquid detector, and the color of the desiccant crystals should be



(Note: The legend is given in Table 5.1)

Figure 5.5 Schematic Diagram of Sensor Network for Condition Monitoring in Hydrogen Auxiliary Cooling System

integrated. Hydrogen gas is likely to become flammable when its purity is degraded. One significant source of impurities is a variety of problems in the gland seal system. Thus, a hydrogen purity meter could provide information about the impurity level of the hydrogen supply in abnormal situations.

5.3.6 Sensor Network for the Gland Seal System

Gland seals, supplied with oil under pressure, are used to prevent the leakage of hydrogen through the clearance between the generator shaft and the frame. There are two kinds of designs. One is a double-flow system and the other is a single-flow system. This study introduces the condition monitoring sensor network concerning the double-flow system. The gland seal ring for the double-flow system has two grooves, one for each oil supply. The different oil supplies, called the air-side (AS) and hydrogen-side (HS) systems, should be kept separate in this overall system.

Figure 5.6 shows the sensor types recommended for use in the hydrogen-side seal

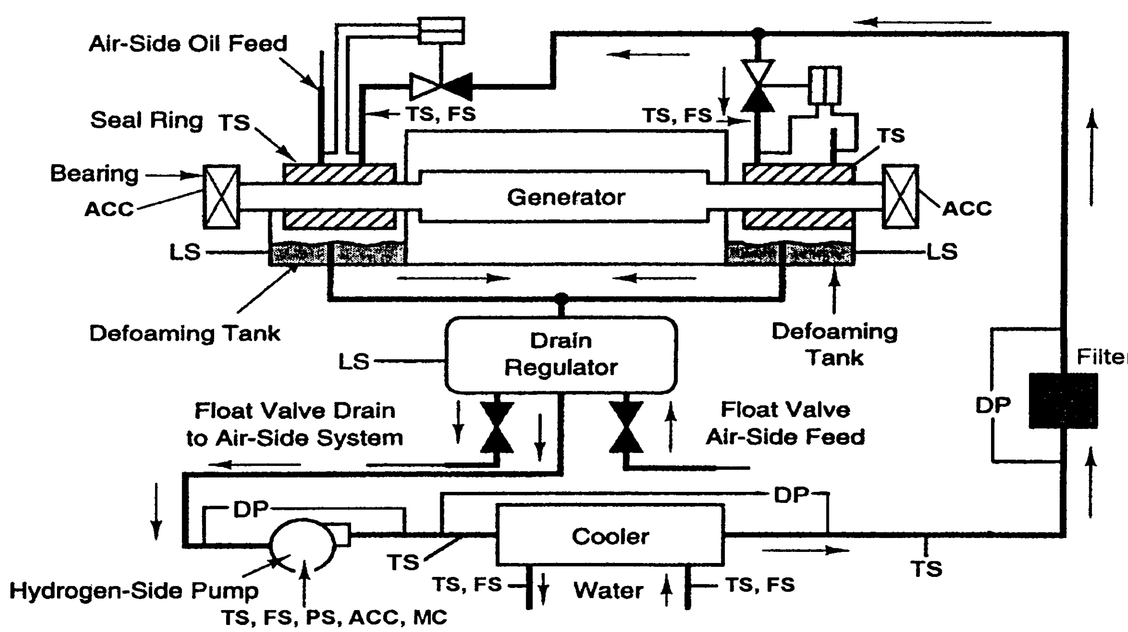


Figure 5.6 Schematic Diagram of Sensor Network for Condition Monitoring in the Hydrogen-Side Gland Seal System (Note: The legend is shown in Table 5.1)

oil system. When a defoaming tank overflows, excess oil can enter the generator frame. A level switch is usually used in each tank to provide a warning when a defoaming tank is in danger of overflowing. Also, the drain regulator tank level should be monitored. The comprehensive monitoring for a pump is recommended, including the monitoring of temperature, pressure, flow, vibration, motor current, and partial discharge, etc. An analysis of economic cost and benefits is recommended for determining the degree of monitoring coverage to use within the seal oil pumps. As the filter progressively accumulates more debris from the oil, it further impedes the flow of oil, causing the pressure drop across the filter to increase commensurately.

In Figure 5.7, sensors for the air-side seal oil system. The air-side system is generally better instrumented than the hydrogen-side, because of its greater complexity and greater economic importance. The air-side seal oil system has one local pressure indicator on each side to measure the oil pressure at the ring. The pressure difference between the hydrogen-side and the air-side systems at the rings is the parameter that determines how much mixing is occurring between the oils from the two systems. Because this mixing has to be minimized it is important to monitor this parameter. The

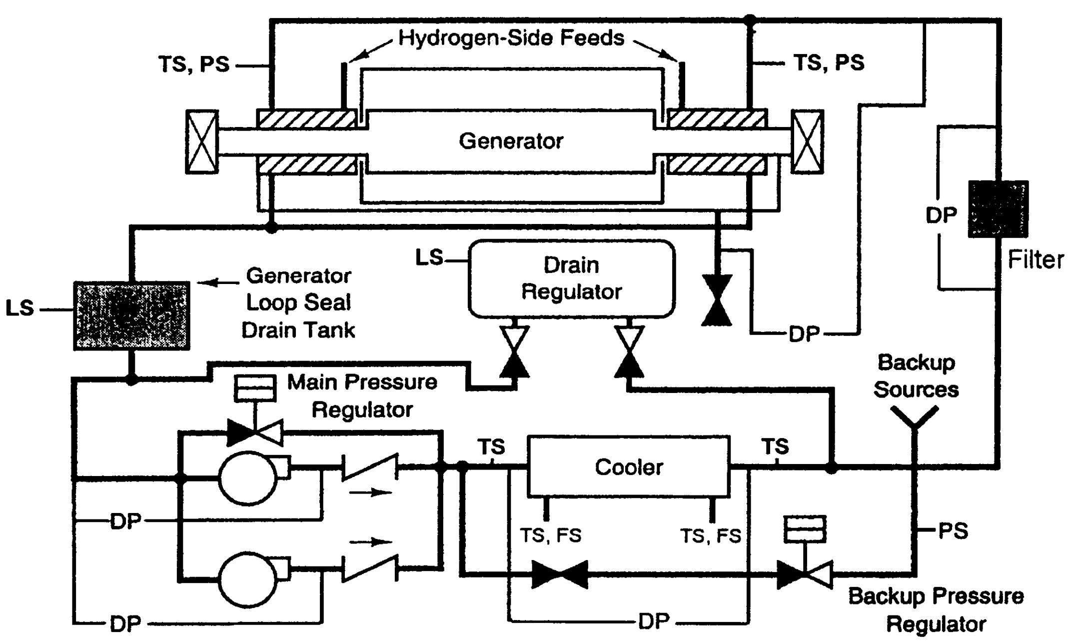


Figure 5.7 Schematic Diagram of Sensor Network for Condition Monitoring in the Air-Side Gland Seal System (Note: The legend is shown in Table 5.1)

differential pressure between the seal oil and the hydrogen gas is important because it determines the ability of the seal oil system to maintain a seal in the generator.

5.3.7 Sensor Network for the Generator Core and Frame

Historically, generator core failures have known been fewer than those considered previously, however, the outage time is rather lengthy. The early indications of the fault are flow of large circulating currents, high temperature, and the pyrolysing of insulation materials. The most common way to monitor the core is through the Generator Core Condition Monitor (GCCM), described in Section 4.3.7. The temperature of the core end is typically measured by the RTDs because the core end has been known to the most likely location for overheating to occur.

Frame cracks are generally the result of long-term operation with high frame mechanical vibrations, possibly because of generator shaft misalignment or unbalance. Such cracks in the frame can cause hydrogen leaks to take place. Gas vented to the outside may create a potentially explosive situation. A tracer-gas detector can be installed for leaks are difficult to detect. Then it is used outside of the generator to detect the presence of a leak at a specific location. One of the typical causes of core damage is detected through vibration measurement using accelerometers.

5.4 Sensor Arrangements for Advanced Condition Monitoring in the Reactor Coolant Pump

The reactor coolant pump (RCP) circulates water through the primary coolant systems in order to transport energy from the reactor core to the steam generator. Figure 5.8 illustrates the monitoring points for subordinate components of the RCP. Table 5.2 relates sensing locations shown in Figure 5.8 to the proper sensor types. The detailed explanation of individual sensor selections is given in Chapter 4. Like the turbine generator monitoring, vibration is an important sensitive parameter indicating the operating state of rotating assembly since every rotating machine has its own characteristic vibration signature, which can be obtained from the frequency spectra of the monitored vibration signals. Proximity probes are the most sensitive to very low amplitude and low frequency vibrations of the rotating shafts in the RCP. A phase reference probe detects phase changes.

An accelerometer measures the acceleration of rotating components such as bearings, the impeller and the rotor because it has high frequency sensitivity. The comprehensive process monitoring including the continuous measurements of temperature, pressure, and flow is recommended for the cooling water inlet and outlet, seal injection flow and component cooling water. Also, bearing oil pump monitoring is recommend in order to utilize a comprehensive sensor set, which can provide information on temperature, pressure, flow, vibration, motor current, and partial discharge monitoring, etc. Analyzing the cost and benefit arising from addition of new monitoring equipment should perform the final decision on coverage of comprehensive monitoring system. Furthermore, water entrained in the oil can be a cause of rusting in the ferrous metal parts with which it comes into contact. Thus, off-line wear debris analysis is recommended for assessing the debris contents and debris type of lubrication oil.

Table 5.4 Sensor Locations and Types in the Reactor Coolant Pump

Sensor Location in Figure 5.8	Sensor Type
1, 2, 11, 16	ACC
3, 4, 9, 19	ACC, TS
6, 18	TS
13, 15, 20	TS, FS, PS
22, 23	PP, KP
24	TS, FS, PS, ACC, MC

(Note: The legend is given in Table 5.1)

Monitoring locations and sensors in the RCP motor are shown in Figure 5.9. While many types of fault detection are available for motors, on-line monitoring is generally provided by some combination of thermal, vibration, and electrical monitoring techniques. The majority of motor failures can be related to the stator, the rotor, insulation and the bearings. The identification of mechanical problems such as rotor bar fracture, airgap eccentricity and bearing wear via on-line analysis of the current as the most frequently monitored on-line parameter for an induction motor can provide an indication of an early stage of failure.

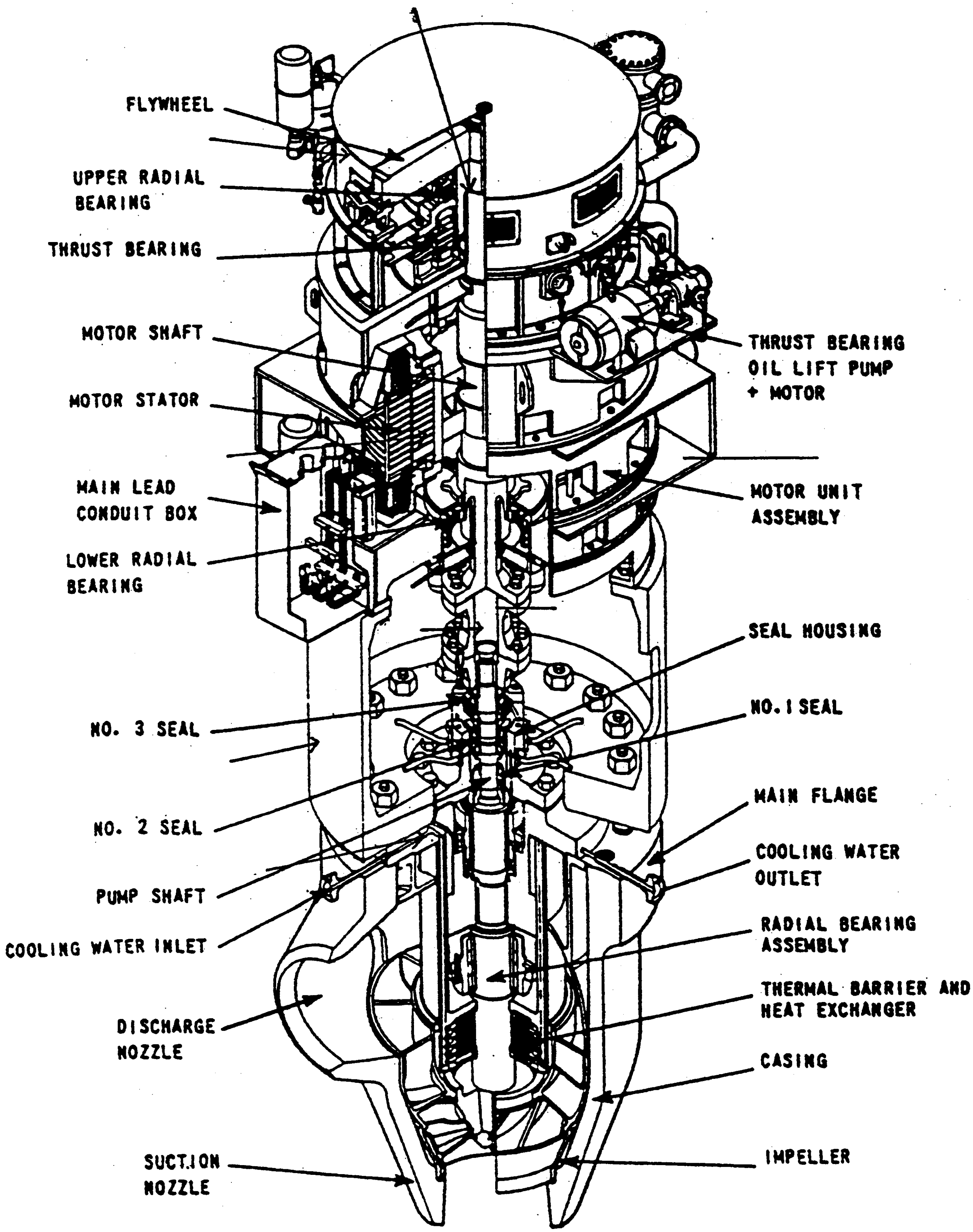


Figure 5.8 Schematic Diagram of Sensor Network for Reactor Coolant Pump Condition Monitoring (MEYE 93)

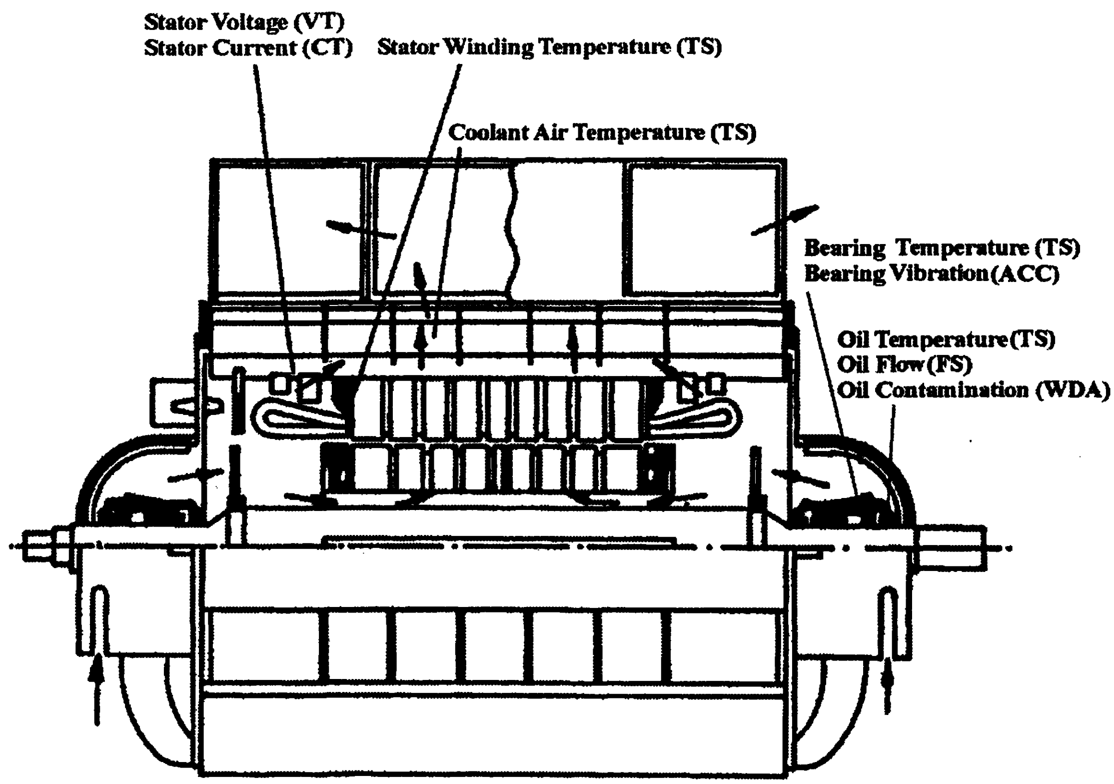


Figure 5.9 Schematic Diagram of Sensor Network for RCP Motor Condition Monitoring (TAVN 87) (Note: The legend is given in Table 5.1)

The supply current is normally monitored very easily, without interfering with the machine, simply by fitting a clip-on current transformer around the supply cable to the motor. The Rogowski coil, which is located around the high voltage terminals of the stator winding as a non-invasive current transducer, can be suggested for use for measurement of high frequency current pulses in the stator windings generated by partial discharge activity in the insulation structure.

5.5 Priority Recommendations of Sensors for Use in On-line Monitoring

This section summarizes recommendations of sensors for use in on-line monitoring and advice for operational availability improvement. The sensors suggested for the target plant components addressed in Chapter 4 and previous sections of Chapter 5 are presented in order of preference priority as recommended in measuring a specific parameter with several candidates of sensors. In cases where there are multiple choices of sensors for the specific monitoring point and parameter, the sensors are recommended in order of priority as shown in Table 5.5. The reasons for these rankings are discussed below.

Table 5.5 Recommended Order of Priority in Measuring the Specific Parameter with Multiple Choices of Suggested Sensors

Monitoring Point and Parameter	Order of Priority of Recommended Sensors
Generator stator winding vibration	1. Fiber optic vibration sensor 2. Accelerometer
High voltage terminal of stator winding (Partial discharge in generator and motor)	1. Rogowski coil 2. Current transformer 3. Capacitive coupling
Generator rotor winding temperature	1. Electronic rotor temperature sensor 2. Resistance temperature detector 3. Thermocouple
Generator stator winding temperature	1. Fiber optic temperature sensor 2. Imbedded temperature detector 3. Resistance temperature detector 4. Thermocouple
Temperature measurement except stator winding and rotor winding	1. Resistance temperature detector 2. Thermocouple
Off-line lubrication oil system wear debris analysis (in generator and motor)	Ferrography or Spectrometric oil
Rotor flux measurement in generator airgap	Flux probe or Airgap search coil
Turbine generator shaft vibration	1. Proximity probe and keyphasor 2. Torsional vibration monitor
Bearings in turbine generator and reactor coolant pump Generator frame Casing in generator and pump	Accelerometer
Turbine rotor speed	Tachometer

1) Vibration Sensor Recommendation

The relative displacement of the shaft is usually measured by proximity probes. A tachometer has been used to measure the shaft rotational velocity. The third one, called an accelerometer, measures the acceleration of rotating components such as bearings, impeller, generator frame and casing and rotor because it has high frequency sensitivity. A phase reference probe (keyphasor) measures the change of phase in a shaft.

As the vibration amplitudes increase, the stator coil end-turns are progressively more fatigued from a mechanical standpoint. Common vibration sensors such as accelerometers are very susceptible to strong electromagnetic fields near the generator stator windings. On the other hand, the fiber optic vibration sensor has one significant advantage, that is, the sensor and all cabling to and from it are nonconducting. Thus, use of a fiber optic vibration monitor enables on-line early detection and identification of developing end winding loosening through the measurement of coil end vibration levels and the trending of vibration levels over time.

A wide variety of electrical disturbances on the transmission system, such as electrical faults and high-speed reclosing of circuit breakers, can cause turbine generator shaft fatigue damage. Torsional vibration monitor have made it possible to understand better how the interactions between the electrical transmission system and the turbine generator would provide an opportunity for early detection of shaft problems.

2) Partial Discharge Sensor Recommendation

There are capacitive couplings, and Rogowski coil, which can serve as transducers for on-line monitoring. The capacitive coupling is housed between the high voltage terminal. Its principal feature of the partial discharge analysis is its ability to reject the electrical interference that typically dominates the high frequency signal emitted by the partial discharge. However, its monitoring instrument is generally not suitable for on-line monitoring of discharge activity. The Rogowski coil can be suggested for on-line use.

3) Temperature Sensor Recommendation

RTDs are generally considered more accurate than thermocouples and exhibit signal linearity. Especially, an embedded temperature detector using a slot RTD is recommended for stator winding use because the space in the stator end winding is very long and narrow. In some parts of the generator, the most likely hotspot is difficult to predict because of the great length of the potentially overheating elements. In order to overcome these limitations under a strong electromagnetic field, the fiber optic temperature sensor has been developed for detecting the location of a hotspot anywhere in its length. For the rotor temperature measurement the electronic rotor temperature sensor (ERTS) is introduced to measure the temperature of the rotor at a specific location.

4) Wear Debris Analysis Recommendation

Two representative methods, the spectrometric oil analysis and wear particle analysis are recommended for use equally in the work reported here.

5) Rotor Flux Sensor Recommendation

Two representative measurements, by the flux probe and the airgap search coil are recommended for use equally in the work reported here.

5.6 Strategy for Sensor Set Determination Utilized in a Nuclear Power Plant

The work reported here recommends much more elaborate sensor arrays at the design stage of the new nuclear power plant than is the typical. Thus, the technical staffs in each power plant should systematically make a final decision concerning which sensors to keep among the suggested sensor set. The value of each sensor can be evaluated in terms of a cost and benefit trade-off to decide whether to use a specific new sensor or not.

The key factors to be considered concerning the total cost of a new sensor are sensor price, sensor installation feasibility to a specific location, and sensor maintenance. Also, a quality evaluation concerning the sensor reliability, lifetime, accuracy, and sensitivity to indicating specific failure mode states of interest should be performed. This evaluation should be followed by preliminary discussions with specialists in the relevant area. In particular, a system that recommends an inappropriate recovery action caused by a wrong sensor measurement, subject to low sensor quality, may lead to financial loss arising from unexpected forced outages and the degradation of power plant system integrity. Once the expected financial loss associated with a sensor of particular quality and total cost are calculated, the expected benefit from use of a new specific sensor should be analyzed. Use of advanced sensing capability can enable both significant financial gains from better plant operations and potential prevention of system integrity degradation by detecting an incipient failure. The sensing capability for an incipient failure mode can be evaluated though the examination of signal correlation with a corresponding failure mode, sensor technology maturation state, availability of advanced auxiliary data processing equipment, and previous applications to analogous cases. Finally, a systematic decision-making process should decide upon the utilization of a new specific sensor, if it proves to yield financial advantages. Equation 5.1 formulates the relationship concerning costs and benefits concerning use of a new sensor.

$$NET\ (B, C, L) = B(PF, PD) - C(PR) - C(IN) - C(MA) - L(RE, AC), \quad (5.1a)$$

$$B(PF, PD) = EFD \times ML, \quad (5.1b)$$

$$L(RE, AC) = P \times UFD \times ML, \quad (5.1c)$$

where,

SUM: net benefit function, B: net present benefit function, C: net present cost function,
L: financial loss function due to incorrect measurements,
EFD: expected forced outage days prevented by new sensor measurements,
ML: expected money loss per one day of forced outage,
UFD: unexpected outage days caused by sensor measurements,
P: probability of having an incorrect measurement that leads to a forced outage
PF: prevention of forced outages, PD: prevention of system degradation, PR: sensor price,
IN: sensor installation, MA: sensor maintenance, RE: sensor reliability, AS: sensor accuracy.

As an illustration using the values, shown below, we evaluate a 1300MW power plant in operation for ten years. We examine the case of a motor current analysis in the reactor coolant pump motor. For this case

EFD = 10 days, ML = \$700,000, P= 0.01, UFD = 3 days,
C(PD) = \$ 50,000, C(IN) = \$ 20,000, C(MA) = &80,000

Use of Equation 5.1 leads to the following results:

Total benefit: \$ 7,000, 000, Total cost: \$1,500,000, Total loss: \$21,000,

NET = &5479000

This means that the utilization of a motor current analysis is recommended. Equation 5.1 is a simple cost and benefit model for selecting sensor sets. In actual decision-making a more detailed, sophisticated model would be needed to include factors (e.g. sensor replacement) not treated here.

Chapter 6. Bayesian Belief Network Based Expert System

6.1 Introduction

The purpose of this chapter is to introduce the needs of a Bayesian Belief Network (BBN) based advisory system, which is supported by a comprehensive sensor network developed in Chapter 5. First, the motivations, of why a BBN is selected as a reasoning tool within an advisory system, are discussed in comparison to the conventional rule-based approach. Then, the BBN concept and fundamental theory are briefly explained. After essential elements, composed of the BBN-based inference algorithms, are defined, an example prototype diagnostic network, formulated in terms of information flow is presented.

6.2 Expert System Applications

Expert systems (ES) are known to be computer-based systems employing human knowledge to solve problems that are thought to require human expertise. One of representative definitions gives the following (STEV 84):

> *Expert systems are machines that think and reason as an expert would in a particular domain. For example, a medical diagnosis expert system would request as input the patient's symptoms, test result, and other relevant facts; using these as pointers, it would search its data base for information that might lead to the identification of the illness. A true expert system not only performs traditional computer functions of handling large amounts of data, but it also manipulates that data so the output is a meaningful answer to a less than fully specified question.*

There are several reasons for using expert systems. Chiefly among them are the following (CAST 97):

1. *With the help of an expert system, personnel with little expertise can solve problems that require expert knowledge. This is also an important factor in cases where human experts are in short supply. In addition, the number of people with access to the knowledge increases.*

2. *The knowledge of several human experts can be combined together, which gives rise to a more reliable expert systems, a system that is based on the collective wisdom of several experts, rather than on the experience of a single expert.*

3. *Expert systems can answer questions and solve problems much faster than the human expert. Thus, expert systems are invaluable in cases where time is a critical factor.*

4. *In some case complexities of the problem prevents the human expert from reaching a solution. In other cases the solutions obtained by human experts are unreliable. Due to the capabilities of computers of processing a huge number of complex operations in a quick and accurate way, expert systems can provide both fast and reliable answers in situations where the human experts cannot.*

5. *Expert systems can be used to perform monotonous operations and others that are boring or uncomfortable to humans. Indeed, expert systems (e.g. an unmanned airplane or a spacecraft) may be the only viable option in a situation where the task to be performed may jeopardize a human life.*

6. *Substantial savings can be achieved from using expert systems.*

Applications of expert systems in many fields of study have grown very rapidly during the last decade or so. Figure 6.1 classifies the use of expert systems according to areas of application and shows the application distribution of each area. This survey examined some 2500 expert systems and classifies them according to several criteria such as fields of applications, task performed, etc (DURK 94).

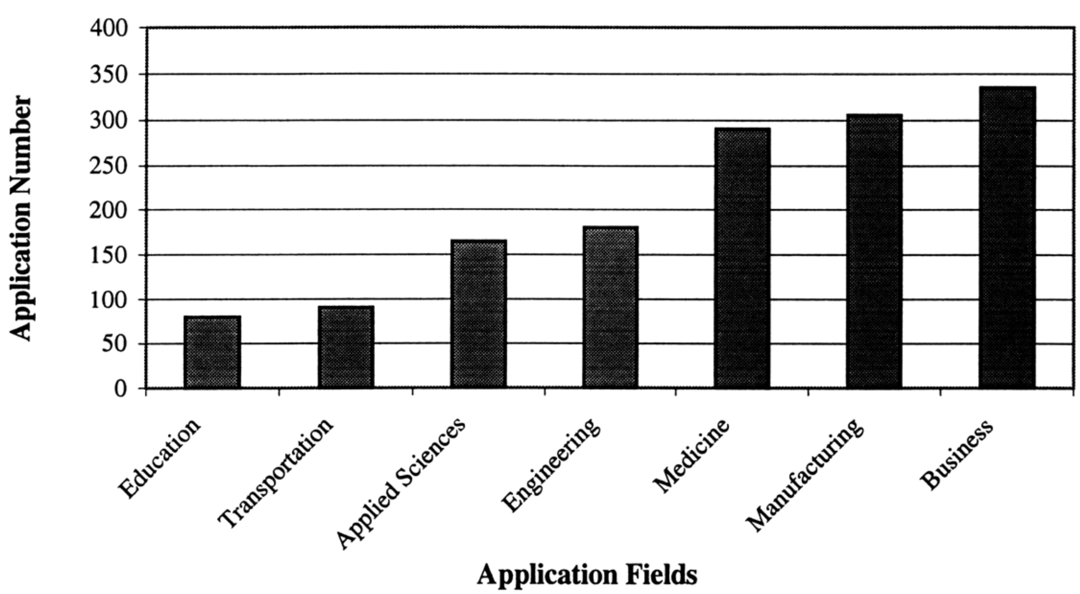


Figure 6.1 Applications of Expert Systems in Many Fields

6.3 Bayesian Belief Network Based Approach

6.3.1 Motivation

Most of existing monitoring systems in the nuclear power plant have been designed mainly from the safety standpoint. Their corresponding safety related operational procedures are usually represented by a set of production rules that express straightforward deterministic problem solving domains or stochastic problem solving domains supplemented with certainty factors.

This broadened concern for the operational availability improvement of complex target systems motivates the work reported here to employ a probabilistic approach, based upon the Bayesian Belief Network, for the diagnosis and maintenance. The availability-driven diagnosis involves a great degree of uncertainty, more than with safety-related sensor values because

(1) The observations made may be uncertain. The sensors themselves are not completely reliable. The information of sensor readings should be interpreted with a degree of uncertainty.

(2) The abstract knowledge obtained is not deterministic. The system states are simplified into several failure states in our diagnostic problem. The associated uncertainty grows when the lower level failure modes are combined to define the higher level failure modes of a complex system.

(3) The relationships among failure modes and measurements of various sensor signals are not deterministic.

(4) Uncertainty can be due to incomplete understanding of target system behavior when a given task is to be modeled in terms of the current state expertise. The accumulated knowledge and experience in the future may overcome such uncertainty.

Even though knowledge-based systems have been widely employed in the area of diagnosis, most of them use a shallow knowledge about target systems, which link an observed phenomenon to an individual system fault itself. This is usually done with shallow understanding or heuristics of the causal evolution of system faults. Even though this can result in fast efficient diagnoses for deterministic faults, it is not suitable for structural and functional domain knowledge in a complex system, which represents the interconnections and the behavior among subordinate components in the complex system. Skilled system management requires sophisticated procedures reflecting the detailed features and performance of the complex target system. Thus, there is a need for the system operator to be able to detect the states of subordinate components and to treat their processes systematically before critical states are reached.

In the early applications of expert systems, a rule-based approach was typically used. However, this treatment is abandoned in the work reported here in favor of Bayesian Belief Networks[1] (BBNs). This is because of the inability of rule-based approaches to properly model the inherent uncertainties and the complexities of the relationships involved. Section 6.4 discusses the pros and cons of two approaches, and demonstrates that BBNs are superior to rule-based approach in the particular domain of complex, incompletely understood system.

6.3.2 Overview

A BBN relies upon Bayes' Theorem, Bayesian updating and influence diagrams for decision making. BBNs represent model domains that are characterized by inherent uncertainty as a relatively new discipline of expert system applications. They estimate the probability of an event as a subjective degree of belief in its occurrence and also provide a measure of uncertainty that takes into account all available relevant knowledge and information. This uncertainty can be due to imperfect understanding of the domain, incomplete knowledge of the state of the domain at the time when a given task is to be performed, randomness in the mechanisms governing the behavior of the domain or a combination of these.

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[1] Other names for Bayesian Belief Networks include probabilistic networks, causal networks, and Bayesian influence diagrams.

Formally, a BBN is a directed acyclic graph[2] that models the relationships of a set of variables. Within a BBN the nodes represent random variables, and the links represent probabilistic state variable having dependencies upon the variables. These dependencies are quantified through a set of conditional probability tables (JENS 96). The availability of powerful computers and a better instrumented plant makes it possible to incorporate an abstract, symbolic knowledge representation and permits the numerical calculation needed to support BBN based reasoning.

A Bayesian Influence Diagram (BID) is a belief network augmented with decisions and utilities. Influence diagrams have been used successfully in uncertain complex decision making problems by graphically representing the diagnostic problem domain through simple topological symbols and links between them. In an advisory system, the output of this diagram is a diagnostic mapping from sensor readings to a determination of the probability distribution of the alternative states of the failure modes. Once the failure modes are identified, a diagnostic inference algorithm suggests the most advantageous action to improve the system availability.

6.3.3 Fundamental Theory

In this section we introduce basic axioms and the theory to explain the theoretical concepts of BBNs.

Basic Axioms: The probability P(A) of an event A is a number in the unit interval [0,1]. Probabilities obey the following axioms.

1. P(A) = 1 if and only if A is certain.
2. If A and B are mutually exclusive, then

$$P(A \vee B) = P(A) + P(B). \tag{6.1}$$

Conditional Probability: The basic concept in the Bayesian treatment of events is conditional probability. A conditional probability statement is of the following kind:

---

[2] A directed acycle graph contains no directed cycle. That is, in a directed acycle graph, we cannot travel from a node and return to that same node along a nontrivial directed path.

Given the event E, the probability of the event A is p.

$$P(A/E) = \frac{P(A,E)}{P(E)} = p \qquad (6.2)$$

The notation for the statement above is as follow. It means that if E is true, and everything else known is irrelevant for A, then P(A) = p.

Joint Probability: A BBN for a set of variables $\{x_1, x_2, \ldots\ldots, x_n\}$ represents a joint probability distribution over those variables. The joint probability distribution is achieved through the chain rule of probability:

$$P(x_1, x_2, \ldots\ldots, x_n) = P(x_i/x_1, \ldots\ldots, x_{i-1}). \qquad (6.3)$$

Conditional Independence: Another important concept for BBNs is conditional independence. Two sets of variables, A and B, are said to be conditionally independent given a third set of variables C if when the values of the variables C are known, knowledge about the values of the variables B provides no further information about the values of the variables A as

$$P(A/B,C) = P(A/C). \qquad (6.4)$$

Consider the simple network shown in Figure 6.2.

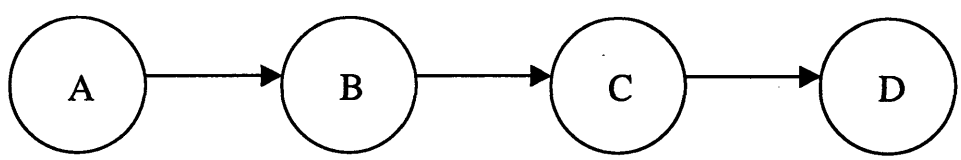


Figure 6.2 A Simple Bayesian Network (I) Illustrating Conditional Independence

Using the chain rule of probability we could calculate the joint probability distribution as follows:

$$P(A,B,C,D) = P(A)\, P(B/A)\, P(C/A,B)\, P(D/A,B,C). \qquad (6.5)$$

However, because of the conditional independence created by the graph structure the calculation of the joint probability distribution simplifies to:

$$P(A,B,C,D) = P(A)\ P(B/A)\ P(C/B)\ P(D/C). \qquad (6.6)$$

Bayes' Theorem: The cornerstone of Bayesian probability theory is the inversion formula due to Bayes' theorem.

$$P(H_i/E) = \frac{P(E/H_i)P(H_i)}{\sum_i P(E/H_i)P(H_i)} \qquad (6.7)$$

In the Bayesian interpretation, the probability of a certain hypothesis Hi, being true, P(Hi) represents our degree of belief in that hypothesis. After we receive new evidence E which reinforce or weakens that hypothesis, this degree of belief becomes P(Hi/E) and can be formally updated according to Bayes' theorem.

Bayesian Updating: Bayesian theorem is particularly useful in contexts where probabilities are more easily obtained in one inferential direction than another, thus providing the flexibility to reason in either the causal or the information flow direction. The inversion formula provides a convenient way of updating belief in a proposition in light of new evidence.

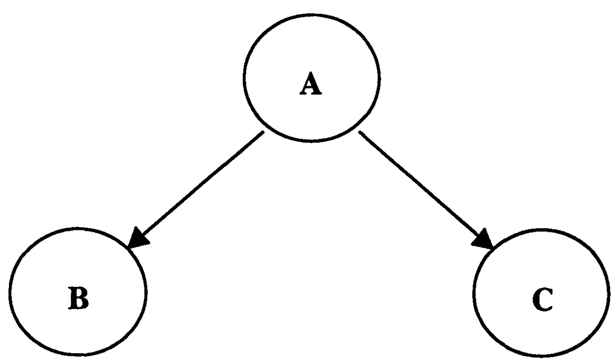
In the causal network the probability distribution of the states of any dependent nodes (a node where the true state is unknown) at a particular domain within the network are defined in terms of the conditional probabilities linking the independent nodal states (those where the nodal state is known with certainty, or is characterized by a probability equal to unity) to the states. Then, in a new domain the probability distributions of the dependent nodes are updated using Bayes' theorem in Equation 6.7 to estimate a posterior probability distribution, f', in terms of the previously obtained probability distribution, f, and new evidence, E, newly obtained in the previous domain, as

$$f' = C\ P(E)\ f\ , \qquad (6.8)$$

where P(E) is the probability of observing the newly obtained evidence and C is constant. Use of this relationship is called Bayesian updating.

The BBN model is a directed acyclic graph where the nodes in the graph correspond to uncertain variables relevant to the problem. An uncertain variable can represent an arbitrary set of mutually exclusive and exhaustive propositions, where each proposition is called an instance of the variable. Each variable in a belief network is associated with a set of probability distributions. The links in the directed acyclic graph represent direct probabilistic dependencies among the uncertain variables. In Figure 6.3, a link from node A to node B reflects an assertion by the builder of that network that the probability distribution of B may depend on the instance of the variable A, we say that A conditions B. Thus, a node has probability distribution for every instance of its conditioning nodes. The lack of links in the network reflects the conditional independence between nodes.

Given a fully specified Bayesian network, the joint probability distribution of the variables can be constructed.



Nodes	A, B, C
Substates	$A(a_1, a_2, \ldots, a_j)$, $B(b_1, b_2, \ldots, b_j)$, $C(c_1, c_2, \ldots, c_j)$
Conditional Probability	$P(b_j/a_k)$, $P(c_j/a_k)$ $(j = 1,2,\ldots,i \quad k = 1,2, \ldots ,i)$

Figure 6.3 A Simple Bayesian Belief Network (II) and its Logic

If evidence from node B and C is provided, the probability distribution of the states of node A is computed from prior probability distributions of node A, and conditional probabilities. If evidence from node A is provided, the probability distributions of the states of nodes B and C are computed from conditional probabilities without considering prior probability distributions of node A.

To sum up, we conclude that BBNs represent uncertain relationships among observation, and inference algorithms for BBNs and allow us to compute the probability of a hypothesis given known evidence.

6.4 Comparison Between Rule-Based and Bayesian Belief Network Based Expert Systems

The rule-based approach to the development of expert systems is based upon the principles of classical logic and is well suited for use in problems involving few exact relationships, or at least relationships having very strong dependencies. In these systems knowledge is represented as a set of rules of the form *'if antecedent then consequent'*, and inference proceeds by changing of the rules once a new relevant piece of evidence appears in the database. Classical deterministic rule-based expert systems usually do not deal with uncertainties because objects and rules are treated deterministically.

In most practical applications, however, there are various sources of uncertainty. Observations may be uncertain, information may be incomplete, and the relations in the domain may be of a non-deterministic type. Thus, there is a need for expert systems that can deal with uncertain situations in a systematic way. Trouble shooting in a rule-based system typically involves simple retrievals of stored candidate lists indexed by failure symptoms.

The work reported here presents BBN based expert systems. The details of their main features and comparison to rule-based expert systems are described. Keeping with the treatment of rule-based expert systems, uncertainty management, knowledge representation, decision making, ease of modification, and systematic root cause tracking of BBN based expert systems are critically examined.

6.4.1 Knowledge Base

There are two different types of knowledge in expert systems. One is concrete knowledge and the other is abstract knowledge. Regardless of expert system type, concrete knowledge is the evidence or facts that are given in a particular situation associated with cases to be analyzed. This type of knowledge is not static and can change from one situation to another. This knowledge is stored in the working memory, not in the knowledge base. Abstract knowledge constitutes knowledge based upon information stored is static, that is, it doesn't change from one situation to another.

The knowledge base of a rule-based system consists of a set of objects (variables) and a set of rules. These rules represent the relationships among a set of objects. The knowledge base in rule-based expert systems is easy to obtain, since there are needs to handle only simple elements such as objects, premises, and rules in simple problem solving domain. However, its knowledge is limited and inappropriate for solving complex problems.

The knowledge base of a BBN based expert system consists of variables and conditional probabilities. This knowledge is able to represent a complex problem domain which cannot be represented by a set of rules because the degree of knowledge that we can store is more advanced. Simultaneously, a large numbers of parameters are involved, which may make the specification of BBN model difficult.

To sum up, shallow rule-based knowledge provides only a limited capability to model and explore problems. Its inference engine is fast and easy to implement. On the other hand, the BBN-based knowledge base is highly suitable for modeling a complex domain where there is a need for advanced degree of expertise capture.

6.4.2 Knowledge Representation and Complexity Management

In rule-based expert systems, the relationships between objects are represented by a set of production rules. Since corresponding knowledge is shown in text format in the form of *IF-THEN* type rather than object-oriented graphics, the entire structure of the modeling is not visible to the developer or user. It is, thus, very hard to obtain an overall picture of the whole system from a set of rules. Moreover, because each rule is developed in an independent manner during all stages of expert system development, great effort is needed to maintain the completeness and consistency of the entire inference algorithm. In complex systems, the rules often force the domain expertise descriptions into an inappropriate representation. Often, the knowledge engineers artificially use uncertainty factors in order to introduce uncertainty measures to an established rule, but many times fail to provide sophisticated diagnosis for the complex mechanisms when subject to inherent uncertainty. Moreover, we note that the complex problem representation in rule-based expert systems requires use of a great number of rules, which are very cumbersome to treat properly when changes must be made.

In comparison, BBN based systems use graphical knowledge representations. The objects are represented as nodes and their relationships as links between the nodes. The BBN makes the domain structure explicit and utilizes the topology of the graph in the control of the inference. This type of object-oriented programming is the result of an evolution of programming, where newly developed tools make some programming tasks easier and more natural. Also, with a BBN it is much easier to maintain the completeness and consistency of the modeling system because the entire structure of model is readily understood. The graphical representation and conditional probabilities used make BBN based systems especially desirable for use in complex problem solving.

Use of Bayesian theory combined with either causal network or information flow networks reduces the amount of conditional independence assumptions and the number of conditional probability values that need to be specified. Furthermore, Bayesian networks are not limited to binary logic, as we can take a Bayesian network node and divide it in as many states as needed. The practical application of this approach can become unmanageable unless one is working with predefined and controlled sets of hypotheses and admissible pieces of evidence.

Thus, BBNs can represent complex problem domains in a consistent and complete way without oversimplifying the complexities and help user to perform object-oriented programming with an easy-to-learn modern graphics.

6.4.3 Uncertainty Management

Deterministic problems are conveniently formulated using a set of rules that relate several well-defined problems or objects. There are numerous practical cases, however, that involve uncertainty. For example, in the diagnosis of mechanical systems, some sensor readings always imply the existence of a degree of abnormality, and may imply the existence of a severe failure. Even though the uncertainty management can be performed using some treatments as a rule-based uncertainty factor and a fuzzy set, these theoretical mechanisms do not have sound theoretical foundations and may even be inherently inconsistent. So, they are hard to interpret and awkward to use. Most such theories simplify the real world and are employed safely only under very limited conditions.

By contrast, the BBN gives the probability of an event as a measure of the uncertainty of its occurrence. The fact that BBNs are based upon probability theory can permit us to use pre-existing knowledge and statistics to learn the prior and conditional probabilities of the network elements.

Heckerman and Shortliffe (HECK 92) review the history and mechanics of uncertainty factors, and delineate their theoretical and practical limitations. They show that the BBN representation overcomes many of the limitations of the uncertainty factor model, and provides a promising approach to the practical construction of expert systems. Therefore, BBNs are an excellent, theoretically based method for providing a complete and consistent treatment of uncertainty.

6.4.4 Decision Making

Once the state of a system is identified, an expert system should draw conclusion and provide advice for efficient management of the system. This means that the final aim of an expert system is to choose an acceptable action on the basis of an imperfectly known state and uncertain predictions of future changes that might follow a particular action. For example, after diagnostic expert systems evaluate signals from a range of sensors, they should finally suggest the most advantageous actions that might remedy particular situations.

In the BBN based expert systems, influence diagrams have been combined successfully in complex decision making problems by graphically representing the diagnostic problem domain through simple topological symbols and links between them. So, this influence diagram is defined as Bayesian influence diagram (BID). Decision nodes represent points at which choices have to be made between well-defined alternatives and links directed to a decision node depict information available at the time of making the decision. The procedure for decision making can be modeled explicitly by taking into account costs and gains in terms of cost benefit competition, or by defining utilities in the utility node associated with particular combinations of management measures and the true state of the system. In the work reported here the alternative action having with the highest expected utility is suggested for use in the inference algorithm imbedded in the advisory system.

By contrast, rule based systems do not have efficient uncertainty management capabilities. So, decision making in rule based systems is either realized qualitatively, which is not satisfactory in many cases, or complemented by some procedural subordinate routines which perform mathematical calculations, thereby introducing new complexity into the system. Artificial decision making using a rule based system typically involves greater effort than with a BBN.

6.4.5 Inference Engine and Mechanism

The inference engine is the heart of every expert system. The main purpose of this component is to draw conclusions by applying the abstract knowledge to the concrete knowledge (CAST 97). For example, in the diagnosis of mechanical systems the symptoms as indicated by sensor readings (concrete knowledge) are analyzed in the light of the symptoms of all abnormalities of subordinate components (abstract knowledge).

Despite some limitations of the rule-based approach, its computational procedure has been so straightforward when used on problems involving exact relationships and or at least having very strong dependencies. The inference engine of BBN based expert systems is more complicated, based upon the evaluation of conditional probabilities. The degree of difficulty of use depends upon the selected model and ranges from low, for general independence models, to high for general dependence models. Fortunately, the computational penalty associated with the probabilistic approach has largely been overcome in the BBN area in recent years through the rapid advancement of computer technology and the development of methods based upon graphical representations of dependencies and efficient updating algorithms which take advantage of the dependency structure.

Inference in rule-based systems where the rules represent purely logical relationships is unidirectional. Their search mechanism is by forward chaining only. However, sophisticated diagnosis in complex systems with inherently uncertain relationships between various subordinate components cannot be achieved using unidirectional reasoning based upon classical rule-based logic. The uncertainty relationships in most diagnostic problems require bi-directional plausible reasoning, a dynamic combination of relationships in terms of information flow and causality, which leads to reliable diagnosis through validation. That is, inferences in the direction of information flow (symptom to cause) and in the direction of causality (cause to symptom) may have to be made, depending upon the evidence available, in the chain of reasoning leading to the final diagnosis and testing. Even though the arrows in the BBN are determined in the specific direction dictated by special concerns, some pieces of evidence can be provided at any nodes in addition to the nodes relating directly to symptoms. Then, the results of the updating of all relevant nodes can be evaluated if the entire inference model works properly.

6.4.6 Modification, Refinement and Verification of Knowledge

Since the knowledge is not complete, there can be greater potential with the BBN for handling newly acquired expertise. Then, the model itself should be readily modified and extended to reflect changes and growth in the real world system. Thus, most of the models of knowledge based systems have no choice but to be extended, fine tuned, and refined incrementally as experience occurs. It is desirable to accommodate such changes at low cost.

In rule based systems being changed, many associated rules usually have to be searched for in order to reflect any changes in the knowledge base. Sometimes their implicit structures make the selection of associated rules more difficult. Moreover, the meaning of an uncertainty factor is artificial, and difficult to explain as a measure of change in belief. Sometimes, in order to correct the expert system's logic, extra rules have to be created to ensure that other rules are triggered in the right order. Thus, generally rule-based systems require rigorous testing and validation due to the problems mentioned above. Domain experts find them difficult to follow during debugging, as the new rule processing does not always flow logically.

In BBN based systems, the software editor module provides facilities for creating and editing the network of interest (i.e., creation and editing of conditional probability tables). Explicit models are much easier to modify because they represent the entire structure of the system represented in a natural, transparent manner. This is a very important feature for practical knowledge based system development and maintenance. Usually such a model is easier to maintain and verify, and thus has a larger life span than that provided by rule-based systems. We conclude that BBNs are superior to rule-based systems in their ability to update programming in reflecting newly acquired knowledge in complex systems, whose behavior is inherently uncertain and complex.

6.4.7 Knowledge Acquisition

Knowledge acquisition is the first step in knowledge based system development and is essential for the success of the expert system. It is usually realized by querying experts and capturing their reasoning process. The reasoning process of the experts is generally vague and large uncertainties are involved, their knowledge is not always conveniently expressed in deterministic rules even when aided by some uncertainty management methods.

In many cases their knowledge is intrinsically probabilistic and can be easily modeled using the conditional probability concept. The experts have high flexibility in modifying the conditional probabilities to find a good match of their implicit model to the real world. Another advantage of BBN based systems in knowledge acquisition is that its graphical knowledge representation can be easily understood by both developers and the experts, which greatly facilitates communication and avoids confusion.

However, experts usually express their knowledge in a form, convenient for themselves if they are not familiar with the Bayesian analyzing procedure. At the beginning stage, work dealing with experts should demonstrate to them that knowledge elicitation is sufficiently natural and easy for them to understand. Documentation should permit easy translation of expertise into the Bayesian formalism. We recommend that the Bayesian expertise capturing procedure should systematically formulate how various levels of knowledge are acquired and synthesized into inference algorithms imbedded in the BBN based expert system.

6.5 Example BBN Based Diagnosis and Management Model

This section briefly illustrates an example prototype diagnosis and maintenance model using a qualitative BBN representation. The detailed, concrete mathematical relationships used are explained in Chapter 8, which introduces the prototype networks using the Hugin expert system shell.

The flowchart depicted in Figure 6.4 suggests several main steps to be taken in developing system diagnoses for provision of operational advice. This inference algorithm consists of five procedures for developing BBN based representations. This algorithm starts from use of input sensor readings and ends with an output prediction of the future system status by means of the recommended action through inference of the current status probability distribution of specific system states and determination of the most advantageous action to take.

Figure 6.5 illustrates how the inference algorithm in Figure 6.4 is encoded into the example diagnosis and maintenance model from the viewpoint of information flow using the BBN formalism. This example model is applied to the diagnosis and maintenance of a bearing component.

In this network sensor nodes are labeled "*S_*", and failure mode nodes are labeled "*F_*". The topological symbols and links between sensor nodes labeled "*S_Temperature*" and "*S_Vibration*" and a failure mode node (prior to action) labeled "*F_BRG_Damage*" represent the relationships between sensor measurements and the system states in a information flow direction. The node named "*F'_BRG_Damage*" represents the status of a failure mode after the recommended action has been taken.

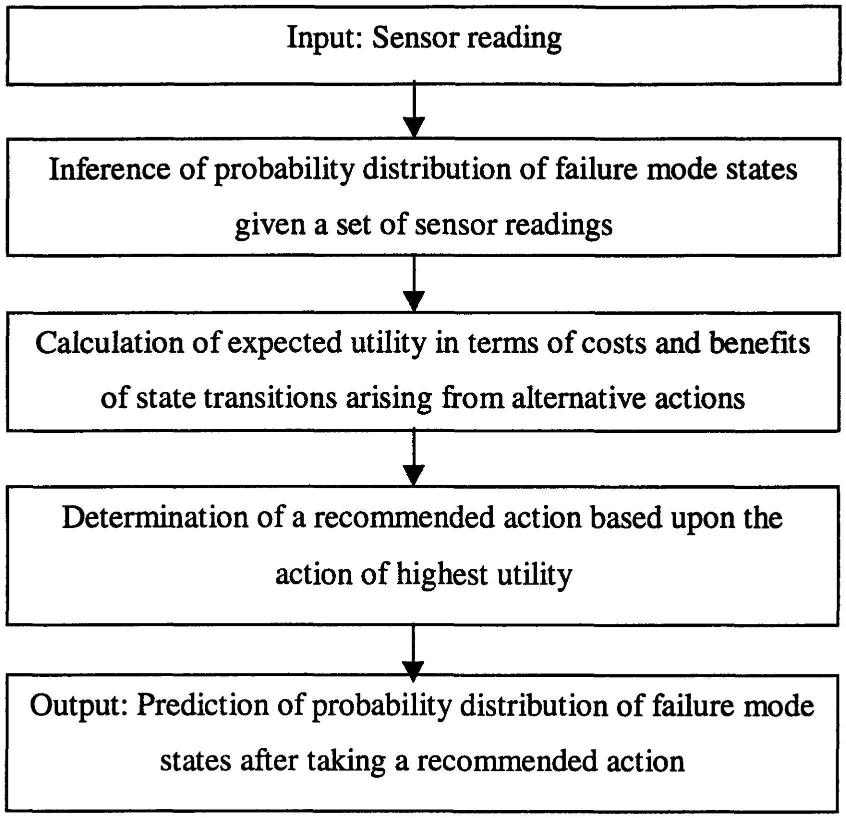
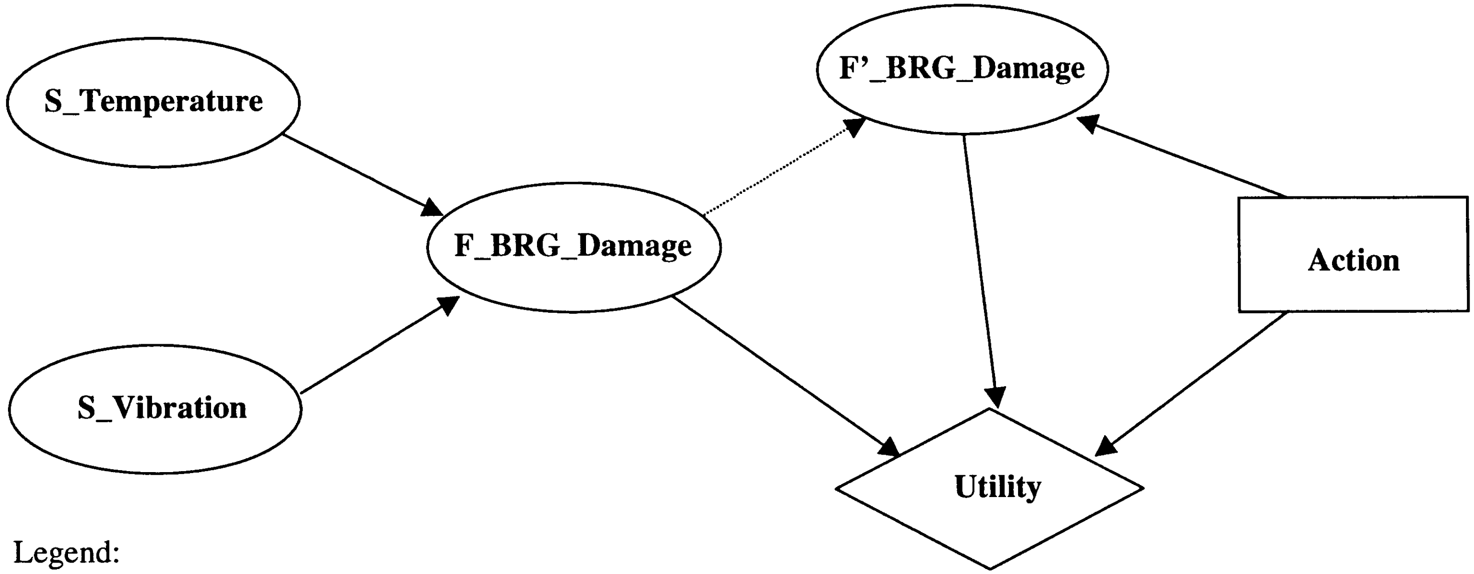


Figure 6.4 Inference Algorithm for BBN Based Diagnosis and Maintenance Advice

The mathematical relationships between sensor nodes and failure mode are expressed with corresponding conditional probability value. The following paragraphs define some informational elements as used in the example network.

1) Findings:

The prototype network operates upon the observable data because in general, the states of a system or the states of an abstracted failure mode are not directly observable. Sensor nodes indicate a useful source of information obtained directly from sensor readings or from advanced data processing systems. In this model, three mutually exclusive states of the sensor readings are discretized into the classes "*Low*", "*Medium*", and "*High*". These ranges are defined in reflecting the expertise of relevant equipment manufacturer and operators.



Legend:

BRG: Bearing

S: Sensor node having *Low, Medium*, and *High* ranges

F: Failure mode node before a recommended action having *Good*, *Incipient*, and *Severe* states

F': Failure mode node after a recommended action having *Good*, *Incipient*, and *Severe* states

Action: Action node for transitions between failure mode states by means of the alternative actions having *No Action, Remedial Action*, and *Trip Action*

Utility: Utility node for evaluation of expected costs and benefits arising from failure mode state transitions caused by alternative actions

Figure 6.5 Example of the BBN Based Diagnosis and Management Network for the Turbine Bearing

2) Hypothesis:

Diagnostic hypotheses are 'artificial' concepts created to give a name to a specific situation or combination of component states in which a system can be found at a given time. In other words, each diagnostic hypothesis is a simplified abstraction built to characterize some abnormal behavior states of a system such as "*Bearing Damage*" as shown in Figure 6.5.

Failure mode nodes, as indicated by sensor readings are discretized into a number of states abstracting the fault progression modes. In Figure 6.5, a node named "*F_BRG_Damage*" stands for the hypothesis of the failure mode that a bearing is damaged before a corrective action is performed. In our model, three mutually exclusive failure mode states in terms of fault progression are labeled "*Good*", "*Incipient*", and "*Severe*". The intermediate sensor range indicates the incipient failure state and the high range indicates a high probability for the severe failure state immediately. The reason for discretization is to simplify the state structure of a failure mode. The structure is associated with the alternative possible actions. This network does not show how the system reaches a certain failure mode state. Rather, it quantifies the static failure mode state probability as indicated by sensor information flow.

This failure mode state probability is changed by the alternative actions that can be selected in terms of the expected utility value. The probability distribution of each state in a transited failure mode enables us to predict the future state of a specific failure mode. A node named "*F'_BRG_Damage*" in Figure 6.5 represents the hypothesis of the transited failure mode after the corrective action has been taken.

3) Actions:

The network can reflect causal effects of actions changing the failure mode states. At this point, action nodes are introduced to represent failure mode state transformation functions. The probability values provided through knowledge elicitation from domain experts are used to support decision making in order to select the action that is the most appropriate.

The rectangular box of Figure 6.5 stands for the alternative possible actions. An action is required to change the specific state of a failure mode. The detailed mathematical formulation of the relationships between failure modes, action nodes, and utility nodes applied in the advisory system is explained in Section 8.6.

4) Utility:

The various possible alternative decisions should be evaluated on the basis of the net value of their various consequences. The decision mechanisms of Figure 6.5 represent points at which choices have to be made between well-defined alternatives and links directed to a utility node depict information available at the time of making the decision.

The diamond-shaped node in Figure 6.5 stands for a utility node. The criterion of the decision is formulated in a utility node, which integrates the information from a failure mode node state before an action, a failure mode node state after action, and the action node depicting the action that will cause the state transition of interest. The usefulness is evaluated on a numerical scale, called a utility scale. In the work reported here, the costs from particular actions and the benefit from state transition are calculated and then algebraic sum gives the net benefits of the action.

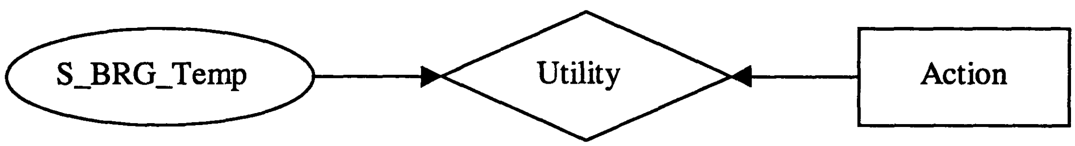
6.6 Reduction to a Rule-based Representation of a General BBN

Previously, in Section 6.3 we outline the theory of BBNs. Section 6.4 demonstrates that the rule-based approach has serious limitations through the comparison to the BBN based approach. Section 6.5 illustrates an example application of BBNs for diagnosis and maintenance concerning a specific mechanical component. This section seeks to demonstrate how general BBNs can be reduced to be a rule-based representation as a special case.

Consider a simplified version of the system shown in Figure 6.5 assuming that only one sensor of that system is considered the resulting system in Figure 6.6. A simple utility table is obtained in order to express the example decision rule. "*IF RCP bearing temperature is more than 195 F, THEN trip the reactor*". When there are two sensor ranges, low or high, the utility table shown in Figure 6.6 indicates that a different alternative action (that having a utility value of unity) should be favored in each range, respectively. This table is very simplified, compared with that shown in Figure 6.5

(whose concrete structure and values are explained in Chapter 8). Moreover, we see that the number of subordinate states in the sensor and failure mode nodes in Figure 6.6 is less than that of Figure 6.5. We conclude that a rule-based knowledge representation is a part of and special case of BBNs.

Example Rule: *IF RCP bearing temperature is more than 195 F, THEN trip the reactor.*



Logic Network

Where,
S_BRG_Temp: Bearing temperature sensor node (Below 195F: Low, Above195: High)
Action: Trip reactor action node (No Trip, Trip)
Utility: Utility node

Sensor	Low		High	
Action	No Trip	Trip	No Trip	Trip
Utility	1	0	0	1

Utility Node Table

Figure 6.6 Rule-Based Representation Using the BBN Formalism

Chapter 7. Selection of Expert System Shell

7.1 Selection Criteria

Humans often solve complex problems using very abstract, symbolic approaches which are not well suited for implementation in conventional languages. Although abstract information can be modeled in these languages, considerable programming efforts is required to transform this information to a format usable with procedural programming paradigms. Programming an expert system from scratch using LISP, PROLOG, C, or any other high level computer language is an arduous and time-consuming task. The major advantage of an expert system shell is to save the time and effort required to develop an inference mechanism and auxiliary features for expert system use. As a result, the efforts can be dedicated to the development and refinement of modeling without getting involved in the details of the programming.

A factor to consider when selecting a shell is whether a commercially available shell is adequate. The rule of thumb to follow is if a commercially available shell exists that satisfies the representation, performance, and support requirements of the task, then use that shell. For the selection of the proper expert system shell, a number of criteria, listed below are considered in this study.

1) Reasoning Paradigm and Knowledge Representation

The most important criterion that the shell must satisfy is that it must support the knowledge representation paradigm and reasoning method used in a convenient way. The main concern and features of specific tasks should be treated efficiently with a proper expert system shell. The key factor for our advisory system is the powerful ability to compute using a series of comprehensive inference algorithms that represent our complex problem solving domain. The type of object-oriented programming is preferred for the convenience of system development and ease of maintenance.

2) Real-Time Processing Capability

The expert system should be able to provide useful results in real time. Thus, the expert system shell should provide the capability to reason and make decisions in real time.

3) System Integration with Other Systems

Expert systems for use in power plants should be compatible with other data processing equipment. Compatible coding and maintenance of the system knowledge base are preferably performed in a higher language like C in terms of system integration, instead of in a special purpose language like LISP.

4) User-friendly Structure

A shell should have features in the structure for system use, which facilitate operator interactions with an easy-to-learn user-friendly, man-machine interface. A user-friendly knowledge editor should have the advantage of maintaining the consistency and completeness of the knowledge base as new information is entered.

5) Graphical Presentation

A graphical presentation is also a highly desirable feature found in many expert system shells. It consists of a graphical display of the relationships between the system's knowledge components. Graphical output is also favored as a more natural way for explaining the system's resulting conclusions.

6) Performance

A shell, which meets all of the above requirements, may perform unacceptably. As the knowledge base grows, performance can quickly degrade. When the performance of a shell is evaluated, the test cases should approximate the size of the intended application to ensure that proper performance will be obtained at the expected size and complexity of the final system.

7) Vendor Support

The shell should be consistently maintained consistently and its creating organization should remain operational during the shell usage lifetime. Ideally, the shell should provide some form of on-line tutorial or assistance in its operation. Just like any other piece of conventional software, a shell's documentation should be complete and easy to read.

8) Cost

The definition of high cost varies with each organization. We note that the cost of a shell does not always reflect its capability. When purchasing any shell, the ratio of its performance to cost should be carefully analyzed.

According to criteria listed above, we searched for a shell and consulted with some specialists in this field. The shell best suited for our application should retain a friendly graphical user interface, have powerful data manipulation capability, use the C coding language, operate on a PC windows platform, have uncertainty management capabilities, and offer proper vendor support.

7.2 Review of Commercially Available Shells

7.2.1 Bayesian Belief Network Based Expert System Shells

Even though the theoretical beauty of Bayesian Belief Network (BBN) was recognized in the past, there was too little computer capability easily available to support BBN-based expert system shells using modern graphic representations. The recent rapid development of computer technologies has made it possible to create BBN-based expert system shells supported by modern graphics. Contrary to most other expert techniques, BBNs are relatively new applications in the area of artificial intelligence. Thus, a good deal of theoretical insight as well as practical experience was considered in determining a well-suited shell for our application.

Table 7.1 shows a comparison of these shells in terms of the selection criteria of language, real time processing capability, graphical representation, software company, computer, and platform.

Table 7.1 Comparison of Alternative BBN Based Expert System Shell Features

Shell	Company	Graphical Representation	Language	Real-time processing	Platform	Uncertainty Management
Baron	KC Associates	Y	C	NA	Windows	Y
BMR	Prevision Inc.	Y	C	Y	Windows	Y
Demos	Luminar Decision System	Y	NI	NA	Windows Mackintosh	Y
Ergo	Noetic Systems Inc.	Y	NI	NA	Windows Mackintosh	Y
Graphical-Belief	Russel G. Almond	Y	C	Y	Windows Unix	Y
HUGIN	HUGIN A/S	Y	C	Y	Windows Unix	Y
NETICA	Norsys	Y	C	Y	Windows Mackintosh Unix	Y

(Y: Yes, NA: Not Available, NI: No Information)

The final candidates for the application to use in this work were Baron (KC associates), BMR (Prevision Inc.), Demos (Lumina Decision Systems), Ergo (Noetic Systems Inc.), Graphical-Belief (Russel G. Almond), HUGIN (Hugin A/S), and Netica (Norsys Software Corporation). This table shows that BMR, HUGIN, and NETICA have all good features in terms of the stated criteria. Thus, the final decision of what shell to use is made through the discussion with specialists in this area, from previous application examples, and direct use in case modeling.

7.2.2 Rule-Based Expert System Shells

Although BBN-based systems have many advantages over rule-based systems, rule-based systems have a much longer development history and many mature rule based expert system shells are commercially available currently, which have been employed in various applications. The use of a good-featured shell that is easy to learn, easy to use and has many powerful features is favored so that the time and effort required for programming can be saved. In order to gather as much information as possible before making final decisions, a survey of rule based expert system shells was performed.

The ideal rule based shell should be written in the C or C++ languages, and be working on PC Windows computer platform for integration with other software and hardware. It should have powerful and fast rule manipulation capabilities, powerful uncertainty management facilities, graphical user interface, interfaces to other software and databases, should support object-oriented programming and procedural programming. The commercially available rule based shells found in this survey are summarized in Table 7.2, from which it can be seen that none of them has all of the desired features. The shells can be categorized into three types, each having its own limitations. Although many shells are mature and have many powerful capabilities, none of them is particularly well suited for the problem solving domain of our application.

First, examples of dedicated shells designed for particular applications include Acquire and XpertRule which are designed for knowledge acquisition, GBB for software integration, KnowledgeMaker for rule generation, Powermodel for design process, PC Plus for classification and some others. These shells are not be good candidates for this work.

Table 7.2 Comparison of Alternative Rule-based Expert System Shell Features

Shell	Language	Platform	Knowledge Representation	Reasoning	Uncertainty	Real-time	Explanation	Graphics
ART	4GL	Windows Unix	Frame, Rule	F	NA	Y	Y	Y
Gold Works III	CLOPS	Windows	Frame, Rule	F	UF		Y	Y
GURU	KGL	Windows	Rule	F, B	UF Fuzzy	Y	Y	NI
FLOPS	OPS5	Windows	Rule	NI	Fuzzy	NA	NA	NA
ILOG-Rules	C	Unix	Object, Rule	F	NA	Y	NA	Y
Kappa-PC	C	Windows	Object, Rule	F, B	NA	NA	Y	Y
M4	C	Windows	NI	F, B	UF	NA	Y	Y
PC+	LISP	Windows	Frame, Rule	F, B	UF	NA	Y	Y
Powermodel	C	Windows Unix	Object, Rule	F, B	NA	NA	Y	Y

(Y: Yes, NA: Not Available, NI: No Information, UF: Uncertainty Factor, B: Backward, F: Forward)

Examples of general purpose shells include Kappa-PC, M.4, GoldWorks III and others. These shells are designed for a wide variety of applications such as business management and technical process control. They usually support object-oriented programming, have powerful graphical user interfaces, have interfaces to other popular software and can be easily integrated with other systems. However, since they are not designed for diagnostic applications, they have very limited uncertainty management facilities, limited real time processing capabilities, and no temporal reasoning capabilities, which make them undesirable for this work.

Examples of shells designed for real time diagnosis applications include ART, KEE and G2. These shells have adequate uncertainty management and real time processing capabilities and have been successfully employed to build many real time diagnostic systems. However, they are themselves complex systems and are much too expensive for our use. Their prices are ten times that of general purpose shells such as M4.

7.3 Features of the HUGIN Expert System Shell

Through an evaluation based upon above criteria and advice from relevant specialists, the HUGIN expert system shell has been chosen as having best combined features and many records of previous applications. The HUGIN system is a high level reasoning tool enabling us to construct expert systems in domains characterized by inherent uncertainty. The HUGIN package provides a source of information on BBNs, including a tutorial, current research efforts, and commercial applications as well as the tools for expert system construction.

The HUGIN system was originally developed at Aalborg University, Denmark in 1993. HUGIN stands for Handling Uncertainty In General Inference Network. It is implemented under the environment of Windows 95 (or NT) and Sun operating systems. The graphical interface is made in NeWS[1]. Contrary to earlier probabilistic attempts and rule-based approaches, this tool makes the overall domain structure explicit and utilizes the topology of the graph using nodes and links in the control of diagnostic inference. We

[1] NeWS is a trademark of Sun Microsystems, Inc.

can use HUGIN through HUGIN Runtime, an easy- to- use graphical environment. This provides an intuitive graphical visualization of the knowledge that is convenient for operator interaction. HUGIN allows us to define both discrete nodes and to some extent continuous nodes in the models imbedded within the advisory system.

HUGIN is implemented using C language. The HUGIN API (Application Program Interface) which comes as a library for C (or C++) can also be utilized. Software coding and maintenance using a higher level language like C are preferable instead of being done within a special purpose artificial language like LISP. This capability enables us to integrate the advisory system with other systems. The application can communicate with the constructed component models by using the HUGIN API (HUGI 94).

A typical HUGIN development and utilization session is divided into three subtasks: Creation of a domain model, (2) generation of a run time system, and (3) the actual problem solving. These tasks must be performed sequentially, but the session can be suspended at any point and resumed later. The HUGIN shell is organized in a modular fashion as indicated in Figure 7.1. The graphical interface module does all of the necessary bookkeeping and provides access to facilities for creation, saving, loading, and

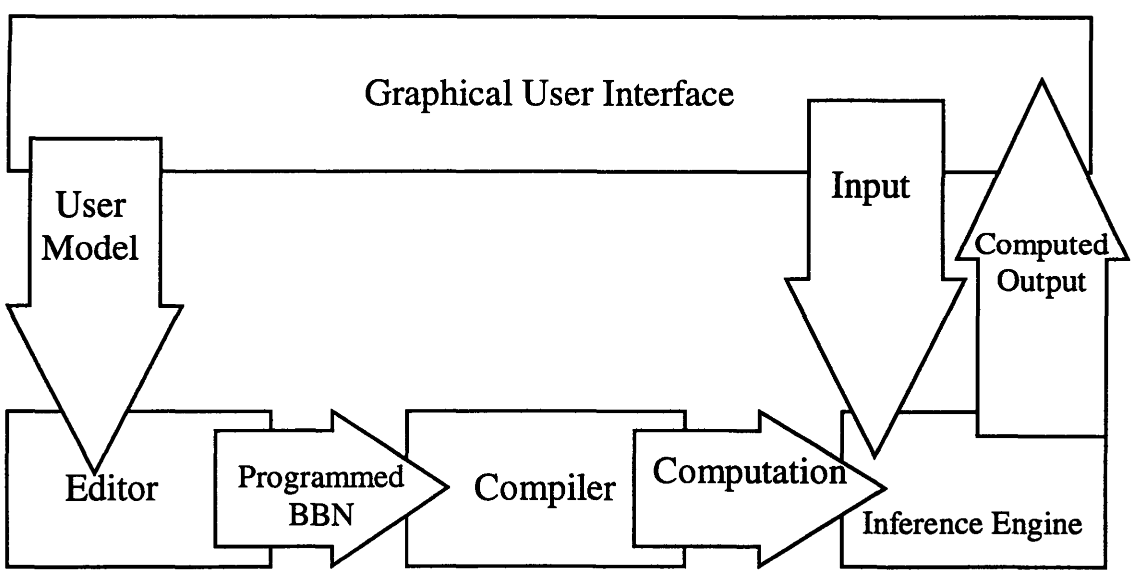


Figure 7.1 Schematic Structure Describing Stages of Development and Use of the HUGIN Expert System Shell

deletion of domains. The editor module offers facilities for creating and editing creation and deletion of nodes, links, and conditional probability tables (CPTs), etc. The compiler module creates a junction tree in which all calculations are performed. The inference module maintains a set of probability values in all nodes in accordance with entered findings (ANDE 89).

Chapter 8. Integration of the Bayesian Belief Network Based Inference Algorithm

8.1 Introduction

The primary purpose of this chapter is to formulate the prototype Bayesian belief network (BBN) using the HUGIN expert system shell. It is applied to the entire diagnosis and maintenance network for each of our target systems. First, the main interpretative modes of our advisory system are defined. These are composed of the advisory mode, the diagnostic mode, and the predictive mode. Then, the reasoning inference method and the utility concept, formulated in the inference algorithm, are explained. Several major steps are suggested for the systematic formulation of the BBN-based diagnostic inference algorithm. These steps are composed of successive development of a structural system hierarchy and a functional system hierarchy, of the refined causal network, of the Bayesian belief network with its inference engine, and of the Bayesian influence diagram with its inference engine. Also, the suggested scheme for systematic knowledge elicitation and synthesis provides the framework for obtaining conditional probability and utility values as essential knowledge bases, which can be elicited from experts. Finally, this chapter presents the computerized causal diagnostic inference algorithm formulated using the HUGIN expert system shell.

8.2 Advisory *System Uses*

Advances in sensor technologies have provided a substantial increase in the quality and operational information during the plant operation. Typically, available diagnostic information is not correlated or otherwise analyzed and presented in a form that is well suited for use by an operator. Our advisory system aims to process and memorize information, to learn and reason in both deterministic and uncertain situations, to communicate with an operator, and to take corrective actions. By the help of advisory systems, the burden on the operator can be reduced by automating some of the decision making tasks that must be performed on a regular basis, thereby relieving the operator to do more demanding tasks. Through the operator interface module of our advisory system information flow to the operator can be reduced to that of key operational advice that is essential to safe and economical operation. In the evaluations performed within the advisory system there are three main interpretative modes:

a. The Advisory Mode, where the known nodes are the sensor outputs, and the probability distributions of the system status and the expected utility value of the alternative actions are estimated. Eventually, these estimates suggest to the operator the most advantageous actions to take.

b. The Predictive Mode, where a particular action is intended and the probability values of future states of the failure modes and the sensor readings are estimated. This mode is useful in indicating to an operator the likely failure mode states and sensor outputs should a particular action be taken. Such estimates provide a basis for comparison of the actual component and sensor set performance to the estimations of the advisory system. Large persistent divergences between the two would indicate that the advisory system is in error for some reason.

c. The Diagnostic Mode, where the highest level failure mode state is known as well as the sensor outputs, and the probability distribution of the states of the subordinate failure modes are reviewed. This estimate is useful in diagnosing the root cause of the observed failure as a basis for planning the needed component recovery actions.

The advisory system developed in the work reported here is set up for use in all such modes, using the graphical user interface of the computer used by the advisory system to display the estimated results. Beside the user-friendly environment of this system, the real-time, on-line execution engine supports the prompt functions of technical personnel and operators during abnormal conditions at the power plant.

8.3 Integrated Architecture for an Advisory System for the Intelligent Diagnosis and Maintenance Integrating a Comprehensive Sensor Network

In the actual operation of a power plant, the accurate advisory information should be provided on-line for efficient diagnosis and maintenance (D&M). However, the process engineer is inevitably confronted by problems of inaccurate measurements and has to interpret redundant and diverse signals in reflecting the system states. Similarly information may be coming from instruments whose accuracy and reliability under infrequent abnormal conditions may be different from what would be expected.

The framework of an integrated architecture for performing modern on-line condition monitoring and intelligent maintenance for operational availability improvement is configured in the work reported here. This integrated architecture is composed of a comprehensive sensor network involving modern signal processing systems, advisory systems for sensor validation, and advisory systems for intelligent diagnosis and maintenance, as shown in Figure 8.1. The work reported here does not address sensor validation. Each box of Figure 8.1 represents a module dedicated to the specific role in the system's development. The D&M advisory system is supposed to operate using a microcomputer and has an interface with a sensor validation advisory system, which also has an interface with a comprehensive sensor network.

Modeling the sensor characteristics to an appropriate level of detail has the advantage of giving more accurate and robust mapping between system physical state being sensed and the sensor readings. The D&M advisory system should be supported by a real-time sensor validation advisory system, providing an efficient and flexible way to address every aspect of the on-line data validation and reconciliation, and sensor monitoring. The prior and conditional probabilities reflecting historical data and expert opinions for use in the BBN should be considered for systematic operation and performance enhancement of this validation advisory system. Finally, the system provides an on-line data configuration file relevant to the D&M advisory system. Specifically for the D&M advisory system, the system should generate probabilities for the mutually exclusive subordinate sensor states being labeled.

Then, the D&M advisory system processes the information from a sensor validation advisory system. Eventually, this integrated architecture should be included under the entire structure of plant wide monitoring and diagnosis system suggested in Section 5.2.

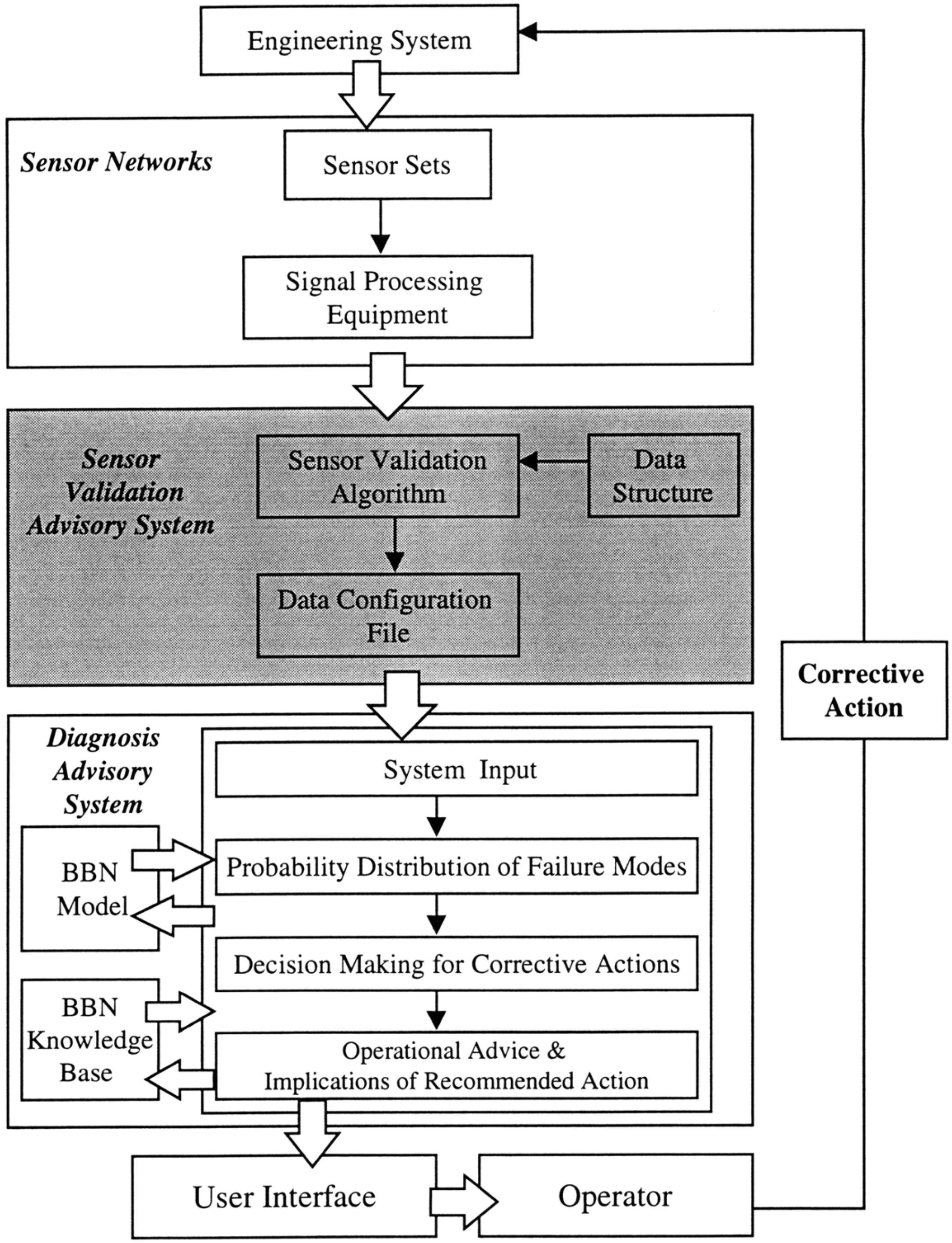


Figure 8.1 Integrated Architecture for the Intelligence Diagnosis and Maintenance Advisory System Integrating the Comprehensive Sensor Network

8.4 Reasoning Inference Method

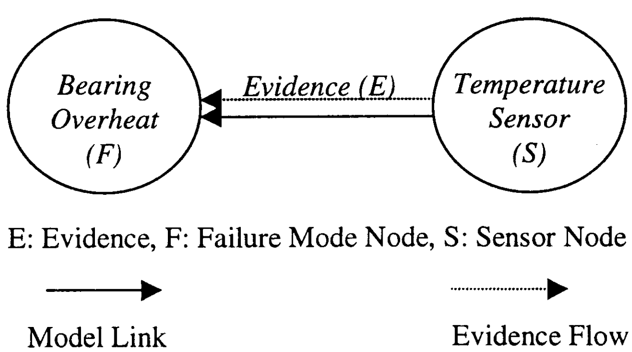
Diagnosis is the process of determining the states of a system given its symptoms. It is difficult to how to make reasoning their relationships. Also, it is an even more difficult task to quantify the relationship between a failure mode and symptoms and to represent the reasonable likelihood of a failure mode when specific sensor readings are provided.

The work reported here discusses two types of reasoning inference methods. One is information flow reasoning and the other is causality flow reasoning. Sometimes, the relationships can be viewed as a mapping of causal behaviors or as a mapping in the information flow direction. The main uses and the specific interests of using the advisory system determine an important aspect of which reasoning inference method is selected.

8.4.1 Information Flow Reasoning

A simple network formulated in terms of information flow reasoning is made up of a finite set of nodes representing the hypothesis of the failure mode and evidence from validated sensor readings, and a finite set of links between pairs of nodes representing their relations. This reasoning is the process of determining the state of a system based upon symptoms.

Figure 8.2 represents a fragment of information flow relationship from a sensor node (S) to a failure mode (F). Here, F is linked with S in the direction $S \rightarrow F$. The



The direction of evidence flow is the same as that of the reasoning procedure for obtaining conditional probability values. Thus, it's called information flow reasoning.

Figure 8.2 A Fragment of Information Flow Reasoning

sensor indicates the failure mode state. The dashed line represents the direction in which way evidence enters. The solid line stands for the link that signifies the conditional dependency direction from S to F where corresponding conditional probabilities are generated.

In this reasoning sense, the direction of evidence flow is the same as that of the reasoning procedure for obtaining conditional probability values. Thus, it's called information flow reasoning. Let us consider the following example of bearing diagnosis. In the case that a sensor indicates a high temperature range, there is high belief (probability value) of the bearing failure mode state being that of severe overheating. Values of the conditional probabilities $P(F_i/S_j)$ are required as a knowledge base. If evidence S is entered, the probability distribution of F is calculated by the following equation.

$$P(F_i, S) = \sum_j P(F_i / S_j) P(S_j), \qquad (8.1)$$

where , i=1,..,n

j=1,..,m

F_i: i-th state of a failure mode

S_j: j-th state of a sensor reading.

The uncertainty in this reasoning inherently grows consistently in the same direction as information from sensor readings is transferred to a specific failure mode. The cumbersome task of assigning the prior probability value of F values in this calculation can be eliminated. The prior probability values of F do not affect the probability distribution of a specific failure mode.

We realize that the number of conditional probability values grows rapidly with an increasing number of sensor nodes in a network in the case that a single failure mode node connects to multiple sensor nodes. Moreover, this correspondence prevents us from doing bi-directional reasoning from a failure mode to multiple sensors. In validating model, only the use of unidirectional checking in the direction of S to F is allowed concerning the final probability distribution of a specific failure mode given a set of sensor readings. In the "diagnostic interpretative mode" performed within the D&M

advisory system, there is a limitation in identifying a root cause in case that concerning a specific failure mode an expected root cause is located in a node not connecting to any corresponding sensor node.

8.4.2 Causality Flow Reasoning

A simple network formulated in terms of causality is also made up of a finite set of nodes representing the hypothesis of a failure mode and evidence from validated sensor readings. The causality flow reasoning is the way to reflect the causal process of system itself.

Figure 8.3 represents a fragment of causal relationship from a sensor node (S) to a failure mode (F). Contrary to Figure 8.2, F is linked with S in the direction F → S. This is a representation of the relationship, where a cause, "*Bearing Overheat*" leads to a symptom, change of "*Temperature Sensor*" value. In this reasoning, the conditional probability values $P(S_j/F_i)$ are required to be assigned to a knowledge base in order to signify the causal conditional dependency from F to S. The direction of the dashed line in Figure 8.3 indicating the direction of evidence is opposite to that of causal reasoning for obtaining its corresponding conditional probability values.

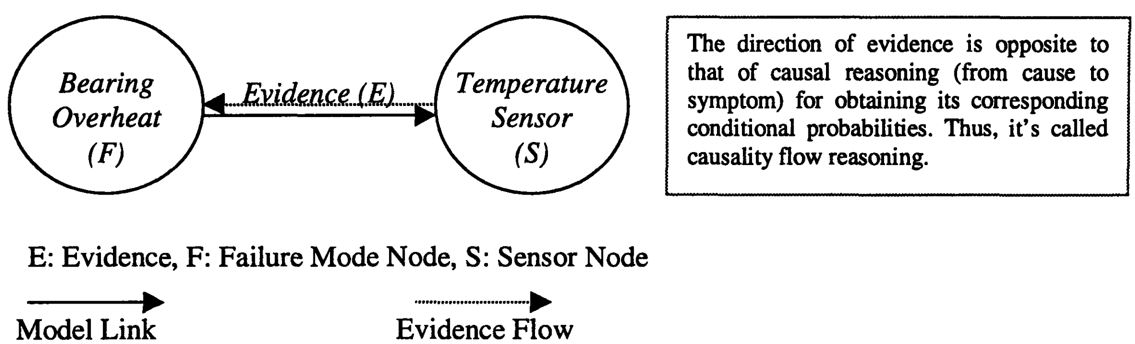


Figure 8.3 A Fragment of Causality Flow Reasoning

In the Bayesian belief network (BBN) after evidence S is entered, the probability distribution of F is calculated using the inversion mapping by Bayes' theorem. Their combined mathematical formula is given as Equation 8.2:

$$P(F_{i,}S) = \frac{\sum_{j} P(S_j / F_i)P(F_i)}{\sum_{i} P(S_j / F_i)P(F_i)} P(S_j), \qquad (8.2)$$

where , i=1,..,n

j=1,..,m

F_i: i-th state of a failure mode

S_j: j-th state of a sensor reading.

Unlike the use of information flow reasoning, the direction of uncertainty growth here is opposite to that of determining the conditional probability values. The prior probability distribution of F affects the inversion mapping in calculating the value of $P(F_i,S_j)$.

In the case that multiple sensors provide symptoms to a single failure mode, we require a number of conditional probability values providing a one-to-one correspondence between a failure mode and each sensor. In validating the model, bi-directional reasoning in either way can be performed, from a failure mode node to related sensor nodes or vice versa. In the diagnostic interpretive mode of the advisory system, the root cause can be tracked systematically among subordinate failure modes where the highest level failure state probability distribution has been observed.

Also, inference in the network can be used to predict the future state probability distribution concerning a failure mode node state and a sensor node given that one of the alternative actions has been executed. In the "predictive interpretative mode", the link between a posterior sensor node and a posterior failure mode node given that one of the alternative actions executed has the same direction consistently as that of the link between a sensor node and a failure mode node before an alternative action is taken.

As the main interpretative modes available performed within the advisory system are utilized, causal inference reasoning is favored rather than information flow reasoning. This occurs for reasons of ease in terms of systematic root cause tracking, bi-directional testing of the network, and convenience of obtaining conditional probability values between multiple sensors and a single failure mode.

8.5 Formulation of the BBN Based Generic Diagnosis Inference Algorithm

We chose the turbine generator and the reactor coolant pump (RCP) for applying the ideas outlined here. Leading causes of the turbine generator (TG) are bearings with lubrication oil system, and stator windings with auxiliary cooling systems. Because the RCP is a relatively less complex system compared to the TG, most of the subordinate components in the RCP are treated in the work reported here.

In Section 8.3 we construct the BBN-based generic inference algorithm in a causal direction. Figure 8.4 illustrates the major steps for formulating a BBN diagnostic inference algorithm. The major steps suggested here are development of a structural system hierarchy and a functional system hierarchy, of a refined causal network, of a Bayesian belief network (BBN) with an associated inference engine, and of a Bayesian influence diagram (BID) for use with the inference engine. These four levels of model construction are supported by required expertise, which is composed of expert-based graphical model development, of an expert's conditional probability table, of a library of corrective actions, and of a library of utility values. The detailed contents of each task area are described in the following sections.

8.5.1 Structural System Hierarchy and Functional System Hierarchy

The knowledge base forms the core of an advisory system, together with well-defined systematic logic network formulating procedures. For sophisticated reasoning driven by operational availability improvement, system-oriented high level understandings are required for complex systems. The knowledge base built upon a deep understanding of the system structure and its malfunctions can play an important role in developing a framework for fault evolution, cause and effect, and characteristics from which to deduce the root causes of the observed behavior.

In order to formulate a BBN-based generic diagnosis inference algorithm in a systematic way, first of all the work reported here employs a structural system hierarchy (SSH) and a functional system hierarchy (FSH). Structural knowledge concerns that part of the model that stores connection information between various components of the

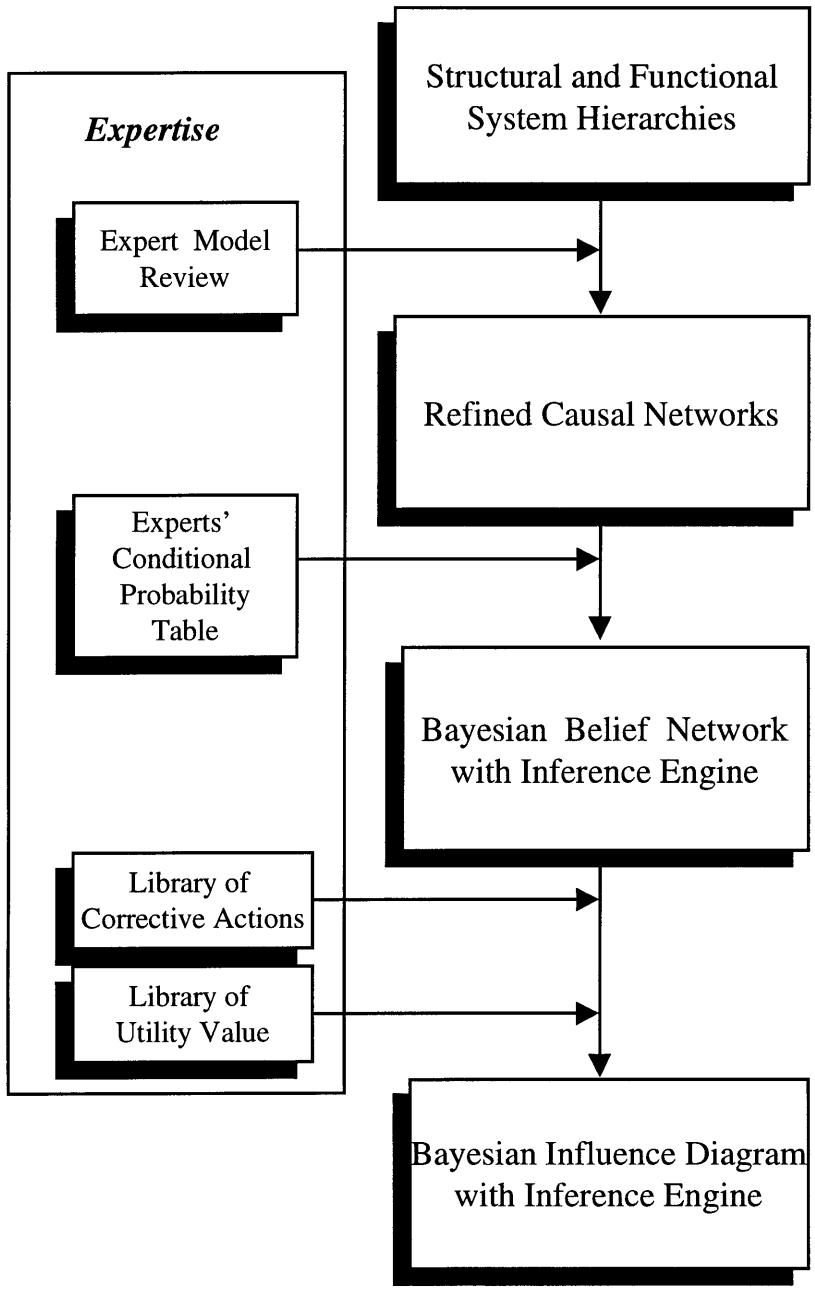


Figure 8.4 Bayesian Belief Network Based Generic Diagnosis Inference Algorithm Formulation Procedure

model. Functional knowledge concerns that part of the model that describes how each component works at the complete system level. In particular, from the FSH major failure modes for system processes and expert knowledge can be identified and then critical parameters or sensor information indicating particular failure modes can be defined. This allows for a natural decomposition of a system functional entity into comprehensible and concrete system functionality, each addressing a logical part of the diagnostic algorithm.

Thus, the graphical representation of the SSH and the FSH taken together can serve as a general frame for structuring a complete graphical algorithm explicitly using object-oriented programming tools. This is because the BBN approach makes the domain structure explicit and utilizes the topology of the graph in the control of inferences. The programming tools of the HUGIN expert system shell offer facilities that make programming tasks easier and more natural. From the view point of system causality, the knowledge from a hierarchical decomposition can be converted into a diagnostic network with causal paths being in the form of a directed link and a conditional probability table between network nodes.

8.5.2 Refined Causal Network

After a structural system hierarchy and a functional system hierarchy are constructed, then the experts are needed to review the graphical algorithm in order to determine whether it can cover all important failure modes and relationships between failure modes and corresponding sensor sets that indicate symptoms. Because the experts typically are poor Bayesian analyzers, at this stage of work their expertise can be elicited in a natural linguistic form. Then, the expertise is translated visually into graphical notations. Such presentation permits easy arrangement of the expert knowledge and makes it easy to elaborate the network's structure because this representation is sufficiently easy to understand for the experts. As the experts become well trained concerning the formalism of the BBN, they may come to represent their knowledge directly in terms of topological symbols. These preliminary minor alterations to the network's structure will reduce the burden of the next arduous, time-consuming steps.

After expert approval the graphical network can be completed. These nodes of the graphical network are connected by directed links that denote causality and make explicit the dependencies between variables, thus leading to construction of a refined causal network.

8.5.3 Bayesian Belief Network with Inference Engine

Once a refined causal network is formulated, the actual operational procedures of the nuclear power plant are reviewed and the utility expert consensus obtained are coordinated. The range of sensor readings can be discretized and then the subordinate states of a failure mode representing the failure progression can be classified.

We realize that different numbers of sensor ranges and subordinate failure mode states are used depending upon their types. In each sensor node, there are usually three mutually exclusive subordinate ranges composed of "*Low*", "*Medium*", and "*High*". In each failure mode node, often three mutually exclusive states are termed "*Good*", "*Incipient*", and "*Severe*" in terms of fault progression relating to sensor ranges. In the work reported here we use this classification for purposes of illustration. In the resulting network the dependencies between variables are quantified by means of conditional probabilities, whereby the probability of each node state is conditional upon the values of its parent node states. Thus, in this step all required conditional probability values can be assigned. This graphical network, incorporated using conditional probability values, becomes a Bayesian belief network.

We should note in this step that electric company utility experts are usually not familiar with Bayesian concepts. So, the scheme developed in the work reported here configures a general frame concerning how to elicit their expertise in plain terms and to translate it into a Bayesian form. Table 8.1 illustrates a standard table for obtaining conditional probability values linking a specific sensor to a failure mode. The number of conditional probability values in a particular link depends upon the number of subordinate states of a failure mode node and those of a sensor node. This means that a sensor node with three subordinate states linked to a three state failure mode requires a 3 by 3 matrix as shown in Table 8.1. If the experts agree on the basic probabilistic matrix structure such as is shown in Table 8.1 for a specific relationship, a belief degree relating to ε value is elicited through discussion with the expert.

Even though a belief degree must be usually represented as a real number in the closed small interval, it is not usual for an expert to express a belief judgement in numeric form. Neither it is easy for a user to attach a correct intuitive meaning to a numeric belief. The work reported here uses vague linguistic labels, which seems more

Table 8.1 Conditional Probability Table from Eliciting Expertise Linking a 3 State Sensor (S) and a 3 State Failure Mode (F) in terms of P(F/S)

		Sensor State		
		S(Low)	S(Medium)	S(High)
Failure Mode State	F(Good)	$1-\varepsilon_1$	ε_2	0
	F(Incipient)	ε_1	$1-\varepsilon_2-\varepsilon_3$	ε_4
	F(Severe)	0	ε_3	$1-\varepsilon_4$

comfortable to experts. For example, let us consider the following question, " *If a bearing temperature sensor indicates a high sensor reading, what's your degree of belief that bearing overheating is in a severe state?*" The expert usually tries to answer this question by choosing among a set of linguistic terms such as {Certain, Extremely Likely, Most Likely, Likely, ...}. Then, this linguistic answer is scaled into numeric value with a small interval and the resulting probability distribution values are then presented to the expert for concurrence. For the benefit of clarity, repeating these procedures elicit more concrete values of conditional probabilities. The proposed elicitation permits a retrieval of needed expert knowledge, reflecting the causal relationships between variables. Then, the conditional probability values of the failure mode states, as shown in Table 8.1, are obtained. The corresponding values of P(F/S) are obtained as the values shown in Table 8.2, in terms of causal reasoning by using Equation 8.2. Over the lifetime of the advisory system these associated conditional probability values should be refined continuously in order to adjust the likelihood distribution of each variable subject to the current understanding of the utility company experts.

Once these conditional probability values are assigned to the BBN within in our advisory system, we wish that the BBN should be responsive to a change in the monitored system status. For example, when an abnormal signal is observed, a high resulting belief that the system is either in the "*Incipient*" or "*Severe*" state should be calculated. If the system status has changed, the new system status cannot be understood unless the relevant signal status has also changed. This means that the calculation on the failure mode state probability distribution, given a corresponding sensor signal state change, starts from the stage where no information is available about the changed system failure mode status. This corresponds to the uniform state probability distribution. It should be assigned to prior probability values of the failure mode. Doing this will result in the most appropriate, sensitive response being attained from the BBN.

Table 8.2 Conditional Probability Table Linking a 3 State Sensor (S) and a 3 State Failure Mode (F) in terms of P(S/F)

		Failure Mode State		
		F(Good)	F(Incipient)	F(Severe)
Sensor State	S(Low)	$1-\varepsilon_5$	ε_6	0
	S(Medium)	ε_5	$1-\varepsilon_6-\varepsilon_7$	ε_8
	S(High)	0	ε_7	$1-\varepsilon_8$

Also, the local and global propagation of belief states of all nodes through entire networks should be reviewed. If examination of these propagation results shows that for some nodes the relatively unexpected belief distributions are observed in specific cases contrary to what the experts would expect, the structure and values of the network should be adjusted until the results are made satisfactory to the experts. These series of test cases and their predictions compared with the expert's expected outcomes are used to refine the models.

8.5.4 Bayesian Influence Diagram with Inference Engine

Once the BBN is constructed, for systematic decision making action nodes and utility nodes are introduced. Nodes for decision making points where choices must be made between well-defined alternatives and links directed to a decision node depict information available at the time of making the decision.

One must incorporate a library of alternative corrective actions according to the states of failure modes and then provide respective alternative action costs and benefits arising from failure mode state transitions in order to assess the values of their consequences given an illustration of a net utility calculation. The criterion of decision is defined as the utility value assigned in a utility node based upon knowledge of failure mode node states before the action, future failure mode states after the action, and the alternative possible actions.

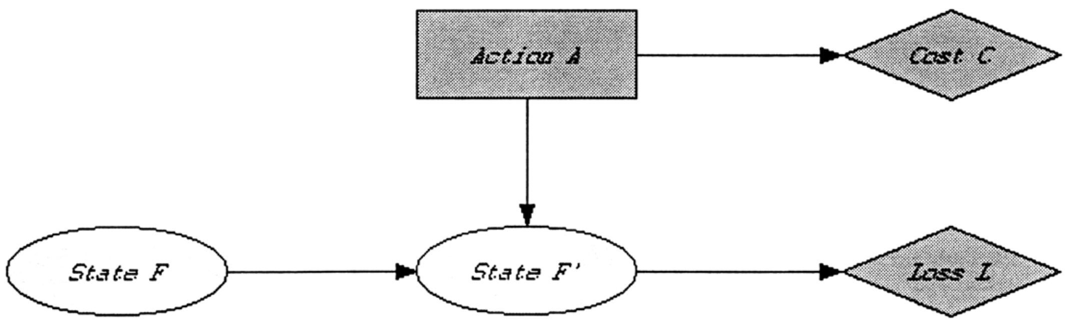
Finally, once action nodes and utility nodes are integrated into the developed BBN, this BBN, when augmented with action nodes and utility nodes, becomes the Bayesian influence diagram (BID). It is the final form to be embedded into the advisory system. Even though the BID is a final standard form, the advisory system developed in the work reported here is called a BBN-based one rather than a BID-based one because its mathematical foundation is emphasized in the terminology.

For the predictive mode performed within the advisory system, the nodes that stand for the future states of a failure mode and sensor reading predictions are introduced. Then, one should assess the conditional probabilities between the future failure mode and sensor states. Such estimates provide a basis for comparison of the actual component and sensor set performance to the estimations of the advisory system. This comparison, performed during actual operation, can lead to successive refinement of the system's predictive mode accuracy. Finally, extensive testing and global propagation mechanisms using simulated cases or historical cases will show the degree of matching with real operational cases during the development and implementation of the advisory system.

8.6 Applied Utility Principle

The Bayesian Influence Diagram (BID) can explicitly illustrate the coupling between diagnosis and management for systematic decision making. The major task of the operator is to choose the most advantageous course of action on the basis of imperfectly known state knowledge and uncertain predictions of future changes that will follow from a particular action. A utility value is a yardstick for decision making. Decision making criteria can be monetary gains and costs, measures associated with particular combinations of particular system states, or abstract satisfaction degree. In our decision making using the BID, the expected utility is modeled explicitly by taking into account costs by defining final economic loss caused by alternative actions and plant performance curtailment. The recommended action that will lead to the least cost utility value.

This section explains the detailed mathematical formulation of the applied utility concept in the BID applied in our advisory system. The network using the HUGIN expert system (ES) shell is illustrated in Figure 8.5. In this network the current system state the probability distribution before any of the alternative actions is taken: $F = \{f_i\}, i = 1,..,n$, where f_i is the probability that the system is in the i-th subordinate state, and n is the total number of subordinate states.



Legend,

State F: Failure mode node before one of the alternative actions is taken,
State F': Failure mode node after one of the alternative actions is taken,
Action A: Action node defining the state transition corresponding to the alternative actions,
Cost C: Utility node defining the costs arising from alternative actions defined in a node *A*,
Loss L: Utility node defining the financial loss arising from final system states

Figure 8.5 Decision Making Network Model Explaining the Principle of the Utility Concept

Before any action is taken, the system is in one of these states and in no other. If the system is in a particular state, k, the probability vector is indicated by the following relationships,

$$f_k = 1, \; and \; f_{i \neq k} = 0. \qquad (8.3)$$

The node F' denotes the transited system state probability vector after the alternative action is taken: $F' = \{f'_i\}, i = 1,..,n$.

A "*Action A*" node is introduced to induce the "state transformation". In a certain sense, introduction of this action node is a way of giving better characterizing the causal relationships between the states. The rectangular shaped node *A* denotes the library of alternative actions that can be taken: $A = \{a_j\}, j = 1,..,m$, where a_j is the j-th action, m is the total number of alternative actions. The diamond shaped node *C* is a utility node: $C = \{c_j\}, j = 1,..,m$, where c_j is the cost of taking the j-th action. The diamond shaped node L is another utility node: $L = \{l_i\}, i = 1,..,n$, where l_i is the associated financial loss resulting from performance curtailment of system being in the i-th system state.

Given the current system state F, the system transition probabilities can be calculated for a particular action a_j is taken as $P(i \mid a_j)$, where

$$P(i \mid a_j) = \sum_{k=1}^{n} P(i \mid k, a_j) * f_{k,} \qquad (8.4)$$

Where,

$i = 1,..,n$

f_k: probability of the k-th current state

$P(i \mid k, a_j)$: conditional probability that the current system in state k will change to a state i after an action a_j is taken.

Now the state probability vector F' can be calculated as follows:

$$f'_i = \frac{1}{m} * \sum_{j=1}^{m} P(i \mid a_j), \qquad (8.5)$$

$i = 1,..,n$.

The utility value associated with each action a_j can be calculated as follows:

$$u_j = c_j + \sum_{i=1}^{n} l_i * P(i \mid a_j), \qquad (8.6)$$

$j = 1,...,m$.

Since there is usually more interest in the difference between the utilities than the absolute values of utilities themselves, it is more revealing to rewrite Equation 8.6 as:

$$u_j - u_k = (c_j - c_k) + \sum_{i=1}^{n} l_i * (P(i \mid a_j) - P(i \mid a_k)). \qquad (8.7)$$

It can be seen from Equation 8.7 that the difference between the utilities associated with different actions comes from analysis of the first term to the right, cost and the second term to the right, gain.

After the value of the utility associated with each alternative action is obtained from Equation 8.6, the most advantageous action is identified to be that with the highest utility value, which is the least total financial loss. In case that action a_k leads to the least financial loss in action node A, the following probability distribution is assigned in Equation 8.8.

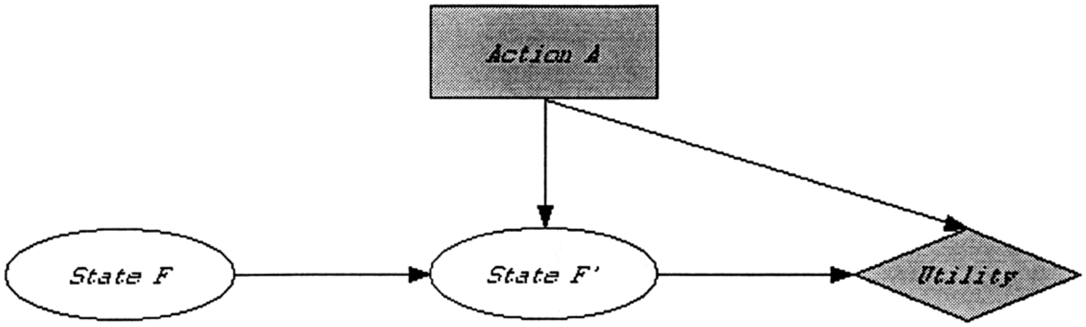
$$P(a_j) = \begin{cases} 0, & j \neq k \\ 1, & j = k \end{cases} \qquad (8.8)$$

Then, our advisory system provides final results, the expected financial loss and the future system state probability distribution once the suggested action is taken.

8.7 Prototype Decision Making Model

The two utility nodes of Figure 8.5 can be collapsed into a single utility node as shown in Figure 8.6. Figure 8.6 becomes a model using the HUGIN ES shell for making a decision upon the best corrective action. This model provides the basis for further development of entire target system being investigated.

Once the suggested action in entered as an input into our advisory system, the single utility node in Figure 8.6 indicates the eventual least financial loss and the system state F' node gives the future probability distribution of system state after the suggested action is taken. During the analysis of this task, each symptom can be observed at a specific moment in time. In this network, the time line is projected onto a unique point when the diagnosis is performed. This means that reasoning starts to be performed with the implicit assumption that any manifestation of an abnormal signal is present at that time.



Legend,

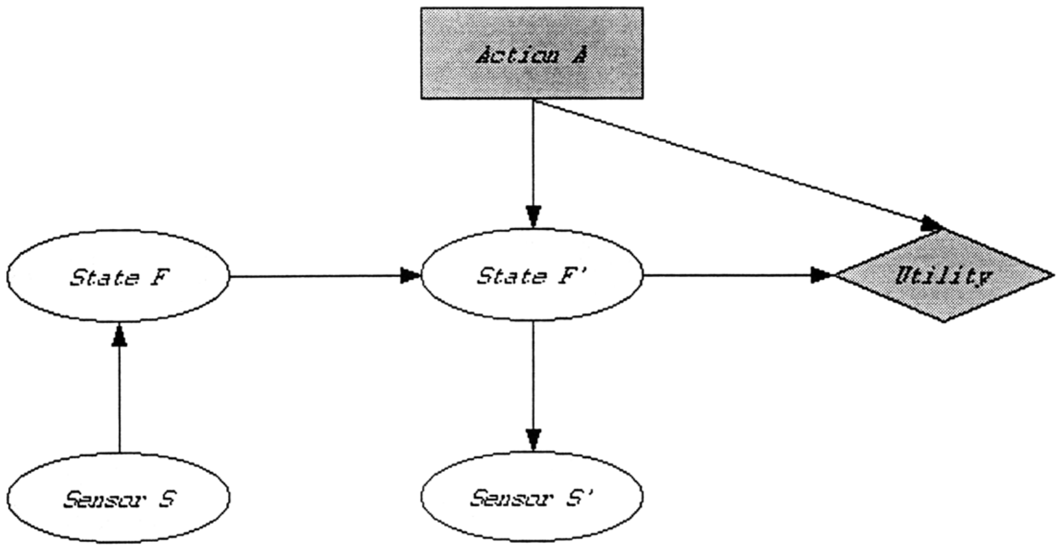
State F: Failure mode node before one of alternative actions is taken,
State F': Failure mode node after one of the alternative actions is taken,
Action A: Action node defining the state transition corresponding to the alternative actions,
Utility: Utility node for evaluation of expected costs arising from failure mode state, transitions caused by alternative actions in defined n a node *A*

Figure 8.6 Implicative Prototype Decision Making Model Network Imbedded within the Advisory System

8.8 Prototype Predictive Mode Model

The network introduced in Figure 8.6 is used to diagnose a system state and provide a corrective action. In this section, inference within the network is used to predict the future state probability distribution of a failure mode given all prior evidence and the most advantageous action taken.

This inference is extended to predict the future sensor value probability distribution corresponding to a failure mode transition. Figure 8.7 represents the prototype model being in the predictive mode in our advisory system. With this analysis, the operator can observe the change of the real sensor state after the corrective action is taken and also can check the predicted probability distribution of the sensor reading from the advisory system.



Legend,

Sensor S: Sensor node before one of the alternative actions is taken
Sensor S': Sensor node after one of the alternative actions is taken
State F: Failure mode node before one of the alternative actions is taken
State F': Failure mode node after one of the alternative action is taken
Action A: Action node defining the state transition corresponding to the alternative actions,
Utility: Utility node for evaluation of expected costs arising from failure mode state, transitions caused by alternative actions in defined n a node *A*

Figure 8.7 Prototype Network for the Advisory System in the Predictive Mode

Such estimates provide a basis for comparison of the actual component and sensor set performance to the estimations of the advisory system. Large persistent divergences between the two would indicate that the advisory system is in error for some reason. In this case, we should react to discrepancies found between the sensor values predicted in our model and the real result, find its cause, and adjust the conditional probabilities of *S'* given *F'* by systematically reasoning upon the model until the variance is accounted for. This model provides the basis for further development of entire predictive modes in the networks.

Chapter 9. Implementation of Intelligent Diagnosis and Maintenance Advisory System

9.1 Introduction

The primary purpose of this chapter is to address the operation and use of the intelligent diagnosis and maintenance (D&M) advisory system, developed in the work reported here. The probabilistic D&M network based upon the Bayesian belief network (BBN), has been developed in our work for example target systems, the turbine generator and the reactor coolant pump. The entire network structure is explicitly constructed using the HUGIN expert system shell.

This chapter illustrates the model structure, presents the conditional probability values and utility values used, explains each probabilistic model, and addresses how some representative models execute the tasks of the advisory system. Also, we focus upon demonstration of the operator interface module structure, and the task execution of which accompanies an operator's interactions with the operator interface module.

Furthermore, actual representative deterministic operational procedures of a power plant have been computerized using the Bayesian belief network (BBN). This chapter briefly suggests several essential features that this advisory system should reflect for purposes of successful practical applications in the actual power plant environment. Eventually, these probabilistic and deterministic models will be applied to solving the actual advisory tasks of the power plant.

9.2 Operator Interface Module

The computer operator interface module, used for editing the network structure, is shown in Figure 9.1. The computer interface is mouse-based. This graphical representation environment allows the user to construct and edit a network using object-oriented programming. The network's modular structure enables one to link the current network with other networks. In order to place nodes and links on the screen, the user select the type of node using the mouse. Then, activating various menu items one can perform operations upon the selected items or in direct manipulation can move or create an object (HUGI 94).

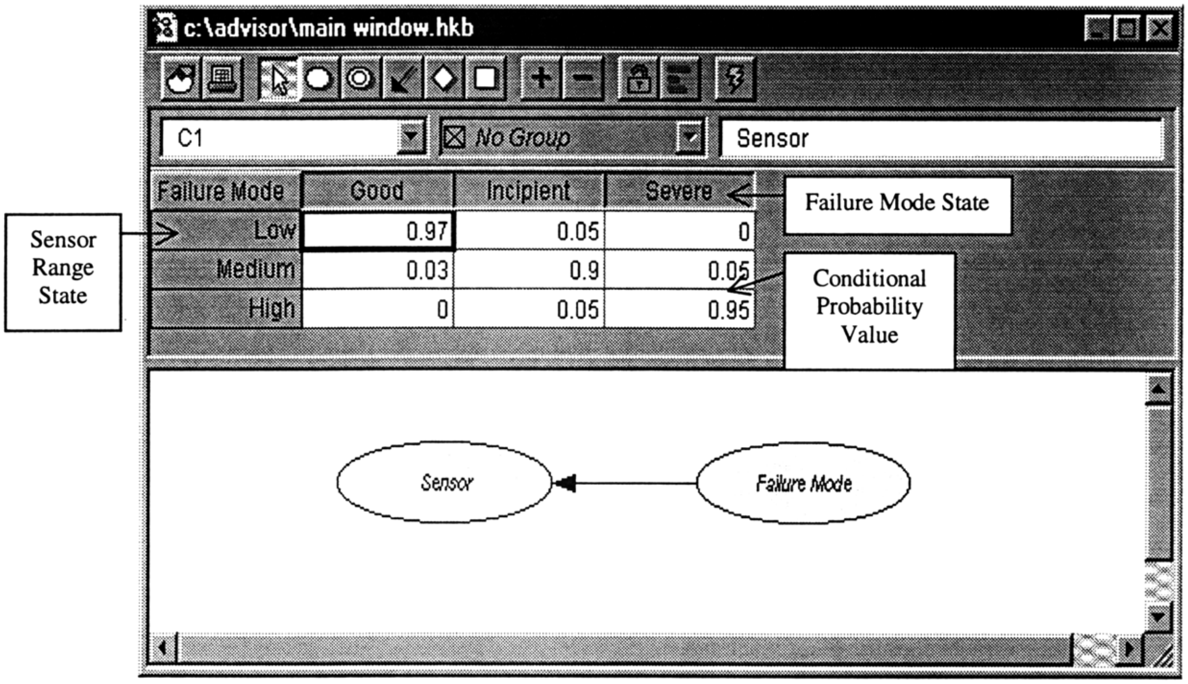


Figure 9.1 Operator Interface Module for Editing the Network

In the matrix placed in the middle of this window is shown three distinct subordinate states of a node "*Sensor*" and also three states of a node "*Failure Mode*". These are linked in a causal direction. Dragging the mouse in the concerned direction draws the link between these two nodes. The matrix values shown are those of the conditional probabilities of the sensor states given the failure mode states. Through assignment of the proper conditional probability values for a parent node linked by several children nodes, a real network is constructed.

Figure 9.2 illustrates the operator interface module for displaying the state of each node. After a piece of evidence about the sensor reading is entered to subordinate states, the probability distribution of a node "*Failure Mode*" can be observed. The former tells what is obtained from the sensor. The letter indicates the outputs that should be provided from the network after the evidence from a sensor reading (i.e., the sensor state) is obtained.

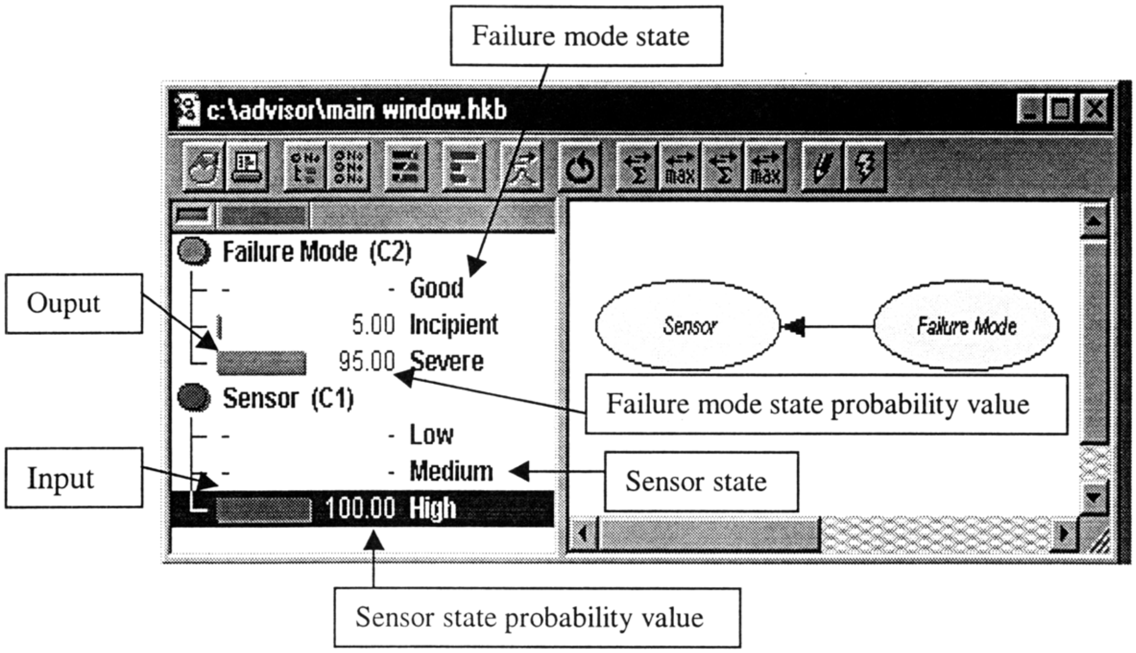


Figure 9.2 Operator Interface Module for Displaying the States and their Respective Probability Values for the Network's Nodes

In actual operation, the procedures from entering on-line data about validated sensor readings to providing the expected probability distribution of a failure mode state is performed automatically by adjusting the internal structure of this advisory system to integrate it with the other support systems. In addition, the advisory system, developed in the work reported here, should provide real-time capability for retrieving and plotting sequential graphical trends in order to assist the operator in diagnosing a situation as it evolves.

9.3 Implementation of the BBN Based Intelligence Diagnosis and Maintenance Network

The objective of this section is the demonstration of the procedures to execute the diagnostic network in the advisory system and to describe the software modules that constitute the environment for its implementation and execution. Then, the diagnosis and maintenance network in the advisory system is explained here.

In practice, for the target systems of the turbine generator and the reactor coolant pump, construction of the diagnostic network is challenging, as there are sometimes insufficient data for computing conditional probability values. This situation is attributed to unfamiliarity with the BBN concept of the plant operators or to the lack of experience in using some of the newly employed sensors suggested in the work reported here. This section constructs probabilistic diagnostic models using the HUGIN expert system shell with a generic inference algorithm and the formalism suggested in Chapters 7 and 8.

Section 9.3.1 explains the networks for the bearing and its lubrication oil system, and Sections 9.3.2 and 9.3.3 show the networks for the stator winding and its auxiliary cooling systems and for the reactor coolant pump. Note that these networks are configured in a modular fashion in order to serve the plant operator with more convenient interactions. Their conditional probability values and utility values obtained from experts' knowledge are given in Appendix B. Section 9.3.4 shows the network performing in the predictive mode, defined in Section 8.8, for the generator core vibration diagnosis. Oval shaped nodes with the first letter "*S*" stand for sensor nodes. Other oval shaped nodes with the first letter "*F*" stand for failure mode nodes, which are artificial constructs, created in order to characterize specific component states. The number following "*F*" signifies the level of a specific failure mode. The node shown as "*F1*" is the highest level node of a failure mode, which is the major concern of the network. The nodes with "*F2*" are subordinate failure modes (i.e., alternative versions of node "F1", each of which may lead to a failure mode labeled "*F1*". The node with the greatest number following "*F*" stands for the lowest level of a failure defined within the entire network. The rectangular shaped nodes named "*ACTION*" contain a library of alternative actions to be taken in order to induce a better system state transformation. The diamond shaped node named "*UTILITY*" denotes the utility node, which evaluates the usefulness of various consequence expected from alternative actions.

In order to aid understanding of the meaning and contents of all nodes in these networks, a corresponding nomenclature table for all nodes is provided after the individual presented network.

9.3.1 *Probabilistic Diagnostic Network for the Turbine Generator Bearing Component*

1) Network Explanation

Figure 9.3 illustrates the probabilistic diagnostic network for the bearing components in the turbine generator using the HUGIN shell. They should be supported by the lubrication oil system, which is also composed of numerous subordinate components. So, these networks, as shown in Figures 9.3, to 9.5 comprise in a modular fashion the entire network for the turbine bearings and their lubrication oil system.

Figures 9.4 and 9.5 describe the networks for the turbine generator lubrication oil system and the lubrication oil pump, respectively. For example, the information on a node, "*F3_LBOS_Failure*" in Figure 9.3 is transferred from that in Figure 9.4 because numerous subordinate nodes determine the final state of a node "*F3_LBOS_Failure*". Also, the information concerning the node, "*F5_Pump_Failure*" in Figure 9.4 is transferred from that in Figure 9.5. Tables 9.1 lists the nomenclature for all nodes presented in Figure 9.3 in order to aid understanding of the overall contents of these networks. Table 9.2 lists the nomenclature for all nodes presented in Figure 9.4 and Table 9.3 for those in Figure 9.5

Table 9.1 Node Nomenclature of Figure 9.3

Node Name	Node Explanation
F1_BRG_Damage	Bearing damage failure mode before action
F1'_BRG_Damage	Bearing damage failure mode after action
F2_BRG_High Temp	Bearing high temperature failure mode
F2_BRG_High Vib	Bearing high vibration failure mode
F3_LBOS_Failure	Lubrication oil system (LBOS) failure mode
S_BRG_Temp	Bearing temperature sensor
S_BRG_Vib	Bearing vibration sensor
S_TG_Load	Turbine generator load sensor

The network shown in Figure 9.3 is implemented for two cases. One is a subjectively nominal or best guess case. The other is a subjectively pessimistic case. These two examples illustrate how experts might bias their probability estimates in order to compensate for uncertainty and for risk aversion purposes.

Their corresponding conditional probability and utility values, obtained from expert interviews, are given in Tables 9.4 and 9.5, respectively. Appendix A shows the corresponding conditional probability and utility values used in the network shown in Figure 9.4.

Table 9.2 Node Nomenclature of Figure 9.4

Node Name	Node Explanation
F3_ LBOS_Failure	Lubrication oil system failure mode before action
F3'_LBOS_Failure	Lubrication oil system failure mode after action
F4_OIL_Contamination	LBOS oil contamination failure mode
F4_OIL_High Temp	LBOS high temperature failure mode
F4_OIL_Low Flow	LBOS low flow failure mode
F5_HX_Failure	LBOS heat exchanger (HX) failure mode
F5_LPP_Failure	LBOS pump failure mode
F6_HX_Fouling	LBOS HX fouling failure mode
F6_SW_Failure	LBOS service water failure mode
F7_SW_Low Flow	LBOS service water low flow failure mode
F7_SW_High Temp	LBOS service water high temperature failure mode
S_HX_D Pressure	LBOS oil differential pressure sensor across HX
S_HX_D Temp	LBOS oil differential temperature sensor across HX
S_Oil_Flow	LBOS oil flow sensor
S_Oil_Purity	Oil purity sensor
S_Oil_Temp	LBOS oil temperature sensor
S_SW_Flow	LBOS service water flow sensor
S_SW_Temperature	LBOS service water temperature sensor

Table 9.3 Node Nomenclature of Figure 9.5

Node Name	Node Explanation
F5_LPP_Failure	LBOS pump failure mode
F6_BRG_Failure	Lubrication oil pump bearing failure mode
F6_MTR_Failure	LBOS pump motor failure mode
F6_SEAL_Failure	LBOS pump seal failure mode
S_LBRG_Temp	LBOS pump bearing temperature sensor
S_LBRG_VIB	LBOS pump bearing vibration sensor
S_MTR_MC	LBOS pump motor current sensor
S_MTR_PDA	LBOS pump partial discharge sensor
S_SEAL_Leakoff	LBOS pump seal leakage sensor

Note:

(1)The nomenclature for this figure is given in Table 9.1.

(2)The conditional probability tables and utility values of a nominal case are given in Table 9.4.

(3)The conditional probability tables and utility values of a pessimistic case are given in Table 9.5.

(4)The input for the state probability distribution of a node, "*F3_LBOS_Failure*" is obtained from the network in Figure 9.4.

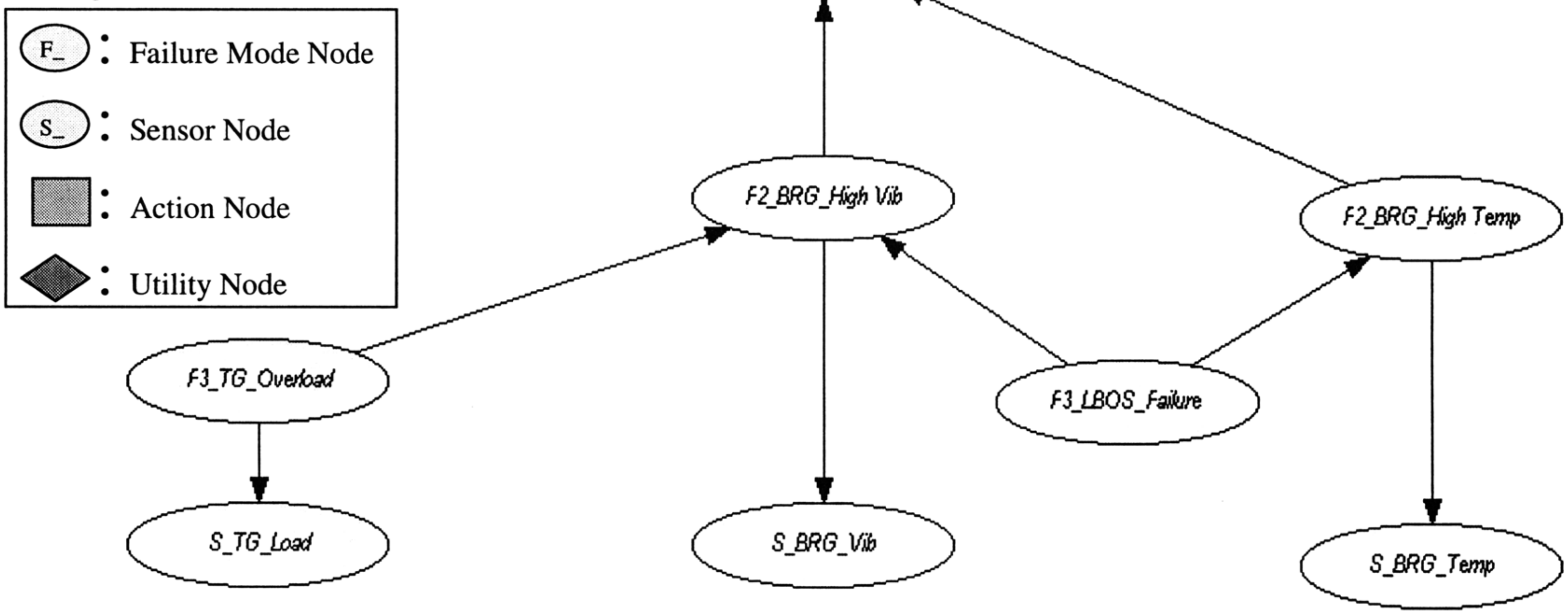


Figure 9.3 Probabilistic Diagnosis and Maintenance Nodal Network for the Bearing in the Turbine Generator

Table 9.4 Conditional Probability and Utility Values in the Nominal Case for the Network Shown in Figure 9.3

(Note: 1.The node nomenclature is given in Table 9.1.
2.Tables (1), (2), and (3) are obtained by the elicitation from experts.
3.Tables (4), (5), (6) are calculated by using the inversion mapping by Bayes' theorem from Tables (1), (2), and (3), respectively.
4.Tables (4) to (12) are illustrated directly from the HUGIN shell graphics.
5.Tables (7) to (12) are obtained through discussions with experts.
6.Utility values are calculated based upon the mean time to repair in a 1300MW plant.

(1)Table 9.4.1 Conditional probability values for P(F2_BRG_High Vib/S_BRG_Vib)

		Sensor State		
		S(Low)	S(Medium)	S(High)
Failure Mode State	F(Good)	0.985	0.04	0
	F(Incipient)	0.015	0.92	0.015
	F(Severe)	0	0.04	0.985

(2) Table 9.4.2 Conditional probability values for P(F2_BRG_High Temp/S_BRG_High Temp)

		Sensor State		
		S(Low)	S(Medium)	S(High)
Failure Mode State	F(Good)	0.985	0.035	0
	F(Incipient)	0.015	0.93	0.015
	F(Severe)	0	0.035	0.985

(3) Table 9.4.3 Conditional probability values for P(F3_TG_Load/S_TG_Load)

		Sensor State		
		S(Low)	S(Medium)	S(High)
Failure Mode State	F(Good)	0.97	0.06	0
	F(Incipient)	0.03	0.88	0.03
	F(Severe)	0	0.06	0.97

Table 9.4 Conditional Probability and Utility Values in the Nominal Case for the Network Shown in Figure 9.3 (Cont'd)

(4) Table 9.4.4 Conditional probability values for P(S_BRG_Vib / F2_BRG_High Vib)

Failure Mode State (columns); Sensor State (rows)

F2_BRG_Hig	GOOD	ICP	SVR
LOW	0.965	0.015	0
MED	0.035	0.97	0.035
HGH	0	0.015	0.965

(5) Table 9.4.5 Conditional probability values for P(S_BRG_High Temp / F2_BRG_High Temp)

Failure Mode State (columns); Sensor State (rows)

F2_BRG_Hig	GOOD	ICP	SVR
LOW	0.961	0.016	0
MED	0.039	0.968	0.039
HGH	0	0.016	0.961

(6) Table 9.4.6 Conditional probability values for P(S_TG_Load / F3_TG_Load)

Failure Mode State (columns); Sensor State (rows)

F3_TG_Overl	GOOD	ICP	SVR
LOW	0.942	0.032	0
MED	0.058	0.936	0.058
HIGH	0	0.032	0.942

(7) Table 9.4.7 Conditional probability values for P(F2_BRG_High Temp / F3_LBOS_Failure)

Failure Mode State (columns); Sensor State (rows)

F3_LBOS_Fai	GOOD	ICP	SVR
GOOD	0.98	0.05	0.001
ICP	0.019	0.9	0.019
SVR	0.001	0.05	0.98

Table 9.4 Conditional Probability and Utility Values in the Nominal Case for the Network Shown in Figure 9.3 (Cont'd)

(8) Table 9.4.8 Library of alternative actions in "*ACTION*" node

No Act	: *No Action*
Remedy	: *Remedial Action*
Trip	: *Trip Action*

(9) Table 9.4.9 Conditional probability values for P(F2_BRG_High Vib/F3_TG_Overload, F3_LBOS_Failure)

State of a Node, "*F3_TG_Overload*"

State of a Node, "*F3_TG_Overload*"

State of a Node, "*F2_BRG_High Vib*"

F3_LBOS_Fai	GOOD			ICP			SVR		
F3_TG_Overl	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.99	0.2	0	0.2	0.05	0	0	0	0
ICP	0.01	0.75	0.1	0.75	0.85	0.05	0.1	0.05	0.01
SVR	0	0.05	0.9	0.05	0.1	0.95	0.9	0.95	0.99

(10) Table 9.4.10 Conditional probability values for P(F1_BRG_Damage/ F2_BRG_High Vib, F2_BRG_High Temp)

State of a Node, "*F2_BRG_High Vib*"

State of a Node, "F2_BRG_High Temp"

State of a Node, "*F1_BRG_Damage*"

F2_BRG_Hig	GOOD			ICP			SVR		
F2_BRG_Hig	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.99	0.15	0	0.15	0.05	0	0	0	0
ICP	0.01	0.75	0.15	0.8	0.85	0.03	0.15	0.03	0.01
SVR	0	0.1	0.85	0.05	0.1	0.97	0.85	0.97	0.99

Table 9.4 Conditional Probability and Utility Values in the Nominal Case for the Network Shown in Figure 9.3 (Cont'd)

(11) Table 9.4.11 Conditional probability values for P(F1'_BRG_Damage/ F1_BRG_Damage, ACTION)

State of a Node, "*F1_BRG_Damage*"

Alternative action

State of a Node, "*F1'_BRG_Damage*"

ACTION	No Act			Remedy			Trip		
F1_BRG_Da	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
Good	1	0	0	1	0.9	0	1	0.97	0.95
ICP	0	0.25	0	0	0.1	0.2	0	0.03	0.05
SVR	0	0.75	1	0	0	0.8	0	0	0

(12) Table 9.4.12 Utility values arising from transited system states and alternative actions (Unit: $1000)

State of a Node, "*F1'_BRG_Damage*"

Alternative action

Utility Value

ACTION	No Act			Remedy			Trip		
F1'_BRG_Da	Good	ICP	SVR	Good	ICP	SVR	Good	ICP	SVR
Utility	0	-500	-1800	-500	-1000	-2300	-1200	-1700	-4000

Table 9.5 Conditional Probability and Utility Values in the Pessimistic Case for the Network Shown in Figure 9.3

(Note: 1.The node nomenclature is given in Table 9.1.
2.Tables (1), (2), and (3) are obtained by elicitation from experts.
3.Tables (4), (5), (6) are calculated by using the inversion mapping by Bayes' theorem from Tables (1), (2), and (3), respectively.
4.Tables (4) to (12) are illustrated directly from the HUGIN shell graphics.
5.Tables (7) to (12) are obtained through discussions with experts.
6.Utility values are calculated in terms of the mean time to repair in a 1300MW plant.

(1) Table 9.5.1 Conditional probability values for P(F2_BRG_High Vib/S_BRG_Vib)

		Sensor State		
		S(Low)	S(Medium)	S(High)
Failure Mode State	F(Good)	0.97	0.03	0
	F(Incipient)	0.03	0.90	0.01
	F(Severe)	0	0.07	0.99

(2) Table 9.5.2 Conditional probability values for P(F2_BRG_High Temp/S_BRG_High Temp)

		Sensor State		
		S(Low)	S(Medium)	S(High)
Failure Mode State	F(Good)	0.97	0.03	0
	F(Incipient)	0.03	0.91	0.01
	F(Severe)	0	0.06	0.99

(3) Table 9.5.3 Conditional probability values for P(F3_TG_Load/S_TG_Load)

		Sensor State		
		S(Low)	S(Medium)	S(High)
Failure Mode State	F(Good)	0.95	0.04	0
	F(Incipient)	0.05	0.88	0.02
	F(Severe)	0	0.08	0.98

Table 9.5 Conditional Probability Values and Utility Values in the Pessimistic Case for the Network Shown in Figure 9.3 (Cont'd)

(4) Table 9.5.4 Conditional probability values for P(S_BRG_Vib / F2_BRG_High Vib)

		Failure Mode State	
Sensor State			
F2_BRG_Hig	GOOD	ICP	SVR
LOW	0.97	0.032	0
MED	0.03	0.957	0.066
HGH	0	0.011	0.934

(5) Table 9.5.5 Conditional probability values for P(S_BRG_High Temp / F2_BRG_High Temp)

		Failure Mode State	
Sensor State			
F2_BRG_Hig	GOOD	ICP	SVR
LOW	0.97	0.031	0
MED	0.03	0.958	0.057
HGH	0	0.011	0.943

(6) Table 9.5.6 Conditional probability values for P(S_TG_Load / F3_TG_Load)

		Failure Mode State	
Sensor State			
F3_TG_Overl	GOOD	ICP	SVR
LOW	0.96	0.053	0
MED	0.04	0.926	0.075
HIGH	0	0.021	0.925

(7) Table 9.5.7 Conditional probability values for P(F2_BRG_High Temp/F3_LBOS_Failure)

		Failure Mode State	
Sensor State			
F3_LBOS_Fai	GOOD	ICP	SVR
GOOD	0.97	0.05	0
ICP	0.03	0.85	0.01
SVR	0	0.1	0.99

Table 9.5 Conditional Probability and Utility Values in the Pessimistic Case for the Network Shown in Figure 9.3 (Cont'd)

(8) Table 9.5.8 Library of alternative actions in "*ACTION*" node

No Act	: *No Action*
Remedy	: *Remedial Action*
Trip	: *Trip Action*

(9) Table 9.5.9 Conditional probability values for P(F2_BRG_High Vib/F3_TG_Overload, F3_LBOS_Failure)

State of a Node, "*F3_TG_Overload*"

State of a Node, "*F3_TG_Overload*"

State of a Node, "*F2_BRG_High Vib*"

F3_LBOS_Fai	GOOD			ICP			SVR		
F3_TG_Overl	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.98	0.1	0	0.15	0.1	0	0	0	0
ICP	0.02	0.8	0.07	0.75	0.8	0.03	0.07	0.03	0.005
SVR	0	0.1	0.93	0.1	0.1	0.97	0.93	0.97	0.995

(10) Table 9.5.10 Conditional probability values for P(F1_BRG_Damage/ F2_BRG_High Vib, F2_BRG_High Temp)

State of a Node, "*F2_BRG_High Vib*"

State of a Node, "F2_BRG_High Temp"

State of a Node, "*F1_BRG_Damage*"

F2_BRG_Hig	GOOD			ICP			SVR		
F2_BRG_Hig	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.98	0.1	0	0.1	0.02	0	0	0	0
ICP	0.02	0.75	0.08	0.75	0.8	0.02	0.08	0.02	0.005
SVR	0	0.15	0.92	0.15	0.18	0.98	0.92	0.98	0.995

Table 9.5 Conditional Probability and Utility Values in the Pessimistic Case for the Network Shown in Figure 9.3 (Cont'd)

(11) Table 9.5.11 Conditional probability values for P(F1'_BRG_Damage/ F1_BRG_Damage, ACTION)

State of a Node, "*F1_BRG_Damage*"

Alternative action

State of a Node, "*F1'_BRG_Damage*"

ACTION	No Act			Remedy			Trip		
F1_BRG_Da	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
Good	0.99	0	0	0.97	0.8	0	0.99	0.95	0.93
ICP	0.01	0.2	0	0.03	0.2	0.2	0.01	0.05	0.07
SVR	0	0.8	1	0	0	0.8	0	0	0

(12) Table 9.4.12 Utility values arising from transited system states and alternative actions (Unit: $1000)

State of a Node, "*F1_BRG_Damage*"

Alternative action

Utility Value

ACTION	No Act			Remedy			Trip		
F1'_BRG_Da	Good	ICP	SVR	Good	ICP	SVR	Good	ICP	SVR
Utility	0	-500	-1800	-500	-1000	-2300	-1200	-1700	-4000

Note:

(1)The nomenclature for this figure is given in Table 9.2.

(2)The conditional probability and utility values are given in Appendix A.

(3)The input for the state probability distribution of a node, "*F5_Pump_Failure*" is obtained from the network in Figure 9.5

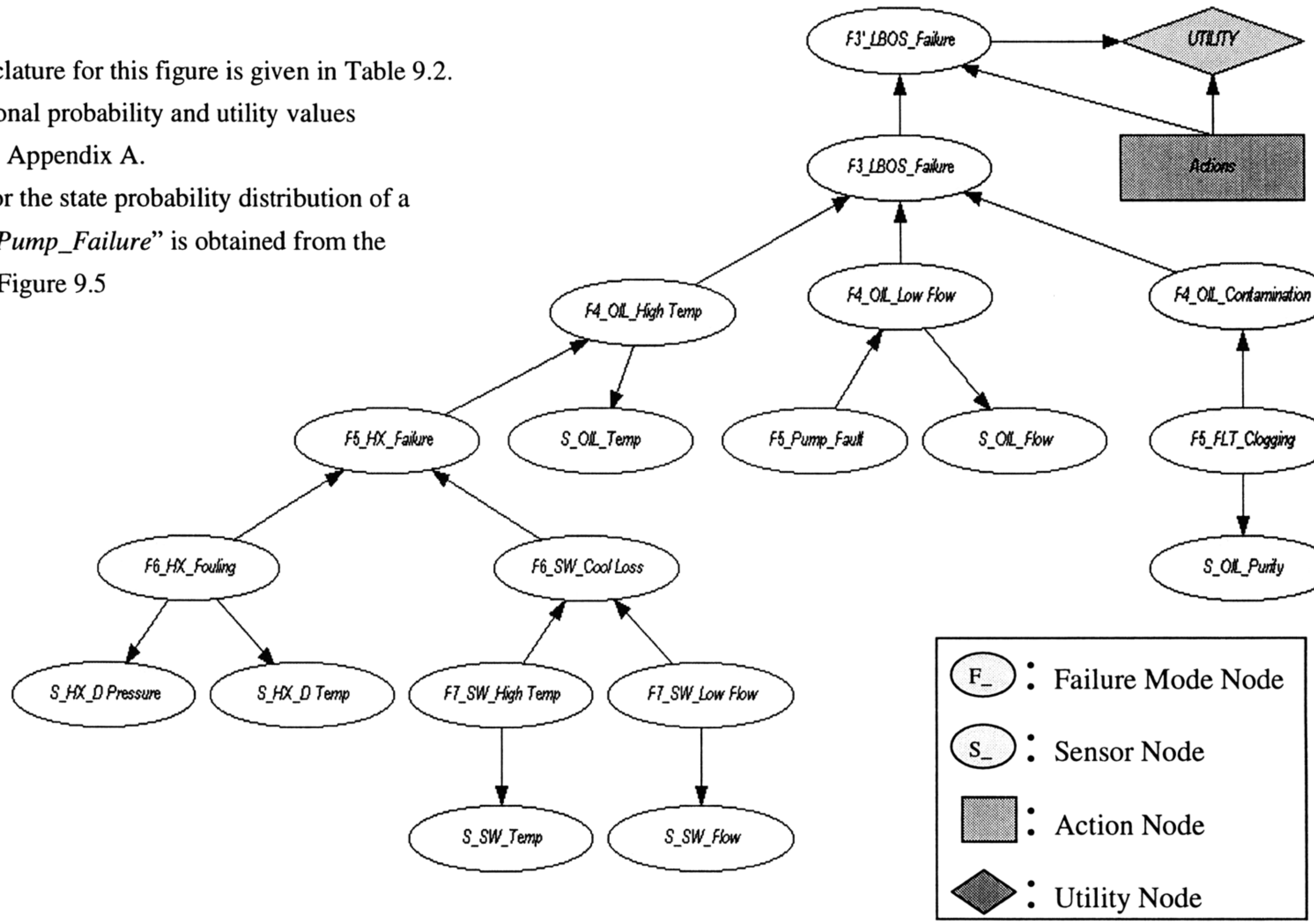


Figure 9.4 Probabilistic Diagnosis and Maintenance Nodal Network for the TG Lubrication Oil System

(TG: Turbine Generator)

Note:

(1)The nomenclature is given in Table 9.3.

(2)The conditional probability and utility values of this network were not obtained.

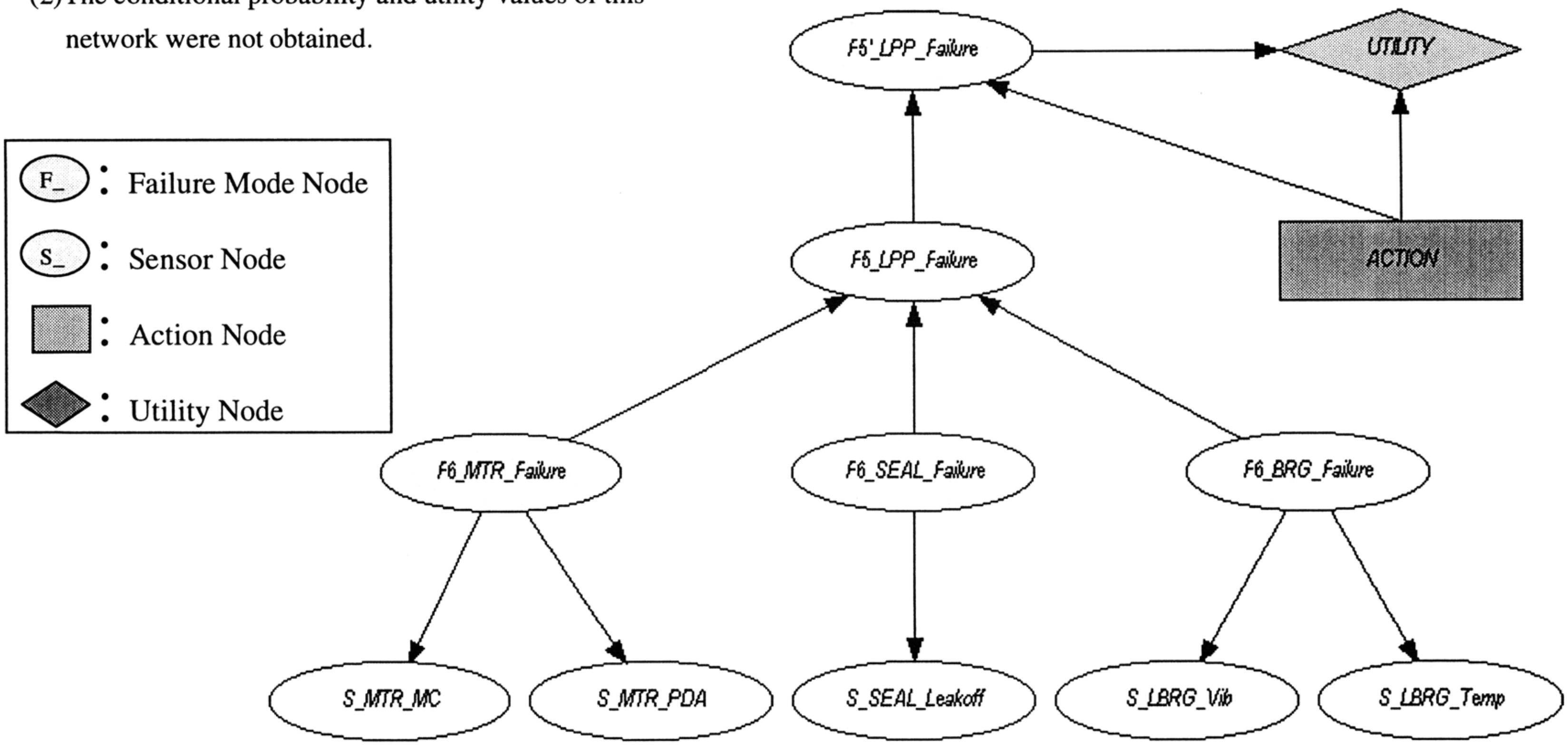


Figure 9.5 Probabilistic Diagnosis and Maintenance Nodal Network for the Lubrication Oil Pump

2) Demonstration of Network Execution

Figures 9.6 to 9.13 illustrates the flow of execution of the network shown in Figure 9.3 given the assumed evidence and presents the result of each step of the system execution displayed in the operator interface module from the inference engine during system simulated operation.

The required conditional probability values have been obtained for two cases, a nominal, or best guess reasoning one and a pessimistic one. Their results are shown in Figures 9.6 and 9.7 for comparison of these two cases of Task I. In task I concerning a nominal case, this evidence used assumes that a bearing vibration sensor and a bearing temperature sensor each indicate the "*Medium*" state, the rest of sensors are in the "*Low*" state, and the state of lubrication oil system, transferred from another file, is assumed to be in the "*Good*" state.

According to Step I of Figure 9.6, the sensor states are entered. This then provides the inference result of the probability distribution of the node, "*F1_BRG_Damage*" shown in Step II, and brings up which alternative action is expected to result in highest utility value. What is indicated in Step III is a recommendation to take a "*Remedial Action*" that leads to the least financial loss. By selecting a remedial action in Step IV, then in Step V the inference engine predicts the expected probability distribution of the states of future failure mode labeled "*F'_BRG_Damage*" resulting from an action recommended in Step III. Note that in actual operation in the power plant this task will be performed automatically.

Figure 9.7 shows that the procedures and the results from the execution of a pessimistic case of Task I. The node, "*F1_BRG_Damage*", shown in Step II, has the higher probability values in the "*Severe*" state and the "*Incipient*" state than those in the "*Severe*" state and the "*Incipient*" state of a nominal case shown in Figure 9.6. Two cases recommend the same action, but the expected utility value of a pessimistic case is lower than that of a nominal case. This means that the small variation in the conditional probability values used in a pessimistic value leads to greater financial loss. It is caused by the worse states of the future failure mode probability distribution even though the same corrective action is taken.

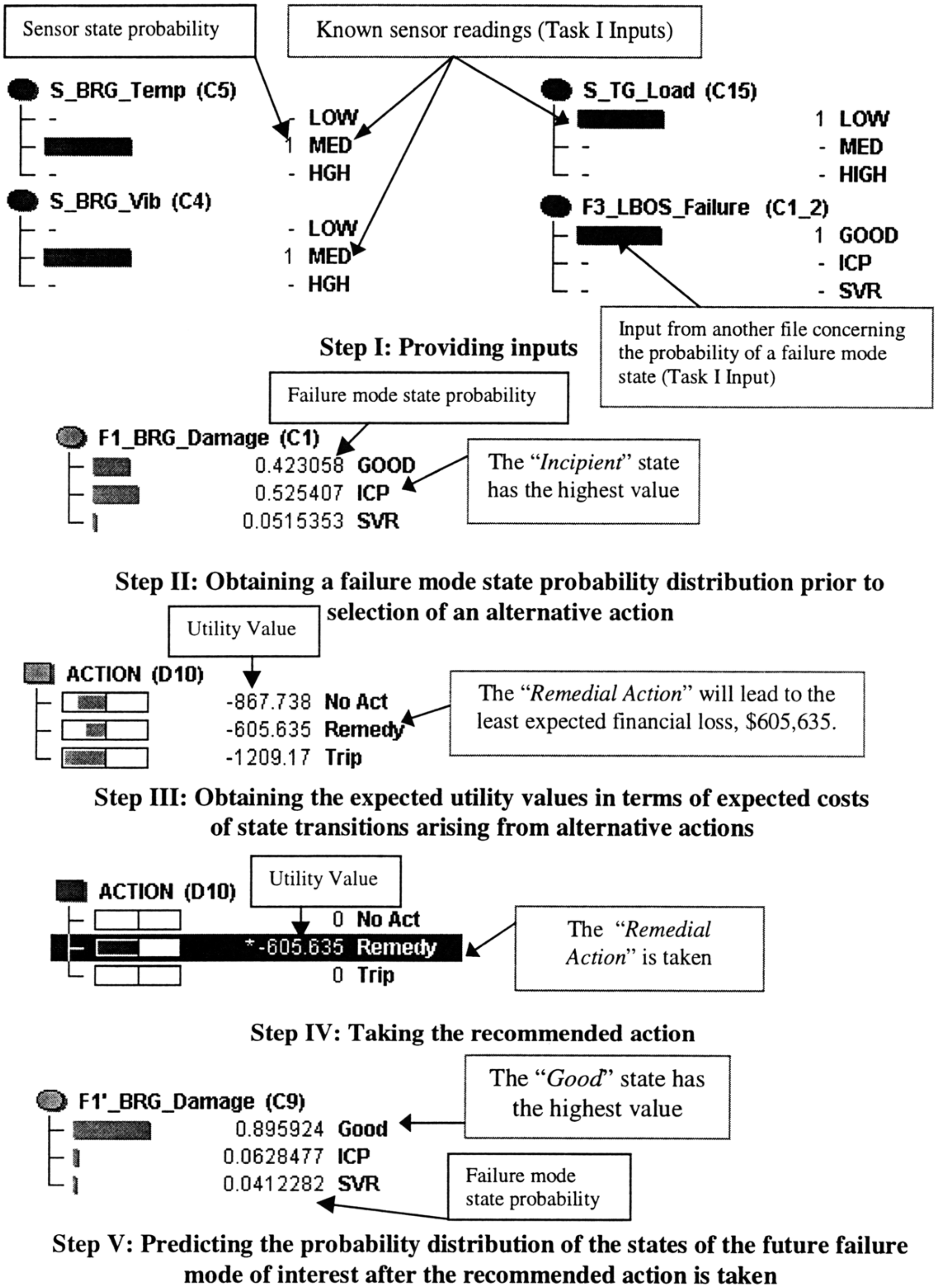


Figure 9.6 Execution Flow in Task I (Nominal Case) for the Network Shown in Figure 9.3

(Legend) LOW, MED, and HGH: Sensor states
GOOD, ICP, and SVR: Failure mode states
No Act, Remedy, and Trip: Alternative actions

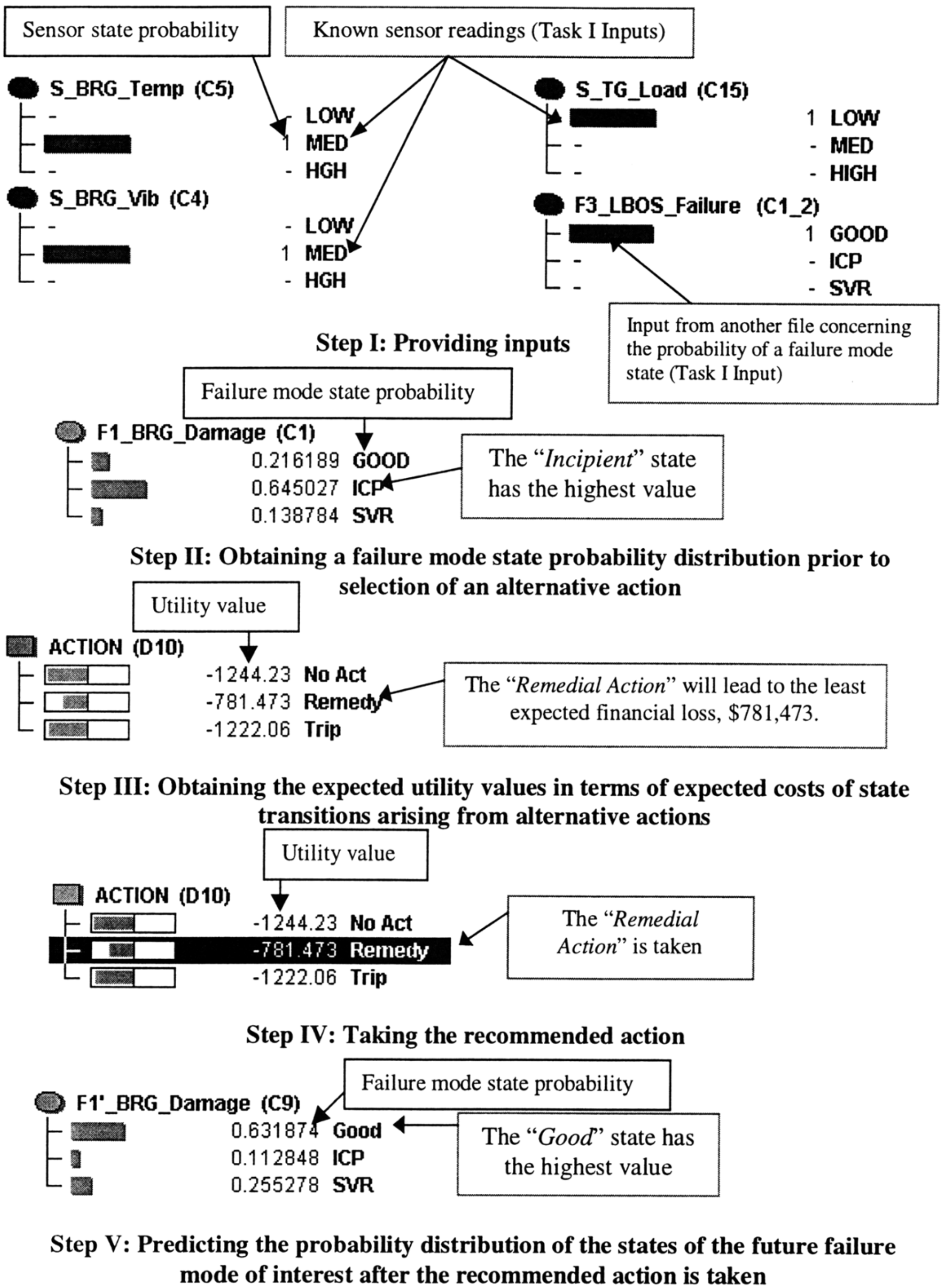


Figure 9.7 Execution Flow in Task I (Pessimistic Case) for the Network Shown in Figure 9.3

(Legend) LOW, MED, and HGH: Sensor states
GOOD, ICP, and SVR: Failure mode states
No ACT, Remedy, and Trip: Alternative actions

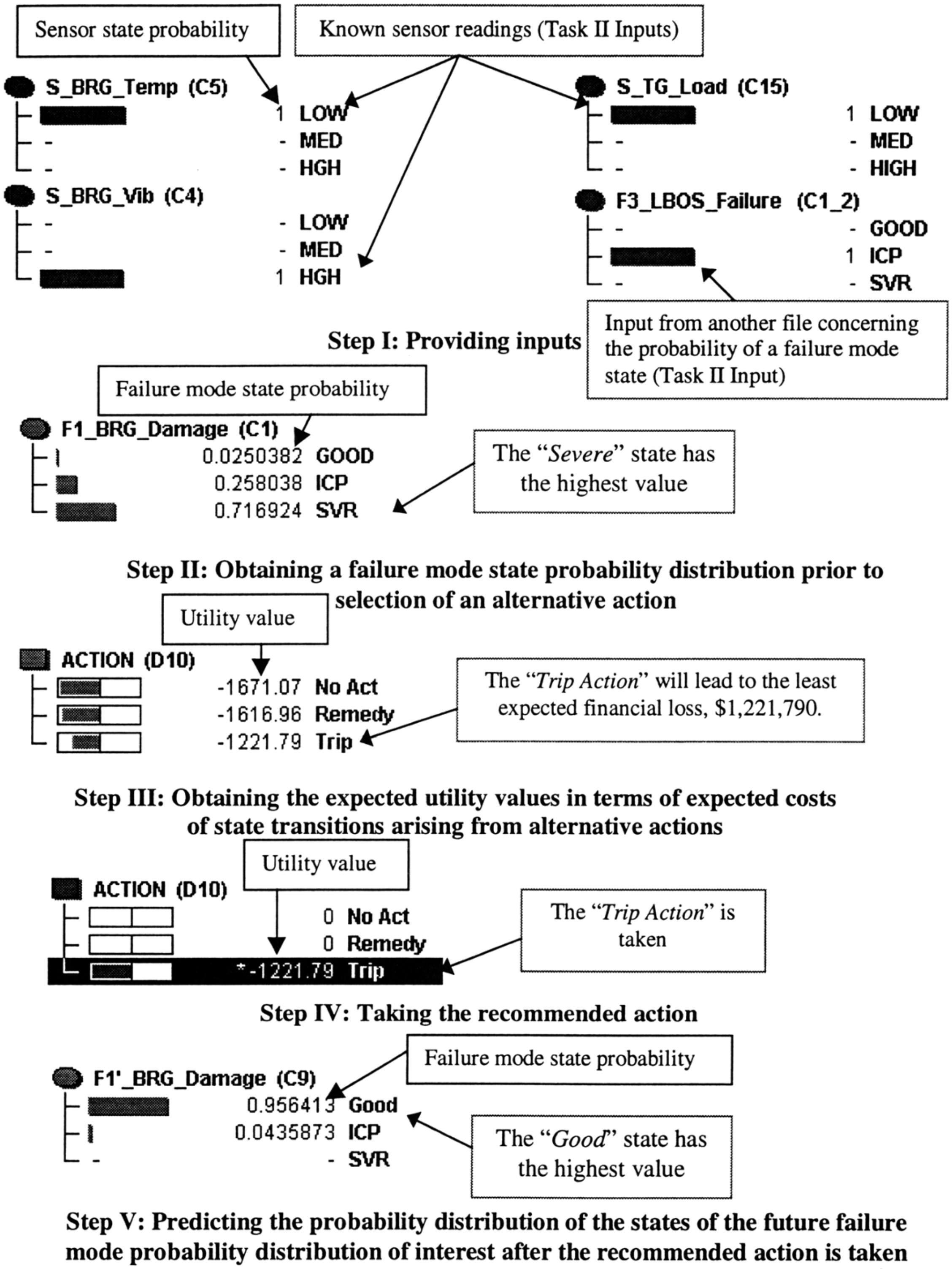


Figure 9.8 Execution Flow in Task II (Nominal Case) for the Network Shown in Figure 9.3

(Legend) LOW, MED, and HGH: Sensor states
GOOD, ICP, and SVR: Failure mode states
No ACT, Remedy, and Trip: Alternative actions

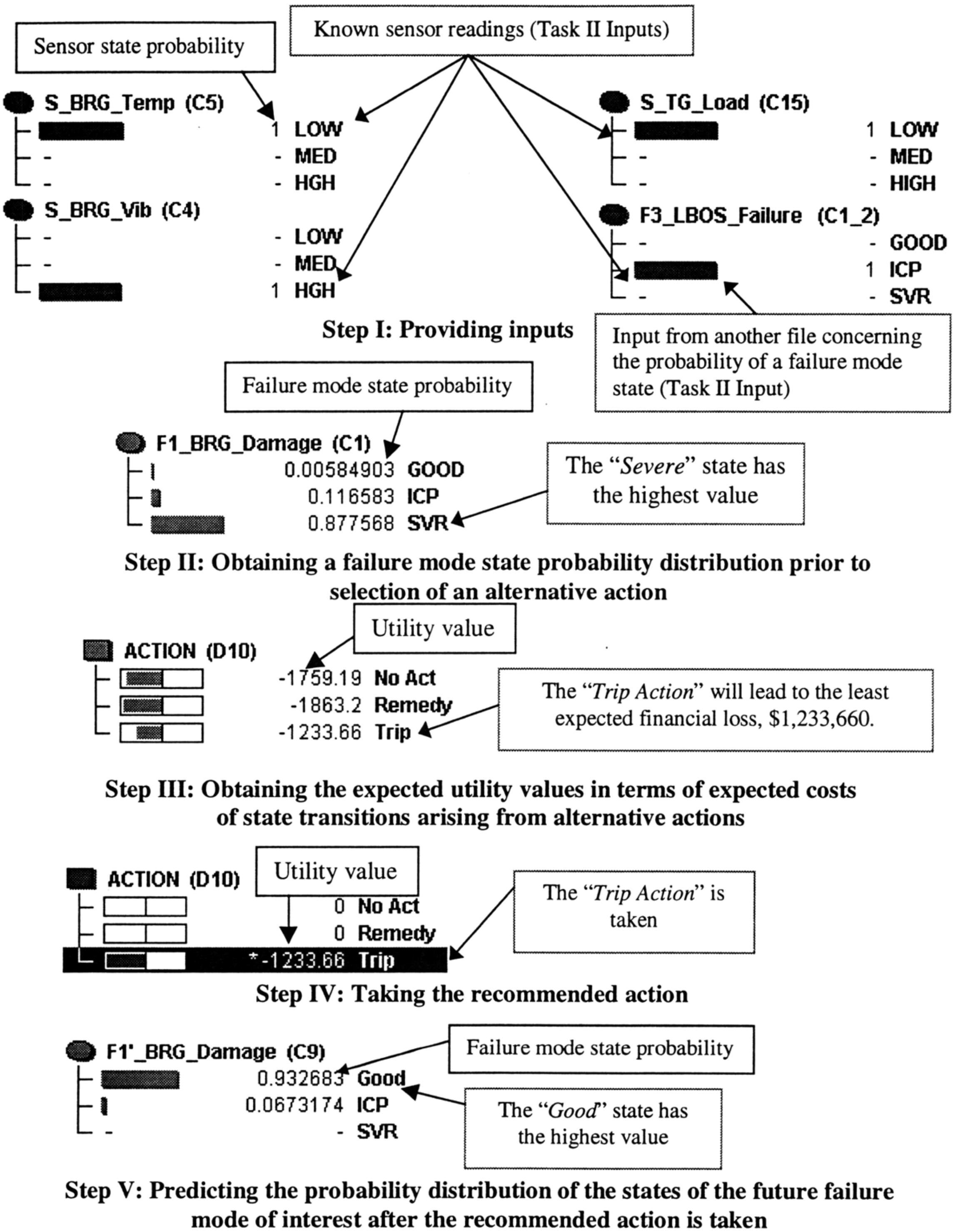


Figure 9.9 Execution Flow in Task II (Pessimistic Case) for the Network Shown in Figure 9.3

(Legend) LOW, MED, and HGH: Sensor states
GOOD, ICP, and SVR: Failure mode states
No Act, Remedy, and Trip: Alternative actions

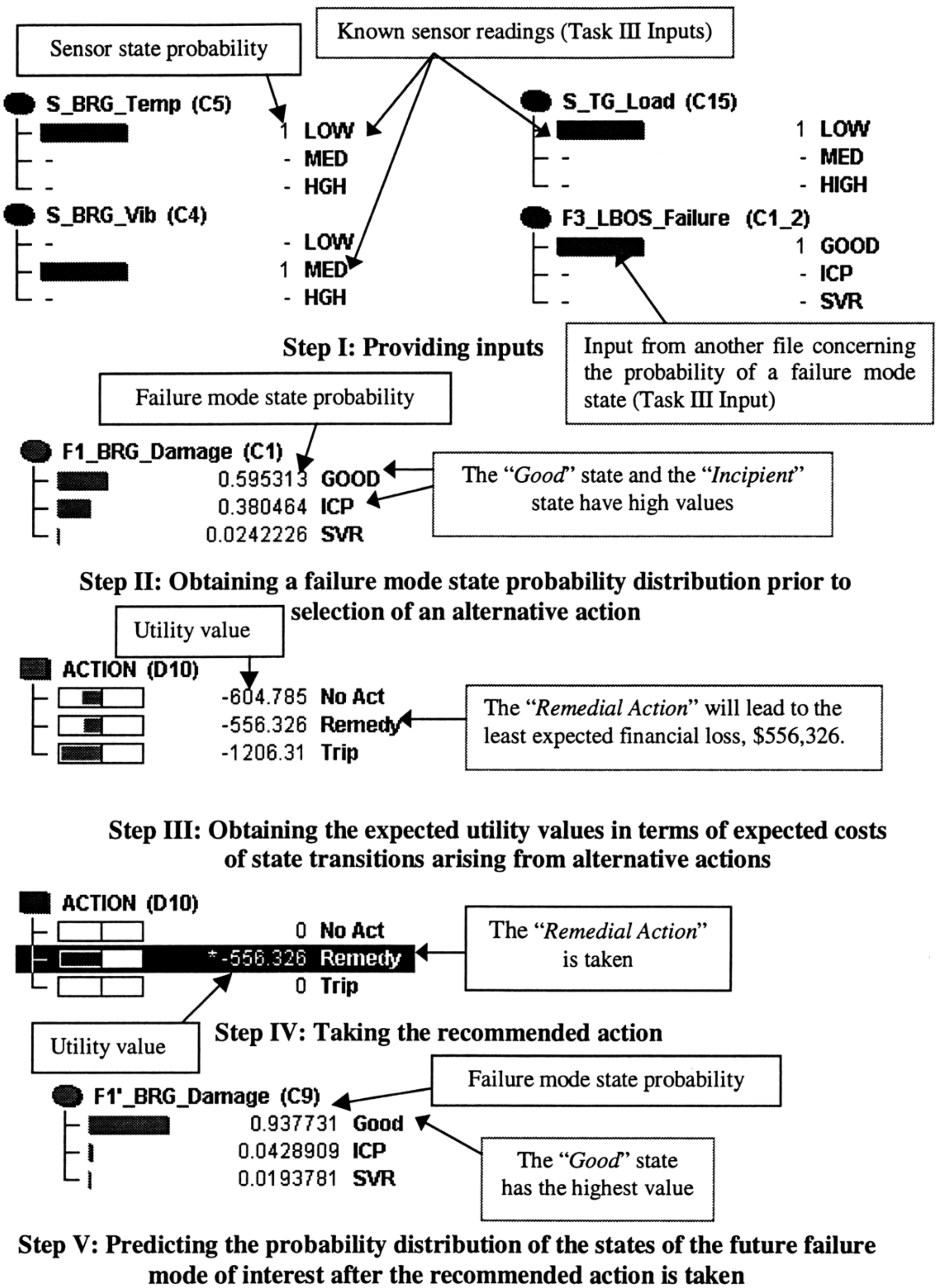


Figure 9.10 Execution Flow in Task III (Nominal Case) for the Network Shown in Figure 9.3

(Legend) LOW, MED, and HGH: Sensor states
GOOD, ICP, and SVR: Failure mode states
No Act, Remedy, and Trip: Alternative actions

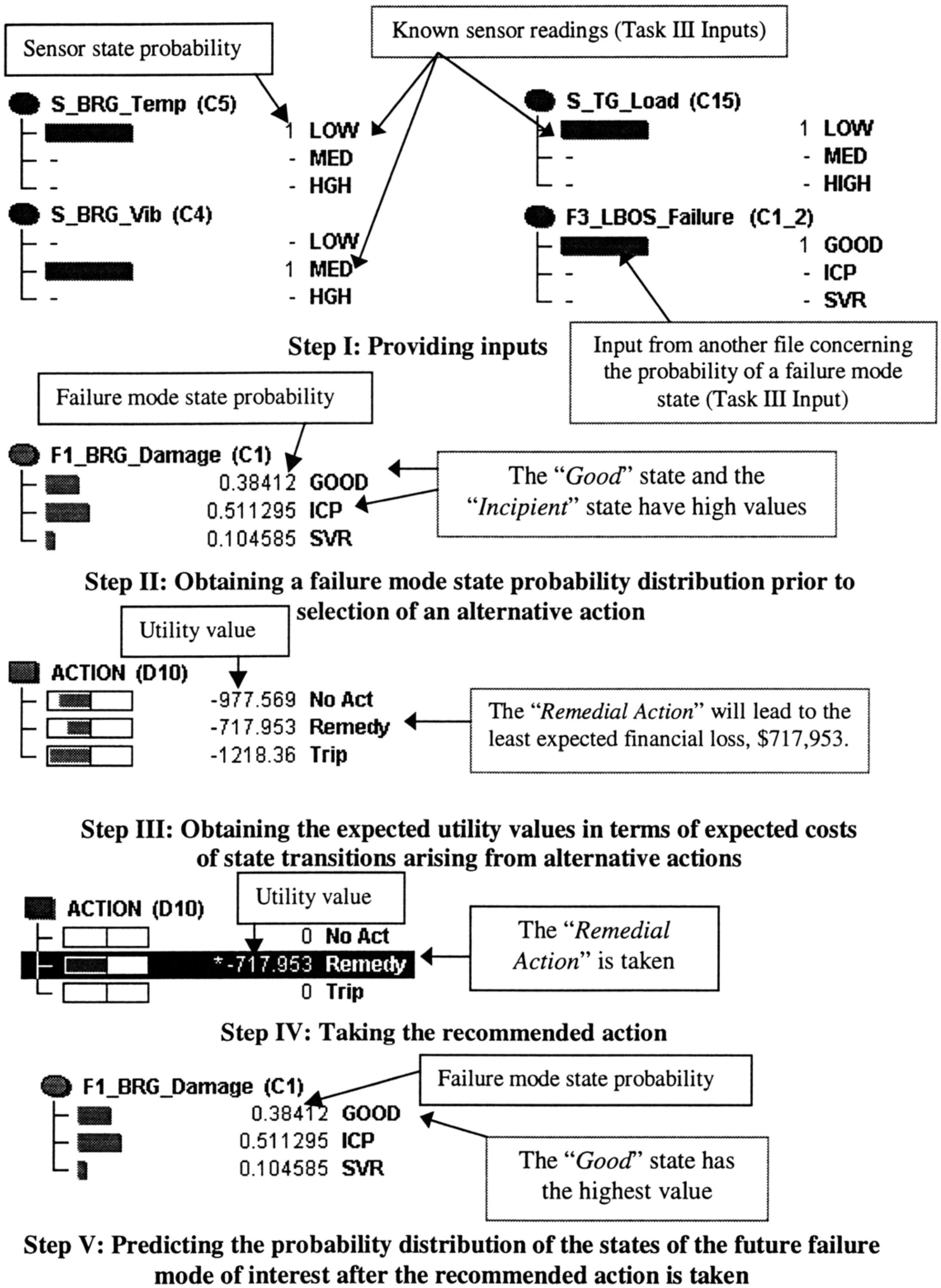


Figure 9.11 Execution Flow in Task III (Pessimistic Case) for the Network Shown in Figure 9.3

(Legend) LOW, MED, and HGH: Sensor states
GOOD, ICP, and SVR: Failure mode states
No Act, Remedy, and Trip: Alternative actions

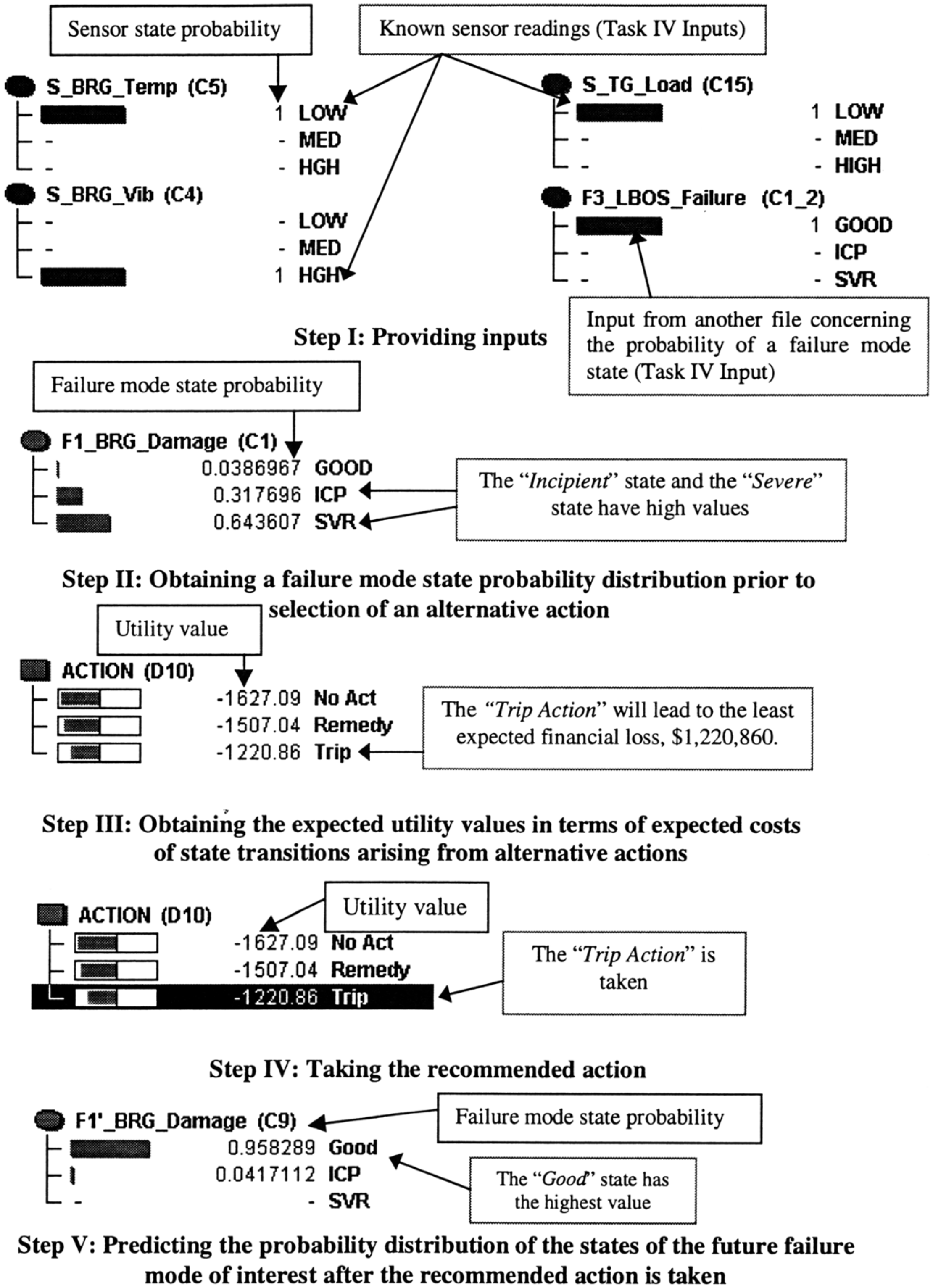


Figure 9.12 Execution Flow in Task IV (Nominal Case) for the Network Shown in Figure 9.3

(Legend) LOW, MED, and HGH: Sensor states
GOOD, ICP, and SVR: Failure mode states
No Act, Remedy, and Trip: Alternative actions

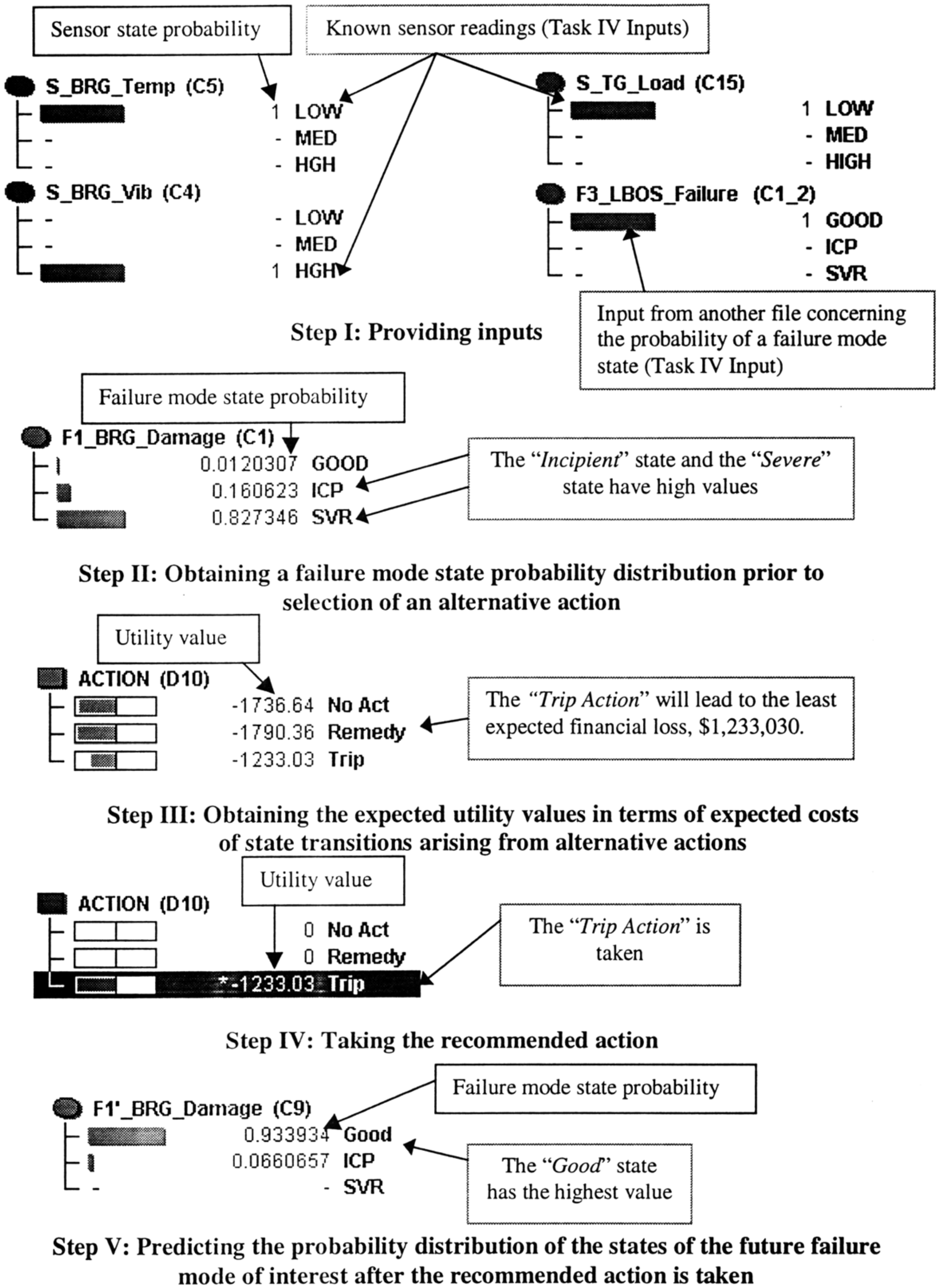


Figure 9.13 Execution Flow in Task IV (Pessimistic Case) for the Network Shown in Figure 9.3

(Legend) LOW, MED, and HGH: Sensor states
GOOD, ICP, and SVR: Failure mode states
No Act, Remedy, and Trip: Alternative actions

Concerning the network shown in Figure 9.3, four different kinds of tasks are executed both for a nominal case and a pessimistic case. Their inputs, procedures, and are illustrated in Figures 9.6 to 9.13. Also, Table 9.6 summarizes the comparison of the results of the nominal case and the pessimistic case in terms of the probability distributions of the states of the failure mode, the recommended alternative action, and the expected utility.

Table 9.6 Results from Tasks I to IV Using the Network for the Turbine Generator Bearing System Shown in Figure 9.3

Task	*Case*	Input	Failure Mode State Probability Distribution	Recommended Action	Expected Utility
I	N	VS: M, TS: M, LS: L, LB: G	G: 0.42 I: 0.53 S: 0.05	Remedial Action	$-605,635
	P	VS: M, TS: M, LS: L, LB: G	G: 0.22 I: 0.64 S: 0.14	Remedial Action	$-781,473
II	N	VS: H, TS: L, LS: L, LB: I	G: 0.02 I: 0.26 S: 0.72	Trip Action	$-1,221,790
	P	VS: H, TS: L, LS: L, LB: I	G: 0.01 I: 0.11 S: 0.88	Trip Action	$-1,233,660
III	N	VS: M, TS: L, LS: L, LB: G	G: 0.60 I: 0.38 S: 0.02	Remedial Action	$-556,326
	P	VS: M, TS: L, LS: L, LB: G	G:0.38 I: 0.51 S: 0.11	Remedial Action	$-717,953
IV	N	VS: H, TS: L, LS: L, LB: G	G: 0.04 I: 0.32 S: 0.64	Trip Action	$-1,220,860
	P	VS: H, TS: L, LS: L, LB: G	G: 0.01 I: 0.16 S: 0.83	Trip Action	$-1,233,030

Legend, N: Nominal case, P: Pessimistic Case, VS: Bearing vibration sensor, TS: Bearing temperature sensor, LS: Turbine generator load sensor, LB: Lubrication oil system failure mode, *L*: Low range, *M*: Medium range, *H*: High range, *G*: Good state, *I*: Incipient state, *S*: Severe state.

These results show that the recommended (i.e., most advantageous) action does not change when employing the pessimistic conditional probability assignments within the network. However, a lower expected utility value (i.e., cost) is evaluated in each pessimistic case than in each nominal case. In the pessimistic case, a task having the remedial action as the recommended action shows a significant expected increase of financial loss compared to that taking the trip action. This is why the sensor reading leading to the remedial action is usually in the "Medium" range. In that sensor range, a higher degree of uncertainty is typically inherent than those in corresponding "Low" or "High" ranges.

9.3.2 Probabilistic Diagnostic Network for the Generator Stator Windings with Auxiliary Cooling Systems

The stator winding system including the stator itself, the stator coil cooling water system (SCCW), and the hydrogen auxiliary system has been identified as the equipment most responsible for lost availability in the turbine generator, as shown in Figure 2.2.

The probabilistic diagnosis and maintenance network for the stator winding is illustrated in Figure 9.14. In Appendix B, their corresponding conditional probability and utility values are given. Since the stator winding is supported by ancillary cooling systems, the networks shown in Figures 9.15 and 9.16 provide some required information for the simulation of the network shown in Figure 9.16. The information concerning the node, "*F3_SCCW_Failure*" in Figure 9.14 is transferred from that in Figure 9.15 because the numerous subordinate nodes determine the probabilities of final states of a node "*F3_LBOS_Failure*". Also, the information concerning the node, "*F3_HAS_Failure*" in Figure 9.14 is transferred from that in Figure 9.16. The status of the node, "*F5_Pump_Failure*" in Figure 9.15 is obtained from another network. Tables 9.7 to 9.9 list the terminology for all nodes presented in Figures 9.14 to 9.16, respectively.

Table 9.7 Node Nomenclature of Figure 9.14

Node Name	Node Explanation
F1_STW_Damage	Stator winding damage failure mode before action
F1'_STW_Damage	Stator winding damage failure mode after action
F2_INS_Degradation	Insulation degradation failure mode
F2_STW_High Temp	Stator winding high temperature failure mode
F2_STW_High Vib	Stator winding high vibration failure mode
F3_HAS_Failure	Hydrogen auxiliary system failure mode
F3_SCCW_Failure	Stator coil cooling water system failure mode
S_STW_PDA	Stator winding partial discharge sensor
S_STW_Temp	Stator winding temperature sensor
S_STW_Vib	Stator winding vibration sensor

Table 9.8 Node Nomenclature of Figure 9.15

Node Name	Node Explanation
F3_SCCW_Failure	SCCW failure mode before action
F3'_SCCW_Failure	SCCW failure mode after action
F4_WTR_Contamination	SCCW water high contamination failure mode
F4_WTR_High Temp	SCCW water high temperature failure mode
F4_WTR_Low Flow	SCCW water low flow failure mode
F5_HX_Failure	SCCW heat exchanger failure mode
F5_SPP_Failure	SCCW pump failure
F5_WTR_High Humidity	SCCW water high humidity failure mode
F5_WTR_High Impurity	SCCW water high impurity failure mode
F5_WTR_Leakage	SCCW water leakage failure mode
S_HX_D Temp	SCCW water differential temperature sensor across HX
S_WTR_Flow	SCCW water flow sensor
S_WTR_Humidity	SCCW water humidity sensor
S_WTR_Leakage	SCCW water leakage sensor
S_WTR_Purity	SCCW water purity sensor
S_WTR_Temp	SCCW water temperature sensor

(SCCW: Stator Winding Coil Cooling System, HX: Heat Exchanger)

Table 9.9 Node Nomenclature of Figure 9.16

Node Name	Node Explanation
F3_HAS_Failure	HAS failure mode before action
F3'_HAS_Failure	HAS failure mode after action
F4_H2_Low Flow	HAS hydrogen low flow sensor failure mode
F4_H2_High Humidity	HAS hydrogen high humidity sensor failure mode
F4_H2_High Temp	HAS hydrogen high temperature sensor failure mode
F5_BLR_Failure	HAS blower failure mode
F5_GLS_Failure	Gland seal system failure mode
F5_H2_Leakage	HAS hydrogen leakage failure mode
F5_HX_D Temp	HAS hydrogen differential sensor across HX
S_BLR_D Pressure	HAS Blower differential pressure sensor
S_H2_Flow	HAS hydrogen flow sensor
S_H2_Leakage	HAS hydrogen leakage sensor
S_H2_Temp	HAS hydrogen temperature sensor
S_HX_D Pressure	HAS hydrogen differential pressure sensor across HX
S_HX_D Temperature	HAS hydrogen differential temperature sensor across

(HAS: Hydrogen Auxiliary System, HX: Heat Exchanger)

Note:

(1)The nomenclature for this figure is given in Table 9.7.

(2)The conditional probability and utility values are given in Appendix B.

(3)The input for the state probability distribution of the node, "*F3_SCCW_Failure*" is obtained from the network in Figure 9.15

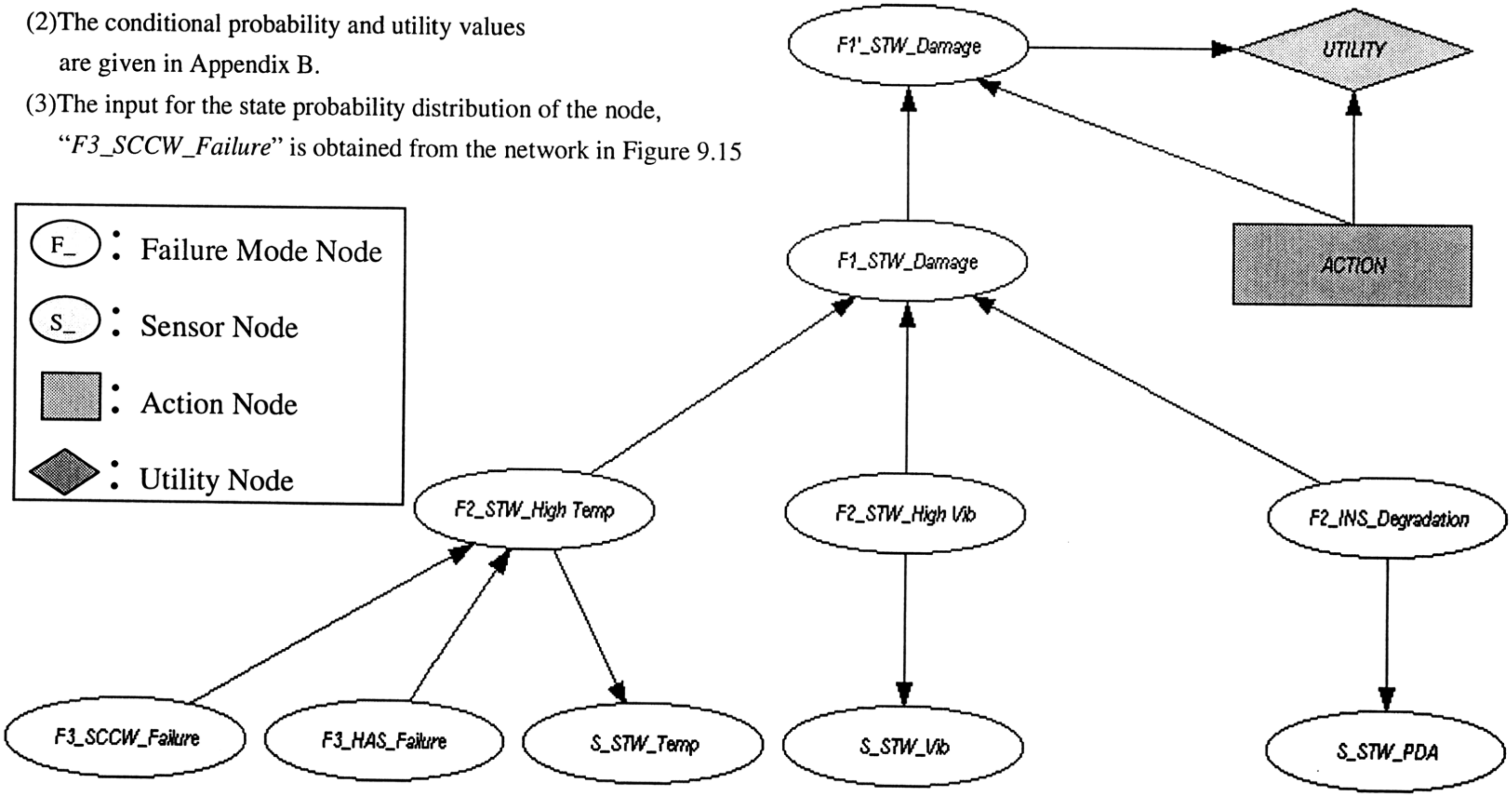


Figure 9.14 Probabilistic Diagnosis and Maintenance Nodal Network for the Generator Stator Winding

Note:

(1)The nomenclature for this figure is given in Table 9.8.

(2)The conditional probability and utility values of this network were not obtained.

(3)The input for the state probability of the node,"*F5_Pump_Failure*" is from another network, which has not been developed in this work.

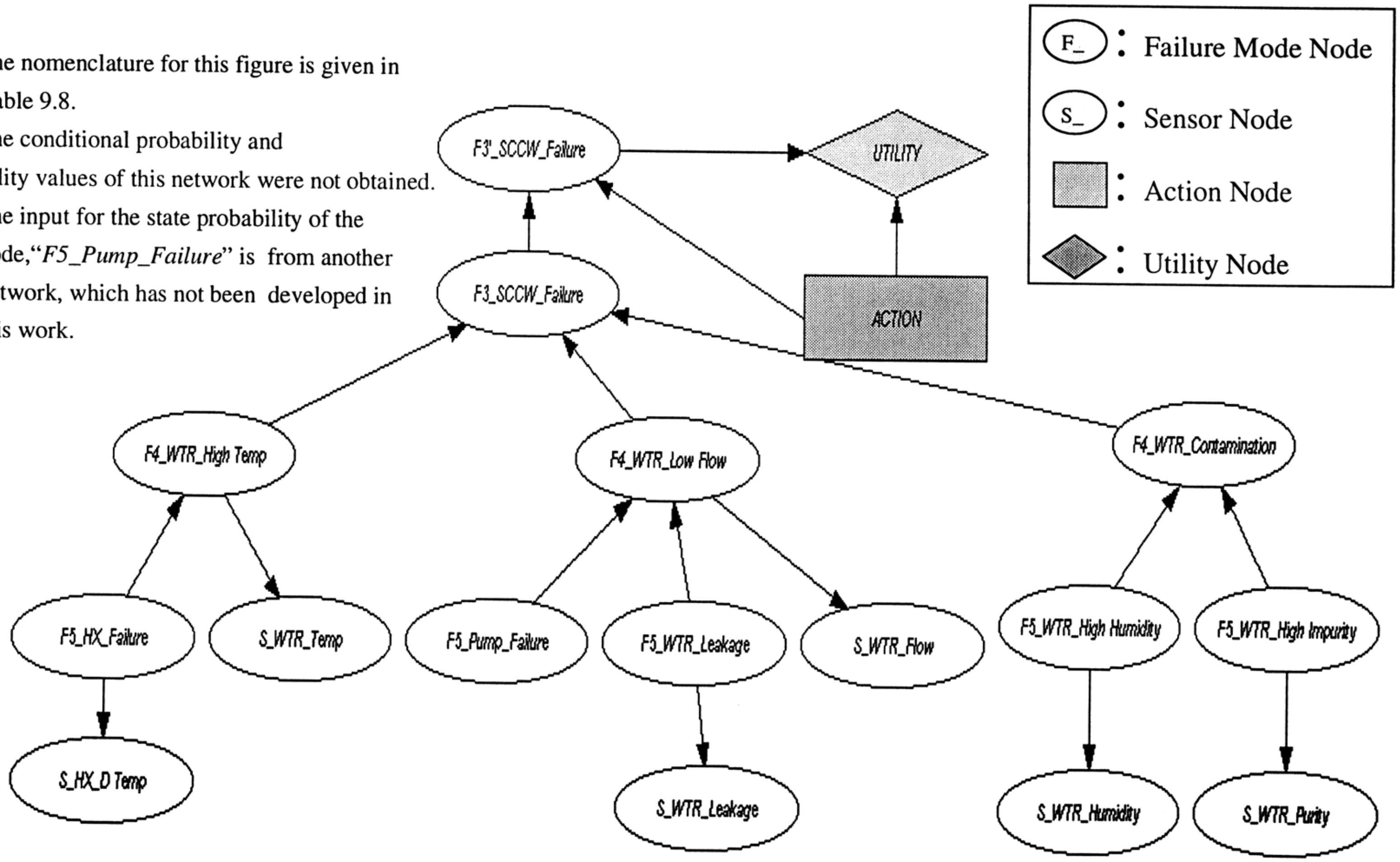


Figure 9.15 Probabilistic Diagnosis and Maintenance Nodal Network for the Generator Stator Coil Cooling Water System

Note:

(1)The nomenclature for this figure is given in Table 9.9.

(2)The conditional probability and utility values of this network were not obtained.

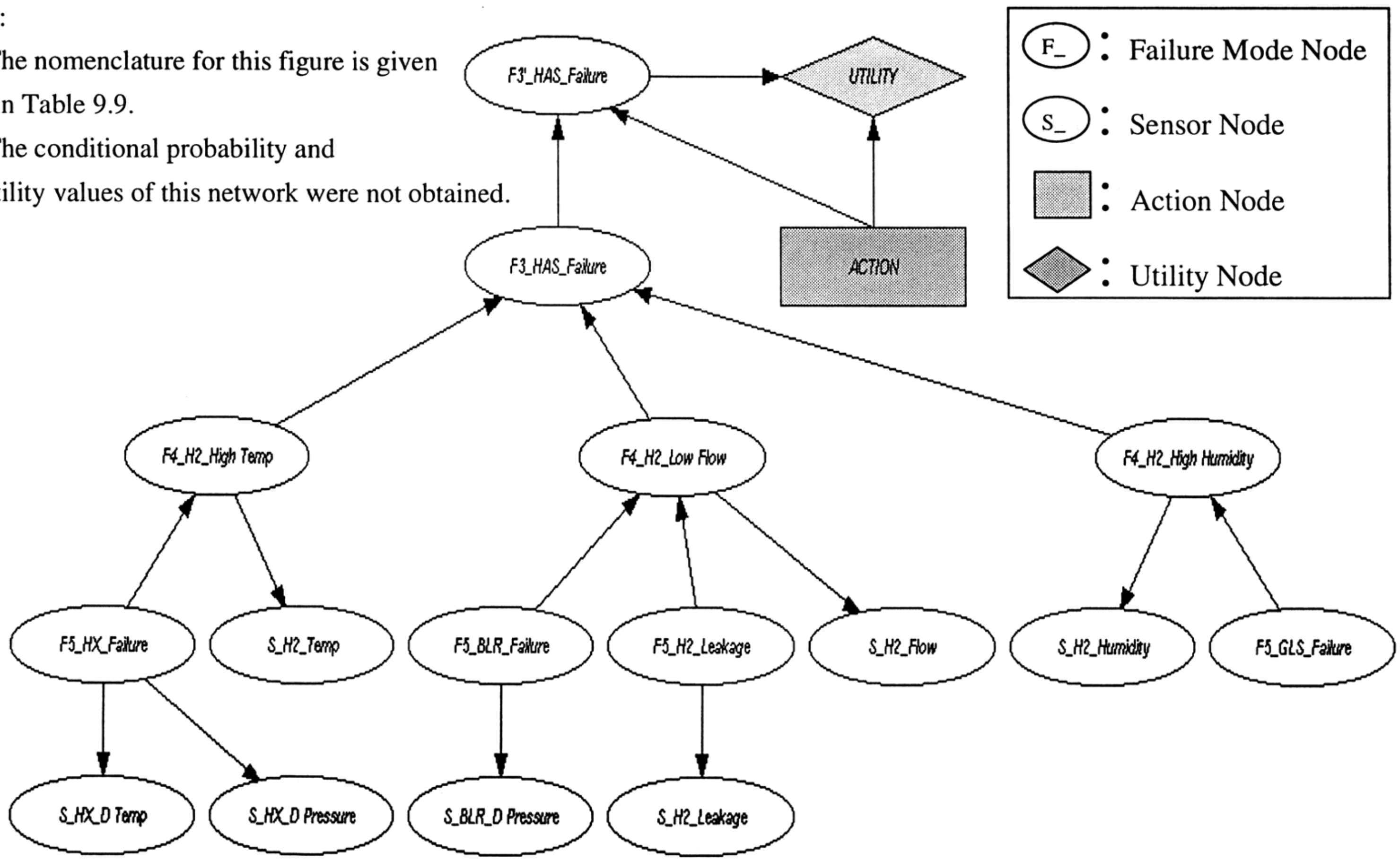


Figure 9.16 Probabilistic Diagnosis and Maintenance Nodal Network for the Generator Hydrogen Cooling System

9.3.3 Probabilistic Diagnostic Network for the Reactor Coolant Pump

In the PWR, reactor coolant pumps (RCPs) circulate water through the primary coolant systems in order to transport energy from the core to the steam generator. The major RCP components leading to forced outages are classified into bearings, bus, motor, and seals.

Figure 9.17 illustrates the network for the diagnosis and maintenance for the bearing components in the RCP. Because they should be lubricated and supported by the lubrication oil system, the network for the lubrication equipment for RCP bearings is shown in Figure 9.18. The information on the node, "*F3_LBOS_Failure*" shown in Figure 9.17 is obtained from that in Figure 9.18. The node, "*F5_Pump_Failure*" shown in Figure 9.18 is obtained from that another network. The states of the node named "*F3_SHT_High Vib*" in Figure 9.7 and those of the node, "*F2_SHT_High Vib*" in Figure 9.20 are transferred from the node, "*F1_SHT_High Vib*" in Figure 9.21. The diagnosis and maintenance networks for the motor, the seal, and the shaft are illustrated in Figures 9.19 to 9.21, respectively. Note that the nodes that begin with "*S*" and end with "*fr*" indicate sensors providing specific frequency from the Fast Fourier Transform (FFT) data processing equipment. Tables 9.10 to 9.14 list the terminology for all nodes presented in Figures 9.17 to 9.21, respectively.

Table 9.10 Node Terminology of Figure 9.17

Node Name	Node Explanation
F1_BRG_Damage	*Bearing damage failure mode before action*
F1'_BRG_Damage	*Bearing damage failure mode after action*
F2_BRG_High Temp	*Bearing high temperature failure mode*
F2_BRG_High Vib	*Bearing high vibration failure mode*
F3_LBOS_Failure	*Lubrication oil system (LBOS) failure mode*
F3_SFT_High Vib	*Shaft high vibration failure mode*
S_BRG_Temp	*Bearing temperature sensor*
S_BRG_Vib	*Bearing vibration sensor*
S_SHT_Vib	*Shaft vibration sensor*

Table 9.11 Node Terminology of Figure 9.18

Node Name	Node Explanation
F3_LBOS_Failure	*Lubrication oil system failure mode before action*
F3'_LBOS_Failure	*Lubrication oil system failure mode after action*
F4_OIL_High Temp	*LBOS high temperature failure mode*
F4_OIL_Low Flow	*LBOS low flow failure mode*
F5_LPP_Failure	*LBOS pump failure mode*
F5_HX_Failure	*LBOS HX failure mode*
S_HX_D Pressure	*LBOS oil differential pressure sensor across HX*
S_HX_D Temp	*LBOS oil differential temperature sensor across HX*
S_Oil_Flow	*LBOS oil flow sensor*
S_Oil_Temp	*LBOS oil temperature sensor*

(HX: Heat Exchanger)

Table 9.12 Node Terminology of Figure 9.19

Node Name	Node Explanation
F1_MTR_Failure	*Motor failure mode before action*
F'_MTR_Failure	*Motor failure mode after action*
F2_GAP_Eccentricity	*Motor airgap eccentricity failure mode*
F2_RTR_Failure	*Motor rotor fracture failure mode*
F2_STW_Damage	*Motor stator winding damage failure mode*
F3_INS_Degradation	*Motor insulation degradation failure mode*
F3_STW_High Temp	*Motor stator winding high temperature failure mode*
S_MC_Bar fr	*Specific frequency for rotor bar fracture*
S_MC_Gap	*Specific frequency for airgap eccentricity*
S_STW_PDA	*Motor stator winding partial discharge sensor*
S_STW_Temp	*Motor stator winding temperature sensor*

Table 9.13 Node Terminology of Figure 9.20

Node Name	Node Explanation
F1_SEAL_Damage	*Seal damage failure mode before action*
F1'_SEAL_Damage	*Seal damage failure mode after action*
F2_SEAL_Leakoff	*Seal leakage failure mode*
F2_SEAL_INJ Failure	*Seal flow injection system failure mode*
S_SEAL_Leakoff	*Seal flow leakage sensor*
S_SEAL_INJ Flow	*Seal injection water flow sensor*
S_SEAL_INJ Temp	*Seal injection water temperature sensor*

Table 9.14 Node Terminology of Figure 9.21

Node Name	Node Explanation
F1_SHT_High Vib	*Shaft high vibration failure mode before action*
F'_SHT_High Vib	*Shaft high vibration failure mode after action*
F2_Bent Shaft	*Bent shaft failure mode*
F2_Unbalance	*Shaft unbalance failure mode*
F2_Misalignment	*Shaft misalignment failure mode*
S_Bent Shaft fr	*Specific frequency for bent shaft*
S_Unbalance fr	*Specific frequency for shaft unbalance*
S_Misalignment fr	*Specific frequency for shaft misalignment*

Note:

(1)The nomenclature for this figure is given in Table 9.10.

(2)The conditional probability and utility values are given in Appendix C.

(3)The input for the state probability of the node,"*F3_LBOS_Failure*" is obtained from Figure 9.18.

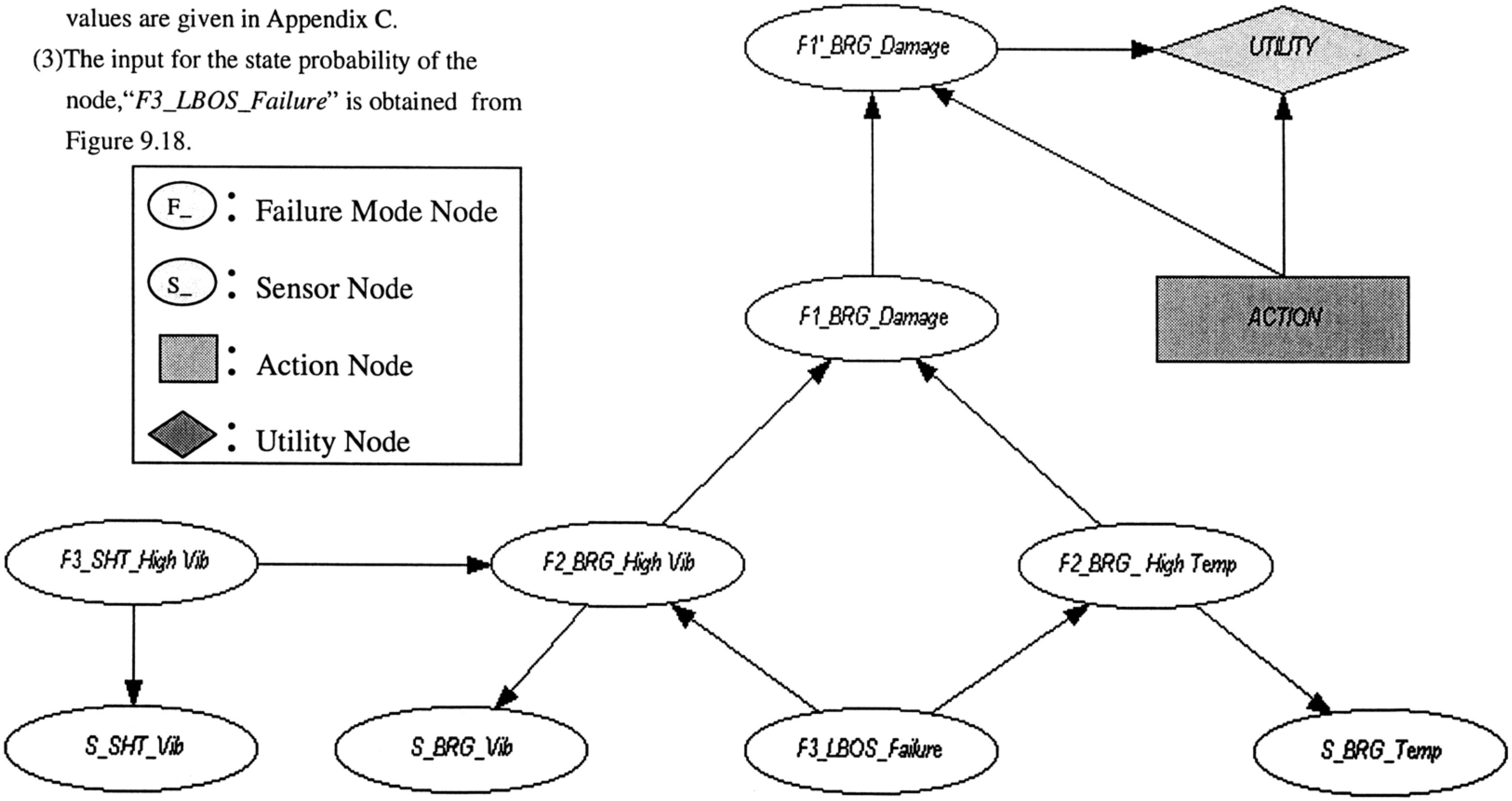


Figure 9.17 Probabilistic Diagnosis and Maintenance Nodal Network for the Reactor Coolant Pump Bearing

Note:

(1) The nomenclature for this figure is given in Table 9.11.

(2) The conditional probability and utility values of this network were not obtained.

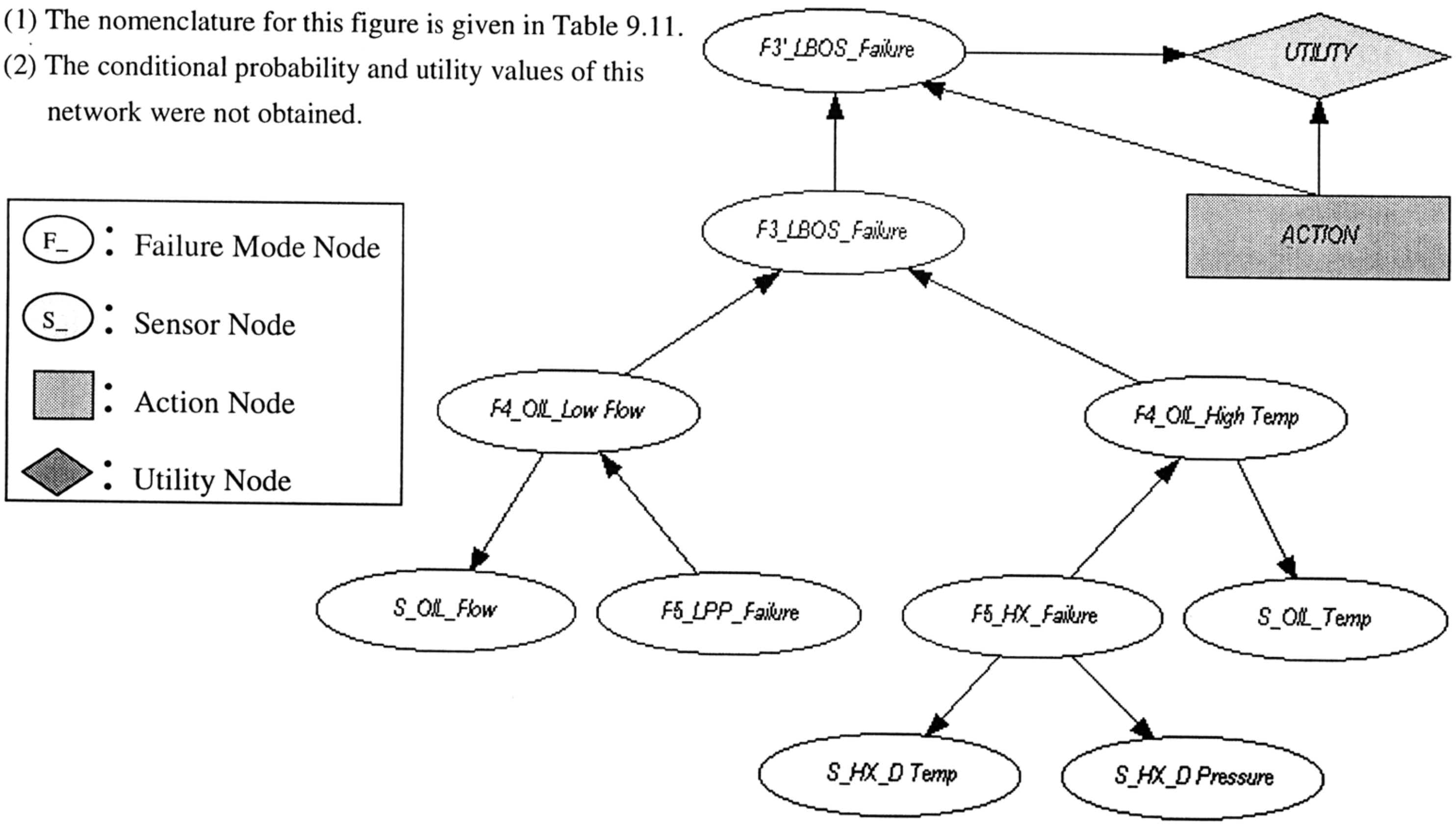


Figure 9.18 Probabilistic Diagnosis and Maintenance Nodal Network for the RCP Bearing Lubrication System

(RCP: Reactor Coolant Pump)

Note:

(1)The nomenclature for this figure is given in Table 9.12.

(2)The conditional probability and utility values of this network were not obtained.

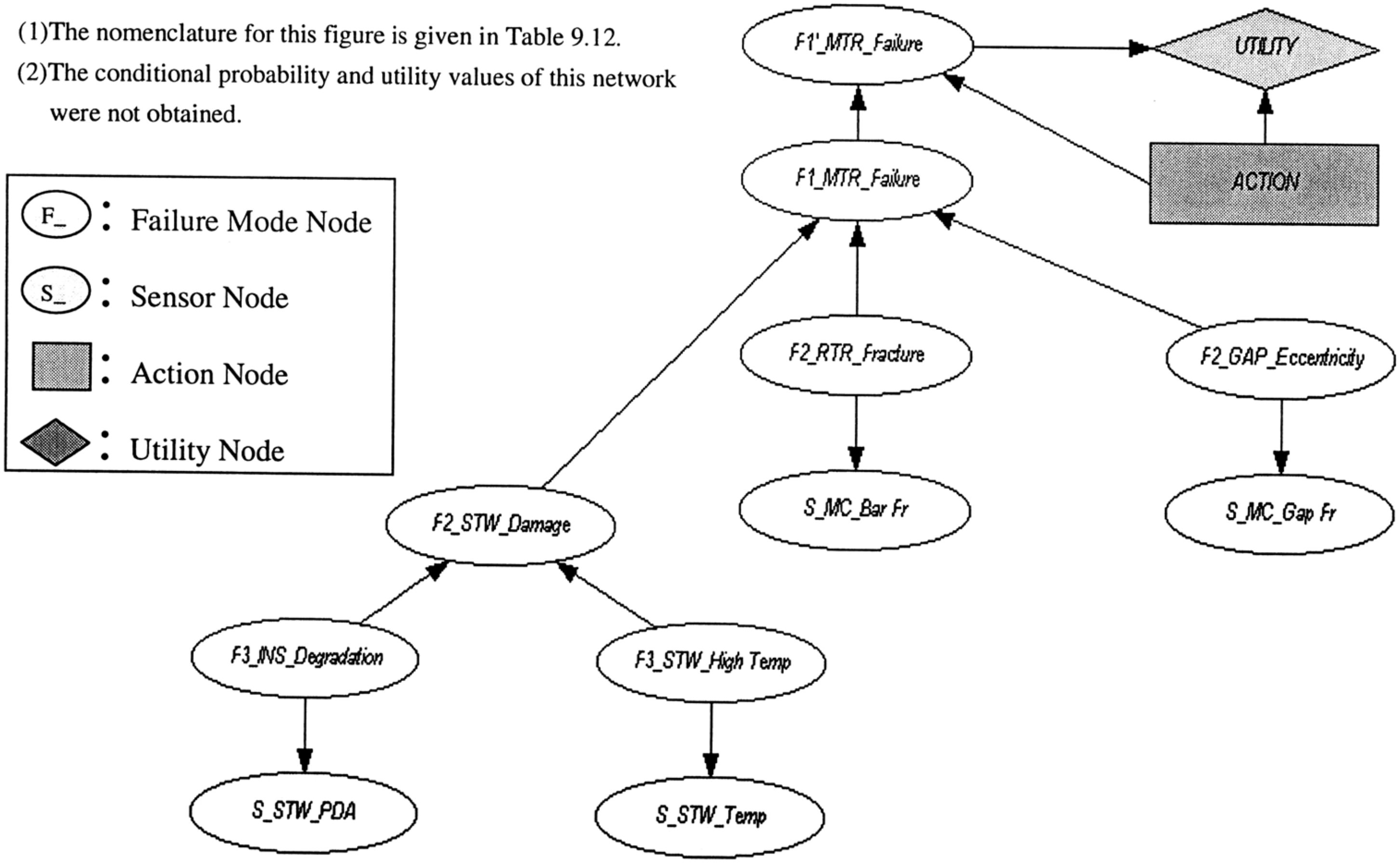


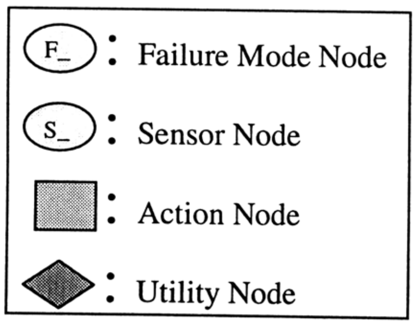
Figure 9.19 Probabilistic Diagnosis and Maintenance Nodal Network for the RCP Motor

(RCP: Reactor Coolant Pump)

Note:

(1)The nomenclature for this figure is given in Table 9.13.

(2)The conditional probability and utility values of this network were not obtained.



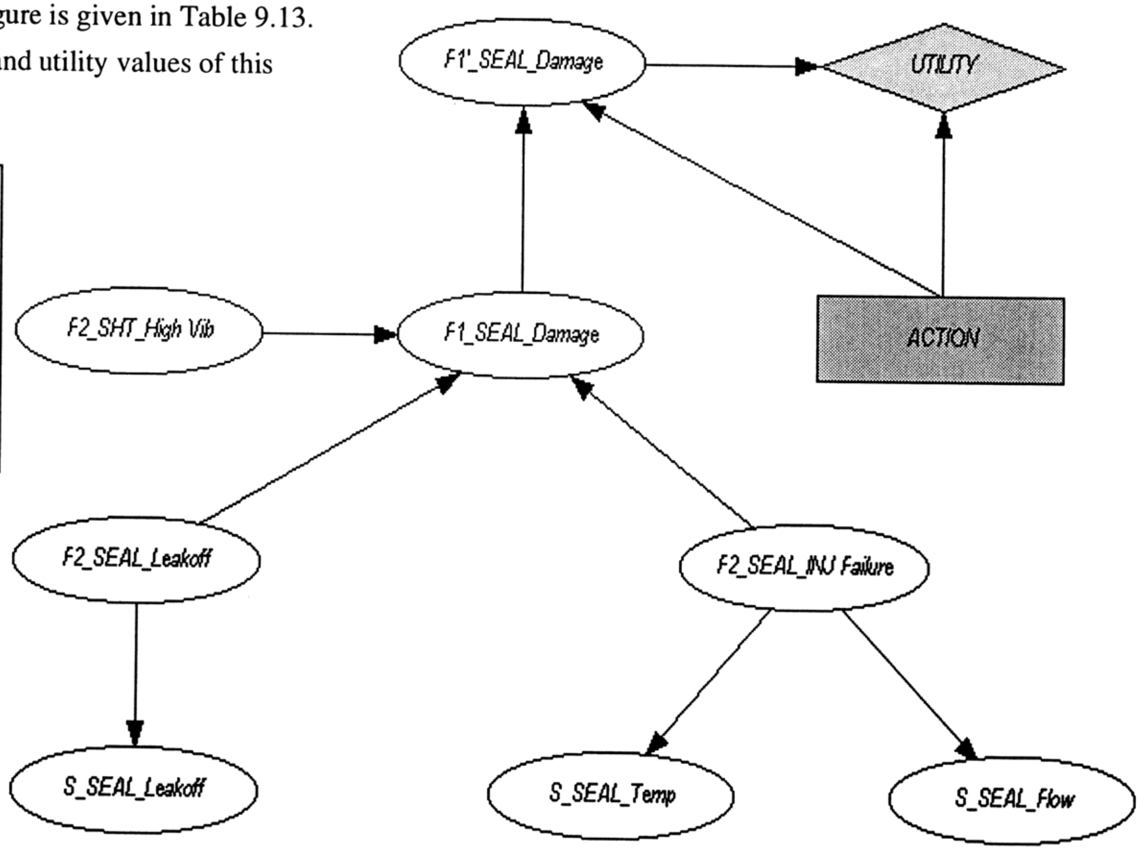


Figure 9.20 Probabilistic Diagnosis and Maintenance Nodal Network for the RCP Seal

(RCP: Reactor Coolant Pump)

Note:

(1)The nomenclature for this figure is given in Table 9.14.

(2)The conditional probability and utility values of this network were not obtained.

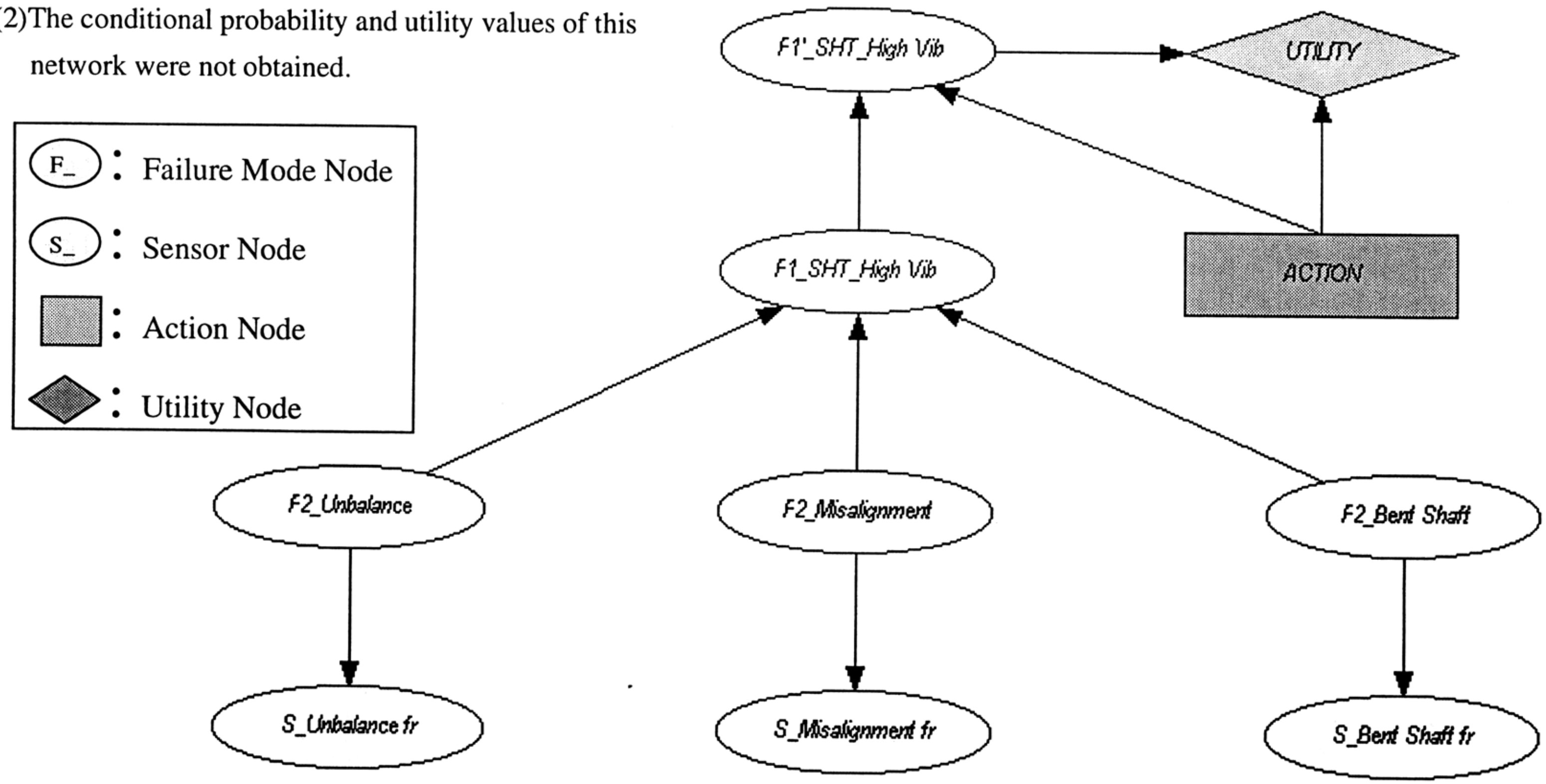


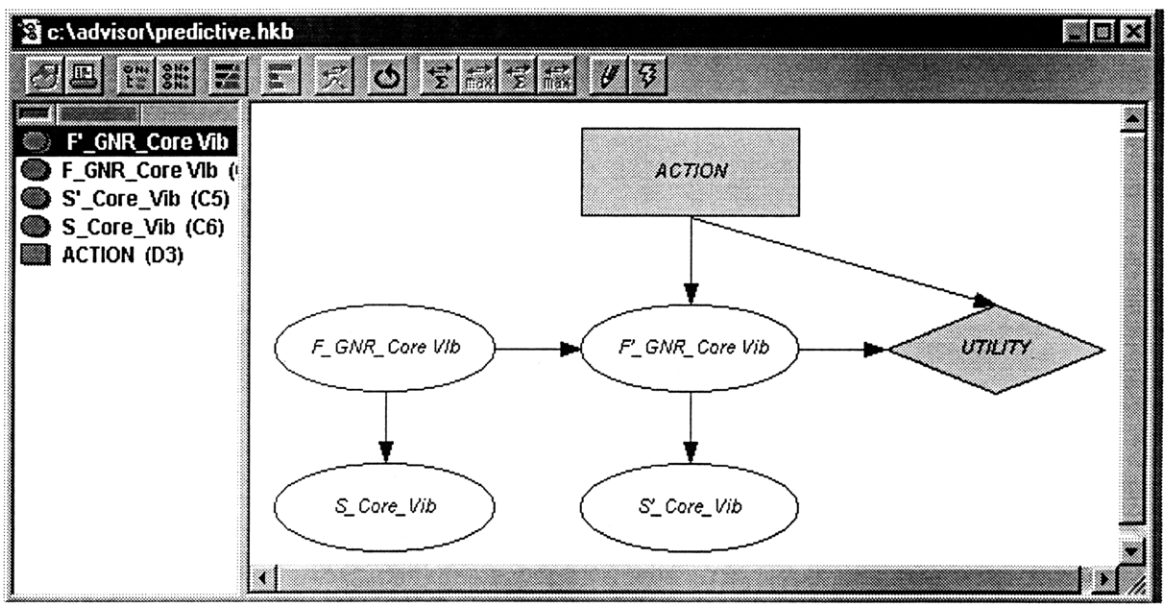
Figure 9.21 Probabilistic Diagnosis and Maintenance Nodal Network for the RCP Shaft

(RCP: Reactor Coolant Pump)

9.3.4 Probabilistic Predictive Network for the Generator Core Vibration

1) Network Explanation

Figure 9.22 presents the operator interface module, which shows the network for monitoring the generator core vibration. This network is a typical prototype model, which includes the "predictive mode", defined in Section 8.8, evaluated within our advisory system. This mode is useful in indicating to an operator the likely failure mode states and sensor outputs should a particular action be taken. Such estimates provide a basis for comparison of the actual sensor output to the estimations of the advisory system. Their conditional probability and utility values are given in Table 9.15.



Legend,

S_Core_Vib: Generator core vibration sensor state probability distribution before the action, having *Low, Medium,* and *High* ranges

S'_Core_Vib: Generator core vibration sensor state probability distribution after the action, having, *Low, Medium,* and *High* ranges

F_GNR_Core Vib: Generator core vibration failure mode state probability distribution before the action, having *Good*, *Incipient*, and *Severe* states

F'_GNR_Core Vib: Generator core vibration failure mode state probability distribution after the action, having *Good*, *Incipient*, and *Severe* states

Action: Action node for transitions between failure mode states by means of the alternative actions, having *No Action*, *Remedial Action*, and *Trip Action*

Utility: Utility node for evaluation of expected costs and benefits arising from failure mode state transitions caused by alternative actions.

Figure 9.22 Probabilistic Predictive Network for the Generator Core Vibration Monitoring in the Operator Interface Module

Table 9.15 Conditional Probability and Utility Values for the Network Shown in Figure 9.22

(1)Table 9.15.1 Conditional probability values for P(S_Core_Vib/F_GNR_Core_Vib)

Failure Mode State

Sensor State

F_GNR_Core	GOOD	ICP	SVR
LOW	0.96	0.016	0
MED	0.04	0.968	0.04
HIGH	0	0.016	0.96

(2) Table 9.15.2 Conditional probability values for P(S'_Core_Vib/F'_GNR_Core_Vib)

Failure Mode State

Sensor State

F'_GNR_Core	Good	ICP	SVR
LOW	0.96	0.016	0
MED	0.04	0.968	0.04
HIGH	0	0.016	0.96

(3) Table 9.15.3 Library of alternative actions in "*ACTION*" node

No Act	: *No Action*
Remedy	: *Remedial Action*
Trip	: *Trip Action*

(4) Table 9.15.4 Table for utility values

State of a Node, "*F1'_BRG_Damage*"

Alternative action

Utility

ACTION	No Act			Remedy			Trip		
F'_GNR_Core	Good	ICP	SVR	Good	ICP	SVR	Good	ICP	SVR
Utility	0	-1500	-5400	-1500	-3000	-6900	-3600	-5100	-12000

(5) Table 9.15.5 Conditional probability values for P(F1'*_GNR_Core Vib /F_GNR_Core Vib* ACTION)

State of a Node, "*F_GNR_Core Vib*"

Alternative action

State of a Node, "*F'_GNR_Core Vib*"

ACTION	No Act			Remedy			Trip		
F_GNR_Core	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
Good	0.99	0	0	0.99	0.9	0	1	0.97	0.95
ICP	0.01	0.25	0	0.01	0.1	0.2	0	0.03	0.05
SVR	0	0.75	1	0	0	0.8	0	0	0

2) Demonstration of Network Execution

Figure 9.23 sequentially shows the task execution of the network shown in Figure 10.7 when the observed "*Medium*" signal in "*the generator core vibration sensor*" in Step I is provided. In Step II the inference engine estimates the state of a node, "*F_GNR_Core Vib*" and which alternative action is most advantageous. In Step III, this recommended action is executed. In Step IV, the states of a future failure mode node, "*F'_GNR_Core Vib*" and a future sensor node "*S'_Core_Vib*", are estimated, given the recommended action. We conclude that this advisory system can perform this "predictive interpretative mode" in a systematic way assisted by user friendly interface.

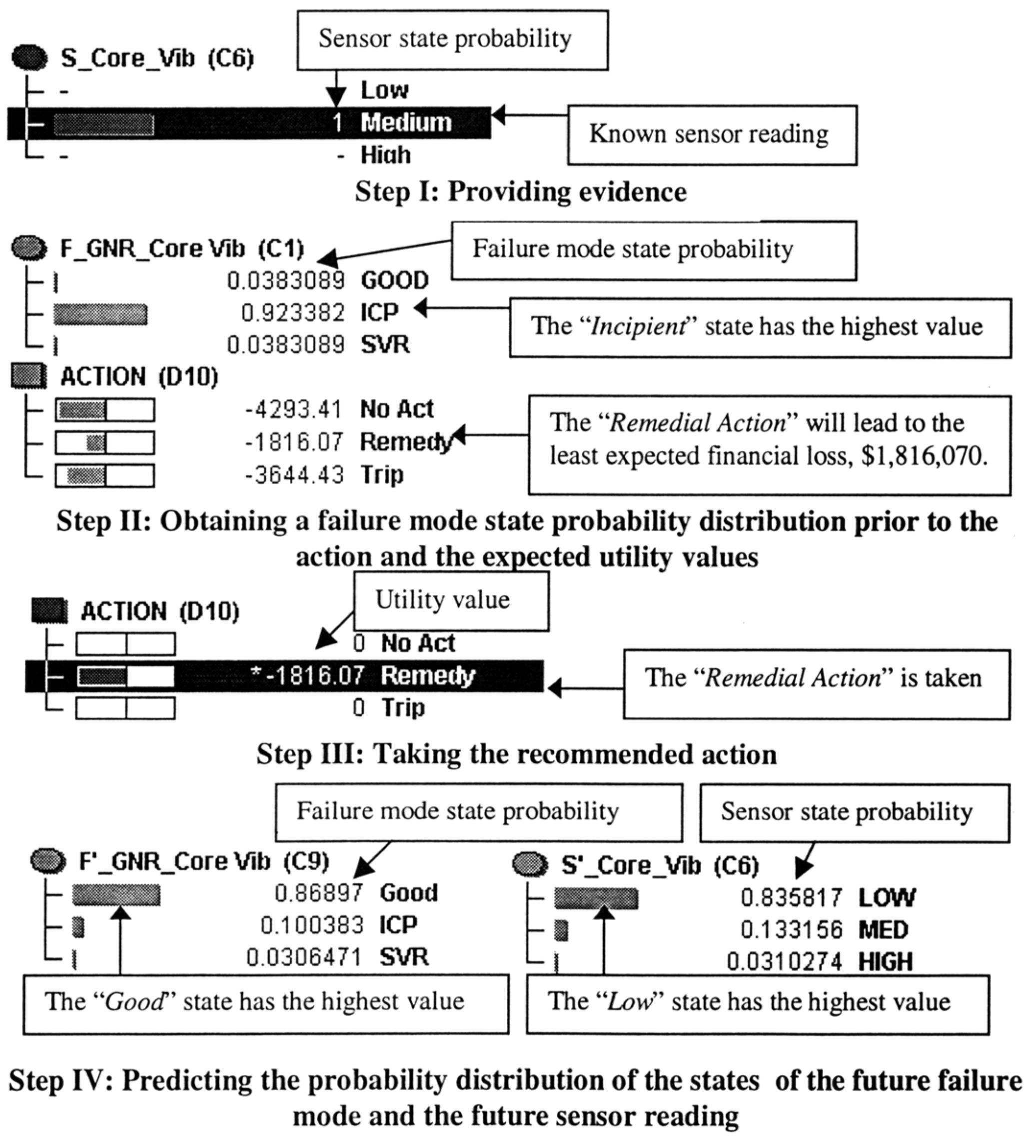


Figure 9.23 Task Execution Flow of the Predictive Mode Shown in Figure 9.22

9.4 Representation of Abnormal Operation Procedures Using the Bayesian Belief Network Formalism

This section shows how to computerize current abnormal operational procedures using the BBN formalism. The operational procedures used here have been obtained from several utilities. Also, this section demonstrates how the HUGIN expert system shell executes a task using network corresponding to a deterministic rule.

The reason why we go though this work is to make sure that the rule-based approach is consistent with the Bayesian belief network based modeling approach. Doing this emphasizes the fact that using the BBN does not exclude the ability to use rule-based logic. However, the BBN is preferred as a high level reasoning tool because the BBN is able to represent complex problems that cannot be represented using a set of rules.

Figures 9.24 to 9.27 shows the turbine generator (TG) abnormal operational procedures and execution task flows using HUGIN expert system shell. Legends below these figures list terminology for all nodes presented in order to aid understanding of the overall contents of these networks. Figures 9.28 and 9.29 illustrate the reactor coolant pump abnormal operational procedure and its execution task flow.

1) Procedure TG-I

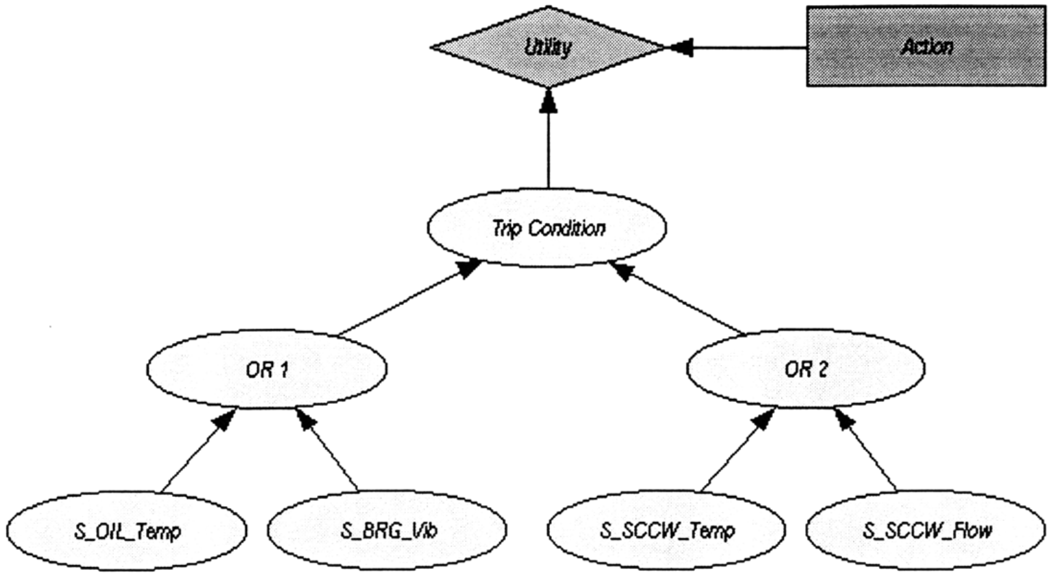
The network in Figure 9.24 suggests a trip action if one of parameters described in Procedure TG-I reaches its setpoint. The sensor nodes have a binary structure where one subordinate state, "*Low*" stands for a range below the setpoint and the other, "*High*" stands for above or equal to the setpoint. In a node "*S_BRG_Vib*", for example, "*Low*" is a range below 0.254 mm and "*High*" is a range equal to or above 0.254 mm.

(Procedure TG-I)

IF one of these generator operating parameters are in the following setpoints,

1) Bearing oil pressure is less than 12psig
2) Bearing vibration is greater than 0.254 mm
3) Stator winding cooling water temperature is greater than 80.4 °C
4) Stator winding cooling water flow is less than 84gpm

THEN perform the trip TG.



Logic Network

Legend,

S_OIL_Temp: Lubrication oil temperature sensor node, having *Low* and *High* ranges
S_BRG_Vib: Bearing vibration sensor node, having *Low* and *High* ranges
S_SCCW_Temp: SCCW temperature sensor node, having *Low* and *High* ranges
S_SCCW_Flow: SCCW flow sensor node, having *Low* and *High* ranges
OR1 and *OR2*: Artificial nodes, similar to the OR gate used in a fault tree, having *Low* and *High* range
Action: Action node having the alternative actions, *No Action* and *Trip Action*
Utility: Utility node for evaluation of the proper action in terms of the probability distribution of the state of the node, *Trip Condition*
Trip Condition: A condition node concerning the trip state having, states *Yes* and *No*

Figure 9.24 Rule-Based Procedure TG-1 Representation Using the BBN Formalism

The action node also has two alternative actions, "*Trip Action*" or "*No Action*". A node "*Trip Condition*" has also two subordinate states, "*Yes*", and "*No*". In order to avoid cumbersome assignment in many matrices of final status node "*Trip Condition*", intermediate nodes "*OR 1*" and "*OR2*" are artificially inserted into the network of Figure 9.24. They play similar roles to the OR gate in the fault tree. Finally, a utility node decides weather the "*Trip Action*" must be performed. Table shown above indicates that the proper action is "Trip" when the value of the "Trip" action state probability is equal to unity for the network shown in Figure 9.24. These states and corresponding probability values for this network are shown in Figure 9.25.

Table 9.16 Conditional Probability and Utility Values for the Network Shown in Figure 9.24

(1) Table 9.16.1 Conditional probability values for P(OR1/ S_BRG_Vib, S_OIL_Temp)

State of a Node, "*S_OIL_Temp*"

State of a Node, "*S_BRG_Vib*"

State of a Node, "*OR1*"

S_BRG_Vib	Low		High	
S_OIL_Temp	Low	High	Low	High
Good	1	0	0	0
Severe	0	1	1	1

(2) Table 9.16.2 Conditional probability values for P(OR2/ S_SCCW_Temp, S_SCCW_Flow)

State of a Node, "*S_SCCW_Temp*"

State of a Node, *S_SCCW_Flow*

State of a Node, "*OR2*"

S_SCCW_Flo	Low		High	
S_SCCW_Te	Low	High	Low	High
Good	0	0	1	0
Severe	1	1	0	1

(3) Table 9.16.3 Conditional probability values for P(Trip Condition/ OR1, OR2)

State of a Node,"*OR1*"

State of a Node,"*OR2*"

State of a Node, "*Trip Condition*"

OR 2	Good		Severe	
OR 1	Good	Severe	Good	Severe
NO	1	0	0	0
YES	0	1	1	1

(4) Table 9.16.4 Utility values given states of a node, "*Trip Condition*"

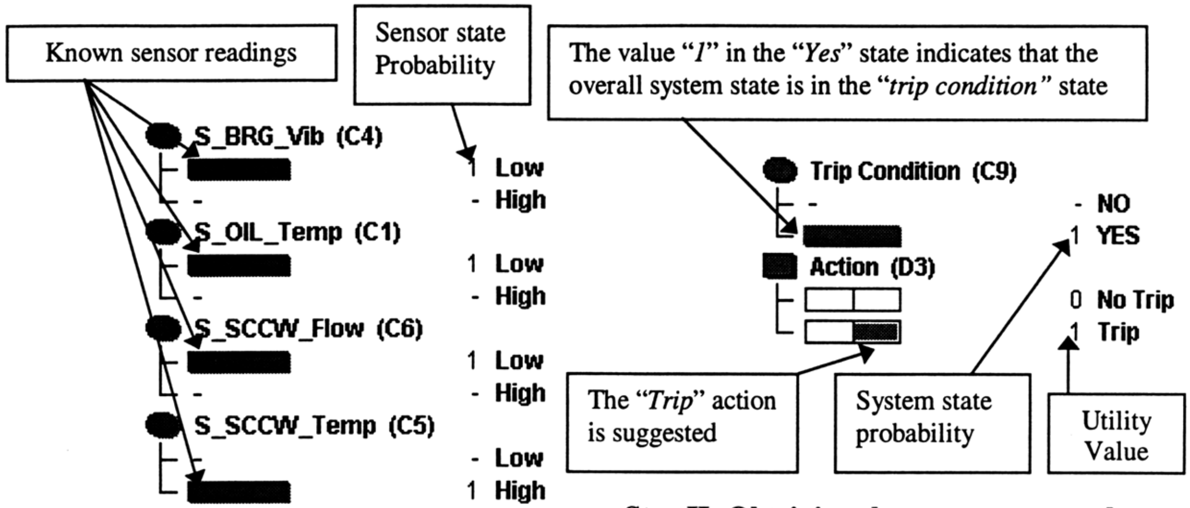
State of a Node, "*Trip Condition*"

Alternative Action

Utility Value

Action	No Trip		Trip	
Trip Condition	NO	YES	NO	YES
Utility	1	0	0	1

Figure 9.25 illustrates the task execution flow of using the network shown in Figure 9.24, assuming that a "*High*" range signal in the "*S_SCCW_Temp*" node is observed. In this example, the assumed sensor state values are entered into the system in Step I. The compilation of the network result shows that the overall system state is in the trip condition. It is recommended to perform the "*Trip*" action.



Step I: Providing inputs

Step II: Obtaining the system state and providing the corrective action

Figure 9.25 Task Execution Flow of the Network Shown in Figure 9.24

2) Procedure TG-II

Figure 9.26 illustrates the networks for Procedure TG-II. This procedure describes the load reduction action when we observe an abnormally high stator winding temperature value.

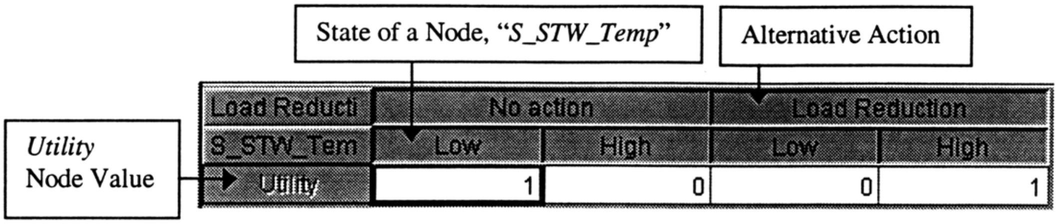
> ***(Procedure TG-II)***
> *IF any main generator stator temperature reaches its respective alarm point, THEN decrease main generator load to reduce temperature to less than setpoint*

Logic Network

Legend,
S_STW_Temp: Stator winding temperature sensor node having *Low* and *High* ranges
Load Reduction: Action node, having the alternative actions,
(*No: No action, Yes: Load Reduction*)
Utility: Utility node for evaluation of the proper action in terms of the state of the node, *S_STW_Temp*

Figure 9.26 Rule-Based Procedure TG-II Representation Using the BBN Formalism

Table 9.17 Utility Values for the Network Shown in Figure 9.26



Load Reducti	No action		Load Reduction	
S_STW_Tem	Low	High	Low	High
Utility	1	0	0	1

Figure 9.27 illustrates the task execution flow of the network shown in Figure 9.26. . Once an assumed "*High*" range signal in the "*S_STW_Temp*" is entered into the system, the compilation of this network result recommends the "*Load Reduction*" action.

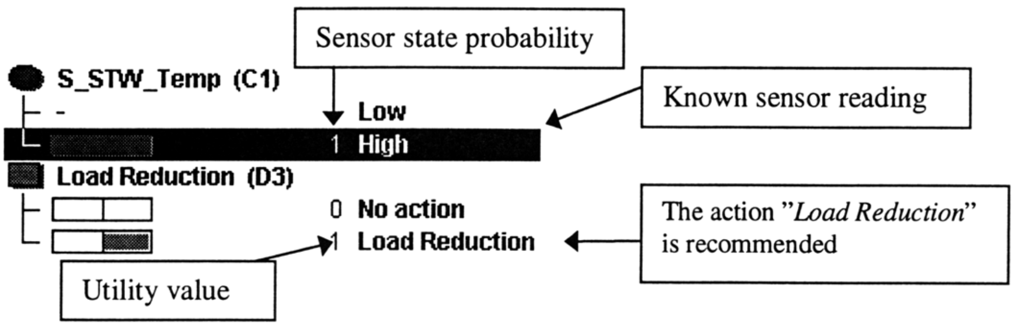


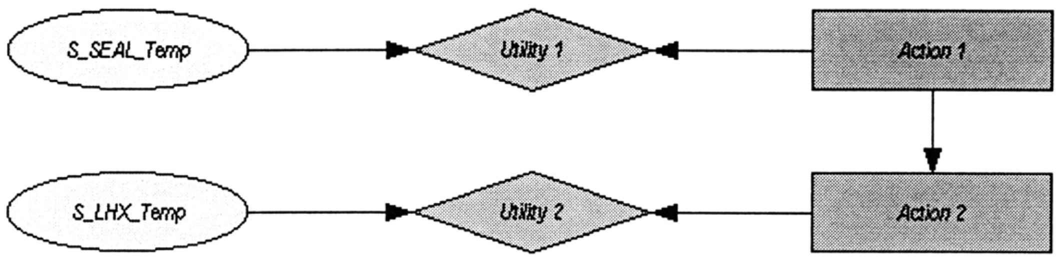
Figure 9.27 Task Execution Flow of the Network Shown in Figure 9.26

(3) Procedure RCP-I

Procedure RCP-I is illustrated in Figure 9.28 using the BBN formalism. This procedure describes the consecutive actions for letdown heat exchanger outlet temperature when an abnormal seal injection temperature is observed.

Figure 9.29 illustrates the task execution of the network shown in Figure 9.28. When the temperature sensor for seal injection water indicates a "*High*" value above the setpoint, then the action "*Check the letdown heat exchanger outlet temperature*" in the node "*Action 1*" is recommended in Step II. In the case that the letdown heat exchanger outlet temperature indicates a "High" range signal in Step III, then the advisory system in Step IV provides the advice *"Adjust component cooling water (CCW) to maintain letdown temperature less than 135 ^{o}F"* in the node "*Action 2*".

(Procedure RCP-I) *(III-1)IF RCP seal injection temperature is greater than 135 °F, THEN check the letdown heat exchanger outlet temperature.* *(III-2) IF letdown temperature is greater than 135 °F, THEN adjust component cooling water (CCW) to maintain letdown temperature less than 135 °F.*



Logic Network

Legend,

S_SEAL_Temp: Seal injection temperature sensor node, having *Low* and *High* ranges
S_LHX_Temp: Letdown heat exchanger temperature sensor node, having *Low* and *High* ranges
Action 1: Action node having the alternative actions, *Yes* and *No*
(*Yes:* Check the letdown heat exchanger outlet temperature, *No:* No action)
Action 2: Action node having the alternative actions, *Yes* and *No*
(*Yes:* Adjust component cooling water (CCW) to maintain letdown temperature less than135 °F, *No*: No action)
Utility 1: Utility node for evaluation of the proper action in terms of the state of the node, *S_SEAL_Temp*
Utility 2: Utility node for evaluation of the proper action in terms of the state of the node, *S_LHX_Temp*

Figure 9.28 Rule-Based Procedure RCP-I Representation Using the BBN Formalism

Table 9.18 Utility Values for the Network Shown in Figure 9.28

State of a node, "*S_SEAL_Temp*"

Alternative action of a node, "*Action1*"

Action 1	No		Yes	
S_SEAL_Tem	Low	High	Low	High
Utility	1	0	0	1

Value of a node, "*Utility1*"

State of a node, "*S_LHX_Temp*"

Value of a node, "*Utility2*"

Action 2	No		Yes	
S_LHX_Temp	Low	High	Low	High
Utility	1	0	0	1

Alternative action of a node, "*Action2*"

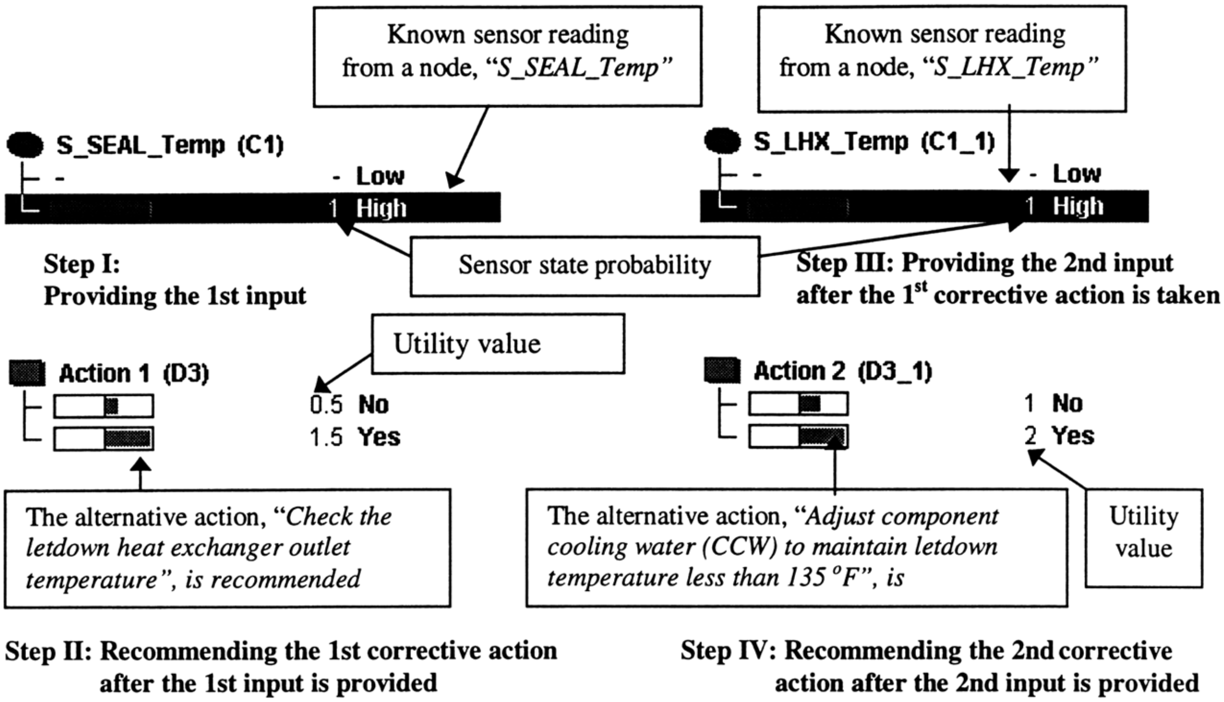


Figure 9.29 Task Execution Flow of the Network Shown in Figure 9.28

9.5 Summary

In this chapter, representative probabilistic networks for intelligence diagnosis and maintenance, using the HUGIN expert system shell, are used for advisory decision-making, given the assumed evidence concerning nominal and pessimistic cases. The results from the probabilistic network shown in Section 9.3 provide sophisticated, reasonable numerical evaluations about the uncertain system status inherent in availability-driven diagnosis for improving economic plant operations. Furthermore, because in Section 9.4 the actual deterministic operational procedures are computerized using the Bayesian belief network formalism, both probabilistic and deterministic advice, provided through interactions with the user-friendly computer operator module, can ensure the improved operation of the power plant.

Chapter 10. Testing and Plan for Validation

10.1 Introduction

Our advisory system is developed using a Bayesian belief network (BBN) based approach for application of intelligent diagnosis and maintenance (D&M). The BBN is a relatively new discipline in the application of artificial intelligence. Moreover, there is little expertise available concerning new sensors and most of the advanced data processing systems recommended through this work because the technical staff of plants has no relevant operational experience using these systems. However, as new experience is gained, this new knowledge correlating the set of sensors and power plant system performance interpreted with the BBN formalism can refine and improve the advisory system developed in the work reported here.

Thus, a rigorous validation process is essential for ensuring that the BBN-based advisory system performs as intended. Testing and validating the adequacy and completeness of this D&M network model are quite complex. This chapter proposes a framework for testing and a plan for validating the advisory system developed for use with a BBN. The proposed validation strategy includes the formal testing using simulated data, field testing, and sensitivity analysis. Also, it itemizes the concrete elements needed to be refined during system validation. Eventually, these extensive validation combined with familiarity with the BBN concept of the operator will result in rapid evolution of more sophisticated models.

10.2 Proposed Validation Strategy

In simple terms, validation is the final step of quality control in knowledge based systems. Assuming that the inference algorithm and engine are verified, validation ensures that the system correctly represents and simulates the domain knowledge. The proposed validation framework considers the process of knowledge acquisition and the performance of an advisory system. It is very important to maintain objectivity during the validation process. Validation of an advisory system's knowledge acquisition method involves assessment of the knowledge sources used, of the criteria for selecting human experts, and of the methods used for knowledge elicitation.

First of all, the system's performance is evaluated through formal tests of the accuracy and the completeness of the knowledge base. Validation by testing requires prepared test cases. In general, the validation of this system mostly depends upon these criteria such as comparison against known results, comparison with experts' predictions, and mock implementation in field testing. If this approach is taken, the system developers must ensure that the operators have no difficulty in operating the advisory system, either in the acts of assisting them through the system's operation or by means of the user interface. In comparison against known results, the results obtained from simulation of the advisory system should cover historical cases. Once the simulation results are presented from the system, the comparison with experts' prediction determines whether they agree or disagree. The resulting answers are compared for agreement with those of an expert or a panel of experts who try to solve the same problem.

Second, the field tests are recommended as a practical way to validate the advisory system because they allow the developer to see how the system performs in its actual operating environment. No matter how extensively the system is validated through various testing cases, field testing may discover unexpected errors or poor modeling approaches. Thus, once comprehensive case testing is performed and the system has been continuously refined, practical field testing should be approached. As the operator is becoming more familiar with the Bayesian analytical approach through testing accompanied by newly accumulated operation, field testing will provide more sophisticated data needed for continual improvement of system's knowledge base.

Finally, sensitivity analysis utilizes techniques similar to those employed when validating simulation models. In this technique the system is given sets of inputs containing slight variations. Effects of the variations in the inputs are studied by observing the resulting changes in the output. This is very useful in BBN based systems since the effects of changes in the conditional probabilities make the final results more general.

As time passes, such systems will likely evolve as result of a natural combination of improvements in expert knowledge, the use of automatic systems for monitoring, better sensor validation, and improved testing devices.

10.3 Plan for Model Refinement

The knowledge encoded in the advisory system may not be complete and so the model itself should be able to be readily modified and extended to reflect changes and growth in the real world system. This will typically occur incrementally. We suggest that knowledge and further refinement ensure evolution of a more sophisticated model. This will enhance the robustness of the advisory system and expand its quality and coverage. The concrete steps needed to refine in the advisory system are itemized as follows.

10.3.1 Model Structure

Cooperative work with technical experts has also shown that graphical representation of the BBN's knowledge base facilitates the processes of model validation and refinement. Such a representation permits easy arrangement of the expert knowledge and removal of errors and unnecessary repetitions. This graphical representation can illustrate entire diagnostic algorithm explicitly at a single glance.

In advance, there is a need to check whether the inference algorithm can cover all important failure modes and relationships between failure modes and the corresponding sensor set which provides the symptom. As new knowledge is obtained, the model should readily reflect it. These preliminary minor alterations to the network's structure will reduce the burden of the next arduous and time-consuming steps taken during system validation.

10.3.2 Sensor Validation

In the operation of a plant, the process engineer is inevitably confronted by problems of inaccurate measurements that can severely impair the instrumentation and control strategy. The successful interpretation from sensor readings and mathematical validation of redundant and diverse signals for a specific fault should be provided.

Thus, we emphasize that an on-line advisory system should be supported by a real-time sensor validation advisory system, which provides an efficient and flexible way to address every aspect of the on-line data validation, reconciliation, and sensor monitoring.

10.3.3 Sensor Range Discretization

After the structure of the sensor network has been determined, the sensor output states are typically discretized into three subordinate states, such as "Low", "Medium", and "High". This classification depends upon the type of sensor being used and its application. These ranges reflect general current operational procedures in the power plant.

However, more mutually exclusive sensor ranges may be used for some monitoring parameters and also fewer ranges for other parameters. Detailed operational knowledge, of what can be sensed and how it would be used, should determine this discretization.

10.3.4 Failure Mode Subordinate State

Mutually exclusive failure mode states are often labeled "Good", "Incipient", and "Severe" in terms of fault progression. These ranges are artificial concepts created to relate system fault states to their respective sensor ranges. They usually also reflect the general operational procedures being adopted in the power plant. As more sophisticated modeling and high level expertise are used, they may suggest use of more finely classified subordinate states, as indicated by corresponding ranges of the sensor readings of interest.

10.3.5 Conditional Probability

We may need to reexamine all the conditional probability values used in the BBN and to modify them in order to adjust the relative likelihood of nodal states estimated in each prediction. As the experts in the power plant are not familiar with Bayesian analysis, the scheme suggested in this work configures a general framework of how to elicit their expertise. We also translate the expert's knowledge and experience into

Bayesian terms. Ultimately, as more sophisticated interviews with industry experts are performed, refinement of the assessment of probabilities used in the network will become completed.

After assigning such conditional probability values into the system, its network is compiled and used to provide the probability distribution in the states of all nodes. If examination of these results shows that concerning some nodes unexpected belief distributions result in a specific case, the results from the system must be reexamined. In such a case the experts' knowledge should independently be presented with a series of case studies where the experts are asked to predict the likely states of specific nodes in the network. These series of test cases and its predictions compared with the expert's expected outcomes could also be used to refine our models. Doing this may result in alterations to the network's structure as well as to the conditional probability values used. Finally, these results should show that the system's predictions generally lay within the range of those of the experts.

Chapter 11. Conclusions

11.1 Results of This Study

So far, existing practical monitoring systems have been designed mainly emphasizing improved safety. In them, their corresponding safety related operational procedures are usually computerized by a set of production rules in the form of rule-based advisory system which usually deals with straightforward deterministic problem solving domains or stochastic problem solving domains supplemented by use of an uncertainty factor.

The work reported here broadens the prime concern of nuclear power plant operations from safe performance to both economic and safe performance through on-line monitoring and advice. Thus, our work is concerned with the advanced design and development of comprehensive sensor networks and new advisory systems in order to improve the operational availability of the turbine generator and reactor coolant pump. These components have had dominant influences upon lost availability in the recent operation of pressurized water reactors in United States. The suggested integrated architecture utilizes comprehensive sensor networks involving modern signal processing systems, advisory systems for sensor validation, and advisory systems using the Bayesian belief network (BBN) treatment.

For the development of the comprehensive sensor network used for complex systems, the work reported here formulates an integrated method incorporating a structural system hierarchy and a functional system hierarchy, a fault-symptom matrix, sensor selection criteria, a sensor installation feasibility study, and advanced instrumentation techniques. The application of this integrated method to reactor coolant pumps and turbine generators has been judged to be systematic and appropriate as the result of discussions with system experts. The details of newly utilized techniques are discussed. They include modern vibration analysis, wear debris analysis, partial discharge analysis, motor current analysis, generator rotor flux analysis, shaft voltage detector, fiber optic end-turn vibration monitor, fiber optic temperature sensor, torsional vibration monitor, hydrogen gas purity sensor, hydrogen dew point monitor, hydrogen leakage detector, and water conductivity detector, etc. Once the sensor types and locations within components are determined definitively after collaboration with relevant experts, they were incorporated into drawings using a computer aided design tool (e.g., AutoCAD) program in order to make sure that it would be possible to install the comprehensive set of recommended sensors on each specific component studied.

The work reported here is also concerned with the development of intelligent diagnosis and maintenance advisory systems. There are complexities and uncertainties inherent in such intelligent diagnosis and maintenance. Thus, our advisory system employs a Bayesian Belief Network (BBN) as a high level reasoning tool for incorporating inherent uncertainty for use in probabilistic inference. This is done assuming that a sensor validation advisory system configures validated data files for use in this advisory system.

Keeping with the treatment of rule-based expert systems, we conclude that BBNs are far superior to the rule-based approach in their ability to treat modeling of complexities, uncertainty management, systematic decision making, inference mechanisms, knowledge representation, and model modification for newly acquired knowledge. Also, the work reported here demonstrates that a rule-based knowledge representation is simply a special case of a general BBN. We do this by showing how the general BBN can be reduced to a rule-based representation.

As the first step for developing our advisory system, the HUGIN expert system shell was selected for use as an inference engine. It has excellent features in terms of its structure for system use, and the degree to which facilitate operator interactions due to an easy-to-learn, user-friendly, man-machine interface and modern graphics.

Then, the research reported here formulates how various levels of knowledge are acquired and synthesized into inference algorithms imbedded within our advisory system development. The four major steps are formulation of a structural system hierarchy and a functional hierarchy, refined causal networks, Bayesian belief networks, and Bayesian influence diagrams.

The prototype diagnosis and maintenance algorithms used are represented explicitly through topological symbols and links between them in a causal direction. The output of this network is a diagnostic mapping from sensor readings to a determination of the likely failure mode state or system states. The inference schemes used in calculate the updated probability distribution of alternative component failure states. This probability distribution is then used for making decisions about taking corrective actions. This capability is routinely improved as new evidence is entered into the model.

In the work reported here, the results from the probabilistic diagnosis using the maintenance network, given the assumed evidence, shows numerical reasonable evaluation of the uncertain system status. Such uncertainty is inherent in availability-concerned diagnosis when a sensor indicates a value between the normal range and the safety-related setpoint. Moreover, the deterministic abnormal operational procedure, computerized using the HUGIN expert system shell, also provides the safety-related deterministic advice.

Practically, the probabilistic advice, supplied by our BBN-based system, supplemented by the deterministic reasoning will be applied to the tasks of improved power plant operations. Finally, the testing and validation strategy suggested in our work can be aimed at ensuring that newly acquired knowledge and further refinement will result in creation of a more sophisticated model.

In conclusion, the advanced design and development of comprehensive sensor networks and Bayesian belief network based advisory systems can lead to the improved plant operation in new power plants, such as is envisioned for the Korea Next Generation Reactor (KNGR).

11.2 Suggested Future Work

Needed future efforts include the five items listed below. These are either extensions of this study or efforts needed to complete the study.

First, the work reported here recommends use of much more comprehensive, elaborate sensor sets in a new envisioned power plant than is typical. This means that the value of each sensor should be evaluated in terms of a cost and benefit trade-off in order to decide whether to utilize a specific new sensor. Thus, a future extension of this study is to construct a sophisticated mathematical model for evaluating the costs and benefits using a new sensor.

Second, several essential features should be incorporated for actual applications of our advisory system to practical tasks in nuclear power plants. The sensor validation advisory system should configure on-line validated data files for use in our advisory system. Also, the real-time capability of retrieving and plotting sequential trends using modern graphics are suggested in order to assist the operator in diagnosing a situation as it evolves.

Third, conditional probability values and utility values used in the knowledge base required for the Bayesian belief network based advisory system were elicited through discussions with relevant experts. However, concerning new sensors, recommended in this study, there is insufficient expertise available for computing conditional probability values. Thus, another future effort that could be that of extension from this study is to synthesize newly acquired knowledge concerning new sensors and their corresponding component failure mode states. Furthermore, familiarity with Bayesian Belief network concepts of the operator can enhance the robustness of the advisory system.

Fourth, currently our advisory system operates only statically giving advice based upon the current state of the monitored system. It does this without considering the pervious system status. This means that its reasoning starts when all the manifestations of abnormal signals are present at such unique time. However, as the sensor output changes dynamically over a time interval, the resulting corresponding failure mode distribution will also change. Thus, the dynamic relationships of the failure mode states and the sensor signal states could be formulated to reflect behavior during a specific time interval. The study on this temporal reasoning process, which depends upon the notion of the time dependence of the system states, could be a valuable future effort.

Lastly, rigorous, extensive testing and validation are essential concerning the adequacy and completeness of our advisory system. In particular, the field tests are recommended as a practical way to ensure that the advisory system can perform as intended in the actual environment. This could perhaps be performed initially using specialized testing devices such as a plant simulator.

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Appendix A. Conditional Probability and Utility Values for the Network Shown in Figure 9.4 (for Turbine Generator Lubrication Oil System)

(Note: The node nomenclature is given in Table 9.2.)

(1) Table A-1 Conditional probability values for P(S_SW_Temp/F7_SW_High Temp)

State of a node, "*F7_SW_High Temp*"

State of a node, "*S_SW_Temp*"

F7_SW_High	GOOD	ICP	SVR
LOW	0.965	0.03	0
MED	0.035	0.94	0.035
HGH	0	0.03	0.965

(2) Table A-2 Conditional probability values for P(S_SW_Flow/F7_SW_Low Flow)

State of a node, "*F7_SW_Low Flow*"

State of a node, "*S_SW_Flow*"

F7_SW_Low	GOOD	INC	SVR
LOW	0.965	0.018	0
MED	0.035	0.964	0.035
HGH	0	0.018	0.965

(3) Table A-3 Conditional probability values for P(S_HX_D Pressure/F6_HX_Fouling)

State of a node, "*F6_HX_Fouling*"

State of a node, "S_*HX_D Pressure*"

F6_HX_Fouli	GOOD	ICP	SVR
LOW	0.97	0.025	0
MED	0.03	0.95	0.03
HGH	0	0.025	0.97

(4) Table A-4 Conditional probability values for P(S_HX_D Temp/F6_HX_Fouling)

State of a node, "*F6_HX_Fouling*"

State of a node, "*HX_D Temp*"

F6_HX_Fouli	GOOD	ICP	SVR
LOW	0.97	0.018	0
MED	0.03	0.964	0.03
HGH	0	0.018	0.97

Appendix A. Conditional Probability and Utility Values for the Network Shown in Figure 9.4 (Cont'd)

(Note: The node nomenclature is given in Table 9.2)

(5) Table A-5 Conditional probability values for P(S_OIL_Flow/F4_OIL_Low Flow)

State of a node, "*F4_OIL_Low Flow*"

State of a node, "*S_OIL_Flow*"

F4_OIL_Low	GOOD	ICP	SVR
LOW	0.94	0.031	0
MED	0.06	0.938	0.06
HGH	0	0.031	0.94

(6) Table A-6 Conditional probability values for P(S_OIL_Temp/F4_OIL_High Temp)

State of a node, "*F4_OIL_High* Temp"

State of a node, "*S_OIL_Temp*"

F4_OIL_High	GOOD	ICP	SVR
LOW	0.963	0.018	0
MED	0.037	0.964	0.037
HGH	0	0.018	0.963

(7) Table A-7 Conditional probability values for P(S_OIL_Purity/F6_FLT_Clogging)

State of a node, "*F6_FLT_Clogging*"

State of a node, "*S_OIL_Purity*"

F5_FLT_Clog	GOOD	ICP	SVR
LOW	0.968	0.02	0
MED	0.032	0.96	0.032
HGH	0	0.02	0.968

(8) Table A-8 Conditional probability values for P(F4_OIL_Low Flow/F5_Pump_Fault)

State of a node, "*F5_Pump_Fault*"

State of a node, "*F4_OIL_Low Flow*"

F5_Pump_Fa	GOOD	ICP	SVR
GOOD	0.99	0.08	0
ICP	0.01	0.88	0.01
SVR	0	0.04	0.99

Appendix A. Conditional Probability and Utility Values for the Network Shown in Figure 9.4 (Cont'd)

(Note: The node nomenclature is given in Table 9.2)

(9) Table A-9 Conditional probability values for P(F4_OIL_Contamination/F5_FLT_Clogging)

State of a node, "*F5_FLT_Clogging*"

State of a node, "*F4_OIL_Contamination*"

F5_FLT_Clog	GOOD	ICP	SVR
GOOD	0.99	0.06	0
ICP	0.01	0.88	0.01
SVR	0	0.06	0.99

(10) Table A-10 Library of alternative actions of a node, "Action"

No Act	: *No Action*
Remedy	: *Remedial Action*
Trip	: *Trip Action*

(11) Table A-11 Conditional probability values for P(F6_SW_Cool Loss/F7_SW_High Temp, F7_SW_Low Flow)

State of a node, "*F7_SW_Low Flow*"

State of a node, "*F7_SW_High* Temp"

State of a node, "*F6_SW_Cool Loss*"

F7_SW_Low	GOOD			INC			SVR		
F7_SW_High	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.99	0.25	0	0.25	0.05	0	0	0	0
INC	0.01	0.7	0.05	0.7	0.85	0.03	0.05	0.03	0.02
SVR	0	0.05	0.95	0.05	0.1	0.97	0.95	0.97	0.98

(12) Table A-12 Conditional probability values for P(F5_HX_Failure/F6_HX_Fouling, F6_SW_Cool Loss)

State of a node, "*F6_HX_Fouling*"

State of a node, "*F6_SW_Cool Loss*"

State of a node, "*F5_HX_Failure*"

F6_SW_Cool	GOOD			INC			SVR		
F6_HX_Fouli	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.99	0.25	0	0.25	0.05	0	0	0	0
ICP	0.01	0.7	0.05	0.7	0.85	0.03	0.05	0.03	0.02
SVR	0	0.05	0.95	0.05	0.1	0.97	0.95	0.97	0.98

Appendix A. Conditional Probability and Utility Values for the Network Shown in Figure 9.4 (Cont'd)

(13) Table A-13 Conditional probability values for P(F4_OIL_High Temp/F5_HX_Failure)

State of a node, *"F5_HX_Failure"*

State of a node, *"F4_OIL_High Temp"*

F5_HX_Failur	GOOD	ICP	SVR
GOOD	0.99	0.06	0
ICP	0.01	0.88	0.01
SVR	0	0.06	0.99

(14) Table A-14 Conditional probability values for P(F3_LBOS_Failure/F4_OIL_High Temp, F4_OIL_Low Flow, F4_Oil_Contamination)

State of a node, *"F4_OIL_High Temp"* | State of a node, *"F4_OIL_Low Flow"* | State of a node, *"F4_Oil_Contamination"*

State of a node, *"F3_LBOS_Failure"*

F4_OIL_Cont	GOOD								
F4_OIL_Low	GOOD			ICP			SVR		
F4_OIL_High	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	1	0.2	0	0.2	0.05	0	0	0	0
ICP	0	0.75	0.05	0.75	0.7	0.03	0.05	0.03	0.01
SVR	0	0.05	0.95	0.05	0.25	0.97	0.95	0.97	0.99

F4_OIL_Cont	ICP								
F4_OIL_Low	GOOD			ICP			SVR		
F4_OIL_High	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.2	0.05	0	0.05	0	0	0	0	0
ICP	0.75	0.7	0.05	0.7	0.65	0.02	0.03	0.02	0.01
SVR	0.05	0.25	0.95	0.25	0.35	0.98	0.97	0.98	0.99

F4_OIL_Cont	SVR								
F4_OIL_Low	GOOD			ICP			SVR		
F4_OIL_High	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0	0	0	0	0	0	0	0	0
ICP	0.05	0.03	0.01	0.04	0.03	0.01	0.01	0.01	0
SVR	0.95	0.97	0.99	0.96	0.97	0.99	0.99	0.99	1

Appendix A. Conditional Probability and Utility Values for the Network Shown in Figure 9.4 (Cont'd)

(15) Table A-15 Conditional probability values for P(F3'_LBOS_Failure/ F3'_LBOS_Failure, Actions)

State of "*F3_LBOS_Failure*"

Alternative action

State of "*F3'_LBOS_Failure*"

Actions	No Act			Remedy			Trip		
F3_LBOS_Fai	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.99	0	0	0.98	0.9	0	1	0.96	0.94
ICP	0.01	0.25	0	0.02	0.1	0.2	0	0.04	0.06
SVR	0	0.75	1	0	0	0.8	0	0	0

(16) Table A-16 for Utility values of a node, "Utility"

State of "*F3_LBOS_Failure*"

Alternative action

Actions	No Act			Remedy			Trip		
F3'_LBOS_Fa	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
Utility	0	-330	-1200	-950	-330	-1500	-800	-1100	-2500

Utility Value (Unit: $1,000)

Appendix B. Conditional Probability and Utility Values for the Network Shown in Figure 9.14 (for the Generator Stator Winding System)

(Note: The node nomenclature is given in Table 9.7)

(1) Table B-1 Conditional probability values for P(S_STW_PDA/F2_INS_Degradation)

State of a node, "*F2_INS_Degradation*"

State of a node, "*S_STW_PDA*"

F2_INS_Degr	GOOD	ICP	SVR
LOW	0.98	0.037	0
MED	0.02	0.926	0.02
HGH	0	0.037	0.98

(2) Table B-2 Conditional probability values for P(S_STW_Vib/F2_STW_High Vib)

State of a node, "*F2_STW_High Vib*"

State of a node, "*S_STW_Vib*"

F2_STW_Hig	GOOD	ICP	SVR
LOW	0.985	0.032	0
MED	0.015	0.936	0.015
HGH	0	0.032	0.985

(3) Table B-3 Conditional probability values for P(S_STW_Temp/F2_STW_High Temp)

State of a node, "*F2_STW_High Temp*"

State of a node, "*S_STW_Temp*"

F2_STW_Hig	GOOD	ICP	SVR
LOW	0.975	0.018	0
MED	0.025	0.964	0.025
HGH	0	0.018	0.975

(4) Table B-4 for Library of alternative actions of a node, "Action"

No Act	: *No Action*
Remedy	: *Remedial Action*
Trip	: *Trip Action*

Appendix B. Conditional Probability and Utility Values for the Network Shown in Figure 9.14 (Cont'd)

(Note: The node nomenclature is given in Table 9.7)

(5) Table B-5 Conditional probability table for P(F2_STW_High Temp)/F3_SCCW_Failure, F3_HAS_Failure)

State of a node, "*F3_SCCW_Failure*"

State of a node, "*F3_HAS_Failure*"

State of a node, "*F2_STW_High Temp*"

F3_SCCW_F	GOOD			ICP			SVR		
F3_HAS_Fail	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.99	0.25	0	0.25	0.05	0	0	0	0
ICP	0.01	0.7	0.05	0.7	0.85	0.03	0.1	0.03	0.01
SVR	0	0.05	0.95	0.05	0.1	0.97	0.9	0.97	0.99

(6) Table B-6 Conditional probability table for P(F1_STW_Damage/F2_STW_High Temp, F2_STW_High Vib, F2_INS_Degradation)

State of a node, "*F2_STW_High Temp*"

State of a node, "*F2_STW_High Vib*"

State of a node, "*F2_INS_Degradation*"

State of a node, "*F1_STW_Damage*"

F2_STW_Hig	GOOD								
F2_STW_Hig	GOOD			ICP			SVR		
F2_INS_Degr	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.995	0.2	0	0.2	0.05	0	0	0	0
ICP	0.005	0.75	0.1	0.75	0.7	0.05	0.05	0.03	0.01
SVR	0	0.05	0.9	0.05	0.25	0.95	0.95	0.97	0.99

F2_STW_Hig	ICP								
F2_STW_Hig	GOOD			ICP			SVR		
F2_INS_Degr	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.2	0.05	0	0.05	0	0	0	0	0
ICP	0.75	0.7	0.05	0.7	0.65	0.02	0.03	0.02	0.01
SVR	0.05	0.25	0.95	0.25	0.35	0.98	0.97	0.98	0.99

Appendix B. Conditional Probability and Utility Values for the Network Shown in Figure 9.14 (Cont'd)

(Note: The node nomenclature is given in Table 9.7)

State of a node, "*F2_STW_High Temp*"

State of a node, "*F2_STW_High Vib*"

State of a node, "*F2_INS_Degradation*"

State of a node, "*F1_STW_Damage*"

F2_STW_Hig	SVR								
F2_STW_Hig	GOOD			ICP			SVR		
F2_INS_Degr	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0	0	0	0	0	0	0	0	0
ICP	0.05	0.03	0.03	0.04	0.03	0.01	0.01	0.01	0
SVR	0.95	0.97	0.97	0.96	0.97	0.99	0.99	0.99	1

(7) Table B-7 Conditional probability table for P(*F1'_STW_Damage/ F1_STW_Damage, ACTION)*

State of a node, "*F1_STW_Damage*"

Alternative action

State of a node, "*F1'_STW_Damage*"

ACTION	No Act			Remedy			Trip		
F1_STW_Da	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	1	0	0	0.95	0.85	0	1	0.92	0.95
ICP	0	0.35	0	0.05	0.15	0.2	0	0.08	0.05
SVR	0	0.65	1	0	0	0.8	0	0	0

(8) Table B-8 for utility values of a node, "Utility"

State of a node, "*F1'_STW_Damage*"

Alternative action

ACTION	No Act			Remedy			Trip		
F1'_STW_Da	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
Utility	0	-3500	-12600	-3500	-7000	-16000	-8400	-12000	-28000

Utility value (unit: $1,000)

Appendix C. Conditional Probability and Utility Values for the Network Shown in Figure 9.17 (for the Reactor Coolant Pump Bearing)

(Note: The node nomenclature is given in Table 9.10)

(1) Table C-1 Conditional probability values for P(S_SHT_Vib/F3_SHT_High Vib)

State of a node "*F3_SHT_High Vib*"

State of a node "*S_SHT_Vib*"

F3_SHT_Hig	GOOD	ICP	SVR
LOW	0.96	0.015	0
MED	0.04	0.97	0.04
HGH	0	0.015	0.96

(2) Table C-2 Conditional probability values for P(S_BRG_Vib/F2_BRG_High Vib)

State of a node "*F2_BRG_High Vib*"

State of a node "*S_BRG_Vib*"

F2_BRG_Hig	GOOD	ICP	SVR
LOW	0.962	0.016	0
MED	0.038	0.968	0.038
HGH	0	0.016	0.962

(3) Table C-3 Conditional probability values for P(S_BRG_Temp/F2_BRG_High Temp)

State of a node "*F2_BRG_High Temp*"

State of a node "*S_BRG_Temp*"

F2_BRG_Hig	GOOD	ICP	SVR
LOW	0.964	0.018	0
MED	0.036	0.964	0.036
HGH	0	0.018	0.964

(4) Table C-4 Library of alternative actions of a node "*ACTION*"

No Act	: *No Action*
Remedy	: *Remedial Action*
Trip	: *Trip Action*

Appendix C. Conditional Probability and Utility Values for the Network Shown in Figure 9.17 (Cont'd)

(Note: The node nomenclature is given in Table 9.10)

(5) Table C-5 Conditional probability values for P(F2_BRG_High Temp/ F3_LBOS_Failure)

State of a node "*F3_LBOS_Failure*"

State of a node "*F3_LBOS_Failure*"

F3_LBOS_Fai	GOOD	ICP	SVR
GOOD	0.99	0.08	0
ICP	0.01	0.88	0.01
SVR	0	0.04	0.99

(6) Table C-6 Conditional probability values for P(F2_BRG_High Vib/ F3_SHT_High Vib, F3_LBOS_Failure)

State of a node "*F3_LBOS_Failure*"

State of a node "*F3_SHT_High* Vib"

State of a node "*F2_BRG_High Vib*"

F3_LBOS_Fai	GOOD			ICP			SVR		
F3_SHT_Hig	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.99	0.25	0	0.25	0.05	0	0	0	0
ICP	0.01	0.7	0.05	0.7	0.85	0.03	0.05	0.03	0.01
SVR	0	0.05	0.95	0.05	0.1	0.97	0.95	0.97	0.99

(7) Table C-7 Conditional probability values for P(F1_BRG_Damage/ F2_BRG_High Vib, F2_BRG_High Temp)

State of a node "*F2_BRG_High Temp*"

State of a node "*F2_BRG_High Vib*"

State of a node "*F1_BRG_Damage*"

F2_BRG_Hig	GOOD			ICP			SVR		
F2_BRG_Hig	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.99	0.29	0.05	0.25	0.05	0.01	0.05	0.01	0
ICP	0.01	0.7	0.25	0.7	0.85	0.14	0.25	0.14	0.01
SVR	0	0.01	0.7	0.05	0.1	0.85	0.7	0.85	0.99

Appendix C. Conditional Probability and Utility Values for the Network Shown in Figure 9.17 (Cont'd)

(Note: The node nomenclature is given in Table 9.10)

(8) Table C-8 Conditional probability values for P(F1'_BRG_Damage/ F1_BRG_Damage, Action)

A state of a node,"*F1_BRG_Damage*"

Alternative action

A state of a node, "*F1'_BRG_Damage*"

ACTION	No Act			Remedy			Trip		
F1_BRG_Da	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
GOOD	0.99	0	0	1	0.88	0	1	0.95	0.98
ICP	0.01	0.25	0	0	0.12	0.25	0	0.05	0.02
SVR	0	0.75	1	0	0	0.75	0	0	0

(9) Table C-9 Table for utility values of a node, "*Utility*"

A state of a node,"*F1'_BRG_Damage*"

Alternative action

ACTION	No Act			Remedy			Trip		
F1'_BRG_Da	GOOD	ICP	SVR	GOOD	ICP	SVR	GOOD	ICP	SVR
Utility	0	-750	-2700	-750	-1500	-3500	-1800	-2500	-6000

Utility value (unit:$1,000)