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Smart Equipment and Systems to Improve Reliability and Safety in Future Nuclear Plants
Final NERI Project Report

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"Smart equipment" embodies elemental components (e.g. sensors, data transmission, computer hardware and software, Health) that continuously monitor the health of the system in terms of failure modes and remaining useful life, to predict changes and potential failures and for maintenance of system performance and operational adjustments.

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Smart Equipment and Systems to Improve Reliability and Safety in Future Nuclear Power Plant Operations
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Smart Equipment and Systems to Improve the Reliability and Safety in Future Nuclear Plants

Final NERI Project Report

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Abstract

This document presents the Final Project Report for the Smart Equipment and Systems to Improve Reliability and Safety in Future Nuclear Power Plant Operations (Smart-NPP) project and presents activities and accomplishments from Fiscal Year (FY) 1999 through FY2003. Smart-NPP is a project under the umbrella of the United States Department of Energy’s Nuclear Energy Research Initiative. The goal of the Smart-NPP project is to design, develop, and evaluate an integrated set of tools and methodologies that can improve the reliability and safety of advanced nuclear power plants through the introduction of smart equipment and predictive maintenance technology. Smart equipment embodies elemental components such as sensors, data transmission devices, computer hardware and software and man-machine interface devices that continuously monitor and predict the failure modes and remaining useful life of the equipment. The Smart-NPP project team worked to accomplish its goal by developing a smart equipment demonstration health monitoring system (HMS) for a selected plant component. The final phase of activities focused on finalizing the development of elements for a prototype demonstration HMS for a pump/lubrication system, including a human machine interface, sensor installation and instrumentation of a test bench, a Bayesian network for relating sensor data to equipment health, and a virtual machine equipment simulator to provide a capability to simulate equipment behavior over future time intervals in order to evaluate the overall benefits to system performance from designing in smart features as well as the consequences of alternative maintenance options. The project goal was realized with the presentation of a prototype demonstration HMS for a selected component that evaluated actual faults in a physical test-bed system as well as faults that were implemented “virtually”; processed sensor features and related these to system fault conditions; generated consequences of alternative maintenance options, and provided indications and details of system health and maintenance options on an HMI.
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Nomenclature

ANS  American Nuclear Society
BN  Bayesian Network
BOP  Balance Of Plant
BWR  Boiling Water Reactor
CBM  Condition-Based Maintenance
CEDM  Control Element Driving Mechanism
CEDMCS  Control Element Driving Mechanism Control System
CMMS  Computerized Maintenance Management System
CMT  Core Management Team
DB  Data Base
DE&S  Framatome ANP DE&S (formerly Duke Engineering and Services)
EPRI  Electric Power Research Institute
FMECA  Failure Modes, Effects, and Criticality Analysis
FY  Fiscal Year
HFE  Human Factors Engineering
HIS-N  Hybrid Intelligent System For NPP Operations
HMI  Human Machine Interface
HMS  Health Monitoring System
I-NERI  International Nuclear Energy Research Initiative
KBS  Knowledge Based System
KOPEC  Korea Power Engineering Company
MIT  Massachusetts Institute of Technology
MOST  Korean Ministry of Science and Technology
MTBF  Mean Time Before Failure
MTTR  Mean Time To Repair
NERI  Nuclear Energy Research Initiative
NI  Nuclear Island
NN  Neural Network
NPP  Nuclear Power Plant
O&M  Operations and Maintenance
OID  Operator Input Device
PMP  Predictive Maintenance Program
PRA  Probabilistic Risk Assessment
PSU  Pennsylvania State University
PWR  Pressurized Water Reactor
RCM  Reliability Centered Maintenance
SNL  Sandia National Laboratories
SSC  Systems, Structures, And Components
TTF  Time To Failure
U.S. DOE  United States Department of Energy
U.S. NRC  United States Nuclear Regulatory Commission
VDU  Video Display Unit
VMES  Virtual Machine Equipment Simulator
WEC  Westinghouse Electric Company (formerly ABB Combustion Engineering)
Executive Summary

This document is the Final Project Report for the Smart Equipment and Systems to Improve Reliability and Safety in Future Nuclear Power Plant Operations (Smart-NPP) project and presents activities and accomplishments from Fiscal Year (FY) 1999 through FY2003. The Smart-NPP project is part of the Nuclear Energy Research Initiative (NERI). The United States Department of Energy (U.S. DOE) created NERI in 1999 to sponsor nuclear energy science and technology research and development in order to overcome the principal barriers to the future use of nuclear energy in the U.S. The specific objectives of NERI are: (1) to overcome the principal technical obstacles to expanded nuclear energy use, (2) to advance the state of nuclear technology to maintain its competitive position in domestic and world markets, and (3) to improve the performance, efficiency, reliability, and economics of nuclear energy. The NERI program began its fourth year with additional domestic projects as well as new international collaborative agreements under the International NERI (I-NERI) program for bilateral, cost-shared research with countries such as Japan, South Korea, France, South Africa, and the European Union.

Among the programs selected for funding in FY1999 was the Smart-NPP project. This project was a collaborative effort bringing together the technical capabilities of Framatome ANP DE&S (DE&S), formerly Duke Engineering and Services, the Massachusetts Institute of Technology (MIT), Pennsylvania State University (PSU), Sandia National Laboratories (SNL), and Westinghouse Electric Company (WEC), formerly ABB Combustion Engineering. SNL is the lead organization for this NERI project. Additionally, early during Phase 2 of the Smart-NPP project, an agreement between WEC and the Korea Power Engineering Company (KOPEC) was established to allow collaboration between the U.S. DOE NERI Smart-NPP project and KOPEC, funded by the Korean Ministry of Science and Technology (MOST), in the area of smart equipment for nuclear power plants (NPPs).

The goal of the Smart-NPP project was to design, develop, and evaluate an integrated set of tools and methodologies that can improve the reliability and safety of advanced NPPs through the introduction of smart equipment and predictive maintenance technology. Smart equipment embodies elemental components such as sensors, data transmission devices, computer hardware and software, and human-machine interface (HMI) devices that continuously monitor the state of health of the equipment in terms of failure modes and remaining useful life, in order to predict degradation and potential failure and inform end-users of the need for maintenance or system-level operational adjustments. The Smart-NPP project team worked to achieve this goal by developing a prototype smart equipment demonstration health monitoring system (HMS) for a selected plant component.

Objectives

The overall objective of the Smart-NPP project is to demonstrate the benefits of an integrated application of smart equipment to an NPP. The following were needed to accomplish this objective:

1. Identify and prioritize, using available maintenance data and probabilistic risk assessment (PRA) studies, nuclear plant equipment that would most likely benefit from the addition of smart features;
2. Develop a methodology for systematically monitoring the health of individual pieces of equipment implemented with smart features (i.e., smart equipment);
3. Develop a methodology to provide plant operators with real-time information through a HMI that supports operator decision making;
4. Demonstrate the methodology on a targeted piece of smart equipment; and
5. Expand the concept to system and plant levels that allow communication and integration of data among the smart equipment, as well as control room systems and plant operators.

As completed, a capability for equipment health monitoring now exists that can be applied to improve performance assessment and reliability of plant equipment by monitoring the symptoms that relate to the state of health of the system, providing a determination of when a problem may be pending, identifying the most likely root fault or set of faults, supporting the most attractive maintenance and operations actions, and indicating the most likely post-action system state. This capability can assist in significantly reducing construction, operations and maintenance costs while improving plant reliability, availability and safety. The methodology will provide plant operators with real-time information required to make decisions and to understand the risk and consequences of those decisions.

Research Progress for FY1999 Through FY2003

The Smart-NPP project team had a productive first year and, building on the accomplishments of Phase 1 made significant additional progress in Phase 2 of the project. During Phase 3 the project team finalize project tasks and presented a prototype demonstration HMS for a selected component that evaluated actual faults in a physical test-bed system as well as faults that were implemented “virtually”; processed sensor features and related these to system fault conditions; generated consequences of alternative maintenance options, and provided indications and details of system health and maintenance options on an HMI. The following is a summary of the significant accomplishments realized during each of the three phases of the project.

Phase 1 of the project was conducted during FY1999 and FY2000. During Phase 1 of the project, the Smart-NPP team:

- Developed system/component criteria to establish priorities for smart equipment applications and using the criteria, completed a system prioritization study for smart equipment applications, and prioritized both pressurized water reactor (PWR) and boiling water reactor (BWR) systems.
- Based on the prioritization study, selected a high energy, horizontal, centrifugal pump as a demonstration component for an HMS.
- Reviewed and assessed sensor technology to develop criteria for sensor element selection and sensor system architecture.
- Reviewed smart equipment HMI technology currently being used in other industries to support development of an HMI prototype.
- Assessed failure modes for the pump and established an optimum health monitoring plan.
- Evaluated methods of equipment health diagnostics and prediction and developed an architecture for an HMS using Bayesian networks (BNs) to translate sensor data into equipment health information based on fault states and conditional failure probabilities.
- Created the design and approach for using a virtual machine to provide a capability to simulate equipment behavior over future time intervals in order to evaluate the overall benefits to system performance from designing in smart features as well as the consequences of alternative maintenance options.
- Procured the use of a demonstration test-bed of the pump lube system built at PSU and begun sensor instrumentation (including development of a PC104 smart sensor), data acquisition and messaging to provide real-world data over the Internet to the HMS.
- Established industry contacts for potential cooperative working arrangements.
Phase 2 of the project was conducted during FY2001 and FY2002. Building on the accomplishments of the first year of the project, the Smart-NPP team made significant additional progress during Phase 2:

- Completed and demonstrated the first version of a prototype HMI and had the prototype reviewed by NPP operations and maintenance staff.
- Completed the Alpha Version of the Virtual Machine Equipment Simulator (VMES) to provide a capability to simulate equipment behavior over future time intervals in order to evaluate the overall benefits to system performance from designing in smart features as well as the consequences of alternative maintenance options. Data for PWR equipment performance from 1990-1995 was analyzed to test the VMES and to illustrate its capability for simulating equipment failures and maintenance. The purpose of this example was to test the reliability simulation capability of VMES and to provide a limited validation of its simulation algorithms. Additionally, an example scenario was evaluated to illustrate the use of VMES in evaluating alternative scenarios that could be considered in response to an HMS notification of a pending equipment failure. The basis for selecting the preferred scenario was the cost of electricity not generated as a result of a scheduled or forced outage.
- Developed detailed BNs to relate sensor features to fault conditions for the pump and its lube system.
- Began assembly of the lube system test bench, including instrumentation and testing of sensors, the data acquisition and messaging systems to provide real-world data over the Internet to the HMS.
- Defined the architecture and messaging format for the HMS to accommodate remote communication and integration among the elements of the HMS and initiated system integration.
- Initiated planning and preparation for demonstration activities, and presented a dry run demonstration of the prototype HMI and the BN elements of the HMS.
- Established a collaborative agreement with KOPEC. A parallel project, Development of the Intelligent Predictive Maintenance Tools and Methodology for NPP, is underway. The strategy for the collaboration was to have KOPEC apply a similar methodology, but for a system diverse from that of the Smart-NPP project. Specifically, the KOPEC team identified a rod control system, including the control element driving mechanism (CEDM) and its control system (CEDMCS) as its target system. The KOPEC effort began in February 2001. Areas were identified where KOPEC engineers could perform work for Smart-NPP team members, while learning critical aspects of the Smart-NPP methods. During Phase 2, KOPEC staff participated in BN training and consulting, HMS development, HMI design, and CEDM failure mode analysis. This approach was successful in allowing the KOPEC team to progress quickly in the development of an HMS for a CEDM/CEDMCS. Efforts included survey of operations experience, failure mode analysis and BN development, and prototype configuration development for the HMS and HMI displays, and virtual machine.

Phase 3 of the project was conducted during FY2002 and extended for completion in FY2003. Phase 3 activities focused on finalizing the development of elements for a demonstration HMS for a pump/lubrication system and culminated with a live over-the-Internet presentation of an integrated demonstration HMS that can replicate faults for a physical, real-world system as well as implementing other faults “virtually”; process sensor features and relate these to system fault conditions; generate consequences of alternative maintenance options, and provide indications and details of system health and maintenance options on an HMI. Additionally, collaboration with KOPEC continued as they completed a
prototype HMS for their target system. Final task reports and this final project report were completed to document the technical work for the project. During Phase 3, the Smart-NPP Team:

- Completed and demonstrated the final version of the dynamic prototype HMI, and integrated it into the demonstration HMS.
- Designed and added new objects to the VMES component to calculate time-to-failure (TTF) and cost statistics. These objects use repeated simulations to determine several statistical measures for both total cost and time to first failure. Statistics available as object properties include mean, standard deviation, and several percentiles.
- Integrated the beta version of the VMES into the HMS so that its results in terms of costs and TTF could be provided as part of the HMS user interface.
- Developed and tested VMES input data sets to calculate the costs and TTF statistics for scenarios included in the HMS Demo. These scenarios take into account the state of several fault conditions in order to calculate system TTF. The scenarios also calculate cost by allowing maintenance to be scheduled at various times in the future considering time-dependent cost of electricity and the increased probability of system failure as maintenance is delayed to later dates.
- Completed the expert system for the demonstration HMS comprised of detailed BNs to relate sensor features to fault conditions for the pump and its lube system.
- Completed assembly of the lube system test bench, including instrumentation and testing of sensors, the data acquisition and messaging systems to provide real-world data over the Internet to the HMS.
- Completed and tested the architecture and messaging format for the HMS to accommodate remote communication and system integration among the elements of the HMS.
- Planned, prepared and implemented demonstration scenarios and activities for a live over-the-Internet presentation of the integrated demonstration HMS prototype at the Electric Power Research Institute’s Wireless Technology exhibit and conference in November 2002.
- Completed efforts on the collaborative parallel project with the Korea Power Engineering Company (KOPEC), Development of the Intelligent Predictive Maintenance Tools and Methodology for NPP. The KOPEC team completed elements for a prototype HMS for their target system of a rod control system, including the control element driving mechanism (CEDM) and its control system (CEDMCS).
1 Introduction

This document is the Final Project Report for the Smart Equipment and Systems to Improve Reliability and Safety in Future Nuclear Power Plant Operations (Smart-NPP) project and presents progress and accomplishments during Fiscal Year (FY) 1999 through FY2003. The Smart-NPP project is part of the Nuclear Energy Research Initiative (NERI). The United States Department of Energy (U.S. DOE) created NERI in 1999 to sponsor nuclear energy science and technology research and development in order to overcome the principal barriers to the future use of nuclear energy in the U.S. The specific objectives of NERI are: (1) to overcome the principal technical obstacles to expanded nuclear energy use, (2) to advance the state of nuclear technology to maintain its competitive position in domestic and world markets, and (3) to improve the performance, efficiency, reliability, and economics of nuclear energy. The NERI program began its fourth year with additional domestic projects as well as new international collaborative agreements under the International NERI (I-NERI) program for bilateral, cost-shared research with countries such as Japan, South Korea, France, South Africa, and the European Union.

Among the programs selected for funding in FY1999 was the Smart-NPP project. This project is a collaborative effort bringing together the technical capabilities of Framatome ANP DE&S (DE&S), formerly Duke Engineering and Services, the Massachusetts Institute of Technology (MIT), the Pennsylvania State University (PSU), Sandia National Laboratories (SNL), and Westinghouse Electric Company (WEC), formerly ABB Combustion Engineering. SNL was the lead organization for this NERI project. Additionally, during the Phase 2 of the Smart-NPP project, an agreement between WEC and the Korea Power Engineering Company (KOPEC) was established to allow collaboration between the U.S. DOE NERI program and KOPEC in the area of smart equipment and predictive maintenance for nuclear power plants (NPPs). The KOPEC project, Development of the Intelligent Predictive Maintenance Tools and Methodology for NPP, began in February 2001 and was completed in October 2002.

The goal of the Smart-NPP project was to design, develop, and evaluate an integrated set of tools and methodologies that can improve the reliability and safety of advanced NPPs through the introduction of smart equipment and predictive maintenance technology. The Smart-NPP project team worked to achieve this goal by developing a smart equipment demonstration health monitoring system (HMS) for a selected plant component.

1.1 Research Objectives

The overall objective of the Smart-NPP project is to demonstrate the benefits of an integrated application of smart equipment to an NPP. The following were needed to accomplish this objective:

1. Identify and prioritize, using available maintenance data and probabilistic risk assessment (PRA) studies, nuclear plant equipment that would most likely benefit from the addition of smart features;
2. Develop a methodology for systematically monitoring the health of individual pieces of equipment implemented with smart features (i.e., smart equipment);
3. Develop a methodology to provide plant operators and maintainers with real-time information through an HMI that supports operator decision making;
4. Demonstrate the methodology on a targeted piece of smart equipment; and
5. Expand the concept to system and plant levels that allow communication and integration of data among the smart equipment, as well as control room systems and plant operators.
As completed for a prototype demonstration HMS, a capability now exists that can be applied to assist in significantly reducing construction, operations and maintenance costs while improving plant reliability, availability and safety. The methodology can provide plant operators with real-time information required to make decisions and to understand the risk and consequences of those decisions.

1.2 Concept and Approach

Our concept provides a unique system-level integration of plant maintenance information and real-time sensor data utilizing self-monitoring and self-diagnostic characteristics built into the equipment. The system was designed around a distributed software architecture that allows scalability to enterprise-wide applications and provides the ability to view real-time equipment performance and safety-related data from remote locations. The structural design of the system was built off non-nuclear programs that were already under way at the outset of this project. Such a system can be deployed to significantly reduce downtime and maintenance costs.

The Smart-NPP team established the following working definition of “Smart Equipment”:

"Smart equipment embodies elemental components (e.g., sensors, data transmission devices, computer hardware and software, HMI devices) that continuously monitor the state of health of the equipment in terms of failure modes and remaining useful life, to predict degradation and potential failure and inform end-users of the need for maintenance or system-level operational adjustments."

The development of a Smart-NPP methodology has taken advantage of related non-nuclear programs that were currently in progress at the outset of this project. The use of methodology and deployment of smart components and systems can be applied to significantly reduce the costs associated with design, unit unavailability and maintenance in future nuclear power plants.

The research project began with a system evaluation and prioritization study that identified and prioritized nuclear plant equipment that would most likely benefit from the addition of smart features such as sensors, computer chips and monitoring devices.

Once the component of interest was identified, an optimum equipment health-monitoring plan was developed for the selected individual piece of smart equipment. The HMS includes a virtual machine capability to simulate equipment behavior over future time intervals in order to evaluate the overall benefits to system performance from designing in smart features.

Methodologies were developed for consolidating and presenting the data obtained from smart equipment as information to ensure that the health of the smart plant is readily understandable to a knowledgeable operator. A strategy was developed to provide the smart equipment information to plant operators, maintenance personnel, and plant management that can be integrated with existing plant HMI systems and includes capabilities for success path monitoring of safety systems.

The equipment health monitoring methodologies were combined with the operator interface methodologies for a demonstration of the smart system. A specific result from these activities is a detailed, documented example of how to apply smart features to a variety of equipment types. These efforts also addressed the development of the design methodology needed to allow communication and integration among the smart components, control room systems, and plant operators.

The final task of this project was to expand the concept of smart equipment to plant levels. We must look beyond systems that improve the reliability and safety of specific pieces of equipment, and determine how to integrate such systems plant-wide. Achievement of this level of integration represents a formidable challenge. To be able to perform this level of integration, it is first necessary to develop techniques to combine equipment health information from individual machines into plant health
information. While it is obviously beneficial to perform health monitoring on individual pieces of equipment, the ultimate goal is to develop methodologies to combine health-monitoring information into a plant-wide system.

1.3 Project Tasks

The Smart-NPP project is comprised of six major tasks. These tasks are summarize below and illustrated in Figure 1.

<table>
<thead>
<tr>
<th>Task</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task 1</td>
<td>Systems Evaluation &amp; Prioritization is a system evaluation and prioritization study that identified and prioritized nuclear plant equipment that would most likely benefit from the addition of smart features such as sensors, computer chips and monitoring devices.</td>
</tr>
<tr>
<td>Task 2</td>
<td>Sensor Technology &amp; Installation Analysis focused on evaluating the availability and adequacy of sensor technology needed to implement smart equipment in future nuclear power plant operations and to address the methodologies needed for consolidating smart equipment data into effective end-user information.</td>
</tr>
<tr>
<td>Task 3</td>
<td>Equipment Maintenance &amp; Reliability Simulation (Virtual Machine) Capability developed a capability to simulate equipment behavior over future time intervals in order to evaluate the overall benefits to system performance from designing in smart features.</td>
</tr>
<tr>
<td>Task 4</td>
<td>Smart Equipment Health Monitoring System developed methods for taking the sensor data from the equipment-monitoring program and translating that data into information about the equipment health.</td>
</tr>
<tr>
<td>Task 5</td>
<td>Sample Application of Smart System identified and implemented an application of the concept of smart equipment.</td>
</tr>
<tr>
<td>Task 6</td>
<td>Enterprise-Level Health Monitoring System developed a strategy to combine equipment-health information from individual machines into overall plant-health information.</td>
</tr>
</tbody>
</table>

1.4 Milestones/Schedule

Figure 2 shows the project schedule along with the reports and milestones for each of the six task areas of the project. This schedule reflects redirection that occurred at the beginning of Phase 2 and an extension that occurred through the end of Phase 3.

1.5 Benefits

The results of the Smart-NPP project have the potential to substantially change the way that NPPs are designed and operated. NPP design today is often restricted by the need for frequent access to equipment for inspection and repair. Further, redundancy and diversity of equipment are needed to ensure safety and reliability under a variety of conditions. Highly reliable smart equipment and systems will allow plant designers to simplify plant designs without compromising reliability and safety. For example, normal operating systems employing smart components may supplement, or even replace, traditional safety systems such as Emergency Core Cooling or Emergency Feedwater. The smart features of the components may provide the basis for assuring that a non-safety system's availability is sufficient to meet safety goals and the demands of regulators. Such plant design innovation can potentially allow
the use of less equipment resulting in more cost competitive and easier-to-construct power plants. Furthermore, the results of the Smart-NPP project are useful to all reactor technologies (e.g., PWR, BWR, MHTGR, and PHWR), including new technologies that might be developed through other NERI projects (e.g., proliferation-resistant or low-output reactors).

A major contributor to high Operations and Maintenance (O&M) costs are maintenance practices that rely heavily on inefficient and costly procedures. This includes periodic overhaul or replacement of parts based primarily on historical maintenance records, without regard to the actual “health” of a component or system. The results of the Smart-NPP project can help predict system performance with high confidence based on predictive and condition-based maintenance (CBM) methods that utilize current and projected conditions of critical components and subsystems to predict their time to failure. This requires understanding how sensor information, given specific environmental and operating conditions, relates to component or system wear and age. Such practices allow overhaul and repair to be performed only when necessary to prevent failure and provide a capability for assessing the risk of delaying indicated maintenance tasks. Maintenance methods that predict system performance while utilizing the maximum useful life of subsystems and components represent an innovative and cost saving approach to O&M activities. The overall reduction of plant safety equipment will likely produce an additional O&M benefit due to reduced surveillance testing requirements in Technical Specifications.

### 1.6 Project Organization

The project was organized around the six tasks identified in Section 1.3. SNL was the Lead organization for this project, and each participating organization had major responsibilities for a given task area. The project organization and task responsibilities are shown in Figure 3. Additionally, in Phase 2 collaboration activities with KOPEC for a parallel project were established. Figure 4 illustrates how KOPEC structured their project to collaborate with the Smart-NPP project and to apply a similar methodology for a different target system.

![Figure 3. Task leaders for Smart-NPP project.](image)

### 1.7 Summary of Research Activities and Accomplishments

Phase 1 of the project was conducted during FY1999 and FY2000. During Phase 1 of the project, the Smart-NPP team:

- Developed system/component criteria to establish priorities for smart equipment applications and using the criteria, completed a system prioritization study for smart equipment applications, and prioritized both pressurized water reactor (PWR) and boiling water reactor (BWR) systems.
- Based on the prioritization study, selected a high energy, horizontal, centrifugal pump as a demonstration component for an HMS.
- Reviewed and assessed sensor technology to develop criteria for sensor element selection and sensor system architecture.
- Reviewed smart equipment HMI technology currently being used in other industries to support development of an HMI prototype.
- Assessed failure modes for the pump and established an optimum health monitoring plan.
- Evaluated methods of equipment health diagnostics and prediction and developed an architecture for an HMS using Bayesian networks (BNs) to translate sensor data into equipment health information based on fault states and conditional failure probabilities.
- Created the design and approach for using a virtual machine to provide a capability to simulate equipment behavior over future time intervals in order to evaluate the overall benefits to system performance from designing in smart features as well as the consequences of alternative maintenance options.
- Procured the use of a demonstration test-bed of the pump lube system built at PSU and begun sensor instrumentation (including development of a PC104 smart sensor), data acquisition and messaging to provide real-world data over the Internet to the HMS.
- Established industry contacts for potential cooperative working arrangements.

Phase 2 of the project was conducted during FY2001 and FY2002. Building on the accomplishments of the first year of the project, the Smart-NPP team made significant additional progress during Phase 2:
- Completed and demonstrated the first version of a prototype HMI and had the prototype reviewed by NPP operations and maintenance staff.
- Completed the Alpha Version of the Virtual Machine Equipment Simulator (VMES) to provide a capability to simulate equipment behavior over future time intervals in order to evaluate the
overall benefits to system performance from designing in smart features as well as the consequences of alternative maintenance options. Data for PWR equipment performance from 1990-1995 was analyzed to test the VMES and to illustrate its capability for simulating equipment failures and maintenance. The purpose of this example was to test the reliability simulation capability of VMES and to provide a limited validation of its simulation algorithms. Additionally, an example scenario was evaluated to illustrate the use of VMES in evaluating alternative scenarios that could be considered in response to an HMS notification of a pending equipment failure. The basis for selecting the preferred scenario was the cost of electricity not generated as a result of a scheduled or forced outage.

- Developed detailed BNs to relate sensor features to fault conditions for the pump and its lube system.
- Began assembly of the lube system test bench, including instrumentation and testing of sensors, the data acquisition and messaging systems to provide real-world data over the Internet to the HMS.
- Defined the architecture and messaging format for the HMS to accommodate remote communication and integration among the elements of the HMS and initiated system integration.
- Initiated planning and preparation for demonstration activities, and presented a dry run demonstration of the prototype HMI and the BN elements of the HMS.
- Established a collaborative agreement with KOPEC. A parallel project, Development of the Intelligent Predictive Maintenance Tools and Methodology for NPP, is underway. The strategy for the collaboration was to have KOPEC apply a similar methodology, but for a system diverse from that of the Smart-NPP project. Specifically, the KOPEC team identified a rod control system, including the control element driving mechanism (CEDM) and its control system (CEDMCS) as its target system. The KOPEC effort began in February 2001. Areas were identified where KOPEC engineers could perform work for Smart-NPP team members, while learning critical aspects of the Smart-NPP methods. During Phase 2, KOPEC staff participated in BN training and consulting, HMS development, HMI design, and CEDM failure mode analysis. This approach was successful in allowing the KOPEC team to progress quickly in the development of an HMS for a CEDM/CEDMCS. Efforts included survey of operations experience, failure mode analysis and BN development, and prototype configuration development for the HMS and HMI displays, and virtual machine.

Phase 3 of the project was conducted during FY2002 and extended for completion in FY2003. Phase 3 activities focused on finalizing the development of elements for a demonstration HMS for a pump/lubrication system and culminated with a live over-the-Internet presentation of an integrated demonstration HMS that can replicate faults for a physical, real-world system as well as implementing other faults “virtually”; process sensor features and relate these to system fault conditions; generate consequences of alternative maintenance options, and provide indications and details of system health and maintenance options on an HMI. Additionally, collaboration with KOPEC continued as they completed a prototype HMS for their target system. Final task reports and this final project report were completed to document the technical work for the project. During Phase 3, the Smart-NPP Team:

- Completed and demonstrated the final version of the dynamic prototype HMI, and integrated it into the demonstration HMS.
- Designed and added new objects to the VMES component to calculate time-to-failure (TTF) and cost statistics. These objects use repeated simulations to determine several statistical measures for both total cost and time to first failure. Statistics available as object properties include mean, standard deviation, and several percentiles.
• Integrated the beta version of the VMES into the HMS so that its results in terms of costs and TTF could be provided as part of the HMS user interface.

• Developed and tested VMES input data sets to calculate the costs and TTF statistics for scenarios included in the HMS Demo. These scenarios take into account the state of several fault conditions in order to calculate system TTF. The scenarios also calculate cost by allowing maintenance to be scheduled at various times in the future considering time-dependent cost of electricity and the increased probability of system failure as maintenance is delayed to later dates.

• Completed the expert system for the demonstration HMS comprised of detailed BNs to relate sensor features to fault conditions for the pump and its lube system.

• Completed assembly of the lube system test bench, including instrumentation and testing of sensors, the data acquisition and messaging systems to provide real-world data over the Internet to the HMS.

• Completed and tested the architecture and messaging format for the HMS to accommodate remote communication and system integration among the elements of the HMS.

• Planned, prepared and implemented demonstration scenarios and activities for a live over-the-Internet presentation of the integrated demonstration HMS prototype at the Electric Power Research Institute’s Wireless Technology exhibit and conference in November 2002.

• Completed efforts on the collaborative parallel project with the Korea Power Engineering Company (KOPEC), Development of the Intelligent Predictive Maintenance Tools and Methodology for NPP. The KOPEC team completed elements for a prototype HMS for their target system of a rod control system, including the control element driving mechanism (CEDM) and its control system (CEDMCS).

1.8 Report Organization

Much of the following sections of this Final Project Report provides a discussion of project tasks, including the objectives, approach, activities and accomplishments. To provide an overall overview of the progress of all project tasks, the list below identifies the tasks completed in each of the three phases of the project. For tasks completed in each phase, references to associated project task reports that provide technical details of the work are cited. If a specific task report reference is not provided, technical details of the work for that task were incorporated in previous annual reports [1, 2], as cited, or in subsequent sections of this Final Project Report, as indicated.

Work Completed in Phase 1 (FY1999-FY2000)

<table>
<thead>
<tr>
<th>TASK 1 – Systems Evaluation and Prioritization [3]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1 – Systems Evaluation and Prioritization Criteria</td>
</tr>
<tr>
<td>1.2 – Critical Equipment and Failure Modes Identification</td>
</tr>
<tr>
<td>1.3 – Optimum Health Monitoring Plan</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TASK 2 – Sensor Technology and Installation Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1 – Sensor Selection Criteria [4]</td>
</tr>
<tr>
<td>2.2 – Plant System Modeling to Support Sensor Development [5]</td>
</tr>
<tr>
<td>2.3 – Advanced Sensor Technology [4]</td>
</tr>
<tr>
<td>2.5 – HMI</td>
</tr>
<tr>
<td>2.5.1 – HMI Technology Assessment [6]</td>
</tr>
</tbody>
</table>
TASK 3 – Equipment Maintenance and Reliability (Virtual Machine) Simulation

**Work Completed During Phase 2 (FY2000-FY2001):**

TASK 2 – Sensor Technology and Installation Analysis
   Task 2.4 – Sensor Installation Support for Demonstration [8]
   Task 2.5 – HMI
      2.5.2 – HMI Prototype Development [2]

TASK 3 – Equipment Maintenance and Reliability (Virtual Machine) Simulation [9]
   Task 3.2 – Integration with HMS

TASK 4 – Smart Equipment HMS [2]

TASK 5 – Sample Application of Smart System [2]

KOPEC Collaboration Activities [2]

**Work Completed in Phase 3 (FY2002-FY2003):**

TASK 2 – Sensor Technology and Installation Analysis
   Task 2.5 – HMI
      2.5.2 – HMI Prototype Development [10]

   Task 3.2 – Integration with HMS

TASK 4 – Smart Equipment HMS [12]

TASK 5 – Sample Application of Smart System [Section 2.5]

TASK 6 – Enterprise-Level HMS [Section 2.6]

KOPEC Collaboration Activities [Section 2.7]

Sections 2 through 8 of this report discuss the activities and accomplishments for each task of the Smart-NPP project, including additional details about the KOPEC collaboration activities. Section 9 discusses other project activities and accomplishments. The Final Report summary and references are provided in Section 10 and Section 11, respectively.
2 Task 1 – Systems Evaluation and Prioritization

Task 1 is Systems Evaluation and Prioritization. The objectives of this task were (1) to develop and demonstrate a methodology for identifying strong candidates for smart equipment in NPPs, (2) to review the current state-of-the-art in equipment condition monitoring, and (3) to select a component for demonstration of smart equipment techniques. This task included three subtasks: Task 1.1, Systems Evaluation and Prioritization; Task 1.2, Critical Equipment and Failure Mode Identification; and Task 1.3, Optimum Health Monitoring Plan.

Work for this task was completed during Phase 1 of the project. The results included:

- A methodology for systematically evaluating plant structures, systems and components (SSCs) to determine those that would benefit most from smart equipment concepts,
- Selection of a demonstration component, and
- An optimum health monitoring plan for the selected component, including identification of its failure modes.

Task activities and accomplishments are discussed in the following paragraphs.

Three major areas of research were identified as being necessary to accomplish the objective. The first area was to develop a system evaluation and prioritization methodology for ranking NPP equipment. The second area was to identify critical equipment and failure modes. The final area was to develop a plan for an optimal health monitoring system.

A set of weighted selection criteria were developed focusing on SSC performance and cost/benefit. Key criteria included:

- A high failure rate
- Well-known failure modes
- Accessible locations allowing data acquisition
- Sufficiently long repair time to cause significant lost generation

A study of failure rates and failure modes considered data of SSC contributions to forced outages. This study used the U.S. Nuclear Regulatory Commission’s MORP 2 Database for Monthly Reports between 1990 and 1999 for 14 PWR and 13 BWR units [13]. SSCs were ranked based on their fraction of the total forced outage time (based on occurrence frequency and mean outage duration). Individual failure modes were similarly ranked for the SSCs with the highest forced outage contributions. This quantitative data was combined with qualitative team assessments of instrumentation feasibility and cost/benefit to result in a SSC prioritization, which is shown in Table 1 for PWRs. The significant result of this effort was identification of rotating machinery, including pumps, as the primary contributors to forced outages in light water reactors. This conclusion, coupled with their application in both charging and feedwater systems, led to the selection of a high energy, horizontal, centrifugal pump as the demonstration component for the Smart-NPP project.

The other Task 1 effort explored the nuclear industry's transition from traditional time-based and corrective maintenance methods to Reliability Centered Maintenance (RCM), including application of Condition Based Maintenance (CBM). Methods for monitoring component health being developed in the Smart-NPP program directly support the transition to CBM. Typical pump failure modes were identified and described fully. Current pump diagnostics however are limited to characterizing only shaft or casing vibration.
Table 1. Weighted Results for PWR Component Prioritization

<table>
<thead>
<tr>
<th>System/Component</th>
<th>Points From Criteria I</th>
<th>Points from Criteria II</th>
<th>Total Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main Turbine</td>
<td>37.9</td>
<td>19.8</td>
<td>57.7</td>
</tr>
<tr>
<td>Main Generator</td>
<td>35.2</td>
<td>18.5</td>
<td>53.7</td>
</tr>
<tr>
<td>SG Feedwater Pump</td>
<td>27.7</td>
<td>20.8</td>
<td>48.5</td>
</tr>
<tr>
<td>Reactor Coolant Pump</td>
<td>27.3</td>
<td>19.3</td>
<td>46.6</td>
</tr>
<tr>
<td>Charging Pump</td>
<td>24.0</td>
<td>21.1</td>
<td>45.1</td>
</tr>
<tr>
<td>Heater Drain Pump</td>
<td>22.2</td>
<td>15.7</td>
<td>37.8</td>
</tr>
<tr>
<td>Auxiliary/Emergency Feedwater System</td>
<td>3.7</td>
<td>10.0</td>
<td>13.7</td>
</tr>
<tr>
<td>Diesel Generator</td>
<td>3.1</td>
<td>9.3</td>
<td>12.5</td>
</tr>
<tr>
<td>Circuit Breakers</td>
<td>2.9</td>
<td>7.9</td>
<td>10.8</td>
</tr>
<tr>
<td>Service Water System</td>
<td>2.5</td>
<td>7.7</td>
<td>10.2</td>
</tr>
<tr>
<td>Steam Generator</td>
<td>5.5</td>
<td>4.3</td>
<td>9.8</td>
</tr>
<tr>
<td>Main Steam System</td>
<td>6.5</td>
<td>2.6</td>
<td>9.1</td>
</tr>
<tr>
<td>Transformer</td>
<td>3.5</td>
<td>3.4</td>
<td>6.9</td>
</tr>
<tr>
<td>Control Rod System</td>
<td>4.5</td>
<td>2.4</td>
<td>6.9</td>
</tr>
<tr>
<td>Main Feedwater System</td>
<td>5.3</td>
<td>1.6</td>
<td>6.8</td>
</tr>
<tr>
<td>Condenser</td>
<td>3.5</td>
<td>1.4</td>
<td>4.9</td>
</tr>
<tr>
<td>Circulating Water System</td>
<td>1.6</td>
<td>3.0</td>
<td>4.5</td>
</tr>
<tr>
<td>RHR and Low Pressure Safety Injection System</td>
<td>1.0</td>
<td>2.7</td>
<td>3.7</td>
</tr>
<tr>
<td>Pressurizer</td>
<td>1.4</td>
<td>1.9</td>
<td>3.3</td>
</tr>
<tr>
<td>Condensate System</td>
<td>1.6</td>
<td>1.5</td>
<td>3.1</td>
</tr>
<tr>
<td>High Pressure Safety Injection System</td>
<td>0.8</td>
<td>1.5</td>
<td>2.3</td>
</tr>
</tbody>
</table>

Integration of advanced diagnostic methods, including infrared thermography, motor monitoring, lubrication assessment, acoustic monitoring and performance parameter measurement are critical to developing an optimum HMS for a pump. Other issues identified as critical to the effectiveness of an HMS include (1) sensor adequacy and location, including potential use of smart sensors (2) data acquisition, particularly with respect to assessing the benefits offered by wireless data transmission, and (3) selection of algorithms and intelligent processing systems to process the data into useable information. The points from Criteria I were derived from performance-based criteria including availability and the points from Criteria II were derived from cost/benefit criteria. As a result of this system evaluation and prioritization study, a high energy, horizontal, centrifugal pump (Figure 5) was selected as the demonstration application being developed under Task 5.

Additional details about the methods and results of the work for this task are provided in a Smart-NPP technical task report, System Evaluation and Prioritization Report [3].
Figure 5. Cross-section of multi-stage high energy, horizontal, centrifugal pump.
3 Task 2 – Sensor Technology and Installation Analysis

Task 2 is Sensor Technology and Installation Analysis. The objectives of this task were (1) to evaluate the availability and adequacy of sensor technology needed to implement smart equipment in future NPP operations and (2) to address the methodologies needed for consolidating smart equipment data into effective end-user information. Work for this task began in Phase 1 and continued through the completion of the project. This task included five subtasks, four focused on sensor technology and system modeling and one focused on HMI technology evaluation and prototype development.

The work for Task 2.1, Sensor Selection Criteria; Task 2.2, Plant System Modeling; Task 2.3, Advanced Sensor Technologies; and Task 2.5.1, HMI Technology Assessment was completed during Phase 1. During the project planning for Phase 2, Task 2.4, Sensor Installation Support for Demonstration, was redirected from general sensor installation feasibility to specific development and installation support of sensors required for the pump/lubrication system demonstration HMS. The sensor installation work under Task 2.4 was completed in Phase 2. Remaining sensor installation work for the demonstration was conducted under Task 5 during Phase 3. Task 2.5.2, HMI Prototype Development was initiated in Phase 2 and was completed in Phase 3. Task activities and accomplishments for each subtask are discussed in the following sections.

3.1 Sensor Selection Criteria

Task 2.1 is Sensor Selection Criteria. The approach followed for this task was to identify the architecture of a smart sensor, and then determine the requirements of the sensing element. A literature search was performed to identify the status of smart sensors, issues related to implementing such sensors in an NPP environment, the use of digital sensors and wireless communication, and the status of sensing elements. The information gathered was used to summarize the status and anticipated future capabilities of smart sensors and their sensing elements.

The sensors are the lowest level component of the smart equipment system. Selection of the sensor architecture and the sensing must facilitate the ability to:

- Indicate state or condition based on Failure Modes, Effects, and Criticality Analysis (FMECA) and physics of failure;
- Withstand local environment, including thermal and radiation environments;
- Interface with user/maintainer, with capabilities for networking, including wireless, and self-calibration;
- Expand as needed to account for generation gap (Moore’s law vs. manufacturer’s generation) and to allow for newly identified failure modes.

Based on these requirements, criteria for the sensor architecture and sensing elements were developed.

3.1.1 Smart Sensor Architecture

The architecture of a smart sensor system for NPP systems and components must have certain characteristics to ensure the reliability and expandability of the system. Fundamentally, the system must be digital to facilitate data communication and manipulation. In addition, it must be able to expand as our knowledge of the system expands. A corollary to the requirements for expandability is the requirement for wireless communication.
One key issue is generational: digital electronics improve at very high rates, whereas equipment and systems associated with nuclear power plants improve at very low rates. Technologies used in prognostics and diagnostics processes associated with condition-based maintenance (such as automated reasoning, signal processing, modeling, etc.) are closely aligned with the electronics growth model. This implies that, although the equipment used in a NPP may not change over its life, the smart sensors and associated electronics may evolve dramatically. Any smart sensor architecture must allow for this evolution, so that we may take advantage of the maturation of the diagnostic and prognostic technologies.

The essential characteristics of the ultimate smart sensor system can be summarized by the following [14]:

1. Smart sensor systems adapt to the environment by optimizing their sensor detection performance, power consumption, and communication activity.
2. Smart sensor systems record raw data and extract information.
3. Smart sensor systems have some degree of self-awareness using built-in calibration, internal process control checking and re-booting, and measures of “normal” and “abnormal” operation of its internal processes.
4. Smart sensor systems are completely re-programmable through their communications port, allowing access to raw data, program variables, and the processed data.
5. In addition to a pattern recognition ability, smart sensor systems are capable of predicting pattern future states and providing meaningful confidence metrics for these predictions.

These basic characteristics represent the starting point for defining the smart sensor node on a network integrating many sensors into a smart system. The use of appropriate noise reduction techniques, data fusion with other sensor information, physical models, and extracting appropriate information from the raw data are necessary to implement such a system.

In order to facilitate local intelligence, a layered sensor hardware architecture (i.e., an Intelligent Node) was investigated. Figure 6 shows the architecture of such a sensor. At the outset of this project, this architecture was being developed on a number of front. Details for the smart sensor architecture constituents and information regarding the smart sensor architecture were provided including the following:

![Basic sensor architecture](image)

**Figure 6. Basic sensor architecture.**
• The components that make up the smart sensor (i.e., the intelligent node),
• The current status of digital sensors,
• Issues related to the use of wireless communication in an NPP,
• Other related issues including power scavenging technologies, and temperature and radiation requirements, and
• The status of current research and development of smart sensor architecture.

3.1.2 Smart Sensing Element Selection

The sensing element itself must be capable of measuring a parameter on the machine or system that will change as the machine or system health deteriorates [15]. Once the appropriate parameters have been identified, sensing elements that are able to accurately and reliably provide the parameter (or the information necessary to derive the parameter) must be selected. Sensors investigated for this task were classified as follows:

• Dynamic Motion
  • Vibration (< 1 Hz to 25 kHz)
  • Ultrasonics (20 kHz to 100 kHz)
  • Acoustic emission (100 kHz to > 1MHz)

• Lube Analysis
  • Wear debris analysis
  • Lubricant condition analysis

• Process Parameters
  • Pressure
  • Flow
  • Level
  • Speed
  • Temperature

• Electrical Parameters
  • Motor current
  • Rotor flux monitor

• Other
  • Thermograph
  • Gas/liquid condition monitors
  • Corrosion/erosion
  • Chemical analysis

There is certainly overlap in these categories. For instance, chemical analysis is used for oil condition monitoring, and motor current analysis is performed using essentially the same tools as vibration analysis. But this is a reasonable classification scheme from which sensor selection may proceed.

3.1.3 Sensor Selection Criteria

Criteria for sensor selection were developed for both sensor elements and sensor system architectures. The criteria identified for a sensor system architecture included the following:
Flexibility;
- A web-based design compatible with the IEEE 1451 standard [16]; and
- A wireless data communications network compatible with the Bluetooth wireless protocol [17].

The criteria identified pertaining to sensor elements included the following:
- The ability to indicate component state based on either the physics of failure mechanisms or FMECA;
- The ability to withstand the local environment (e.g., temperature or radiation effects);
- Accuracy; and
- Reliability.

The technological horizons for such a sensor architecture guided us to a system that
- Is web-based (IEEE 1451 compatible);
- Has a reconfigurable wireless network (Bluetooth compatible) system;
- Has sensor-based analog-to-digital conversion; and
- Has health parameter valuation (Dedicated Diagnostic Processing Module).

Additional details about the methods and results of the work for this task are provided in a Smart-NPP technical task report, Sensor Selection Criteria [4].

### 3.2 Plant System Modeling to Support Sensor Development

Task 2.2 is Plant System Modeling. The approach for the Plant System Modeling task was to review current reliability issues related to these pumps with the Electric Power Research Institute’s (EPRI) Nuclear Maintenance Application Center (NMAC) and with DE&S engineering personnel. These identified failure modes were addressed via rotor/bearing dynamics modeling to enhance sensor placement and sensor development, and to identify “virtual sensor” opportunities.

Nuclear plant component diagnostic technologies have lagged other industries because modifications/enhancements to plant components require costly and time-consuming system modification. For high-energy pumps, the technology in today’s NPPs is quite dated, diagnostic sensor coverage is low, and sensor placement is limited. Rotor/bearing dynamic modeling has proven effective in extending the reach of a limited number of sensors. For smart equipment, dynamic modeling, when calibrated with pump operating data, can provide an array of “virtual” sensors that can aggressively assess the condition of the equipment. An example rotor dynamics model is shown in Figure 7.

Rotor/bearing dynamic analysis consists of the development of analytical models for the pump rotor, bearings, and interstage seals to emulate the dynamic (vibratory) behavior of the pump. The mass, stiffness and damping of the system, the “building blocks” of vibration behavior, are approximated and used to assess the rotor dynamic characteristics under a variety of pump operating conditions. Analysis output includes pump vibration levels at all rotor locations (not just at sensor locations) as well as pertinent pressures, temperatures, and flows relative to pump bearings and interstage seals.

Several mechanical issues, as identified by industry contacts, were addressed in the analysis. These included:
Figure 7. Example rotor dynamics model.

- The effect of loss of coolant to the lubrication for radial and thrust bearings on bearing function and pump rotor dynamics;
- The effect of the various shaft materials on pump rotor dynamics;
- The effects of impeller fits on the shaft (interference vs. clearance) on pump rotor dynamics;
- The balance sensitivity of the rotor including balancing on the seal sleeve nuts;
- The effects of bearing housing deflection on pump rotor dynamics (to the extent possible with these models);
- The effects of shaft crack on pump rotor dynamics (to the extent possible with these models);
- The effect of wear-ring clearance on pump rotor dynamics; and
- Optimum sensor placement for the known failure modes of the pump.

Recommendations were made relative to sensor development, sensor placement, and use of “virtual” sensors. Additionally an effort was undertaken to determine how to best integrate the pump dynamic modeling with the virtual machine pump model being developed in Task 3.

Additional details about the methods and results of the work for this subtask are provided in a Smart-NPP technical task report, Plant System Modeling to Enhance Sensor Development [5].

3.3 Advanced Sensor Technology

Task 2.3 is Advanced Sensor Technology. This task was performed in conjunction with Task 2.1. Advanced sensor technologies were evaluated for use in the commercial nuclear industry. Table 2 contains a survey of the major categories and subcategories of sensor devices that were currently in use or on the horizon when this worked was performed in Phase 1. Applicable sensing elements were identified according to the primary application of each, type of fault monitored, monitored parameters, and the transducer element. This information provided input to future Smart-NPP tasks, and identified where additional research is required to improve sensor technology to meet the needs of future NPPs. Specific equipment and components must be investigated individually to identify which of these sensors or which other, more focused sensor technologies should be used for measuring key parameters for the diagnosis and prognosis of equipment health for a specific component. This strategy was applied in subsequent tasks for the sensors used in the Smart-NPP demonstration HMS.
Table 2. Sensor Types and Sensor Characteristics

<table>
<thead>
<tr>
<th>Sensor Type</th>
<th>Primary Applications</th>
<th>Fault Monitored</th>
<th>Monitored Parameters</th>
<th>Transducers</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vibration (&lt; 1 Hz to 25 kHz)</td>
<td>Gears</td>
<td>Fatigue, Wear, Misalignment</td>
<td>Acceleration, Velocity, Displacement</td>
<td>Accelerometer, Velocity probe, Proximity probe</td>
<td>Vibration is still the “flagship” of condition monitoring. Accelerometers are best for seismic (absolute) motion; proximity probes for relative motion.</td>
</tr>
<tr>
<td></td>
<td>Bearings</td>
<td>Misalignment, Wear, Fatigue</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Shafts</td>
<td>Fatigue, Misalignment, Imbalance, Mechanical looseness</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Structures</td>
<td>Fatigue</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ultrasonics (20 kHz to 100 kHz)</td>
<td>Anti-friction bearings</td>
<td>Wear</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Valves</td>
<td>Valve and valve seat wear, Cavitation, Leaks</td>
<td>Un-scaled proportional to acceleration</td>
<td>Piezoelectric transducers, Microphones</td>
<td>Contact transducers most useful.</td>
</tr>
<tr>
<td></td>
<td>Pumps</td>
<td>Cavitation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Vessels</td>
<td>Crack propagation, Leaks</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Insulation</td>
<td>Arcing, breakdown</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acoustic Emission (100 kHz to &gt; 1 MHz)</td>
<td>Same as ultrasonics</td>
<td>Same as ultrasonics</td>
<td>Un-scaled, proportional to acceleration</td>
<td>Piezoelectric transducers</td>
<td></td>
</tr>
<tr>
<td>Wear Debris analysis (bearings, gears, etc.)</td>
<td>Oil-wetted components</td>
<td>Metal fatigue, Bearing pitting, Debris</td>
<td>Particle size and shape</td>
<td>LASERNET Fines, others</td>
<td>On-line or in-line monitoring most applicable to Smart Equipment.</td>
</tr>
<tr>
<td>Oil Analysis</td>
<td>Lubricated systems</td>
<td>Additive depletion, Contaminant identification</td>
<td>Various</td>
<td>Spectrometer, etc.</td>
<td>Most useful when fused with other monitoring.</td>
</tr>
</tbody>
</table>

Vibration is still the “flagship” of condition monitoring. Accelerometers are best for seismic (absolute) motion; proximity probes for relative motion.
<table>
<thead>
<tr>
<th>Sensor Type</th>
<th>Primary Applications</th>
<th>Fault Monitored</th>
<th>Monitored Parameters</th>
<th>Transducers</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Process Parameters</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steady State Analysis</td>
<td>Process equipment Pressurized systems Lubricated systems Drive systems</td>
<td>Various</td>
<td>Pressure • Flow • Level • Speed • Temperature • Torque • Displacement • Efficiency (derived)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Motor Current</td>
<td>Induction Motors</td>
<td>• Bent shaft • Broken rotor bars • Cracked end rings • Stator/rotor wear</td>
<td>Current</td>
<td>Induction coils</td>
<td>Currently tested periodically (walk-around).</td>
</tr>
<tr>
<td>Rotor Flux Monitor</td>
<td>Synchronous Machines</td>
<td>• Shorted turns</td>
<td>Magnetic flux</td>
<td>Induction coils</td>
<td>Used in generators.</td>
</tr>
<tr>
<td>Thermography</td>
<td>Various</td>
<td>• Loose electrical connections • Switch gear • Bearing wear or fatigue • Leakage • Machine degradation</td>
<td>Temperature</td>
<td>IR detector/ Digital camera</td>
<td>Difficult to automate.</td>
</tr>
<tr>
<td>Corrosion/ Erosion</td>
<td>Piping Vessels</td>
<td>• Corrosion/ Erosion</td>
<td>Various</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Surface &amp; Internal Defect Detection</td>
<td>Various</td>
<td>• Surface &amp; Internal Defects</td>
<td>Defect size</td>
<td>Various</td>
<td>Non-Destructive Testing (NDT) probably not a candidate for a smart system at this time.</td>
</tr>
</tbody>
</table>
Additional details about the methods and results of the work for this task are provided in a Smart-NPP technical task report, Sensor Selection Criteria [4].

3.4 Sensor Installation Support for Demonstration

Task 2.4 is Sensor Installation Support for Demonstration. As a result of the system evaluation and prioritization study of Task 1 in Phase 1, a high energy, horizontal, centrifugal pump (Figure 5) was selected as the demonstration application being developed under Task 5. As noted in the study, pumps are major components to overall downtown of NPPs and the supporting lubrication systems are also a major contributor to overall pump reliability and maintainability. Use of the BN methodology provided a decomposition of the pump down to specific functions and components that are required for operation, identification of system faults and failures, and determination of relationships between sensor features to faults and failures. The specific subsystem that was chosen for the demonstration is the supporting lubrication system for the pump bearings. An existing pump oil lubrication test system at PSU was utilized for actual instrumentation and testing. Fault conditions for other parts of the pump were implemented virtually. Under Task 2.4, the lubrication system test bench (LSTB) was modified to incorporate the sensors and data acquisition functions to support the Smart-NPP project demonstration.

Smart-equipment technology has at its foundation the ability to determine and communicate system health parameters using validated sensor data that is provided continuously in real-time. Quantification of system health is achieved through the monitoring of feature algorithms and/or health indices that relate trends of the monitored variables to known failure mechanisms. The tracking of these features and indices can subsequently lead to the detection of incipient faults and the estimation of remaining useful life.

3.4.1 Real-time Monitoring

To establish indices of lubrication system/component health that are capable of isolating specific fault events, it is necessary to have access to continuous, real-time sensor data. Real-time sensors provide continuous monitoring capabilities. This is beneficial on many levels, especially in data trending and responding to incipient fault conditions. Real-time sensors also provide the ability to integrate derived health information into diagnostic and prognostic maintenance systems, thereby enhancing the ability to catch faults before they progress and to limit collateral damage. Moreover, real-time sensors eliminate the burdensome cost of oil sampling and laboratory analysis. Before the health indices or feature algorithms, can be calculated, validation of the sensor data integrity must be accomplished to ensure the legitimacy of the feature results.

Real-time monitoring is performed in-situ, and the sampling of the lubrication system can be either on-line or in-line. On-line monitoring refers to a system in which a portion of the oil is sampled and analyzed by direct connection to the lubrication system. On-line monitoring has little impact on system flow (i.e. pressure drop, flow velocity, etc.), provides direct results, and reduces the risk of secondary contamination resulting from poor sampling techniques. Results from on-line monitoring could poorly represent the system if the flow through the sampling leg is small relative to the system flow. Best results would be obtained by placing the lubricant sensor (wear-debris or otherwise) directly in-line with the main lubricant distribution line(s). However, in-line monitoring may be more difficult to implement due to space limitations, and can potentially influence the system flow characteristics.
3.4.2 Wear Debris

The lubrication system can have many types of fault effects that are coupled with the functioning of the oil system and its related components. A common focus for oil analysis is the production of wear debris associated with its wetted components (such as bearings and gears). This occurs during initial break-in wear, stable wear over component life with some degree of dynamic equilibrium, and in some cases, abnormal wear due to component damage or improper lubrication. The gradual accumulation of wear debris in lubricant systems can lead to various system or component faults, including filter clogging and bearing or gear damage. The analysis of the debris rates and content may also be used as a measure of the wear or damage to the wetted component.

Common wear mechanisms include pitting fatigue of gears or bearings, abrasion, scuffing corrosion and fretting wear. When solid contamination of the lubricant occurs, the result is what is often referred to as “three-body” abrasion wear. Oil-wetted component, lubricant property, and lubrication system functional failures manifest themselves as features that can be roughly divided into three categories: oil quality, delivery, and wetted component damage. The oil quality issues largely regard the lubricant degradation, contamination, and debris fault effects. The delivery issues are composed of mechanical faults, flow problems and leakage. The wetted component damage issues include the various types and stages of wear and component failure.

3.4.3 Model-based Diagnostics

Model-based diagnostics, one of many CBM techniques, can be an optimum method for damage detection and condition assessment because empirically validated mathematical models at many state conditions are still deemed the most appropriate knowledge bases [18]. System models, enabling a model-based diagnostics approach, provide the most general detection capability since most types of performance degradations and some specific failure modes can be detected by monitoring the model component and system responses. This technique can be augmented by other methods that tend to be more focused on specific failure modes, such as vibration or debris sensing, thus improving the overall system monitoring capability. A combination of methods is usually required to provide the desired detection and diagnosis capability.

The actual system output response (event and performance variables) is the result of nominal system response plus fault effects and uncertainty. The model-based analysis and identification of faults can be viewed as an optimization problem that produces the minimum residual between the predicted and actual response. The development of a model-based diagnostic/prognostic capability for CBM requires a proven methodology to create and validate physical models that capture the system response under normal and faulted conditions.

The development of diagnostic features requires the association of fault symptoms with the potential failure states of the lubrication system. Advanced progression of a failure state will usually produce a readily understandable symptom, (i.e., lube oil delivery pressure dropping below a lower limit is a symptom of loss of oil, pump failure, or gross leakage, the actual root cause of which can be determined through consideration of additional data sources). However, detecting and associating symptoms of incipient failure conditions requires more capability than what is provided by simple threshold checking.

Features were developed to model the characteristics of several lubrication system faults. These include heat exchanger faults, filter clogging, and flow blockage of distribution branches (bearing leg clog). Sensor data obtained from the LSTB were utilized to associate the faults with changes in state and debris sensed parameters in the LSTB, and to fine-tune the models. Variations of the oil properties
(viscosity, specific heat and density) are taken into account to ensure that the model features accurately represent the actual flow conditions.

3.4.4 LSTB System Faults and Sensor Features

The LSTB is designed to emulate general lubrication systems and utilizes a varied array of sensors and instrumentation to provide an accurate assessment of the salient system parameters. The lubrication system on the target component, the high energy, horizontal centrifugal pump, was evaluated, and potential system faults were identified. From a study of the system, three classes of lubrication faults were identified: delivery system faults (lubricant flow); lubricant temperature faults; and lubricant quality faults. A subset of the possible faults associated with these classes was identified as critical and tractable. A causal tree (Figure 8) was developed to relate these faults to higher-level faults that could impact system reliability and availability. Note that two of the sensor-level entries in this tree (viscosity meter and spectroscopy) are considered important sensors, but actual installation of these sensors was beyond the scope of this project. On-line and in-line viscosity meters are currently available, but fairly expensive. On-line and in-line spectroscopy sensor development is in its infancy, but will probably be commonplace in the next decade.

On the basis of the evaluation of the pump lubrication system, a set of sensors were identified to support the three model-based diagnostic features, as well as debris trending for ferrous and non-ferrous particles, for the lube system. These include:

- Oil Inlet Temperature
- Oil Outlet Temperature
- Water Inlet Temperature
- Oil Flow Rate
- Water Flow Rate
- Filter Inlet Pressure
- Filter Outlet Pressure
- MetalSCAN Debris Sensor

The smart sensing capabilities for the model-based diagnostics are implemented with the wireless PC-104 intelligent node (Figure 9). The intelligent node runs a custom Windows application that act as an automated data collection, processing and archival service. The second purpose of the intelligent node is to process the raw sensor data and calculated lube oil diagnostic features. Local communication was provided with an area reasoner using TCP/IP over a wireless network. A data socket server was utilized for higher-level communications with the integrated HMS software.

The LSTB was readied for testing and development of demonstration activities during Phase 2 of the project. Additional details about sensor development, installation and analysis for the LSTB are provided in a Smart-NPP technical task report, *Lubrication System Sensor Installation Report* [8]. Work for Task 2.4 continued in Phase 3 under Task 5.

3.5 HMI Prototype Development

Task 2.5 is Human Machine Interface (HMI). Work for this task began in Phase 1 and continued through the completion of the project. This task included two subtasks focused on HMI technology
Figure 8. Lubrication system causal network.

Figure 9. Intelligent node (PC104) used on LSTB.
evaluation and prototype development. The work for Task 2.5.1, HMI Technology Assessment, was completed during Phase 1. Task 2.5.2, HMI Prototype Development was initiated in Phase 2 and was completed in Phase 3. Task activities and accomplishments for each subtask are discussed in the following sections.

### 3.5.1 HMI Technology Assessment

Task 2.5.1 is HMI Technology Assessment. The approach for this task was to perform a broad-based literature search for smart equipment and predictive maintenance HMI applications and focus on areas that were identified to be promising for potential application in the nuclear power industry. The review included investigation of smart sensor technology, data communications, automatic process control including the use of agents, and display and messaging techniques employed for smart equipment.

The HMI technology assessment investigated smart equipment applications in other industries for potential use in nuclear power plants. Initial investigations of industrial experience with smart sensors identified potential HMI applications for calibration, internal diagnostics, alarm reporting, developing audit trails and data retrieval. Investigations of predictive maintenance technologies being employed in power generation industries revealed HMI techniques such as trend analyses, pattern recognition, correlation techniques and statistical process analysis being used. Advanced process control applications identified included predictive control logic and self-learning controllers. The aerospace industry uses agents to both sense and control a dynamic environment to accomplish a predetermined goal. This has the potential in future nuclear plants to move smart equipment from the realm of only monitoring to that of automatic control.

The technology assessment identified various techniques for presentation of smart equipment and predictive maintenance information, including display and messaging techniques. Display types identified as potential candidates for presenting smart equipment information include multidimensional displays, traditional mimic diagrams, model-based displays, multi-media and virtual reality displays, and predictor displays. Other issues identified included how to integrate smart equipment information with displays from other computerized operator support systems. Smart equipment warning message types included alerts such as auditory or visual signals. The initial concept for an integrated HMI display system is illustrated in Figure 10.

Additional details about the methods and results of the work for this task are provided in a Smart-NPP technical task report, *Smart Equipment MMI Technology Assessment Report for Task 2* [6].

### 3.5.2 Static HMI Prototype – Development in Phase 2

Task 2.5.2 is HMI Prototype Development. During Phase 2, the HMI development efforts focused primarily in four areas. These are (1) development of a canned prototype of the HMS display set; (2) creation of the software database and messaging capability to allow data communication between the HMI and HMS (in conjunction with other tasks activities); (3) performing and documenting a task requirements assessment for nuclear plant use of HMS information; and (4) preliminary development of the display set for the HMS pump/lubrication system demonstration. Each of these topics is discussed in the following paragraphs.

In addition to HMI development work for the HMS demonstration, project staff investigated new display and control paradigms for facilitating the rapid interpretation of predictive-maintenance information to support complex decision-making behaviors. The result of this work on new display and
control paradigms, An Interactive-Timeline-Display Approach to Providing Health-Monitoring System Information, is provided in an appendix of the final HMI development report [10].

3.5.2.1 Static (Canned) HMI Prototype Development

Initially a preliminary set of smart equipment display objects was created based on expected outputs of the BNs and HMS. The project team and potential end users subsequently reviewed these. A refined set of display objects was created and used to develop a preliminary set of HMS displays for typical nuclear plant components that may benefit from smart equipment technology. A top-level display indicates integrated equipment health for all selected components. Second level displays provide expected time to failure, mean time to repair and the importance index for each failure of a given component. The third level displays include detailed BN output, component mimics, sensor features, historical data, maintenance logs and a cost function. An illustration of the HMS display hierarchy is provided in Figure 11. The centrifugal pump displays were based on the actual BN fault tree structure developed for the pump in Task 4.

The HMI work next focused on using the displays related to the centrifugal pump to develop a canned HMI demonstration. The canned HMI demonstration is a self-contained, PC-based program that (1) depicts all display features and examples of all levels of display pages, including third level detailed displays; (2) allows navigation through the entire display set; and (3) allows input of dummy values simulating BN input to demonstrate filtering equipment health states from fault to failure modes to component on the various HMI display levels. A human factors review of these displays was conducted based on accepted industry standards and principles. Recommended improvements were implemented in the prototype display designs based on feedback from the review. The resulting set of the canned HMI displays is shown in Figures 12 through 19. The canned HMI prototype software was made executable and forwarded to SNL to allow for preparation of HMI demonstrations.

3.5.2.2 HMI Database and HMS Messaging Development

A significant effort was expended developing a relational database to allow display implementation from the Visual Basic environment in which they were created. The database was configured to allow displays to be drawn on the HMI screens from the database and display features to be
easily changed in the database, since numerous changes are expected during the development process. The database was also structured to receive data from the HMS and provide it for real-time presentation on the HMI displays as demanded. This capability would allow the canned demonstration to be easily extended to receive live data as part of the HMS demonstration.

Proposed architectures for both a plant HMS and the planned demonstration HMS for the centrifugal pump and lube oil system were created. A report was generated defining the scope of inputs, processing and outputs expected for each functional component of the HMS (separately for the demonstration). The interface between the HMI and HMS was a key to continued database and messaging development. The report was circulated to the project team and feedback was obtained and incorporated. This architecture provided direction on all design fronts for continued development of the demonstration HMS, while maintaining the eventual target of installing a HMS in an NPP.

At the next level of detail the scope and formats of messages providing data communications between the HMS client and HMI client were determined. A working meeting was held between SNL and WEC to assure that the software being developed for the HMI will work properly with the software of the virtual machine and HMS client. Messages and message structures were developed. An initial software communications test using the message center was demonstrated. A program structure for the HMI and its messaging function is provided in Figure 20.

3.5.2.3 **HMS Task Requirements Assessment**

Interviews were conducted with DE&S personnel to discuss their responsibilities for equipment health. The personnel included (a) one licensed Senior Reactor Operator with experience at multiple nuclear units (at multiple utilities), (b) a Senior Reactor Operator currently and with experience serving as a Systems Engineer (c) a maintenance planner with extensive experience in many facets of plant maintenance. The following specific issues were addressed with each individual:

- Identify equipment-related responsibilities/tasks (structured Q&A)
- Identify equipment-related information needs (structured Q&A)
- Identify what's needed, but not available now (ad hoc discussion)
Figure 12. Tier-1 Display: Overview of current plant-wide health status.
### Figure 13. Tier-2 Display: Failure mode display.

<table>
<thead>
<tr>
<th>Failure Mode</th>
<th>Failure Predicted Within (Hours)</th>
<th>Nominal Down Time (Hours)</th>
<th>Importance Index (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bearings</td>
<td>100</td>
<td>48</td>
<td>90</td>
</tr>
<tr>
<td>Seals</td>
<td>200</td>
<td>48</td>
<td>90</td>
</tr>
<tr>
<td>Lube Oil System</td>
<td>350</td>
<td>48</td>
<td>90</td>
</tr>
<tr>
<td>Shaft</td>
<td>350</td>
<td>48</td>
<td>90</td>
</tr>
</tbody>
</table>

### Figure 14. Tier-3 Display: BN output display.
Figure 15. Tier-3 Display: Typical mimic display.

Figure 16. Tier-3 Display: Typical sensor data display.
Figure 17. Tier-3 Display: Typical historical data display.

Figure 18. Tier-3 Display: Maintenance log display.
From the data collected, a summary of results was generated. Among the most significant findings were:

1. Systems Engineers, not operations, was the primary HMS users.
2. HMS displays may be particularly useful during shift turnovers.
3. Real-time risk assessment from a safety perspective would be a useful addition to the HMS information.
4. HMS guidance, similar to alarm response procedures, would be helpful.
5. Direct links to other electronic plant systems, such as a corrective actions program or maintenance scheduling tool would be helpful.

Feedback on the canned HMI demonstration displays was also received and incorporated. Consideration was given to alternative display types such as calendar based predictive maintenance displays and multidimensional displays.

### 3.5.2.4 HMS Demonstration Preliminary Display Set

After the canned HMI demonstration prototype matured, HMI efforts focused on developing the HMI for the HMS prototype demonstration using the PSU LSTB. An initial set of level three displays for the lube oil system was developed. After discussions with other team members regarding consistency with the BN fault trees, a revised display architecture was developed based on the current BN structure.
This included redefining Tier-1, 2 and 3 displays and moving the overview display of all components to an “apex” of the hierarchy. Modified displays were created reflecting the new hierarchy and BN structures. The current set of Tier-3 displays was mapped to the new hierarchy to facilitate operator access. An HMI prototype set of displays was created for one complete fault and provided for implementation in the databases to obtain feedback before the entire display set was completed. This completed a preliminary set of the HMS demonstration displays. This set of displays was used in dry run presentations of the HMS demonstration. In conjunction with the HMI display changes, modifications to the HMI database were made and coordinated with SNL to accommodate the data structure that was developed for the HMS.
3.5.3 Dynamic HMI Prototype – Development in Phase 3

Using the previously described static prototype as a starting point a database driven dynamic HMI prototype for use in demonstrating the HMS was developed. This section describes the HMI dynamic prototype, in particular the HMI differences from the static prototype. These primarily resulted from (1) HMI evaluation results, (2) continued development of the HMS, and (3) development of the demonstration scenarios.

3.5.3.1 Display Organization and Hierarchy

For the dynamic HMI prototype, component health status was determined via BN network logic. The computed health state (as determined by the BN) was stored within the HMS database and was extracted periodically by the HMI program. A common HMS “Message Center” was utilized by the HMI to extract the health status information from the HMS database.

The dynamic prototype was developed based on a defined “functional tree” for a “Bearing Seizure Failure Mode” of a representative system pump. The functional tree for the Bearing Seizure Failure Mode is discussed in Section 2.3.3 and provides an indication of the corresponding “faults” that were defined for the bearing seizure failure mode and the sensor features that were utilized to determine each of the faults. Related sub-faults are grouped together under major fault headings.

Based on the defined functional tree for the “Bearing Seizure Failure Mode,” the original display hierarchy utilized for the HMI static prototype was revised as follows:

- Apex – A single overall health status page that allows the enterprise-level health status to be quickly ascertained, in an unambiguous manner from a single display page, via use of color-coded “failure domains”.
- Tier-1 – A series of display pages that provide specific details on the expected failure modes for impending equipment and system failures.
- Tier-2 – A series of display pages that provide specific details on the individual Faults that are associated with each of the failure modes. Each failure mode can have multiple Faults that can cause the failure to occur. There is generally one (but possibly more) Tier-2 display associated with each failure mode.
- Tier-3 – A series of detailed information display pages that are used for analysis, diagnostics and repair planning purposes.

Figure 21 illustrates the display hierarchy utilized for the dynamic HMI prototype. Figure 22 illustrates the relationship between failure modes and faults for the Bearing Seizure Failure Mode. Related sub-faults are grouped together under main faults.

3.5.3.2 Display Design and Information Content

The display set for the dynamic HMI prototype was designed based on the defined “Functional Tree” for the “Bearing Seizure Failure Mode.” From this “Functional Tree” the applicable display set was defined. The display design and information content for the dynamic HMI prototype displays are indicated below. These displays are organized in a multi-level hierarchy as previously noted.
Apex Display

Figure 21. Display hierarchy for dynamic HMI prototype.

Apex Display

Figure 23 illustrates the interactive display for the apex display that provides the overall (plant-wide) health status. A uniquely identified box indicates each plant component or system that is being monitored for health status. The corresponding health status of each component is designated via color-coding of the corresponding box. The 1A, 2B, etc. designations on the tiles adjacent to the component labels in the display correspond to typical nuclear plant mechanical divisions and trains to which the components would be associated.

The health status of each component or system is presented by indicating its membership within one of several pre-defined failure domains. The use of failure domains allows rapid and intuitive recognition of the failure status by the user.

The display is based on a “Green Board” concept, such that when all component boxes are displayed in green (and all numerical indicators are blank), there is no equipment that has an increased probability of failing. Any equipment that is displayed with other than a green color (and a numerical indicator) has a significant probability of a failure occurring. A red color and numerical indicator of 1 indicates a severe probability of component failure. A yellow color and numerical indicator of 2 indicates an intermediate probability of component failure.

The display is interactive in that any of the component boxes may be selected and interrogated to determine the prevailing failure modes. This is accomplished by simply designating the component (box) of interest by selecting via the computer mouse and activating the selection via the mouse button. (The user first maneuvers the mouse to place the cursor on the desired component (box) and then activates the selection using a “mouse click” button.) Figure 24 provides the display navigation strategy for the dynamic prototype. This is simply an extension of that used in the static prototype.
Note:
1. Health status migrates upward in the fault tree, from the lowest level fault to the failure mode, and is depicted via color-coding.

Figure 22. Illustration of pump fault tree.
Figure 23. Final Apex HMS Display: Overview of current plant-wide health status.
To navigate to the Failure Modes display from the Apex display
- Place cursor on an individual component tile
- Single click Left mouse button

To navigate to the Fault display from the Tier 1 displays
- Place cursor on an individual failure mode
- Single click left mouse button.

To navigate to the Detailed Data displays from the Tier 2 displays
- Place cursor on an individual failure mode
- Single click left mouse button

To select various Detailed Data (Tier 3) displays
- Place cursor on desired TAB label
- Single click left mouse button

Figure 24. Navigating the display set for the dynamic HMI prototype.

**Tier-1 Display**

Figure 25 illustrates a typical interactive display for the Tier-1 Sub-component Health page. This display indicates what specific failure mode(s) are present in the plant component or system. If the HMS detects multiple concurrent conditions that are predicted to cause subsequent failures, then each of these failure modes is depicted and displayed. The identified failure modes are arranged on the display page in the expected time-sequence order that they are predicted to occur. The indicated failure modes utilize the same color-coding as the Apex (plant-wide) health status page for consistency and to provide additional visual clueing to the user.

The display indicates the expected TTF for each failure mode in terms of a lower bound, nominal and upper bound value. This represents a significant improvement over the single value of predicted time to failure that was presented in the static prototype. An expected down time (renamed from the static
Figure 25. Final Tier-1 HMS Display: Sub-component health.
The prototype’s “nominal repair time”) for each component is indicated. This provides the user with information that supports planning of strategies on how to cope with impending failures and prioritizing repair work. After significant discussion it was decided to eliminate the “importance index” included in the static prototype because of the difficulty in determining a sound basis for such information.

The display is interactive in that any of the failure modes may be selected to access the corresponding Tier-2 “Fault” pages. This is accomplished by simply designating the failure mode of interest by selecting it via the computer mouse and activating the selection. (The user first maneuvers the mouse to place the cursor on the desired failure mode and then activates the selection using a “mouse click” button.) See Figure 24 regarding the display navigation strategy for the dynamic prototype.

**Tier-2 Display**

Figure 26 illustrates a typical interactive display for the Tier-2 Fault page. This display indicates what specific Faults are associated with one of the failure modes. The identified faults are arranged on the display page by groups of related sub-faults. The indicated faults utilize the same color-coding as the Apex (plant-wide) and Tier-1 display pages for consistency and to provide additional visual clueing to the user.

The display indicates the conditional probabilities calculated by the BNs of the individual fault being in a normal state, intermediate state and severe state. This provides the user with information that supports diagnosis of the fault conditions contributing to an impending failure of the equipment.

The display is interactive in that any of the faults may be selected to access the corresponding Tier-3 displays. This is accomplished by simply designating the fault of interest by selecting it via the computer mouse and activating the selection. (The user first maneuvers the mouse to place the cursor on the desired fault and then activate the selection using a “mouse click” button.) See Figure 24 regarding the display navigation strategy for the dynamic prototype.

**Tier-3 Displays**

A number of Tier-3 display pages provide supporting information to the user. Each page supplies detailed low-level data, which is used for analysis, diagnostics and repair planning purposes. Each display on Tier-3 can be rapidly accessed via use of the Tab Index, which is located on the top of each Tier-3 page.

Maneuvering through Tier-3 pages is achieved via the “Tab Index” access mechanism. This allows all of the lower level displays to be quickly accessed via “horizontal” maneuvering, in an intuitive manner. The Tier-3 tab index is accessed rapidly via a single “click” access mechanism from Tier-2 fault display pages by selecting and activating any fault via the computer mouse. See Figure 24 regarding the display navigation strategy for the dynamic prototype.

The Tier-3 display pages that were implemented within the dynamic HMI prototype are similar to the Tier-3 display pages utilized for the static HMI prototype. Changes were incorporated to address the feedback provided by several project team reviews. This included format changes (e.g., the state probability display), usability features (e.g., adding sensors and features pull downs to the Historical Data Display) and content changes (e.g., adding a graphic indication of the replacement cost on electricity on the cost function display). The complete set of dynamic prototype Tier-3 displays is contained in Figures 27 through 33.
### Figure 26. Final Tier-2 HMS Display: Failure mode faults.

<table>
<thead>
<tr>
<th>Faults</th>
<th>Normal State Probability (%)</th>
<th>Intermediate State Probability (%)</th>
<th>Severe State Probability (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Improper Clearances</td>
<td>27</td>
<td>40</td>
<td>26</td>
</tr>
<tr>
<td>Clearances Too Tight</td>
<td>69</td>
<td>23</td>
<td>9</td>
</tr>
<tr>
<td>Clearances Too Loose</td>
<td>8</td>
<td>64</td>
<td>28</td>
</tr>
<tr>
<td>Axial Asymmetry</td>
<td>90</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>Improper Loading</td>
<td>27</td>
<td>34</td>
<td>39</td>
</tr>
<tr>
<td>Static Overload</td>
<td>67</td>
<td>33</td>
<td>0</td>
</tr>
<tr>
<td>Static Underload</td>
<td>12</td>
<td>70</td>
<td>18</td>
</tr>
<tr>
<td>Dynamic Overload</td>
<td>24</td>
<td>22</td>
<td>54</td>
</tr>
<tr>
<td>Improper Lubrication</td>
<td>32</td>
<td>38</td>
<td>30</td>
</tr>
<tr>
<td>Bad Lube Flow</td>
<td>52</td>
<td>29</td>
<td>20</td>
</tr>
<tr>
<td>Bearing Leg Clogged</td>
<td>70</td>
<td>20</td>
<td>10</td>
</tr>
<tr>
<td>Clogged Filter</td>
<td>70</td>
<td>20</td>
<td>10</td>
</tr>
<tr>
<td>Bad Oil Temperature</td>
<td>62</td>
<td>26</td>
<td>12</td>
</tr>
<tr>
<td>Inadequate Oil Quality</td>
<td>49</td>
<td>32</td>
<td>19</td>
</tr>
<tr>
<td>Chemical Contamination of Oil</td>
<td>70</td>
<td>20</td>
<td>10</td>
</tr>
<tr>
<td>Dirt/Debris in Oil</td>
<td>30</td>
<td>22</td>
<td>48</td>
</tr>
<tr>
<td>Oil Degradation</td>
<td>70</td>
<td>20</td>
<td>10</td>
</tr>
</tbody>
</table>

Failure State Probability:
- Normal: 
- Intermediate: 
- Severe: 
- Insufficient Data:
Figure 27. Final Tier-3 HMS Display: Failure state probability.

Figure 28. Final Tier-3 HMS Display: Component mimic display.
Figure 29. Final Tier-3 HMS Display: Sensor/feature data.

Figure 30. Final Tier-3 HMS Display: Historical data display.
Figure 31. Final Tier-3 HMS Display: Maintenance log.

Figure 32. Final Tier-3 HMS Display: Cost function (maintenance cost vs. time).
3.5.3.3 HMI Comments and Feedback

During the course of developing and refining the dynamic HMI prototype displays, feedback/comments were received from other team members that greatly shaped the displays captured in the previous sections. This information provides valuable insights into the basis for the final display set and is provided chronologically in the appendix of the final HMI development report [10].

3.5.3.4 Development Of HMI Prototype Software

The HMI prototype required software development to implement the features of the HMI prototype design. This section provides a software overview and describes the database structure, the message center, and the user interface software components of the HMI prototype.

Software Overview

Figure 34 illustrates the software structure for the HMI software. The HMI client application utilizes a local database, Client DB, for application processing. The application is comprised of the following internal program modules:

The Load and Display Main Application Form module loads and displays the main display page form, which automatically enables timer T1. The module processes message requests to the Health Monitoring Database, using the Message Processor modules, to obtain component and failure mode data and to update the local database. Communication messages are pre-coded and stored in the Message Types module. As a result, the latest component and failure mode data, as determined by the Health
Figure 34. Software structure for dynamic HMI.
Monitoring Status Module and stored in the Health Monitoring database, are made available to the local database.

The Load and Display Component Type and Component Data module loads and displays the HMS Overview Current Health Status form (Tier-1 display), which automatically enabled the timer T3. That module uses the local client database to retrieve the latest component and component type data and to dynamically create the HMS Overview Current Health Status form, consistent with the database. As a result, any changes made to the client database are reflected on the HMS Overview Current Health Status form each time that form is displayed or refreshed.

The Load and Display Failure Mode Data for a Specific Component module loads and displays the HMS Component Failure form, which automatically enables the timer T4. This module uses the local client database to retrieve the latest failure mode data for a specific component and to dynamically create the HMS Component Failure form consistent with the database. As a result, any changes made to the client database are reflected on the HMS Component Failure form each time that form is displayed or refreshed.

At application startup, the main form (HMS Overview Current Health Status form) is opened. Timer T1 continuously automatically triggers requests for component and failure mode data from the HMS server at specific time intervals. Consequently, the client database is updated periodically with the latest information. Timer T1 is enabled until the main form is closed.

Upon displaying the HMS Overview Current Health Status form (Tier-1 form), timer T3 is continuously triggered to refresh the HMS Overview Current Health Status form with the latest component information. As a result, the most recent component data is displayed on the HMS Overview Current Health Status form based on the frequency at which the form is being refreshed. Timer T3 is enabled until the HMS Overview Current Health Status form is closed. Upon displaying the HMS Component Failure form (Tier-2 form), timer T4 is continuously triggered to refresh the HMS Component Failure form with the latest component information. As a result, the most recent failure mode data for a specific component is displayed on the HMS Component Failure form based on the frequency at which the form is being refreshed. Timer T4 is enabled until the HMS overview form is closed.

Upon display of the HMS Component Failure form (Tier-2 form), Timer T2 also periodically requests the Tier-3 drill-down data.

**Database Structure**

There are two important fundamental aspects of the HMI application as it relates to the database structure and its importance:

1. The database is designed specifically to allow the application to be flexible, user configurable, and code independent.

2. The need for a local database allows the application to be powerful and self-contained.

The database is designed in such a way to support the dynamic aspects of the HMI application. Some of the controls on the application screens, including the menus, are dynamically created or generated based on information in the database. This makes the application flexible and easily extendable in the future. Since the menus are derived from the database, the user has the capability to control the type and format of information that is displayed on a screen. Some of the functional logic is also controlled at the database level in order to make the application as code independent as possible when it is necessary or applicable. For example, the sorting of failure modes or faults associated with a given
component is done by priority and performed at the database level without having to develop application code logic for this purpose.

By taking the database approach, as the application grows and the need for changes is necessary to support the screens/displays or the behavior of the application, the time and effort required to implement these changes are minimized. Changes can be easily implemented and supported with very little or no change at the programming/code level.

Most of the information that is needed for the HMI client is stored in a local HMI database after being obtained from the HMS. The HMI client uses this persistent approach to obtain information to maximize the performance (e.g., time response) of the application. For example, when a drill-down Historical Data page is accessed the data is presented immediately, rather than having to wait for messages to be transferred between the HMI and HMS.

Another huge advantage of the local database is that the application (HMI client) can be modularized and easily treated as a stand-alone application. This is only possible because the logic being used to retrieve data and information to support the application is consistent with the database design and kept within the HMI Client boundary.

**Message Center**

A common “Message Center” was utilized to interface the HMI (client) with the HMS (server). The messages within the Message Center request and send specific information between the HMI and HMS.

The Message Center consists of the following message types.

1. Login: Sent from the HMS Client to the HMS Server to log on to the server prior to receiving data.
2. Logout: Sent from the HMS Client to the HMS Server to log out.
3. Fault_Request: Sent from the HMS Client to the HMS Server to request current fault information.
4. Feature_Request: Sent from the HMS Client to the HMS Server to request current feature information.
5. Drill_Down_Data_Request: Sent from the HMS Client to the HMS Server to request drill-down data.
6. Fault_Response: Sent from the HMS Server to the HMS Client in response to a request for current fault information.
7. Feature_Data_Response: Sent from the HMS Server to the HMS Client in response to a request for current feature information.
8. Drill_Down_Data_Response: Sent from the HMS Server to the HMS Client in response to a request for drill-down data.
9. Sensor_Health: Sent from the HMS Server to the HMS Client to indicate a failed sensor.
10. Display_Message: Sent in either direction as information. For example, sent from the HMS Client to the HMS Server to request that a particular fault be initiated.
11. Component_State_Information_Request: This message is used to request the failure states of a single HMS plant component.
12. Component_State_Information_Response: This message is sent in response to a Component Failure State Request Message. This message provides the probability of failure for each failure state (for example - Low, Medium, High) of the component.

13. Failure_Mode_Information_Request: This message is used to request detailed HMS information for each failure mode that is associated with a single plant component.

14. Failure_Mode_Information_Response: This message is sent in response to a Failure Mode Information Request Message and provides detailed HMS information for each failure mode that is associated with a single plant component.

15. Feature_Data_Request_Message: This message is used to request Feature Data.

16. Sensor_Feature_History_Request: This message is used to request historical Feature data from a specified start time.

17. Sensor_Feature_History_Response: This message is sent in response to a Sensor History Request Message. This message provides the historical Feature data from the specified start time.

18. Drill_Down_Request: This message is used to request drill-down data for a specified Feature.

19. Schedule_Request: This message is used to request maintenance log schedule data.

20. Schedule_Response: This message is sent in response to a Schedule Request Message. This message provides the maintenance log status information.

**User Interface**

The Health Monitoring Display Module client application utilizes a local database, Client DB, for application processing (see Figure 34). The application is comprised of the following internal program modules:

Accessing the HMI application program (initial program startup and execution) automatically enables timer T1. This initiates the processing of message requests to the Health Monitoring DataBase, using the Message Processor modules and , to periodically obtain sub-component and fault data and to update the local database. Communication messages are pre-coded and stored in the Message Types module. As a result, the latest sub-component and fault data, as determined by the Health Monitoring Status Module and stored in the Health Monitoring DataBase, are made available to the local database.

Whenever the Apex display is accessed (requested to be displayed) on the VDU, timer T3 is activated. Once the timer is activated, it will periodically retrieve the latest component health data from the local database and update the Apex display screen. Software module loads and displays the Apex screen on the VDU.

Whenever a plant component on the Apex display is designated on the VDU using the OID, timer T4 is activated. Once the timer is activated, it will periodically retrieve the latest health data for the sub-components that are associated with the selected plant component from the local database and update the associated Tier-1 display screen. Software module loads and displays the Tier-1 screen (Sub-component Health) on the VDU.

Whenever a sub-component on a Tier-1 display is designated on the VDU using the OID, timer T5 is activated. Once the timer is activated, it will periodically retrieve the latest fault data for the selected sub-component from the local database and update the associated Tier-2 display screen. Software module loads and displays the Tier-2 screen (Faults) on the VDU.
Whenever a plant fault on a Tier-2 display is designated on the VDU 10 using the OID 11, or whenever a “drill down” menu selection is made (on a display menu bar) via the VDU 10 using the OID 11, timer T2 31 is activated. Once the timer is activated, it will periodically retrieve the latest “drill down data” from the local database 20 and update the associated Tier-3 display screen. Software module 32 loads and displays the appropriate Tier-2 screen (“Drill Down” data) on the VDU 10.

Additional details about the methods and results of the work for all phases of the HMI development are provided in a Smart-NPP technical task report, *Development of the Human Machine Interface for a Predictive-Maintenance Health Monitoring System* [10].
4 Task 3 – Equipment Maintenance & Reliability Simulation (Virtual Machine) Capability

Task 3 is Equipment Maintenance and Reliability Simulation (Virtual Machine) Capability. The objective of Task 3 was to develop a capability to simulate equipment behavior over future time intervals in order to evaluate the overall benefits to system performance from designing in smart features.

For convenience, we will refer to the capability to simulate equipment behavior as the virtual machine equipment simulator (VMES). The VMES is part of a larger system that provides real-time information on equipment condition, referred to as HMS. A number of steps are required to meet the objective of this task:

1. Expand the VMES concept and clearly identify how it is integrated into the HMS. The VMES is intended to simulate equipment failures, repairs, scheduled maintenance, and inspections in order to support HMS software testing, optimization, and integration. To fulfill this role, it must be nearly indistinguishable from actual equipment to the HMS. This step defined the features of VMES and its interface with the HMS.

2. Develop a detailed information architecture design for VMES.

3. Design the object model for the VMES. The VMES design is object-oriented. This step developed a detailed design of the objects that made up the virtual machine software components.

4. Develop reusable VMES software components. For the VMES to become an integral part of the HMS, its computational “engine” was created as a software component that exposes its objects, properties, and methods to the host application.

5. Develop a user interface to support software testing and verification. While the key VMES software is the reusable components that comprise its “engine,” a limited user interface was required for software testing.

6. Integrate the VMES components into the full HMS. Integration with the HMS consisted primarily of designing an HMS – VMES interface that mimicked data flows from actual equipment to the HMS.

The first three of these steps for the design of the VMES software were completed under Task 3.1, Virtual Machine Architecture, during Phase 1 of the project. Most of steps 4 and 5 were completed during Phase 2, and Step 4 was completed during Phase 3 by adding objects to calculate cost and time-to-failure (TTF) statistics. Step 6 was completed during the final phase of the project under Task 3.2, Integration With HMS. Task activities and accomplishments for each subtask are discussed in the following sections.

4.1 Virtual Machine Design

Task 3.1 is Virtual Machine Design. A major issue in developing the smart machine concept for NPP equipment is the unavailability of a test bed that can provide rapid turn-around for test results. Real equipment, no matter how well suited for the smart machine concept, experience failures and repairs at a rate that is far too slow to fully support design and optimization of the smart machine system. For example, rules must be developed and tested to allow the smart system to “learn” the equipment being monitored and for making “repair/do not repair” recommendations. The parameters that control these rules need to be optimized for the equipment behavior and the quality of starting data. For these reasons, a means of simulating equipment behavior is required. In effect, a “virtual machine” is needed that can realistically generate the same failure, inspection, and repair events that real equipment experiences.
During Phase 1 of the project, the virtual machine architecture was developed under Task 3.1. The virtual machine was designed as a reusable software component that can readily be incorporated into other software applications. Object-oriented design principles were applied to give the virtual machine properties, methods, and events that allow it to mimic the reliability, inspection, and maintenance characteristics of real equipment. The virtual machine supports design and testing of the HMS, allows evaluation of the benefits of incorporating smart features and provides a platform for realistic demonstrations. Figure 35 illustrates the original concept developed in Phase 1 for the overall architecture of an HMS with a virtual machine employed to supply data instead of an actual component.

![Virtual Machine Architecture Diagram]

Figure 35. Initial concept for the virtual machine architecture.

The virtual machine depicted in Figure 35 consists of three primary components: a reliability module, a scheduling model and a simulation engine. The reliability model identifies failure modes and their relationships including maintenance impact and effects of aging, based on historical data supplemented with engineering judgment. The scheduling module defines schedules for equipment use and maintenance. The simulation engine generates the components behavior (e.g., state changes) based on inputs from the scheduling module and reliability model and provides it as input to the Computerized Maintenance Management System (CMMS) and the HMS software.

During the Phase 1 of the project, the reliability and scheduling module designs were for the centrifugal pump, and the simulation engine was almost completed. Development of an overall HMS architecture integrating the virtual machine, BNs and HMI began. Software design for the alpha version of all components of the virtual machine began with completion planned for Phase 2 of the project.

In Phase 2, the alpha version of the VMES software was completed and a draft user manual was prepared. While all the functionality planned for the VMES was not complete, the more difficult portions
were operational. This version of the VMES software was used in dry run presentations of the HMS demonstration. In Phase 3, the VMES software component was modified to support integration with the HMS. An input manual was prepared that provides details of the VMES object model and input requirements.

**VMES Software**

The VMES uses discrete event simulation to model the reliability behavior of equipment. It does not simulate motion or other physical behaviors. Figure 36 shows an overview of the final VMES architecture.

![VMES Architecture Diagram](image)

**Figure 36. VMES architecture.**

The VMES can be used to mimic the reliability behavior of equipment in terms of simulated equipment failures, repairs, and scheduled maintenance. The simulation is based on user-defined maintenance and inspection schedules, a reliability model with TTF and time-to-repair distributions for all failure modes, and user-specified operational states. The virtual machine provides high-speed simulation of equipment operation, and the HMS generates feedback to modify the behavior of the virtual machine. This feature enables the virtual machine to provide realistic development and demonstration support for the HMS.

By running repeated simulations, the VMES can calculate reliability performance metrics, such as mean time before failure (MTBF), mean time to repair (MTTR), availability, maintenance cost, downtime, etc. This capability allows the VMES to examine the consequences of alternative equipment maintenance scenarios.

Equipment failures are, by definition, unplanned interruptions of the planned use of equipment. Simulation of equipment reliability behavior can be viewed as creating a chronology of equipment state changes and must begin with the planned use for the equipment. The schedule module provides the means to specify the planned equipment usage schedule so that component aging, simulated failures, maintenance, etc., can occur in the context of the planned schedule.

The reliability model is a collection of equipment failure modes. In the final version of the VMES used for this project, the system is assumed to be represented by a series relationship between the
failure modes. A later version may provide an option to characterize the relationship between the system state and failure mode states using a fault tree or block diagram model. The current model contains reliability data including TTF and time-to-repair distribution for the failure modes. The reliability model is intended to provide equipment reliability modeling capabilities for the HMS. For this reason, the model includes properties required to support both predictive maintenance analysis and simulation.

The cost module assumes that the cost of downtime can be characterized by a function that is piecewise constant, in terms of cost per hour for equipment downtime in the current time interval.

The VMES uses discrete event simulation to model the reliability behavior of equipment. Within the simulation engine, the VMES maintains the planned schedule (unchanged during the simulation), the actual schedule (the result of the simulations), and a collection of current events. The actual schedule initially contains only the simulation event; other events are added during the simulation. At any time during the simulation, three possibilities exist for the next system state change:

1. The end of the current event;
2. The occurrence of a failure mode (i.e., implemented in the LSTB); or
3. The beginning of a planned event.

The VMES determines which of these occurs next and takes the appropriate action. If the next event is a failure mode or a planned event, the event is added to the actual schedule and to the current events collection. If the end of a current event causes the next state change, that event is removed from the current events collection. Time is then advanced to the next state change and the process continues. The simulation is complete when no events remain in the current events collection.

The coding for the Schedule Module, Reliability Model, Cost Module, and most of the Simulation Engine portions of VMES were completed during Phase 2. Additionally in Phase 2, an example problem was analyzed to test VMES and to illustrate its capability for simulating equipment failures and maintenance. The purpose of this example was to test the reliability simulation capability of VMES and to provide a limited validation of its simulation algorithms.

The example application was based on data from pressurized water reactors (PWRs) in the United States during the period of 1990 – 1995 [13]. The applicable data were summarized in an MIT report in 1998 [19]. This data identifies the PWR power plant components most responsible for forced outage time. Results of the example are highlighted in the following paragraphs.

The PWR data was used as a basis for a VMES simulation. To provide some validation for VMES, its output should reproduce the PWR reliability metrics as characterized by the original PWR data set. Specifically, VMES should reproduce the MTBF, MTTR, and relative contributions of various components to plant outage time. MTBF and MTTR comparisons are shown in Table 3.

### Table 3. Comparison of Simulation Results with PWR Data

<table>
<thead>
<tr>
<th>Performance Measure</th>
<th>PWR Data</th>
<th>Simulation Results</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>MTBF</td>
<td>4170 Hours</td>
<td>4154 Hours</td>
<td>0.4</td>
</tr>
<tr>
<td>MTTR</td>
<td>171 Hours</td>
<td>172 Hours</td>
<td>-0.6</td>
</tr>
</tbody>
</table>

For both MTBF and MTTR, the simulation results are within 1% of the original data. The contribution of each simulated component to plant outage time is compared to the original data in Figure 37.
The comparison results presented above demonstrate that the VMES has accurately recreated the reliability behavior of the PWRs as represented by the original data set.

![Graph comparing outage times by system/component.](image)

**Figure 37. Comparison of outage times by system/component.**

An example scenario was evaluated to illustrate the use of VMES in evaluating alternative scenarios that could be considered in response to an HMS notification of a pending equipment failure. The basis for selecting the preferred scenario was the cost of electricity not generated as a result of a scheduled or forced outage.

Cost calculations assume a 1300 MW plant and use a wholesale electricity price forecast provided by Reliadigm, a subsidiary of Public Service Company of New Mexico. Daily average forecast prices for 2002 are shown in Figure 38. As shown in the figure, daily average wholesale prices are forecast to range from less than $20/mwh to about $130/mwh.

The example scenario postulates that on June 10, 2002, HMS vibration sensors indicate that a turbine failure appears likely to occur in 1 to 2 weeks. In this case, excessive vibration would be expected to cause the turbine to trip. The VMES was then run for two cases. The first case assumes that we let the turbine run to failure (trip) and the second case assumes that turbine maintenance is scheduled within a day of the warning indication. The two cases are compared based on the cost of lost electricity generation using the wholesale price projections in Figure 38. The results for the two cases are shown in Figure 39. The expected cost of lost electricity generation for the run-to-failure scenario is about $6.7M whereas the expect cost when maintenance is scheduled immediately is about $2.9M. Figure 40 shows the trend for expected cost for one maintenance option if maintenance is delayed.

Additional details and results of the work for this task are provided in the Smart-NPP technical task reports, *Virtual Machine Architecture Report* [7], *Virtual Machine Equipment Simulator (VMES) Alpha Version User Manual* [10], and *Virtual Machine Equipment Simulator (VMES) Beta Version Input Manual* [9].
Figure 38. Daily average wholesale electricity price forecast for 2002.

Figure 39. Cost comparison for two maintenance scenarios.
4.2 Integration with HMS

Task 3.2 is Integration with HMS. The concept of the virtual machine was planned for at least three possible uses in this project, including:

1. Rapid testing and optimization of the rules that govern smart machine decision-making;
2. Estimating the gains, in terms of increased availability, of applying the smart machine concept to specific equipment; and
3. Providing a capability for projecting actual machine performance as an integral part of the smart machine system.

In the first two applications, integration of the virtual machine with the HMS means that the virtual machine must provide inputs to the HMS in much the same way as a real machine. That is, the virtual machine must provide failure, inspection, and repair events, along with simulated sensor data, as direct input to the HMS. For these uses, the virtual machine was used in an application that provided outputs compatible with the HMS interface. The third possible use for the virtual machine would require direct integration of the virtual machine object into the HMS software. Such direct integration was enabled by the fact that the virtual machine object was designed to be an encapsulated, reusable software component.

The major activity for Task 3.2 is development of the HMS software that integrates each of the elements of the system, including the HMI, the physical equipment and sensors, and the BN and VMES. Software integration is achieved by the development of a data hierarchy, software architecture, and message structure that facilitates the exchange of data information among the elements of the HMS.
4.2.1 Data Architecture and Hierarchy

Efforts on software integration during Phase 2 focused on the definition of the data architecture and hierarchy to be used consistently throughout the elements of the HMS. Initially, the development of the data architecture focused on a hierarchical organization of the data and information that would be processed within the elements of the HMS, for example raw sensor data, sensor features, component faults and failure modes and their respective probabilities, up through higher-level system and plant health status. A hierarchical organization of this information is required for the purposes of navigating through the information within the HMS. This organization is embedded within the object model of the HMS software. In developing the elements of the HMS, most importantly the BN, discussed in Section 2.3, but also the HMI, it became evident that the functional relationships among the data information are also important and that a hierarchical organization did not fully support a representation of the functional relationships.

Focusing on the application for the pump/lubrication system, efforts were made to clearly define the relationships between failure modes, faults, sensor features and sensors so that an organizational structure for the data and information could be developed to support both navigation through the HMS software and representation of the functional relationships for a physical system. Fault trees developed earlier in the project were revisited and extended to relate the component failure modes and faults to sensor features. In defining these relationships, it became evident that additional flexibility was required within the object model of the HMS to support the functional relationships of a physical system. As a result of these efforts, a revised structure for the HMS data and object model was developed to represent the functional relationships, as illustrated in Figure 41 and Table 4, with an associated hierarchical structure to support navigation through the HMS. Consistent naming conventions were used by each project team member in the development of their component of the HMS to facilitate message and data transfer, and thus, overall system integration. This information was subsequently used to update the design and development of the HMI, BN, VMES, and related messaging among these elements of the HMS. Additionally, these considerations support the extension of the HMS for a specific component to an enterprise level HMS, as discussed for Task 6 in Section 2.6.

4.2.2 HMS Software Architecture

The HMS architecture can be divided into three parts: the HMS server, the HMI server, and the HMI client. This division allows the HMI client to be run anywhere, locally or remotely over the Internet, and essentially allows multiple instances to support enterprise level implementation. For the purposes of the Smart-NPP prototype demonstration system, the HMS server was located at PSU, the HMS server was located at SNL, and the HMI client was located wherever the demonstration was being presented. The functionality of each of these three parts is as follows:

- The HMS server can be viewed as the data-warehousing server (from an external view, the HMS server only supplies data when requested) that acquires and archives raw sensor data and performs data fusion and sensor feature extraction.
- The HMI server at SNL (or anywhere) can be viewed as the server of the system that receives command requests from the HMI client(s); supplies data response to the HMI client(s); handles feature archiving, BN and VMES computation; and requests data from the HMS server as needed.
- The HMI client(s) is (are) the human-machine interface to the system that is used to request data from the HMS server for display.

The HMI Server is the communication link between the HMS Server and the HMI Client. Therefore, it must already be running before the other two can connect to it. When the application is first
Figure 41. Hierarchy for functional relationships for bearing seizure failure.
Table 4. Functional Hierarchy of Faults and Features for Bearing Seizure Failure

<table>
<thead>
<tr>
<th>BEARING-SEIZURE</th>
<th>Bearing Seizure (Failure Mode)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BE-CLR</td>
<td>Improper Clearances (Fault)</td>
</tr>
<tr>
<td>CLR-TGT</td>
<td>Clearances Too Tight (Fault)</td>
</tr>
<tr>
<td>BRG-LUB-TMP</td>
<td>Bearing Oil Temperature (Feature)</td>
</tr>
<tr>
<td>BABBIT-TMP</td>
<td>Babbit Temperature (Feature)</td>
</tr>
<tr>
<td>CLR-LSE</td>
<td>Clearances Too Loose (Fault)</td>
</tr>
<tr>
<td>RATIO-HARM</td>
<td>Ratio of Harmonic Vibrations (Feature)</td>
</tr>
<tr>
<td>ACCELEROMETER</td>
<td>Accelerometer (Sensor)</td>
</tr>
<tr>
<td>PROX-PROB-X</td>
<td>Proximity Probe X (Sensor)</td>
</tr>
<tr>
<td>PROX-PROB-Y</td>
<td>Proximity Probe Y (Sensor)</td>
</tr>
<tr>
<td>NUM-HARM</td>
<td>Number of Harmonics (Feature)</td>
</tr>
<tr>
<td>ACCELEROMETER</td>
<td>Accelerometer (Sensor)</td>
</tr>
<tr>
<td>PROX-PROB-X</td>
<td>Proximity Probe X (Sensor)</td>
</tr>
<tr>
<td>PROX-PROB-Y</td>
<td>Proximity Probe Y (Sensor)</td>
</tr>
<tr>
<td>CLR-ASY</td>
<td>Axial Asymmetry (Fault)</td>
</tr>
<tr>
<td>BRG-LUB-TMP</td>
<td>Bearing Oil Temperature (Feature)</td>
</tr>
<tr>
<td>1X-PHASE</td>
<td>1X Phase</td>
</tr>
<tr>
<td>PROX-PROB-X</td>
<td>Proximity Probe X (Sensor)</td>
</tr>
<tr>
<td>PROX-PROB-Y</td>
<td>Proximity Probe Y (Sensor)</td>
</tr>
<tr>
<td>2X-SHAFT-VIB</td>
<td>2X Shaft Vibration</td>
</tr>
<tr>
<td>PROX-PROB-X</td>
<td>Proximity Probe X (Sensor)</td>
</tr>
<tr>
<td>PROX-PROB-Y</td>
<td>Proximity Probe Y (Sensor)</td>
</tr>
<tr>
<td>BE-LOAD</td>
<td>Improper Loading (Fault)</td>
</tr>
<tr>
<td>LOAD-STO</td>
<td>Static Overload (Fault)</td>
</tr>
<tr>
<td>BRG-LUB-TMP</td>
<td>Bearing Oil Temperature (Feature)</td>
</tr>
<tr>
<td>BABBIT-TMP</td>
<td>Babbit Temperature (Feature)</td>
</tr>
<tr>
<td>RATIO-ORBAX-AXES</td>
<td>Ratio of Orbit Axes (Feature)</td>
</tr>
<tr>
<td>PROX-PROB-X</td>
<td>Proximity Probe X (Sensor)</td>
</tr>
<tr>
<td>PROX-PROB-Y</td>
<td>Proximity Probe Y (Sensor)</td>
</tr>
<tr>
<td>SHAFT-ECCY</td>
<td>Shaft Eccentricity (Feature)</td>
</tr>
<tr>
<td>PROX-PROB-X</td>
<td>Proximity Probe X (Sensor)</td>
</tr>
<tr>
<td>PROX-PROB-Y</td>
<td>Proximity Probe Y (Sensor)</td>
</tr>
<tr>
<td>LOAD-STU</td>
<td>Static Underload (Fault)</td>
</tr>
<tr>
<td>RATIO-ORBAX-AXES</td>
<td>Ratio of Orbit Axes (Feature)</td>
</tr>
<tr>
<td>PROX-PROB-X</td>
<td>Proximity Probe X (Sensor)</td>
</tr>
<tr>
<td>PROX-PROB-Y</td>
<td>Proximity Probe Y (Sensor)</td>
</tr>
<tr>
<td>ENERGY-BAL</td>
<td>Energy Balance (Feature)</td>
</tr>
<tr>
<td>SHAFT-ECCY</td>
<td>Shaft Eccentricity (Feature)</td>
</tr>
<tr>
<td>PROX-PROB-X</td>
<td>Proximity Probe X (Sensor)</td>
</tr>
<tr>
<td>PROX-PROB-Y</td>
<td>Proximity Probe Y (Sensor)</td>
</tr>
<tr>
<td>SUB-SYNC-VIB</td>
<td>Subsync. Vibration (Feature)</td>
</tr>
<tr>
<td>PROX-PROB-X</td>
<td>Proximity Probe X (Sensor)</td>
</tr>
<tr>
<td>PROX-PROB-Y</td>
<td>Proximity Probe Y (Sensor)</td>
</tr>
</tbody>
</table>
Table 4. Functional Hierarchy of Faults and Features for Bearing Seizure Failure (concluded)

<table>
<thead>
<tr>
<th>LOAD-DYO</th>
<th>Dynamic Overload (Fault)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BABBIT-TMP</td>
<td>Babbit Temperature (Feature)</td>
</tr>
<tr>
<td>2X-VANE-PASS</td>
<td>2X Vane Pass (Feature)</td>
</tr>
<tr>
<td>ACCELEROMETER</td>
<td>Accelerometer (Sensor)</td>
</tr>
<tr>
<td>SHAFT-VIB</td>
<td>Shaft Vibration (Feature)</td>
</tr>
<tr>
<td>PROX-PROB-X</td>
<td>Proximity Probe X (Sensor)</td>
</tr>
<tr>
<td>PROX-PROB-Y</td>
<td>Proximity Probe Y (Sensor)</td>
</tr>
<tr>
<td>VISCOSITY</td>
<td>Oil Viscosity (Feature)</td>
</tr>
<tr>
<td>VISCOSITY-METER</td>
<td>Viscosity Meter (Sensor)</td>
</tr>
<tr>
<td>BE-LU</td>
<td>Improper Lubrication (Fault)</td>
</tr>
<tr>
<td>LU-PRE</td>
<td>Bad Oil Pressure (Fault)</td>
</tr>
<tr>
<td>LUB-OUTPUT-PRE</td>
<td>Lube Oil Output Pressure (Sensor)</td>
</tr>
<tr>
<td>LU-TMP</td>
<td>Bad Oil Temperature (Fault)</td>
</tr>
<tr>
<td>BRG-LUB-TMP</td>
<td>Bearing Oil Temperature (Feature)</td>
</tr>
<tr>
<td>LU-QUAL</td>
<td>Inadequate Oil Quality (Fault)</td>
</tr>
<tr>
<td>QUAL-CHM</td>
<td>Chemical Contamination of Oil (Fault)</td>
</tr>
<tr>
<td>SPECTROSCOPY</td>
<td>Spectroscopy (Sensor)</td>
</tr>
<tr>
<td>VISCOSITY</td>
<td>Viscosity (Feature)</td>
</tr>
<tr>
<td>VISCOSITY-METER</td>
<td>Viscosity Meter (Sensor)</td>
</tr>
<tr>
<td>QUAL-DRT</td>
<td>Dirt/Debris in Oil</td>
</tr>
<tr>
<td>PART-COUNT</td>
<td>Particle Count (Feature)</td>
</tr>
<tr>
<td>GAS-TOPS</td>
<td>Gas Tops (Sensor)</td>
</tr>
<tr>
<td>BABBIT-MASS</td>
<td>Babbit Mass (Feature)</td>
</tr>
<tr>
<td>GAS-TOPS</td>
<td>Gas Tops (Sensor)</td>
</tr>
<tr>
<td>QUAL-DEG</td>
<td>Oil Degradation</td>
</tr>
<tr>
<td>VISCOSITY</td>
<td>Viscosity (Feature)</td>
</tr>
<tr>
<td>VISCOSITY-METER</td>
<td>Viscosity Meter (Sensor)</td>
</tr>
</tbody>
</table>

Color Code: Failure Mode; Fault; Sensor Feature; Sensor

executed, it also launches a data socket server, thus enabling communication between itself and HMS Server in PSU. At this time, the HMS Server can be manually connected to the data socket server. From this point in the system operation, the HMS Server and HMI Server are transparent and the HMI Client(s) can now connect to the HMS Server via the data socket server.

The login/logout step from HMI server to HMS Server is not necessary since both was running continuously and must maintain the data socket connection to function properly. Login will only be require when connecting from the HMI Client to HMI Server since HMI Client is the only human interface to the system.

The HMI server consists of a data socket message center, a BN object for fault states probability calculation, one VM object for TTF calculation, and one VM object for maintenance cost calculation. The message center is divided into two pieces, one to designate communication with the HMI client, and the other for communication with the data acquisition system (DAQ) at PSU.

The HMI server is an event driven system that will do nothing until a message is received from either the HMI client or the DAQ system. When a message is received, it is processed it according to the message type.

When a data request message is received from the HMI client, the system will first check what kind of request it is and process accordingly. For a basic data request, such as feature/sensor data,
feature/sensor history, and sensor snapshot, the system will forward (pass through) that request to the DAQ system with no change. For other request like faults, TTF, or maintenance cost, the system will send a request for feature data to the DAQ system. The system will also set a calculation flag to notify itself that the next feature data receive from the DAQ is for faults, TTF, or maintenance cost calculation.

When a data response message is received from the DAQ, the HMI server will first check what type of message it is. If the message type is feature data and the calculation flag is set, the system will call the calculation routines according to the calculation flag. If the calculation flag was not set, the system will forward the feature data message to the HMI client. All other message types are also forwarded back to the HMI client as a simple data request.

Requests that require further calculation like faults, time to failure, and cost maintenance work together in a daisy chain fashion. Fault calculations require feature data that came from the DAQ system. Time to failure require the state probability that was the result of fault calculation. Maintenance cost requires the time to failure results. So for maintenance cost calculation, the system first calculates the faults using the latest feature data from DAQ, then uses the result for to calculate TTF, and finally uses TTF to calculate maintenance cost. For data consistency, each time a section is done calculating its result, it will send it back to the HMI client. Each of the three key calculations section are described in the following paragraphs:

Fault Request

When a fault request is received, the HMI server sends out a feature request to the DAQ. When the new feature data is received from the DAQ, the HMI converts it into the three state probability using data interpolation, and uses that as the input for the BN object. After the BN object is done calculating the faults states, the result is assemble and sent back to the requesting HMI client.

TTF

TTF is found by first calculating the fault states, so the HMI server will go through the steps above of finding the fault states. The resulting fault states are used as input to the virtual machine for the TTF calculation. The system is set up to run 100 simulations to get the final TTF. The resulting data is assembled as a TTF message and sent back to the requesting HMI client.

Maintenance Cost

To calculate cost data, the HMI server requires the TTF for the main component. Again, the server will go through the fault state calculation and the TTF calculation. The result is put into another virtual machine simulation object to calculate the cost. The resulting data is assembled as maintenance cost message and sent back to the requesting HMI client.

Figure 41 illustrates the functionality of the HMS software module.

4.2.3 Interface Between the HMS Server, HMI Server and HMI Client

The interface between the HMS server, HMI server, and HMI client are defined by the formats of messages that are passed between them. During Phase 2, the set of messages and message structures were defined and used in the design and development of each element of the HMS, and several communications tests were conducted to demonstrate this capability. These messages included the following:
Figure 42. HMS software functionality.

Between HMI Client and HMI Server
1. Login: Sent from the HMI Client to the HMI Server to log on to the server prior to receiving data.
2. Logout: Sent from the HMI Client to the HMI Server to log out.

Between HMI Client and HMI Server or HMI Server and HMS Server
3. FaultRequest: to request current fault information.
4. FeatureRequest: to request current feature information.
5. DrillDownRequest: to request drill-down data.
7. FeatureResponse: response to a request for current feature information.
8. DrillDownResponse: response to a request for drill-down data.
9. SensorHealth: to indicate a failed sensor.
10. DisplayMessage: Sent in either direction as information. For example, sent from the HMS Client to the HMS Server to request a particular fault be initiated.

Testing and refinement of these message structures continued in Phase 3 during actual system integration and implementation of demonstration activities.
5 Task 4 – Smart Equipment Health Monitoring System

Task 4 is Smart Equipment Health Monitoring System. The objective of this task was to develop methods for taking sensor data from the equipment-monitoring program and translating that data into information about the equipment health. Developing methods for taking sensor data from the component monitoring and translating it into information about the equipment's health is the heart of the Smart-NPP program. Equipment health can include information about predicted lifetime of the equipment, estimated percentage wear out on various components, recommendations for preventive maintenance activities, predictions of likely failure modes and causes and cost impact of maintenance-related decisions. The first step was to select a methodology for evaluating the health of a system and ultimately the health of the total enterprise. This methodology must be able to relate sensor data to the component health. In addition, sensor data filtering and reduction by the methodology must be developed. The final system should include the utilization of historical maintenance data as part of the HMS. The work for this task began in Phase 1 and will continue through the completion of the project. This task includes three subtasks: Task 4.1, Relate Sensor Data to Component Health; Task 4.2, Sensor Data Filtering and Reduction; and Task 4.3, Utilization of Historical Maintenance Data.

During Phase 1, work began on Task 4.1, Relate Sensor Data to Component Health. A significant accomplishment in Phase 1 of the project was the decision to follow the smart equipment methodology outlined by Golay and Kang [19] at MIT. This previous work at MIT provided a structure for developing comprehensive sensor networks and analysis of the data provided from them to create an intelligent diagnostic and maintenance advisory system. Adoption of this methodology provided direction to development of the demonstration HMS. Specifically, fault trees were constructed providing a functional decomposition of the centrifugal pump. Starting at the highest level of "pump failure" the fault trees break down pump subsystems until individual cause-consequence branches are identified.

Also of importance to the HMS development was the endorsement of Bayesian networks (BN) as the engine needed to capture the expertise relating sensor data to system states using conditional probabilities. The BN approach was selected because (1) it has been shown to work better than rule-based and neural network systems; (2) it is very flexible and tolerant of complexity; and (3) it is available on personal computer with a convenient user interface. The Hugin Expert A/S BN shell was selected for use on the project and an initial canned demonstration of an application was completed. The effort to populate the conditional probabilities based on input from pump and maintenance experts was initiated in Phase 1 and continued through Phase 2 and Phase 3.

Task 4.2 is Sensor Data Filtering and Reduction. The objective of this task was to determine effective data reduction methods that preserve the essence of the needed information. During the project planning for Phase 2, the work for Task 4.2 was redirected from general investigation of methods for data filtering and reduction to specific data and filtering needed to support the LSTB and the BN for the Smart-NPP demonstration HMS to support Tasks 4.1 and Task 5 (through the work for Task 2.4). The work for this task can be broadly characterized as “sensor fusion.” This work included looking at low-level data manipulation, translating voltage readings from sensors to the appropriate scale for the monitoring variable, and determining appropriate methods for making diagnostic decisions based on multiple sensor inputs. Task activities and accomplishments in this area are reflected in the work for Task 2.4, Sensor Installation Support for Demonstration, discussed in Section 2.2.4.

Task 4.3 is Utilization of Historical Maintenance Data. During the project planning for Phase 2, the work for this task was redirected from general consideration of utilizing historical maintenance data to specific application for the pump/lubrication system demonstration HMS to support the development of the BNs in Task 4.1. This work included investigations of how to effectively utilize historical RCM data, equipment failure reports, rotor dynamics models, and root cause assessments to optimize sensor placement, monitoring techniques, and data processing for the high energy, horizontal, centrifugal pump.
Incorporation of maintenance data with the sensor data to aid in the prediction of component health was investigated. Task activities and accomplishments in this area are reflected in the work for Task 4.1, discussed in the following sections.

5.1 Relating Sensor Data to Component Health

Task 4.1 is Relating Sensor Data to Component Health. The objectives of this task were to develop methods for translating sensor data from equipment monitoring programs into equipment health information, evaluate methods of equipment health diagnostics and prediction, and evaluate methods of data reduction. BNs were selected for modeling the qualitative and quantitative knowledge about relationships among failure modes, faults, and sensor features.

An NPP must be maintained to satisfy the Technical Specifications and other rules and regulations during all operating phases, including normal and unscheduled operations. Adherence to these requirements leads to handling a large information database involving numerous plant components. Prediction of the possible fault occurrences, diagnosis of failures to identify which component(s) to maintain is usually time-consuming and is vulnerable to human errors and omission due to the large scale of information to be handled. Another problem is to determine whether taking a plant component out of service to repair or to apply on-line maintenance to the component is the most beneficial decision. To this effect, a reliable expert system is necessary for sound decision support, on-line diagnosis and predictive maintenance in the nuclear plants. For this, the knowledge of the experts in the relevant area needs to be assimilated for implementation within the technical information database, that is to say, within the knowledge base of the expert system. The goal of an expert system is to develop a software tool that achieves a high level of performance on problems that are difficult enough to require significant human expertise and understanding for their solution. The knowledge representation and reasoning paradigm that are adopted for our project are based on Bayesian Theory and BNs. The software tool that is used in preparing the expert system is Hugin Professional 5.6.

5.1.1 BNs and Bayesian Methods

Numerous representations and techniques are available for data analysis, including rule bases, decision trees, neural networks, etc., and density estimation, classification, regression, and clustering. BNs and Bayesian methods were selected for several reasons. BNs can readily handle incomplete data sets. When one of the input variables is not observed, most other models will produce an inaccurate prediction, because they do not encode the correlation between the inputs variables. BNs offer a natural way to encode such independence. BNs allow one to learn about causal relationships. This process is useful when one is trying to gain understanding about a problem domain. In addition, knowledge of causal relationships allows us to make predictions in the presence of interventions, namely in decision making. BNs in conjunction with Bayesian statistical techniques facilitate the combination of domain knowledge and data. It is very important to have prior or domain knowledge, especially when data is scarce or expensive. The fact that expert systems can be built from prior knowledge alone is a proof to the power of knowledge. BNs have causal semantics that makes the encoding of causal prior knowledge particularly straightforward. In addition, BNs encode the strength of causal relationships with probabilities. Consequently, prior knowledge and data can be combined with techniques from Bayesian statistics. BNs facilitate the decision maker’s reasoning under uncertainty, because it can provide a complete probabilistic description of a domain. This is important because the probabilistic reasoning or modeling, together with decision theory, is a key theoretical tool for addressing uncertainty in intelligent systems of all kinds. In this way, BNs provide also a better resolution for variable representation than other methods.
5.1.1.1 BNs And The Fundamental Theory

This section introduces the basic definitions and the theory to later explain the reasoning in the theoretical concepts of BNs.

**Conditional probability:** The basic concept in Bayesian treatment of uncertainties in causal networks is conditional probability. It represents the probability of an event, $A$, given that the event $E$ is true and everything else known is irrelevant for $A$. The notation for this statement is $P(A|E)$.

**Fundamental rule:** The fundamental rule for probability calculus is

$$P(A|E)P(E) = P(A,E),$$

$$P(E|A)P(A) = P(A,E),$$

where $P(A,E)$ is the probability of the joint event $A \land E$.

**Bayes’ rule, Theorem:** From Equation 1, it follows that

$$P(A | E) = \frac{P(E | A)P(A)}{P(E)}$$

which is known as the Bayes’ rule. In the Bayesian interpretation, the probability of certain hypothesis $A$ being true, $P(A)$, represents the degree of belief in that hypothesis. After new evidence $E$ is received, which may reinforce or weaken that hypothesis, this degree of belief becomes $P(A|E)$ and can be formally updated according to the Bayes’ rule.

**Subjective probability:** Bayesian technique does not only consider probabilities based on frequencies. Probabilities may also be completely subjective estimates of the certainty of an event. The fundamental rule and Bayes’ rule are also proved for subjective probabilities [20].

**Bayesian network:** A BN is a method of quantifying the strength in the causal relations. It consists of the following [20]:

- A set of variables and a set of directed edges between variables
- Each variable has a finite set of mutually exclusive states
- The variables together with the directed edges form a directed acyclic graph (DAG).
- To each variable $A$, with parents $B_1, ..., B_n$, there is attached the conditional probability table, or potential table, $P(A|B_1, ..., B_n)$.

**Conditional independence:** The blocking of transmission of evidence information is, in Bayesian calculus, reflected in the concept of conditional independence. Two variables $A$ and $C$ are conditionally independent given a third variable $B$, if when the value of $B$ is known, knowledge about the variable $C$ provides no further information about the variable $A$, or vice versa. This implies the result,


**Chain rule for BNs, Theorem:** Given a fully specified BN, the joint probability of all the variables can be constructed using the chain rule theorem.

Let BN be a BN over the set of variables $U = \{A_1, ..., A_n\}$. Then the joint probability distribution $P(U)$ is the product of all potentials specified in BN [20]:

$$P(U) = \prod_i P(A_i | pa(A_i))$$
where $pa(A_i)$ is the parent set of $A_i$.

**Evidence and Bayesian updating:** BNs are used for calculating new probability values when particular information is received. Some finding on the variable $A$ with $n$ states is represented as an $n$-dimensional evidence table, $e$. Let BN be a BN over the set of variables $U = \{A_1, ..., A_n\}$, and let $e_1, ..., e_n$ be findings; then the joint probability distribution for the variables and the new findings is obtained as

$$P(U, e) = \prod_j P(A_j | pa(A_j)) \prod_j e_j$$

which yields, from Bayes’ rule, Equation 2, the result

$$P(A_i | e) = \frac{\sum_{U \not= A_i} P(U, e)}{P(e)}$$

where the probability of obtaining the observed evidence is $P(e) = \Sigma e(P(U, e))$.

This theorem is particularly useful in contexts where findings are more easily obtained in one inferential direction than another. It provides the flexibility to reason in either the causal or consequential direction. Therefore, it presents a convenient way of updating belief in a proposition in light of a previously obtained probability distribution, and new evidence.

### 5.1.1.2 Diagnostic BN Structure

Given some information about the state of the variables, one can infer additional information. If this inference is used to deduce an effect from a given cause, it is called prediction. If it is used to find a cause, given an effect, it is called diagnosis. It involves drawing possible inferences rather than a certain one. Both directions of information flow can be inferred in BNs. However, the primary purpose of the implementation of the Bayesian model within the scope of our work is the fault diagnostic task, in order to provide interpretation of the current status of the monitored SSC using the domain knowledge and recent measurements. Therefore, it is called the BN diagnostic model. In addition, consistent with its definition, the pending failures are predicted by the Bayesian model, too. The following sections describe the methodology used in the design of the diagnostic model. This model is implemented focused upon the target component, which is the bearing system as used in high-energy horizontal charging pumps.

**Variables And States**

The variables that are included in the BN diagnostic model are the primary and higher level faults and the failure modes of the monitored SSCs, and the sensor features that collect information about the status of the relevant faults. All of the variables have mutually exclusive states.

The states of the sensor features aim to interpret the measurements by the sensors. The measurements can range from “low” to “high” readings. Therefore, we define the states of sensor features parallel to this range. However, the detail used in partitioning the measurement range into feature states should be feasible, considering the exponentially growing knowledge base size with the variables and their states. Therefore, we recommend three states for the sensor features to be implemented in this work. These states are low, medium and high. The meaning of these states may vary from sensor to sensor. For instance, a “low” reading on a sensor signal may be a good indication, whereas a bad one for another sensor signal.
The states of the fault and failure mode variables should indicate the severity of the progress of these events, as well as the normal operational conditions. Hence, we define the states of these variables, i.e., $F$, as normal, intermediate and severe. There may be some exceptions to this set of states depending on the characteristics of the fault. Nevertheless, they hold valid for the large majority of the possible faults. For a fault or failure mode variable, $F$, the normal state indicates that no fault or failure exists in the system due to $F$. The intermediate state indicates the incipient occurrence of $F$, which means that $F$ is pending to become serious. The severe state indicates that $F$ has already progressed to full occurrence.

As a result of the inference, the states of any fault or failure mode variable $F$ in the diagnostic model are provided with a probability value which defines the likelihood of that variable being in a particular state given the current conditions. The details of the inference mechanism are presented in the Section 2.4.2.5.

Causal Relations

The relations between causes and effects, namely the causal relations, in the monitored SSC are represented graphically in the BN diagnostic model. The causal relations in the model actually define the physical behavior of the functions of the monitored component.

The changes in the sensor feature states are caused by the changes in the primary level basic fault event status. Hence, we treat the primary fault variables as the initiators during fault propagation in a physical system. The causal relation between the primary fault variables and sensor feature variables in the BN diagnostic model is shown in Figure 43 with a simple representative structure. The arrow is directed from the cause to the effect, hence from fault to sensor features.

The changes in the states of the higher level faults or failure modes are caused by the changes in the status of the primary level faults or other higher-level faults or failure modes. This type of causal relation is simply illustrated in Figure 44. The arrow is directed from the cause to the effect, hence from the faults to the failure mode. Similarly, the effect variable in Figure 44, instead of a failure mode, can be a higher-level fault caused by the primary level faults.

![Figure 43. Bayesian diagnostic model for one primary fault event and two sensor features.](image1)

![Figure 44. Bayesian diagnostic model for two primary fault events and one failure mode.](image2)
5.1.2 Knowledge Acquisition For The Knowledge Base Construction

Three distinct approaches can be taken to acquire the relevant knowledge for a particular domain:

- The knowledge is elicited from the domain experts;
- The builder of the knowledge-based system is a domain expert;
- The system learns and generates its knowledge base from a set of examples.

In this work, we adopted the first approach in constructing the knowledge base of the BN diagnostic model. The domain knowledge that is elicited from the experts is encoded in the knowledge base of the model with the BN representation. The domain knowledge is acquired from the experts through interviews that communicate this knowledge to the diagnostic model of the target system. However, the BNs themselves have the capability to enhance the constructed knowledge base by utilizing the third approach in acquiring knowledge, at later operating stages of the model. This is done by updating the input conditional probability values in the light of the data collected during the operation of the model. This feature of BNs has two advantages. The first is the enhancement of the knowledge base if the initial input to it is imperfect. The second is the ability to adapt to changing operating environments.

The knowledge acquisition is the “bottleneck” of the design of knowledge-based systems. The completion of the knowledge base construction is a long, iterative, and tedious stage. The interviews with the domain experts involve a lot of questioning, which may sometimes be unclear to the domain experts if they do not know about the properties of Bayesian techniques. Therefore, the interaction with the domain experts while eliciting the knowledge should be structured appropriately. We recommend that the candidate domain experts be trained briefly on this technique. After the training, regular meetings should be held for acquiring the domain knowledge into the knowledge base. In addition, articulating the knowledge to the representation of the system requires very much effort. Particular attention should be given to this stage of work because the usefulness of the system relies upon two main factors, one of which is the properness of the knowledge base. We recommend that the questions be well explained. Use of visual tools can help clarifying the questions being asked in the knowledge elicitation process. The other important factor in reliable operation of the system is the sufficiency of the amount of data that is collected during the operation. We recommend using as many as appropriate amounts of sensor features in the model. The cost of the sensors can be the restricting criterion in the decision for the amount of sensor features to be utilized.

The knowledge base of the BN diagnostic model is structured around two elements. First one is the qualitative knowledge base, and second one is the quantitative knowledge base [21]. We explain both of these elements in the following sections.

5.1.2.1 Qualitative Knowledge Base

The qualitative knowledge base acquisition of the BN diagnostic modeling for the NPP operations starts with the construction of the functional hierarchy of the target SSC. The functional hierarchy is an efficient and organized way of expressing the prestructure of the system on which the diagnostic system was applied. It also reflects the range of problems that the expert system is expected to solve. The functional hierarchy in the target SSC is composed of the following:

- Top event, failure of the SSC;
- Failure modes of the SSC;
- High level faults that would cause the failure modes to activate;
• At successive states of the hierarchy, faults that would cause the higher level of faults in the hierarchy, i.e., primary level faults;
• Features that are measured to get information on the status of the relevant primary level faults.

Figure 45 shows the form of the functional hierarchy that is adopted for the design of the Bayesian model.

However, the functional hierarchy itself is not enough to specify all the causal links among the variables of the diagnostic model. Some faults or failure modes in different branches of the functional hierarchy may be dependent upon each other, whereas these dependencies cannot be explicitly represented in the hierarchy; for instance the possible common cause failures. After the completion of the functional hierarchy of the operation of the target system, we derived all the causal relations that actually define the physical behavior of the SSC and added them to the qualitative knowledge base.

The next step is representing the qualitative knowledge in the BN knowledge base. The complete functional hierarchy and thorough determination of all causal relationships in the monitored SSC, in effect, provide all the variables and the directed links that are to be represented in the graphical structure of the Bayesian model. Then, considering the characteristics of the features, faults, and failure modes, we assigned the relevant mutually exclusive states to all the variables. The DAG structure in the Bayesian model is prepared at this stage, by using all the variables and causal links. Nodes of the graph represent the variables. The causal links are represented by directed arrows, which are directed from cause to effect. The final DAG embodies all the qualitative knowledge necessary for the BN diagnostic model.

The graph determines the structure and the semantics of the reasoning in the diagnostic task on the target SSC. The models in Figures 43 and 44 are examples of small-scale graphs in a BN diagnostic model. The nodes in these figures represent the sensor feature, fault, and failure mode variables. The arrows represent the causal directed links.

### 5.1.2.2 Quantitative Knowledge Base

The quantitative knowledge base quantifies the strength of the causal relations in the graph structure of the Bayesian model. The quantification involves defining the strength of causal links in terms of conditional probabilities. Each causal link is associated with a conditional probability table. The conditional probabilities represent the belief that an effect variable is in a certain state, given that the state of the cause variable is known. Thus, in this step, all required conditional probability values are subjectively elicited from the domain experts and assigned in the relevant entries of conditional probability tables.

We note that the domain experts in the nuclear industry are usually not yet familiar with Bayesian concepts. Therefore, the scheme developed in this work configures a general framework concerning how to elicit their expertise at this stage, and then to articulate it into a Bayesian form.

Figures 43 and 44 are the graph structure in a Bayesian model. They are actually the two standard sub-networks in the larger scale diagnostic BNs. Therefore, delineating the form of the quantitative knowledge base of these networks yields a general form for constructing the knowledge base for larger scale networks.

Table 5 illustrates a standard table for obtaining probability values linking a specific sensor to a primary level fault mode. The number of conditional probability values in a particular link depends upon the number of states of a fault mode node and those of a sensor feature node. This means that a sensor node with three states linked to a fault mode node with three states requires a 3 by 3 matrix as shown in Table 5. In this table, $P(i|j)$ is the probability for sensor feature to be at state $i$ given that the fault is at
Table 5. Conditional probability table for linking one three-state fault mode to one three-state sensor feature, in terms of $P(S|F)$

<table>
<thead>
<tr>
<th>Sensor State</th>
<th>Normal</th>
<th>Intermediate</th>
<th>Severe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>$P(l</td>
<td>n)$</td>
<td>$P(l</td>
</tr>
<tr>
<td>Medium</td>
<td>$P(m</td>
<td>n)$</td>
<td>$P(m</td>
</tr>
<tr>
<td>High</td>
<td>$P(h</td>
<td>n)$</td>
<td>$P(h</td>
</tr>
</tbody>
</table>

state $j$, where $\Sigma_i P(i|j) = 1$. A degree belief relating to each value of $P(i|j)$ is elicited through interviews from domain experts.

The corresponding causal reasoning values for the BN in Figure 44 are illustrated in Table 6. The number of conditional probability values in such links with multiple causes depends on the number of cause variables, the number of states of the cause variables, and those of the effect variables. For two three-state causes and one three-state effect, as in Figure 44, this means the conditional probability table becomes a 3 by 3 by 3 matrix. This matrix is shown in a layered form in Table 6. In this table, $P(i|j, k)$ is the probability for failure mode to be at state $i$ given the faults are at states $j, k$, where $\Sigma_i P(i|j, k) = 1$. A belief degree relating to each value of $P(i|j, k)$ is elicited through interviews from domain experts.
Table 6. Conditional probability table for linking two three-state fault modes, $F_1$ and $F_2$, to one three-state failure mode, $F_3$, in terms of $P(F_3|F_1, F_2)$

<table>
<thead>
<tr>
<th>Failure-3 State</th>
<th>Fault-1 State = Normal</th>
<th>Fault-2 State</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>$P(n</td>
<td>n, n)$</td>
</tr>
<tr>
<td>Intermediate</td>
<td>$P(i</td>
<td>i, n)$</td>
</tr>
<tr>
<td>Severe</td>
<td>$P(s</td>
<td>n, n)$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Failure-3 State</th>
<th>Fault-1 State = Intermediate</th>
<th>Fault-2 State</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>$P(n</td>
<td>i, n)$</td>
</tr>
<tr>
<td>Intermediate</td>
<td>$P(i</td>
<td>i, n)$</td>
</tr>
<tr>
<td>Severe</td>
<td>$P(s</td>
<td>i, n)$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Failure-3 State</th>
<th>Fault-1 State = Severe</th>
<th>Fault-2 State</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>$P(n</td>
<td>s, n)$</td>
</tr>
<tr>
<td>Intermediate</td>
<td>$P(i</td>
<td>s, n)$</td>
</tr>
<tr>
<td>Severe</td>
<td>$P(s</td>
<td>s, n)$</td>
</tr>
</tbody>
</table>

The size of such input matrices grows exponentially as the number of causal nodes feeding into an effect node increases. However, we found that it was almost impossible for the domain experts to provide consistent values for such tables if there are three or more causal nodes. Therefore, we found it most appropriate to limit the number of causal nodes feeding into one effect node to two. In the cases where there are more than two causes to one event, a BN trick called “divorcing” was applied [20]. The divorcing method separates the cause variables into partial groups that are combined with mediating variables. The mediating variables then cause the final effect. We implemented this method when thought necessary in our target system application.

5.1.2.3 Method Of Knowledge Base Construction

In this work, while implementing our methodology at the target system, we performed the elicitation of the domain knowledge through interviews with the domain experts. The domain experts were two engineers who had expertise in the operation of the charging pumps, and the corresponding bearing system. The domain experts were educated on the basics of the BN techniques with a short course prior to the work of actual modeling. We asked the domain experts two main categories of questions: the first related to the qualitative causal structure of the model, the second related to the quantification of the strength of the causal relations in the model. The procedure of the interview is summarized as follows.
First, the interviewees are asked to determine the possible failure modes, faults and the symptoms (sensor features) that the faults can give concerning the target system operation. The answers to this question yield all the variables in the BN diagnostic model. The determination of the mutually exclusive performance states of these variables is also attained in this step of the interviews. Then, the domain experts are requested to structure the indicated failure modes, faults and the sensor features in a functional hierarchy. The functional hierarchy yields part of the causal relations. Last, the domain experts are asked to explicitly point out which variables constitute the causes and effects in the BN model. This procedure finalizes the qualitative graphical structure in the BN diagnostic model of the target physical system.

Second, the domain experts are asked to quantify the strength of the causal relations between the variables of the BN diagnostic model. In this stage, the subjective values of the conditional probabilities defined in Tables 5 and 6 are elicited from the interviewees. The meanings of the values in these tables are explained in the previous subsection under the “Quantitative knowledge base” heading.

During the interviews, we avoided bias and prejudice about the answers we get from the domain experts. This is important in reflecting the actual subjective estimate of the domain experts into the model. However, we checked the consistency of the values in individual probability tables and among several related tables during and after each of the interviews with the domain experts. The purpose of the consistency check was to maintain the reliability of the logic behind defining the relations and the values.

5.1.2.4 Refinement Of The Knowledge Base For Verification

In this work, we observed that it is necessary to first construct the qualitative knowledge base, then complete the quantitative knowledge base, as the conditional probability tables depend on the structure of the model. However, once the qualitative and quantitative knowledge base discussion comes to the end of first round, it is also necessary to test the model to verify its results. We performed the testing of this model both by asking the domain experts judgements and by comparing the results with experimental data from the test bed. Both during the design stage and after the test stage, the model was refined and iterated many times in order to give the best possible and consistent results. Acquiring the conditional probability tables during the quantitative knowledge elicitation is especially a very difficult phase for the domain experts. They sometimes feel under pressure, and sometimes are exhausted, that the subjective probability values that they present are not necessarily always the most appropriate ones. Considering this, we revisited the BN diagnostic model knowledge base, both its qualitative and especially quantitative parts, many times. We note that the refinement of the input and verification of the results are important pieces of the knowledge acquisition stage to ensure the reliability of the model.

5.1.3 Expert System Shell

In translating the acquired knowledge base to Bayesian inference, one either needs to program a software model using AI languages, such as LISP or PROLOG, or one needs to find an appropriate expert system shell with which the Bayesian modeling can be accomplished in an easier way. The major advantage of an expert system shell is to save time and effort required to develop a graphical and inferential mechanism, and other auxiliary features for expert system use. We preferred to choose an appropriate expert system shell, and to dedicate this effort to the development and refinement of modeling without getting involved in the details of programming.

Even though the theoretical advantages of BNs have been recognized in the past, there was insufficient capability to support Bayesian expert system shells using modern graphical representations. The recent rapid development of computer technologies has made it possible to create BN based expert system shells supported by modern graphics. Since the graphical representation of the knowledge base is
a valuable feature of BNs, it is important to choose an expert system shell with graphical representation capability. Other important factors in choosing the expert system shell were the system integration capability with other systems, user-friendly structure, computational performance, and cost.

Through an evaluation based upon this set of criteria, we chose the HUGIN expert system shell as having the best set of combined features and good record of previous applications in other industries. The HUGIN system is a high level reasoning tool enabling one to construct BNs based experts systems in domains characterized by inherent uncertainty. HUGIN stands for Handling Uncertainty In General Inference Network [22]. It was originally developed at Aalborg University, Denmark in 1993. The HUGIN tool makes the overall domain structure explicit by utilizing the graphical topology, with nodes and causal links. This capability provides an intuitive graphical visualization of the knowledge base that is convenient for the operator interactions. The application can communicate with the constructed component models and can be integrated with other systems by using the HUGIN API (Application Program Interface), which comes as a library for Visual Basic or C++.

A typical model development in HUGIN and its utilization is divided into two subtasks. The first is the construction of the domain model, which is actually transferring both the qualitative and quantitative knowledge base to the BN framework. This task is done in the editor module of the HUGIN system. The second is the actual problem solving which involves maintaining and compiling the relationships used for calculating the output probability values pertaining to particular situations. The inference engine of the HUGIN system performs this task. These tasks must be performed sequentially, but the task sessions can be suspended at any point to be resumed later, and they may be subject to iteration many times. Figure 46 shows the schematic structure of the stages of development and use of the model. The function, and mechanism of the inference engine are explained in Section 2.4.2.5. Illustrations of inference problems with the BN diagnostic model that is designed with the HUGIN expert system shell are also presented in Section 2.4.2.5.

![Schematic structure for the stages of development and use of the HUGIN expert system shell for the diagnostic task in the HMS.](image)

### 5.1.4 Inference Mechanism In The BN Diagnostic Model

The inference mechanism in BNs relies on Bayes’ Theorem and Bayesian updating for reasoning under uncertainty. It permits a probabilistic assessment of the confidence level in a given finding, i.e., fault diagnosis or prediction in the NPP operations. In this section, we discuss the inference engine for the BN diagnostic model, inference problems that are solved by the BN diagnostic model, and propagation of evidence and probability updating in the BN diagnostic model, and present example inference problems that are solved by the BN diagnostic model.
5.1.4.1 Inference Engine

The inference engine is the heart of every knowledge-based system. The main purpose of this component is to draw conclusions by applying abstract knowledge to concrete knowledge. For example, in the diagnosis of mechanical systems in operation, symptoms as indicated by sensor readings are analyzed in terms of the symptom set of all abnormalities of the components. In this example, sensor readings are the concrete knowledge, and the set of all possible abnormalities of the components comprise the abstract knowledge.

In general two important types of inference engines can be distinguished in intelligent systems: data-driven and goal-driven. The inference engine with BN diagnostic model is data-driven. The BN diagnostic model takes the available information as evidence at the observable node(s) in the network, and generates as many derived results for each of the other variables as it can. The output encompasses the results from all the other nodes of the network. This way of inference is especially useful in diagnostic problems.

5.1.4.2 Inference Problems That Are Solved By The BN Diagnostic Model

Two main inference schemes can be derived by the BN diagnostic model in NPP operations. First is the full specification of the underlying joint probability distribution over all the variables, namely the sensor feature, fault and failure mode variables, which are present in the Bayesian model. Second is the most likely setting of all the underlying fault variables and the marginal posterior probabilities, given the prior probability distribution of these fault variables and the set of observed findings. The set of observed findings is the evidence of the model. Evidence during NPP operations is generally comprised of the data collected from sensors mounted on the monitored SSC, which is translated to sensor feature state likelihood values in the BN model. However, evidence input is not restricted to sensor feature variables, which relate to symptoms of faults. Some pieces of evidence can be provided at any variable node in the model. For instance, an unexpected fault, which could not be detected by the model, can also be an observation. This observation can be input to the model at the relevant fault variable, in order to reflect the additional facts in the operation of the monitored SSC. The second inference is especially important in dealing with competing fault scenarios or with multiple fault events.

There are other inferences that are provided by the BN diagnostic model, which take these two main schemes as a base reference, but which involve user observation as well. For instance, a fault may be progressing in the monitored physical system, with competing symptoms, which may be other lower level faults. The observation in the state probability distribution of the possible set of causal faults yields the main cause(s) of the progressing fault. Another example can be on-line use of the model in predicting the consequences of a hypothesized fault event. This is a useful inference feature of the model at the decision making stage, preferably for off-line use rather than real-time operation.

Some examples of inference from the BN diagnostic model on the target system, which is the bearing system in high-energy horizontal charging pumps, are presented later in this section. Before the illustrative examples, the propagation of evidence in updating the probability values in the model is briefly explained in the next section.

5.1.4.3 Propagation Of Evidence And Probability (Belief) Updating

The inference mechanism in BNs is complicated, based upon evaluation of conditional probabilities. Inference in BNs actually consists of calculating sums and products of probability values. The degree of difficulty in executing the inference depends upon the selected model and ranges from low, for general independence models, to high, for general dependence models.
Given new evidential information, to obtain the inference from the BN model, it is sufficient to access $P(U, e)$, as in Equation 5. In this expression, in the context of the diagnostic task in NPP operations, $U$ is the set of all the sensor feature, fault and failure mode variables, and $e$ is the collected evidence. Hence, $P(U, e)$ represents the joint probability tables over all the variables given the prior knowledge and new evidence. However, the size of such joint probability tables increase exponentially with the number of variables, which results in very high computational requirements. This burden has partially been overcome in the recent years, through the rapid advancement of computational techniques and computer technologies. Methods based on graphical representations of dependencies and relatively efficient probability updating algorithms, which take advantage of the dependency structure in the graphs, have been developed. The BN tool in this work, which is designed within the HUGIN expert system shell, uses the method of inference proposed by Lauritzen and Spiegelhalter [23-25] and Jensen et al. [26]. This graphical algorithm is among the most efficient methods known in BNs inference mechanism. The algorithm encompasses graphical and algebraic procedures that underlie the evidence propagation by implementing the theory that is presented in Section 2.4.2.1.

The high level procedural concepts in evidence propagation with this algorithm can briefly be listed as follows:

- Identification and organization of belief universes introduced as *cliques*\(^1\) in the undirected graph equivalent of the BN model;
- Initialization of the BN model, such that the marginal probability density for all the variables is reached;
- Propagation of new evidence throughout the initialized network. This step calculates the new marginal probability density for all the variables given the new findings. This proceeds by the propagation of simple “flows” of information through the variables, which are bi-directional, in two steps over the whole network that are *collection* and *distribution*. The flows of information in both directions, involve only two adjacent cliques. The purpose of this strategy is to keep consistent probability values at nodes common to different cliques.

The technical details of the evidence propagation algorithm are presented in the articles by Lauritzen and Spiegelhalter [23-25] and Jensen et al. [26].

One main advantage of evidence propagation in BNs lies in its basic structure. Unlike rule-based or model-based systems, evidence can be entered at any node in the network, and the resulting marginal probability density can be collected from all the other variables in the model. In NPP operations, in on-line execution of the diagnostic model, the evidence is the collected data from sensors that are translated to sensor feature state probabilities in the BN diagnostic model. This set of evidence is propagated upstream in the model to find the marginal probability density for all the faults and failure modes and the joint distribution, $P(U, e)$, as in Equation 5. However, the user of the model at NPP operations may require, or need, to foresee what the effect or significance of a fault might be on other faults which maybe downstream in the network. The causal structure and the Bayesian theory allow the user to enter such hypothetical evidence at any variable of the model, and predict its consequences to any other part of the model, by updating the probability density relevant to the rest of the variables.

### 5.1.4.4 Example Inference Problems Solved By A BN Diagnostic Model

Illustrative examples for clarifying the inference from the BN diagnostic models in NPP operations are presented in this section. The Bayesian diagnostic models in these examples are taken as

\(^1\) A clique is a set of pair wise linked nodes, which is not a subset of another set of pair wise linked variables (a maximal complete set).
subset parts of the larger model developed in this work for the target bearing system. The first example demonstrates the initiation of a primary level fault followed by the progression of other faults. The second example shows the inference in finding the main cause of an observed high-level fault.

The figures for the graph representation of the relevant BN models are presented in the following examples. The nodes in the figures refer to all the sensor feature, fault and failure mode variables. The notation in naming the sensor feature nodes is as “S_sensor-feature-name.” The notation in naming the fault nodes is “C_fault-name.” The notation in naming the failure mode nodes is as “F_failuremode-name.” The details of the variable names are given in the relevant examples. The input for the quantitative knowledge base, which are the conditional probability tables in the form of Tables 5 and 6 were prepared by eliciting the subjective values for the probabilities from domain experts.

**Initiation And Progression Of A Fault**

The faults related to clearances are some of the contributors to the failure of the bearings system. Therefore, the clearance problems appear in the functional hierarchy of the bearing system. The initiating faults related to clearances are due to either misalignment or improper dimensions, i.e., looseness or tightness. The BN graph structure that encompasses only the clearance related variables is shown in Figure 47. This model is part of the larger diagnostic model for the bearing system itself. Figure 47 shows explicitly the causal relations between the sensor features and the primary level faults and those between the primary level faults and the high level fault variable. The nomenclature for this figure is presented in Table 7.

Under normal operating conditions all the sensor features would have good readings. This refers to being at the “low” state for all sensor features except for babbitt metal temperature, for which the “medium” state is good. This is because both lower and higher metal temperatures refer to degraded states of the dimensional conditions of the bearing clearances, whereas all other features physically should have low values for proper alignment and dimensions of the clearances. Given the initialization of the network over all the variables, and the evidence from the sensor features, the model is run to obtain the state probability density of each variable, as in $P(U, e)$ of Equation 5. This inference is the full specification of the underlying joint probability distribution over all the variables, which indicates the condition of each fault and the overall health condition of the monitored component. Figure 48 shows the evidence and state probability distribution for the entire fault variables, denoted as $P(U|e)$. $U_f$ stands for the set of fault variables in this network.

![BN graph structure for the clearance related variables in the Bayesian diagnostic model.](image-url)
It is important to notice that, even though the sensor features are indicating 100% good conditions from measurements only in Figure 47, the primary level faults are not at 100% normal conditions. This is explained by the form of the quantitative knowledge base that is input to this model. The domain experts expressed their view of having two uncertainties. First is the possibility of sensors operating somewhat unreliably. Second is the possibility of having done the physical modeling in an incomplete way, i.e., possibility of other unknown mechanisms that can alter the state of misalignment. In the case of this example, the modeling is quite simple and well known. Therefore, the dominant factor is the first possible source of uncertainty. The same sort of reasoning was followed by the domain experts in specifying the conditional probability tables for the other parts of the BN diagnostic model, too. The uncertainty at each level of the model is incorporated into the knowledge base. It is observed that the uncertainty grows, due to accumulation, at the resulting higher levels of the model.

Over the operating lifetime of the bearings, the misalignment fault can occur, possibly due to design error close to the beginning of life of the component, or due to maintenance errors at later stages.

Table 7. Nomenclature for the variables used in Figure 47

<table>
<thead>
<tr>
<th>Abbreviated Name</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>C_BE-CLR</td>
<td>Bearing clearances</td>
</tr>
<tr>
<td>C_CLR-ASY</td>
<td>Misalignment</td>
</tr>
<tr>
<td>S_1X-PHASE</td>
<td>1x Phase</td>
</tr>
<tr>
<td>S_2X-SHAFT-VIB</td>
<td>2x Shaft vibration</td>
</tr>
<tr>
<td>C_CLR-DIM</td>
<td>Misdimensions</td>
</tr>
<tr>
<td>S_RATIO-HARM</td>
<td>Ratio of harmonics</td>
</tr>
<tr>
<td>S_NUM-HARM</td>
<td>Number of harmonics</td>
</tr>
<tr>
<td>S_BABBIT-TMP1</td>
<td>Babbit temperature</td>
</tr>
</tbody>
</table>

Figure 48. Evidence at sensor features and the state probability density for the fault variables, $P(U|e)$, in the Bayesian diagnostic model for clearances.
The indicators for this fault are the measurements for the sensor features 1xPhase and 2xShaft vibration. Hence, a shift in the states of these features towards medium and high ranges, results in a change in the state probability distributions of the relevant fault variables. The result for each fault variable is found by updating the state probability density given the new findings from the sensor features and the prior state probability density. Figures 49 and 50 show the change in evidence from the sensor features that is reflected to the fault state probability distributions by Bayesian updating. The updated state probability distribution for all the fault variables is denoted as \( P'(U|e) \). The evidence in these figures is changing because of the shift to medium and high ranges, respectively, in the 1xPhase and 2xShaft vibration.

The change of \( P'(U|e) \) in Figures 49 and 50 reflects two pieces of related inference. First is the increase in the severity of the misalignment fault itself. Second is the progression of the misalignment fault to change the health status of the overall clearances in the bearing system. As the clearance dimensional fault variable and the misalignment variable are conditionally independent in the BN, no change is observed in the state of the variable for clearance dimensional fault.

**Root Cause Of A High Level Fault**

Some faults may have a characteristic such that they individually affect more than one function in the system. Consequently, they affect more than one fault variable in the BN diagnostic model. It is important to determine efficiently the main cause of a problem in NPP operations, in order to act quickly, save effort and avoid fault progression. The problem of searching the root cause of a fault that is observed to be pending can be solved by some inference that involves rearward observation from the BN diagnostic model. This inference is illustrated with a simple case here.

![Figure 49](image-url)  
Figure 49. Updated state probability density for the fault variables, \( P'(U|e) \), in the Bayesian diagnostic model for clearances, given the evidence of shift in “1x phase” and “2x shaft vibration” sensor feature states to “medium” from “low.”
The mechanical failure of the bearing can occur due either to clearance problems or to load problems. Therefore, clearances and load conditions are direct causes for any change in the mechanical condition of the bearings. However, changes in the clearance conditions are affected also by the changes in the load conditions. For instance, if the load is too high, it could worsen the status of the clearances, and hence the mechanical condition of the bearings. If it is too low, it wouldn’t worsen or enhance the status of the clearances, but would play a direct role on the mechanical status of the bearings. This relation is represented in the BN diagnostic model, by having the load variable being the cause of the other two variables. Figure 51 shows the part of the larger BN diagnostic model, which, for clarity, only covers the three variables involved in this description. We note that both the clearances and load variables, in fact, do have parent nodes that affect them from lower levels in the larger model. This illustration was elicited from the larger model. Figure 47 shows the primary level faults and symptoms related to the clearance variable, in the previous inference problem illustration.

At a given time, t, the health condition of these three variables, and that of the parent nodes of the clearance variable, are shown with their state probability distributions in the first three columns of Table 8. The states of the fault variables in this table are denoted as N, I and S, which stand for normal, intermediate and severe, respectively. As the operating conditions change, and new findings are entered into the system, at time t’, the model is updated to access the new \( P'(U_f|e) \), for all the fault variables. The results are shown in the second three columns of Table 8, which indicate a minor health status degradation in the bearing mechanical fault variable, by a shift in the probability distribution toward intermediate and severe states.

The purpose is to find out the main reason for this progression. The first step in finding this is to search backward to the causal variables of this fault. The two other nodes, i.e., clearances and load variables, are the causes to the change in bearing mechanical status. However, it is not straightforward from this step to see the main cause, as they also both show minor health status degradation by a shift in the state probability distributions toward intermediate and severe states. Nevertheless, if we look back at Figure 51, it is explicit that a change in clearances status can as well be due to a change in load status. The second step should be to observe the primary fault variables, which are parents to the clearances
variable. These variables are the misalignment and misdimension faults. It is seen from the results in Table 8 that no change is reflected in the health status of these variables. Therefore, we conclude that the main and only cause of the mechanical fault progression is an adverse change in the load conditions. The last three columns of Table 8 show the further progression of this fault at time t’, which strengthens the conclusion about the main cause, because the change in load conditions is more severe than that for clearances. However, one should not wait too long to reach a conclusion in order to act quickly and avoid the progression of the fault. Hence, the inference from BN diagnostic model is a good way of approaching such problems. Its value is even higher in more complex situations.

5.2 Dynamic estimation of mean TTF of multi-state SSCs

The Bayesian diagnostic model provides the current operational health status of the monitored SSC in a probabilistic way taking into account the multi-state fault and failure modes of the SSC. However, the information only on the current health status of the SSC is not sufficient for determining the significance of certain events. The advance and progression of some faults may be faster than the others. Therefore, it is important to predict when the faults and failures may be pending in the system. The objective of this section is to define a method to estimate the time to occurrence of fault events and the overall TTF of the monitored SSCs during operation. Two related methods were developed in this work. First, the motivation for the dynamic estimation of mean TTF of the multi-state SSCs is explained.

Table 8. Updated state probability density, $P’_\gamma(j|e)$, for the fault variables in the Bayesian diagnostic model for clearance, load, and bearing mechanical conditions, at time $t$, $t’$, and $t”$

| Fault, $f$ | $P’_\gamma(j|e)$ at $t$ | $P’_\gamma(j|e)$ at $t’$ | $P’_\gamma(j|e)$ at $t”$ |
|-----------|-----------------|-----------------|-----------------|
|           | $j=N$ | $j=I$ | $j=S$ | $j=N$ | $j=I$ | $j=S$ | $j=N$ | $j=I$ | $j=S$ |
| C_Be-M    | 0.62  | 0.25  | 0.13  | 0.59  | 0.27  | 0.14  | 0.48  | 0.35  | 0.17  |
| C_Be-Load | 0.64  | 0.25  | 0.11  | 0.59  | 0.29  | 0.12  | 0.38  | 0.47  | 0.15  |
| C_Be-Clr  | 0.67  | 0.26  | 0.07  | 0.65  | 0.27  | 0.08  | 0.57  | 0.33  | 0.10  |
| C_Clr-Asy | 0.96  | 0.03  | 0.01  | 0.96  | 0.03  | 0.01  | 0.96  | 0.03  | 0.01  |
| C_Clr-Dim | 0.90  | 0.09  | 0.01  | 0.90  | 0.09  | 0.01  | 0.90  | 0.09  | 0.01  |

$\gamma$ stands for the states of the fault variables. It represents N for normal, I for intermediate and S for severe states.

The C_Clr-Dim variable has 5 states. Given the condition for this example, the first two states have negligibly small probability to occur. Therefore, the rest of the three states are evaluated here.
Second, the methods that were developed in this work for estimating the distribution of TTF for the monitored events is presented. Third, a demonstrative example is shown, which illustrates the TTF estimation methods developed in this work.

5.2.1 Motivation

The indication of the time to occurrence, or activation, of faults and failure modes, or the failure of the component itself is vital information to the user at NPP operations. This information serves for many purposes, such as understanding the severity of the certain configurations in the plant, critical decision making, planning for maintenance, etc. Therefore, the sensor data, which are analyzed by the diagnostic models should go through another step of analysis by the HMS in order to also provide the TTF information. There is already some work reported in the literature within this field to assess the TTF of components. However, most of such work does not address the three important features of the problem domain that is described in this work. These issues are as follows:

- The components have different performance-levels, which can be discretized into multiple operating states. The component can fail from any of these state with different respective probabilities associated with the failure. Therefore, the estimation of the TTF should take into account multi-state operation of the SSCs.
- The operating state of the component changes during operation. The performance may be degrading or enhancing during a transient, which can induce a state transition. Therefore, the state transition and dynamic characteristics of the monitored systems should be considered in evaluating the expected TTF of the components.
- The basic fault events are the main initiators of the faults. If the progression of basic events can be avoided in a timely fashion, the failure of the component is also prevented. Therefore, it is important also to predict when basic fault events are pending to become more serious in order to prevent effects that can lead to failures.

We note that there is not sufficient work for handling the problem of dynamic multi-state component analysis of TTF estimation, starting from basic fault events, in the literature. The type of attempts to address such issues was made based on Markov processes and system structure functions [27, 28], which are used to represent the dynamic transitions in the monitored system states. However, it is also stated and understood that this method is only applicable to small multi-state systems because as the system size and complexity increase, the number of system states increase very rapidly and becomes difficult to control and run. Consequently, the analysis of the basic fault events is not included in such methods.

The HMS for this work already has the modules that can define the dynamic state transitions of the faults, failures, and the overall SSCs, in a probabilistic way. It assesses the operational performance of the monitored components by estimating the probability distribution over the operating states of all the variables. Besides, these modules readily handle the complexities in large-scale systems. Therefore, there is no need to carry another step of complexity while estimating TTF, since these probabilistic results can readily be used for this purpose.

This section presents the method developed for estimating the expected time to occurrence of faults and failures at the monitored SSCs, by using the output from the diagnostic models in HMS and additional fault-specific information [29].

The objectives of evaluating the TTF information include:
- Defining the meaning of the performance states of the basic fault events (normal, intermediate, severe) in terms of the time to the occurrence of those faults
- Estimating the TTF distributions for primary level basic fault events, given the dynamic evidence during actual operation.
- Estimating the TTF distributions for higher-level failure modes, which may have multiple causes, given the dynamic evidence during actual operation.

5.2.2 Operational States Of The Basic Event Faults

It is necessary to define the values of expected time to occurrence of a fault or failure mode of the monitored SSC at each operating performance state. These states are defined in the diagnostic models of the HIS-N for the physical system that is monitored. In addition, it is important to describe the assumed behavior of the failure rate of a component and that of the time to occurrence of a fault or a failure mode and consequently TTF of the SSC. The distribution for the time to occurrence of the faults and the TTF of the SSC is denoted as TTF in this work.

For the TTF estimation method in this work, the failure rate is modeled as either a constant value in time or the wear-out distribution, depending on the characteristics of the fault. The latter is a three-part distribution, which includes a steeply declining behavior during the burn-in period, an almost constant value during normal life, and a steeply increasing behavior close to the end-of-life of the component. The likelihood of TTF is assumed to be Gaussian distributed as the component approaches its end of life. The $\tau_{F,j}$ and the $\sigma_{F,j}$ are denoted, respectively, as the mean and the standard deviation of the distribution for time to occurrence of a basic fault event $F$, when the fault variable performance is at state $j$. The states for the faults and failure modes are dictated as normal (n), intermediate (i), and severe (s), in general in the diagnostic models. The real form of the failure distribution at the end-of-life period is not clearly known. The assumption of the Gaussian distribution for the failure likelihood is a choice of convenience, because the relevant distribution parameters are easy to elicit. If sufficient data can be collected at later stages of implementation, the assumption about the failure distribution can be improved.

There are two primary input values that are needed for the modeling of the TTF. First is the expected time to occurrence of a fault or failure mode at its normal state, $\tau_{F,n}$. Second is the value for the standard deviation of the governing distribution for the time to occurrence of the relevant fault, $F$, when it is at normal state, $\sigma_{F,n}$. These values can be elicited from the domain experts as subjective estimates or can be derived from a possibly existing historically recorded data. The relevant distribution parameters for the intermediate and severe operating states should be determined, too. However, the estimation of these parameters is not trivial, even subjectively. There is no single methodology or formulation that could cover the behavior of TTF for the intermediate and severe operating states of the faults or failure modes at all times of operation. These values are primarily definition-dependent and show subjective characteristics. Therefore, it is recommended that these parameters also be elicited from the domain experts. However, if the domain experts are not able to provide such values without any guideline, some heuristic models can be of help. The following discussion provides some heuristic guidelines to help the domain experts incorporate the values of $\tau_{F,j}$ and the $\sigma_{F,j}$, for $j=i,s$, into the complete modeling of TTF.

5.2.2.1 A Plausible Basis For Estimation Of Values Of $\tau_f, J$ And $\sigma_f, J$ Where $J=i, s$

A heuristic approach to estimating the Gaussian failure distribution parameters, the mean and standard deviation, for the intermediate and severe states is presented in this section as a supportive guide for the domain experts.
The distribution parameters, mean and standard deviation, for the intermediate and severe states are proposed to follow the behavior as presented in Figure 52. This figure shows that as the severity of the fault increases, the probability that it will affect the system increases, the mean time to its occurrence decreases, and the uncertainty about the occurrence of the fault decreases.

We suggest the following behavior for the decrease in the standard deviation, $\sigma_{F,j}$, and the mean, $\tau_{F,j}$, for the failure distribution of the intermediate and severe states, which represent the uncertainty and the mean time to occurrence of the fault $F$.

TTF Distribution Parameters for the Intermediate Operating State:

$$\sigma_{F,i} = c_{F,i} \times \sigma_{F,n}$$

$$\tau_{F,i} = 3 \times \sigma_{F,i}$$

(7)

TTF Distribution Parameters for the Severe Operating State:

$$\sigma_{F,s} = c_{F,s} \times \sigma_{F,n}$$

$$\tau_{F,s} = 3 \times \sigma_{F,s}$$

(8)

where $c_{F,i}$ and $c_{F,s}$ are constants.

The reasons for choosing these distribution parameters for the intermediate and severe states are as follows:

- The 99% confidence interval of the mean in the Gaussian distribution is within the $3\sigma$-boundary about the mean value (of the time to occurrence of the fault event $F$ within this context). We assume that the criterion for negligible probability of fault occurrence is 1%. Then, the likelihood of the failures starting from $t = \tau_{F,j} - 3 \times \sigma_{F,j}$ for $j = i, s$ should be considered as non-negligible. Therefore, the value for $\tau_{F,j}$ is taken as $3 \times \sigma_{F,j}$ ahead of the time that the component enters state $j$. This explanation is visually presented in Figure 53.

Figure 52. Failure density distributions in time of fault $F$, for $j=n,i,s$
- We expect $\sigma_{F,s} < \sigma_{F,i} < \sigma_{F,n}$, because, at most occasions, as the severity of the fault status increases, the uncertainty about the time when the fault will take effect decreases. Therefore, $\sigma_{F,j} = c_{F,j} \times \sigma_{F,n}$, where $0.0 < c_{F,j} < 1.0$ to linearly scale the standard deviation for the TTF distribution for fault $F$. Consequently, $\sigma_{F,s} < c_{F,j}$. This explanation is visually presented in Figure 54.

However, it is primarily recommended that $\sigma_{F,s}$ and $\sigma_{F,i}$ be elicited either from data or subjectively from the domain experts, whenever it is possible to obtain the relevant values more reliably, rather than using the above stated scaling formulation.

This approach for estimating the values of the parameters $\tau_{F,j}$ and $\sigma_{F,j}$ provides the basis for two important pieces of information to be provided to the user through the HMS in real-time operation at the NPPs, in addition to the information on the state probability distribution output from the diagnostic models. The first one is the definition of each operating performance state for the monitored SSC, in terms of the expected time to occurrence of its faults or failure modes. The second one is the estimated parameters of the overall TTF distribution of all the basic fault events, failure modes or of the monitored SSC itself. The resulting individual TTF distributions for each basic fault event $F$ is abbreviated as $T(F|j, \tau_{F,j}, \sigma_{F,j})$. This stands for the distribution in time, of fault $F$, to occur given the current performance state of $F$ is $j$, where $j = n,i,s$.

### 5.2.3 Estimation of the TTF distribution for basic fault events

The TTF distribution for fault $F$ includes the contribution of the likelihood of being at each performance state $j$. At different operating times, the fault variables in the diagnostic model results was at different operating states with different discrete probability distribution over their states. The probability distribution over the states of any fault $F$ is updated as the new evidence is collected and propagated through the diagnostic models in HIS-N. Hence, the TTF probability distribution for $F$ is also updated as the new evidence is collected on-line during the operation of the SSC, parallel to the update in the SSC.
Figure 54. Comparison of failure density distributions in time of fault $F$, for $j=n,i$

performance state probability distributions. $T(F)$ is denoted as the TTF distribution of the fault $F$ for the current performance state probability distribution at time $t$. Therefore, $T(F)$ includes the effect of the performance state probability distribution, $P_F$, and that of $T(F|j, \tau_F, j, \sigma_F)$ for all $j$, where $P_F$ indicates that the likelihood for fault variable $F$ to be in performance state $j$ at a given instant of time. Then, the expected time to occurrence of a fault is dependent on the possible health states and the probability distribution over those health states. As the performance status of the variable $F$ starts shifting into the intermediate-severe, i-s, range, we concluded that the apparent time to effect of event $F$, $\tau_F$, is moving closer to the end-of-life portion of the distribution. The uncertainty, $\sigma_F$, in the remaining expected life is also reduced. The uncertainty, $\sigma_F$, in the remaining expected life of the variable $F$, is computed by considering all the performance states, $j$, as:

$$\sigma_F = \sum_j (\sigma_{F,j} \times P_{F,j})$$

which is valid for the Gaussian distribution. It should be noted that, $P_{F,j}$ in this expression is a time dependent value, since its value is updated as new evidence is propagated in the diagnostic model.

5.2.3.1 Method 1

The first method for estimating the mean time to occurrence of the initiating fault $F$ is based upon the assertion that the component enters the end-of-life portion of the failure distribution at some limit point such that the fault variable performance status moves to more likely values of the intermediate-severe area. The uncertainty in the remaining expected life is further reduced and becomes predominantly severe. The following heuristic method is adopted in this approach:

- The standard deviation, $\sigma_F$, for the TTF distribution of variable $F$, is calculated by taking into account the probability distribution for the states of $F$, as in Equation 9.
A limiting normal state probability, $P_{F,n}(E)$, below which the fault variable enters the end-of-life portion of the TTF distribution is determined. The value of $P_{F,n}(E)$ may vary for different fault variables.

- If $P_{F,n} > P_{F,n}(E)$, the mean time to occurrence of fault variable $F$, $\tau_F$, is interpolated between $\tau_{F,n}$ and $3\sigma_F$, following the first argument in the stated reasons for a plausible basis.

- If $P_{F,n} \leq P_{F,n}(E)$, $\tau_F$ is set to $3\sigma_F$, which changes as a function of time due to the time dependent state probability distributions.

Figure 55 describes the behavior of $\tau_F$ in this method, with respect to $P_{F,n}$, at a given instant of time, $t$. Equations 10 describe the formulation adopted for computing $\tau_F$, which is parallel to Figure 55.

\[
\tau_F(t) = \tau_{F,n} - \frac{\left(\tau_{F,n} - 3\sigma_F(t)\right)(1 - P_{F,n}(t))}{1 - P_{F,n}(E)} \quad \text{For } P_{F,n}(t) > P_{F,n}(E)
\]

\[
\tau_F(t) = 3\sigma_F(t) \quad \text{For } P_{F,n}(t) \leq P_{F,n}(E),
\]

Figure 55. Behavior of $\tau_F$ according to $P_{F,n}$ at Time=$t$

### 5.2.3.2 Method 2

The second method for estimating the mean time to occurrence of the initiating fault $F$ is based upon the assertion that the rate of occurrence of the fault $F$ can be treated piece-wise constant in time. As stated before, $\tau_{F,j}$ represents the mean time to occurrence of fault $F$ at state $j$. Equivalently, $\lambda_{F,j}$ represents the rate of occurrence of fault $F$ from its performance status $j$, which can then be expressed as $\lambda_{F,j} = 1/\tau_{F,j}$. The rate of occurrence of fault $F$, $\lambda_F$, changes as a function of time due to the change in the probability distribution over the states of $F$. Then, $\lambda_F$ can be expressed as:

\[
\lambda_F = \sum_j \left(\lambda_{F,j} \times P_{F,j}\right),
\]

Then, the mean time to occurrence of fault $F$, $\tau_F$ is the inverse of the rate of occurrence of $F$, and takes the form:
\[ \tau_F = \left[ \sum_j \left( \frac{1}{\tau_{F,j} \times P_{F,j}} \right)^{\gamma^{-1}} \right]^{-1}, \]  

(12)

From both models, the failure distribution \( T(F) \) can quantitatively be expressed as \( T(F) = T(F|\tau_F (t), \sigma_F(t)) \). This value is time dependent and is updated as long as new evidence is collected and propagated through the HIS-N to update the values of \( P_{F,j} \), for \( j=n,i,s \). We recommend that both \( P_{F,j} \) and \( T(f) \) be provided by the HMS.

### 5.2.4 Estimation of the TTF distribution for high level faults and failure modes

In many of the causal relations, multiple fault events (parents) are the cause for a single high level fault or failure mode (child). The parents are either the primary fault events, or the lower level failure modes. All the parents are assumed to represent mutually independent events and are associated with separate TTF distributions, \( T(F) \), that are estimated by the method described in the previous sections. Therefore, the TTF for the higher level fault or failure modes must be calculated by taking into account the joint distribution of the TTF of the parents of the relevant child node.

The joint TTF is then represented as; \( T(F_c) = T(F_{p1}, F_{p2}, ..., F_{pn}) \), where \( T(F_c) \) is the TTF distribution for the next higher level failure mode (child), and \( T(F_{p1}, F_{p2}, ..., F_{pn}) \) is the joint TTF distribution over the parents, \( F_{p1}, F_{p2}, ..., F_{pn} \), of the child failure mode \( F_c \).

The same updating logic applies for the on-line estimation of higher level failure modes. \( T(F_c) \) is to be updated as long as new evidence is collected and propagated in the HIS-N to update the values of \( P_{F,j} \), for \( j=n,i,s \).

### 5.2.5 Base distribution models

Two types of distribution models can be used to form the basis of the computations. The first one is the exponential distribution and the second one is the wear-out distribution. The parameters of these distributions should be elicited from the domain experts.

The use of the exponential distribution is equivalent to assuming a constant failure rate. This distribution should only be used when the fault or failure mode is thought to occur randomly. Problems caused by external events may fall in this category.

The wear-out distribution is a three-part distribution. It assumes a linearly declining failure rate during the burn-in period of the SSC, a constant failure rate during normal life, and an increasing failure rate in the end-of-life. The time-dependent failure rate for the wear-out distribution is shown in Figure 56. As the component approaches its end of life, the TTF for single fault or failure mode is assumed to follow a Gaussian distribution. This distribution should be used if the fault or failure mode results from component wear or any process that worsens over time. The probability density function (PDF) for this TTF distribution is shown in Figure 57.

The wear-out distribution is characterized by five parameters, which are:

1. The mean of the Gaussian portion of the TTF distribution.
2. The standard deviation of the Gaussian portion of the TTF distribution.
3. The probability that the component will fail during burn-in.
4. The duration of the burn-in portion of the distribution.
5. The probability that failure will occur randomly after burn-in.
These parameters can either be elicited subjectively from domain experts or be derived from historically recorded data.

5.2.6 Application example for dynamic TTF estimation

This section presents an application example of the method developed in this work for dynamically estimating the TTF distribution for multi-state SSC. The target component is the bearing system of a high energy horizontal charging pump, which is essential in safe operation of NPPs.

5.2.6.1 TTF Estimation For Bearing System Faults And Failure Modes

The initial input for the TTF estimation, which is the set of values for $\tau_{F,j}$ and $\sigma_{F,j}$ for $j=n,i,s$, were elicited by interviews from the domain experts for the structure that is established in the diagnostic model for the bearing system. Different scenarios for normal and abnormal operating conditions were run and the probabilistic results were input to the TTF calculations. The demonstration example is the propagation of a fault in time due to the primary level fault variable *Dirt in lubricant*. The event is initiated by increase in particle count and babbitt mass, which affect the indicated fault variable. The next level fault variable is the *Quality degradation of lubricant*. Its health states shift from normal to severe as the fault propagates in time. The consequent failure mode that is initiated by the primary fault is the *Bearing lubrication system failure*. During this scenario, all the sensor features, except for particle count...
and babbitt mass had good level readings. The propagation of the primary level fault within the lubrication system structure is shown with red dashed arrows in Figure 58.

The performance status of all the fault variables, except for Dirt in lubricant=C_QUAL-DRT, Quality degradation of lubricant=C_LU-QUAL and Bearing lubrication system failure=C_BE-LUBE, do not change and remain at good health state, since the rest of the features keep having good level of readings during the transient. Therefore, only the TTF distributions of the fault/failure mode variables of which health state deteriorate undergo transitions from high to low values of $\tau_F$ and $\sigma_F$. The transition of probability distribution for fault propagation in time from Case T1 to Case T9 is shown in Figure 58. This transition follows the evidence collection with measurements from the sensors. All the primary fault variables have been treated as explained in Section 2.4.3.3 for estimation of each $T(F)$.

5.2.6.2 Results Based On Method 1

The last column of the table in Figure 58 shows the change in time of the $\tau_F(t)$ with method-1 and $\sigma_F(t)$ for the Dirt in lubricant fault variable, in parallel to the change in health status probability distribution. In this estimation, the critical value of $P_{F,n}(E)$, below which the fault is thought to have entered the end-of-life portion of the TTF distribution, is taken as 0.3.

The joint distribution of each $T(F)$ is sampled for the higher level fault/failure mode, i.e., Quality degradation of lubricant and Bearing lubrication system, to obtain $T(F,\cdot)$, as described in Section 2.4.3.4.

Figure 59 shows the joint distribution $T(F,\cdot)$ for Bearing lubrication system failure over the three parent fault variables shown in Figure 58. The y-axis of Figure 59 is the relative frequency of occurrences in the statistical sampling. Therefore, $T(F,\cdot)$ in Figure 59 also represents the probability density function for the failure to occur.

5.2.6.3 Results Based On Method 2

Figure 60 show the time to occurrence of individual faults concerning the bearing lubrication system failure, based on method-2. Such results are useful in concentrating on the faults that are progressing rather than others.

Figure 61 shows the joint distribution for $T(F,\cdot)$ for the lubrication system, based on method-2. The results from method-2 are more conservative estimates of TTF.

5.2.7 Summary of Dynamic TTF Estimation

The BN diagnostic model for the target system proved to present consistent and useful results in monitoring the health status during the operation of the component. Its main advantages are fault diagnosis and prediction capability with reasoning under uncertainty and graphical structure that matches the physical behavior of the monitored component. This information by itself is not sufficient in determining the significance of certain events. The progression of some faults may be faster than the others.

A new method to provide dynamically changing estimates for the mean TTF of the monitored SSCs was also developed to address the stated issue. This method takes into account the multi-state performance status of the SSC and its fault and failure modes. It uses two important pieces of information from the diagnostic model of the monitored SSC: the structure and the probabilistic performance status results for all the fault and failure modes of the SSC. It also uses externally defined rate functions and distributions for the faults. The relevant parameters can be elicited from the
58-a: BN diagnostic model structure within the HIS-N for the failure mode “Bearing lubrication system failure” of the bearing system mock-up for the high energy horizontal charging pumps.

<table>
<thead>
<tr>
<th>Cases in time</th>
<th>Measurements for</th>
<th>Fault propagation in time</th>
<th>Mean and standard deviation (hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Partial count</td>
<td>Babbit mass (mg)</td>
<td>Health state probabilities: P_{fa} P_{fi} P_{fs} (%)</td>
</tr>
<tr>
<td>T_1</td>
<td>11</td>
<td>500</td>
<td>99.1 0.9 0.0 84.8 13.3 1.9</td>
</tr>
<tr>
<td>T_2</td>
<td>11.9</td>
<td>567.5</td>
<td>94.6 5.3 0.1 83.6 14.3 2.1</td>
</tr>
<tr>
<td>T_3</td>
<td>12.9</td>
<td>612.5</td>
<td>85.4 14.3 0.3 81.0 16.3 2.7</td>
</tr>
<tr>
<td>T_4</td>
<td>13.1</td>
<td>657.5</td>
<td>63.2 36.2 0.6 75.0 21.1 3.9</td>
</tr>
<tr>
<td>T_5</td>
<td>14</td>
<td>725</td>
<td>10.9 87.7 1.4 59.1 33.9 7.0</td>
</tr>
<tr>
<td>T_6</td>
<td>14.9</td>
<td>807.5</td>
<td>8.8 79.3 11.9 56.2 33.4 10.4</td>
</tr>
<tr>
<td>T_7</td>
<td>15.5</td>
<td>862.5</td>
<td>6.5 61.2 29.5 50.7 33.0 16.3</td>
</tr>
<tr>
<td>T_8</td>
<td>16.1</td>
<td>917.5</td>
<td>5.2 38.4 56.4 42.1 32.8 25.2</td>
</tr>
<tr>
<td>T_9</td>
<td>17</td>
<td>1000</td>
<td>3.9 5.0 91.1 30.2 33.0 36.9</td>
</tr>
</tbody>
</table>

58-b: Behavior of the fault propagation in time for the changing measurements, and fault/failure performance status.

**Figure 58. Propagation model analysis of the basic fault event “Dirt in Lubricant.”**
Figure 59. The change in time for the joint distribution $T(F_c)$ based on method-1 for “Bearing lubrication system failure.”

Figure 60. The mean time to occurrence of the faults and the failure of the “Bearing lubrication system.”
historically recorded data or from the domain experts. The probabilistic performance status results for the basic fault events and the rate and distribution functions for faults were combined to provide dynamic estimates of the time to occurrence of individual faults and the overall failure of the monitored components within this method. The parameters for the base distribution models, $\tau_{F,j}$ and $\sigma_{F,j}$, are the main unknowns within our method. These parameters may be obtained by elicitation from domain experts or from statistically recorded data whenever it is available. During the course of this work, it was observed that better results in TTF estimates are obtained when the $\tau_{F}$ and $\sigma_{F}$ are elicited from domain experts than the cases when these parameters are calculated by linear formulation. The linear formulation presented as part of the plausible basis is recommended only when there is no available expert judgment for these values. The joint of the TTF distributions of the lower level faults were obtained to give the estimates of higher level TTF distributions.

This method, very importantly, provides means to observe the change in the TTF of all possible faults and failure modes of the monitored SSC. In addition, the overall MTBF and the TTF distribution of the monitored SSC is updated with each collected new evidence, parallel to the updated health status. This combined feature enables the user to attain the estimation of TTF distributions in complex domains involving uncertainty as in NPP operations. The estimation that is developed in this method uses a plausible heuristic approach, which can be improved by further work and more tests. A similar method which uses piecewise (in time) constant $\tau_F$ could be another possible approach with comparable advantages.

5.3 The BN Diagnostic Model for the Pump/Lubrication System

The BN diagnostic model for the target system proved to present consistent and useful results in monitoring the health status during the operation of the component. Therefore, a larger diagnostic model
that is designed with the BN technique promises valuable inference in NPP operations. Its main advantages are fault diagnosis and prediction capability with reasoning under uncertainty and graphical structure that matches the physical behavior of the monitored component.

The failure and fault modes and the features in Table 4 compose the variables in the BN diagnostic model, as explained in Section 2.4.2. The final setting of these variables while translating the functional hierarchy to the representation of the BN diagnostic model went through much iteration for refinement and consistency of the model, through interviews with the domain experts.

The states of the variables represent the performance level of the variables during operations. The states were defined as described in Section 2.4.2. In general, three states were adopted for optimizing the quality of the input knowledge vs. the benefit gained from the detailed output. For some fault variables, however, we found that more states, i.e., five states, were appropriate and implemented accordingly.

The quantitative knowledge base for the BN diagnostic model, which describes the strengths of the relations between the variables, was elicited from the domain experts. The strengths of the relations between the variables were quantified with the conditional probability values that refer to the performance states of the variables. The form of the quantitative knowledge base expressed in terms of the conditional probabilities is explained in Section 2.4.2 and is illustrated in Tables 5 and 6. The values in the quantitative knowledge base also went through long term refinement and verification during the design stage for obtaining consistent and reliable results from the BN diagnostic model.

The final graphical representation of the BN diagnostic model for the bearing system is illustrated in Figure 62. The nodes in this model represent the variables and the directed links represent the causal relations between the variables. A conditional probability table is attached to each of the causal links. Such a table quantifies the behavior of the connected variables, as explained in Section 2.4.2. This model is used in the final demonstration scenarios to monitor for failure of a pump by bearing seizure.

5.4 Extension of BN Applications for Equipment Health Monitoring

The activities under Task 4 included the development of methods for relating sensor data to component health. For the purposes of the Smart-NPP prototype demonstration HMS developed for this project, the BN and TTF methods were implemented to provide fault diagnosis and TTF calculation. The BN methods, however, were extended to investigate other approaches for advisory and decision-making capabilities, as well as to address the computational limitations of BNs, which will exist as these methods are applied to multiple components in a complex system, such as an advanced NPP. These other approaches included the use of influence diagrams and neural networks. Consideration of these methods resulted in the development of a hybrid system that also holds promise for application to advanced equipment health monitoring. In this hybrid structure, BN and neural network techniques were used in conjunction, for the first time, in order to provide complementary probabilistic performance status estimates and fault diagnosis concerning the monitored SSCs. All of the work for Task 4, as well as the integration of the BN and TTF calculations in the demonstration HMS, comprised PhD graduate research supported by this project.

Additional details and results of all the work for this task are provided in a Smart-NPP technical task report, Development of the Smart Equipment Health Monitoring System [12].
Figure 62. BN diagnostic model for failure of a pump by bearing seizure.
6 Task 5 – Sample Application of Smart System

Task 5 is Sample Application of Smart System. The objective of this task was to identify and implement an application of the concept of smart equipment. The first step in developing a sample application was to identify a specific component for the demonstration of the HMS. The next step was the identification of the test bench for the HMS. The third step was the implementation of the HMS demonstration. Finally, the last step was to aid in the validation of the smart equipment concepts of this program.

A significant accomplishment during Phase 1 of the Smart-NPP program was the selection of a high energy, horizontal, centrifugal pump as a demonstration component. This pump is used in both charging and feedwater systems for LWRs and was selected based on the criteria established in Task 1 during Phase 1. Its selection has allowed subsequent program activities during Phase 2 to focus methodological developments on a specific application.

Another important milestone was the identification of a related physical test bench. The Smart-NPP team felt that a software only demonstration using the virtual machine could be perceived as doing little to address real world problems in developing a HMS. For example, data acquisition may be much more difficult from an actual sensor network, compared to simulated sensor data. To address this concern a pump oil lube test system at PSU (see Figure 63) was utilized for actual instrumentation and testing of a subsystem typical of the selected centrifugal pump. The LSTB was instrumented during Phase 2 as discussed in Section 2.2.4 and 2.5.1. Additional faults were implemented virtually using data files of typical sensor features. Additionally, under this task included all activities to prepare for presentation of the demonstration HMS. Planning and preparation of demonstration activities began in Phase 2 and concluded in Phase 3. Task activities and accomplishments for this task are discussed in the following sections.

6.1 Lubrication System Test Bench

The LSTB at PSU (Figure 63) is designed to emulate general lubrication systems. The setup includes a counter flow concentric tube heat exchanger, a 5-10 micron filter followed by division into three distribution branches. The LSTB is also capable of adding a metered amount of foreign matter through a fixed-volume, dispensing pump, which is used to inject metallic and non-metallic debris, dirty oil, fuel and water into the system. Contaminants are injected into a mixing block, and pass through the GasTOPS MetalSCAN, located upstream of the filter.

The LSTB utilizes a varied array of sensors and instrumentation to provide an accurate assessment of the salient system parameters. Figure 64 provides a detailed schematic of the test bench with instrumentation locations. The LSTB is currently outfitted with the instrumentation listed in Table 9. Temperature measurements can be taken at 9 locations, and pressure is measured at 4 positions. Temperature is recorded using low-noise, E-type thermocouples from Omega. Temperatures are taken at the following locations: pump outlet, heat exchanger outlet (oil), heat exchanger inlets, each of the legs, oil sump and at the heating element. Omega pressure transducers are employed at the main pump outlet, heat exchanger outlet, filter inlet and filter outlet in conjunction with analog Helicoil gauges. The gauges allow for periodic recalibration of the transducers and data validation. Note that the extensive instrumentation was developed to facilitate the use of this test bench for a variety of applications. For the purposes of this project, a parsimonious subset of these sensors was used. The transducers used on the LSTB have a range of 150 psig with a voltage output and 1ms response time. Flow meters are also located on the LSTB to monitor variations in flow due to oil quality or delivery faults. The flow meters are voltage output devices, having a range of 0.5 to 7.5 gpm. A GasTOPS MetalSCAN inductive debris
Figure 63. The LSTB at PSU.

Figure 64. Schematic of LSTB.
Table 9. LSTB Sensor List

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Type</th>
<th>Range</th>
<th>Power Supply</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main Pump Thermocouple (TC)</td>
<td>E</td>
<td>N/A</td>
<td>None</td>
</tr>
<tr>
<td>Heat Exchanger Outlet TC</td>
<td>E</td>
<td>N/A</td>
<td>None</td>
</tr>
<tr>
<td>Gear/Bearing Leg 1 TC</td>
<td>E</td>
<td>N/A</td>
<td>None</td>
</tr>
<tr>
<td>Gear/Bearing Leg 2 TC</td>
<td>E</td>
<td>N/A</td>
<td>None</td>
</tr>
<tr>
<td>Gear/Bearing Leg 3 TC</td>
<td>E</td>
<td>N/A</td>
<td>None</td>
</tr>
<tr>
<td>Main Pump Pressure Transducer (PT)</td>
<td>Thin Film Millivolt Output</td>
<td>150Psig</td>
<td>10VDC</td>
</tr>
<tr>
<td>Heat Exchanger Output PT</td>
<td>Thin Film Millivolt Output</td>
<td>150Psig</td>
<td>10VDC</td>
</tr>
<tr>
<td>Filter Inlet PT</td>
<td>Thin Film Millivolt Output</td>
<td>150Psig</td>
<td>10VDC</td>
</tr>
<tr>
<td>Filter Outlet PT</td>
<td>Thin Film Millivolt Output</td>
<td>150Psig</td>
<td>10VDC</td>
</tr>
<tr>
<td>Main Pump Pressure Gauge (PG)</td>
<td>Bourdon Tube</td>
<td>0-160psi</td>
<td>None</td>
</tr>
<tr>
<td>Heat Exchanger Output PG</td>
<td>Bourdon Tube</td>
<td>0-160psi</td>
<td>None</td>
</tr>
<tr>
<td>Filter Inlet PG</td>
<td>Bourdon Tube</td>
<td>0-160psi</td>
<td>None</td>
</tr>
<tr>
<td>Filter Outlet PG</td>
<td>Bourdon Tube</td>
<td>0-160psi</td>
<td>None</td>
</tr>
<tr>
<td>Heat Exchanger Lube Output Flowmeter</td>
<td>Paddlewheel</td>
<td>.75-.7.5 gpm</td>
<td>24VDC</td>
</tr>
<tr>
<td>Gear/Bearing Leg 1 Flowmeter</td>
<td>Paddlewheel</td>
<td>.5-.5 gpm</td>
<td>24VDC</td>
</tr>
<tr>
<td>Gear/Bearing Leg 2 Flowmeter</td>
<td>Paddlewheel</td>
<td>.5-.5 gpm</td>
<td>24VDC</td>
</tr>
<tr>
<td>Gear/Bearing Leg 3 Flowmeter</td>
<td>Paddlewheel</td>
<td>.5-.5 gpm</td>
<td>24VDC</td>
</tr>
<tr>
<td>MetalSCAN Debris Monitor</td>
<td>Inductive</td>
<td>125+ microns ferrous</td>
<td>120VAC</td>
</tr>
<tr>
<td>Chilled Water Flowmeter</td>
<td>Paddlewheel</td>
<td>0-9 gpm</td>
<td>10VDC</td>
</tr>
<tr>
<td>Kavlico Dielectric Sensor</td>
<td>N/A</td>
<td>5VDC</td>
<td></td>
</tr>
<tr>
<td>Heat Exchanger Input Thermocouple</td>
<td>E</td>
<td>N/A</td>
<td>None</td>
</tr>
<tr>
<td>Heat Exchanger Output Thermocouple</td>
<td>E</td>
<td>N/A</td>
<td>None</td>
</tr>
</tbody>
</table>

sensor (Figure 65) monitors the size and amount of both ferrous and non-ferrous metallic debris. The MetalSCAN sensor module used on the LSTB is capable of detecting particles as small as 120 and 335 microns (mean diameter) for ferrous and nonferrous debris, respectively.

During Phase 3, different failure modes were investigated. The LSTB was designed to monitor three faults: Clogged Bearing Leg, Clogged Filter, and Fouled Cooler. Different sensor parameters were monitored and analyzed to provide health predictions for each of these three faults. These different failures where designed into system by physically restricting flow and/or virtually changing parameter values of virtual sensors. For example, an inline value was used to simulate a restriction in flow for a fault such as a bearing leg clog and a particle injection system could be used to add debris.
into the system to simulated bearing failure. Data from virtual sensors/features were also feed into the data acquisition software to simulate sensors that were unavailable at the PSU test rig.

6.1.1 Hardware Description

The hardware architecture for the LSTB consisted of two major components: Intelligent Node and Area Reasoner. Figure 66 shows the basic network architecture of the LSTB. The Intelligent Node was composed of a small PC-104 Pentium-based computer platform that consists of National Instruments data acquisition board and a wireless IEEE 802.11b PCMCIA card. The PC-104 form factor is a board that is approximately 3.5-in. square in size and uses an ISA bus backplane. The computer has all the functionally of a desktop computer and operates on a Microsoft Windows-based operating system (Windows 98). Figure 67 shows the stack of inter-connoted PC104 computer boards used for recording and processing sensory data.

Figure 66. Lube oil data network system.
Figure 67. PC-104 data acquisition system.

The Intelligent Node collects and records data from a subset of the sensors that are listed in Table 9 and computes different lube oil related health features. The sensors range from temperature, pressure, and flow rates of the oil and chill water systems. Seven of the eight channels are currently dedicated to the lube oil test bench analysis. Table 10 shows the sensor signal mapping to the DAQ and the recording parameters used for this experiment.

Table 10. Sensors and Data Acquisition Channels

<table>
<thead>
<tr>
<th>Channel</th>
<th>Description</th>
<th>Frequency (Hz)</th>
<th>BlockSize (pts)</th>
<th>Period (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Oil Inlet Temperature</td>
<td>5000</td>
<td>1000</td>
<td>0.2</td>
</tr>
<tr>
<td>2</td>
<td>Oil Outlet Temperature</td>
<td>5000</td>
<td>1000</td>
<td>0.2</td>
</tr>
<tr>
<td>3</td>
<td>Water Inlet Temperature</td>
<td>5000</td>
<td>1000</td>
<td>0.2</td>
</tr>
<tr>
<td>4</td>
<td>Oil Flow Rate</td>
<td>5000</td>
<td>1000</td>
<td>0.2</td>
</tr>
<tr>
<td>5</td>
<td>Water Flow Rate</td>
<td>5000</td>
<td>1000</td>
<td>0.2</td>
</tr>
<tr>
<td>6</td>
<td>Filter Inlet Pressure</td>
<td>5000</td>
<td>1000</td>
<td>0.2</td>
</tr>
<tr>
<td>7</td>
<td>Filter Outlet Pressure</td>
<td>5000</td>
<td>1000</td>
<td>0.2</td>
</tr>
<tr>
<td>8</td>
<td>Not Currently Used</td>
<td>5000</td>
<td>1000</td>
<td>0.2</td>
</tr>
</tbody>
</table>

The DAQCard-1200 is one of National Instruments multifunction I/O devices for PCMCIA. It offers up to 100 kS/s, 12-bit performance on 8 single-ended or 4 differential analog inputs and also has the capability of offering two 12-bit analog outputs. The board provides 24 digital I/O lines for monitor and control signals. The data processing performed within the intelligent node is shown schematically in Figure 68.

All of the health features and sensory data are made available to the Area Reasoner by means of a standard TCP/IP server interface.
6.1.2 Fault Recognition on the LSTB using Model-Based Features

The development of diagnostic features requires the association of fault symptoms with the potential failure states of the lubrication system. Advanced progression of a failure state will usually produce a readily understandable symptom, (i.e., lube oil delivery pressure dropping below a lower limit is a symptom of loss of oil, pump failure, or gross leakage, the actual root cause of which can be determined through consideration of additional data sources). However, detecting and associating symptoms of incipient failure conditions requires more capability than what is provided by simple threshold checking.

Features were developed to model the characteristics of several lubrication systems faults. These include heat exchanger faults, filter clogging, and flow blockage of distribution branches. Sensor data obtained from the LSTB is utilized to associate the faults with changes in state and debris sensed parameters in the LSTB, and to fine-tune the models. Variations of the oil properties (viscosity, specific heat and density) are taken into account to ensure that the model features accurately represent the actual flow conditions.

6.1.2.1 Heat Exchanger Fault Detection

The heat exchanger effectiveness, $\varepsilon$, can be used to identify increased heat transfer resistance resulting from the deposit of wear debris on the internal elements, thus leading to decreased efficiency. A fouled cooler will also exhibit an increased pressure drop resulting from larger flow restrictions. This effect represents an alternative method for detecting heat exchanger fouling. The calculation of the heat exchanger effectiveness is shown below.

$$\varepsilon = \frac{C_h (T_{h,i} - T_{h,o})}{C_{\text{min}} (T_{h,i} - T_{e,i})}$$

$$C = m_c \rho$$

where,

- $\varepsilon$ = Heat exchanger effectiveness
- $C_h$ = $m_{oil} \cdot C_{p,oil}$
- $m_{oil}$ = mass flow rate of the oil at the outlet of the heat exchanger (pph)
\( C_{\text{p-oil}} = \) specific heat of the oil (using the oil temperature at the heat exchanger inlet)
\( C_c = \dot{m}_{\text{water}} \cdot C_{\text{p-water}} \)
\( \dot{m}_{\text{water}} = \) mass flow rate of the chilled water at the inlet to the heat exchanger (pph)
\( C_{\text{p-water}} = \) specific heat of the water (using the water temperature at the heat exchanger inlet)
\( C_{\text{min}} = \) either \( C_c \) or \( C_h \), whichever is least
\( T_{h,I} = \) temperature of the oil at the inlet to the heat exchanger
\( T_{h,o} = \) temperature of the oil at the outlet of the heat exchanger
\( T_{c,I} = \) temperature of the chilled water at the inlet to the heat exchanger
\( T_{c,o} = \) temperature of the chilled water at the outlet of the heat exchanger

### 6.1.2.2 Filter Clogging/Bearing Debris Accumulation

Filter clogging due to inadequate filter replacement intervals or accumulation of excessive wear debris from bearings or gears is another lubrication system fault that was examined. The mass flow effects of the fault was examined in the following manner:

\[
\dot{m} = C_D A_{\text{FILT}} \left( \frac{2 \rho \cdot g_c \Delta p}{144} \right)^{1/2} \times \frac{3600}{X}
\]

\( X = \left[ 1 - \frac{\% \text{Clogged}}{100\%} \right] \)

where,
\( \dot{m} = \) oil flow rate (at outlet of heat exchanger)
\( C_D = \) discharge coefficient
\( A_{\text{FILT}} = \) cross-sectional area of oil flow through filter
\( \rho = \) density of the oil (using temperature of oil at the outlet of the heat exchanger)
\( g_c = \) gravitational constant
\( \Delta p = \) pressure drop between the filter inlet and the filter outlet
\( X = \) filter clog parameter

The \( X \) parameter allows the clogging effect of the filter to be modeled by taking into account the reduction in available flow area due to clogging.

### 6.1.2.3 Lubrication Leg Clogging/Bearing Fault

A clog in a distribution leg for bearing lubrication may be evaluated using effective flow area:

\[
\text{area} = \frac{\dot{m} \rho}{C_D \sqrt{2 \rho \cdot g_c / 144 \cdot (p \cdot 3600)}}
\]

where,
\( \dot{m} = \) oil flow rate (through the distribution leg)
\( \rho = \) density of the oil (using temperature of oil at the outlet of the heat exchanger)
\( C_D = \) discharge coefficient
\( g_c = \) gravitational constant
\( p = \) gage pressure at the leg inlet (outlet to tank is at atmospheric pressure)
The feature estimates the equivalent orifice area for the distribution branch of the lubrication system. This value can be compared to a nominal value to determine if bearing wear particle accumulation or other clogging mechanisms have restricted lubricant flow.

6.1.3 Software Description

The intelligent node module runs a custom Windows application that acts as an automated data collection, processing and archival server. The DAQ portion of the software is user configurable in every aspect, e.g., nothing is hard-coded or hidden from the user. Once the system is configured, the user may collect data in a manual mode where the user presses a button for each snapshot of data or it may be configured in an automated fashion, where the system collects snapshots on a preset interval. The settings are all remotely configurable via a TCP/IP interface. In normal operation for the NERI demonstration runs, the intelligent node was configured and controlled from a remote computer (the area reasoner).

The second purpose of the intelligent node is to process the raw sensor data and calculated lube oil diagnostic features. After the collection of each snapshot, the intelligent node first preprocesses the block by taking and average, and then calculates three fault features; clogged filter, fouled cooler and bearing leg clog. If the user manually requests a snapshot, the averaged channel data and three features was display to the screen. However, if a remote application requests the data, the information will also be passed back to the requesting application. Figure 69 shows the local graphical user interface for the intelligent node module.

The Area Reasoner is a desktop computer with remote Internet access privileges and a wireless interface. The Area Reasoner will communicate with the intelligent node using a custom TCP/IP message over the wireless network. This allows the data acquisition unit to be placed virtually anywhere within 300ft of the computer without the need for expensive cabling. The graphical user interface for the area reasoner is show in Figure 70. This software is to remotely configure the intelligent node and set threshold limits for warnings and alarms. The main purpose of the software is to gather sensory and health information from remote intelligent node and fuse the result for export to remote applications.

The second purpose of the Area Reasoner is to act as a data server to higher-level software applications such as the HMS software module discussed in Section 2.3.2. The data socket sever allows a publish/subscribe mechanism for interfacing and transferring requested data. Custom message packets enable login, configuration, data transfer. Figure 71 shows the integration of the LSTB hardware and software in the entire HMS demonstration system.

6.2 Demonstration Activities

As early as the end of Phase 1, the Smart-NPP began planning and preparation for the presentation of the prototype demonstration HMS in Phase 3. Once the component and physical test bed was identified, development of the architecture for the demonstration was begun. Work continued throughout Phase 2 and Phase 3 to refine the demonstration architecture. The final demonstration architecture for the integrated system is shown in Figure 71.

A preliminary script for the demonstration was developed during Phase 2. A dry run of the demonstration, which focused on the canned HMI displays and the stand-alone BN developed during Phase 2, was presented at SNL in June 2001, in part to set a baseline for how information on each of the HMS elements could be presented. Feedback from this presentation was incorporated in the further
development of the demonstration during Phase 3. Additionally, project staff developed specific scenarios to demonstrate fault implementation and notification.

The direction for the demonstration was to make this a web interface to allow testing and demonstration of the HMS at a variety of locations. The HMS demonstration in part helps to develop a methodology for systematically evaluating equipment to determine how best to improve its reliability. In addition, it can provide an opportunity to evaluate and optimize smart equipment and predictive maintenance strategies and to support the HMI validation.

During Phase 3, demonstration scenarios were finalized for the demonstration presentation. Final versions of each of the software components were provided to SNL for integration with the HMS software. These included:
The dynamic HMI prototype from WEC,
The BN from MIT, and
The VMES from SNL.

Subsequently, SNL and PSU worked to integrate the HMS and HMI with the LSTB at PSU, to test the demonstration HMS, and to run the demonstration script.

The final demonstration scenario was based on the progression of the bearing leg orifice clog. The bearing leg orifice clog is a basic fault which initiates flow related failures in the lubrication system,
and hence in the operation of the bearings. The interrelationship of lubrication to the overall pump system is fairly complex, and the progression of this fault includes indications from the lube system, but also indications from other parts of the pump, for load and clearance. The indications in the lube system were provided by the actual physical LSTB and were simulated on the LSTB by adjusting the flow area with the valve on the flow leg. The indications in the other related fault areas were provided by a data file that included time series of expected signals from other “virtual” sensors that would monitor load and clearance faults (for example, accelerometers and proximity probes) over the expected time period for the
progression of the fault. During the live demonstrations, all sensor data were transmitted over a high-speed Internet connection from the PSU LSTB to the demonstration location.

The initial conditions are such that all the sensor features indicate the good operational ranges of measurements. The progression of the faults due to initiation and progress of the bearing leg clog takes the following steps:

1. The clogging of the bearing leg is initially detected by the smart sensor features orifice parameter, and oil pressure. The deviation in the reading of these features shows a performance status change in the oil flow condition.

2. The temperature of oil before the orifice decreases due to insufficient flow circulation.

3. The flow to the bearing clearances to cool the babbit becomes insufficient. The babbit metal temperature increases due to lack of lubricant flow to the bearings. This stage of the event is detected by the babbit temperature feature.

4. The increase in the babbit metal temperature raises the temperature of the lubricant in the clearances, which cannot circulate sufficiently. The viscosity of the lubricant decreases with the increasing temperature. The decrease in the viscosity degrades the capability of the fluid to support the load. This condition yields the symptoms of static overload fault. The initiation of the static overload condition is detected by the shaft eccentricity and the ratio of orbit axis features.

5. As the static overload fault progresses to be more severe, babbit wear due to contact of the bearing surfaces starts. The worn babbit material in the lubricant is detected by the babbit mass feature.

6. After sufficient babbit wear, the ferrous material under the babbit starts degrading. The ferrous particles in the fluid are detected by the particle count feature. (The wear of the babbit outer surface and inner material is presented with two progression steps in the results.)

Figure 72 shows the change in the performance status of the flow condition in six time steps of the fault progression, in terms of the probabilities for normal, intermediate, or severe operating states. These probabilities were generated by the BN as a result of the sensor data provided by the pump/lubrication system and are the basis for the values presented by the Tier-3 HMS display for the failure state probability (Figure 27). After the third time step, no further degradation is observed in the status of the flow, because the fault starts having a different nature. Figure 73 illustrates the change in the performance status of the static load during the progression of the bearing leg orifice clog event. The first two time steps have no effect on the load condition. Only the third stage of the event starts showing the symptoms of static overload condition. Figure 74 presents the overall operating condition of the bearing system throughout the progression of the fault event. The results presented in this figure are consistent with the changes observed in Figures 72 and 73.

For the live demonstrations, the HMI Client, and the HMS software (HMI server, BN, VMES, and TTF), were loaded on a laptop computer. As discussed in Section 2.2.3, these two elements are not required to be co-located. The laptop was connected to the HMS server at PSU via the data socket message center. At the request of the demonstration presenter, a person at the PSU LSTB initiated the scenario by closing the flow valve to several progressive pre-determined settings before completely closing the valve. Coordination between the demonstration presenter and the person at the LSTB was achieved via cell phone communication. As the presentation progressed, as requested by the presenter, the person at the LSTB would hold the various flow valve settings for as long as required to match the pace of the presentation and to accommodate discussion.
At the outset of the demonstration, all features are set for normal operating conditions, and all indicators on the Apex, Tier-1, and Tier-2 HMS displays (Figures 23, 25, and 26) are green. As the scenario for the bearing leg orifice clog progressed, the fault progression could be viewed by changes in the various indicators from green to yellow to red on the Tier-2 HMS display for failure mode faults (Figure 26) and the probability values for the fault states changed as indicated in Figure 74. These changes were also propagated up to the Tier-1 HMS display for sub-component health as the bearing indicator changed from green to yellow to red and the TTF values changed as the component neared failure. The changes could also be viewed on the Apex HMS Display as the charging pump indicator changed from green to yellow to red. At each time interval for the scenario, the Tier-3 HMS displays for drill down data were also presented. For most of the Tier-3 HMS displays (Figures 27 through 33), with the exception of the state probability and the cost function, representative static information was presented that was not necessarily directly tied to the live scenario. Most runs of the demonstration concluded by viewing the cost function, which displayed the results generated by the VMES and TTF computations, and discussing the types of decisions that might be supported by the information that resulted and was presented for the scenario.

The final demonstration was presented during the industry expo at the EPRI Wireless Technology Conference, held November 19-21, 2002, in Orlando, FL. The demonstration was presented numerous times to a large audience of industry professionals who attended the two-hour exhibit session. Additionally, a formal presentation on the Smart-NPP project was given as part of the technical conference program. Project team representatives were very successful in presenting the demonstration without any significant technical difficulties, and the demonstration was very well received.
Figure 73. Probability distribution over the performance states of the static load condition during the bearing leg orifice clog event.
Figure 74. Probability distributions over the performance states of the bearing system during the bearing leg orifice clog event.
7 Task 6 – Enterprise-Level HMS

Task 6 is Enterprise-Level HMS. The objective of this task was the development of a methodology that combines equipment-health information from individual machines (produced by Task 4) into overall plant-health and enterprise information.

This task provided preliminary development of a methodology that combines equipment-health information from individual machines into overall plant-health information. Within the limited scope of the task, it provided some preliminary ideas and concepts for expanding the health-monitoring concept to system and plant levels, providing a strategy for communication and integration of data among the smart equipment, as well as control room systems and plant operators. An advanced information system architecture was designed to support data transfer and storage at the enterprise scale. The preliminary system architectures was designed to:

1. Provide data and configuration information required for interpreting and displaying real-time sensor and health data at the machine, system, and plant levels;
2. Provide historical performance and maintenance data required for analyzing reliability, spares, and maintenance conditions;
3. Store machine, system, and plant configuration models and simulation data; and
4. Support data requirements of selected reliability and maintenance analysis techniques.

The methodologies from other task activities were developed using object-based design approaches where the functionality of each element of the system was contained in a separate “module” with specified relationships to other elements in the system. The strategy for this task, then, was to compile and then extend these relationships to develop a preliminary architecture design for an enterprise level HMS.

7.1 Data Structures to Support HMS Operations

In considering data structures to support HMS operations, the Smart-NPP team looked at the NPP power generation enterprise as a hierarchical tree structure comprised of plant areas, systems, subsystems, components, failure modes, sensor features, and sensors. This could also be extended up one or two more levels to define the enterprise as plant sites with multiple units or as utilities with multiple plant sites. This hierarchical tree structure is illustrated in Figure 75. The hierarchy is deeply nested and designed to accommodate the large amounts of data that would be required for different levels of the hierarchy; some would require more than others. This hierarchy is flexible in that, for a given branch from top to bottom, all levels do not need to be present if they are not required for that branch. The recommended approach here is to separate the actual data hierarchy, so that the application is insulated from the underlying database. Using a tree structure to define the hierarchy, object classes for each level in the hierarchy are defined (i.e., failure mode data class, sensor data class, …) to store and manipulate data and interface with the database.

The hierarchy, then, is defined by a collection of “TreeNode” objects. This approach provides several advantages. The structure of the hierarchy is stored separately from the data. Level(s) of the hierarchy may be omitted, and thus this approach provides flexibility for applying different approaches for health monitoring for different types of equipment. For example, some systems may need to be decomposed into subassemblies then components for effective health monitoring. Other plant areas may be decomposed directly into components. Via naming convention IDs, each TreeNode object points to a data object of the right type and encapsulates the required interface with the underlying database. The overview of the HMS data architecture is provided in Figure 76.
Figure 75. Enterprise NPP power generation as a tree structure.

Figure 76. HMS data hierarchy and architecture.

When this data architecture is in use, the TreeNode data is retrieved from the TreeNodes table in the database when an application starts. This data is used to construct the power generation object hierarchy. Using the hierarchy, a collection of objects is built for each level in the tree. These object
retrieve their data from the corresponding tables in the database. When the application is running, objects periodically update the database. When the application exits, objects update the database.

This hierarchy was implemented for the Smart-NPP prototype demonstration HMS. As part of the HMS integration the necessary database and routines to support the hierarchy were developed. SNL, PSU, WEC, and MIT worked together to develop consistent naming conventions, message structures and communication tools for each of the key element of the HMS, including the BN, VMES, and HMI. Because of the success of the prototype demonstration HMS, it is evident that this type of approach is effective for handling the amount and variety of data need to support an enterprise-level HMS.

### 7.2 Conceptual Enterprise-Level HMS Architecture

Figure 77 provides an illustration of a conceptual HMI for an Enterprise-Level HMS. Sensors, located on plant equipment, record plant and plant process parameters (such as temperatures, flow rates, pressures, radiation levels, valve positions, pump rotation speeds, vibration levels, acoustic signatures, etc.). These sensors are interfaced to a DAQ that transmits the acquired sensor data to a digital computer. Equipment may also be instrumented with advanced smart sensors that process raw sensor signals to extract relevant sensor features that can then be related to equipment health status.

Video Display Units (VDUs), located at Engineering Workstations, are used to present predictive maintenance information to the operators and maintenance personnel. Operator Input Devices (OIDs) are also located at each Engineering Workstation and allow the plant staff to interface with the digital computer as further discussed below. The OID may be a trackball, computer mouse, VDU touch-screen, finger pad, keyboard, keypad, etc. An audio output device can be used to provide annunciation whenever equipment or systems are predicted to have a severe failure potential.

There are five major components of the HMS that are contained within the digital computer:

- Data Communications Module
- Health Monitoring Data Base
- Health Monitoring Status Module
- Health Monitoring Display Module
- Maintenance Log and Scheduler Module

These components interface with Video Display Units (VDUs) and OIDs located at the Engineering Workstations via a Data Network, and via the audio output device.

#### 7.2.1 Data Communications Module

The data communications module interfaces the digital computer with the DAQ. Wireless communication may also be applied to transfer smart sensor features from instrumented equipment to the DAQ and subsequently to the data communications module. This module transfers plant equipment data, as acquired by the DAQ, from the DAQ to the Health Monitoring Database. Plant data are subsequently accessed from the database by the Health Monitoring Status Module.

#### 7.2.2 Health Monitoring Data Base

The Health Monitoring Database stores plant equipment data, acquired by the DAQ, for subsequent access by both the Health Monitoring Status Module and the Health Monitoring Display
Figure 77. Enterprise-level HMS.
Module. The Health Monitoring Database would also store failure predictions and equipment health state
information, as determined by the Health Monitoring Status Module, for subsequent access by the Health
Monitoring Display Module. The recommended approach for designing an implementing data structures
for an enterprise-level HMS is discussed in the previous section.

7.2.3 Health Monitoring Status Module

The Health Monitoring Status Module within the Digital Computer determines if any equipment
is in imminent danger of failing and determines the predicted remaining equipment life until the
equipment must be repaired, refurbished, or replaced.

To perform its incipient failure detection function, the Health Monitoring Status Module
periodically and/or continuously (as appropriate) performs the necessary algorithmic processing on the
requisite component and/or process measurements obtained from the DAQ. Due to the wide variety of
equipment and plant processes that exist within a plant, a variety of techniques will necessarily be utilized
to ascertain the potential of incipient equipment failures and to predict the equipment remaining life.

The following have been identified as being typical of the methodologies to be used by the Health
Monitoring Status Module to ascertain the potential of incipient equipment failures and to predict the
equipment’s remaining life.

- **Trend Analysis** – Trend analysis is used to assess equipment health and degradation by
  monitoring for changes in selected measurement parameters over time. The trended information
  may be in either the time domain (such as absolute vibration level tracked against time) or in the
  frequency domain (such as vibration amplitude over a frequency spectrum which is monitored –
  in this case significant increases/changes in amplitude at various frequencies are tracked in time).
  To perform trend analysis, parameters to be trended are first identified, the trend periodicity to be
  utilized is then defined, and alert/warning criteria for early identification of impending problems
  are finally developed. Typically, the equipment manufacturers' recommendations and industry
  experience are used to develop alert/alarm criteria. Statistical methods are utilized to enhance the
  trend accuracy.

- **Pattern Recognition** – Pattern recognition techniques are utilized to assess equipment health and
degradation by analyzing the selected measurement parameters relative to state or status patterns.
Statistical methods are used to improve pattern recognition accuracy. Techniques such as Time
Source Analysis and Fast Fourier Transform are typically used to process the data in conjunction
with pattern recognition algorithms.

- **Correlation Techniques** – Related sets of data may be correlated to assist in performing
predictive analysis. Correlation coefficients are developed to aid in the recognition of patterns or
the recognition of sequences of events that are related.

- **Limits and Ranges** – Component monitoring may utilize alarm/alert limits using thresholds,
bands and frequency filters. This approach allows subsequently gathered information to be
compared to expected regions of operation for the monitored components.

- **Data Comparison** – Several comparative methods may be utilized for preventative maintenance
data analyses. Data for a particular system or component can be compared to standard values,
manufacturers' recommendations, technical specifications, code limits, or normal baseline data or
ranges. Data may be compared on an absolute basis or a relative basis. As an example, data from
a specific component may be analyzed to identify discontinuities (breaks) in a performance curve,
or data trends, or data offsets. In addition, data on similar components can be compared to
develop comparison data relative to similar components. This comparison of data is used for equipment or system health and aging.

- **Statistical Process Analysis** – Statistical methods are used extensively in the analysis of Predictive Maintenance Program (PMP) data. Techniques, such as curve fitting, data smoothing, predictive techniques and probabilistic inference techniques (such as BNs), and mean standard deviation are extensively being used. The predictive maintenance algorithms utilized by the Health Monitoring Status Module will likely employ a variety of the aforementioned techniques, depending on the equipment or system that is being analyzed. The following describes a number of the predictive analysis applications that can be employed by the Health Monitoring Status Module to predict remaining equipment life.

- **Vibration Analysis** – Vibration analysis is utilized to determine the health and useful remaining service life of critical equipment and components in the Nuclear Island (NI) as well as for suitable Balance of Plant (BOP) components. Vibration detectors transmit vibration information associated with steady-state operation and other operating regimes, such as equipment startup, coast-down and breakaway analyses can be used to enhance the capabilities of the predictive program to detect incipient failures. The remaining equipment life is inferred from vibration frequency analysis by trending amplitude changes in the spectrum over time. Equipment transient analysis techniques (for startup, coast down and breakaway conditions) include vibration spectral data as a function of machine speed. These analyses are utilized to determine the presence of equipment structural response frequencies, as they are excited during the equipment transients (such as startup and coast down). Trending, comparative analysis and signature frequency analysis techniques are utilized to detect indications of component degradation and to predict remaining component useful life.

- **Temperature Measurement** – Indications of incipient mechanical and electrical problems can often be determined by the presence of excessive heat generation or by the absence of suitable heat output. Temperature measurement technologies, such as contact pyrometry and thermography, are used by the Health Monitoring Status Module to support predictive maintenance applications. Measurements obtained via infrared thermography and contact pyrometry are used to determine the remaining life of electrical switchgear, motor control centers, and transformer. The remaining life of electrical connections, insulation, and equipment that is experiencing friction induced heating can also be inferred by monitoring heat generation.

- **Flow Measurement of Liquids** – For certain equipment and systems, flow change is an indicator of impending component failure and remaining equipment life. Existing process monitoring instrumentation can usually be utilized for the requisite data measurements. Flow measurement is typically collected for trending, and for correlation predictive analysis.

- **Valve Analysis** – The Health Monitoring Status Module predicts potential failures, degradations and remaining life for valve by analysis of valve and switch timing, number of operational cycles, and trending in-service valve test results. Valve operator types will include air, motor, hydraulic and solenoid.

- **Electrical Analysis** – Electrical measurement analysis is used to determine the health and to predict the remaining useful service life for electrical motors, breakers, switches, cables, transformers, controllers, and cables. The following types of analysis techniques are applied to such equipment as appropriate: motor current signature analysis, contact resistance measurements, breaker closing time, voltage drop, and circuit ground resistance. Infrared thermography capability is also used to collect heat generation data, which can provide additional indications of impending equipment failure or reduction in service life. In addition, ultrasonic monitoring is also for detection of Corona discharge activity in transformers. Methodologies
utilized for early detection of electrical component degradation include trending, comparative analysis, and signature frequency analysis.

- **Thickness Measurement Analysis** – For certain plant equipment and components (such as associated piping), thickness measurement is used to provide an indication of equipment integrity and its remaining useful service life. Thickness measurement sensors (such as ultrasonic sensors) are utilized to determine the degree of wear, erosion, and corrosion that has occurred and to predict the remaining useful life of the equipment. Trending and correlation analysis techniques are typically used for analysis and predictive purposes.

- **Efficiency Analysis** – The calculation and tracking of equipment efficiency is used for indications of degrading performance and impending failures. Operational efficiency is determined for appropriate equipment, components, and systems utilizing suitable measurements. Trending and correlation analysis is applied to note changes in operational efficiency and predict when operation no longer becomes cost-effective or when equipment replacement is advisable. Examples of efficiency analysis include determining the efficiency for heat transfer processes for applicable equipment and systems. Changes in efficiency serve as an indicator of equipment degradation, fouling, or subsystem failures.

- **Analysis of Position and Alignment** – For some equipment and components, position/alignment measurement serves as an indicator of equipment integrity and an indication of remaining useful service life. Position/alignment measurements from plant sensors are used to determine the degree of misalignment and to track the change in misalignment over time. Trending and correlation analysis techniques have been proposed for analysis and predictive purposes.

Predictions of incipient equipment failures, as determined by the Health Monitoring Status Module are stored in the Health Monitoring Database for subsequent access and display by the Health Monitoring Display Module.

### 7.2.4 Health Monitoring Display Module

The Health Monitoring Display Module collects and displays the equipment and system failure predictions as determined by the Health Monitoring Status Module. It also collects and displays plant equipment sensor data acquired by the DAQ and maintenance log and schedule information as provided by the Maintenance Log and Scheduler Module.

The information collected by the Health Monitoring Display Module is presented in the multi-tier display hierarchy as defined in Section 2.2.5.3.

### 7.2.5 Maintenance Log and Scheduler Module

The Maintenance Log and Scheduler Module collects relevant maintenance log entries and maintenance schedule information from other plant databases and provides them to the Health Monitoring Display Module for presentation.

### 7.2.6 Integration of HMS Elements

As with the Smart-NPP prototype demonstration HMS, system integration for an enterprise-level HMS would be achieved by design and implementation of an effective and flexible data structure hierarchy, including consistent definitions and naming conventions and messaging structures defined for all the key exchanges between the elements of the system.
7.3 Summary of Enterprise-Level HMS Architecture Design

This task provided preliminary development a methodology that combines equipment-health information from individual machines into overall plant-health information. Within the limited scope of the task, it provided some preliminary ideas and concepts for expanding the health-monitoring concept to system and plant levels, providing a strategy for communication and integration of data among the smart equipment, as well as control room systems and plant operators. An advanced information system architecture was designed to support data transfer and storage at the enterprise scale.

The methodologies from other task activities were developed using object-based design approaches where the functionality of each element of the system was contained in a separate “module” with specified relationships to other elements in the system. This approach can be logically extended for the design for an enterprise level HMS.
8 KOPEC Collaboration Activities

At the encouragement of the DOE during the FY00 annual review, the three NERI programs led by the coalition of SNL, WEC, and DE&S sought to establish collaborative agreements with similar international programs. As a result, a joint R&D program was established with KOPEC based on their established working relationship with WEC and the availability of funds to support their work from the Korean Ministry of Science and Technology (MOST). No additional DOE funds were made available to support this collaborative effort.

Initially meetings were held with representatives of KOPEC regarding their interest in participating in the Smart-NPP project. On behalf of the Smart-NPP Core Management Team (CMT), WEC developed a cooperative agreement and statement of work for the planned participation by KOPEC. The CMT and KOPEC representatives in Korea reviewed draft documents and a final version of the document was issued. This document defined the working arrangement and work scope and allowed KOPEC to proceed with procuring funds for their participation from the Korean government. In February 2001, KOPEC initiated work on their collaborative project, Development of the Intelligent Predictive Maintenance Tools and Methodology for NPP, after receiving funding from MOST.

The objective of the KOPEC project was to develop an HMS application for a selected NPP component that is diverse from the high energy, horizontal, centrifugal pump being used as a demonstration component by the Smart-NPP team. This application followed the methodology being developed in the Smart-NPP project and demonstrated its robustness for enterprise wide applications.

Initial plans regarding coordination of the KOPEC program and NERI Smart-NPP work centered around involving KOPEC engineers in the NERI team efforts to quickly bring them up to speed on the methodology. The KOPEC Project Manager attended Smart-NPP CMT meetings to directly facilitate this coordination. An on-the-job approach to training was identified as the most appropriate and effective collaboration approach. Areas were identified where KOPEC engineers could perform work for team members, while learning critical aspects of the Smart-NPP methods.

During the second half of Phase 2, the initial KOPEC efforts focused on developing their capability to use BNs and identifying and studying their target smart equipment system. Initial studies of BNs were performed including KOPEC participation in the HUGIN BN training at SNL in February 2001. The KOPEC team purchased BN and HMI software and developed examples using the BN software with Visual Basic. Subsequently, KOPEC procured hardware for their HMS including an HMS server, a data acquisition module and a D/A converter.

Also during Phase 2, KOPEC conducted three international trips to participate in collaborative work with NERI team members. During a three-week assignment at SNL, a KOPEC engineer participated in HMS integration tasks. These included developing a sample data exchange program using the data socket to allow communication between the HMS and LSTB demonstration facility at PSU. Preliminary plans for the HMS demonstration were also developed. A one-week consulting trip to MIT focused on BN application. This included consulting about how to apply BN techniques to calculate failure probabilities for smart equipment components. Sample BN structures were constructed and influence diagrams for the mechanical failures of the rod control system were developed. A one-week trip to WEC focused on creating the HMI displays and database. After understanding the current HMI approach for the NERI program, the KOPEC engineer developed a set of displays for the HMS demonstration system for an entire failure mode. The KOPEC team concluded the development and demonstration of their prototype HMS in Phase 3.
8.1 Predictive Maintenance System Methodology

The KOPEC program generally followed the NERI Smart-NPP project direction. The two major areas in their program included a study of basic technologies and development of a prototype application for the target system. The KOPEC activities for each of these areas are summarized in the following sections.

8.1.1 Study Of Basic Technologies For The Predictive Maintenance System

The study of basic technologies focused on the following five areas:

- FMECA of the target system
- Smart sensor system design
- Expert system for predictive maintenance
- RCM (Reliability Centered Maintenance) application
- Interface technologies for a predictive maintenance system

8.1.1.1 FMECA of the target system

The target system for the KOPEC work is the rod control system (Figure 78), which consists of the Control Element Driving Mechanism (CEDM), which is a mechanical part, and its control system (CEDMCS), which is the mechanical control part. A survey of operation and test experiences of this system at Korea Standard Nuclear Plants was conducted, and a survey of failure modes for the CEDM/CEDMCS was completed. Through the FMECA for the CEDM/CEDMCS, the structural and functional system hierarchies were presented for decomposing the complexity of system (Figure 79). Three failure modes, coil damage, rod drop and motion failure, were evaluated for the CEDM/CEDMCS, and the associated fault trees were constructed (Figures 80 and 81). Additionally, the CEDM operating model and temperature model were developed through analysis of the CEDM. These models were used in virtual machine design and smart sensor design of the prototype HMS.

8.1.1.2 Smart sensor system

A survey of sensor signals for the rod control system included evaluation of available sensor signals, and studying data acquisition and signal processing for selected sensor signals. Several sensor signals are available such as CEDM coil current/voltage, CEA position, and total travel steps. Coil current is used as the primary sensor signal since it implies health status of both the CEDM and CEDMCS. Various sensor signals can be extracted from this current signal including:

- Timing Sequence
- Glitch (timing & depth)
- Signal level
- Ripple (frequency & level)
- Coil Temperature
- Wave pattern
- Noise
The smart sensor for the CEDM was conceptually designed to extract sensor signals and sensor features from the CEDM and to implement the following state of art features:

- IEEE 1451 standard
- Small size
- Intelligent function
- Network based interface
8.1.1.3 Expert System for Predictive Maintenance

As with the NERI program, BNs were selected as the expert system to construct the intelligent maintenance system. BNs represent model domains that are characterized by inherent uncertainty as a relatively new treatment of expert system applications, augmented with decisions and utility functions. For the rod control system, input signals for the BN were sensor features that were extracted from the coil current signals, and output signals were probability values of each state for the component nodes and utility functions.

A BN for the prototype was constructed using the results of the failure modes analysis for the CEDM. Seven sensor features are used for the three failure modes of each coil.

- **S_Coil_I**: Coil current level status
- **S_Coil_T**: Coil temperature status

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![CEDM Failure](image1)

**Figure 80.** Failure modes for the CEDM.

![CEDMCS Failure](image2)

**Figure 81.** Failure modes for the CEDMCS.
8.1.1.4 **RCM Application**

RCM is a methodology used to define a maintenance program while having reliability as an input to the decision making process. For the KOPEC project, the RCM methodology was reviewed, and subsequently a commercial RCM tool was applied to calculate the failure rate, MTBF and reliability for the electronic components of CEDMCS. The results of the RCM application are provided in Figure 83.

8.1.1.5 **Interface Technologies for a Predictive Maintenance System**

The HMI provides predictive maintenance system output via a database to the user and contains an input device to allow the user to interactively communicate with the system. The display set provides a set of HMI displays and display objects used to convey the current health status and the predicted future health status of the components to the user. Displays types consist of mimics, trend, graphical, and textual formats.

The HMI display set has four levels. The 1\(^{st}\) level display shows the overall health status of the system. The 2\(^{nd}\) level display shows the health status of the major components. The 3\(^{rd}\) level display shows the status of each failure mode. The 4\(^{th}\) level provides drill down information including BN output, a mimic diagram, data trends, maintenance information, and a cost function.

The database contains the requisite information to perform HMI tasks, including equipment information, sensor features, failure modes and probability for the equipment, cost functions, repair log, and other required information. The database also acts as a data center to communicate with other CIMS application programs. Most of the information to be displayed in the HMI pages comes from the database; therefore the HMI program includes connection routines that periodically read data from database.

The HMI display pages are shown in Figures 84 through 88.

8.2 **Development of the CEDM/CEDMCS Prototype Application**

As with the Smart-NPP prototype demonstration HMS, the KOPEC team had to integrate the various elements for a predictive maintenance system to develop a prototype application. The prototype application for the CEDM/CEDMCS Intelligent Maintenance System (CIMS) was developed to demonstrate the methodology and to verify its functions and performance. The CIMS prototype consists of an integrated system of related hardware and software parts shown schematically in Figure 89. A photograph of the actual CIMS equipment is shown in Figure 90.
Figure 82. BN for CEDM/CEDMCS.
Automatic CEDM Timing Module  +
Subgroup Filter Panel  .
Phase Sync Pulse & CEA Select  0
P/S Control Circuit  ◦
Zero Crossing Detector  □
Switch Device  ★
Fuse  ★
Connector  ▽
Opto Isolator Card  ▼
Circuit Breaker  ▽
Coil Driver Actuating Logic  △

Figure 83. Reliability change of CEDMCS subgroup components.

Figure 84. Top level HMI display for CEDM/CEDMCS prototype HMS.
Figure 85. Level 2 HMI display for CEDM/CEDMCS prototype HMS.

Figure 86. Level 3 HMI display for CEDM/CEDMCS prototype HMS.
Figure 87. Level 4 HMI display for CEDM/CEDMCS prototype.

Figure 88. Level 4 HMI display for CEDM/CEDMCS prototype.
Figure 89. Hardware and software structure of prototype CIMS.
An API (Application Program Interface) program provides the interface to the BN file, influence engine and database on-line basis. Through this API program the system status is automatically recorded and monitored periodically. The CIMS database functions as an information center since most of the input and output signals are recorded in database. In the prototype, the database is linked with the smart sensor (DAQ PC), BN API and the HMI program. The database file can be located in any remote server since it supports the ADO (ActiveX Data Object) type of data access.

8.2.1 Smart sensor development

The function of smart sensor is embedded in DAQ PC of the prototype. DAQ PC receives current signals of four coils from a CEDM virtual machine and converts them to digital signals. The
DAQ PC then extracts various sensor features, which are required for the diagnosis of system status, and sends these features to CIMS server via network. Extracted sensor features are:

- Coil current level
- Coil temperature and change rate
- Driving sequence status
- Driving cycle time
- Driving load
- Coil voltage
- Coil voltage firing status

A schematic of the smart sensor for the CIMS is provided in Figure 91.

**Figure 91. Schematic of CEDM smart sensor.**

### 8.2.2 Virtual Machine

A virtual machine was developed to provide real-time information of equipment condition of CEDM and CEDMCS. The CEDM Virtual Machine (CVM) is a collection of algorithms, software and hardware that can be used to simulate CEDM behavior. Two types of signal generation were implemented; one is to generate actual current waves of various loads and the other is to simulate CEDM operation parameters such as coil voltage, coil current, coil temperature, etc., in real time. The displays for the CVM are provided in Figures 92 and 93.
Figure 92. CEDM Load-current simulator display for CVM.

Figure 93. Real-time CEDM simulator display for CVM.
8.2.3 Verification and Evaluation of the CIMS

Three demonstration scenarios were selected to verify and evaluate the function and performance of the CIMS prototype.

- Control rod friction increase – When the wave files of different weight rod were supplied using the CVM, the output of CIMS was reviewed in view of the effect on motion failure due to the friction increase.
- Upper Gripper coil voltage high – When high voltage was supplied on UG coil using the CVM, the output of CIMS was reviewed in view of the effect on coil damage due to the current increase.
- Upper Gripper coil holding current low – When low current was supplied on UG coil using the CVM, the output of CIMS was reviewed in view of the effect on rod drop due to the current decrease.

8.3 Summary KOPEC Activities and Accomplishments

The KOPEC team was very successful in applying the Smart-NPP methodology for the rod control system. They effectively applied, adapted, and extended Smart-NPP methods to develop and demonstrate the CIMS for the rod control system. The KOPEC team concluded that these methods can be applied to an actual system, generalized for application to other systems, and potentially expanded to a plant-wide system for intelligent predictive maintenance.
9 Other Project Activities and Accomplishments

Other important activities for this project include presentations and papers to disseminate project activities and progress, as well as industry collaboration and university student participation. These are summarized in this section.

9.1 Presentations and Papers

Throughout the project, Smart-NPP team has effectively disseminated information about research developments for this project through its participation in technical conferences. In most cases, Smart-NPP project team members leveraged their participation in these meetings with activities and travel for other projects. Presentations and papers on the Smart-NPP project [21, 29-40] include the following:

- April 2000 – Presentation and paper on Smart-NPP project activities for the Korean Nuclear Society/Korea Atomic Industrial Forum (KNS/KAIF) Conference in Seoul, Korea [30].
- October/November 2000 – Presentation and paper on Smart-NPP project activities for Pacific Basin Nuclear Conference in Seoul, Korea [31].
- November 2000 – Presentation and paper on Smart-NPP project activities at the American Nuclear Society (ANS) Nuclear Plant instrumentation, Controls, and Human-Machine Interface Technologies (NPIC/HMIT) 2000 Conference [32].
- April 2001 – Poster session presentation on the BN expert system development for the International Symposium on the Role of Nuclear Energy in a Sustainable Environment, CANES, at MIT [33].
- May 2001 – Presentation and paper on Smart-NPP project activities for Maintenance and Reliability Conference (MARCON) in Gatlinburg, TN [34].
- May 2001 – Article on Smart-NPP project for May issue of Nuclear Engineering International [35].
- August 2001 – Presentation and paper on BN expert system development for the 2001 EPRI International Conference in Houston, TX [21].
- June 2002 – Presentations and papers on four topic areas (HMI development, BN development, VMES, and HMS demonstration activities) for the International Conference on Probabilistic Safety Assessment and Management (PSAM6), in San Juan, Puerto Rico [36-39].
- November 2002 – Exhibit, presentation and paper for the final Smart-NPP prototype demonstration at the EPRI Wireless Technology Conference in Orlando, FL [40].

9.2 Collaboration Activities

In addition to the very effective formal collaboration agreement with KOPEC for this project and the pursuit of related work by Smart-NPP project team organizations, other collaboration activities included:

- Collaboration discussions with Flowserve, a commercial pump vendor, with February 2001 CMT meeting held at the company’s Los Angeles location.
• *Hugin* training course at SNL in February 2001, with participation from project team staff, KOPEC staff, Flowserve staff, and other interested staff from SNL and Los Alamos National Laboratory.

• Participation in other related NERI and INERI projects, including advanced control for IRIS with WEC and the University of Michigan, and advanced condition monitoring with SNL, Korea Atomic Energy Research Institute, and PSU.

• Discussions with and presentations to the Westinghouse Owners Group on advanced equipment monitoring.

• Follow-up discussions with EPRI after the demonstration presentation.

### 9.3 University Student Participation

Through the course of this project, university student involvement included participation of two PSU students, one graduate research assistant and one undergraduate research assistant, supporting the development of the LSTB. Additionally, all of the work for Task 4, as well as the integration of the BN and TTF calculations in the demonstration HMS, comprised the PhD graduate research of Bilge Yildiz at MIT.

### 9.4 Recognition Award and Patent

Other project accomplishments include a patent and a project team recognition award.

WEC applied for and received a patent for its design of an HMI for an advanced equipment health monitoring system.

Finally, for the very successful presentation of the Smart-NPP prototype demonstration HMS and all the supporting technical work and organizational coordination and collaboration, this project was nominated and selected for a technical project team award at SNL (see Figure 94).

![Figure 94. Project team recognition award.](image-url)
10 Summary

The Smart-NPP team effectively achieved its goal to design, develop, and evaluate an integrated set of tools and methodologies that can improve the reliability and safety of advanced nuclear power plants through the introduction of smart equipment and predictive maintenance technology. Smart equipment embodies elemental components such as sensors, data transmission devices, computer hardware and software and man-machine interface devices that continuously monitor and predict the failure modes and remaining useful life of the equipment. The Smart-NPP project team worked to accomplish its goal by developing an integrated smart equipment prototype demonstration HMS for a selected plant component, a high-energy centrifugal charging pump. The project goal was realized with the very successful development and presentation of a prototype demonstration HMS that accomplished the following:

- Evaluated actual faults in a physical test-bed system for a lubrication system, as well as faults that were implemented “virtually” through modeling of a high-energy centrifugal charging pump;
- Processed sensor features, including those acquired through the application of advanced smart sensor technology;
- Related sensor features to system fault conditions through the application of a BN expert system;
- Generated consequences, in terms of cost and probability of lost generation capacity, of alternative maintenance options with a VMES capability; and
- Provided indications and details of system health and maintenance options on an HMI.

Additionally, in effective collaborative efforts, the Smart-NPP methods were applied by KOPEC in their design and development of a CIMS for a rod control system.

The results of the DOE NERI Smart-NPP project have contributed much to the advancement of equipment health monitoring for complex systems. Each major element on its own is a significant accomplishment and contribution. The cumulative contribution of the demonstration of an integrated system as a whole has the potential to substantially change the way that future nuclear power plants are designed and operated. By providing the capability to predict future component and system performance with high confidence, the development of smart equipment has the potential to help improve the cost competitiveness of nuclear power by (1) providing substantial operations and maintenance savings and (2) reducing capital costs by allowing front-line systems in normal operation to supplement or even replace dedicated safety systems.

The project addressed many issues along the way and has developed a foundational set of information and methods, but much remains to be done to have this type of system incorporated in the design of an advanced NPP. It was a significant accomplishment of this project to demonstrate an integrated system on a physical test bed. One of the challenges of equipment health monitoring remains that the equipment, systems and components are designed to be highly reliable, and often a significant investment such that equipment owners are not necessarily willing use the equipment to deliberately investigate failures and fault conditions. The level of understanding of the physics and mechanics of equipment failures on which smart equipment health monitoring must be based is a major challenge of this type of application and will remain a key area of endeavor to successfully implement smart equipment monitoring. It is noteworthy that one other INERI program is pursuing research of this type for advanced condition monitoring, the PSU ARL continues to pursue this area of research, Flowserve, a major pump vendor, understands the need for these types of studies, and EPRI also sponsors these types of studies with the energy industry.
Another key challenge at the outset of this project was the use of advanced smart sensor technology, including wireless communication, in an NPP. At the completion of the project it is noteworthy that commercial utilities are now investing in plant modifications to support wireless communications, and thus a key element of the infrastructure need to support smart equipment on an enterprise level. Again, PSU is pursuing and EPRI supports research studies to demonstrate and validate the use of such equipment in commercial energy plants.

Knowledge acquisition and the validation of expert systems approaches for how different types of sensor signals can be related to equipment fault and failure conditions are other areas that will require significant additional development. Equipment manufacturers, vendors, operators and maintainers must not only think in terms of equipment reliability, but also shift to developing an understanding and a dialog of how sensor features, individually and in combination, relate to fault conditions and potential failures modes to provide support for developing plant system models, model-based diagnostics and expert systems for smart equipment health monitoring.

The methods and results employed to develop the Smart-NPP prototype demonstration HMS provide a framework within which to address these areas identified in the preceding paragraphs and to move forward to incorporate this type of integrated system in advanced NPP designs. Each organization that is a member of the Smart-NPP project team is involved in related work that can build on the results of this work. Additionally, it is likely that the formal KOPEC collaboration with this project will result in the application of these methods to the active design and construction programs for Korean NPPs. Finally, the Smart-NPP team has actively disseminated the methods and results of this work to industry members and research organizations that can also move this work forward.
### References


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