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Local-Level Prognostics Health Management Systems Framework for Passive AdvSMR Components – Interim Report

September 2014

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U.S. DEPARTMENT OF ENERGY

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Executive Summary

Advanced reactors, and advanced small modular reactors (AdvSMRs; based on modularization of advanced reactor concepts) may provide a longer-term alternative to traditional light-water reactor concepts, given their passive safety features and the ability to incrementally add modules over time.

Two issues are likely to challenge the ability to deploy these reactor concepts widely. First, AdvSMRs suffer from loss of economies of scale inherent in small reactors when compared to large (greater than ~600-MWe output) reactors. While some of this loss can be recovered through reduced capital costs, the controllable day-to-day costs of AdvSMRs will be dominated by operation and maintenance (O&M) costs. A second potential challenge is the relatively lower level of operational experience with advanced reactor concepts (when compared with light-water-cooled reactors), and the consequent limited knowledge of physics of failure mechanisms in advanced reactor environments. Information on component condition and failure probability is considered critical to maintaining adequate safety margins and avoiding unplanned shutdowns, both of which have regulatory and economic consequences.

A significant component of O&M costs is associated with the management and mitigation of degradation of passive components because of their increased safety-significance in AdvSMR concepts (which increasingly rely on passive safety mechanisms), and the need to provide longer lead-times for maintenance planning as passive components constitute large capital expenditures. In particular, degradation (such as cracking, creep, or creep-fatigue damage) in passive components, if not addressed in a timely fashion, is likely to result in unplanned plant shutdowns. Traditional approaches to detecting and managing degradation such as periodic in-service nondestructive inspections are likely to have limited applicability to AdvSMRs, given the expectation of longer operating periods and potential difficulties with inspection access to critical components because of compact designs and submersion of primary-circuit components in pool-type designs.

Technologies such as prognostics health management (PHM) systems that help advance the state of the art of diagnostics and prognostics are important for controlling O&M costs by providing enhanced awareness of component or equipment condition and predictive estimates of component failure that are customized for each AdvSMR unit and accounts for the specific operational history of the unit. Such information, when integrated with plant control systems and risk monitors, helps control O&M costs by enabling lifetime management of significant passive components, relieving the cost and labor burden of currently required periodic in-service inspection, and informing O&M decisions in real-time to target maintenance activities.

PHM systems may be applied at several levels in the hierarchy of AdvSMR systems. For example, component-level PHM systems may be applied to assess the condition of components or sub-systems, such as the intermediate heat exchanger. The use of multiple PHM modules provides increased opportunity to monitor the health of critical subsystems within the plant. However, it increases the amount of information that must be aggregated prior to use with risk monitors and in plant supervisory control actions. Figure ES.1 shows a possible scenario for the aggregation; where each PHM module is associated with a risk monitor resulting in predictive estimates of the subsystem health and the associated risk metrics. This information is used to augment data used for supervisory control and plant-wide coordination of multiple modules by providing the incremental risk incurred due to aging and demands placed on components that support mission requirements.

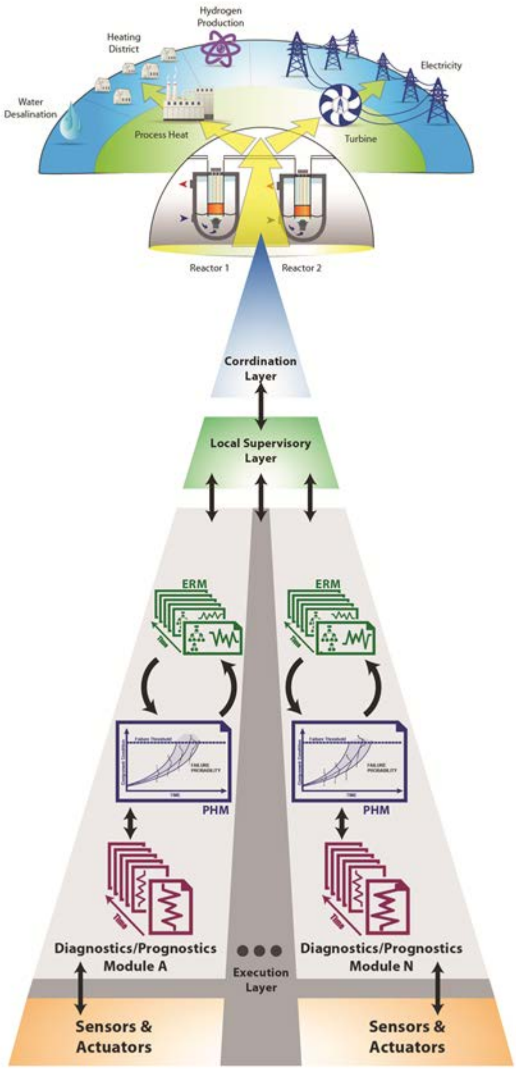

Figure ES.1. Schematic Showing the Integration of PHM Systems with Enhanced Risk Monitors, and Their Location within the Hierarchy of Supervisory Control Algorithms for AdvSMRs

PHM is a proactive maintenance philosophy in which maintenance or repairs to systems or components are performed prior to failure based on models that predict when failure is likely to occur. To predict failure, prognostic models require some type of input about the state of the component(s) of interest, which could be historical failure data, information on stressors to which the system or component is exposed, or information on the condition of a specific system or component. Thus, measurements and diagnostics, in addition to prognostics, are key elements to a PHM system. The results of prognostic calculations should provide actionable information to influence O&M decision making. In nuclear power applications, the impact of prognostics can be felt by incorporating the results into enhanced risk monitors (ERMs), which provide time-dependent measures of risk of failure for individual systems or components and integrate these results into an overall risk metric for the reactor or plant (Coble et al. 2013).

This report describes research results to date in support of the integration and demonstration of diagnostics technologies for prototypical AdvSMR passive components (to establish condition indices for monitoring) with model-based prognostics methods. The focus of the PHM methodology and algorithm development in this study is at the localized scale. Multiple localized measurements of material condition (using advanced nondestructive measurement methods), along with available measurements of the stressor environment, enhance the performance of localized diagnostics and prognostics of passive AdvSMR components and systems.

To provide a context for the development of prognostics algorithms, high-temperature creep is selected as the prototypical degradation mechanism in passive components. This mechanism is relevant to several of the advanced reactor and AdvSMR concepts that are being considered, including the liquid-metal and high-temperature gas reactor concepts. The mechanism also enables the verification and validation of several concepts unique to proposed AdvSMRs, including multiple phases of degradation that require monitoring, variable loading, and long-term effects in harsh environments.

An initial methodology for estimating remaining useful life (RUL) from spatially localized nondestructive evaluation (NDE) measurements was developed. This methodology for PHM uses Bayesian approaches and multiple filtering algorithms to diagnose and predict the RUL of the material subjected to high-temperature creep damage. Applying this type of "tracking" filter to the problem of predicting degradation accumulation in materials from NDE measurements requires two models—one (Degradation Rate model) that captures the progressive accumulation of degradation in the material from one or more stressors, and the second (Measurement model) that relates the level of material degradation to one or more NDE measurements. The classical tracking filters need modification to enable longer-term prediction; however, the approach provides a relatively simple Bayesian mechanism for updating the predictions when additional measurements are available.

The Bayesian approaches were tested using synthetic data to verify their ability to provide predictive estimates of secondary-stage creep strain accumulation, and the ability to update these predictions as additional measurements become available. Modifications to these algorithms to account for model selection and uncertainty quantification, to address primary and secondary stage creep prognostics and measurement/model uncertainty, were also made and are being evaluated.

To perform initial validation of the prognostic algorithms, a laboratory-scale creep degradation test-bed was designed and built. The test-bed enables interrupted creep testing, where specimens are removed after a defined amount of time, measured using advanced NDE techniques, and re-inserted into the test-bed for further degradation accumulation. Initial (or baseline) measurements using multiple NDE methods were completed on several creep specimens, including on a specimen set aside as a reference or verification standard. The relative change in the measurements provides an understanding of the sensitivity of the NDE technique, and can be related back to the level of accumulated creep strain in the specimen.

The results of the RUL estimation from simulated data show that a Bayesian approach is feasible for this purpose. The proposed Bayesian prognostics approach also allows for updates to the RUL estimates as new measurements are acquired. The results also indicate that the uncertainty associated with the RUL projections appears to improve for particle filters as additional data becomes available. This behavior does not seem apparent using other Bayesian filtering algorithms, and may provide a metric for selecting appropriate filtering algorithms. The use of uncertainty may also help address the model selection problem for lifecycle prognostics; however, this needs further evaluation and confirmation using simulated and experimental data. The improvement in uncertainty in the RUL estimates will also need to be validated further.

NDE measurements on the specimens indicate variability in the parameters as a function of accumulated creep strain. The data, as well as accumulated creep strain, appear to vary from specimen to specimen, as well as within a specimen. This variability is likely because of differences in the starting material microstructure for the specimens; this will be confirmed using additional measurements.

Ongoing research includes: (1) completing the evaluation of lifecycle prognostics and uncertainty quantification approaches and (2) incorporating stressor information into the prognostics methodology, to address variable loading scenarios and reduce uncertainty in the predictive estimates of remaining life. In addition, future research will focus on PHM at the component level, utilizing one or more measurements of component health and the stressor environment. Examples of such measurements include acoustic emission and vibration. These measurements may be augmented with localized NDE measurements on the component. Research will also be conducted towards developing approaches to integrate information from multiple PHM systems resulting in enhanced awareness of advanced reactor/AdvSMR system condition. These activities will be supported by continued acquisition of necessary NDE measurements using appropriate additional specimens.

Acknowledgments

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Acronyms

AdvSMR	advanced small modular reactor
Code	ASME Boiler and Pressure Vessel Code
EKF	Extended Kalman Filtering
ERM	enhanced risk monitor
GIF	Generation IV international Forum
ISI	in-service inspection
LFR	lead (or lead-bismuth) cooled fast reactor
LWR	light-water reactor
NDE	nondestructive evaluation
O&M	operations and maintenance
PDF	probability density function
PF	Particle Filtering
PHM	prognostic health management
POF	probability of failure
PRA	probabilistic risk assessment
RI-ISI	risk-informed in-service inspection
RUL	remaining useful life
RVACS	reactor vessel auxiliary cooling system
SFR	sodium-cooled fast reactor
SMR	small modular reactor
SSC	systems, structures, and components
TTF	time-to-failure
UKF	Unscented Kalman Filtering

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1.0 Introduction

Nuclear energy is expected to constitute a significant fraction of the U.S. electrical generation capacity over the next 30 years, and several reactor concepts are being explored to meet the anticipated increase in demand. Advanced reactors and small modular reactors are two classes of reactor concepts that are at the forefront of this evolution.

Small modular reactors (SMRs) generally include reactors with electric output of ~350 MWe or less. This cutoff varies somewhat but is substantially less than full-size plant output of ~600 MWe or more. Advanced SMRs (AdvSMRs) refer to a specific class of SMRs and are based on modularization of advanced reactor concepts. AdvSMRs may provide a longer-term alternative to traditional light-water reactors (LWRs) and SMRs based on integral pressurized water reactor concepts currently being considered, given their passive safety features and the ability to incrementally add modules over time.

Leading AdvSMR designs are based on advanced reactor concepts identified by the Generation IV International Forum (GIF) (Abram and Ion 2008) and include liquid-metal-cooled, gas-cooled, molten-salt, and supercritical water reactor concepts. Of these, the greatest amount of operating experience comes from liquid-metal-cooled and gas-cooled reactors. Both of these advanced reactor concepts have also been used in AdvSMR designs, and are likely to be closer to moving through the design and deployment cycle than AdvSMR concepts based on other coolant materials.

Two issues are likely to challenge the ability to deploy AdvSMRs widely. First, AdvSMRs suffer from loss of economies of scale inherent in small reactors when compared to large (greater than ~600-MWe output) reactors. Some of this loss can be recovered through reduced capital costs through smaller size, fewer components, modular fabrication processes, and the opportunity for modular construction. However, the controllable day-to-day costs of AdvSMRs will be dominated by operation and maintenance (O&M) costs. A second potential challenge to wider deployment of AdvSMRs is the relatively lower level of operational experience with advanced reactor concepts (when compared with light-water-cooled reactors), and the consequent limited knowledge of physics of failure mechanisms in advanced reactor environments. Information on component condition and failure probability is considered critical to maintaining adequate safety margins and avoiding unplanned shutdowns, both of which have regulatory and economic consequences.

Technologies that provide improved awareness of system condition, when integrated during design of the AdvSMR, can provide the tools necessary for quantifying the operational envelope for safe economic O&M of the AdvSMR, and in coordination with supervisory control algorithms, enable these reactors to stay within the operational envelope while maintaining adequate safety margins.

Prognostic health management (PHM) systems are one such class of technologies that help control O&M costs through:

- Enhancing affordability and safe operation of AdvSMRs over their lifetime by enabling lifetime management of significant passive components and reactor internals (especially for critical passive safety components) in harsh environments (high-temperature, fast flux, and corrosive coolant chemistry);

- Relieving the cost and labor burden of currently required periodic in-service inspection during refueling outages, especially for components in hard-to-access areas such as those in-vessel/in-containment;
- Reducing risks by providing increased understanding of plant equipment conditions and margins to failure, particularly in conditions where knowledge of physics of failure is limited;
- Informing O&M decisions to target maintenance activities during infrequent refueling outages; and
- Supporting a science-based justification for extended plant lifetime by ensuring reliable component operation.

Periodic in-service nondestructive inspection technologies already exist and are used in operating nuclear power plants to provide an assessment of passive component condition, including whether significant cracking exists that could compromise structural integrity. However, the applicability of existing technologies may be limited in AdvSMRs, because of their compact design, modular characteristics, restricted access to key in-vessel and in-containment components, and extended periods between inspection and maintenance opportunities. PHM systems, with their emphasis on increased in-situ structural health monitoring and prognostics to assess remaining service life (also referred to as remaining useful life or RUL) provide a mechanism to address the limitations of current in-service inspection approaches for use with AdvSMRs.

This report documents research towards developing and deploying prototypical PHM systems that, if integrated with supervisory plant control systems and enhanced risk monitors, can provide the capability requirements listed and meet the goals of controlling O&M costs.

1.1 Research Objectives

This report describes research results to date in support of the integration and demonstration of diagnostics technologies for prototypical AdvSMR passive components (to establish condition indices for monitoring) with model-based prognostics methods. Achieving this objective will necessitate addressing several of the research gaps and technical needs described in Meyer et al. (2013a). Specifically, this research is addressing the need for quantitative nondestructive examination (NDE) analysis tools by examining the sensitivity of advanced NDE methods to relevant degradation mechanisms. Degradation condition indices (along with any associated uncertainties) calculated from these measurements are integrated with models of material or component failure to enable estimation of remaining life of passive components with detected degradation. Gaps with respect to deployment of sensors and instrumentation, and integration with plant control algorithms, exist and will be addressed as this research progresses.

The focus of the PHM methodology and algorithm development described in this report is at the localized scale. Multiple localized measurements of material condition (using advanced nondestructive measurement methods) along with available measurements of the stressor environment are used to enhance the performance of localized diagnostics and prognostics of passive AdvSMR components and systems.

1.2 Organization of Report

This technical report is organized as follows. Section 2 includes background information on AdvSMR concepts and characteristics, PHM for AdvSMRs, and requirements and assumptions for PHM methodology development for AdvSMRs. Section 3 describes the overarching PHM methodology and the approaches to model selection being used for the initial, local-level prognostics. Uncertainty management for prognostics and their incorporation into prognostic algorithms are also presented. Section 4 presents the status of the PHM using Bayesian framework and laboratory-scale measurements for use in verification and validation of the local-level prognostics algorithms. Finally, Section 5 summarizes the status of research to date and briefly outlines ongoing research.

2.0 Background

The vast majority of nuclear power plant operating experience involves light-water-cooled reactors and includes small LWRs. AdvSMRs are derived from advanced reactor technologies, and are generally distinguished from other nuclear power plant concepts by three factors:

- Using non-light-water coolants—coolants being proposed for AdvSMRs include liquid sodium, lead or lead-bismuth eutectic, helium, and molten-salt.
- Deliberately small in size—typically, AdvSMR concepts are expected to have electrical output less than about 300 MWe.
- Anticipated to be modular in configuration and operation, with one or more reactor modules in one power block, and multiple power blocks making up a plant.

Below, we briefly discuss advanced reactor concepts relevant to this research and provide background information on NDE and health monitoring for nuclear power applications. This is followed by the technical assumptions that bound the research described in the rest of this document. Additional details of AdvSMR concepts and likely O&M approaches are provided in the previous reports in this series associated with AdvSMR prognostics and enhanced risk monitor research (Coble et al. 2013; Meyer et al. 2013a; Ramuhalli et al. 2013b; Ramuhalli et al. 2014).

2.1 AdvSMR Concepts and Characteristics

As stated earlier, leading AdvSMR designs are based on the advanced reactor concepts (Abram and Ion 2008). Given the amount of operating experience with liquid-metal-cooled and gas-cooled reactors, it is likely that these concepts would be targets for near-term AdvSMR designs.

Details of advanced reactor concepts that are likely to be adapted for AdvSMR concepts are available in the previous report in this series (Ramuhalli et al. 2014). Additional background on other advanced reactor concepts and operational experience are available in the report on prototypic prognostic techniques for AdvSMRs passive components (Ramuhalli et al. 2014).

There is some experience with select advanced reactor concepts, which may be used to identify potential faults and failure modes for key components in AdvSMR concepts. Some of these issues are expected to be resolved in new AdvSMR designs (e.g., moisture intrusion through water-lubricated bearings may potentially be avoided by using sealed magnetic bearings), while other issues may still be relevant (Meyer et al. 2013a); although, relevant data may not be easily accessible. These issues are likely to drive inspection and maintenance requirements for AdvSMRs.

There are several characteristics of AdvSMRs that are expected to be relevant to the design and implementation of PHM systems. These characteristics are applicable to multiple advanced reactor concepts, and are determined from consideration of likely scenarios for AdvSMR operations and maintenance, concepts of operation, balance-of-plant configurations, materials and materials degradation, and refueling intervals (Meyer et al. 2013a).

2.2 Prognostics Health Management for AdvSMRs

While several concepts for prognostic health management exist, they all have certain elements in common. PHM systems encompass several elements including: (1) sensors for performing measurements of both process parameters as well as indicators of degradation; (2) diagnostics algorithms that use the sensor measurements to estimate the condition of the component; (3) prognostics algorithms to calculate the remaining service life of the component with degradation; and (4) interfaces to decision and control systems that are used to make O&M decisions.

Keys to effective PHM are the ability to detect incipient failure through increased monitoring, application of advanced in-situ diagnostics tools for degradation severity assessment, and estimation of remaining service life (also often referred to as remaining useful life [RUL]) through the use of prognostic tools (see Meyer et al. 2013a). This is particularly important for systems, structures, and components (SSCs) proposed for use in AdvSMR designs that differ significantly from those used in the operating fleet of LWRs (or even in LWR-based SMR designs), as operational characteristics for these SSCs may not be fully available.

The operating characteristics of proposed AdvSMR designs impose challenges to developing and deploying PHM systems. Several AdvSMR concepts use pool-type or integral configurations or very compact arrangements, which reduces accessibility to key components for frequent testing and maintenance. These designs are also expected to have fewer offline component testing and maintenance opportunities because of longer operating cycles between refueling. Additionally, modularity in AdvSMRs can, in some cases, introduce interconnections or dependencies between SSCs in reactor modules, resulting in event and failure trees that are very different from those present in current operating nuclear power reactors.

Several factors have a role in driving the requirements of PHM systems for passive AdvSMR components (Figure 2.1). These requirements were derived from relevant operating experience of several deployed advanced reactors, expected operational characteristics of proposed AdvSMR concepts, and current approaches to diagnostics and prognostics. Functional requirements identified using these drivers, along with a brief discussion of the basis for each requirement, are discussed in Meyer et al. (2013a).

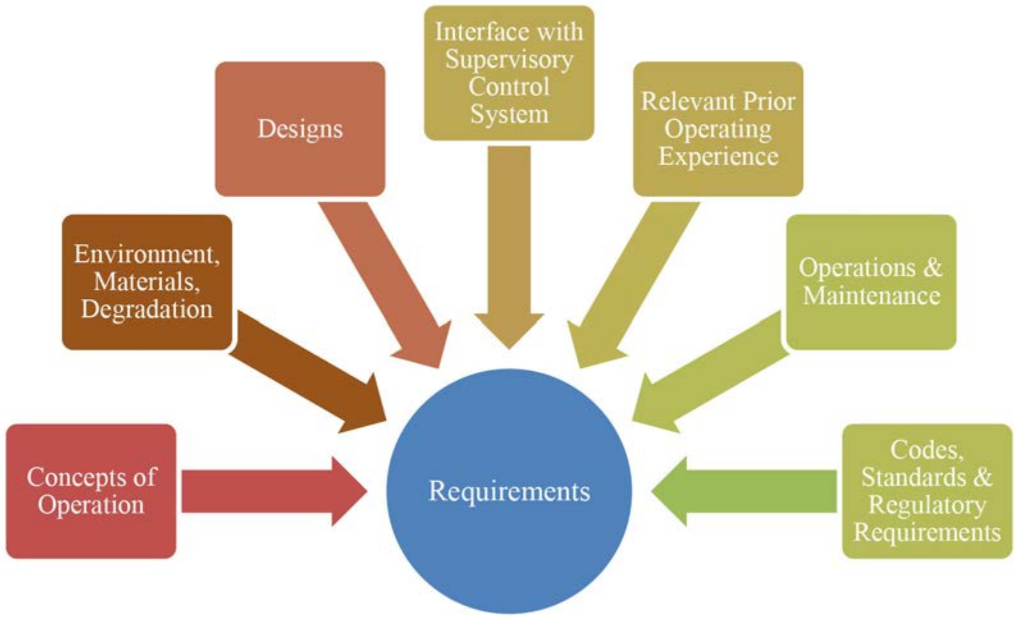


Figure 2.1. Some of the Factors that Drive Requirements of PHM Systems for Passive AdvSMR Components

2.2.1 PHM for Passive Components

Passive components in AdvSMRs include components that are internal to the reactor vessel (such as core support structures) as well as components such as heat exchanger tubing or Class 1 piping that is external to the vessel. Knowledge of degradation in these components is important because of the following:

- Safety-significance. Proposed AdvSMR concepts incorporate a greater reliance on passive components for safety. By providing information about degradation and the remaining safe life to risk monitors and plant control systems, decision-making relative to operational safety using components with small levels of degradation may be made efficiently.
- Unexpected plant shutdowns are expensive, both from lost generation and unplanned expenditures to address the cause of the shutdown.
- Sufficient lead time to plan O&M activities. In general, passive components constitute large capital expenditures, and repair/replacement decisions are likely to be economically viable if there is advance warning of impending degradation or component failure.

In general, a PHM system for passive components will consist of the elements described earlier—sensors, diagnostic and prognostic algorithms, and interfaces to other elements of plant operations and control. The process of applying the various stages in the PHM system is iterative, and is illustrated in Figure 2.2.

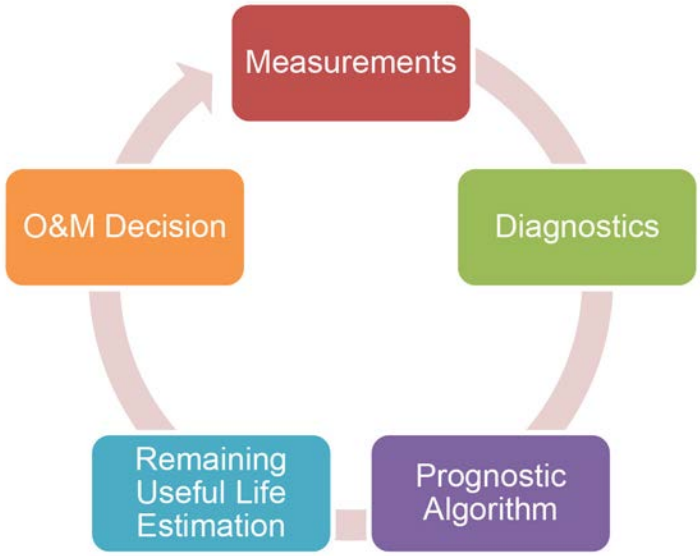


Figure 2.2. Elements of a PHM System for Passive AdvSMR Components

In proposed AdvSMR designs, a number of passive components may be identified for condition monitoring. Determining whether available condition monitoring techniques may be applicable to these components is a necessary step to leveraging existing technologies to the fullest extent possible. Below, we briefly discuss the use of in-service inspections (ISI) and NDE methods for detecting and monitoring degradation in passive components.

2.2.2 Risk-informed In-service Inspection and Monitoring

Risk-informed in-service inspection (RI-ISI) as used by the NRC implies that decisions on component selection for periodic inspections are based on risk insights along with deterministic and licensing basis information (Phillips 2005). The concept of RI-ISI has been successfully implemented in several countries, as reported in the CSNI state-of-the-art report (OECD/NEA 2005). Current practice for in-service degradation detection in passive components in the nuclear industry is generally geared towards the detection of macroscopic degradation (such as cracking or material loss). Given the likely impracticality of inspecting every component in a power plant, recommended practice in the nuclear industry is to follow RI-ISI (Atkinson and Kytömaa 1992) to identify risk-significant components and prioritize inspection activities.

The Benchmark Study on Risk-Informed In-Service Inspection Methodologies (RISMET) project (OECD/NEA 2010) compared qualitative and quantitative RI-ISI with traditional in-service inspection programs, and augmented programs developed in response to a particular issue (e.g., break exclusion regions, flow assisted corrosion, and localized corrosion). This comparative study was aimed at identifying the impact of such methodologies on reactor safety and how the main differences influence the final result (i.e., the definition of the risk-informed inspection program). Included was the recognition that the next challenge facing the industry is the development of RI-ISI programs for new reactor designs. Conclusions of the RISMET project supported further RI-ISI research efforts in the field of risk-informed selection of components for inspection. Among the questions reported for future RI-ISI R&D efforts to provide answers were the following relevant to this PHM effort:

- Consistent criteria are needed to determine when the potential for a certain damage mechanism occurs;
- Better information is needed regarding the efficacy of various NDE methods;
- The use of probabilistic methods to determine inspection intervals needs further exploration; and
- Methods enabling reliable probabilistic analyses for some damage mechanisms.

For AdvSMRs (and advanced reactors in general), an assessment of risk-significance may not be the sole deciding factor for deployment of PHM systems as degradation growth may occur fastest in locations that are not considered to be high-risk. Further, taking a plant off-line for unplanned maintenance or repairs (even on non-risk-significant components) will impact the economics of operation. Thus, achieving reliability and integrity goals for passive components will require careful choices in design, fabrication, operation, and maintenance, with PHM systems forming the final level of defense-in-depth for selected components.

2.2.3 Nondestructive Evaluation

Once the set of passive components requiring PHM have been identified (using RI-ISI or other approaches), methods for the nondestructive evaluation of component health are needed. The health of a passive component or system may be inferred from measurements of the contributors (such as temperature, stress, and neutron fluence) to degradation, and their effects (such as material microstructural changes) on the materials. Traditional approaches to detect degradation in passive safety systems are based on periodic in-service nondestructive inspection methods (such as those used in current LWRs) during re-fueling or other planned outages (Bond and Doctor 2007). A number of advances in NDE have been ongoing, although no single NDE method is likely to be sensitive to all degradation mechanisms of interest in advanced reactors. In addition, in proposed AdvSMR designs, degradation may occur at different locations, have different causes and growth rates, and consequently may require a number of different measurement methods to ensure overall detection reliability (Gros 1997; Dion et al. 2007). Details of conventional and advanced techniques, and research on sensors for harsh environments that may be leveraged for use in PHM, are available in a number of previous reports in this series (Meyer et al. 2010; Meyer et al. 2011; Meyer et al. 2013a; Meyer et al. 2013b).

2.3 Role of PHM in AdvSMR Control and Coordination

PHM systems (Figure 2.3) can potentially contribute to the affordability of AdvSMRs by providing greater awareness of in-vessel and in-containment component and system conditions. In turn, such increased awareness can help inform O&M decisions to target maintenance activities that reduce risks associated with safety and investment protection through a greater understanding of precise plant component conditions and margins to failure.

Keys to effective PHM are the ability to detect incipient failure through increased monitoring of both the component under test as well as the environmental stressors that affect the component, application of advanced in-situ diagnostics tools for degradation severity assessment, and estimation of remaining service life (also often referred to as RUL) through the use of prognostic tools. Available information from AdvSMR design concepts, expected operational characteristics, and relevant operating experience may be used to both define requirements for the various elements of the PHM system, as well as bound estimates of RUL with high confidence. Interfaces with plant supervisory control systems ensure that the information about component RUL and system conditions are utilized as a basis for planning maintenance activities. In particular, the ability to estimate remaining life provides a basis for determining whether continued safe operation (over some pre-determined interval) is possible, or whether operating conditions need to be changed to limit further degradation growth until a convenient maintenance opportunity presents itself.

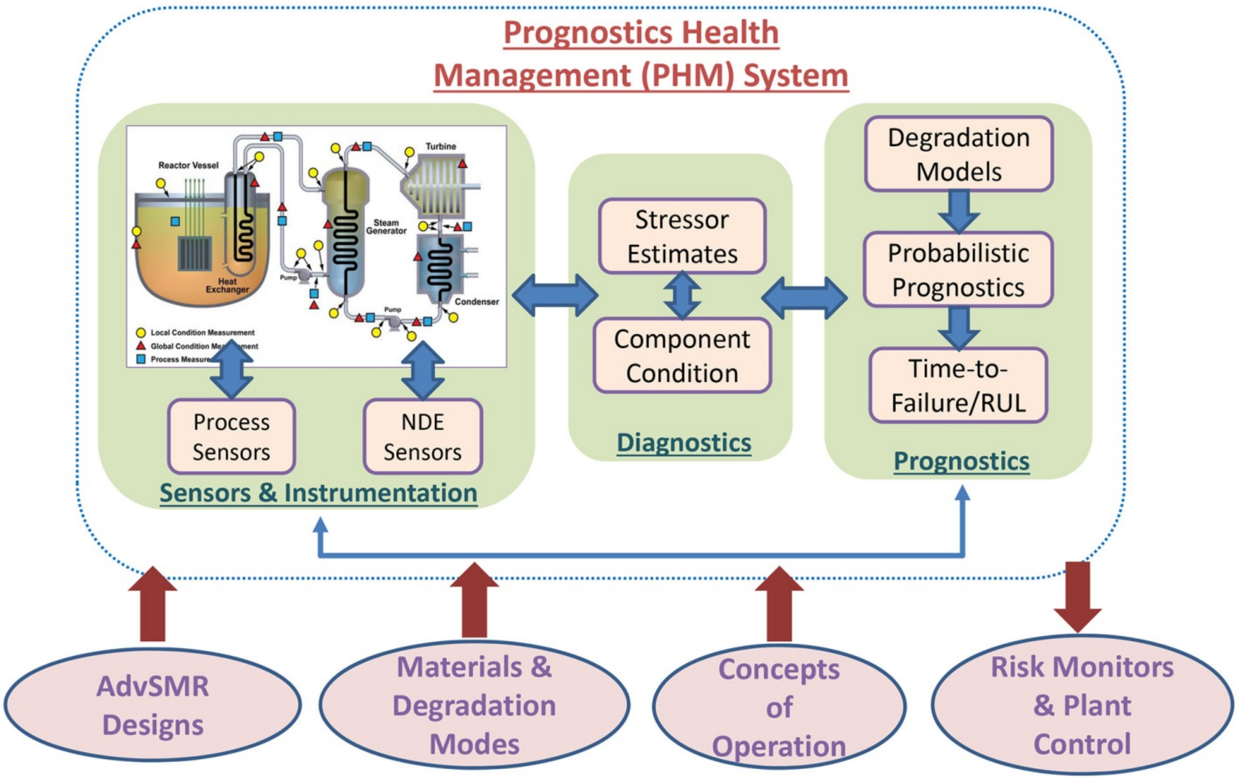


Figure 2.3. Overview of a Typical Prognostics Health Management System

2.3.1 PHM, Risk Monitors, and Plant Control Technologies

PHM technologies for nuclear power (Coble et al. 2012b) have generally focused on active components, although several recent efforts have begun to examine the feasibility of PHM for passive components in nuclear power plants. The result of a PHM system is the projection of probability of failure (POF) values as a function of time. Current risk monitors use probabilistic risk assessment (PRA) techniques to assess the risks associated with operation (Wu and Apostolakis 1992a) by systematically combining event probability and POF for key components to determine the hazard probability for subsystems and the overall system (Kafka 2008). PRA models 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 (Vesely and Wolford 1988; Arjas and Holmberg 1995); however, these are usually not specific to the component. Ramuhalli et al. (2013b) discuss the potential for integrating predicted POF values from PHM systems with risk monitors to obtain a realistic assessment of dynamic risk that is unit-specific and accounts for the operational history of the component.

In general, PHM may be applied to several SSCs within an AdvSMR, with each providing an estimate of the condition of the component. The challenge is then to integrate the information being provided by these multiple systems.

In this research, the overall approach taken is illustrated in Figure 2.4. The figure illustrates a system-of-systems approach, with individual PHM systems monitoring the different SSCs, with additional systems in the hierarchy integrating the output from the individual PHM systems and providing the necessary interfaces to plant supervisory control systems, operational risk monitors, and O&M decision making. A representative drill-down into an individual PHM system is shown in Figure 3.2.

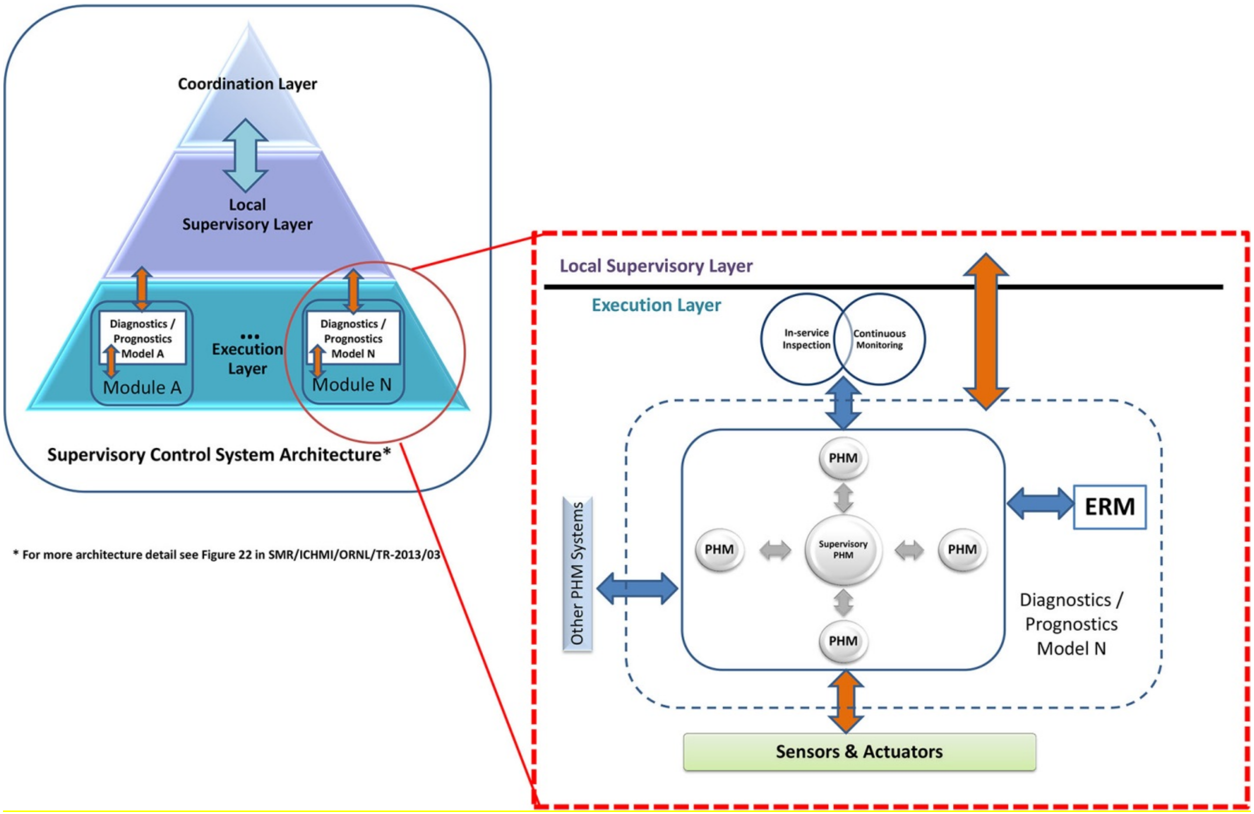


Figure 2.4. Overview of PHM System Hierarchy and Its Relationship with an AdvSMR Supervisory Control Architecture (adapted from SMR/ICHMI/ORNL/TR-2013/03)

2.4 Requirements and Assumptions for PHM Methodology Development in AdvSMRs

2.4.1 Requirements for Prototypic Prognostics Health Management Systems

Based on an assessment of the drivers for PHM in AdvSMRs, Meyer et al. (2013a) described the initial requirements for PHM systems for passive components in AdvSMRs. These are summarized below:

- Sensors and instrumentation for condition assessment of AdvSMR passive components
- Fusion of measurement data from diverse sources, such as NDE and stressor information
- Address coupling between components or systems, and across modules
- Incorporate lifecycle prognostics
- Integrate with risk monitors for real-time risk assessment
- Interface with plant supervisory control system

2.4.2 Assumptions

Several assumptions are made in the development of the prototypic prognostic methodology for PHMs for use in AdvSMRs that utilize time-dependent stressor information with measurements of material or component condition:

- Information about representative materials and conditions in AdvSMR concepts, and concepts of operations for these designs, is available.
- Research is focused on detection of early stages of degradation in selected safety-critical passive components (e.g., heat-exchanger tubing and major structural elements such as vessel and key piping), and the assessment of the RUL of these components. Specifically, the PHM will be on inaccessible passive components key to the safe operation of AdvSMR concepts, such as liquid-sodium-cooled fast reactors or high-temperature gas-cooled reactors.
- Laboratory-scale test-bed for degradation assessment and prognostics for a prototypical AdvSMR passive component will only simulate conditions and features necessary for proof-of-principle demonstration for target degradation mechanism.
    - High-temperature creep will be the focus of measurements and prognostics in this stage of the research effort as it is a damage mechanism of concern in several advanced reactor concepts. Specifically, the goal will be to examine primary and secondary stages of creep damage. The material of choice is austenitic stainless steel because of its anticipated wide use in several advanced reactor concepts (O'Donnell et al. 2008).
    - NDE methods that provide measurements sensitive to creep-damage in austenitic stainless steel are available and may be readily applied. Localized NDE measurements of material condition, along with measurements of temperature and mechanical load, are assumed sufficient to detect creep damage and predict its progression.

- Measurements will be taken periodically (interrupted testing); such testing is assumed to not impact the NDE measurement of progression of creep degradation in the material.
- Accelerated creep-testing is assumed to result in measurements and damage accumulation that is representative of creep damage that occurs during the lifetime of components in advanced reactors.

- Harsh-environment sensors for measurement/monitoring of safety critical AdvSMR passive components are assumed to be available and provide measurement sensitivity similar to those obtained from sensors in a laboratory setting.

The choice of degradation mode, measurements, and prognostic models are based on a state-of-the-art summary included in requirements, research gaps, and technical needs analysis documented in Meyer et al. (2013a).

2.4.3 Simplified-model AdvSMR Design to Develop and Demonstrate Methodology

A simplified-model AdvSMR (power block) design (Appendix A) is used as the context for the research on the development of a framework for the PHM. (The same simplified design is also used as the context for the research into enhanced risk monitors (Ramuhalli et al. 2013b; Ramuhalli et al. 2014), and its use here provides the unifying theme for future integration of the PHM methodology into enhanced risk monitors for condition-based risk assessment). This hypothetical design is intended to be prototypical and resembles proposed liquid-metal-cooled designs. The example design is defined to provide a simple level of abstraction but contains enough resolution and specific design elements to inform the development of PHM systems for AdvSMRs.

2.4.4 Creep Degradation in Reactor Materials

Components in AdvSMRs will be subject to relatively harsh operating conditions. Materials for advanced nuclear reactor applications generally consider radiation damage resistance, environmental stability, and high-temperature capability as paramount (Yvon and Carre 2009; Zinkle and Busby 2009). Volumetric swelling and dimensional stability, embrittlement, stress corrosion cracking, irradiation and thermal creep, and corrosion are critical materials degradation issues. Welds are problematic in nuclear structures as preferred sites for environmental degradation and stress-assisted degradation processes. Compatibility issues arise with regard to liquid-metal coolants for liquid-metal fast reactors (lead- [or lead-bismuth-] cooled fast reactors [LFRs] and sodium-cooled fast reactors [SFRs]) when metals and alloys in flowing coolant experience unwanted chemical reactions or leaching.

Creep degradation is the plastic deformation that occurs in materials under stress at high temperatures. In this case, high temperature is roughly defined as temperatures greater than $0.3T_m$ where T_m is the melting temperature of the material. Unlike the deformation of materials under stress at low temperatures, which is dependent only on the stress and independent of time, deformation from creep is a function of time, temperature, and stress (Ashby and Jones 2012).

Creep in metals tends to occur through the movement of dislocations within the material, and through atomic diffusion processes (Ashby and Jones 2012). In dislocation creep (power-law creep), the rate of creep depends on the movement of dislocations within a material, and is affected by intrinsic lattice resistance and resistance caused by obstacles such as precipitates, solute atoms, or other dislocations. These obstacles can initially block the motion of dislocations, but this resistance to movement can be overcome by dislocation climb, which results from the diffusion of atoms in a given material.

Diffusion of atoms in a material can occur through bulk diffusion processes in which the diffusive motion is the result of atoms moving to adjacent interstitial or vacancy locations. Diffusion can also occur by atoms traveling along grain boundaries or through dislocation cores. In addition to the diffusion of atoms, the application of stress can also help dislocations overcome obstacles with the effect that a greater number of dislocations are freed from obstacles as the stress is increased. At low enough stresses, creep by dislocation motion ceases to be dominant and the majority of creep deformation is from the atomic diffusion processes.

The discussion above is limited to steady-state or secondary creep. However, prior to steady-state creep, materials undergo a primary or transient creep stage where the rate of creep strain is proportional to the amount of creep strain already accumulated. In addition, after the secondary creep stage, materials will enter a tertiary stage, which signals the beginning of material fracture from creep. A conceptual depiction of the evolution of creep through the primary, secondary, and tertiary stages is shown in Figure 2.5. Secondary or steady-state creep is generally emphasized over primary or tertiary creep because of the relatively large fraction of creep life within the secondary stage.

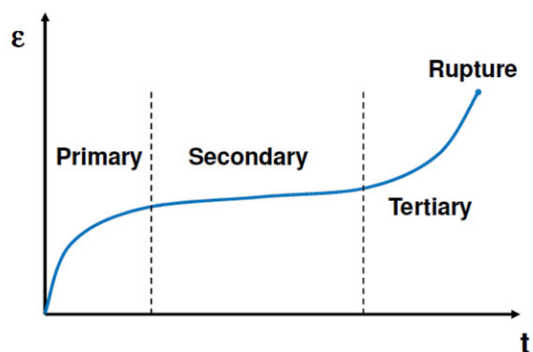


Figure 2.5. Creep Strain vs. Time during Creep. Under constant load, creep exhibits three distinct phases from fault onset to rupture. Adapted from Sposito et al. (2010).

2.4.4.1 Measurement Techniques to Estimate Creep Degradation

Current ISI practices for LWRs are based on requirements in the ASME Boiler and Pressure Vessel Code (Code), which were originally developed in the 1960s. The driving philosophy of the Code requirements is the management of fatigue degradation (Doctor 2008), although these requirements are now being applied to detect the existence of diverse and challenging degradation mechanisms such as stress corrosion cracking. These same requirements are now being evaluated for their applicability to anticipated new degradation mechanisms (Wilkowski et al. 2002) as these plants continue to age. AdvSMRs, with their higher operating temperatures and corrosive coolant chemistry, can be expected to experience mechanisms not commonly seen in LWRs (O'Donnell et al. 2008). Mitigation of such degradation mechanisms will require early warning to ensure that appropriate actions can be taken before significant degradation accumulates to the point where the only possible mitigating action is to replace the component. While the Code continues to evaluate and converge on requirements for advanced reactors (and, by extension, to AdvSMRs), it is likely that these new mechanisms will require a different set of nondestructive condition evaluation techniques.

To address these issues, it is likely that a combination of online, in-situ monitoring with periodic offline measurements of component or material condition will be needed (Meyer et al. 2013a). The intent of real-time monitoring of materials degradation is to provide a better understanding of the surface and volumetric material changes occurring during the early stages of the incubation and micro-damage accumulation. By detecting the presence of material degradation mechanisms early in the process, better insights are gained about the state of the material that can be used to understand the precise margins to failure. A brief state-of-the-art assessment for real-time monitoring of early degradation in materials used in the production of nuclear power, including creep measurement techniques, is covered in McCloy et al. (2013).

A critical step in achieving this objective is to develop an appropriate means to detect minor changes in material microstructures at the onset of degradation. Measurement techniques to estimate creep degradation are intended to facilitate this move beyond the current approach of ISI through periodic NDE of structural materials by developing the ability to use real-time monitoring of material degradation. However, the use of sensors for long-term condition monitoring in harsh environments is likely to result in a gradual change in the sensor response and sensitivity because of aging and degradation especially in regions of high temperatures and irradiation (neutron and gamma) (Daw et al. 2012). While recent advances (Coble et al. 2012a) may be used to monitor sensor drift and calibration, techniques to compensate for decreasing sensitivity may be needed to maintain the ability to monitor the materials/components over the long term.

Several NDE technologies have emerged as potential candidates to meet the requirements for early material degradation measurement, especially for creep damage, including micromagnetic techniques such as magnetic Barkhausen noise, ultrasonic nonlinear techniques that are sensitive to early-stage material degradation, and electromagnetic methods such as eddy currents, which evaluate changes in material conductivity.

2.4.5 Laboratory-Scale High-Temperature Creep Test System

As described earlier, high-temperature creep (and creep-fatigue) is expected to be mechanisms of concern in passive components in advanced reactors (O'Donnell et al. 2008). Within the simplified-design being considered in this research, creep is expected to be of concern in vessel internals and in the materials comprising the heat-exchanger. A laboratory-scale creep test system was therefore designed to induce creep damage in materials common to advanced reactors and generate NDE data for detecting and monitoring the onset of creep degradation. The test-bed is designed to be expandable to address future needs for component-scale measurements and prognostics.

The laboratory-scale creep test system currently consists of a mechanical load frame, furnace, 5-ton actuator, power supply, and control system. The control system encompasses the electronics that run the system. The load frame is the base for mounting the other components. A photograph of the system is provided in Figure 2.6. Figure 2.7 shows the touch screen interface (also referred to as a human machine interface or HMI) used for controlling the operation of the system.

The control system enables active control of load and temperature through the use of a programmable logic controller (PLC). The PLC also enables real-time data acquisition of key parameters (force, temperature, strain) for use in both the control system as well as for future prognostics use as stressor values. Key control parameters (such as test speed and furnace control [proportional, integral, and derivative [also known as PID] settings) may be adjusted to accommodate various test scenarios, and provide the ability to simulate both steady-state and variable-loading scenarios (where the load and/or temperature are varied according to some predetermined function) that are expected to be common given the inherent operational nature of AdvSMRs.

The creep test system allows the user to specify a force to be applied to the specimen, as well as a temperature for testing. Initial tests are being conducted by applying a constant load and constant temperature to the test specimen, and recording the resultant time-dependent deformation. Appendix B contains additional information on the test-bed and planned future additions to the test-bed.

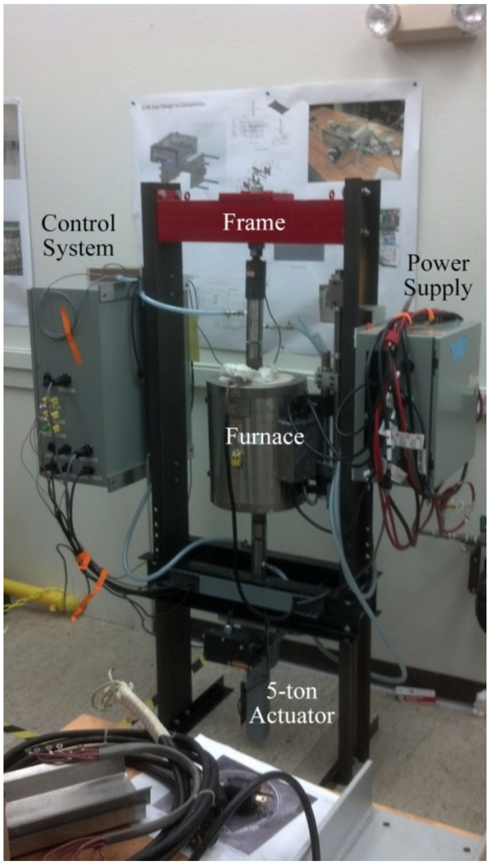


Figure 2.6. Creep Test System for Validating Prognostic Algorithms

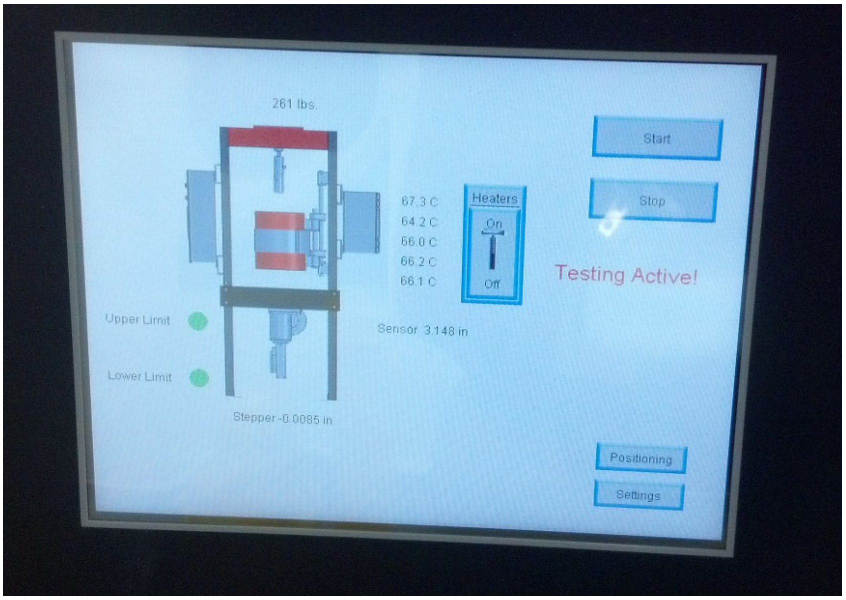


Figure 2.7. Main Screen of the User Control Interface for Creep System to Validate Prognostic Algorithms

2.4.6 Summary of Considerations for Passive Component Monitoring in AdvSMRs

Fundamental challenges with AdvSMR passive components include the potential for detecting and managing degradation mechanisms not common to the existing LWR fleet, and the potential for changing plant conditions as new operating regimes (including potential load-following and peak-demand power generation) and diverse missions (both electrical generation and process heat production) are being proposed. Degradation mechanisms (such as creep or creep-fatigue) are expected to be significant in the harsher operating environments in AdvSMRs and are expected to challenge NDE technologies currently used in ISI that are sensitive to macroscopic cracking. At the same time, the introduction of modularity can introduce interconnections or dependencies between SSCs in reactor modules. Such interconnections can impact overall degradation accumulation rates in ways that are significantly different from current operating nuclear power reactors, and challenge approaches to estimating remaining service life of these components.

Given the need to maintain the integrity of passive components, and the possibility of degradation in passive components affecting the ability to safely and economically operate AdvSMRs, there is a need for techniques that can monitor passive components for the onset of degradation. Ideally, measurements from such techniques should be capable of identifying changes in material properties that are leading indicators of degradation, providing sufficient warning for the implementation of mitigation techniques. However, the cost-effective planning and application of mitigation techniques will also require the ability to predict the remaining service life of components with degradation and the corresponding risk to safety and economic metrics. Progress towards condition-based risk evaluation is documented elsewhere (Ramuhalli et al. 2014); the rest of this report discusses the prognostic methodology and progress towards achieving a prognostic health management system based on localized degradation detection.

3.0 Prototypic Prognostic Methodology

The overall approach to PHM that is taken in this research is a system-of-systems approach. As shown in Figure 2.3, individual systems are expected to be needed to address the prognostics requirements for each component or subsystem; higher levels in the hierarchy are used to mediate the information flow and integration from these lower-level PHM systems.

The specific details of these interfaces are not yet determined. In this research, the focus is on further developing the framework for the lower-level PHM systems. This framework, and a potential approach to performing prognostics, is described below.

3.1 Prognostics Health Management

Advanced plant configuration information, improved component or equipment condition information, and risk monitors are needed to support real-time decisions on O&M (Yoshikawa et al. 2011). To provide enhanced awareness of component or equipment condition, measurements capable of providing component health or state need to be integrated with measurements of the environmental stressors. Such integration provides predictive estimates of component failure (IAEA 2013) that are customized for each AdvSMR unit and account for the specific operational history of the unit.

Such integration will lead to a prototypic PHM system, and will need the following technologies:

- Diagnostic Technologies: Fusion of information from advanced NDE methods sensitive to earlier stages of degradation, to detect and characterize the present state of the component; and
- Prognostic Technologies: Advanced algorithms for prognostics that incorporate models of degradation accumulation while accounting for any uncertainties in the available information.

Given these needs, the overall approach taken in this research is illustrated in Figure 2.3. The figure illustrates a system-of-systems approach, with individual PHM systems monitoring the different SSCs, with additional systems in the hierarchy integrating the output from the individual PHM systems and providing the necessary interfaces to plant supervisory control systems, operational risk monitors, and O&M decision making. A representative drill-down into an individual PHM system is shown in Figure 3.1, and illustrates the process flow from measurement to diagnostics, prognostics, and decision making.

The hierarchy within the system-of-systems may be developed in many ways. The approach taken in this research is to largely map the PHM system hierarchy to the measurement location hierarchy, resulting in PHM systems operating on localized measurements, PHM systems operating on component-wide measurements, and global PHM systems that integrate diagnostics and prognostics information across multiple components.

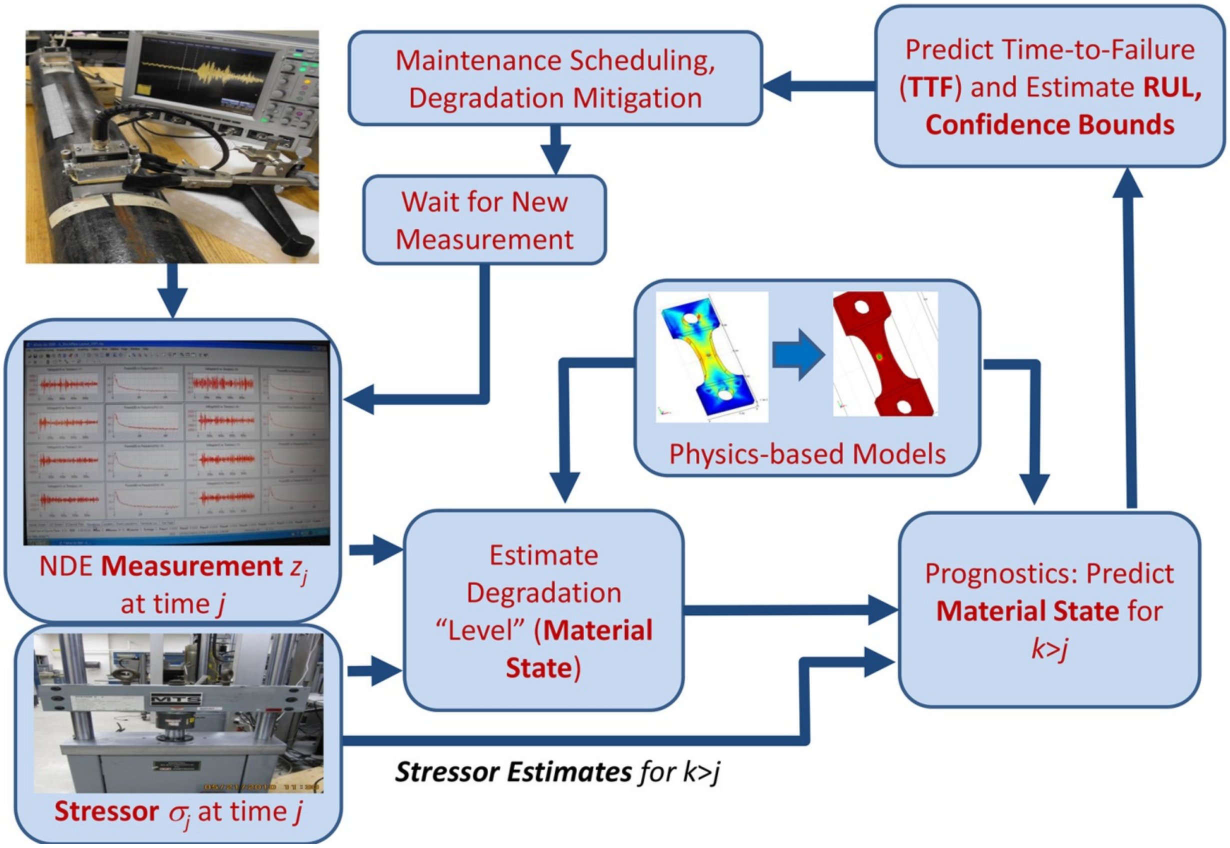


Figure 3.1. Process Flow Diagram for a Local-level PHM System. j and k refer to time indices with $k > j$.

As envisioned, the local-level PHM system refers primarily to direct measurements of material condition at a single location performed by the application of NDE technologies during an outage or possibly on-line. The component level of the PHM system is envisioned to consist of the measurements and algorithms used for diagnosis and prognosis of failure of a component. Measurements of stressor variables will be a key source of information for component-level diagnostics and prognostics, as will be the integration of information from several localized PHM systems. Other potential sources of information include global condition measurements such as vibration measurements or acoustic emission measurements. The system level consists of multiple interconnected components to perform a given function. Failure at the system level may be defined in terms of diminished functional capacity. Failure of an individual component may or may not cause the whole system to fail, but its consequences could propagate through the system causing additional components to fail, eventually compromising the system functional capacity. At the system level, measurements from several components may be combined to interpret overall system health. In addition, PHM at the system level will require models to capture the interdependence and cross-coupling effects between components within the system.

At the local level, the PHM system uses measurements that can provide indicators of condition for each of the key SSCs. These may include process measurements (e.g., flow, temperature, and pressure) or direct measurements of localized component condition (e.g., vibration, ultrasonic NDE measurements, etc.). Challenges from the harsh environments in AdvSMRs may necessitate novel measurement methods, such as optical measurements (Anheier et al. 2013) of process parameters, or the use of sensors tolerant to these conditions (Daw et al. 2012).

These measurements are then applied to analysis algorithms to map the available measurements to condition or health indicators. The condition indicator is then projected to future times using appropriate prognostic algorithms (Coble et al. 2012b; Meyer et al. 2013a) to estimate POF distributions for each key SSC at some point in the future. These estimated POF distributions may then be used by enhanced risk monitors (Ramuhalli et al. 2013b) to provide a more accurate assessment of the dynamic risk. The ability to predict (or estimate for future times) the POF based on equipment condition assessments and incorporate these in enhanced risk monitors (ERMs) may also help compensate for a relative lack of knowledge about the long-term component behavior of some materials and components that are being proposed for AdvSMRs.

3.2 PHM Framework for AdvSMRs

Figure 3.1 highlights the various elements of an individual PHM system at the local level. Within this process, there is a need for a systematic approach to determining current state of the material/component, and using models and the measurement data to project the condition into the future. Such a framework needs to account for uncertainty, ability to change models of degradation as needed, accommodate redundancies in information, update current state and projections as new information becomes available, and be able to handle a modest amount of missing information (ambiguity).

Based on a number of factors (documented in Meyer et al. 2013b) and the needs summarized above, we chose a Bayesian state-space framework to prognostics that lends itself to relatively easy integration into typical PHM systems. Bayesian approaches provide a mechanism for including prior knowledge (through a prior distribution), and enable updates as new information becomes available (Wang et al. 2011; Weiwen et al. 2013). The use of a probabilistic mechanism for this update also enables the integration of uncertainty in knowledge for computing posterior distributions (Wang et al. 2009).

Key to using Bayesian approaches for prognostics is the ability to define mathematical models of degradation accumulation in materials and use them with stochastic information on the inputs. Two models are needed (Ristic et al. 2004):

- Degradation Rate model: represents the degradation accumulation rate (i.e., the degradation level at the next time instant given the degradation level at all times up to and including the present time), and
- Measurement Physics model: represents the quantitative relationship between the measurement and the degradation state at the present time instant.

These two models naturally incorporate uncertainties in the form of probability density functions (PDFs). They are used to compute the conditional probability density of the degradation state at the present time conditioned on all measurements up to and including the present time. A recursive approach is used, with the Degradation Rate model, to project the conditional probability density of the state to future time instants and compute the likely time-to-failure, from which the RUL is estimated along with confidence bounds for the estimate.

The next few sections give an overview of the Bayesian-based approaches, and their application to materials prognostics, in greater detail.

3.3 Prognostics Using Bayesian Approaches

Damage accumulates in materials over time from one or more stressors and may be monitored using one or more of the measurements discussed earlier. These measurements, when combined with a model that defines the relationship between the measurement and the underlying material condition or state, are used to assess the underlying material condition. Given the assessment of the current material condition, the RUL can be determined by using a model of degradation accumulation and growth. As additional measurements become available, the current material state estimate and RUL may be updated using the same process.

Mathematically, the process is described through two models as discussed earlier. The Degradation Rate model defines the relationship between degradation levels x_k and x_j ($k > j$) and is a representation of the evolution of damage in the material with time. The model may also include information on stressor history; that is,

$$x_k = f\left(x_j, \sigma_k, \sigma_{k-1}, \ldots \sigma_j, \eta_k\right) \tag{3.1}$$

where $\sigma_k, \sigma_{k-1}, \ldots, \sigma_j$ are the stressor values at times $k, k–1, \ldots, j$, with $j < k$. In this Degradation Rate model (Eq. 3.1), η_k represents the uncertainty in the state transition model and is a measure of the amount of knowledge available regarding the damage accumulation process. Typically, this is represented by a PDF. In this model, the degradation level or material state x_k is a numeric quantity that describes the condition of the material in the early stages of damage. For the moment, we postpone the discussion of how the material state is defined.

The second (Measurement Physics) model relates the degradation level to the measurements z_k at the present time instant:

$$z_k = h\left(x_k, \nu_k\right) \tag{3.2}$$

with the quantity ν_k representing the level of uncertainty in the relationship between the material condition and the measurement. As with η_k, ν_k is generally represented by means of a PDF.

The problem of prognostics (estimating the RUL from the measurements) is decomposed into the two related problems discussed above—estimation of x_k from z_k (i.e., determining the current material state from the measurements) and the estimation of the corresponding time-to-failure (TTF) and the RUL.

Mathematically, the problem of estimating x_k from z_k using these two models is identical to the formulation of a tracking problem (Arulampalam et al. 2002; Ristic et al. 2004; Khan and Ramuhalli 2008), and therefore, solutions to the tracking problem can also be applied to the material state prognostics problem. If the functions $f(\bullet)$ and $h(\bullet)$ are linear (Horn and Johnson 1985), and η_k and v_k are independent and Gaussian-distributed, the optimal solution to the tracking problem can be shown to be the Kalman filter (Ristic et al. 2004). However, when the functions are 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. Several options are available and are briefly described next.

3.3.1 Algorithms

Based on the nature of Degradation Rate model $f(\bullet)$, and the nature of different uncertainties quantified by means of PDFs, different algorithms exist to solve the material state tracking problem given by Eqs. (3.1) and (3.2). Three key algorithms for addressing this problem are:

1. Extended Kalman Filtering (EKF)
2. Unscented Kalman Filtering (UKF)
3. Particle Filtering (PF)

The underlying solution methodology for the above stated algorithms comprise of two recursive stages. The first stage is to obtain an estimate of material degradation state x_k at time k using the process model defined in Eq. (3.1). This stage is also referred to as the 'prediction stage' wherein an estimate of the material degradation level and its associated probability distribution is obtained based on the Degradation Rate model. The subsequent stage, known as 'correction stage', updates this estimation using Bayes' theorem with available/known measurements z_k using the Measurement model PDFs for the process noise and measurement uncertainty are assumed to be known *a priori*.

The EKF algorithm fundamentally linearizes the non-linear models $f(\bullet)$ and $h(\bullet)$, and assumes a Gaussian probability distribution for all random variables. The noise terms η_{k-1} and v_k are also assumed to be Gaussian. The UKF, on the other hand, approximates both the prior (material state transition) PDF $P_{x_{k|k-1}}$, and the posterior distribution $P_{x_{k|k}}$ as Gaussian distributions with a set of deterministically chosen sample points (Ristic et al. 2004) that capture the true mean and covariance of the material degradation states up to second order. Particle filters are sequential Monte Carlo methods based on point mass (or "particle") representations of probability densities that can be applied to any state-space model and that generalize traditional Kalman filtering methods (Arulampalam et al. 2002; Ristic et al. 2004). In this approach to state estimation, the posterior PDF of the state is constructed based on all available information, including the set of received measurements. An overview of EKF, UKF, and the particle filter method is given elsewhere (Ristic et al. 2004).

3.3.2 Material State Prognostics

The two stage process of predicting a material state x_k using the Degradation Rate model $f(\bullet)$ and subsequently updating the predictions using available measurements through the Measurement model $h(\bullet)$ is repeated for each time increment. In general, measurements may not be available at all time steps. For instance, for typical ISIs, measurements are only performed during an outage. Even with online monitoring, it is expected that data will be available only at discrete instants in time (for instance, once every few minutes, few hours, or few weeks). The frequency with which online NDE and process measurements are acquired may be different as well. As an example, process measurement data may be available every few minutes while online NDE measurements may only be available once every day. The prognostic algorithms will need to operate with a time granularity that matches (or is better than) the finest granularity at which measurements are available. The traditional prognostic algorithms approach (i.e., predict and update during every time step) is therefore modified to handle missing measurements at intermediate time steps by simply running the prediction step forward for several time steps without the corresponding update step. The validity of this approach, however, needs to be evaluated using simulated experiments and suitable tests and is part of the current research focus.

3.3.3 Remaining Useful Life Estimation

Estimating the RUL from this information is a two-step process (Orchard and Vachtsevanos 2007). First, a failure probability density $p(\text{failure at time } k \mid x_k)$ is defined giving the probability of failure for a given damage index or material state. Failure need not be defined as the point at which the structural integrity of the component of system is breached. Failure in the context of PHM means the inability to achieve the desired functionality of the material or component. For instance, failure of a passive component may be defined as the point at which a macroscopic crack becomes large enough to be reliably detected using conventional NDE methods. The failure PDF is then used in the second step to compute the TTF probability density $p(TTF)$, from which the mean TTF and RUL can be computed.

The failure density defines the POF of the material or component, given each possible material state. The use of a PDF captures the inherent uncertainty associated with failure. Typically, the failure density would be defined using either simulation studies or experiments. Using the law of total probability (Carlson and Crilly 2010), the POF at time k is then:

$$p\left(\text{failure at time } k \mid z_k\right) = \sum_m p\left(\text{failure at time } k \mid x_k, z_k\right) p\left(x_k \mid z_k\right) \tag{3.3}$$

where $p(x_k|z_k)$ is the result of the particle filtering algorithm described above. The TTF probability density $p(TTF)$ can be computed using

$$p\left(TTF = r \mid z_k\right) = p\left(\text{failure at time } r \mid z_k\right) \prod_{j=1}^{r-1} \left[1 - p\left(\text{failure at time } j \mid z_k\right)\right] \tag{3.4}$$

The TTF density gives the probability of failure at all-time instants, and the mean TTF (TTF_e) is the expected value of this PDF:

$$TTF_e = E\left[\, p\left(TTF\right)\right]. \tag{3.5}$$

The TTF density can also be used to compute the confidence limits (for instance, the 95% confidence limits) for bounding the mean TTF estimate. The RUL is then the difference between the measurement time instant and the mean TTF estimate, and can be bounded as well using the TTF confidence bounds.

3.4 Model Selection for Prognostics

3.4.1 Physics-of-Failure Models for Prognostics

Many passive SSCs experience slow degradation, with a long period from fault onset to failure. In many cases, the degradation progression can be divided into several phases with distinct models describing the accumulation of degradation in each phase.

As described earlier, creep degradation is the plastic deformation that occurs in materials under stress at high temperatures, and is used in this research as a prototypic degradation mechanism for demonstrating the utility of PHM in AdvSMRs and advanced reactors. Unlike the deformation of materials under stress at low temperatures, which is independent of time, deformation from creep is a function of time, temperature, and stress (Ashby and Jones 2012). In general, the evolution of creep appears over three distinct phases (Li and Dasgupta 1993; Hosford 2005) from fault onset to rupture: primary, secondary, and tertiary (Figure 2.5). In the primary (or transient) phase, the rate of creep strain decreases with time. In the secondary phase, the strain rate is approximately constant. The strain rate increases rapidly in the tertiary phase until material rupture or failure.

Several Degradation Rate models have been proposed to describe the primary, secondary, or tertiary phase of creep (Naumenko and Altenbach 2007). Some of these models have been proposed to describe two phases in a unified model (Brear and Aplin 1994). The most appropriate Degradation Rate models for each phase of creep depend on the material properties and environmental conditions.

The strain rate in each stage of creep depends on the applied load and environmental conditions (e.g., temperature). Consequently, Degradation Rate model parameters will vary as a function of the load (mechanical and thermal) (Figure 3.3). The variation introduces uncertainties in Degradation Rate model parameters that prognostics algorithms utilize for RUL prediction. Further, the dependence of creep rates on the material microstructure (which may not always be known in practice) indicates that a source of uncertainty is the set of creep model parameters.

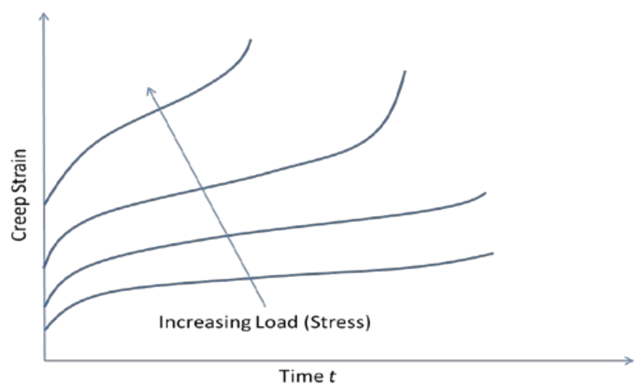


Figure 3.2. Schmatic Showing Variation of Creep Strain with Load. Adapted from Li and Dasgupta (1993).

As a result of these dependencies, the problem of creep Degradation Rate model selection at any time instant reduces to:

- Determining the appropriate phase (primary, secondary, or tertiary) of creep damage.
- Selecting an appropriate creep Degradation Rate model (from many possible models) for the current phase of creep damage.

- For a defined time horizon, selecting the creep Degradation Rate model parameters (with uncertainties) as a function of expected future load and temperature (and any other environmental variables).
- As the component ages, repeating the three steps above to update the creep Degradation Rate model and parameter selection.

3.4.2 Quantitative NDE and Data Fusion for Degradation Level Assessment

Although multiple phases can be delineated in many degradation regimes, it is often not trivial to identify with certainty a component's current degradation phase. For example, the strain rate versus time curve can potentially be used to determine the degradation phase during creep failure, but it is difficult to measure strain in situ. Several NDE technologies have emerged as potential candidates to meet the requirements for early material degradation level assessment, including for creep damage (Sposito et al. 2010). While these nondestructive measurements have been correlated to measures of degradation level (for example, Raj et al. 2006), there are inherent uncertainties in the measurements and in the Measurement Physics models to relate those measurements to degradation.

Each of these NDE techniques is sensitive to a different aspect of microstructural changes that can occur during degradation. For example, magnetic Barkhausen noise is sensitive to ferromagnetic changes in material microstructure due to either the formation of precipitates or phase changes; for instance, from austenitic to martensitic phase (McCloy et al. 2013). On the other hand, nonlinear ultrasonic techniques are sensitive to the formation of dislocations and interstitial loops (Matlack et al. 2012). Given these differences, it is not unlikely to expect that combining information from more than one measurement type will improve ability to characterize damage-phase and estimate RUL.

In the prognostics framework described earlier, Measurement Physics models representing the relationship between the NDE measurement and the material state are defined as Eq. (3.2). As discussed in Khan and Ramuhalli (2009) multiple Measurement Physics models may be defined in these Bayesian frameworks, with each representing the relationship between a specific NDE measurement type and the underlying degradation level. Uncertainties in Measurement Physics model parameters may be included with each such model. The framework itself is modified slightly to enable the use of multiple Measurement Physics models, and is seen to reduce the overall uncertainty associated with the material state estimation (Khan 2009). This approach to data fusion may be easily adapted for use in the present problem of prognostics, and is the focus on ongoing evaluation efforts.

3.4.3 Degradation Lifecycle Prognostics and Uncertainty Management

The lifecycle of components used in AdvSMRs generally transitions from fabrication and installation to operation, with potential degradation and failure as end-of-life. Repairs or other mitigation activities will change the time horizon for each of these lifecycle stages, as do changing operational conditions such as unanticipated contamination of the primary system coolant, which can cause and accelerate component degradation. Degradation in materials and components also follows a lifecycle, going from precursor formation to initiation of microscopic cracks followed by coalescence and macro-crack growth to failure.

An effective PHM system for AdvSMRs should be able to adapt or adjust its prognostics methodology to the stage the component or degradation is in its lifecycle (Hines et al. 2009). This helps to ensure accurate and timely determination of RUL based on the available information. Part of this requirement is determining the appropriate Degradation Rate models and updating these models in response to changes in operating conditions.

The problem of lifecycle prognostics for passive components is fundamentally one of Degradation Rate model selection based on available data. Indeed, different models may be more appropriate (e.g., more accurate, more precise, or suitable to runtime requirements) during different stages of component degradation (Nam et al. 2012).

For passive components, the lifecycle prognostics problem may be posed in terms of degradation growth lifecycle. This is particularly useful where classical population-statistics based approaches for prognostics may not be viable, as the volume of historical failure data necessary to develop reliability models may not be available for long-lived passive structures like reactor vessels or piping.

For accurate RUL estimates in these cases, a lifecycle prognostics framework will be needed that can account for the type of information (stressor, or condition-based) as well as the degradation phase of the material, to ensure that the appropriate Degradation Rate and Measurement Physics models are applied. As discussed in Section 3.4.1, the problem of Degradation Rate model selection may be addressed using a set of sequential operations.

A wrinkle in this process is introduced by the fact that the Degradation Rate model selected (with parameters) is used in a predictive mode, to predict the time-to-failure of the component. However, the prediction algorithm will need to transition from one Degradation Rate model to another, and will need to do so without the benefit of measurements that may be used to constrain the degradation phase. As an example, consider the case where measurements may indicate that the material is currently in the primary creep phase and an appropriate primary creep Degradation Rate model is selected. As the prognostic algorithm attempts to estimate the RUL, it uses the primary creep model and projects it forward in time (Figure 3.4). However, for accurate RUL estimates, it will need to transition to a secondary creep phase model during the estimation process (Figure 3.4).

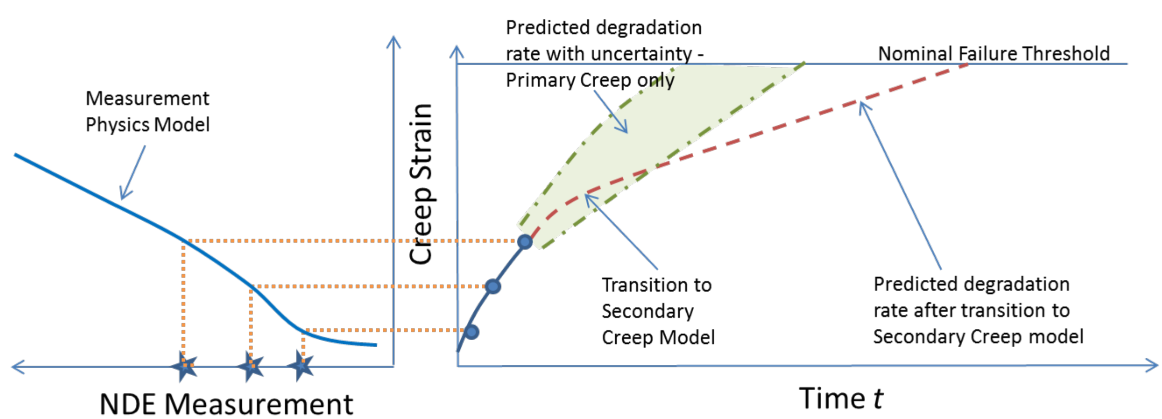


Figure 3.3. Schematic of Model Selection for Lifecycle Prognostics

As a result of these constraints, the problem of Degradation Rate model selection for lifecycle prognostics may be modified as follows, to address lifecycle prognostics:

- Determining the appropriate current phase of degradation (for instance, primary, secondary, or tertiary creep) by fusing information from available measurements.
- Selecting an appropriate Degradation Rate model (from many possible models) for the current phase of degradation.
- Selecting the Degradation Rate model parameters (with uncertainties) as a function of expected future load and temperature (and any other environmental variables).
- Projecting the degradation-growth to future time instants. During this prediction step, transitioning to appropriate Degradation Rate models (and model parameters) will be needed. For example, if starting with primary creep models, smoothly transition to secondary and tertiary phase Degradation Rate models to predict failure of the component.
- As the component ages, repeating the four steps above to update the lifecycle prognostics Degradation Rate model and parameter selection as more measurements become available.

One of the approaches to incorporating different Degradation Rate models is to use Bayes' theorem. Specifically, this requires the definition of a likelihood probability $p\left(x_k / M_a\right)$, which is the probability of material degradation state for a given Degradation Rate model M_a (a = 1, …, *Nmodels*). *Nmodels* is the total number of Degradation Rate models available for consideration. According to Bayes' theorem (Carlson and Crilly 2010),

$$p\left(M_a / x_k\right) = \frac{p\left(M_a\right) p\left(x_k / M_a\right)}{p\left(x_k\right)} \tag{3.6}$$

where $p\left(M_a / x_k\right)$ defines the posterior probability of model M_a for a given damage state x_k. Model selection, in a simplistic fashion, may be performed by computing this probability for all the *Nmodels* and selecting a model based on the posterior probability.

Using this approach requires the introduction of one or more parameters, the value of which defines the different models M_a as described by Chiachıo et al. (2013); Daigle and Goebel (2013). The use of such parameters to transition between models also enables the incorporation of uncertainty (Section 3.5).

An alternate approach to Degradation Rate model selection leverages research into integrating Markov-Chain methods with particle filters (Berzuini and Gilks 2001). These so-called Resample-Move algorithms essentially modify the representation given by Eqs. (3.1) and (3.2) by assuming that multiple Degradation Rate models exist, although there is uncertainty associated with the true model. Uncertainties associated with Degradation Rate model parameters are represented by additional PDFs (Guan et al. 2011). At a given instant in time, this information may be used to determine which of the Degradation Rate models is most likely to explain the measurement data, given the Measurement Physics models.

The basic Resample-Move algorithm (Green 1995) assumes that the system behavior may be described by one of the Degradation Rate models over the entire period of observation (although it does not know a priori which of the models is true). As a result, this basic algorithm does not account for changes in Degradation Rate model over the lifecycle of the component.

We are modifying this approach in two ways. First, we are integrating Bayesian transition methods (Nam et al. 2012) into the Resample-Move algorithm to enable a smooth transition between different Degradation Rate models during the prediction step. Second, we are incorporating multiple Measurement Physics models to fuse multiple measurement types for improving overall predictive accuracy. Evaluation of these enhancements is ongoing.

3.5 Uncertainty Management for Prognostics

Quantification of uncertainties and their incorporation into prognostic algorithms is vital to determine the confidence bounds in RUL estimates. A number of sources of uncertainty exist when attempting to calculate RUL estimates for nuclear structural materials. These include:

- Stochastic variations in macro- and micro-structure of the material
- Unknown material fabrication history
- Variability and uncertainty in stressor severity (past and future)
- Measurement noise, both in the monitoring of stressor levels as well as in the nondestructive evaluation of material degradation state
- Uncertainties in the parameters in Measurement Physics and Degradation Rate models that relate stressor levels, current material degradation state, and future degradation material states
- Uncertainty in the damage index threshold for failure.

One of the advantages of the Bayesian prognostics algorithm when used for prognostics is its ability to incorporate uncertainty about the Measurement Physics and the Degradation Rate model parameters through the quantities η_k , ν_k . Doing so provides a built-in mechanism for uncertainty quantification (UQ) in prognostics. However, basic information (such as the standard deviation or higher-order moments) about the quantities η_k , ν_k will need to be available. Ideally, this information would be quantifiable based on knowledge of the degradation process or measurement physics and available measurement instrumentation. For example, if it is known that measurement noise is primarily due to Johnson noise (which is temperature-dependent), then the level of measurement noise is easily quantifiable from existing theories (Britton Jr. et al. 2012). In the absence of such information, these quantities will need to be inferred using available data (Bilionis et al. 2013; Ramuhalli et al. 2013a).

As described in the previous section, the use of model parameters in the model selection framework enables one method for uncertainty quantification and management. The uncertainty in the model parameters can be incorporated by using a random walk model as described in Chiachıo et al. (2013); Daigle and Goebel (2013), where model parameters are updated using a random walk to sequentially improve model predictability. Specifically, if $\theta^{(a)}$ represents the Degradation Rate model parameter vector corresponding to model M_a, a small perturbation or artificial noise term ξ_k can be introduced for the model parameter vector at time step k (Chiachıo et al. 2013):

$$\theta_k = \theta_{k-1} + \xi_k. \tag{3.7}$$

The artificial noise term ξ_k will dictate the performance of the prognostic algorithm under uncertain model parameter vectors. As a result, the noise term needs to be carefully selected. It is usually small and decreases with time k to address the issue of increasing variance, if any, due to the perturbation step.

In this project, we are also investigating utilizing the integration of Monte Carlo methods with the particle filters (Resample-Move algorithm described earlier) to assist in UQ. In this case, we assume that uncertainties from the various sources described above are quantifiable using data-driven UQ methods such as those described in (Bilionis et al. 2013; Ramuhalli et al. 2013a), using experimental NDE data as well as data from material degradation growth rate experiments. Given these quantities, the Resample-Move method provides a straightforward approach to projecting the uncertainty for prognostics purposes. Further, the approach also uses incoming measurement data to gradually learn about the model parameters and make the predictions more robust (Berzuini and Gilks 2001).

4.0 Assessment of Local-Level PHM Framework for Passive AdvSMR Components

4.1 PHM Using Bayesian Framework: Application to Creep Prognostics

Here we describe efforts to develop prognostics for AdvSMR passive components using the three filtering algorithms based on Bayesian framework to predict creep damage, that were briefly identified in Section 3.3.1. As discussed earlier, they primarily differ from one other in the approximations used in modelling damage accumulation in the material and inferring the current damage state using sensor measurements.

Initially, for this effort, the model for steady-state power-law creep is incorporated in a particle filter algorithm to predict secondary creep degradation. The Degradation Rate model for creep degradation is derived by rewriting the steady-state power law for creep as:

$$\varepsilon_k = B\sigma^n \left(t_k - t_{k-1}\right) + \varepsilon_{k-1} \tag{4.1}$$

where

$$x_k = \varepsilon_k \tag{4.2}$$

and

$$B = Ae^{\frac{Q}{RT}}. \tag{4.3}$$

The parameters for the creep state transition model in Eq. (4.3) for 316L stainless steel weld material provided in Nassour et al. (2001) are used for the initial algorithm development and demonstrations assuming a temperature of T = 700°C. At this stage, the parameters are assumed to be Gaussian-distributed variables and the values from Nassour et al. (2001) are interpreted as mean values for these Gaussian distributions, although other distributions for these variables can be accommodated. The values of these parameters are provided in Table 4.1, along with assumed standard deviations.

Table 4.1. Summary of Parameters and Variables Used in Norton's Law Model to Forecast Thermal Creep Failure

Parameter	Value (mean)	Standard Deviation
n	9.05	3.33%
B	2.93×10^{-22} (N m^{-2})$^{-n}$ h^{-1}	10%
σ	125 MPa	---

The steady-state creep equation may also be used to generate simulated NDE measurement data. We assume at this stage in the research and development that the NDE measurement is directly proportional to creep strain (to avoid having to develop or adapt algorithms to estimate creep strain from the NDE measurement), and by using appropriate proportionality constants, an estimate of the creep strain value is derived from the data. In this case, the model is developed in anticipation of accelerated aging studies that will provide data to validate the model illustrated here and potentially other models. The measurement uncertainties are assumed to have a Gaussian distribution. To provide a quantitative scenario for evaluation, the uncertainty in the NDE measurements is arbitrarily assumed to be 0.1% of creep strain and the failure criterion is 3% creep strain. The actual failure time for this failure criterion, assuming zero initial strain is 10.8 hours, according to Eq. (4.1). The NDE measurements are simulated to be performed every hour. This selection was made to approximate the relative frequency that offline NDE measurements may be performed on an AdvSMR, assuming the failure time in the accelerated studies is correlated with a plant lifetime.

Figure 4.1 shows the schematic for calculating RUL based on end-of-life projections by the filtering algorithms using current and previous sensor measurements. Figures 4.2 through 4.7 show the output of different prognostic algorithms using the creep strain propagation model defined by Eq. (4.1) and (4.2). Uncertainty (defined above) in the Degradation Rate model and the Measurement model is also taken into consideration in the prognostics. The results from the algorithms are shown for a specific instance wherein Degradation Rate model uncertainty (i.e., standard deviation of the related Gaussian density) is assumed to be 0.1% of the creep strain. The Measurement noise level is also assumed to be 0.1% of the measurement. Both the process and measurement noise are assumed to be additive Gaussian in form. It can be seen from the figures that because of high process noise, almost all the algorithms have high variance in the estimation of creep strain as well as in the RUL prediction. The variance for PF decreases as more measurements become available. This aspect is however not observed in either EKF or UKF, which suffer from high variance until the failure strain is reached indicating robustness of the PF algorithm. However, such improvement in uncertainty in the RUL estimates will need to be validated further.

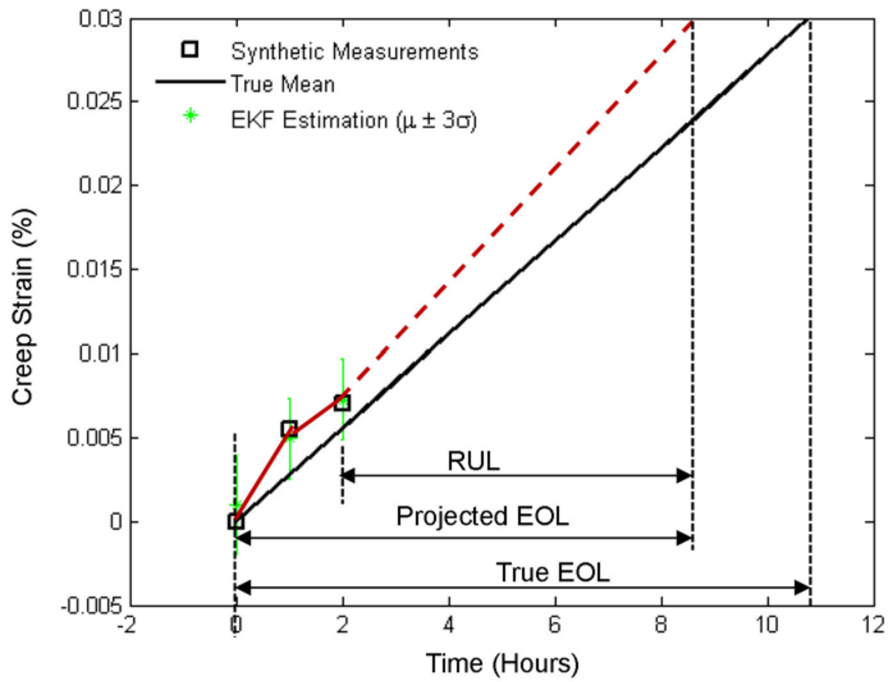


Figure 4.1. Schematic to Calculate RUL from the Projected EOL as Calculated by Filtering Algorithms Using Measurements at 0, 1, and 2 Hours Only

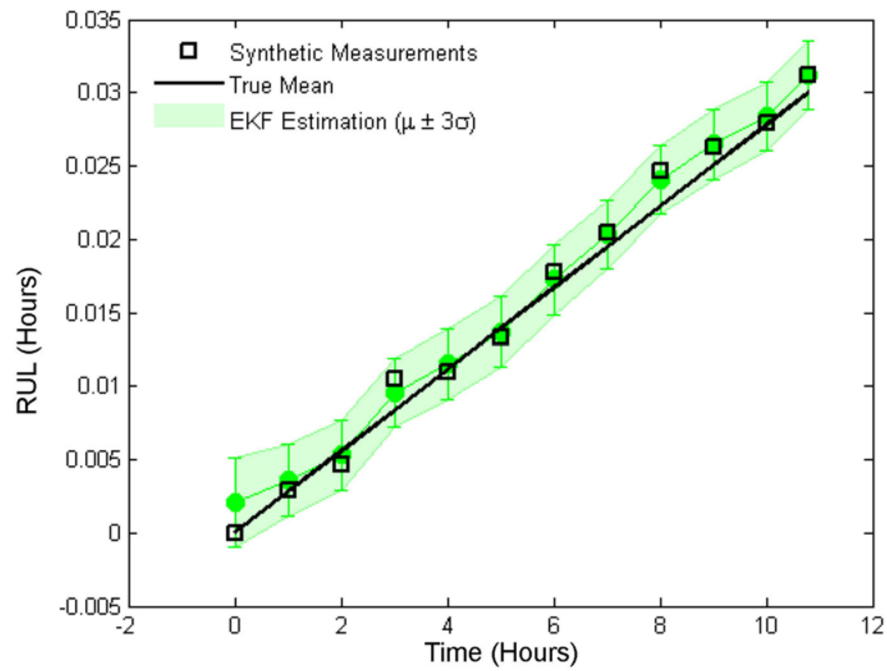


Figure 4.2. Estimation of Creep as a Function of Time Using EKF Algorithm

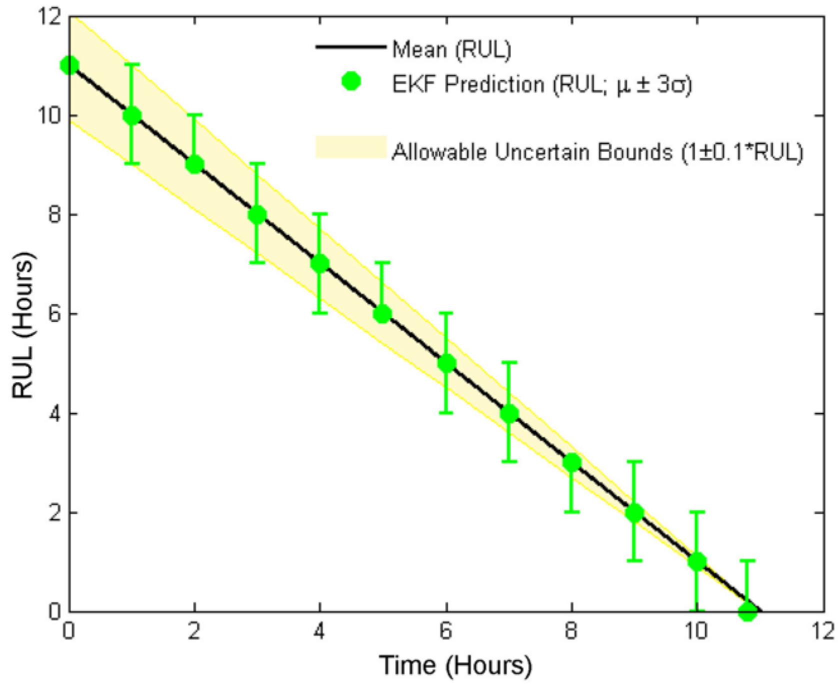


Figure 4.3. RUL Prediction at Each Measurement (synthetic) Instance (measurement noise = 0.1% of creep strain, process noise = 0.1% of creep strain)

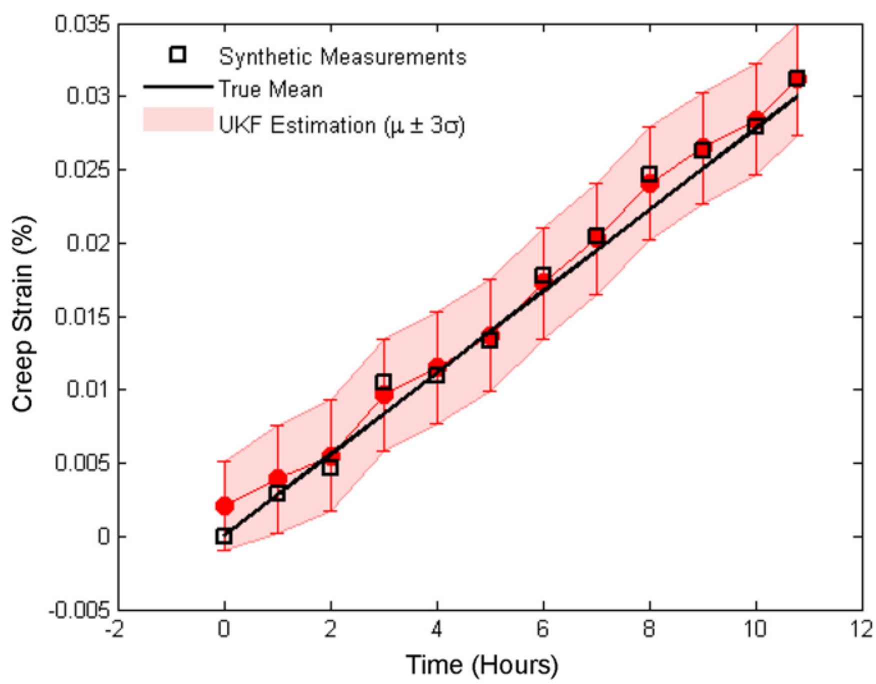


Figure 4.4. Estimation of Creep as a Function of Time Using UKF Algorithm

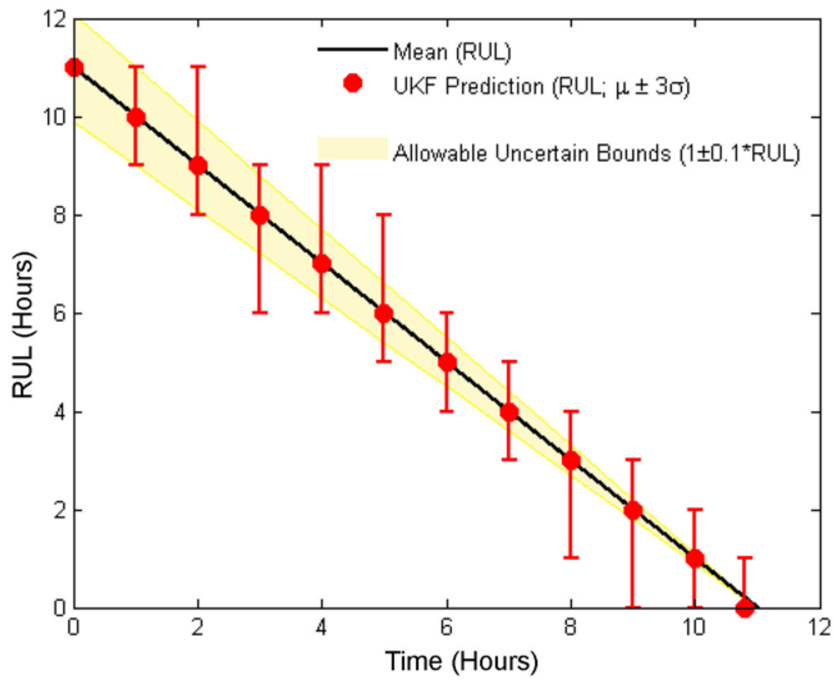


Figure 4.5. RUL Prediction at each Measurement (synthetic) Instance (measurement noise = 0.1% of creep strain, process noise = 0.1% of creep strain)

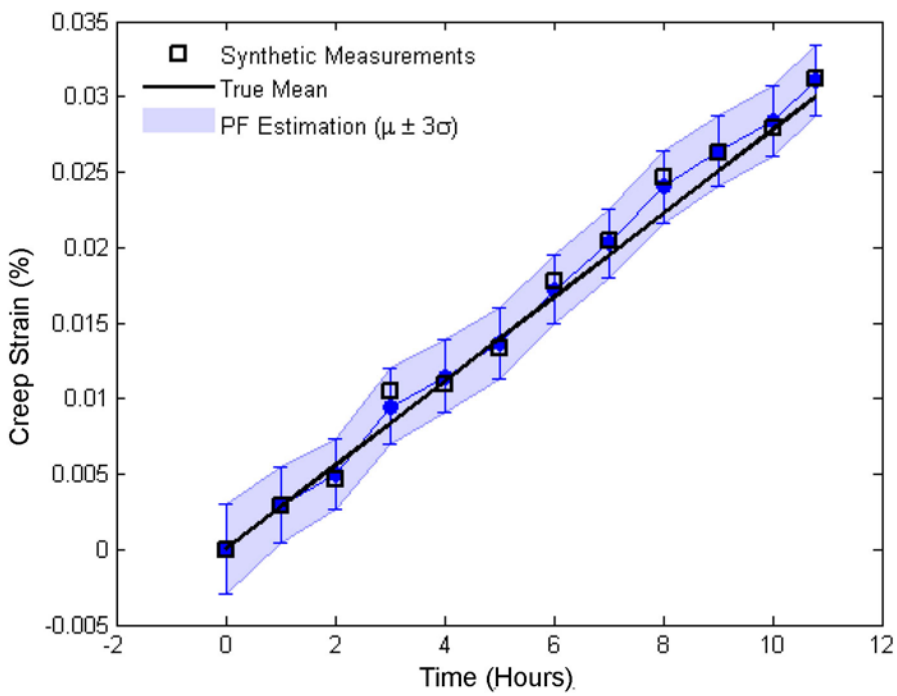


Figure 4.6. Estimation of Creep as a Function of Time Using PF Algorithm (1000 particles)

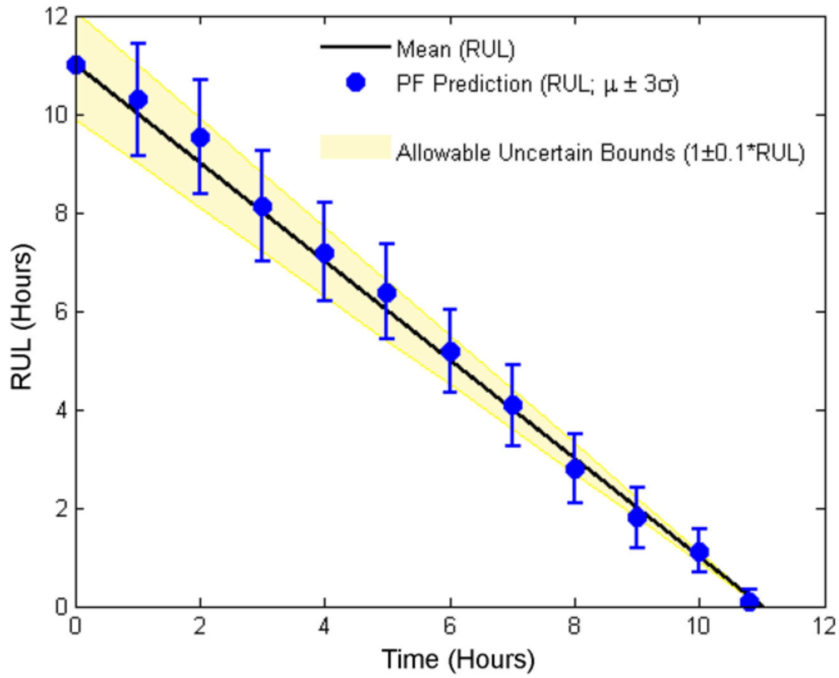


Figure 4.7. RUL Prediction at Each Measurement (synthetic) Instance (measurement noise = 0.1% of creep strain, process noise = 0.1% of creep strain)

4.2 Laboratory-Scale Measurements for Algorithm Validation

The models and prognostics approaches for localized PHM described in Section 3.0 need to be validated using experimental data. A laboratory-scale test-bed was designed and built for this purpose, and a series of measurement campaigns are being conducted for evaluating multiple NDE measurement methods for sensitivity to primary and secondary stages of creep. This section briefly describes the laboratory-scale test-bed, modeling efforts to define the experimental parameters, and the measurements to date.

Initial measurements pointed the way for improvements in specimen design to improve measurement data acquisition uncertainty. These measurements and the improvements in specimen design are described below. The accelerated aging and measurements using the new specimens are ongoing and will be used to complete the evaluation of the prognostic algorithms over the next few months.

4.2.1 Creep Modeling Efforts

The prognostics example described in Section 4.1 focused on secondary stage creep degradation. However, creep undergoes an initial transient stage (primary stage of creep) where the rate of creep strain is proportional to the amount of creep strain already accumulated (Li and Dasgupta 1993; Ashby and Jones 2012). Accurate simulation of creep behavior is needed to determine the relative importance of primary and secondary stages of creep damage, and to evaluate the need to develop prognostics models for primary stages of creep. The ability to model creep behavior can potentially also be used to determine the parameters (such as temperature and load) for laboratory-scale creep experiments. Further, if the potential for coupling with models of stress wave propagation or electromagnetic simulation models exists, such models can be applied to determine the parameters (such as sensor position and excitation frequency) for NDE measurements of creep damage in prototypical specimens.

Modeling efforts were focused on assessing the capability of ANSYS Mechanical simulation software (ANSYS 2013) to model thermally activated creep behavior. ANSYS Mechanical incorporates material models to represent the primary and secondary stages of thermally induced creep as well as irradiation-induced creep. Both implicit and explicit time integration models are available. Creep law equations range from generalized exponential, Graham, Blackburn, Garofalo, and rationalized polynomial. Of particular benefit for this study are the built-in creep law equations and data for 304 and 316 stainless steels. The parameter data for 316 stainless steel creep equation is valid in the 482°–704°C temperature range. The initial ANSYS analysis was conducted for an elevated temperature of 500°C.

The preliminary test specimen geometry is shown in Figure 4.8. The corresponding quarter-symmetry 2-D plane stress ANSYS model is shown in Figure 4.9. Despite the presence of the circular loading hole, a uniform pressure was applied to the edge of the specimen as illustrated by the red arrows in Figure 4.9. The pressure load was initially selected to give 1% creep strain in 10,000 hours. The resulting equivalent (von Mises) stress (232 MPa peak) and creep strain at 10,000 hours are shown in Figure 4.10. Results at 1000 hours are presented in Figure 4.11. The creep strain is at 0.5% while the stress of 234 MPa is slightly above the 10,000 hour peak value. The analysis was repeated with elastic-only material properties and the peak stress of 253 MPa is shown in Figure 4.12. Comparison of the creep strain results with the elastic results demonstrates that the stress relaxation and development of creep strain are being modeled as expected.

Figure 4.13 shows the creep strain history over the 10,000-hour test. The axial and transverse deformations are plotted in Figure 4.14. These results demonstrate the ability of the simulation tool to model thermally induced creep behavior using the classic macroscopic equations.

The results also indicate that the primary stage of creep can be relatively short but significant—for the simulation parameters used, about half the amount of creep strain accumulates during the primary phase of creep degradation. This indicates the need to account for primary creep in the measurements, diagnostics, and prognostics. Further, the transition from primary to secondary creep is not sharp, and prognostics algorithms will need to transition between different models to account for the differing rates of creep strain accumulation.

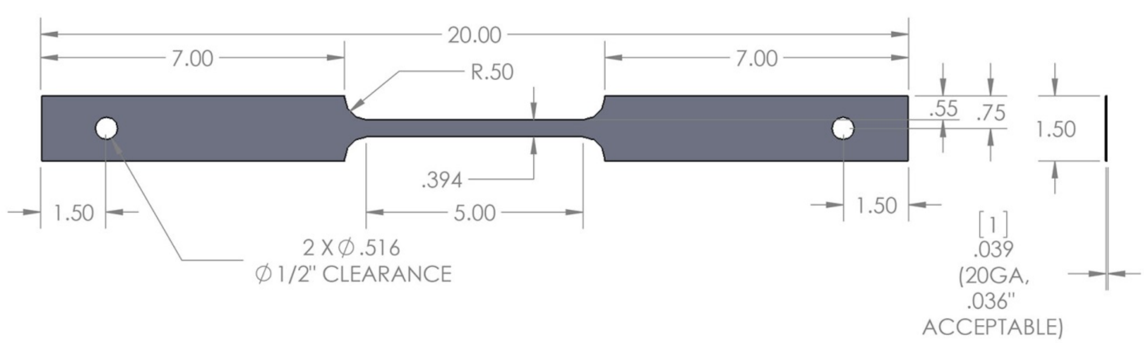


Figure 4.8. Creep Test Preliminary Specimen Geometry

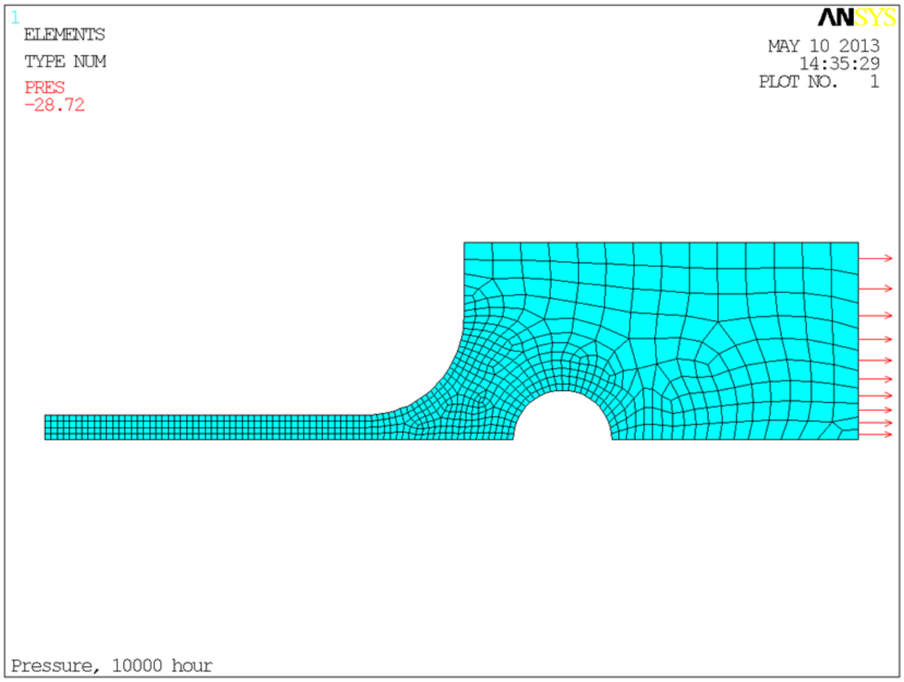
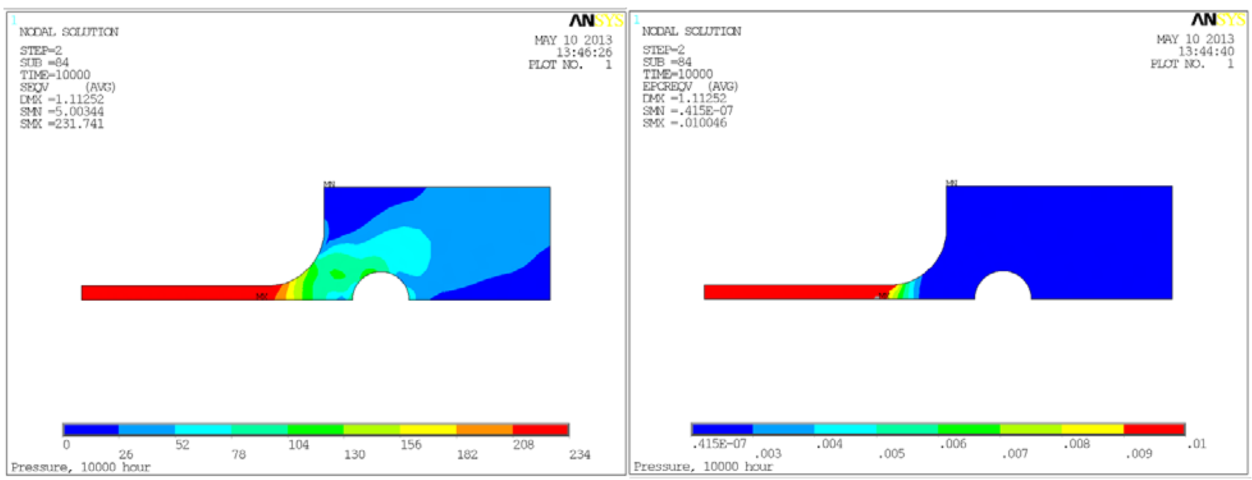
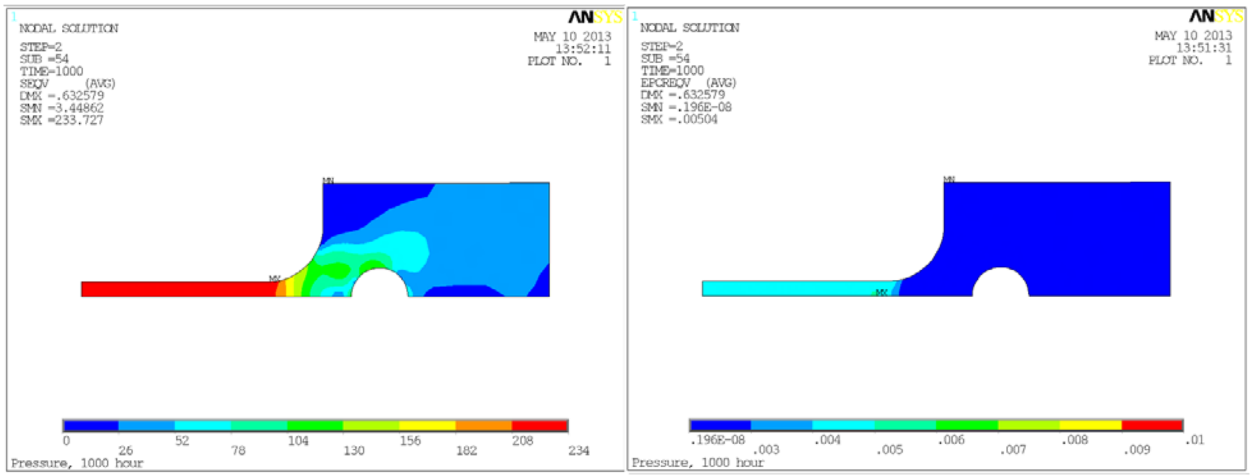


Figure 4.9. ANSYS Mechanical Quarter-Symmetry Creep Model



(a) (b)

Figure 4.10. Thermal Creep Simulation Results at 10,000 Hours: (a) equivalent stress and (b) creep strain



(a) (b)

Figure 4.11. Thermal Creep Simulation Results at 1,000 Hours: (a) equivalent stress and (b) creep strain

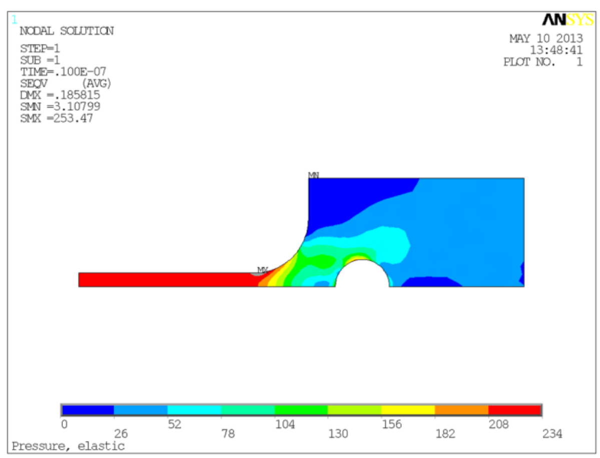


Figure 4.12. Elastic Behavior Simulation Results (equivalent stress)

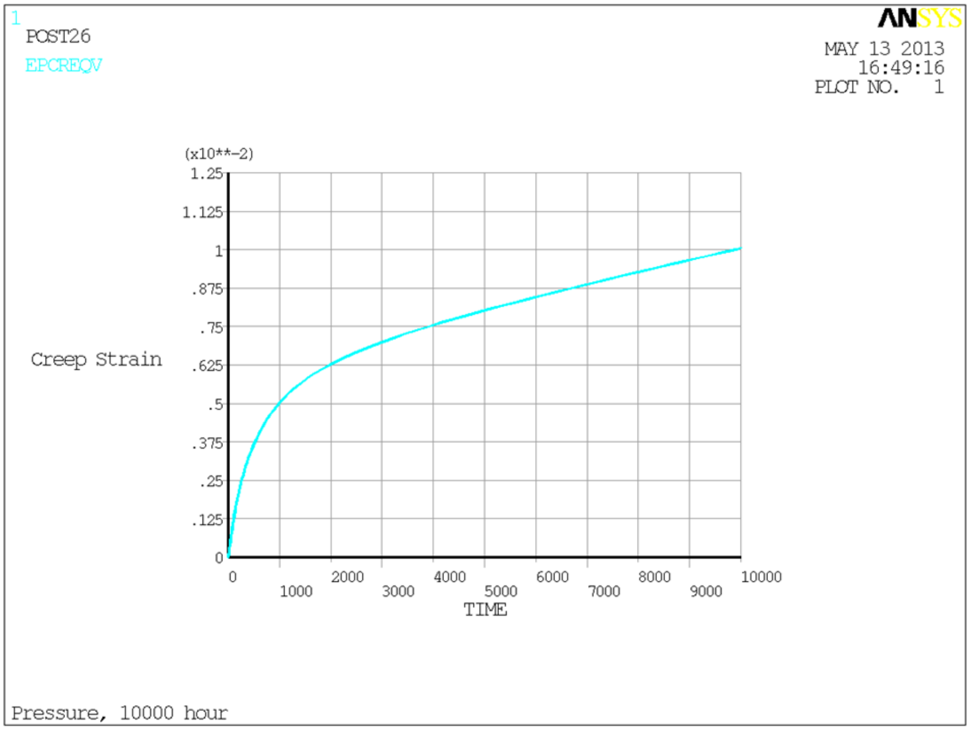
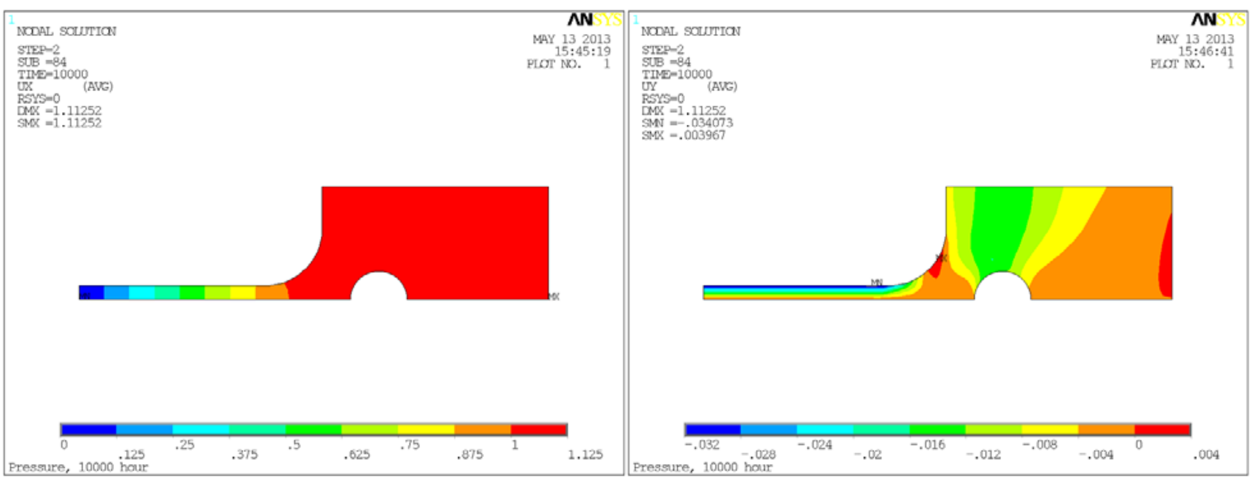


Figure 4.13. Creep Strain History Results from the ANSYS Simulation



(a) (b)

Figure 4.14. (a) Axial and (b) Transverse Deformations at 10,000 Hours

ANSYS Mechanical and other commercial finite element simulation software tools use classic macroscopic creep equations wherein creep strains develop and the stress is relieved. The literature contains data and equations suitable for component design purposes for a range of materials. However, these relationships do not address changes at the microstructural level, which may be relevant to ultrasonic inspection methods. Other researchers have reported changes in the modulus of elasticity and density (and correspondingly a change in sound velocity) with creep (Lee 2005). Such changes to the material properties are not incorporated in current finite element creep law equations. However, modeling studies, in conjunction with an experimental program, may prove to be a valuable tool in distinguishing different effects that are difficult to isolate using testing alone. In addition, custom material models can be implemented in ANSYS Mechanical, which could include more fundamental property changes. Sufficient data would need to be generated to support the development of a creep model that would include these material property changes.

4.2.2 Initial Creep Tests

Creep specimens fabricated from 304-grade stainless steel are used to generate validation data in these studies. A photograph of the creep specimens used is shown in Figure 4.15. The gage section is approximately 12.5-cm (5-in.) long, 1.0-cm (0.4-in.) wide, and 0.1 cm (0.04-in.) thick. The specimens were designed to determine the constraints associated with the NDE measurements and with attempting timely thermal creep aging of specimens at high temperature. The specimens are also marked with scribe lines in the gage section to facilitate a redundant and potentially more accurate measurement of creep strain, in addition to the displacement measurements.

Seven specimens (SMR-001 through SMR-007, referred to as specimens 1, 2, 3, 4, 5, 6 and 7 in the rest of this document) were used in the experiments, with additional specimens planned for use in later stages of the testing to evaluate the effects of variable load/temperature on the NDE measurements. One of these five initial specimens (Specimen 1) was considered a reference standard and retained in a virgin state (i.e., no creep damage). Baseline measurements from this reference standard provide a data set that can be used as a reference measurement for comparison with measurements acquired after each creep test interval. The relative change in the measurements (before and after each creep test interval) provides a measure of the sensitivity of the NDE measurement to accumulated creep damage. A second high-temperature reference standard (Specimen 2) was heat-treated at the selected creep-damage temperature (700°C) for 24 hours. This high-temperature reference standard was used to provide an estimate of the impact of thermal aging on the NDE measurement. The remaining five specimens were used in the interrupted creep testing.

Initial testing employed a stainless steel creep specimen (Specimen SMR-000, Figure 4.15) at high temperatures. A temperature of 700°C and load of 100 MPa was selected for the testing to obtain creep rates that are measureable in a reasonable amount of time. Initial testing was done to optimize settings for the control system, and to establish furnace settings that would result in a relatively flat thermal profile over the gage length of the specimen. It should be noted that the specimen is much longer than is customary for tensile testing, and this feature was used to assure that the gage ends of the specimen were outside the hot zone of the furnace to reduce the difficulties in gripping the specimen at elevated temperatures.

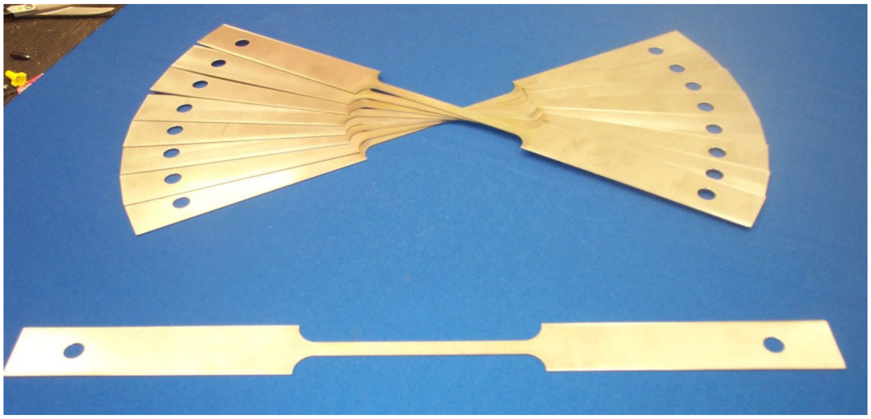


Figure 4.15. Flat Stainless Steel Specimens for Creep Testing to Validate Prognostic Algorithms

Initial testing using a separate specimen (numbered specimen 0) showed that both the load and temperature control systems were functioning as designed. Tests were conducted over several days, until creep deformation of the specimen exceeded the available travel in the load train. Figure 4.16 shows the shakedown tests that were conducted at 600°C (where only minimal creep is expected at the applied stress of 100 MPa), 650°C (where low creep rates are expected), and 700°C (where high creep rates are expected). Load (shown in red) is constant at 220 lbs, which corresponds to 100 MPa. Temperature was initially 600°C for ~24 hours, then was increased to 650°C for ~24 hours, then was increased to 700°C until the test was terminated. The measured displacement (shown in blue in Figure 4.16) shows the expected increase in creep rate with temperature.

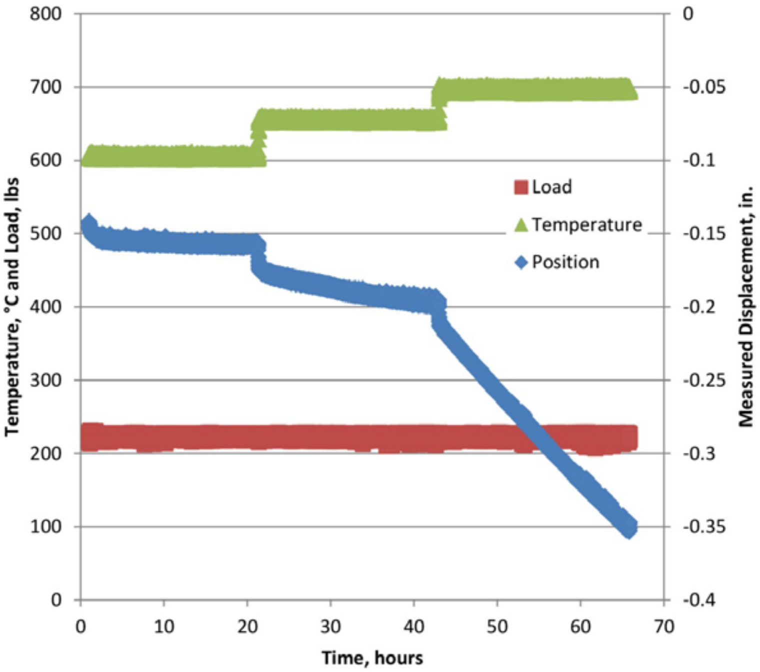


Figure 4.16. Results of Creep Frame Shakedown Testing Performed at 600°C, 650°C, and 700°C

Creep testing for the rest of the specimens used similar conditions. Specimens 3 and 4 were subjected to a thermal load of 650°C and a mechanical load of 220 lbs. The loading was interrupted after 24 hours of continuous exposure for NDE measurements. Specimen 5 was maintained at a thermal load of 625°C and a mechanical load of 220 lbs, and its loading was interrupted in intervals of 72 hours. Specimens 6 and 7 were subjected to 625°C and a mechanical load of 220 lbs, and creep testing was uninterrupted for roughly 200 hours and 500 hours, respectively.

Permanent deformation along the length of the specimens is determined by measuring the position of scribe marks, which were placed perpendicular to the longitudinal axis of the specimen, approximately 1.27 cm (0.5 in.) apart (Figure 4.17). The measurement device (microscope with a scanning stage) used for these measurements is more accurate than the caliper and micrometer that is used for overall dimensional measurements. The results of these measurements after four creep intervals for Specimens 3, 4, and 5 are shown in Figure 4.18. This represents the true-state information for each of the specimens, and appears to indicate both specimen-to-specimen variability and material variability within a given specimen is significant. The variability in strain along the gage section is most significant for Specimen 3 and appears to be least significant for Specimen 5. This indicates that more uniform specimen aging may be occurring in response to the moderate temperature decrease.

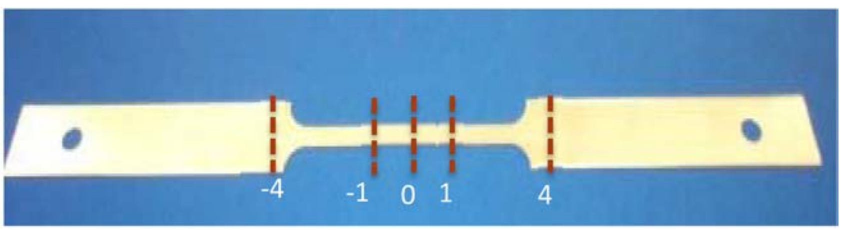


Figure 4.17. Schematic Showing Some of the Locations at which Strain Measurements were Made. The locations were marked using scribe lines on the specimens, and were also used as fiducial marks for the NDE measurements.

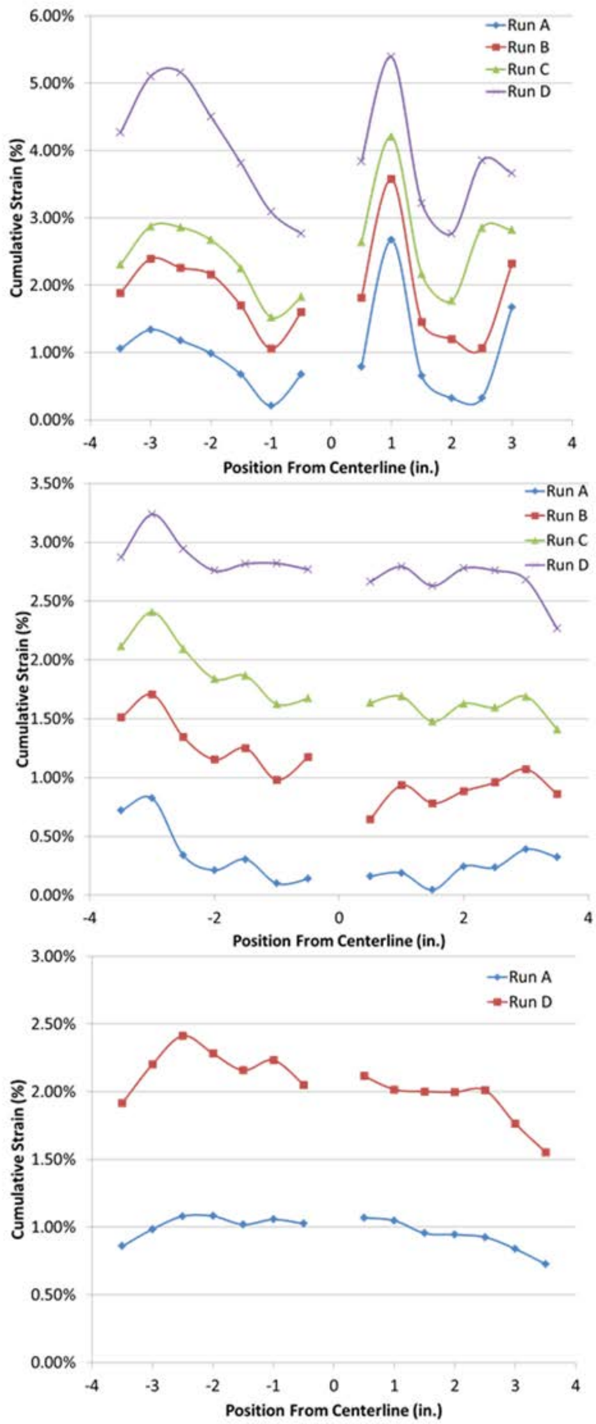


Figure 4.18. Axial Strain Measurements for Specimens 3 (top), 4 (middle), and 5 (bottom)

4.2.3 NDE Measurements

Multiple NDE measurement techniques were initiated for acquiring data from the laboratory-scale test-bed described in Section 2.4.4. NDE measurements include ultrasonic velocity and attenuation, nonlinear ultrasonic parameter, magnetic Barkhausen noise, and eddy currents.

Baseline NDE measurements were being performed on each of the specimens and a brief assessment of completed baseline measurements is provided below.

4.2.3.1 Eddy Current

The test protocol for eddy current uses an X-Y scanning apparatus for translation of the probe. Figure 4.19 shows the placement of the creep specimen during testing and the reference point for probe alignment.

The scan region is 8-in. long and 0.05-in. wide (Figure 4.20), and includes the entire length of the gage section of the specimen, and extends out into the grip section of the specimen to assess the conditions outside the creep area. The scan resolution (in both directions) is 0.01 in.

The measured data may be analyzed as an image of the scanned area, with each pixel in the scan containing the impedance (magnitude or phase) of the probe at the corresponding location. Figure 4.21 shows an example image and data table from the reference standard, at an excitation frequency of 3 MHz. Additional measurements were also acquired at 1 MHz and 6 MHz excitation frequencies.

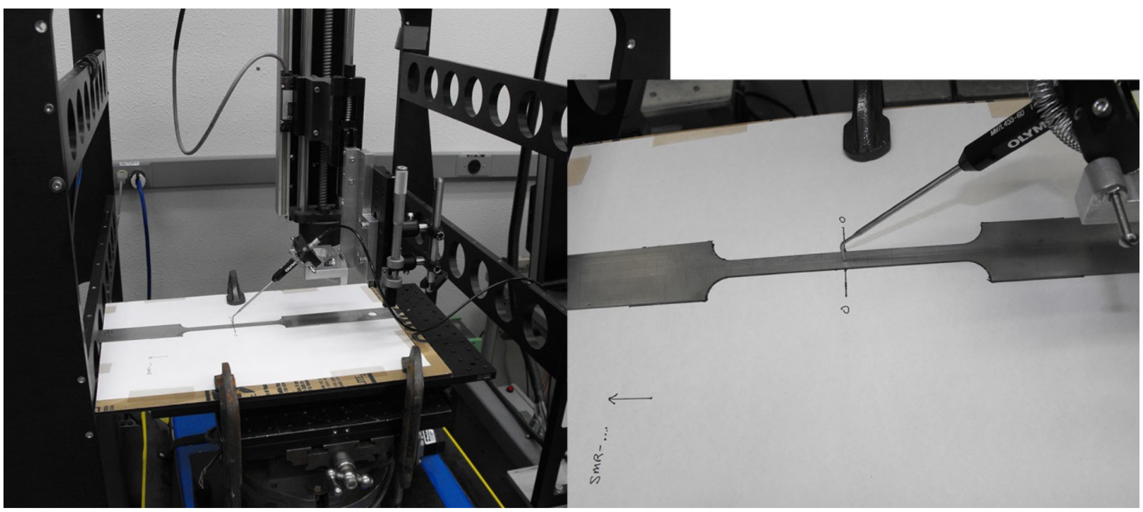


Figure 4.19. Creep Specimen Scanning Apparatus for Eddy Current Measurements

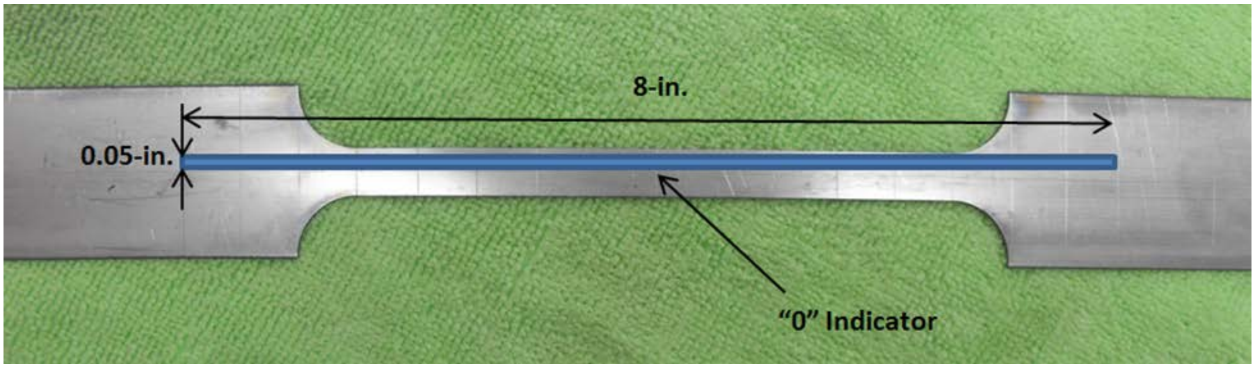
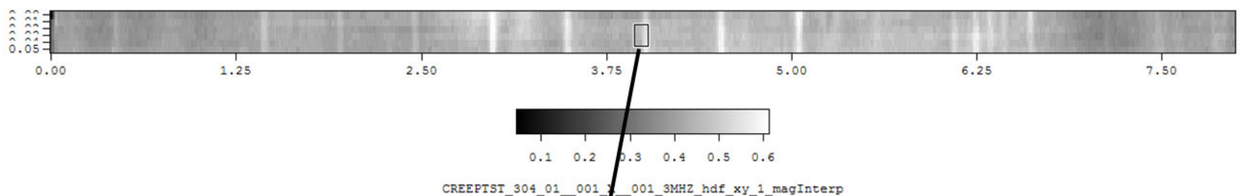


Figure 4.20. Creep Specimen Scan Parameters



CREEPTST_304_01__001_X__001_3MHZ_hdf_xy_1_magInterp

	3.940	3.950	3.960	3.970	3.980	3.990	4.000	4.010	4.020	4.0
0.000	0.398223	0.396261	0.399502	0.419488	0.423125	0.457598	0.503505	0.499895	0.492449	0.4
0.010	0.438409	0.443257	0.441554	0.446501	0.457182	0.502271	0.544848	0.543500	0.524407	0.5
0.020	0.444685	0.463384	0.446720	0.472457	0.468466	0.501611	0.541836	0.539928	0.534643	0.5
0.030	0.445224	0.441126	0.446735	0.441234	0.463836	0.504488	0.539296	0.547019	0.545867	0.5
0.040	0.439254	0.436969	0.437383	0.442000	0.427094	0.504214	0.545493	0.548595	0.564985	0.5
0.050	0.445883	0.470484	0.462282	0.463717	0.483415	0.501557	0.559766	0.561850	0.573125	0.5

Figure 4.21. Eddy Current Measurement Data (image, and measurements from highlighted region) for Verification Standard

The eddy current data is analyzed by averaging the magnitudes of several impedance measurements obtained near the center of the specimen with respect to a reference. The data is analyzed in this way for measurements performed at 1 MHz and 3 MHz, and the ratio of the resulting average magnitudes at 3 MHz to those at 1 MHz is formed. This result is normalized with respect to a similar response obtained from the reference specimen before and after loading. The result of this analysis is provided in Figure 4.22. The error bars indicate the measurement error and are computed from measurements performed on the reference specimen.

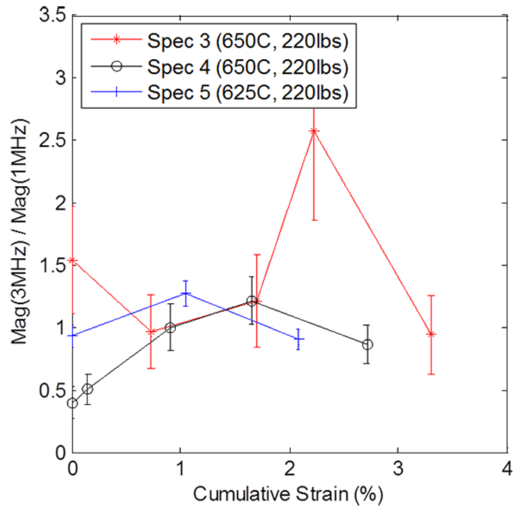


Figure 4.22. Eddy Current Response for Specimens 3, 4, and 5 Subject to Creep Loads Versus Cumulative Creep Strain

4.2.3.2 Magnetic Barkhausen Noise

Magnetic Barkhausen noise measurements use the same scanning apparatus as the eddy current measurements to provide positional repeatability (Figure 4.23) and consistent coupling of the probe to the specimen. The arrangement allows for two sets of measurements—one with the magnetization direction perpendicular to the creep direction, and a second set with the magnetization direction parallel to the creep direction. In addition, measurements may be obtained with the probe placed at several locations along the gage section of the specimen to track local changes in magnetic properties as a result of creep.

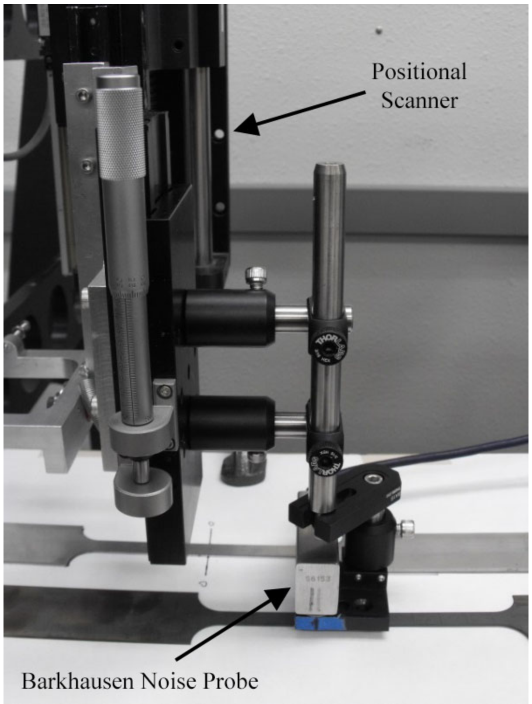


Figure 4.23. Barkhausen Noise Data Acquisition Setup

Figures 4.24 and 4.25 show plots of the magnetic Barkhausen signals versus creep strain for Specimens 3, 4, and 5, with the probe located at the center of the specimen for perpendicular and parallel magnetization orientations, respectively. The data presented are the root mean square (RMS) value of the magnetic Barkhausen signals averaged across the specimen gage length, and indicate significant trends in the parameter that are translatable across specimens.

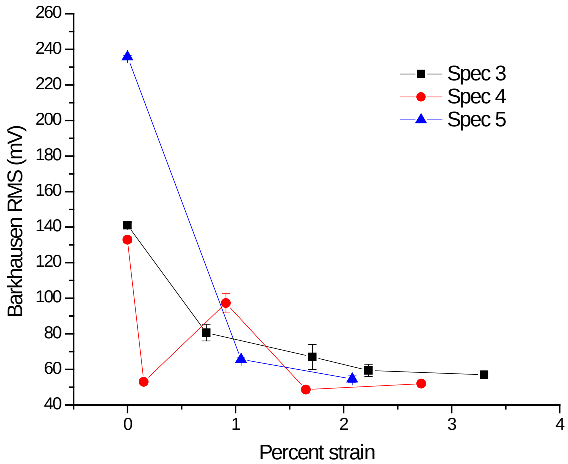


Figure 4.24. Magnetic Barkhausen Response with Magnetization Perpendicular to Specimen Longitudinal Direction for Specimens 3, 4, and 5 Subject to Creep Loading

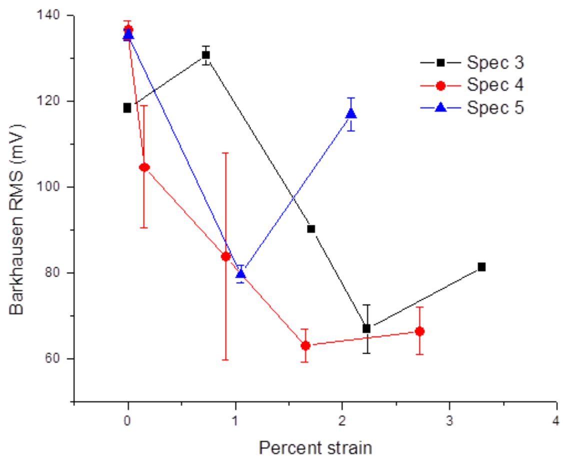


Figure 4.25. Magnetic Barkhausen Response with Magnetization Parallel to Specimen Longitudinal Direction for Specimens 3, 4, and 5 Subject to Creep Loading

4.2.3.3 Nonlinear Ultrasonics

Nonlinear ultrasonic measurements generate a surface wave using a transmitting probe and record the resulting interaction of the material with the applied energy using a receiving probe (Figure 4.26). The transmit-receive arrangement with the two probes enables the measurement to account for material property changes over a larger volume and generally provides improved signal-to-noise capability. Measurements are acquired at multiple input voltages and excitation frequencies, enabling better characterization of the nonlinear response of the material while separating out any nonlinearities in the instrumentation or probes. Initial (baseline) measurements were acquired at an excitation (transmitting) frequency of 4.5 MHz to 5.5 MHz, and a receiving transducer frequency centered at 10 MHz (enabling measurement of the second harmonic). As with the other NDE measurements, baseline measurements are acquired from each specimen, including a reference standard. Figure 4.27 shows an example of the measurement data from the reference standard, and includes the measurements at 4.5 MHz, 5 MHz, and 5.5 MHz.

Figure 4.26. Ultrasonic Probe Arrangement for Nonlinear Ultrasonic Measurement

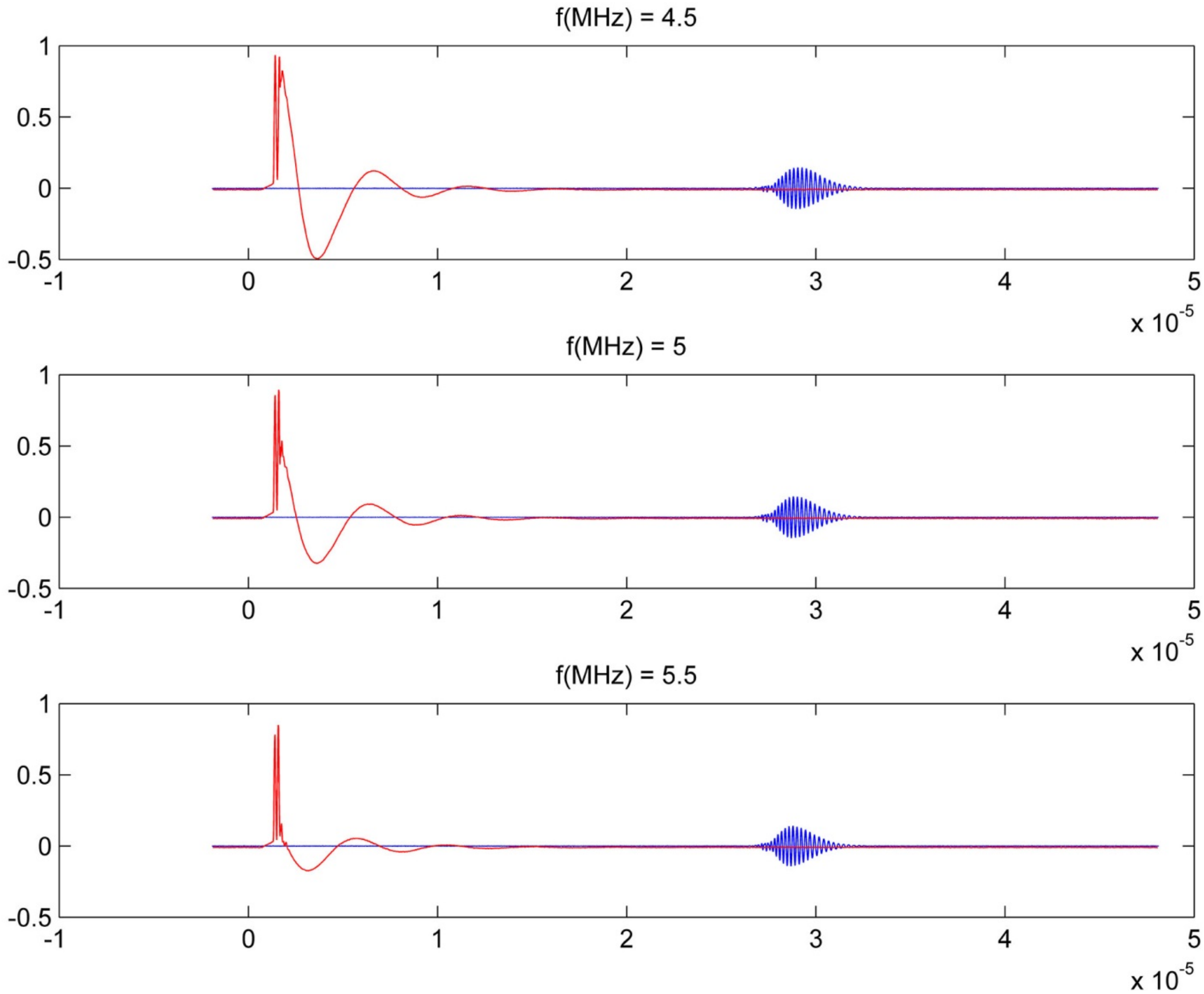


Figure 4.27. Example of Ultrasonic Measurement Data from Verification Standard. The measured data at three frequencies, at an excitation voltage of 95 V, is shown.

The measured data from the nonlinear ultrasonic measurement was analyzed (using Fourier analysis) to extract the amplitude of the fundamental and second harmonic frequencies. This analysis was performed on the baseline measurements from each of the four specimens (the reference and three additional specimens—the temperature-aged reference was not included in this initial analysis). The intent was to examine the linearity of the measurements with applied voltage and compare the data from the different specimens to understand the potential for measurement uncertainty from one specimen to the next. Figure 4.28 shows the baseline measurements (at a fundamental frequency of 4.5 MHz) for the four specimens, with the measurement taken in the center of the gage length of each specimen. The plot shows the amplitude of the second harmonic (vertical axis) plotted against the square of the amplitude at the fundamental frequency (horizontal axis). As the applied voltage increases, the amplitude of the fundamental frequency component increases; for each specimen, six different input voltages (between 50 V and 95 V) were used to generate these plots. Similar data (at 5 MHz and 5.5 MHz) are shown in Figures 4.29 and 4.30. In each of these plots, the data from the different specimens are color-coded. The data show that, within any specimen, the measurement is generally linear with respect to the applied voltage. The nonlinear parameter β is defined as the ratio of the amplitude at the second harmonic frequency to the square of the amplitude of the fundamental frequency, and is seen to be a function of the frequency. However, the response appears to vary from specimen to specimen.

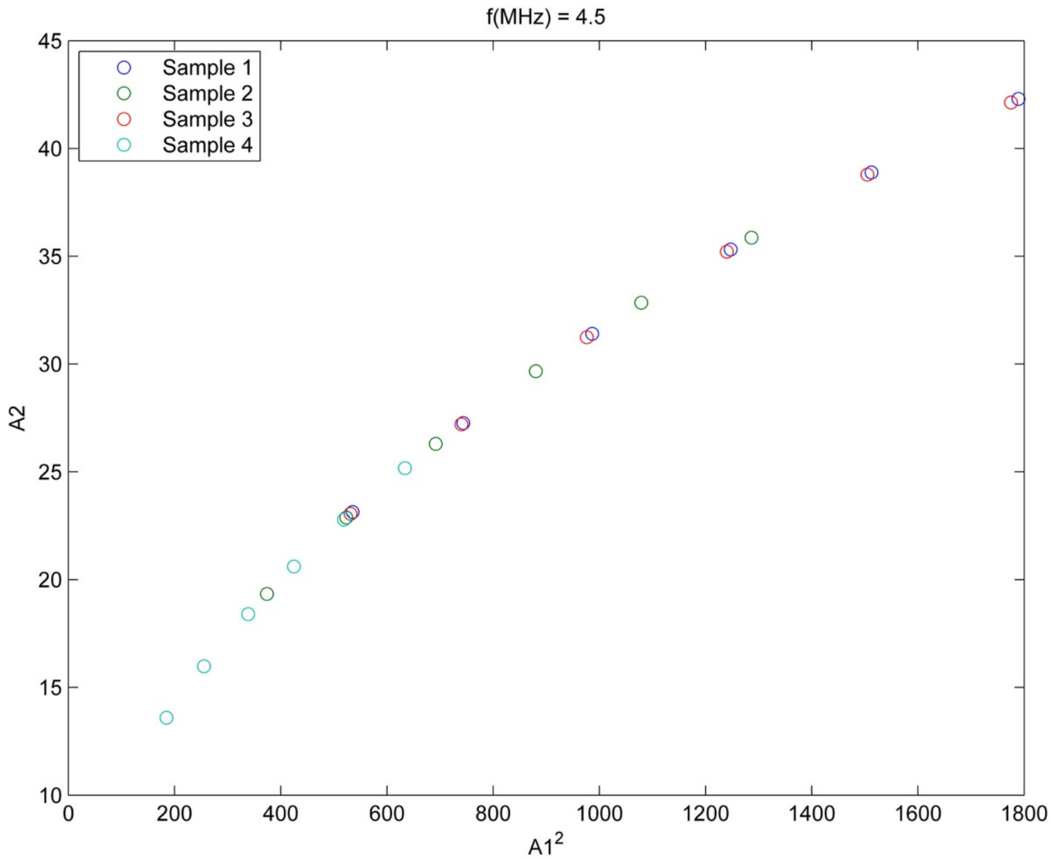


Figure 4.28. Nonlinear Ultrasonic Measurement at 4.5-MHz Excitation Frequency. The horizontal axis shows the square of the amplitude at the fundamental frequency (4.5 MHz) and the vertical axis shows the amplitude of the second harmonic (9 MHz).

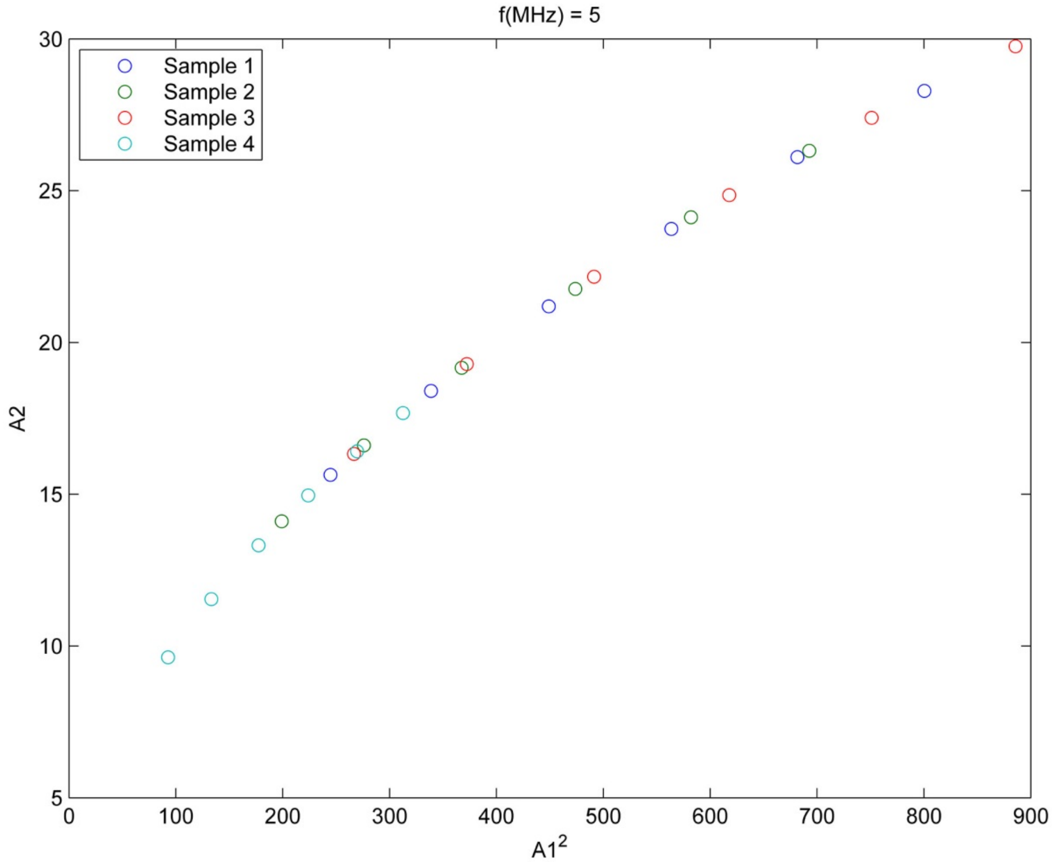


Figure 4.29. Nonlinear Ultrasonic Measurement at 5-MHz Excitation Frequency. The horizontal axis shows the square of the amplitude at the fundamental frequency (5 MHz) and the vertical axis shows the amplitude of the second harmonic (10 MHz).

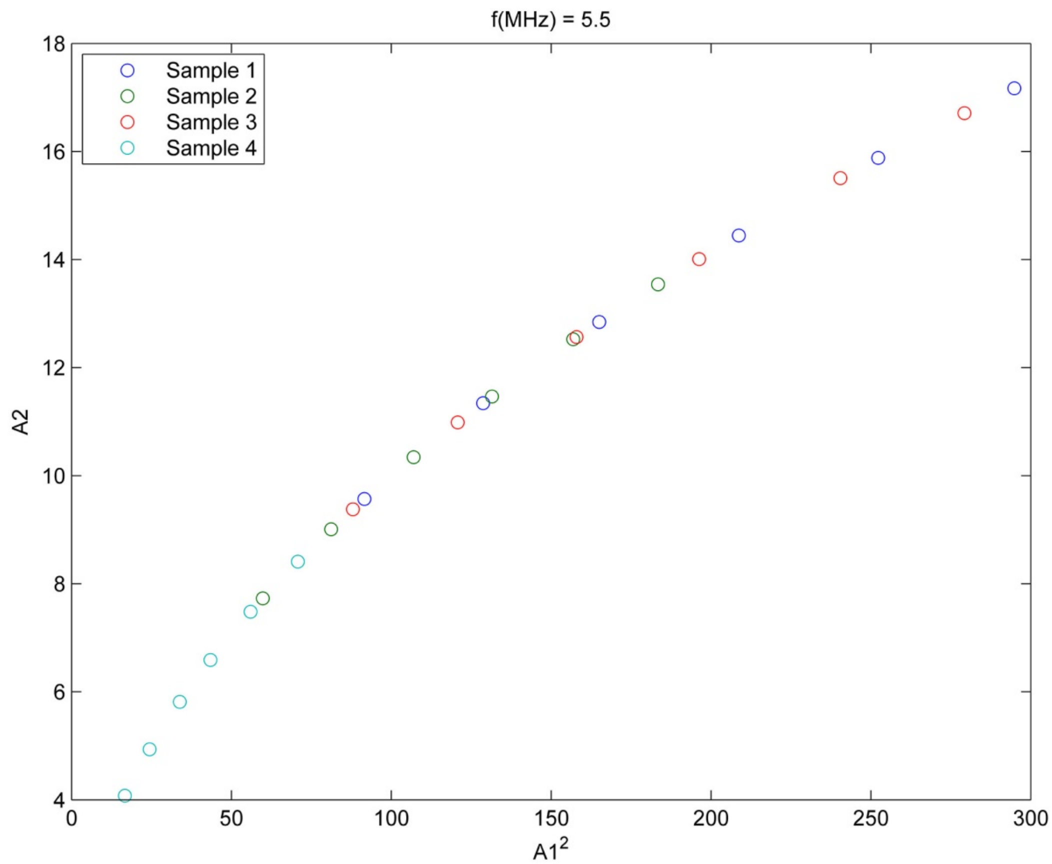


Figure 4.30. Nonlinear Ultrasonic Measurement at 5.5-MHz Excitation Frequency. The horizontal axis shows the square of the amplitude at the fundamental frequency (5.5 MHz) and the vertical axis shows the amplitude of the second harmonic (11 MHz).

The measurement data from the interrupted creep tests were also processed to extract the nonlinear parameter β at the different frequencies, and the results at 4.5 MHz and 5.0 MHz are plotted in Figures 4.31 and 4.32. The measurement data acquired to date indicate large uncertainties as well as little sensitivity to the creep strain. It is unclear whether this is due to an innate lack of sensitivity of the parameter itself, or is a function of the specimen design that resulted in difficulties in coupling of the probes to the specimen.

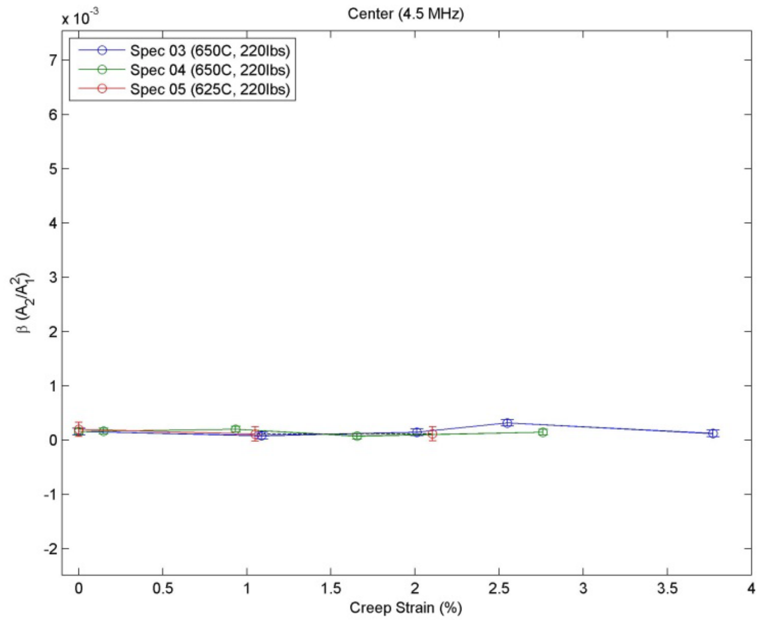


Figure 4.31. Nonlinear Ultrasonic Parameter β as a Function of Accumulated Creep Strain at an Excitation Frequency of 4.5 MHz

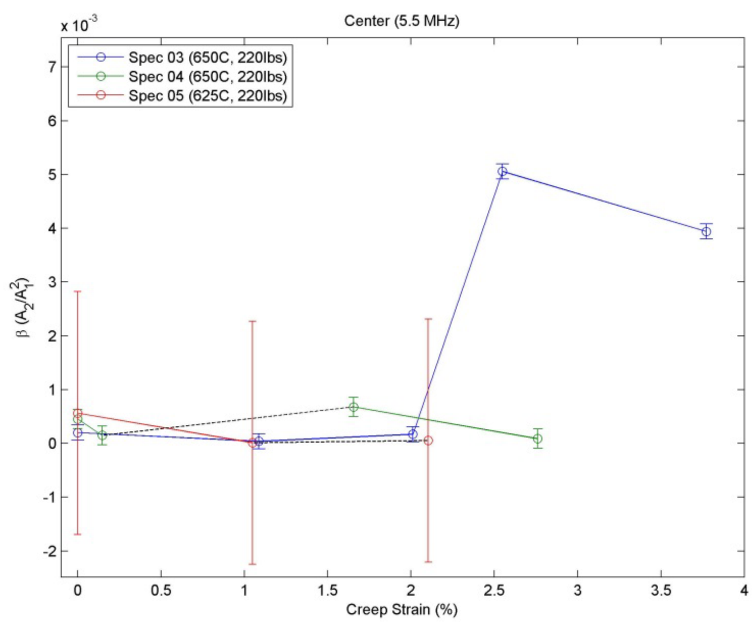


Figure 4.32. Nonlinear Ultrasonic Parameter β as a Function of Accumulated Creep Strain at an Excitation Frequency of 5 MHz

4.3 Discussion

Of the three NDE measurement techniques that were explored in this study to date, the magnetic Barkhausen measurement parameter appears to consistently correlate with the level of accumulated creep damage. The trends in this parameter appear to be applicable to all specimens, although the rate of change in the parameter may be a function of the experimental settings (thermal and mechanical load). The ability to rotate the probe to change magnetization direction provides an opportunity to examine anisotropic behavior due to creep accumulation, where the properties may vary differently in the longitudinal direction and the transverse direction. The data appear to indicate variable behavior in these two directions, indicating the potential onset of anisotropies as creep damage accumulates.

The analysis of NDE data to date appears to indicate that classical measures of eddy current measurements (such as magnitude or magnitude ratios) may not provide a suitable parameter for predictive analysis that is generalizable. This is reflected in Figure 4.22 where the ratio of magnitudes at two frequencies (a measure of the change in electrical conductivity due to creep damage two different depths in the material), does not appear to show any significant trends with accumulated creep strain that may be generalized across specimens. However, the parameter does appear to show a statistically significant change in each specimen, indicating that the eddy current measurement technique itself may contain sufficient information to distinguish accumulated creep damage levels.

Results from the eddy current data may also be influenced by the specimen design. The relatively thin specimens required high frequencies to limit the depth of penetration of the electromagnetic energy (ASNT 2004), and the resulting limited variability in depth of penetration may have challenged the ability to consistently measure the changes in conductivity with depth in the specimen. The use of probes that are symmetric also limits the ability to measure anisotropic behavior using eddy current data.

The nonlinear ultrasonic measurement data presented difficulties in the analysis, and the data indicated large uncertainties as well as apparent limited sensitivity to accumulated creep strain. It is unclear at this stage whether this is from an innate lack of sensitivity of the parameter itself, or is a function of the specimen design that resulted in difficulties in coupling of the probes to the specimen. A survey of literature appears to indicate mixed success (Sposito et al. 2010) in correlating the nonlinear parameter to creep strain, indicating that the ability to measure and predict creep strain accumulation from this parameter is a strong function of the specimen design and experimental protocol.

Additional ultrasonic measurements (for computing sound speed and attenuation) were also made at the same time as the nonlinear measurements, and are being analyzed for applicability. However, the issues identified with the eddy current and ultrasonic data analysis to date have indicated the need for modifying the specimen design and for examining novel data analysis techniques. Specimens with the new design (Figure 4.33) have been acquired and measurements are underway; in addition, analysis of the data acquired to date using measures of entropy has also been initiated. Results of these activities will be reported in the next report in this series.

Figure 4.33. New Specimen Design for Creep Tests and NDE Measurements

5.0 Summary

Technologies such as prognostic health management systems that help advance the state of the art of diagnostics and prognostics are important for controlling O&M costs by providing enhanced awareness of component or equipment condition and predictive estimates of component failure that are customized for each AdvSMR unit and accounts for the specific operational history of the unit. Such information, when integrated with plant control systems and risk monitors, helps control O&M costs by enabling lifetime management of significant passive components, relieving the cost and labor burden of currently required periodic in-service inspection, and informing O&M decisions to target maintenance activities.

An initial methodology for estimating RUL from spatially localized NDE measurements was developed. This methodology for PHM uses Bayesian approaches, and multiple filtering algorithms were used to diagnose and predict the RUL of the material subjected to high-temperature creep damage. The Bayesian approaches were tested using synthetic data to verify their ability to provide predictive estimates of secondary-stage creep strain accumulation, and the ability to update these predictions as additional measurements become available. Modifications to these algorithms to account for model selection and uncertainty quantification, to address primary and secondary stage creep prognostics and measurement/model uncertainty, were also made, and are being evaluated.

To perform initial validation of the prognostic algorithms, a laboratory-scale creep degradation test-bed was designed and built. The test-bed enables interrupted creep testing, where specimens are removed after a defined amount of time, measured using advanced NDE techniques, and re-inserted into the test-bed for further degradation accumulation. Initial (or baseline) measurements using multiple NDE methods were completed on several creep specimens, including on a specimen set aside as a reference or verification standard. The relative change in the measurements provides an understanding of the sensitivity of the NDE technique, and can be related back to the level of accumulated creep strain in the specimen.

The results of the RUL estimation from simulated data show that a Bayesian approach is feasible for this purpose. The proposed Bayesian prognostics approach also allows for updates to the RUL estimates as new measurements are acquired. The results also indicate that the uncertainty associated with the RUL projections appears to improve for particle filters as additional data becomes available. This behavior does not seem apparent using other Bayesian filtering algorithms, and may provide a metric for selecting appropriate filtering algorithms. The use of uncertainty may also help address the model selection problem for lifecycle prognostics; however, this needs further evaluation and confirmation using simulated and experimental data. The improvement in uncertainty in the RUL estimates will also need to be validated further.

NDE measurements on the specimens indicate variability in the parameters as a function of accumulated creep strain. The data, as well as accumulated creep strain, appear to vary from specimen to specimen, as well as within a specimen. This variability is likely because of differences in the starting material microstructure for the specimens; this will be confirmed using additional measurements.

Ongoing research includes: (1) completing the evaluation of lifecycle prognostics and uncertainty quantification approaches and (2) incorporating stressor information into the prognostics methodology, to address variable loading scenarios and reduce uncertainty in the predictive estimates of remaining life. In addition, future research will focus on PHM at the component level, utilizing one or more measurements of component health and the stressor environment. Examples of such measurements include acoustic emission and vibration. These measurements may be augmented with localized NDE measurements on the component. Research will also be conducted towards developing approaches to integrate information from multiple PHM systems resulting in enhanced awareness of advanced reactor/AdvSMR system condition. These activities will be supported by continued acquisition of necessary NDE measurements using appropriate additional specimens.

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Appendix A

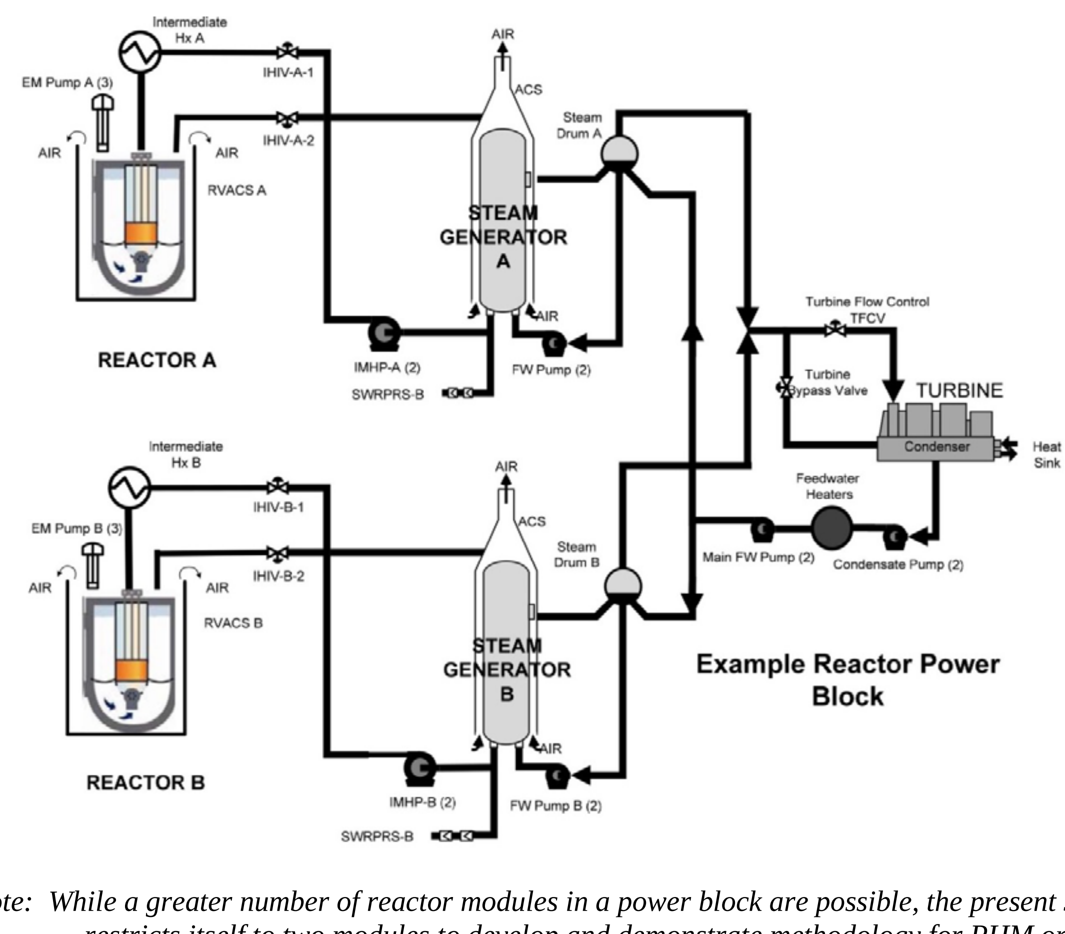
Simplified-model AdvSMR Design to Develop and Demonstrate Methodology for PHM or ERMs

Appendix A

Simplified-model AdvSMR Design to Develop and Demonstrate Methodology for PHM or ERMs

A.1 Primary Features of Simplified-model AdvSMR Design

A simplified-model AdvSMR (power block) design is used in the development of the PRA model used for the research that supported the development of frameworks for both PHM and ERMs. This simplified model is shown in Figure A.1. This hypothetical design is intended to be prototypical and resembles proposed liquid-metal-cooled SMR designs. The example design is defined to provide a simple level of abstraction but contains enough resolution and specific design elements to inform the development of a PRA model that, when quantified, produces a cogent set of results in support of PHM systems for AdvSMRs. The choice of this simplified design also enables the future integration of the results of the PHM methodology with enhanced risk monitors (Ramuhalli et al. 2013b; Ramuhalli et al. 2014).



(*Note: While a greater number of reactor modules in a power block are possible, the present study restricts itself to two modules to develop and demonstrate methodology for PHM or ERM.*)

Figure A.1. One-Line Diagram of Simplified-Model AdvSMR

The simplified-model AdvSMR design in Figure A.1 is a small, modular, pool-type, liquid-metal-cooled reactor assumed to be producing 200 to 500 MWt[(a)] of power. The primary features of the simplified design are the primary cooling loop, intermediate cooling loop, secondary system including the steam generators, and residual heat removal systems consisting of a passive reactor vessel auxiliary cooling system (RVACS) and passive steam generator cooling system. The plant design consists of an unspecified number of identical power blocks, with each power block comprised of two reactor modules. Each module is connected to its own intermediate heat exchange system and steam generator. The secondary side (i.e., steam side) equipment is located in a different building and connects two modules to form a power block. A power block feeds a single variable capacity turbine generator.

A.2 Active Components for Simplified-model AdvSMR Design

The simplified-model AdvSMR design primary loop is contained entirely within the reactor vessel. Liquid metal is pumped by electromagnetic pumps up through the reactor core and out through the top. Flow is then forced back down through the space (annulus) between the outer wall and reactor core past two intermediate heat exchangers. The key active components in this loop are the electromagnetic pumps, which are suspended into the reactor pool from above. Because electromagnetic pumps have no moving parts and therefore there is no associated "flywheel effect," a synchronous coast-down function is designed into pumps to provide coast-down upon loss of power.

The intermediate loop transfers heat to the secondary system via two steam generators. The primary active components of this system are the intermediate cooling pumps, and the intermediate loop isolation valves. The intermediate cooling pumps force flow of heated liquid-metal from the intermediate heat exchangers to the steam generators during both normal and upset conditions. The isolation valves close to isolate the reactor from a pressure increase resulting from the liquid-metal-water interaction that would occur in the event of a steam generator tube rupture event. The signal to close these isolation valves is based on a passive liquid-metal-water pressure-relief system connected directly to the steam generators.

The secondary system consists of a steam generator and a steam drum for each reactor module connected to a single turbine generator. The secondary system delivers steam from the steam generators to the inlet of the turbine. Turbine steam exhaust flows through the condensers and then to main condensers and feedwater pumps back to the reactor module steam drums where it can be pumped by the reactor module feedwater to the steam generators. The turbine bypass valves allow steam to flow past the turbine and directly into the condenser when required. This allows a means of residual heat removal from the reactor modules during reactor shutdown and startup, and provides a flow path that will be needed in case of load rejection and some event that trips the turbine. Each steam generator has a liquid-metal-water reaction pressure-relief system that relieves pressure in the event of a generator tube rupture. This is a passive system and provides a path for the increased steam pressure that would occur from liquid-metal-water reaction.

A.2.1 PRA for Simplified-Model AdvSMR

PRA techniques have been used in U.S. nuclear power plants to assess the risks associated with operation since the 1980s (Wu and Apostolakis 1992b; Wu and Apostolakis 1992a). PRA systematically

(a) The electrical output of a reactor depends on the efficiency of the power conversion process.

combines event probability and probability of failure (POF) for key components to determine the hazard probability for subsystems and the overall system (Kafka 2008). In general, PRA models use a static estimate for event probability and POF, typically based on historic observations and engineering judgment. More recently, time-based POF values have been used (Vesely and Wolford 1988; Arjas and Holmberg 1995); however, these are derived from operating experience and traditional reliability analysis and are usually not specific to the operating component.

Uncertainty in PRA modeling arises from a number of sources that are typically divided into aleatory variability and epistemic uncertainty (EPRI 2011). Aleatory variability is related to the statistical confidence we have in failure probability data, while epistemic uncertainty is related to the uncertainty in the accident sequences used to develop the PRA model. Epistemic uncertainty is dealt with by developing event and fault trees as complete as possible, identifying keys sources of uncertainty, and performing sensitivity analyses. The aleatory variability is addressed explicitly by propagation of parametric data uncertainty for initiating basic event data. Uncertainty analysis is performed through a sampling strategy (e.g., Monte Carlo sampling) over some number of observations.

(*Note: The term "aleatory" when used as a modifier implies an inherent "randomness" in the outcome of a process (Dezfuli et al. 2009).*

As PRA models are integrated into plant management, they have become living models that reflect the as-modified and as-operated plant configuration and are able to estimate the changing likelihood of undesired events. Risk monitors extend the PRA framework by incorporating the actual and dynamic plant configuration (e.g., equipment availability, operating regimes, and environmental conditions) into the risk assessment, although failure data on equipment is based on operational experience and reliability analysis, and unit-specific failure information is generally not used.

The PRA model developed for the simplified-model AdvSMR is capable of modeling fault (or accident) sequences that could occur, induced by a perturbation (or initiating event) in the system, and of identifying the combinations of system failures, support system failures and human errors that could lead to core damage. The general framework for the PRA model includes the following analyses, each of which are discussed in (Ramuhalli et al. 2014):

- Initiating Event Analysis
- Accident Sequence Analysis
- Systems Analysis
- Data Analysis
- Common Human Reliability Analysis
- Cause Failure Analysis
- Quantification

A.3 Passive Components for Simplified-model AdvSMR Design

Passive components within the primary loop include the reactor vessel itself, as well as the internal components (such as core support structures) and the two intermediate heat exchangers. The intermediate loop transfers heat to the secondary system via two steam generators. The primary passive components in this system are the steam generator tubing, nozzles, and piping associated with the intermediate cooling pumps and the intermediate loop isolation valves. Welds are assumed used between piping, as well as from the nozzles to the steam generator vessel. Materials of interest include ferritic-martensitic steels and high-nickel alloys that provide good heat transfer and general corrosion resistance.

The secondary system consists of a steam generator and a steam drum for each reactor module connected to a single turbine generator. In this case, we assume that the components of interest include the piping for both the secondary system, as well as the service water plumbing system which may use non-metallic piping.

The simplified-model AdvSMR design residual heat removal system consists of RVACS and the passive steam generator cooling system. The passive steam generator cooling system removes heat by air circulation past the steam generators. This airflow is initiated by remote manual opening of louvers at the inlet and outlet of the shroud around the steam generators. In this mode, heat is removed by natural convection to the air. This system can operate with forced or natural circulation of intermediate cooling loop sodium. If operators are unsuccessful at opening louvers to initiate convective cooling or if the intermediate cooling flow or inventory is lost, then a residual heat can by removed by natural air circulation around the containment vessel that surrounds the reactor vessel via the RVACS. Heat will be transferred from the reactor vessel to the containment vessel by radiative heat transfer and then to the air around the containment vessel and ultimately the atmosphere via convective heat transfer. A key design feature of RVACS is that no components or operator actions are required to initiate RVACS, because it is continually operating during normal power operation and is designed to be able to accommodate residual heat transfer after reactor shutdown.

A.3.1 Prognostic Algorithms

Prognostic health management is a proactive maintenance philosophy where maintenance or repairs to systems or components are performed prior to failure based on models that predict when failure is likely to occur. To predict failure, PHM systems require some type of input (data) about the state of the component(s) of interest. These inputs could be in the form of information on stressors to which the system or component is exposed, or information on the condition of a specific system or component. Consequently, measurements and diagnostics, in addition to prognostics, are key elements to a PHM system.

Given the potential need to provide PHM for several systems within the hierarchy of an AdvSMR design (Meyer et al. 2013a), a hierarchy of PHM systems is being explored (Meyer et al. 2013b), with information at one or more levels of this hierarchy being supplied to a supervisory plant control system for optimizing plant operations with respect to O&M requirements. This hierarchy corresponds to PHM systems operating on localized measurements, PHM systems operating on component-wide measurements, and global PHM systems that integrate diagnostics and prognostics information across multiple components.

As described in previous reports (Meyer et al. 2013a; Meyer et al. 2013b), the requirements for PHM systems include:

- Fusion of measurement data from diverse sources

- Address coupling between components or systems, and across modules
- Incorporation of lifecycle prognostics
- Integration with risk monitors for real-time risk assessment
- Interface with plant supervisory control system

When these requirements are considered in the context of passive components in AdvSMRs, specific research needs associated with enhancements to PHM algorithms may be identified:

- Physics-of-failure models for passive component degradation
- Quantitative NDE analysis tools that relate NDE measurements to the degradation state of the passive component. Such tools include methods to fuse information from multiple measurements (NDE and stressors).
- Algorithms for transitioning between different models of degradation accumulation over the lifecycle of the component
- Uncertainty quantification in RUL estimates

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Appendix B

Passive Component Test-Bed for Demonstrating Prognostics

Appendix B

Passive Component Test-Bed for Demonstrating Prognostics

B.1 Background

PHM is a proactive maintenance philosophy in which maintenance or repairs to systems or components are performed prior to failure based on models that predict when failure is likely to occur. To predict failure, PHM systems require some type of input about the state of the component(s) of interest. These inputs could be in the form of information on stressors to which the system or component is exposed, or information on the condition of a specific system or component. Thus, measurements and diagnostics, in addition to prognostics, are key elements to a PHM system.

As described in previous reports (Meyer et al. 2013a; Meyer et al. 2013b), PHM for prototypical AdvSMR passive components will require measurements of component condition in addition to measurements of stressors. Given the potential need to provide PHM for several systems within the hierarchy of an AdvSMR design, a hierarchy of PHM systems is being explored, with information at one or more levels of this hierarchy being supplied to a supervisory plant control system for optimizing plant operations with respect to O&M requirements. The hierarchy corresponds to PHM systems operating on localized measurements, PHM systems operating on component-wide measurements, and global PHM systems that integrate diagnostics and prognostics information across multiple components.

In order to evaluate the algorithms at each level of this hierarchy, test-beds are required to be able to generate relevant data sets (unless such data sets are available through other sources). Given the sequential progression of R&D, beginning at the localized level, a laboratory-scale test-bed that can be scaled with the different stages of R&D is preferable. A preliminary set of requirements for such a test-bed are described next.

B.2 Preliminary Requirements for Laboratory-scale Test-bed

The laboratory-scale test-bed concept must address the need to measure nondestructive evaluation (NDE) data from a representative passive component at multiple length scales—localized, component level, and potentially at a global level. A number of potential requirements for the test-bed may be identified based on the need to use the test-bed to validate the PHM algorithms, including:

- <u>Materials and degradation</u>: The test-bed should be capable of incorporating components made of materials relevant to AdvSMRs. In addition, as the objective is to evaluate prognostics for degradation accumulation in passive components, the test-bed should include degradation modes of relevance to AdvSMRs.
- <u>Accelerated aging</u>. The time taken to age a specimen should be accelerated when compared to the time taken to field-age specimens.
- <u>Simulate operational conditions</u>. The test-bed should be capable of simulating operational conditions likely to be seen in AdvSMR concepts (such as varying the temperature or load on a component over time).

- Measurements: The test-bed should enable periodic or continuous measurements using one or more NDE methods. In addition, measurements of the stressors (temperature, load, etc.) on the materials or components should be enabled. Continuous measurements (of condition or stressors) should be performed synchronously.
- Scalability. To increase efficiency and reduce costs, the test-bed must be capable of addressing PHM evaluation needs at component and global scales with potentially modest changes to the test-bed.

B.2.1 Summary of Considerations for Passive Component Monitoring in AdvSMRs

The operating experiences of several advanced reactor concepts are summarized in Table B.1, along with information on the specific reactors from which this experience is derived. It is likely that lessons learned from the construction and operation of advanced reactors will also be relevant to the operation of future AdvSMRs.

Table B.1. Operating Experiences of Several Advanced Reactor Concepts (Meyer et al. 2013b)

Passive Components	Structural Materials	Degradation Modes	Desired Measurements
– Heat exchangers – Turbines/compressors – Reactor vessel – Core, shields, reflectors, absorber – Piping – Tanks	– F/M steels – ODS F/M steels – Austenitic SS – Ceramics/composites – Ni-base superalloys	– Oxidation/corrosion – Loss of fracture toughness/ embrittlement – Creep/irradiation creep – Stress corrosion cracking	– Novel coolant temperature, pressure, and flow sensors – Neutron flux sensors – Coolant level – Contamination in coolant and cover-gas[(a)] – Coolant chemistry[(b)] – Debris in coolant[(c)] – Loose parts monitoring

(a) Examples of important applications include monitoring of moisture ingress in VHTRs (Beck and Pincock 2011) and air and oil contamination of sodium coolant in SFRs (Guidez et al. 2008).
(b) Instrumentation to assess the chemical state of fluoride salts has been identified as a critical need for MSR type reactors (Unknown 2004; Greene et al. 2010). Instrumentation to monitor the oxygen content in lead coolant has been identified as a critical need for corrosion control in LFR type reactors (Smith 2010).
(c) Examples of debris-in-coolant monitoring applications include the monitoring of corrosion products in the coolant of LFRs (IAEA 2007) and monitoring of graphite dust in VHTRs (Beck and Pincock 2011).

B.3 Test-bed Concept

B.3.1 Localized Degradation and Measurements

To provide an initial context for the development of prognostics algorithms, high-temperature creep (effect of loads below the yield point for long periods of time, especially at elevated temperatures) was selected as the prototypical degradation mechanism for initial evaluation of prognostics for passive components.

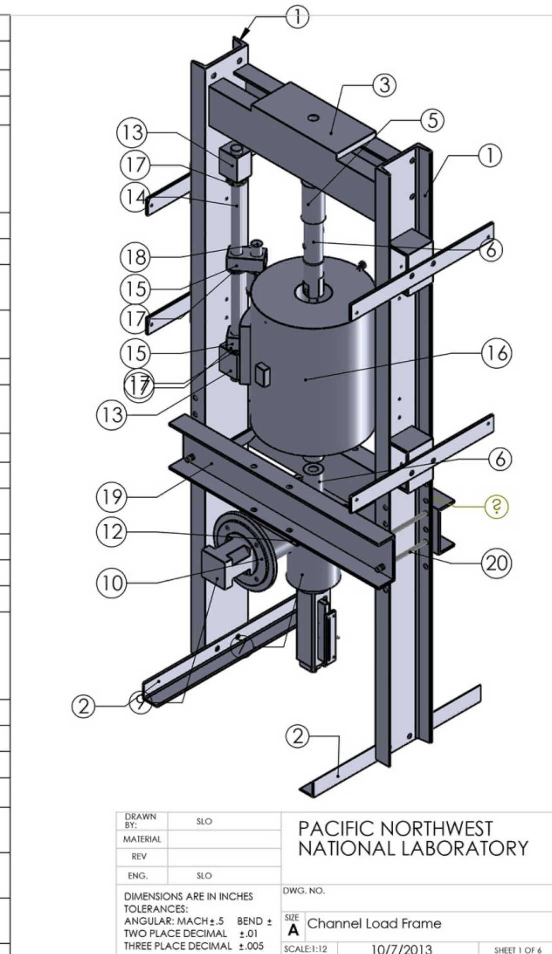
A laboratory-scale creep test machine was designed as the test-bed for the first phase of measurements and prognostics. Figure B.1 shows a design schematic for this machine, with the major components highlighted, while Figure B.2 shows a picture of the fabricated creep-test machine. Figure B.3 shows the interface used for control of this test-bed. The creep test machine consists of a mechanical load frame, furnace, 5-ton actuator, power supply enclosure, and control system enclosure. The control system enclosure houses the electronics that run the system, including the motor drive for the stepper motor that is used in conjunction with the 5-ton actuator. The load frame is the base that all components are mounted to, and is based off a 20-ton shop press. The furnace, actuator, and both electrical boxes mount to the load frame. The machine allows the user to specify a force to be applied to the specimen, as well as a temperature for testing. During a test, the machine logs the date, stepper position, sensor position, temperatures, and force applied to a file for future analysis.

A programmable logic controller (PLC) is used to control the operation of the test-bed, and enables independent control of temperature and load. Heating is controlled by means of three control circuits for the heater, with a 5-point thermocouple to control the heat independently in each of the three heater circuits. The load is controlled by means of a 5-ton actuator with a 24:1 gear reduction ball screw, which allows the system to apply a force of 5 tons to the specimen. A stepper motor with a 100:1 gear reduction allows for very precise control of the actuator. A separate position sensor is mounted to the actuator to monitor the position of the actuator.

Materials and Degradation: High-temperature creep is relevant to several of the AdvSMR concepts that are being considered, including the liquid-metal and high-temperature gas reactor concepts. The mechanism also enables the verification and validation of several concepts unique to proposed AdvSMRs, including multiple phases of degradation that require monitoring, variable loading, and long-term effects in harsh environments. Initial studies are being conducted using austenitic stainless steel, though the test-bed may be used with other structural materials of relevance to AdvSMRs.

Accelerated Aging and Simulation of Operational Conditions: The ability to independently control temperature and load on a specimen enables the application of different stressor profiles on the test specimen to perform accelerated aging tests as well as simulate stressor profiles for different operational conditions in AdvSMRs.

ITEM NO.	PART NUMBER	DESCRIPTION	QTY.
1	Press Upright	X	2
2	Foot	X	2
3	Press Top Mount	X	1
4	Universal Mockup	eel Take-Apart Pin & Block Universal Joint 2" Joint Diameter, 5-7/16" Overall Length	1
5	Load Cell	X	1
6	Cold Block	X	2
7	Ball Screw Actuator	X	1
8	Nema 56 Bell Housing	X	1
9	Gearhead	X	1
10	Gearbox Coupling Plate	X	1
11	Shaft Coupler	FLEXIBLE SPIDER COUPLING	1
12	Plate, Actuator	X	1
13	Heater Main Swival Block	X	2
14	Shaft Main Pivot	X	1
15	Heater Pivot Block	X	2
16	Heater	X	1
17	2380K28	Zinc-Plated Steel Two-Piece Clamp-on Collar 1-1/8" Bore, 1-7/8" Outside Diameter, 1/2" Width	6
18	Shaft Heater Pivot	X	1
19	Press Lower Mount	X	1
20	91247A739		4
21	50785K115		1
22	Electrical Box Mount Block	X	4
23	Electrical Box Mount Plate	X	2
24	Electrical SmallBox Mount Plate	X	2
25	Duff Norton Anti Rotation Block	X	1



Figure°B.1. Design Schematic of Creep-Test Frame

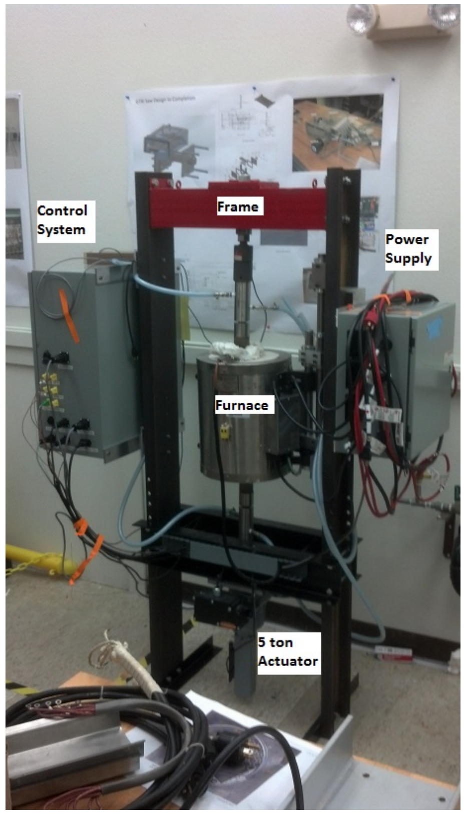


Figure B.2. Laboratory-scale High-temperature Creep Test Machine

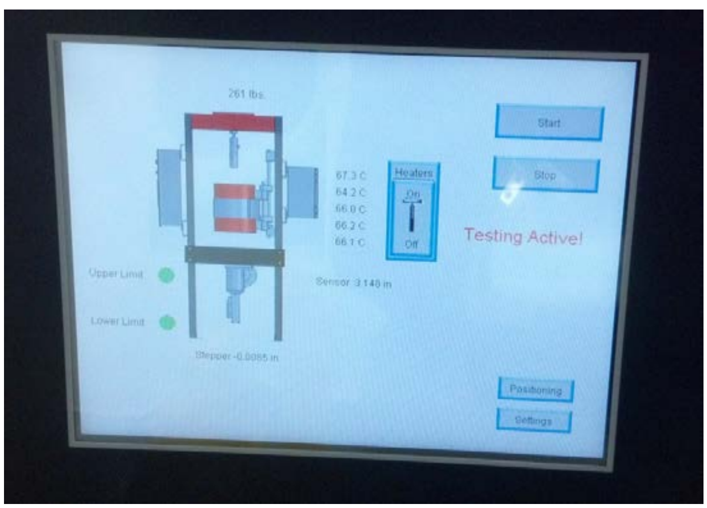


Figure B.3. Main Screen of the User Control Interface for Creep System to Validate Prognostic Algorithms

<u>Measurements</u>: A measurement protocol has been developed that enables periodic condition measurements on specimens in the creep test-bed. Each specimen is placed in the test-bed and subjected to elevated temperatures and loading for a prescribed time period. After this time, the specimen is

unloaded, allowed to cool, and NDE measurements are performed. The specimen may be either re-inserted into the test-bed after the measurements (for an additional cycle of creep-testing, followed by more measurements), or set aside for future destructive testing. NDE measurements that are available for use with this test-bed include:

1. Nonlinear ultrasonic testing
2. Ultrasonic through-transmission testing
3. Eddy current testing
4. Magnetic Barkhausen emission
5. Digital measurements of thickness and width
6. Linear strain assessment using a Smartscope

As described earlier, measurements of the stressor variables (temperature, load, position) are also recorded and time-stamped.

B.3.2 Component-scale and Global-scale Measurements

The creep test-bed is flexible enough to be modified for future component-scale and system-scale measurements. Specifically, the system may be augmented to incorporate a small-scale flow-loop that includes the ability to change (and monitor) temperature, loading, and chemistry. Figure B.4 presents a simplified concept diagram for such an extension, and shows a tube-within-a-tube arrangement that may be used for inducing localized degradation (such as corrosion or creep) while studying its effects on component- or system-level measurements (such as flow-induced vibration). The diagram does not show a furnace or heat source; however, such a source may be included through the use of induction or resistance heating, or a conventional furnace.

As the test-bed grows to include component- or system-level features, additional measurements will be needed to evaluate the ability to measure and monitor the growth of degradation in larger-scale test specimens. For this purpose, accelerometers and acoustic emission sensors can be used to augment the periodic localized measurements listed above. In the example of concentric tubes, the sensors may be placed inside the inner tube to protect them from a corrosive environment in the space between the tubes. The test-bed contains sufficient flexibility to allow other measurement techniques (and sensor locations) as needed.

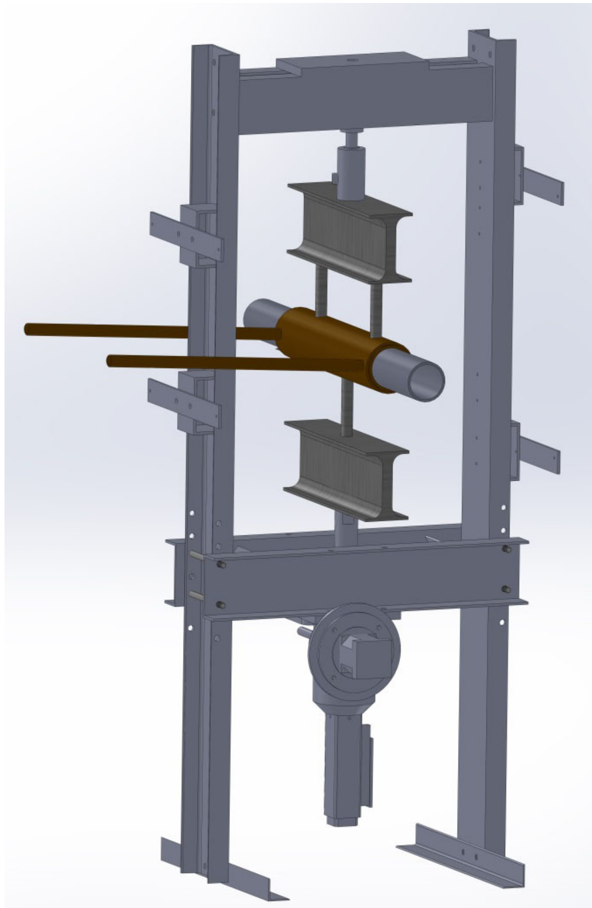


Figure B.4. Concept Drawing, Showing a Potential Modification to Creep Test-Bed, to Enable Testing of Scaled Versions of Components

B.4 Summary

A test-bed concept has been developed to acquire condition and process measurements for evaluating the proposed hierarchical PHM system and associated prognostics algorithms. The test-bed for evaluating prognostics based on localized measurements has been built and is currently in use. Future modifications to this test-bed are envisioned to address measurement needs at component- and global-system levels.

In addition to the test-bed described here, PNNL is exploring the possibility of accessing other test-beds or component-scale test facilities that may be available within the national laboratory complex, or at universities. This effort to determine available facilities and any access restrictions is at an early stage, and information gathered during this effort will be documented in future reports.

Ongoing efforts in this project revolve around using the test-bed to acquire a range of NDE measurements on creep-damaged specimens, and using the data to evaluate and improve prognostics algorithms.

B.5 References

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