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Summary Describing Integration of ERM Methodology into Supervisory Control Framework with Software Package Documentation

Advanced Reactor Technology Milestone: M4AT-16PN2301052

September 2016

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U.S. DEPARTMENT OF ENERGY

Prepared for the U.S. Department of Energy
under Contract DE-AC05-76RL01830

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Abstract

This project involved the development of enhanced risk monitors (ERMs) for active components in Advanced Reactor (AdvRx) concepts by integrating real-time information about equipment condition with risk monitors. Health monitoring techniques in combination with predictive estimates of component failure based on condition and risk monitors can estimate the future risk posed by continued plant operation in the presence of detected degradation. This combination of predictive health monitoring based on equipment condition assessment and risk monitors can also enable optimization of maintenance scheduling with respect to both economic and safety metrics. This report summarizes PNNL's multi-year project on the development and evaluation of an ERM concept for active components while highlighting FY2016 accomplishments. Specifically, this report provides a status summary of the integration of the prototypic ERM framework with the plant supervisory control algorithms being developed at Oak Ridge National Laboratory (ORNL), and describes additional case studies conducted to assess sensitivity of the technology to different quantities.

Acknowledgments

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Acronyms and Abbreviations

AdvRx	advanced reactor(s)
AdvSMR	advanced small modular reactor
AFI	aging fractional increase
ART	Advanced Reactor Technologies
AST	aging start time
CDF	core damage frequency
ECA	equipment condition assessment
EMP	electromagnetic pump
ERM	enhanced risk monitor
ICHMI	instrumentation, control, and human-machine interface
LWR	light-water-cooled reactor
O&M	operations and maintenance
ORNL	Oak Ridge National Laboratory
PHM	prognostics and health management
PNNL	Pacific Northwest National Laboratory
POF	probability of failure
PRA	probabilistic risk assessment
RUL	remaining useful life
RWB	Reliability Workbench
SCS	supervisory control system

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1.0 Introduction

The goal of the research described in this report was the development of enhanced risk monitors (ERMs) for active components in advanced reactor (AdvRx) concepts by integrating real-time information about equipment condition with predictive risk monitors. Health monitoring techniques can be used to establish condition indicators for active components in AdvRx; in combination with predictive estimates of component failure based on condition and risk monitors, such health monitoring techniques can serve to estimate changes in future risk posed by continued operation in the presence of detected degradation. This combination of predictive health monitoring based on equipment condition assessment and risk monitors can also enable optimization of maintenance scheduling to avoid unplanned plant shutdowns while maintaining required safety margins. The multi-year project involved the development of a framework for ERM, and the evaluation of this concept for active components using a series of case studies.

The research conducted in this project supports the safe, efficient, and economic operation of AdvRx by providing a real-time assessment of changes in system risk based on component degradation by: (1) informing operations and maintenance (O&M) planning for targeted maintenance activities during outages, (2) optimizing plant performance to maintain safety margins and maximize economics while operating with components with detected degradation, and (3) supporting extended operating cycles by ensuring reliable component operation over the long term.

1.1 Research Objectives

The overall objective for this project under the Advanced Reactor Technologies (ART) Program was to develop a framework to move from measurements through condition assessment and predictive estimates of probability of failure (POF) assessment to ERMs.

Research on this project in prior fiscal years (FYs) (Coble et al. 2013; Ramuhalli et al. 2013; Ramuhalli et al. 2014; Ramuhalli et al. 2015) focused on: (1) assessing the state-of-the-art in ERMs to identify technical gaps, and developing a preliminary framework for ERMs for prototypic active components that includes a methodology for combining equipment condition assessments with enhanced risk monitor frameworks; (2) evaluating this framework for enhanced risk monitors; and (3) integrating prototypic ERM framework with uncertainty quantification and non-traditional risk metrics.

Activities described in this report focus on the specific objective of integrating the prototypic ERM framework with the plant supervisory control algorithms being developed at Oak Ridge National Laboratory (ORNL).

1.2 Research Assumptions

The following assumptions are being made in the research described in this report:

- Background information about representative AdvRx designs, components, and concepts of operations for these designs is assumed to be available.
- The overall focus will be on active components key to the safe operation of AdvRx (including advanced small modular reactor; AdvSMR) concepts, such as liquid metal-cooled fast reactors or high temperature gas-cooled reactors.
- AdvRx-specific information about active components as well as representative component testbeds, simulations, and/or other design information for active components will be available.

- Available active component reliability data sets from AdvRx operations are representative of active components expected to be used in future AdvRx concepts.
- Equipment condition assessment (ECA) methods are assumed to be available, or can be adapted for application to key AdvRx active components.
- Integration of research results with ORNL supervisory control algorithm development is possible and can be used to establish acceptance criteria for different risk measures.
- Availability of supervisory control simulation environment to integrate the ERM framework software into the platform currently being utilized by ORNL for demonstrating the supervisory control algorithms is assumed.

1.3 Organization of Report

This technical report is organized as follows. Section 2 includes background information on AdvRx and briefly summarizes previous research in this project. Section 3 describes additional evaluations of the prototypic ERM framework that have occurred since Ramuhalli et al. (2015). Section 4 summarizes the integration of ERM module with the ORNL supervisory control system framework. Section 5 summarizes this report and discusses the envisioned role of ERM in O&M of AdvRx and future research needs in this area.

2.0 Background

This section briefly describes background information on O&M characteristics for AdvRx and summarizes ERMs and previous research accomplished on this project.

2.1 Overview and Operational Characteristics for Advanced Reactors

Advanced reactors generally encompass all non–light-water-cooled reactor (LWR) concepts, and are being considered as a longer-term option for meeting electrical generation and process heat needs in the United States (Abram and Ion 2008). AdvRx and AdvSMRs (based on modularization of advanced reactor concepts) with their passive safety features and the ability to incrementally add modules over time offer alternatives to traditional LWRs. However, the challenging environments found in AdvRx increase the possibility of degradation of safety-critical active and passive components adding to the challenges of their deployment and extended operation. For example, harsh environments within the primary and intermediate loops of AdvRx include high temperatures (in excess of 500°C), potential for fast spectrum neutrons, and corrosive coolant chemistry. These environments in proposed AdvRx concepts increase the possibility of degradation of safety-critical components and therefore pose a particular challenge for deployment and extended operation of these concepts. Therefore, critical to longer-term adoption and ensuring wider deployment of AdvRx concepts are management of O&M costs including the prediction and management of component integrity as a way to impact planning for maintenance activities and staffing levels.

Health monitoring techniques are among a class of technologies that can be used to establish condition indicators; in combination with predictive estimates of component failure based on condition, such techniques can be applied to manage O&M costs through improved scheduling of maintenance activities and selection of operational decisions that minimize the risk of unplanned plant shutdowns.

Recent Pacific Northwest National Laboratory (PNNL) research has focused on developing technologies in the areas of various condition monitoring methods for assessing component condition (Dib et al. 2016; Prowant et al. 2016); predicting passive (Ramuhalli et al. 2016; Roy et al. 2016) and active (Coble et al. 2013) component integrity, and development of a prototypic ERM framework (Ramuhalli et al. 2013; Ramuhalli et al. 2014; Ramuhalli et al. 2015).

Detecting and managing component degradation has been and continues to be critical to ensuring the safe operation of nuclear reactor components. In general, the ability to monitor, assess, and predict component/equipment health in terms of POF or planning O&M actions is fundamental in the ability to achieve overall enterprise risk management in AdvRx.

Figure 2.1 depicts the areas considered by this project to develop a framework to move from measurements through condition assessment and predictive estimates of POF assessment to ERMs. The overall concept for integration of prognostic health management (PHM) systems with ERMs, and their location within the hierarchy of supervisory control algorithms as envisioned for AdvRx is depicted in Figure 2.2.

Additional details of AdvRx concepts and likely O&M approaches are provided in the previous reports in this series associated with AdvRx and AdvSMR prognostics and ERM research (Coble et al. 2013; Meyer et al. 2013a; Ramuhalli et al. 2013; Ramuhalli et al. 2014; Ramuhalli et al. 2015). Given the possibility of frequently changing plant configurations to meet multiple mission goals, and the relative lack of component reliability data for AdvRx, techniques to integrate advanced plant configuration information, equipment condition information, and predictive risk monitors are needed to support plant control and real-time decisions on O&M (Coble et al. 2013).

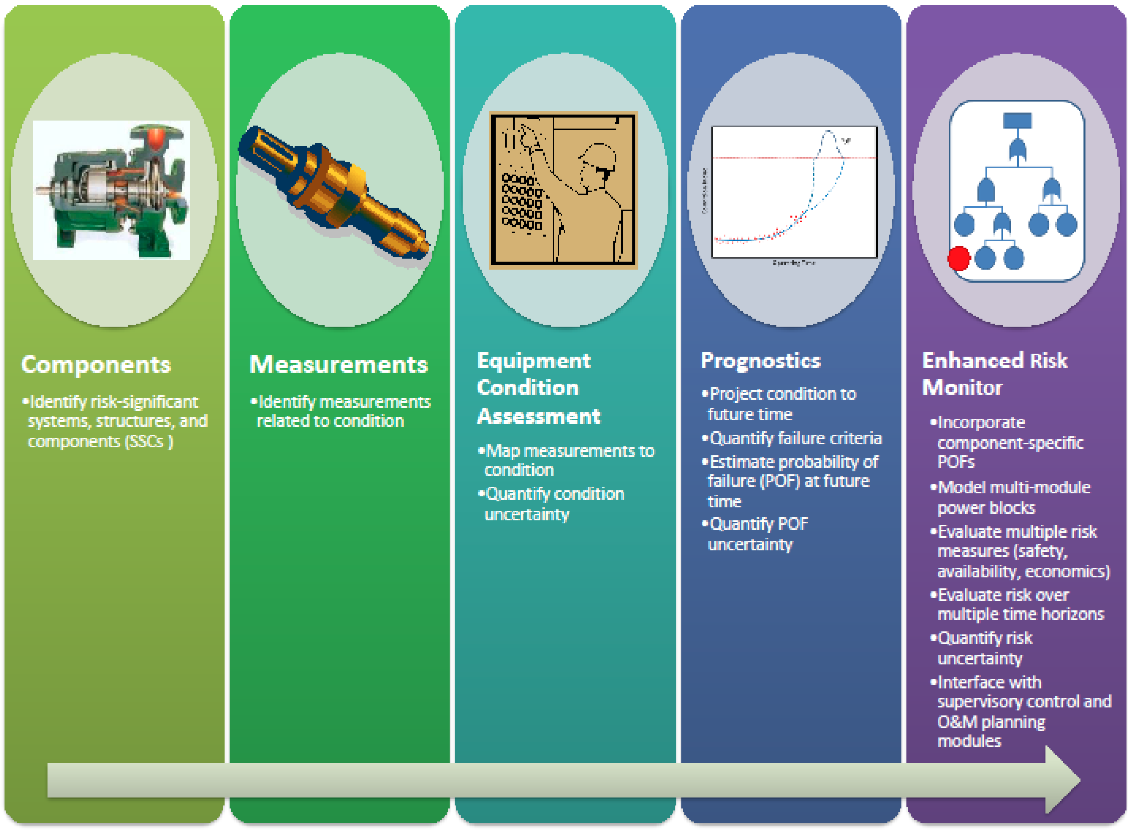

Figure 2.1. Considerations and Steps to Achieving an Enhanced Risk Monitor (Coble et al. 2013)

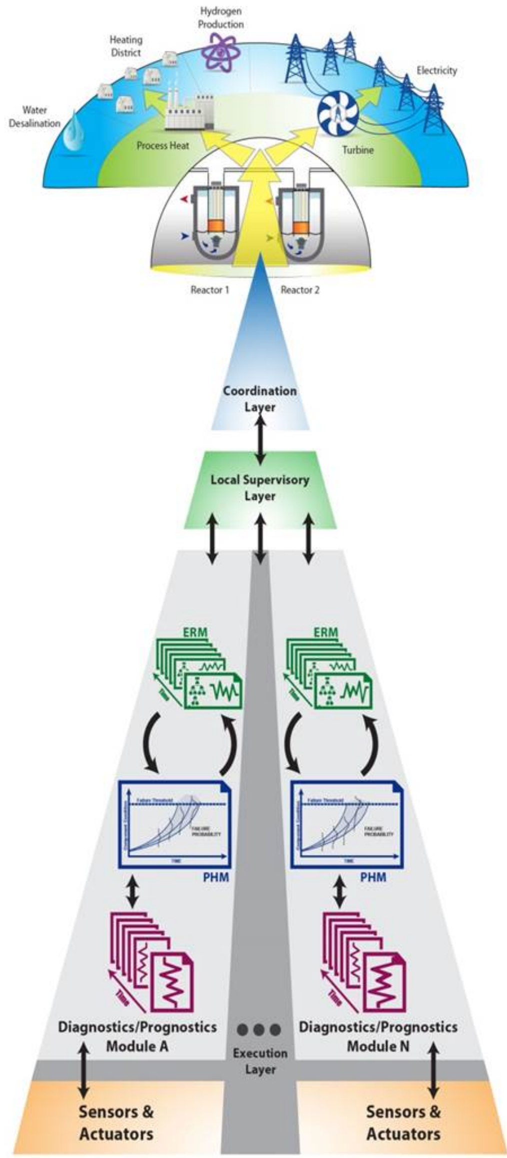

Figure 2.2. Schematic Showing the Integration of PHM Systems with Enhanced Risk Monitors, and Their Location within the Hierarchy of Supervisory Control Algorithms for AdvSMRs

2.2 Brief Overview of ERMs for Advanced Reactors

ERM, as a component of overall enterprise risk management, is a proactive philosophy where greater situational awareness can be provided to plant supervisory control and O&M planning routines as depicted in Figure 2.3. Essentially, ERMs are predictive risk monitors that incorporate the time-dependent failure probabilities from PHM systems to dynamically update the risk metric of interest. Specifically for AdvRx, enhanced risk assessment of AdvRx that incorporates real-time degradation information of critical active components will greatly improve overall asset protection and management, allowing for safe, reliable generation during extended operating cycles and longer reactor lifetimes.

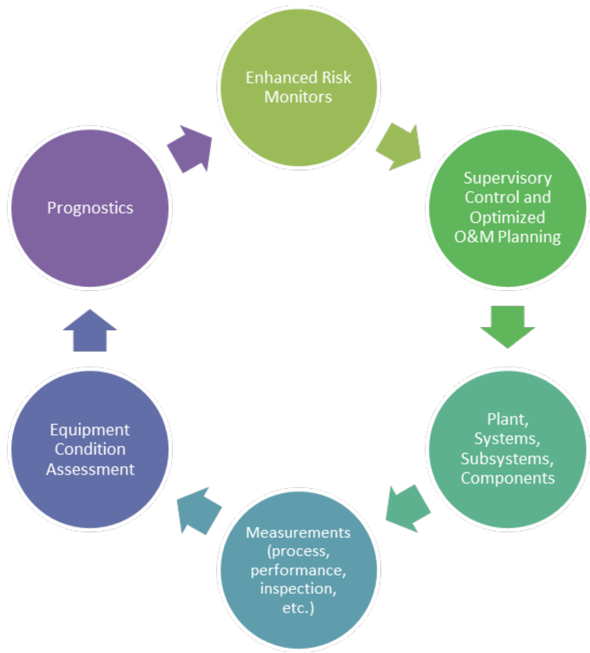

Figure 2.3. ERMs Can Provide Greater Situational Awareness to the Plant Supervisory Control and O&M Planning Routines (Coble et al. 2013)

Risk monitors expand on probabilistic risk assessment (PRA) by incorporating changes based on day-by-day plant operation and configuration (e.g., changes in equipment availability, operating regime, environmental conditions). Currently deployed risk monitors assume that components are either available or unavailable. For complex engineered systems like nuclear power plants, PRA systematically combines event likelihoods and the POF of key components, and combined with the magnitude of possible adverse consequences determines risk. Currently, most nuclear power plants have a PRA that reflects the as-operated, as-modified plant; this model is updated periodically, typically once a year.

Traditional PRA uses population-based POF information to estimate the average plant risk over time. Health monitoring techniques, like PHM, can be used to establish condition indicators and monitoring capabilities that estimate the component-specific POF at a desired time (or over a desired time-horizon), which can then be incorporated in the risk monitor to provide a more accurate estimate of future risk (and changes in future risk) under different plant operational configurations.

This is particularly important for active systems, structures, and components (SSCs) proposed for use in AdvRx concepts. These SSCs may differ significantly from those used in the operating fleet of LWRs (or even in LWR-based small modular reactor designs). Additionally, the operating characteristics of AdvRx can present significantly different requirements, including operations in different coolant environments, higher operating temperatures, and longer operating cycles between planned refueling and maintenance outages. These features, along with the relative lack of operating experience for some of the proposed advanced designs, may limit the ability to estimate event probability and component POF with a high degree of certainty. Incorporating real-time estimates of component POF may compensate for a relative lack of established knowledge about the long-term component behavior and improve O&M planning and optimization.

In their use of real-time component condition, ERM technologies differ from conventional risk monitors (Kafka 2008; Wu and Apostolakis 1992) that use a static estimate for event probability and POF, typically based on historical observations and engineering judgment. More recently, time-based POF values derived from operating experience and traditional reliability analysis have been used (Arjas and Holmberg 1995; Vesely and Wolford 1988); however, these are usually not specific to the component. Critical to the ERMs is a predictive estimate of POF of the component, which is precisely what PHM provides (Coble et al. 2012). As a result, PHM technologies are likely to be applicable to achieving enhanced risk monitoring to obtain a realistic assessment of dynamic risk that is unit-specific and accounts for the operational history of the component (Ramuhalli et al. 2013). Therefore, ERM systems are expected to play a vital role in AdvRx operations specifically by incorporating real-time component condition into the calculation of plant risk [usually measured in terms of core damage frequency (CDF) or some other safety-related risk metric (Coble et al. 2013; Ramuhalli et al. 2014)].

3.0 Prototypic ERM Framework Evaluation

The ERM framework was developed with the intent that timely component wear-out detection, monitoring, and proactive maintenance scheduling leads to optimal performance and viable economic operation of the plant through avoidance of unplanned outages. Earlier case studies distinguished ERM-based preventive component maintenance from conventional strategies relying on replacement at the end-of-service-life or on aging failure rate models. The need for an ERM methodology and the benefits of implementing it for developing an array of decision alternatives were discussed through the estimation and comparison of safety and economic metrics across various case studies. In this study, we describe additional results on the safety and economic metrics associated with changes to maintenance strategies in light of new component health condition information acquired during the life of a plant. In particular, we investigate in this study through sensitivity analysis changes to maintenance strategy following a deteriorated or improved health condition, as determined by ECA, and the sensitivity of the result to prognostic model output.

3.1 Economic Model

In this section, we briefly review the economic model before venturing into the individual impact and case studies. We use the PRA model that was developed for a simplified generic two-reactor (each a liquid metal reactor) power block, with a common balance of plant (Ramuhalli et al. 2014; Ramuhalli et al. 2015). The PRA model was vetted for cutsets that would lead to operational failures and associated unplanned shutdowns as opposed to core damage. Cutset probabilities for these specific cases were quantified so that expected replacement costs, keeping in view the replacement time, could be evaluated. In particular, electromagnetic pumps (EMP) are used for illustration of the effects of ECA. Two out of three of these pumps are required to be PRA functional at any time, in the absence of which an unplanned shutdown may be required for replacement. The reactor is assumed to be taken offline for maintenance and refueling every two years. During this maintenance and refueling time, ERM-informed repairs based on a chosen maintenance strategy are assumed to be performed. While costs associated with lost power are considered during operational periods, costs associated with minimal repairs are considered during planned shutdowns. During both operational and planned shutdown periods, random failure and replacement costs are considered. These costs are accounted for on a two-year basis for quantifying the economic index. Aggregation of these biennial costs across the reactor life provides an overall reactor economic index for comparative purposes. The EMP replacement and repair cost, and associated time, for the existing fleet of pressurized water reactors is used as a proxy for that of AdvRx technologies.

3.2 Component Aging

In the absence of specific ECA-based measurements for EMP1A, we assume that the failure rate for this component follows a two-part piecewise nonlinear aging profile. Similarly, we also assume the presence of a prognostics algorithm that would in essence take these measurements into consideration and predict component failure rate following the same aging profile. The base failure rate λ remains constant until an aging start time (AST) and then nonlinearly increases with time based on a notional aging fractional increase (AFI):

$$\lambda'(t) = \begin{cases} \lambda', & t < \mathrm{AST} \\ \lambda\left[\dfrac{t}{\mathrm{AST}}\right]^{\mathrm{AFI}}, & t \geq \mathrm{AST} \end{cases} \tag{3.1}$$

For demonstration purposes, AST was assumed to be 9.0 years and AFI was 3.5. The base failure rates (independent, common cause failure, failure to start and run) were assumed to be equivalent to those observed in the current fleet of reactors.

3.3 Evaluation of Prototypic ERM Framework

3.3.1 Changes to Maintenance Strategy

The presence of uncertainties in measurement, diagnostics, and prognostics results in a window of opportunity to choose among decision alternatives and to implement a feasible maintenance strategy. In the case studies discussed earlier, it was assumed that such maintenance actions reset the failure rate of a degrading component instead of assuming an as-bad-as-old or worse status (also called imperfect repair). This is, however, seldom the case, especially with aging systems. The combination of uncertainties and imperfect repairs has impacts on maintenance decisions taken in response to the outcomes of prognostics. An accelerated component aging and maintenance action not enough closely spaced could lead to early system failure. A slowly degrading component maintained too often results in economic burden. We illustrate these implications and the need for making changes to the maintenance strategy in light of new component health information through the following case study.

The electromagnetic pump EMP1A is assumed to degrade at a rate as estimated by the diagnostics module. The measurements reflect a constant failure rate until an aging start time (assumed nine years) and a prognostics algorithm indicates that the component health will follow a nonlinear profile thereafter. While all components age with time, it is assumed that EMP1A ages the most and is identified as such by a predictive PRA importance measure (e.g., Fussell-Vesely importance) (van der Borst and Schoonakker 2001). Let us assume that a change to the maintenance frequency is decided for such an identified component after observing its condition index. A notional plot of condition index for EMP1A is presented in Figure 3.1 and Figure 3.2 under different maintenance assumptions. Assume that a condition index of 0.5 is unacceptable and would represent a threshold for replacement of the component rather than a cost-effective repair. Also, consider a requirement in change of maintenance strategy when condition index is reduced or increased by at least a point (e.g., 10%) within an observation window of four years. The following cases are discussed in this case study:

- Decision 0: Hypothetically, there is no significant aging, minimal repairs are conducted as necessary, and hence the condition index remains at 1.0.
- Decision 1: There is accelerated nonlinear aging; however, no maintenance is performed. The condition index drops below 0.5 around 30 years, signaling the requirement for a major corrective action such as replacement.
- Decision 2: A default maintenance frequency of once in six years starting at 12 years is assumed for the rest of the reactor life. The condition index never falls below a point and does not fall below the threshold during the design life.
- Decision 3a: Follows Decision 2, but the component condition degrades around 20 years (index drops from 0.9 to 0.7 within an observation window of four years). However, maintenance interval continues to be six years.
- Decision 3b: Follows Decision 2, but the component condition degrades around 20 years (index drops from 0.9 to 0.7 within an observation window of four years). Maintenance interval is changed to four years.

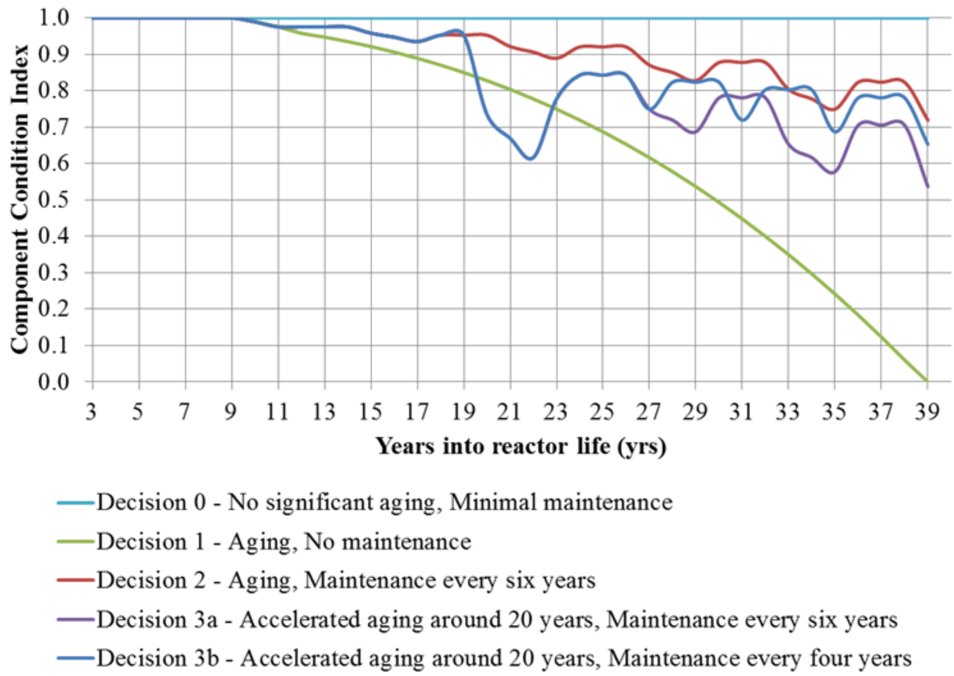

Figure 3.1. Component Condition Index Corresponding to Various Maintenance Decisions (worsening case)

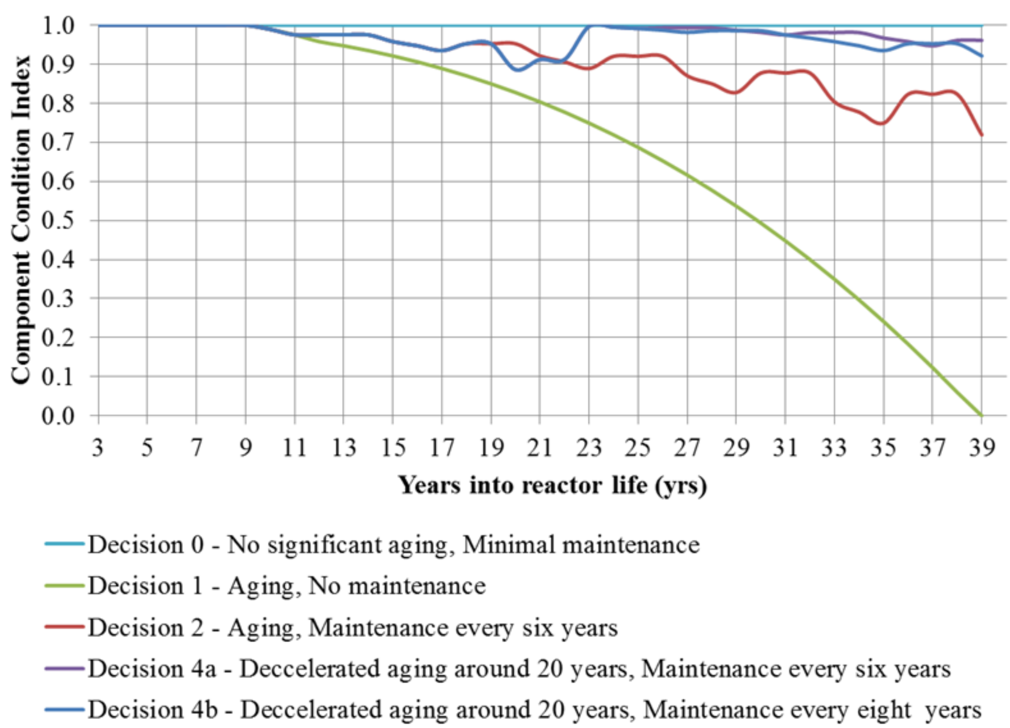

Figure 3.2. Component Condition Index Corresponding to Various Maintenance Decisions (improving case)

- Decision 4a: Follows Decision 2, but the component condition improves around 20 years (index increases from 0.9 to 1.0 within an observation window of four years). However, maintenance interval continues to be six years.
- Decision 4b: Follows Decision 2, but the component condition improves around 20 years (index increases from 0.9 to 1.0 within an observation window of four years). Maintenance interval is changed to eight years.

3.3.1.1 Decision 0

Decision 0: Hypothetically, there is no significant aging, minimal repairs are conducted as necessary, and hence the condition index remains at 1.0. The CDF is the lowest in the case remaining around the static value of 4.19E-07 and at the least economic index of 22.23.

3.3.1.2 Decision 1

Decision 1: There is accelerated nonlinear aging; however, no maintenance is assumed. The condition index drops below 0.5 around 30 years signaling the requirement for a major corrective action such as replacement.

Consider the first decision involving no maintenance strategy in which case the CDF is anticipated to cross the safety threshold around 30 years as illustrated in Figure 3.3 (Decision 1: green curve). In the absence of maintenance, the economic index follows the shape of safety profile as seen in Figure 3.4. The time-averaged CDF is 8.1E-7 and the economic index is 26.54. In the next few sensitivity studies, we demonstrate the value of ERM-based decision-making with the added analysis of reacting to changes in the reactor component health and the need to switch decisions along the reactor's aging life.

3.3.1.3 Decision 2

Decision 2: A default maintenance frequency of once in six years starting at 12 years is assumed for the rest of the reactor life. The condition index never falls below a point and does not fall below the threshold during the design life.

Consider a second decision, which involves a maintenance conducted on EMP1A every six years starting from year 12. It is assumed that these maintenance actions do not represent perfect repair activities, rather improve the component's health to a state at which it was three years earlier. The impact of this decision as indicated by the prognostics module is shown in Figure 3.3 (Decision 2: red curve). There is a drop in the predicted CDF every six years starting from age 12 and the economic index spikes correspondingly owing to ERM-related maintenance costs involving minimal repairs and replacement costs due to chances of random failure. Also notice that the economic index in general increases with time due to increasing degradation rate and relatively higher probability of system failure leading to unplanned shutdowns (not necessarily core damage). The estimated safety and economic indices in this case are 5.0E-7 and 23.02, respectively.

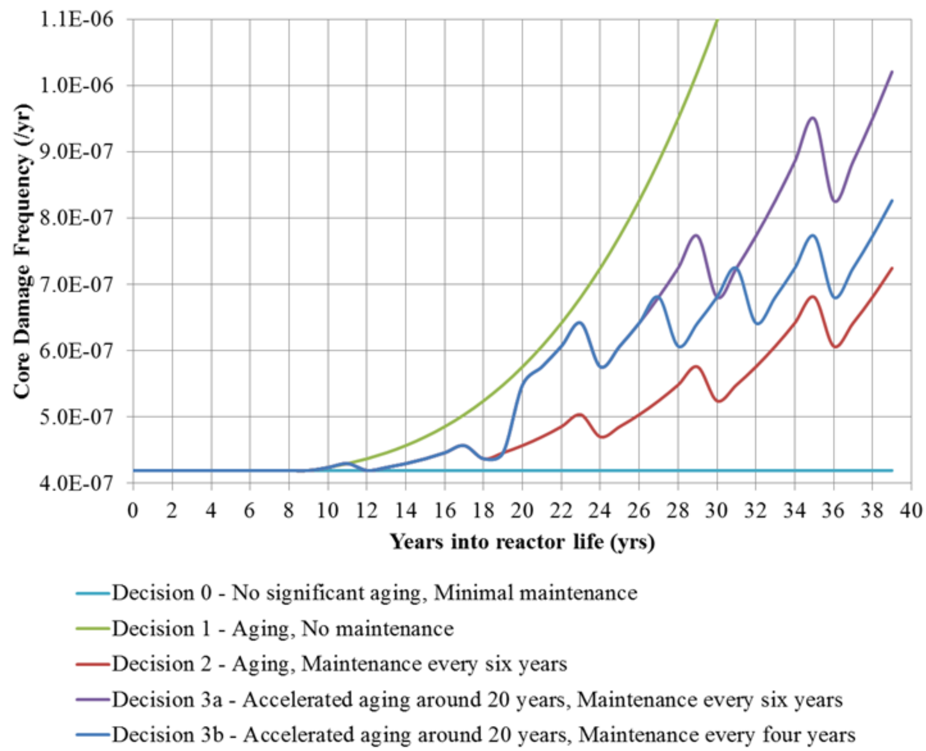

Figure 3.3. CDF Profiles Following Different Decisions (worsening case – case 1)

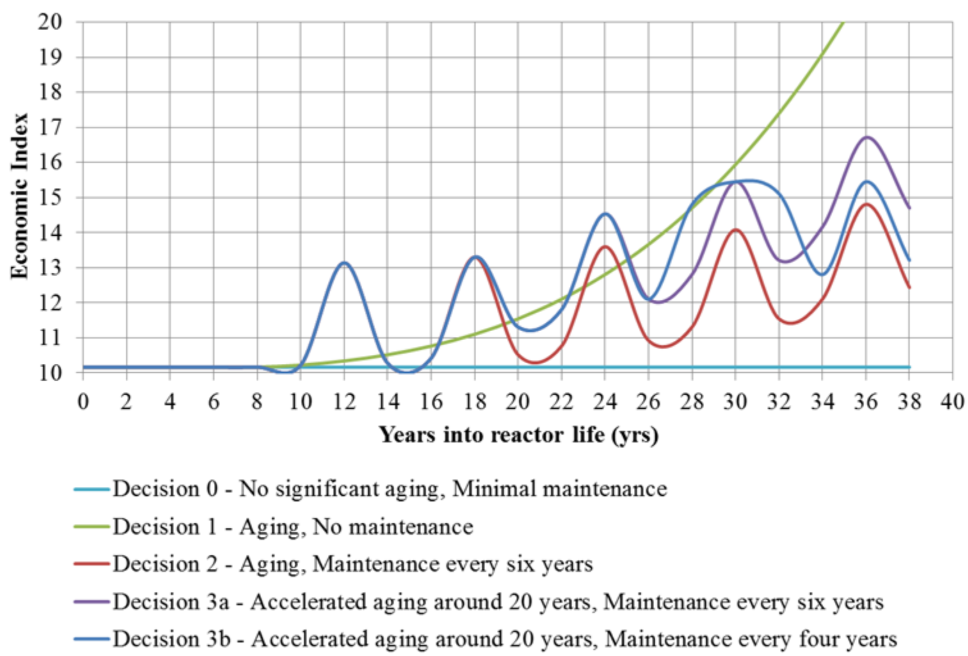

Figure 3.4. Cost Profiles Following Different Decisions (worsening case – case 1)

3.3.1.4 Decision 3

Decision 3a: Follows Decision 2, but the component condition degrades around 20 years (index drops from 0.9 to 0.7 within an observation window of four years). However, the maintenance interval continues to be six years.

While component health improves after a scheduled maintenance, let us assume that aging and operating environment lead to an accelerated aging that overrides the recent repair activity. This leads to a condition where at around 20 years the component is assumed to be as old as one whose age is already advanced by three more years than anticipated. If the same maintenance interval of six years is continued, the predicted CDF is expected to cross the safety threshold after 38 years as presented in Figure 3.3 (Decision 3a: violet curve). The safety metric is 5.9E-7 and economic index is 24.49. At this point in time, a decision is required to ensure CDF is within the safety goal at least until the design life of the reactor. So we consider a four-year maintenance interval in the next case.

Decision 3b: Follows Decision 2, but the component condition degrades around 20 years (index drops from 0.9 to 0.7 within an observation window of four years). Maintenance interval is changed to four years.

The observed increase in the CDF owing to EMP1A that could potentially lead to a safety breach is now brought under a four-year maintenance interval following the CDF spike at 20 years. This action is anticipated to decelerate the aging process and help manage the safety metric stay within the safety goal for at least the stipulated design life of the reactor as seen in Figure 3.3 (Decision 3b: blue curve). Correspondingly, the economic index does not increase at 20 years as there is no maintenance undertaken until the next scheduled maintenance at 24 years (every four years from age 20). The impact of this decision is observed in the safety and economic indices (5.5E-7 and 24.47). Although degradation continues to grow despite the four-year schedule, which corresponds to increased cost of maintenance, the overall economic index has decreased following the spike in observed degradation at 20 years. The reason for this profitable economic index is attributed to the fact that if no decision is taken at 20 years to increase the maintenance frequency, the predicted costs would be relatively larger owing to accelerated aging.

This is an example for the application of ERM methodology to risk-inform changes to the maintenance strategy over time as more observations are made available to update the economic index along with the presence of a robust prognostic algorithm.

In this case study, change of maintenance frequency from once in six years to once in four years was chosen for illustration. The use of an optimization algorithm with safety and economic constraints is anticipated to provide a customized schedule that better meets objectives of the decision maker.

3.3.1.5 Decision 4

Decision 4a: Follows Decision 2, but the component condition improves around 20 years (index increases from 0.9 to 1.0 within an observation window of four years). However, maintenance interval continues to be six years.

While component health improves after a scheduled maintenance, let us assume that maintenance strategy has paid off to the extent that it leads to a condition where at around 20 years the component is assumed to be as healthy as one whose age is earlier by three years than anticipated. The earlier maintenance action at 18 years witnessed a drop in the overall CDF and due to the improvements there is further dip in the CDF at 20 years; however, there is no increase in the economic index because this decrease does not correspond to a maintenance action. If the same maintenance interval of six years is continued, the predicted CDF is expected to be within the safety goal as shown in Figure 3.5 (Decision 4a: violet curve).

The expected safety and economic indices are 4.24E-7 and 21.87 if there is no change made to the maintenance schedule. These metrics indicate a relatively healthier and economically profitable state for the residual life of the reactor. Though no change is required at this time, we will study the sensitivity of relaxing the maintenance interval from six to eight years given the further improvement in the overall safety.

Decision 4b: Follows Decision 2, but the component condition improves around 20 years (index increases from 0.9 to 1.0 within an observation window of four years). Maintenance interval is changed to eight years.

Frequent maintenance on an otherwise healthy component may lead to an increased economic burden. Let us assume that a decision is made to relax the maintenance schedule by conducting it every eight years instead of six years. This strategy leads to a predicted CDF at 40 years that is relatively larger than that observed due to Decision 4a; however, the CDF is still within the safety goal with slight increase in the economic index. This visual comparison in CDF and cost is shown in Figure 3.5 and Figure 3.6, respectively (Decision 4b: blue curve). The next maintenance action owing to this decision would be at 36 years. The increase in the economic index is due to continuation in the aging process despite the improvement at 20 years. Cost associated with maintenance would decline by relaxing the maintenance frequency; however, the economic index would still increase due to aging and relatively higher probability of equipment failure and unplanned shutdowns. The expected safety and economic indices if the maintenance frequency is relaxed to eight years would be 4.27E-7 and 22.23, respectively.

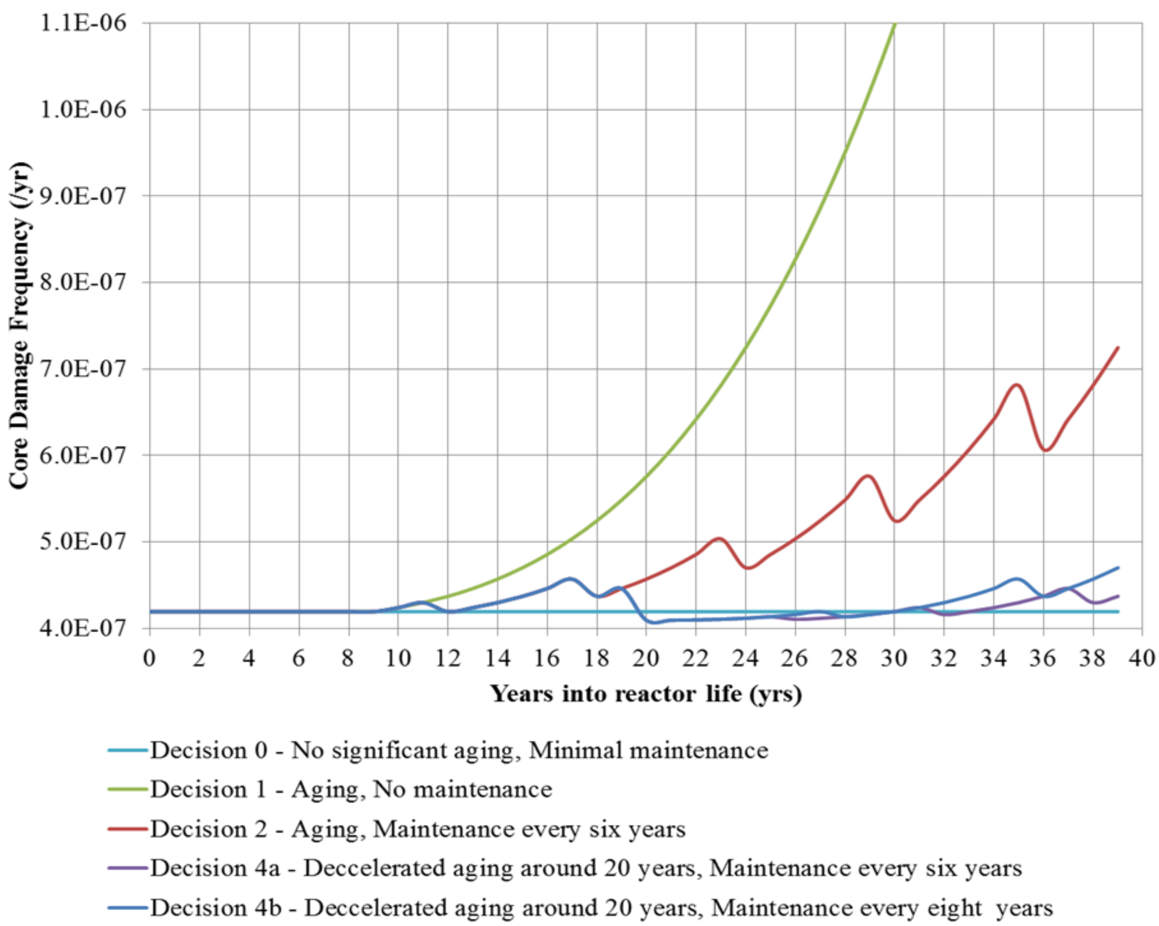

Figure 3.5. CDF Profiles Following Different Decisions (improving case – case 2)

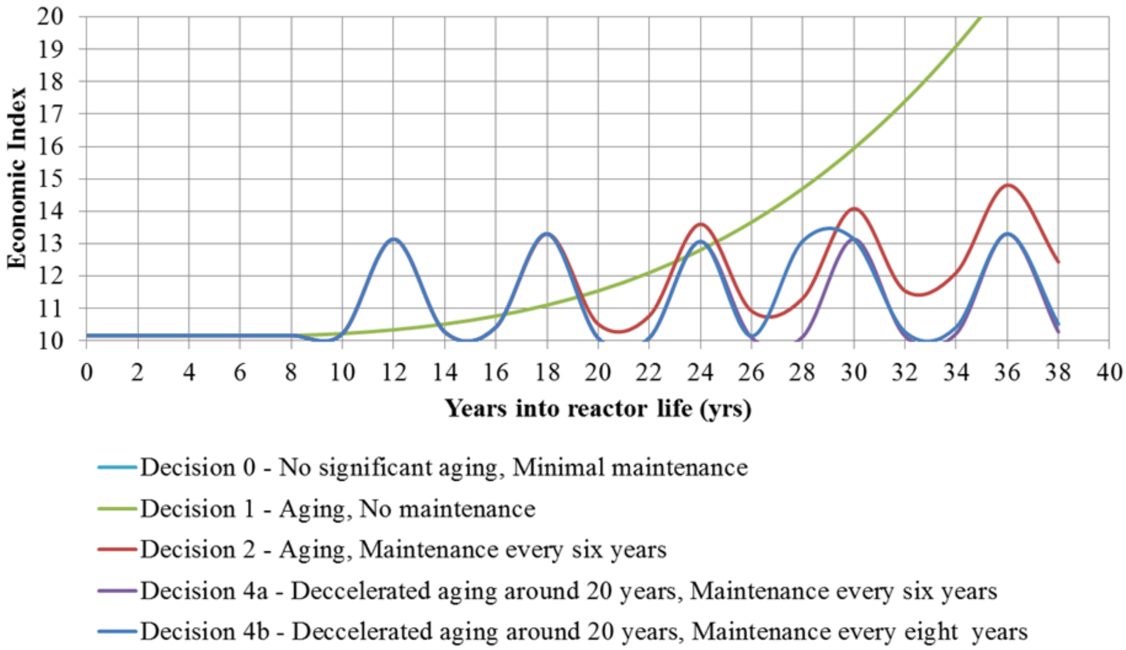

Figure 3.6. Cost Profiles Following Different Decisions (improving case – case 2)

3.3.1.6 Discussion

The safety and economic summary of results for the worsening and improving case studies are presented in Table 3.1. In the worsening case, there is merit in increasing the maintenance frequency both in the safety and economic sense. In the improving case, it is better to remain on the same schedule for economic reasons although there is further improvement in the safety metric by relaxing the schedule. These recommended decisions are for demonstration purposes only; specific circumstances, regulations, and business interests might warrant a different decision trajectory.

Table 3.1. Summary of Safety and Economic Metrics Associated with Each Decision

Decision	Safety (time-averaged CDF)	Economic Index
Decision 0: No significant aging; minimal maintenance	4.19E-07	20.32
Decision 1: Aging; no maintenance	8.07E-07	26.54
Decision 2: Aging; maintenance every 6 years	4.95E-07	23.02
Decision 3a: Accelerated aging around 20 years; maintenance every 6 years thereafter	5.86E-07	24.49
Decision 3b: Accelerated aging around 20 years; maintenance every 4 years thereafter	5.48E-07	24.47
Decision 4a: Decelerated aging around 20 years; maintenance every 6 years thereafter	4.24E-07	21.87
Decision 4b: Decelerated aging around 20 years; maintenance every 8 years thereafter	4.27E-07	22.23

3.3.2 Prognostic Result

In this section, we describe sensitivity analyses results, conducted to evaluate the sensitivity of the ERM metrics to the prognostic result. We will restrict this analysis to investigating the impact of predicting a nonlinear aging profile for a component that happens to be linearly aging, and vice versa. Such analysis enables an assessment of the impact on maintenance decisions and overall plant safety risks when the prognostic results are non-conservative.

For this specific case study, consider a change to the component profile. The following profile for EMP1A varies based on the AFI and is scaled such that the CDF at the age of 40 is the same despite a variation in the profile during the plant life:

$$\lambda'(t) = \lambda \left[\frac{t}{T_{\max}} \right]^{\mathrm{AFI}} \tag{3.2}$$

For this study, we examine the impact on CDF and economic risk metrics as a function of the predicted aging profile, where the predicted aging profile (using a fixed value of AFI) is assumed to be the output of the prognostic model.

3.3.2.1 Evaluation Results

T_{max} is assumed to be 40 years with AFI ranging from 0.2 to 1.8. A value of 0.2 represents early wear out and gradual worsening of component condition as opposed to a value of 1.0, which represents a linear increase in degradation. Though all components in the plant age simultaneously with varying degrees, this case study assumes EMP1A ages according to the specified profiles. The impact of this aging influences the overall CDF as seen in Figure 3.7, in the absence of any maintenance actions. The time-averaged CDF remains relatively stable (within the same order of magnitude, ranging from 4.13E-7 to 4.18E-7) and the economic index stays constant as well (around 20). The largest increase within this range is observed for early wear-out (with AFI of 0.2 for EMP1A). It is also of interest to observe the metrics in the presence of maintenance actions such that the end of design life CDF is approximately constant. In this case, the maintenance start time and maintenance frequency were adjusted to achieve the desired assumptions. These configurations included maintenance start times of 6, 12, 12, 24, and 28 years corresponding to the AFI assumptions of 0.2, 0.6, 1.0 (linear), 1.4, and 1.8 respectively. The corresponding maintenance intervals were set to 4, 6, 16, 16, and 16 years, respectively. These settings strive to achieve the same end of design life CDF by letting the degradation rate increase at a level sufficient to follow approximately the same assumed aging profile as the case without maintenance. The results shown in Figure 3.8 once again indicate that time-averaged CDF slightly decreases relative to the no-maintenance case and remains within the range of 4.12E-7 to 4.17E-7. The economic index varies by about one point. However, the observations indicate that decisions about the choice of an appropriate maintenance strategy are relatively insensitive to the aging profile.

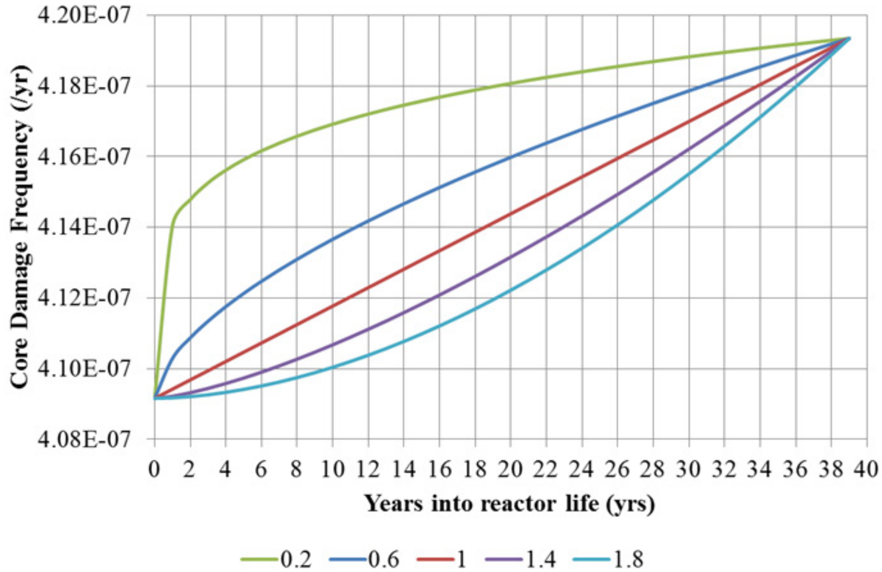

Figure 3.7. CDF Assuming Various Aging Profiles

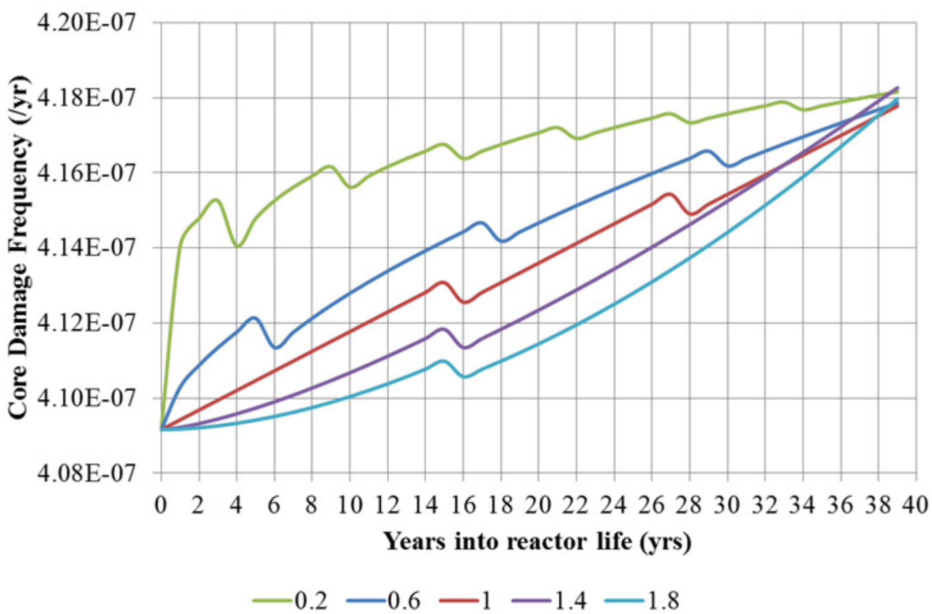

Figure 3.8. CDF Assuming Various Aging Profiles and Maintenance Intervals

3.3.2.2 Discussion

The safety and economic summary of results for sensitivity around the choice aging predictions from a prognostic module in the presence and absence of maintenance is shown in Table 3.2. In both cases, it is seen that small differences in prognostic predictions may not lead to significant changes to the choice of maintenance strategy. Though safety implications are unlikely to be far-reaching, there could be additional economic implications that make a difference from a business perspective. A thorough sensitivity analysis capturing these uncertainties and an informed decision is needed to support a viable decision.

Table 3.2. Summary of Safety and Economic Metrics Associated with Each Assumption

	No Maintenance		Maintenance	
EMP1A AFI	CDF	Economic Index	CDF	Economic Index
0.2	4.18E-07	20.29	4.17E-07	21.76
0.6	4.15E-07	20.26	4.14E-07	21.13
1.0 (Linear)	4.14E-07	20.24	4.14E-07	21.12
1.4	4.13E-07	20.23	4.13E-07	20.81
1.8	4.13E-07	20.22	4.12E-07	20.50

3.3.3 Evaluation Summary

Earlier studies proved the importance of ERM for risk-informed decision making. The present study investigated the impacts of (1) decisions made during subsequent condition assessment of degrading components for which preventive maintenance was scheduled earlier, and (2) choice of underlying prognostics models, with respect to both CDF and economic risk metrics. Additional sensitivity studies are needed that incorporate short-term component maintenance decisions that do not require shutting down the plant.

4.0 Integration of ERM Module with Supervisory Control System Framework

4.1 Overview

Oak Ridge National Laboratory developed a supervisory control system (SCS) that integrates with a plant model and a risk model. The plant model provides the initial component failure rate and operational state of the device (e.g., is a valve open or closed, flow rates and pressures, etc.). In the event of a component failure, the plant risk model is utilized by the SCS to assess potential success paths (i.e., actions that maintain the plant within an operational window).

PNNL's ERM module, which consists of both a prognostic element for remaining life estimation and a risk-informed decision making module, will need to provide component health predictions based on measurements of component health. The output from the PNNL module is given in terms of a POF for the component over time, and exported to the risk models. This information on expected POF as a function of time enables the SCS to obtain improved estimates of probabilities of success for the different potential success paths.

One challenge with the integration and testing is the nature of the available testbed. The ORNL SCS software platform is entirely simulation-based. As a result, hardware solutions for monitoring equipment are not viable for integration and testing. The alternative selected here is a purely software-based approach for simulating equipment condition monitoring, whereby sensors are simulated for monitoring the condition of components. The data from these simulations provide the necessary sensor information for condition monitoring and prognostics. The ORNL plant model contains enough component granularity to adequately drive the prognostics portion of the ERM module. The necessary simulated sensor data for the prognostics and risk-informed decision supplements the ORNL plant model data. This approach will allow for use cases to be developed and analyzed.

4.1.1 ERM Software Design

The ERM software was written around three functional blocks:

- Equipment condition assessment and prognostics for predictive health assessment. This module simulates the sensor data for ECA and includes the prognostic modules. For initial testing and evaluation of the integration activity, the components selected for ECA are valves.
- Predictive risk assessment (safety and economic). This module contains the predictive risk-informed decision-making elements, and includes the ERM with both safety and economic metrics. These are described in earlier reports in this series.
- Uncertainty quantification. This module interacts with the other two modules and evaluates the effects of uncertainty from various sources on the prognostic and predictive risk monitors.

The software modules were written in the Python language and unit tested to ensure proper functionality.

4.1.2 Evaluation Scenarios

The evaluation scenarios for the integrated SCS-ERM software are based on a two-reactor power block, with a common balance-of-plant (Figure 4.1). Several scenarios may be considered, focused on the power conversion module. For initial integration evaluation, the following initiating events are considered:

1. Turbine Control Valve from reactor 1 drifts in closed direction
2. SG 1 FW FCV drifts in closed direction
3. SG 1 FW FCV drifts in open direction

In all instances, it is clear that the initiating event is based on a valve failure, and therefore, the ability to monitor the condition of a valve and predict the time to failure is critical to ERM and its integration with SCS. To this end, the focus of the prognostic module was on valve prognostics, with several possible degradation modes considered in the prognostic analysis. This module is described in the next section.

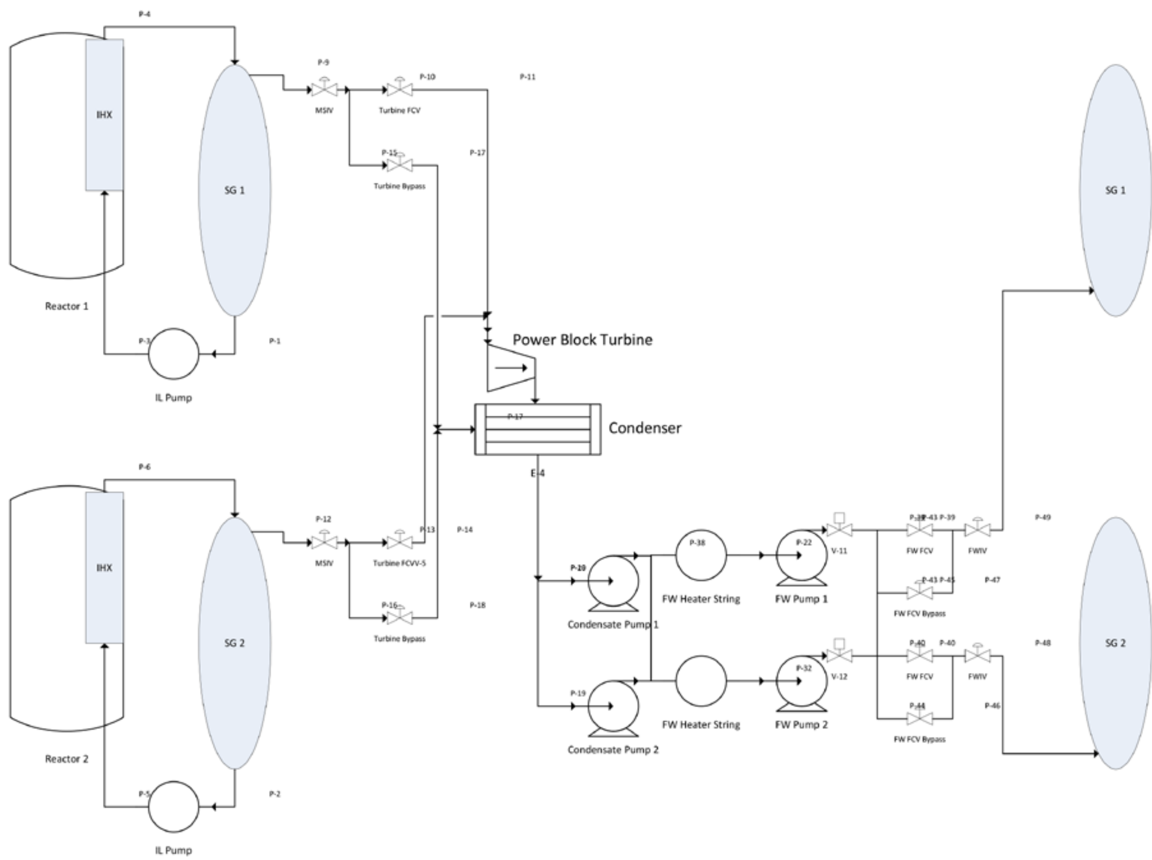

Figure 4.1. Prototypic Advanced Reactor Power Block, Used for the Integration Testing with the SCS

4.2 Integration Specification

Integration with the SCS required the development of a specification document, describing the various modules in the SCS and within the ERM. Functional requirements for the integration were also included in this specification document. The complete document is included as Appendix A.

Given the focus of the integration on the prognostic module, the following sections describe this module in greater detail, with the models of valve degradation used in this initial assessment, and examples of prognostic results for different operational conditions.

4.2.1 Valve Prognostic Modules

The prognostic module uses a Bayesian approach for predicting the remaining life, given the estimated condition of the component. The Bayesian module utilizes a component-specific Degradation State evolution model, and a Measurement Physics model (Khan and Ramuhalli 2008). For the integration testing, as described earlier, condition assessment and prognostics for a valve were implemented.

The valve degradation state evolution utilizes a state dynamics model that relates the system state and material degradation accumulation rate (i.e., the states and degradation level at the next time instant given their values at all times up to and including the present time). The Measurement Physics model represents the quantitative relationship between the measurement and the system states and degradation level at the present time instant.

Several State Dynamics models exist for valves. For the purposes of integration testing, a pneumatic valve model (Daigle and Goebel 2011) was utilized for simplicity of implementation and testing. This State Dynamics model is capable of accounting for multiple degradation modes. Further, the valve can be controlled using signals representing pneumatic pressure inputs that drive the valve to a desired valve position.

The dynamic evolution of system states and material degradation can be obtained by using the solution of state tracking problem (Arulampalam et al. 2002; Khan and Ramuhalli 2008; Ristic et al. 2004). For a linear system with Gaussian additive noise (uncertainties in the measurements and physical model), the optimal solution to the tracking problem can be shown to be the Kalman filter (Ristic et al. 2004). However, when the system is nonlinear and/or the noise terms are non-Gaussian (as is likely in the early degradation estimation problem), then more general solutions to the tracking problem are necessary, and include algorithms such as the extended Kalman filter, unscented Kalman filter, and the particle filter. A detailed description of the Bayesian approach used here is given elsewhere (Arulampalam et al. 2002; Ristic et al. 2004), and its applicability to prognostics is discussed in Ramuhalli et al. (2012) and Meyer et al. (2013b).

4.3 Progress Summary

The schematic of the SCS is shown in Figure 4.2. This framework is composed of four main modules:

1. Components/Sensors: Plant components of interest that are required to be monitored for possible degradation. Each component has a set of sensors associated with it that provided sensory information and can be interpreted by the ERM system.
2. Enhanced Risk Monitoring: The main purpose of this module is to perform diagnostics and prognostics on the components of interest based on the provided sensory information. This requires a mathematical model representing the component. Such a model can be a physics-based model, or a data-driven model using historical data of the component or related components. The desired output from diagnostics is an estimate of the POF for each component and the confidence in this estimate. The desired output from prognostics is an estimate of the remaining useful life (RUL) for each component and the confidence in this estimate.
3. Decision Making: This module is invoked if any of the component RULs computed by the ERM module are smaller than the time to the next outage. Decision making involves two steps: probabilistic risk assessment and deterministic assessment. Essentially, this module ranks possible action paths that will not cause tripping the plant's safety system. See Cetiner et al. (2014) and Muhlheim et al. (2014) for more information about the functionality of the decision-making module. Note that, at this stage, the decision-making module within the SCS does not include an assessment of

costs (i.e., economic) and predictive safety risks (i.e., predictive CDF). These added functionality will need to be added at a later date.

4. Verification: Once the Decision Making module decides on a single solution for the operational strategy of the plant, the solution is verified using a lower-order model of the plant. The required actions will be given as inputs to instantiate the lower-order model. This model will output the states (sensor data) of the plant components. Then another instance of the ERM module is used to re-compute the RUL of all components, and verifies that they all now are within the prescribed criteria.

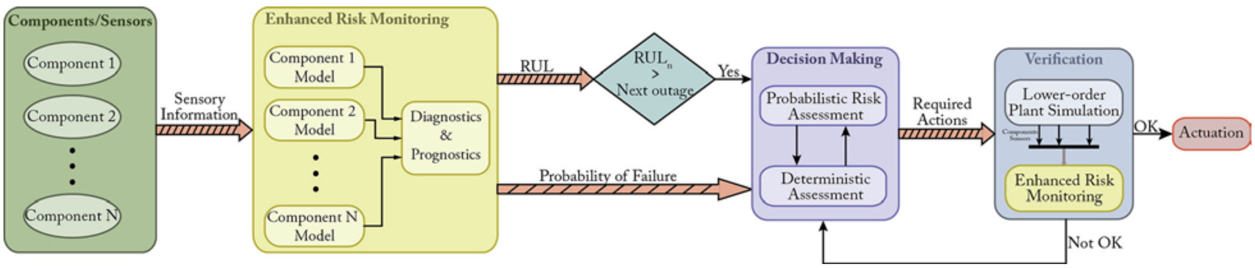

Figure 4.2. Schematic of the General Architecture of the Supervisory Control System

In the following sections, the functionality of the ERM module will be discussed in detail.

4.3.1 Integration

As described in the previous section, ERM requires modeling each plant component for performing diagnostics and prognostics. To demonstrate the functionality of SCS, this work considers models for the feedwater control valve only. A physics-based model of a pneumatic valve was used to represent the feedwater control valve. The implementation of the pneumatic valve is based on the model by Daigle and Goebel (2011). Only the parts of the model relevant to this problem and the parts that have been modified will be described in the following.

4.3.1.1 General Description of the Pneumatic Valve

The valve has a return spring that ensures that it is in the closed position by default when there is no air pressure applied to the valve. The valve has two chambers with orifices for the air flow that controls the position of the valve. This valve controls the fluid flow rate in the feedwater tube. This is done by a control system, which has a specified fluid flow rate set point, and a feed-back controller from the valve, which changes the air supply within the top and bottom chamber to reach the required flow rate set point.

The functional requirements are two-fold:

1. When air supply within the valve chambers is lost, the valve should be in the closed position.
2. The fluid flow rate going through the pipe should be achieved within a given time requirement.

Damage could happen within the valve, which may hinder its ability to satisfy its functional requirements. Four sources of damage are possible for this specific valve, and are included in the model used to simulate valve operation:

1. Friction Damage: The contact area between sliding bodies increases with time due to the wear down of surfaces. This results in an increase of the friction coefficient, which makes it harder to open/close the valve.

2. Spring Damage: The spring softens due to use, resulting in a decrease in the spring constant. This might result in the valve not being able to fully close when air supply is lost.
3. Internal Leaks: Internal leaks could result from the sliding wear near the seal surrounding the piston.
4. External Leaks: Connections for the pneumatic gas supplies at the top and bottom chambers in valve are subject to corrosion. This might result in leaks, affecting the supply gas pressure going into the valve.

4.3.2 Evaluation of Valve Prognostic Model

To test the performance of the prognostic module, input data for the valve and measurements were synthesized to represent simplified measurements and inputs from a typical feedwater control valve. It is assumed that the plant operates in a load-following mode, and thus the position of the valve, which controls fluid flow-rate changes based on demand.

Figure 4.3 shows the control signal (pneumatic pressure) history for the valve, and corresponding measured valve position. In this instance, the valve damage parameters are increased as a function of time, and it can be seen from the figure that the valve progressively requires more time to open due to increased wear damage.

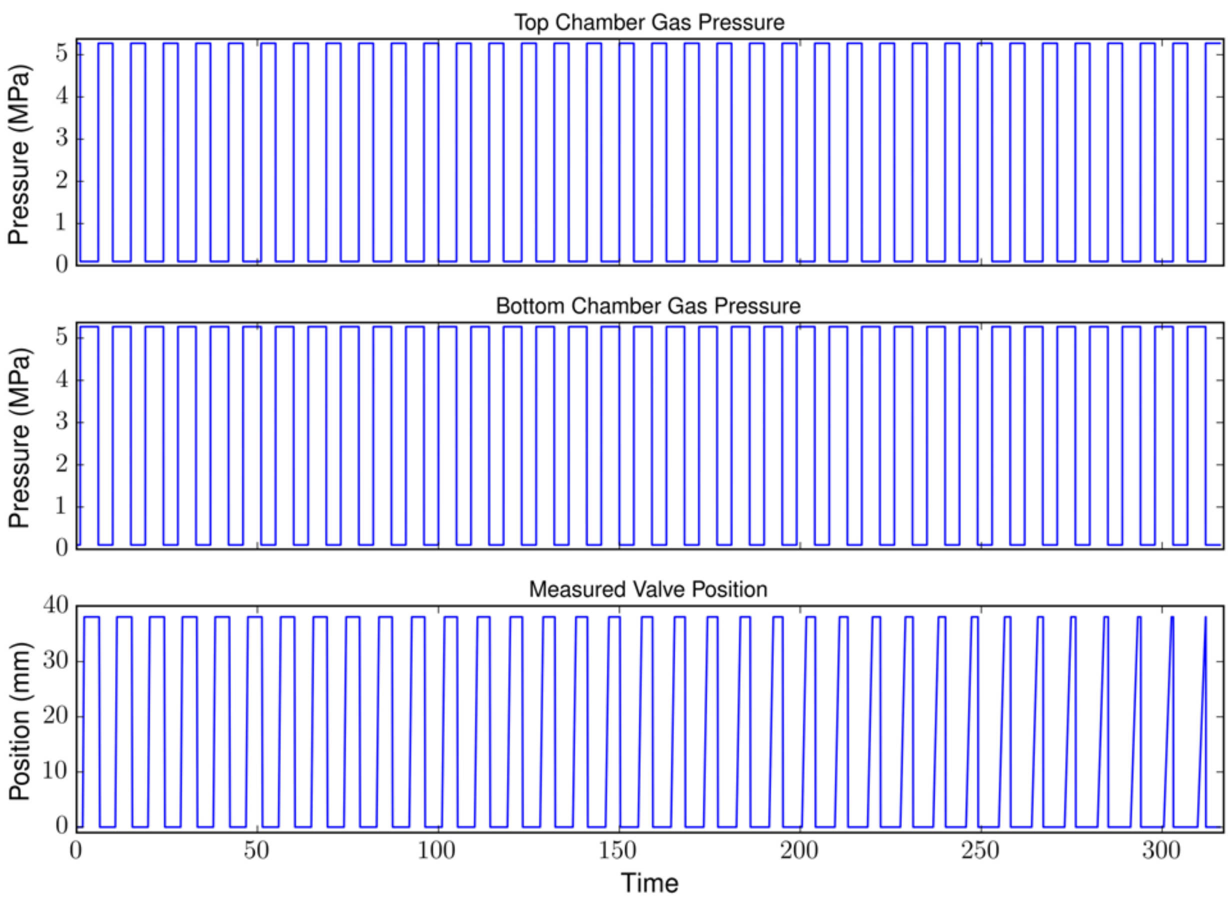

Figure 4.3. Input Pressure History for Pneumatic Valve with Corresponding Measured Valve Position

The prognostic evaluation using the measured valve position and the degradation accumulation model indicates that RUL estimate decreases over time, where the remaining life is computed based on an estimated time it would take the degraded valve to fail to meet its functional requirements. Figure 4.4 shows the RUL estimates for this specific example.

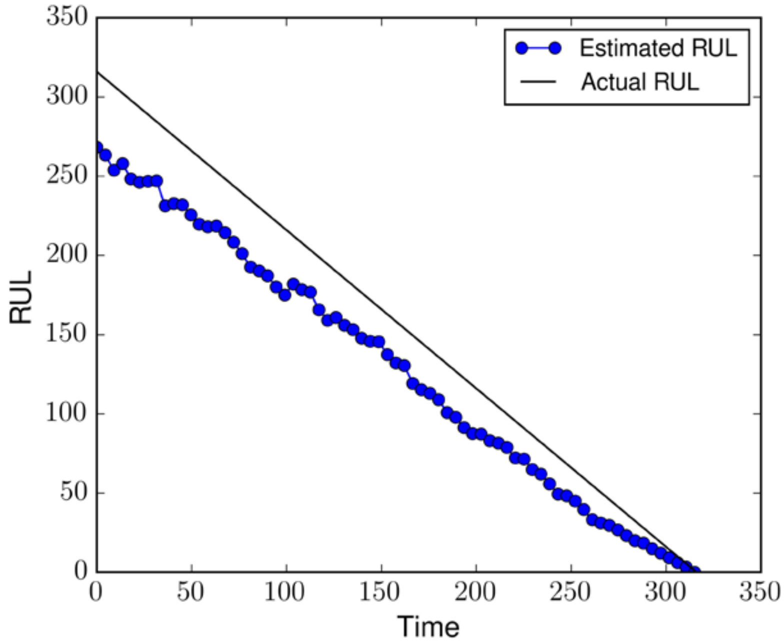

Figure 4.4. Pneumatic Value RUL Estimates

In general, other possible demand profiles can be used to generate RUL estimates. Within the SCS, the expectation is that multiple demand profiles (representing expected demand variations in the future) will be used to estimate the RUL for degraded valves. The information across these estimates can be combined in several ways to provide a general estimate of POF as a function of time and incorporated into the risk models for SCS utilization.

5.0 Summary

This M4 report is the final one in a series of technical reports documenting progress on research in the area of enhanced risk monitors that integrate equipment condition assessment, predictive assessment of POF, and risk monitors. The result is a predictive estimate of changes in plant risk metrics (economic and safety) due to changes in the condition of components from degradation and aging. The ERM uses component-specific real-time condition information rather than population averages, and is able to respond to the effects of degradation that can affect the ability of the component to meet its functional requirements. As a result, the ERM has greater flexibility than existing risk monitors that generally only utilize component availability or unavailability (binary variable).

This report covered: (1) background information on AdvRx and briefly summarizes previous research in this project; (2) modifications to prototypic ERM framework, with evaluations of the prototypic framework, that have occurred since Ramuhalli et al. (2015); and (3) and a status summary of the software development activities supporting integration of ERM module with the ORNL supervisory control system framework.

The additional analyses outlined in this report were focused on the sensitivity of the ERM result (predictive safety and economic metrics) to decisions that lead to changes in maintenance strategy, and to prognostic model outputs that may be at variance with the actual aging curve. In the first case, the ability to dynamically adjust maintenance schedules based on the actual condition of the component is highlighted. The results also indicate a relative lack of sensitivity to small changes in the prognostic output. Collectively, these are an indication of the robustness of the approach. However, these results need to be further verified using additional case studies.

An aspect that was only briefly assessed in this work was the time-lines for the predictive risk estimates. The work documented here and in previous reports assumed a long time horizon, with predictions being performed out to several years in the future. This was a conscious choice for the early research and was selected to illustrate the ability to schedule maintenance actions in the future and the associated trade-offs for plant economics that may occur to maintain the required safety margins. However, the time horizons for plant SCS integration will require much shorter time horizons (hours to a couple of days) as the control actions will need to be taken relatively quickly to ensure that the plant operation is within an approved envelope that maintains the necessary margins. Research this year on the predictive models for valves has looked into this question, and has shown the ability to use the same general approach for predictive assessment of condition over shorter time horizons. We believe that this result can be readily integrated with the risk monitor to provide real-time estimates of predictive risk and changes in future risk over the shorter time horizons (hours to days) instead of the longer time-lines (years) that were examined in previous reports.

5.1 Envisioned Role of ERM in O&M for Advanced Reactors

Critical to wider deployment of AdvRx concepts are management of O&M costs through the prediction and management of component integrity as a way to impact planning for maintenance activities and staffing levels. ERMs can be used to inform O&M decisions to (1) target maintenance activities during outages and (2) optimize plant performance to maintain safety margins and maximize economics while operating with components with detected degradation. Specifically, using ERMs can support extended operating cycles by ensuring reliable component operation over the long-term through assessment of component and equipment health using ECA. ERM-supported selection of operational decisions can help minimize the risk of unplanned plant shutdowns. Finally, predictive health monitoring based on equipment condition assessment, and predictive risk monitors, can enable optimization of maintenance scheduling with respect to the economics of AdvRx plant operation.

5.2 Research Contributions towards Advanced Reactor O&M Optimization

The research conducted under this project has resulted in advances in predictive risk-informed decision making for advanced reactors that are expected to directly impact AdvRx O&M practices. Given the possibility of frequently changing plant configurations to meet multiple mission goals, and the relative lack of component reliability data for AdvRx, techniques to integrate advanced plant configuration information, equipment condition information, and predictive risk monitors are needed to support real-time decisions on O&M. For AdvRx, enhanced predictive risk assessment that incorporates real-time degradation information of critical active components will greatly improve overall asset protection and management, allowing for safe, reliable generation during extended operating cycles and longer reactor lifetimes.

5.2.1 Overview of Achievements during this Project

This project succeeded in developing a prototypic framework that moved from measurements through condition assessment and predictive estimates of POF assessment to ERMs. It presented an overall concept for integration of ECA, PHM, and risk monitors to develop a framework for predictive risk monitors that are capable of being integrated with AdvRx plant SCS for real-time, risk-informed decision making. The ERM framework was developed with the intent of enabling timely component wear-out detection, monitoring, and proactive maintenance scheduling. These capabilities lead to plant operational control decisions and result in viable economic operation of the plant through avoidance of unplanned outages.

During the last year of this project, we performed sensitivity analyses of the prototypic ERM framework (Section 3.0) and collaborated with ORNL in the integration and evaluation of our ERM module (Section 4.0) with their SCS simulation-based software platform.

5.2.2 Recommended Path Forward

The need for an ERM methodology and the benefits of implementing it for developing an array of decision alternatives were demonstrated through this project using various case studies. These case studies were based on a simplified AdvRx model, and incorporated hypothetical O&M decisions and associated costs. These studies will need to be augmented with additional use cases that utilize more realistic quantities (costs, decision processes that mimic actual plant operations, etc.). This is difficult as there is limited information on AdvRx plant operation. A possible solution is to incorporate information on costs and current decision processes from current reactors (light-water), realizing that these may not be fully reflective of AdvRx O&M. This leads to the need for additional evaluations of sensitivity and uncertainty in the ERM, such as assessing sensitivity to short-term component maintenance decisions leading to configuration changes not requiring a shutdown.

As described in previous reports in this series, implementation of ERM requires modeling component operation and degradation accumulation for performing diagnostics and prognostics in addition to any need for component modeling by the SCS. As AdvRx concept development progresses further, there will be the need for additional research to model proposed plant components (active or passive) for performing diagnostics and prognostics in support of integrating an ERM methodology into the SCS.

Sensor technologies for monitoring the condition of these components will also be needed to address the need for equipment/component condition assessment. Timely research on component modeling, health monitoring and prognostics, and improvements in the ERM methodology can complement advances in SCS research in its support to developing AdvRx concept designs and O&M strategies.

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Appendix A

Specification for Integration of Diagnostics and Prognostics Module of Enhanced Risk Monitoring with Supervisory Control System

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Specification for Integration of Diagnostics and Prognostics Module of Enhanced Risk Monitoring with Supervisory Control System

This appendix lays out input-output specifications for integrating diagnostics and prognostics module of the enhanced risk monitoring methodology (PNNL) with supervisory control system (ORNL).

A.1 Overview of Supervisory Control System

ORNL's functional architecture in Figure A.1 shows acquired sensory data flowing into two different modules—(1) plant state estimation and (2) diagnostics and prognostics. Assuming sensory measurements reflect component state, at a minimum, diagnosis enables detection of component degradation and prognosis allows for time-dependent estimation of component failure probability.

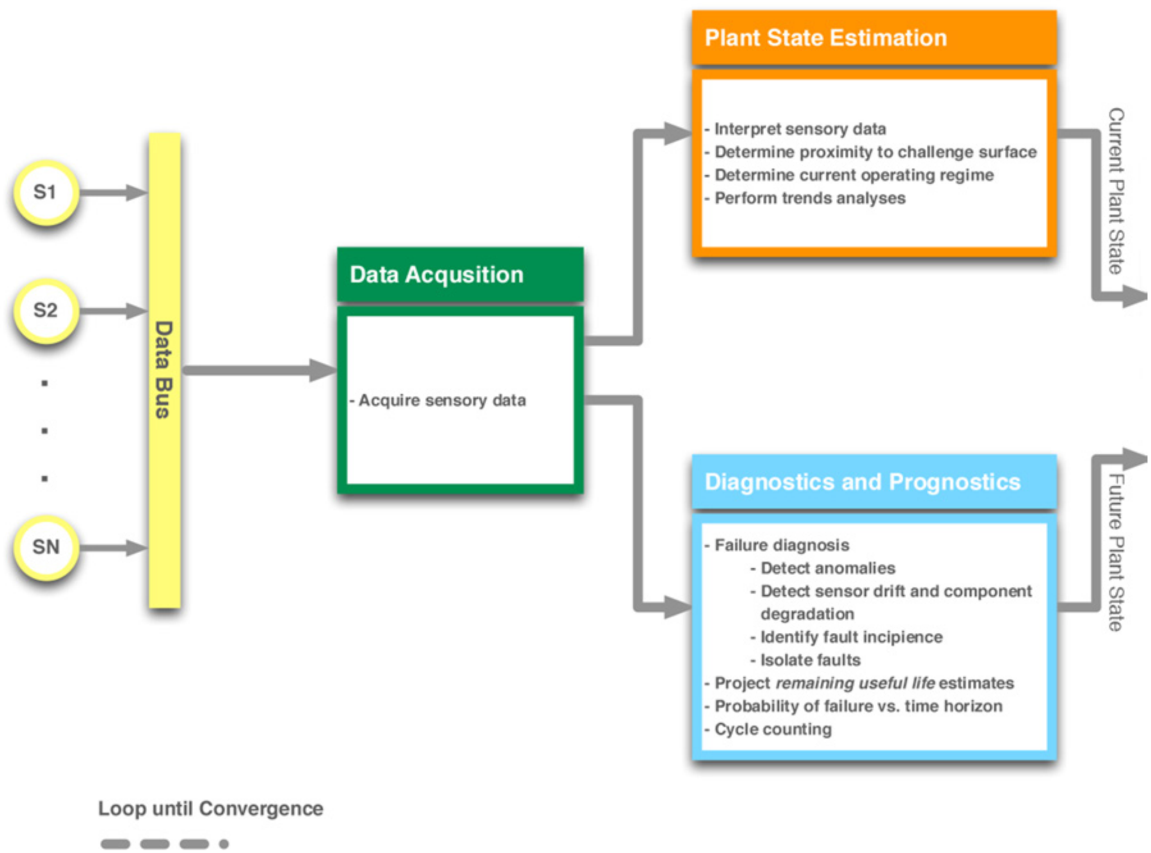

Figure A.1. Partial Snapshot of the Functional Architecture of the Supervisory Control System (flowing into decision making module) (Cetiner et al. 2014)

Figure A.2 shows the central role of the supervisory control system in passing inputs to and receiving outputs from various modules. For instance, (5) and (6) deal with state of components and command alternatives through time-dependent projection of component states.

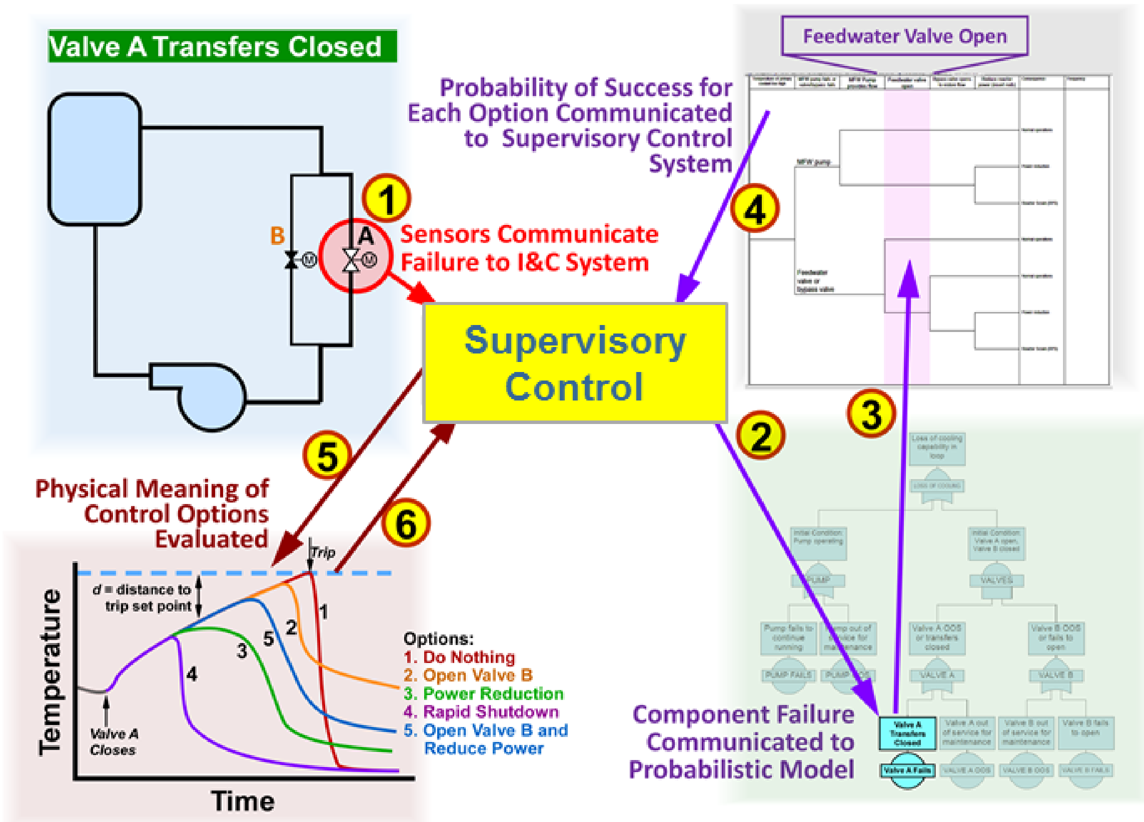

Figure A.2. Semi-autonomous Nature of Supervisory Control System (Cetiner et al. 2015)

A.2 Overall Software Architecture

The software requires different components written by PNNL and ORNL to work together. Figure A.3 shows the overall proposed software architecture. Packages written by ORNL are colored green, packages written by PNNL are colored orange, and the other packages are required for interfacing. This figure provides a high-level view of the software architecture, conveys the programming language used for each component, and also shows how the different components talk to each other. However, it does not convey how and what data flows between different modules.

The software modules have (or need) the following functionality:

- Modelica: Written in Modelica language standard, and developed by ORNL. Simulates plant operation in normal and off-normal conditions. Embeds supervisory control logic. This component receives initial conditions and solver settings from the user, and returns the solution for all the time-dependent variables in the plant model. Access to internal variables (at the different time steps, as the simulation runs) is needed for integration purposes.

- Prognostics: Written in Python, and developed by PNNL. Provides probability of failures (POFs) of plant components. Currently, this component only implements a prognostic model for the valve. This requires measurement inputs related to the valve and outputs the RUL and POF for the valve. Note that the other elements (such as the predictive risk calculations and the economic/safety risk computation modules) are also available in Python but are not included in this version of the software being integrated with the ORNL SCS.
- Python Interface: This is a middle-ware component used to route information from the Main application (described below) to the Prognostics component and Modelica (through the JModelica Python library). This middle-ware routes requests coming from the Main application through the standard input stream to the appropriate Python component (Prognostics or JModelica). On the other hand, it sends data returned from the Python components to the Main application through the standard output stream. The purpose of this interface is to separate data transfer between components of different languages from the data. Then, it is the responsibility of the Main application to appropriately handle the data returned from the Python components. The Python Interface module uses the JSON format for transferring objects between the Main application and the Python modules.
- RWB Model: Developed by ORNL using the Reliability Workbench (RWB) commercial software. A DLL file is used to provide an interface with the Main application for modifying and executing this model.
- Main Application: Written in .NET C#, this provides the graphical user interface, and allows the user to input data to be sent for configuring and executing the other components.
  - Any I/O sent or received to/from components written in Python (Prognostics or JModelica) is handled by the Python Handler component.
  - The RWB Handler handles the data I/O between the Python components and controlling the RWB model.

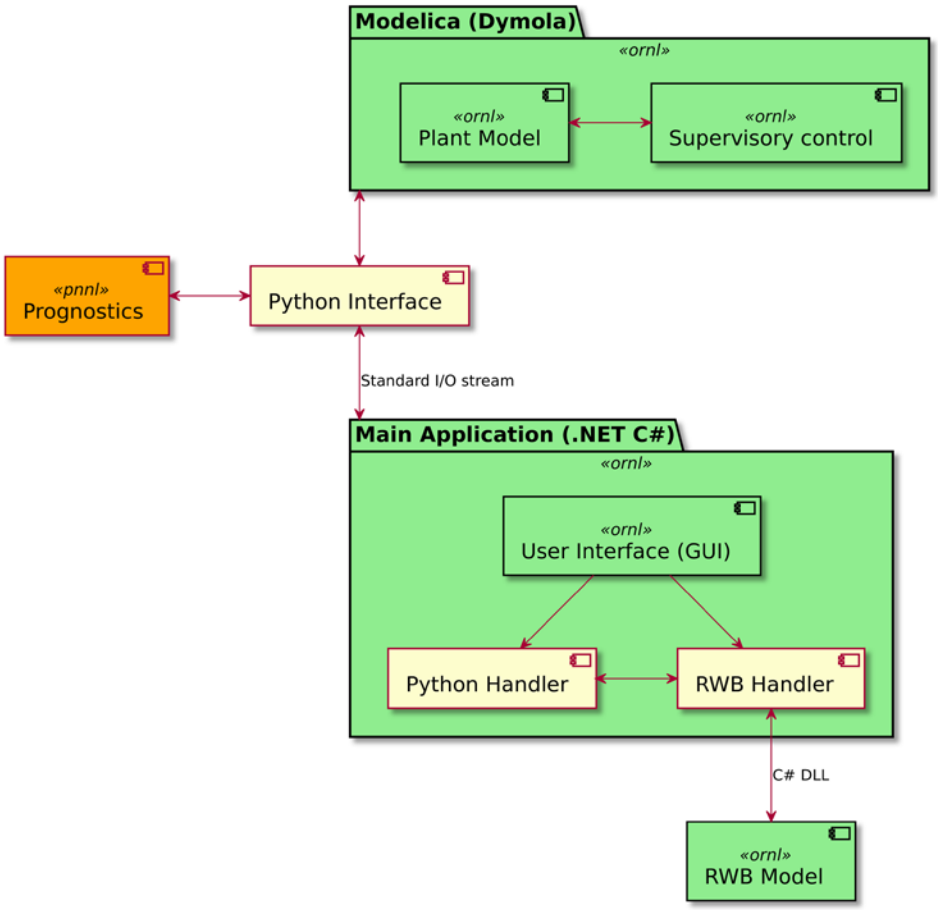

Figure A.3. Different Software Components and Their Interactions with Each Other. The packages are color-coded, where the green components represent packages written by ORNL, orange are packages written by PNNL, and beige are components required for interfacing PNNL and ORNL packages.

A.3 The Prognostics Module

The prognostics module requires defining a mathematical model for the failure progression of each component. Currently, only the model for the turbine control valve is implemented. However, the module is designed such that it is easy to plug any type of model on top of the existing one, without changing any of the base code. This is implemented by specifying two Abstract classes: MeasurementModel and StateModel. These provide the template (or interface) for which ParticleFilter class expects the model to provide.

If the Prognostics module is treated as a black box, then all the inputs and output for the module, assuming a valve prognostic model, are shown in Figure A.4. The necessary inputs and outputs will change with the type of component.

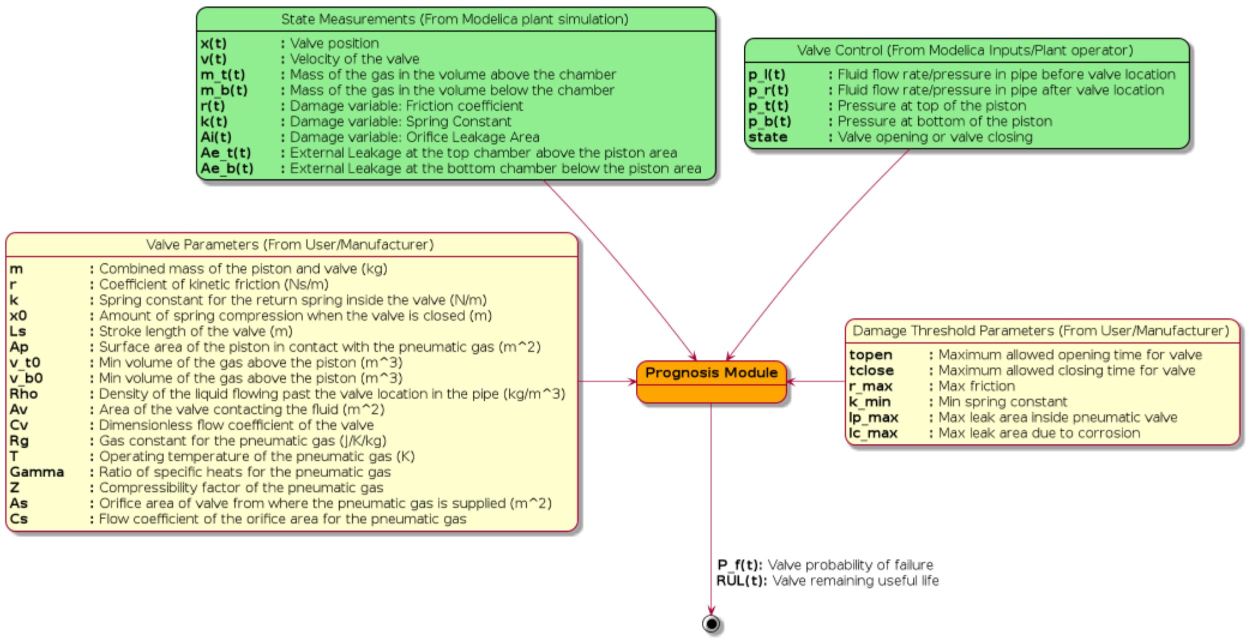

Figure A.4. All the I/O Parameters for the Prognostics Module

A.3.1 External Dependencies

Currently the ERM module integrated with the SCS simulation-based software platform (framework) depends on interfacing with Modelica and the RWB Model as defined in Section A.2. Specific input/output parameters related to the Prognostics Module are depicted in Figure A.4.

A.4 References

Cetiner SM, MD Muhlheim, GF Flanagan, DL Fugate and RA Kisner. 2014. *Development of an Automated Decision-Making Tool for Supervisory Control System*. Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Cetiner SM, MD Muhlheim, RA Kisner, DL Fugate and GF Flanagan. 2015. "Supervisory Control of Multi-Modular Advanced Reactor Plants (AT-15OR230202)." Presented at *ICHMI Program Review*. May 12–13, 2015.

Table A.1. Functional Requirements for the Prognostics and Diagnostics Module for Integration with Supervisory Control System

Requirement No.	Category and Reference to Step in Figure A.2	Functional Requirement	Specific Requirement	Expectations
Prognostics and Diagnostics Module (PDM) 0	Definition of success	The diagnostics and prognostics module should seamlessly integrate with the SCS	Need to define what success means for a seamless integration. Possible criteria are: Demonstrate successful change of POF in RWB Model, successful passing of valve degradation measurements to prognostic module, etc.	ORNL and PNNL to jointly define success metrics
PDM1	Overall expectations (Step 5 and 6)	The supervisory control system expects components' time-dependent POF curve from the diagnostics and prognostics module	Components of interest should be known: 1. Turbine control flow valve(s)	ORNL to confirm component identification numbers from RWB/JModelica
PDM2	Input (Step 5)	Diagnostics should detect component degradation	Component sensory measurement data should be available for component degradation detection. PNNL assumption is that sensory data will be provided that reflects a pre-set degradation profile. Sensory data could be process measurements, as well as (simulated) sensor data. At a given time instant, a measurement will be provided (either via ORNL process variables or other appropriate mechanism). Model (physics-based) will relate measured data to diagnostic condition of valve or pump.	ORNL to confirm feasibility of the following strategy: 1. PNNL to develop a pre-set degradation profile for a set of agreed upon components. 2. Sensory measurement data coming into the diagnostics module from the SCS/Data Acquisition should reflect the profile in Step 1.

Requirement No.	Category and Reference to Step in Figure A.2	Functional Requirement	Specific Requirement	Expectations
PDM3	Input (Step 5)	Prognostics should generate time-dependent POF estimates	Component's state variable information should be available (e.g., valve displacement, temperature)	PNNL to confirm component-specific, relevant physical variables (e.g., temperature, pressure) required for the module. ORNL to confirm variable names from JModelica for the corresponding physical characteristics. Where specific required information is not available, PNNL should use literature and expert judgment.
PDM4	Input (Step 5)	The current time for which the measurements correspond should be known	When SCS passes component's physical state information, the following are the options for time information: 1. Component state information comes with time stamp 2. Sensory measurement time is explicitly passed to the module	ORNL to confirm how component condition measurement-related time information is passed from the SCS. If stored in a separate variable, identify variable names.
PDM5	Process	Diagnostics should take into account component's condition history	When SCS invokes diagnostics, it passes a component's physical variables of interest. The diagnostics module should be able to maintain this condition history locally between calls.	PNNL is moving forward with local archival of component condition history within the diagnostics module. ORNL to confirm if there are limitations/restrictions around this scheme.

Requirement No.	Category and Reference to Step in Figure A.2	Functional Requirement	Specific Requirement	Expectations
PDM6	Output (Step 6)	Prognostics should return time-dependent POF estimates	The SCS should expect to receive two vectors for a component: time and corresponding POF.	PNNL's current implementation returns a vector of POF values for a component since the beginning of simulation (time zero) until component failure probability reaches 1.0 or the end of reactor life, whichever comes earlier.
PDM7	Invocation	The diagnostics and prognostics module should be invoked once for each component of interest at a single time instant.	There is design philosophy around whether diagnostics and prognostics module receives information about all components at once or once for each component. The specific invocation mode must be mutually understood.	Given the modular nature of the functional architecture shown in Figure A.1, PNNL assumes that one function call per component of interest at one time instant. ORNL to confirm if this assumption holds true.
PDM8	Invocation	The diagnostics and prognostics module should be invoked as often as necessary for each component of interest. (Equivalently, the module should receive a trigger when sensory measurements are made available through the SCS.)	One of the specific options must be selected: 1. SCS invokes module when a change in measurement is detected with certain sensitivity. 2. SCS invokes module at frequent intervals irrespective of change in measurement. Can this be tied to the ORNL simulation timeline where events may unfold at some rate? We will need to sense/characterize at a rate that can capture these events. Is there value in an experiment where some of the events may not be captured?	PNNL to move forward assuming option 1. ORNL to confirm that invocation happens multiple times associated with measurement changes for each component of interest.
PDM9	Post-Processing	Access to recorded diagnostics/prognostics information	Does SCS require locally recorded diagnostics/prognostics information for post-processing?	ORNL to confirm if access to recorded history is available for plotting. If so, the mechanism for data access should be stated.

Requirement No.	Category and Reference to Step in Figure A.2	Functional Requirement	Specific Requirement	Expectations
PDM10	Post-Processing	Dashboard metrics and visualization	Does the SCS require aggregate summaries for dashboard display?	ORNL to confirm what summary information is required. Assumption is that visualization, if any, will be taken care of by ORNL. Please confirm. If so, what are the expectations around data access from PNNL?
PDM11	Post-Processing	Test plan	A test plan with scenarios including what events occur, how frequently, what data is captured, what are metrics of success, etc. should be captured.	ORNL to document test plans with scenarios for the diagnostics and prognostics module with PNNL.

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