Role of Prognostics in Support of Integrated Risk-based Engineering in Nuclear Power Plant Safety

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ABSTRACT

There is a growing trend in applying a prognostics and health management approach to engineering systems in general and space and aviation systems in particular. This paper reviews the role of prognostics and health management approach in support of integrated risk-based applications to nuclear power plants, like risk-based in-service inspection, technical specification optimization, maintenance optimization, etc. The review involves a survey of the state-of-art technologies in prognostics and health management and an exploration of its role in support of integrated risk-based engineering and how the technology can be adopted to realize enhanced safety and operational performance. An integrated risk-based engineering framework for nuclear power plants has been proposed, where probabilistic risk assessment plays the role of identification, prioritization and optimization of systems, structures, and components, while deterministic assessment is performed using a prognostics and health management approach. Keeping in view the requirements of structural reliability assessment, the paper also proposes essential features of a 'Mechanics-of-Failure' approach in support of integrated risk-based engineering. The performance criteria used in prognostics and health management has been adopted to meet requirements of risk-based applications.

1. INTRODUCTION

Nuclear power, with over 430 nuclear power plants (NPPs) operating around the world, is the source of about 17% of the world's electricity. The nuclear industry has arrived at a point where it is dealing with two major issues. First, addressing life extension for legacy units while complying with present day safety regulations. Second, designing new systems with enhanced safety features so that the core damage frequency meets the target of 10^{-6} failures per reactor years or less. The literature available suggests an increasing role for a risk-based (RB) / risk-informed (RI) approach to the design, operation, and regulation of nuclear power plants in order to improve safety (IAEA, 2010; IAEA, 1993, 2010; Kadak and Matsuo, 2007). Even though the risk-based / risk informed applications are growing for many engineering systems, like process or chemical plants, aviation systems and many societal applications, the applications to NPPs have inherent / specific aspects that need to be addressed. These requirements are implemented by employing a defense-in-depth approach through a) Efficient and fast acting mechanisms to address dynamics of nuclear reactions, b) highly reliable and effective cooling systems to remove the decay heat, c) maintenance containments by series of barriers to contain source of radioactivity, c) maintenance of emergency measures in general and long terms consequences. Level 1 Probabilistic Safety Assessment (PSA) models allow development an integrated model of the plant that enables assessment of core damage frequency, i.e. statement of safety. These PSA models are employed to develop risk-based applications for nuclear power plants. The prognostics approach requires development of models and methods for irradiation induced degradation. Apart from this the aspects related to accessibility to reactor core components is a special issue that needs to be addressed while developing applications of prognostics as part of a risk-based / informed approach to NPPs.

However, the major limitations in the risk-based approach in its present form are a) it is not capable of handling dynamic scenarios, e.g. fault trees and event trees are static in nature, b) uncertainty in prediction of life and reliability of components and systems, c) no well defined framework in monitoring / tracking the performance of the system and d) no mechanism to generate input for dynamic PSA models. The prognostic approach is promising to overcome or reduce the above limitations. Since, the prognostic framework envisages on-line monitoring of precursor and feature extraction towards predicting degradation trend and the life of the component. This feature enables application of dynamic PSA while reducing uncertainty in life or reliability prediction as the predictions are based on real-time operational and environmental stresses. The failure mode, effect and criticality analysis performed as part of a prognostic approach provides an effective framework to monitor the precursor parameters. The predictions, so performed provide required input to dynamic PSA models and updates of the risk models in real-time. This paper presents a role for prognostics - a relatively new paradigm, as part of risk-based approach to extend the present activities of monitoring, surveillance, in-service inspection, and maintenance from the periodic to condition-based through the application of prognostics methods.

The major elements of prognostics are online monitoring of precursor parameters and the detection of deviation from the reference conditions using prognostic algorithms (Pecht, 2008). Here, the evaluation of remaining useful life (RUL) for the monitored component or system and the use of insights from this evaluation is a crucial part of risk-based / risk informed applications (Coble and Hines, 2010). Figure 1 shows the major steps in prognostics as part of integrated risk-based engineering (IRBE) applications. The main aim here is to monitor the degradation in a dynamic manner and enable prediction of the failure well in advance so that failure can be avoided altogether or advance action can be taken to repair or mitigate the consequences associated with the failure.

Traditionally, the nuclear industry has employed online status monitoring of safety and process parameters so that any deviation from the reference operating conditions can be detected in time and, if necessary, automatic safety actions can be initiated. Also, there exist various levels of defense in the form of alternate provisions that provide coping time for systems and equipment should the preceding level of defense fail.

However, there is a need to predict the life and reliability of each level of defense in order to enhance the safety of a plant. The prognostic approach facilitates the health management of systems and components based on the remaining life prediction of components. Even though in the current generation of plants, prognostic principles are used in the form of qualitative reliability and life attributes, the full potential of prognostics has yet to be realized through the formal implementation of a prognostics-based health management program.

The available literature shows that the role of prognostics is growing in many fields of components and systems where safety forms the bottom line, such as in aerospace (Wheeler, Kurtpglu and Poll, 2010), electronics systems (Kalgren et.al.2010; Bhambra, J.K, 2000; Mishra et. al., 2004)), telecommunications, and structural systems (Guan, Liu, Jha, Saxena, Celaya, and Geobel, 2011).

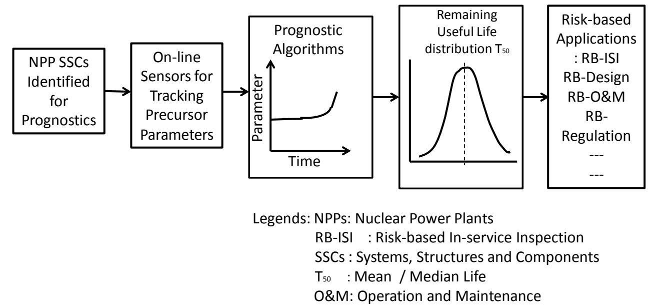


Figure 1. Simplified representation of prognostics as part of integrated risk-based application.

Specific engineering applications include prognostics for bearings and gears (Klein, Rudyk, Masad, and Issacharoff, 2011), engine/turbine condition monitoring (Wu, 2011; Hyres, 2006), aircraft engine damage modeling (Saxena, 2008), aircraft ac generator model simulation (Tantawy, Koutsoukos, Biswas, 2008), health monitoring of lithium ion batteries (Chen and Pecht, 2012), and development of an intelligent approach in support of diagnostics and prognosis (Chen, Brown, Sconyers, Zhang, Vachtsevanos and Orchard, 2012). Based on the experience in these fields and the knowledge that has been generated over the years, it can be argued that a prognostics-based approach, as an extension of a condition-monitoring approach, is expected to go a long way to address the surveillance and monitoring requirements of new as well as old nuclear plants. For old plants, the life extension program can be implemented on a sound footing by integrating prognostics and health management models to complement the risk-based approach. For new systems, enhanced safety can be achieved by the implementation of prognostics-based health management of systems and components. To realize risk reduction through the prognostic approach, design specifications should ensure that a plant is built with online monitoring capabilities for the identified precursor parameters. This basic setup will focus on online prediction of remaining life and reliability considering the postulated loads and stresses such that risk reduction by detecting failure in advance can be realized. The same approach applies to legacy plants also. In these plants, the existing sensors and monitoring systems can be adopted in support of prognostics, like the vibration monitoring data on rotating machines can be utilized for prognostics and health management. It is relatively easy to install a vibration monitoring network for existing check-valves. However, there will be issues related implementing on-line monitoring for some specific locations (e.g. for in-core and reactor support and structural components which may not be easily accessible). For these systems the monitoring of derived or secondary parameters may work. For example the annulus gas monitoring system provides information of leakage, if any, as an on-line assessment for integrity of coolant channel in the existing fleet of Pressurized Heavy Water Reactors. Periodic inspection, installation of coupons (e.g. to assess corrosion of sub-soil piping) may also provide effective approach in the absence of on-line monitoring for existing plants.

This paper presents a review of the current approaches to monitoring and surveillance. We assess the prognostic requirements as a part of an integrated risk-based approach for old and new NPPs. Even though the implementation of prognostics varies depending on the type of components and the objective of prognostic applications, this paper emphasizes proposing a general framework that addresses the basic or broader aspects of various applications. The prognostic performance metrics and other related issues that are relevant to NPPs are also discussed.

2. SURVEILLANCE AND CONDITION MONITORING IN NUCLEAR PLANTS: A BRIEF OVERVIEW

The design safety philosophy for nuclear plants requires the implementation of defense-in-depth, fail-safe criteria: the design is fault-tolerant to the extent that a single failure event will not adversely affect plant safety. The selection of online process parameters and associated limiting condition settings ensure the monitoring of all postulated conditions and the taking of timely action such that safety is not compromised. Most of NPPs operating world over belong to first- and second-generation systems. Based on the accumulated operating time logged by the operating NPPs, the average life of the NPPs works out to be over 20 years (Bond, Doctor and Taylor, 2008; Bond, Tom, Steven, Doctor, Amy, Hull, Shah, and Malik, 2008). In general, NPPs have a design life of more than 40 years. The evidence of aging may manifest in many ways, like frequent failure of components in process and safety systems and subsequent interruption of plant operation, overall reduction in plant availability, adverse impact on available redundancy or safety margin in safety systems, etc. (IAEA, 1995; IAEA, 2009b). With effective inspection and maintenance practices, degradation due to age can be managed and operational life can be extended. For over 30 years the United States (U.S.) nuclear power industry and the U.S. Nuclear Regulatory Commission (USNRC) have worked together to develop aging management programs that ensure the plants can be operated safely well beyond their original design life (Gregor and Chokie, 2006).

Third generation plant designs are characterized by the use of inherent safety features such as negative void coefficient of reactivity, incorporation of passive features, the shift from analogue to digital plant protection systems, and added redundancy from 2-out-of-3 in second generation to 2-out-of-4 trains and channels (including the control and protection system and improved accident management features in containment). Application of the leak-before-break concept in design and operation has been associated with new plants. Apart from this, condition monitoring using vibration signatures, current signatures, insulation resistance assessments, temperature trends, acoustic signatures and other process parameter variations forms part of diagnostics and in a limited way prognostics assessment of the third generation plants components and systems. Some examples of condition monitoring include assessment of the health of the fuel by online monitoring of radiation level, assessment of rotating machine mechanical bearing condition based on online or off-line measurement of vibration and temperature, current signature analysis to assess the health of induction motors, electromagnetic interference mapping to assess the effect of magnetic field, pump shaft performance monitoring using eddy current technique, exhaust air temperature and smoke quality monitoring to assess health of the diesel generators, and oil sample analysis for foreign material to assess degradation and wearout of mechanical parts.

There are also examples of built-in-test (BIT) facilities for online diagnostics in systems and control systems. For safety channels, the protection channel will be activated only when there is demand. In these types of systems, the latent fault remains passive and reveals itself only when a channel is required to be activated. For such cases periodic testing is conducted to reveal a passive fault so that a system is available when there is an actual demand. However, the test interval determines system availability. The safety objective requires that the channel should be tested as frequently as possible to ensure the maximum availability of the channel. For a protection channel this testing is conducted by incorporating a fine impulse test (FIT) feature. An FIT module sends an electrical pulse of very short duration of around ~2 milliseconds. This duration is long enough to test electronic cards but short enough to not activate an actuation device, such as an electro-magnetic relay as actuation of a 48 VDC relay requires a signal that prevails at least for ~ 40 milliseconds.

From the structural health monitoring point of view, annulus gas monitoring, where CO_2 gas is passed between an annular gap between the pressure tube and a calandria tube, is a good example of condition monitoring (IAEA, 1998; Baskaran, 2000). The dew point of the CO_2 is monitored at the exit point of the channel to identify any indications of leak. Any increase in dew point from the reference dew point of around -40^{o}C indicates a possible leak in the annular region from the pressure tube or calandria tube and prompts an analysis of the region. This is an example of an implementation leak before the break strategy in real-time mode. The examples listed above are not exhaustive. They indicate the state of the art in operating nuclear plants that have condition monitoring provisions and limited features for prognostics. However, this background provides a basis for identifying gap areas for the implementation of prognostics and health management program as part of a risk-based approach.

Component / System type (*Representative items*)	M	OFL ISI	OFL CM	OFL D	OFL P	ONL D	ONL P	Remarks / (references)
a) Reactor Structure: Reactor Pressure Vessel, ***Coolant Channels***, Reactor block, Reactor vault and its lining, Shielding structures, Steam Generator, and associated fittings and penetration and nozzles, and, Ventilation plenum and ducts etc.	***	****	***	***	****	***	**	The life prediction for Candu / PHWRs) coolant channels (pressure tube; IAEA, 1998; Dharmaraju, 2008; Chatterjee, 2012)
b) Non-Reactor Structure: ***Containment*** and civil structures, Fuel Transfer and Storage block, Overhead tanks and reservoirs, Airlocks, Structural support, RB Dampers, Bridges and jetties**,** guide and support etc	****	****	****	***	***	***	**	Structural health prediction in R&D stages.(Andonov, 2011; Coble, 2012),
c) Mechanical Components: ***Pumps*** **& Turbines**, **Piping**, Valves, Heat Exchangers (Shell and Tube and plate type, Fueling Machine, Fans and Dampers, Hydraulic drives and systems, Strainers and Filters, Bearings, Diesel Generators, Compressors, Cranes, Travelling water screens, etc	****	****	****	****	**	***	***	State of the art is available on on-line diagnostics. Prognostics in R&D stages, (Heng A, 2009; Samal, 2010; Coble, 2012)
d) Electrical Power System: Electrical buses and cables, HV Transformers, **Motors**, Breakers and Isolators, Power Relays, Motor Generator / alternator Sets, Battery banks etc.	****	***	***	***	***	**	**	CM for rotating machines. (Heng, 2009)
e) Power Electronics systems: ***Un-interrupted Power Supplies***, Convertors, Invertors and rectifiers etc.	***	**	**	**	**	**	*	R&D work on Capacitor, IGBT reported. (Yin, 2008; Smith, 2009; Ye, et.al., 2006)
f) Micro-electronic Systems: ***Digital Cards***, ICs, PLCs and FPGAs, interconnects and Control Cables, Control Connectors etc.	****	***	****	***	**	****	**	Prognostics in R&D stages (Pecht, 2008)
g) Process Instrumentation: Electrical and Pneumatic ***transmitters***, Level, Pressure and Flow gauges, RTDs and Thermocouples, Impulse tubing, Control Valve telemetry, Solenoids, pH, Conductivity meters.	****	****	****	***	**	****	**	Smart sensors and periodic calibrations, (Hashemian, IAEA-CN-164-7S05)
h) Nuclear instruments: ***Fission Counters***, Ion Chambers, etc.	****	****	****	***	**	****	**	Often saturation characteristics indicate reaming useful life.

Note: The characterization of the metrics has been done considering the 'representative items' identified in column with 'bold and italics'.
Legends: M*: Monitoring;* ***CM****: Condition Monitoring,* ***D****: Diagnostics;* ***P****: Prognosis;* ***OFL****: Off-line;* ***ONL****: Online; ISI: In-service-Inspection;*
*'****': Technology Available for NPPs; '***' : Technology Available further qualifications are required for specific applications;*
*'**': Technology in R&D domain, feasibility demonstrated; '*' : Work initiated; x : No work reported in literature.*
IMPORTANT: The items shown in table provide an overview and do not claim, in any way, to provide specifics/guidelines.

Table 1: Categorization of SSCs and Status of Monitoring, Diagnosis and Prognostics in Existing (up to Generation III NPPs)

The first step in implementing a prognostic program for a complex system such as an NPP is to classify the systems, structures, and components (SSCs) into different categories, keeping in view the NPP's design and operation characteristics that will also determine the type and level of prognostics. The classifications and categorizations performed in this paper are not comprehensive but rather indicative. The objective here is to present the state of the art of monitoring for these components from the point of assessing the prognostic maturity level for these components. Table 1 shows the status of online monitoring, condition monitoring, in-service inspection, and diagnostic prognostics. This categorization has been primarily done keeping in mind the pressurized heavy water reactor systems and components and is representative and not exhaustive. The basic idea is to categorize the systems and components, as shown in Table 1, keeping in mind the reactor type and prognostic requirements. The following are points drawn from this table with respect to criteria required for the classification of NPP SSCs, the status of various surveillance methods, and existing gaps in the implementation of prognostics:

This classification is required for both new and old reactors. In fact this table provides a good starting point to generate prognostic specifications for the new design. In each category, the representative components are chosen such that they fulfill one or more of the following criteria: the component allows prognostic implementation (the most challenging), the component allows prognostic, diagnostic, in-service-inspection or condition monitoring implementation, the component represents a typical sample from the category, and that for other components in the group, prognostic implementation will be similar to the representative component. The monitoring program has matured for all the categories of components in NPPs. In-service-inspection (ISI) is applicable to mechanical components in general and piping and associated fittings in particular. It may be noted that the capability of ISI in terms of various coverage factors such as detection, location, and isolation remains a subject of research and development (Coppe, Haftka, Kim, and Bes, 2008). The surveillance activities, which include testing and maintenance, performed on electronics channels and electrical power supply systems have also been categorized under the ISI program. Condition monitoring programs for reactor coolant channels, pumps, motors, bearings, reactor containment, fission counters, and transmitters is mature in NPPs.

Generally, diagnostics is provided for selected components, such as diesel generators, pumps, and digital cards. For example, the complete protection channel is monitored in an online mode for detecting failure of any card using a built-in-test or a fine impulse test facility.

There are many examples of online surveillance and health management programs in NPPs. Some of the examples include coolant channel inspection activities (item (a) in Table 1) in a pressurized water reactor or an advanced aging management program for mechanical components. Similarly, the fine impulse test facility for monitoring all the redundant channels (item (f) in Table 1) is also an example of a Verification and Validation (V&V) tool for the health assessment of electronic parts of protection channels. The saturation characteristics of ion chambers or fission counters provide an online indication of the remaining life of these components. However, regulation and protection channels only have diagnostic features, and research and development is required for the implementation of prognostics for these components.

At the component level, the condition monitoring of rotating machines using vibration and temperature monitoring and diesel generators sets are arguably a mature health management program, except that they lack the capability of life prediction. Our literature search suggests that online prognostics either have not been developed or still in a research and development stage for most of the components in NPPs.

3. Integrated Risk-based Approach

The term 'risk' in nuclear parlance deals with assessing the likelihood and consequences for a given scenario. When the modeling is performed considering risk as the major objective metric by integrating probabilistic and deterministic methods, then the approach is called as integrated risk-based engineering (IRBE). Even though the majority of risk modeling is performed considering hardware failures, incorporation of human factor modeling into plant modeling also forms a significant feature of risk models. Another major feature of this approach is that it provides a quantified statement of safety (Tsu-Mu, 2007). Deterministic criteria, design, and operation information form part of the risk assessment to reflect a realistic representation of the plant model. There are many approaches to risk assessment, including hazard and operability analysis, failure modes and effects analysis (FEA), what-if approaches, cause/consequence analysis, and quantitative methods for nuclear plants. The probabilistic risk assessment (PRA) methodology is a well-accepted methodology for risk assessment of the plant. Apart from this, probabilistic interference modeling using stress-strength distribution approaches is also used for determining failure criteria at the component level. The following section provides a brief discussion on PRA, as this approach handles the probabilistic element of the integrated risk-based approach.

3.1. Probabilistic Risk Assessment

Probabilistic risk assessment (PRA) is an analytical approach to predicting the potential off-site radiological consequences of accidents for a nuclear power plant and research reactor. PRA is performed at three levels. Level 1 PRA deals with system modeling to provide estimates of core damage frequency. Level 2 PRA deals with the release mode and mechanisms from reactor containment to provide estimates of radioactivity release frequencies for various source terms. In level 3 PRA consequences for various releases are estimated to provide an assessment of risk. As level 1 PRA deal with SSCs modeling level 1 PRA is directly relevant to prognostics application. Hence, for prognostic applications, results and insights from level 1 PRA with assessments of system-level unavailability and core damage frequency as indicators of safety are proposed in this paper.

The major elements of level 1 PRA methodology include: identification of the postulated initiating event (both internal and external), assessment of the response of the plant using event tree methodology, modeling for safety system failure employing a fault tree approach, quantification of the model by using failure data including human error probabilities and common cause failure data, etc., iterative simulation of an integrated plant model to estimate the core damage frequency and uncertainty bounds, and sensitivity analysis for critical assumptions made during the study. Figure 2 shows the general level 1 PRA methodology.

Risk-based applications, such as an equipment surveillance test interval and allowable outage time optimization, precursor event identification and analysis, evaluation of emergency operating procedures, and risk monitoring for plant configurations studies are generally based on level 1 PRA studies. The reason for this is that level 1 PRA deals with modeling plant configurations with consideration of component failures, human actions, test and maintenance data, and operational procedures and plant technical specifications to predict unavailability and core damage frequency at system level and plant level. Accordingly, we deal with level 1 PRA, wherein the estimates of core damage frequency represents a statement of risk.

PRA methodology can be considered mature enough to be used in decision support. The main reasons for the growth of this field are because it enables the quantification of the statement of plant safety by estimating the core damage frequency and unavailability at the system level, it provides a mechanism to capture random elements of safety characterizing uncertainty in safety and performance estimates, it provides a strong framework for integrated performance of SSCs into the model of the plant, and it facilitates integration of the human factor into an integrated model of the plant. When the PRA framework is employed in support of regulatory decisions, then the application is called “risk-informed.”

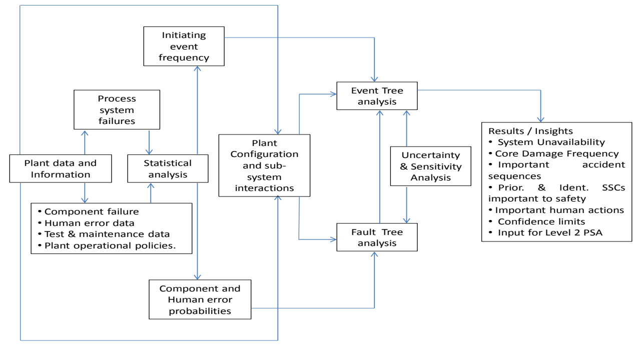


Figure 2. Level 1 PRA methodology.

3.2 Role of PRA in Risk-based Applications

PRA provides a systematic framework for the identification of safety and reliability issues, safety-based prioritization of components, human actions, and assessment of plant configuration. The major result of PRA is a statement of core damage frequency per year, while the assessment of design strength and weaknesses of the plant, characterization of uncertainty, and sensitivity analysis also form part of the major insights.

The level 1 PRA model and framework is used for many risk-based applications, including risk-based design optimization, risk-based in-service inspection, risk-based maintenance management, risk-based technical optimization, risk monitoring, and precursor analysis. Among these, the risk monitors are used to address real-time issues and have gradually become an integral part of the operation of NPPs in many countries. This is the reason why PRA applications are becoming an integral part of regulatory review as part of a risk-informed approach (Tsu-Mu, 2007).

3.3 Living PRA and Risk Monitor

Even though the traditional approach to PRA modeling is static in nature, the application of PRA as ‘living PRA’ and ‘risk monitor’ make this approach in a limited sense dynamic in nature. The living PRA approach ensures updating of the plant PRA model on a periodic basis such that it reflects the as-built and as-operated features of the plant. These living PRA models are updated based on modifications or change in operating procedures or regulatory stipulations. Changes are documented in such a way that each aspect of the model can be directly related to existing plant information, technical specifications, and emergency and normal operating procedures. The verification of assumptions within the analysis and the associated sensitivity analysis forms part of living PRA approach (IAEA, 1999).

There is a noticeable growth in on-line application of PRA as risk monitor. These risk monitors provide assessment of risk for real-time changes in equipment configurations and technical specification parameters like allowable outage time or change in test intervals, etc. Risk monitors reflect the current plant configuration in terms of status of the various systems and components. Basically, risk monitors are developed as an operator aid in decision-making support in the plant control room environment. The operator may like to assess change in risk levels for an action involving, for example, taking any components out of service for maintenance or tests. Given the above background, living PRA and risk monitors make the risk assessment process dynamic in a limited sense. This means that it addresses discrete events/changes in time not in the continuum sense of time. The risk monitor models should be consistent with living PRA models and should be updated at least with the same frequency as living PRA models (NEA/CSNI, 2005). The change in core damage frequency or core damage probability for a given scenario assessment and its comparison with the quantitative criteria is used in support of decisions as part of risk-informed approach.

3.4 Limitations of the Risk-based Approach

The risk-based framework in its present form is essentially ‘static’ in nature and often incapable of conducting evaluations involving dynamic scenarios evolving in through time. Hence, there is a need to make the whole approach more dynamic in nature for addressing real-time scenarios. It must also account for degradation, which is inherent in systems and components, and have a predictive capability with reasonable accuracy such that it can provide a time window for corrective actions. It should also have risk mitigation or management features. This is where a prognostics approach can enable evaluation of dynamic scenarios. The probabilistic tools and methods, on the other hand, can provide the required framework for assessment of available safety margins and characterization of uncertainty. This approach has been extensively applied to mechanical and structural systems, like risk-based in-service inspection of piping and structural systems, risk-based maintenance for process systems, etc. However, radiation-induced degradation poses a challenge to life prediction of structural components in NPPs. There are some areas in NPPs where radiation-induced degradation modeling and assessment have been performed to predict the remaining life of structural systems, such as pressure tube life prediction in PHWRs and CANDU reactors, reactor vessel health assessment modeling, and aging of control and power cables. However, these pose a challenge to the assessment of life of in-core components. Extensive research and development is being performed to implement this approach for micro-electronic and power-electronic systems (Tsu-Mu, 2007; Patil, et. al., 2009).

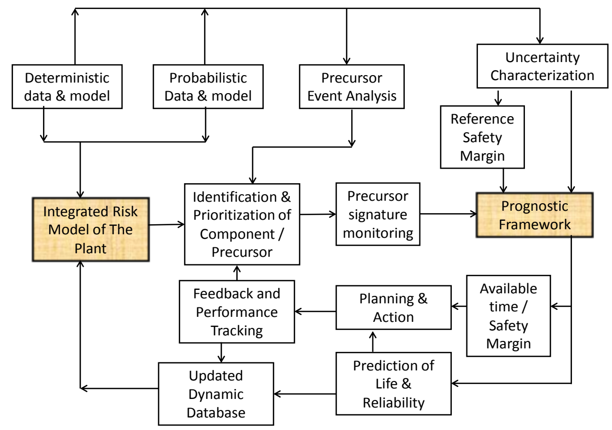


Fig. 3 Interrelationship of IRBE and prognostics approach.

4. PHM and IRBE

Figure 3 shows the interrelationship between integrated risk-based engineering (IRBE) and a prognostics framework. As can be seen, the deterministic and probabilistic methods together can be used to build an integrated risk model of the plant. The integrated risk model provides information about safety issues in general, which is vital for the implementation of prognostics. This includes information on components and modes and sequences of system failure, which are precursors that can form candidate components for implementation of prognostics. From here the organization gets vital input to focus on a small group of safety-critical items to improve technical specifications. This approach provides a valuable tool for prognostic coverage so that maximum benefits can be realized by investing the available resources.

While probabilistic input is critical for uncertainty characterization in prognostics, the overall effect is to help in the assessment of a safety margin at the reference level. Once a prognostic assessment is performed, it is possible to understand the safety margin in a dynamic manner. The prognostic strategy complements the present risk-based framework by online performance tracking and generation of feedback for operators as well as regulators. The overall gain from the implementation of a prognostics strategy is that it allows the assessment of safety issues by predicting life, reliability, and prognostic distance in a dynamic manner.

5 REQUIREMENTS OF PROGNOSTICS FOR IRBE APPLICATIONS

There are three major areas that need to be strengthened in the risk-based approach. These include dynamic modeling, improved methods for uncertainty characterization, and

Parameter	Applicable Levels				
	1	2	3	4	5
Plant – stage (* and #)	**Under Design New**	**Operating plant (Useful Life)**	**Aged Operating plant**	**Shutdown Under-refurbishing**	**Operating After refurbishing**
Objective (* and #)	Improve Safety	Improve Availability & Safety	Monitoring of remaining useful life	Follow-up after retrofitting	Reduction in Operational Cost
State-of-the-art enabler (*)	Online Monitoring, Off-line Diagnosis.	Online Monitoring Off-line Diagnosis and Conditioning Monitoring.	Online Monitoring, diagnosis and condition monitoring.	Online Monitoring, diagnosis and condition monitoring, off-line prognosis.	Online Monitoring, online diagnosis and condition monitoring, online prognosis.
Subject (* and #)	Micro-Electronics / Digital Control Channels	Power Electronic	Electrical	Structural / Mechanical	Interdisciplinary
Implementation Level (* and #)	Level 1	Level 2	Level 3	Level 4	-
Risk Assessment Approach (* and #)	Qualitative / Deterministic	Failure Mode Effect and Criticality Analysis	Hazard and Operability Analysis	System Level Reliability Modeling Fault tree. Event Tree	Level 1 Probabilistic Risk Assessment (L-1)
Existing Maintenance /Health Management Strategy (*)	Preventive Maintenance and Scheduled Testing	Condition based test and Maintenance	Reliability Centered	Risk-based Test and Maintenance	Online reconfiguration
Stakeholders (* and #)	Design Team	Operating organization	Regulators	-	-
Implementation Approach (* and #)	Model Based	Data Based	Risk-based	Fusion	-
Availability of Tools and Methods / Challenges (* and #)	Prognostic algorithm	Availability of Sensors	Degradation Models	Feature Extraction Methods	-
Cost-benefits (* and #)	In the context of NPPs, cost benefits for a particular level is assessed using safety and availability indicators.				

Legend *: applicable to old plants; # : applicable to new plants

Table 2.0 Prognostics Design Requirement realistic assessment of safety margins. It can be argued that a risk-based approach is a rational one, in that it combines the plant configuration, including operational logic, and performance parameters through probabilistic reasoning. Hence, this approach, in conjunction with the deterministic approach, is expected to provide more flexibility compared to the traditional approach. Apart from this, performance monitoring and generation of feedback following the implementation of changes and modifications forms an integral feature of risk-based engineering. Development and implementation of prognostic program is expected to address the above issues in the following manner:

Develop suitable sensors that can measure a precursor parameter of interest. Assess online the reliability and remaining useful life of the monitored systems based on identified precursors or degradation characteristics. Develop a prognostic algorithm that provides advance remaining life prediction with an adequate time window. Characterize uncertainty in the prediction, instead of point estimates of RUL, such that management issues can be addressed in an efficient and effective manner. Employ multi-objective algorithms that take into consideration risk, cost, and reduction in radiation dose. The prognostic framework should have provision for database, model-based (Physics of Failure (PoF) and Mechanics of Failure (MoF)), and fusion approaches, keeping in view the varying nature of prognostics programs for a range of components, such as mechanical and electrical systems, electronics, and nuclear components. The prognostic algorithm also should have a provision to provide feedback online to track the performance of modifications in a component that has been replaced or has undergone a maintenance procedure or calibration of some instrumentation.

It may be noted that use of input from prognostics may require modification to the existing risk assessment approach. For example, an existing database in the risk-based approach may have only static reliability data, failure criteria, and maintenance and test schedules. However, when the dynamic aspects are implemented as part of prognostic feedback to risk-based engineering, then there is a need to re-organize the complete database framework such that dynamic inputs and outputs can be managed.

5.1 Prognostics Design Requirements

The complex nature of NPP design requires a different set of design metrics that satisfies the requirements of a particular application. There are many areas that require research and development with respect of material degradation, development of special sensors, and suitable algorithms for online feature extraction and analysis. In some situations, the design constraints may make it challenging to implement a prognostic program. Table 2 shows the requirements that can be used for the design of a prognostics program for a given application. The applicability of these parameters for old or new plants is indicated in the table by * and #, respectively.

5.1.1 Plant Stage

The scope of a prognostic program will be governed by such factors as at what stage of the plant the prognostics is being implemented. As mentioned earlier, for the implementation of a prognostic program in new plants, prognostic requirements and specifications should be part of the design strategy. Since the plant has yet to be built, provisions can be made in advance, keeping in view criteria such as safety and availability. Prognostics as part of life extension will have activities focused on select systems, components, and structures. However, the plant's design and operational constraints will dictate the implementation levels. Prognostic requirements for refurbished plants will be similar to a plant whose life has been extended. In a refurbished plant prognostics is useful particularly for those systems where clear insights into the remaining life of certain components is not available, while the cost of bulk replacement would have been prohibitive, and where it is felt that online prognosis and diagnosis would be useful, such as in coolant channels, piping, and power supply cables.

5.1.2 Objective

The objective of prognostics is defined as keeping in view the plant status, logistics, and data and knowledge base, particularly the understanding of the material degradation phenomenon and the availability of prognostic algorithms. For new plants, the institutive reaction will be to go for a model-based approach, while for older plant, where enough data are available, the data-driven approach will be preferred. It should be noted that most of the nuclear plants in the world either have a level 1 PRA model with internal initiating events for full power conditions or a reactor core as the source of radioactivity. These plants have an obvious advantage over using risk modeling to formulate or identify and prioritize a prognostic program. The available literature shows that most prognostic implementations produce improvement in availability and cost-benefit objectives (Hyers et al. 2006). There have been applications of prognostics to aircraft health monitoring, where the emphasis has been on safety. There have also been applications of PHM with mission safety as a driving force.

5.1.3 State of the Art

The state of the art refers to the current status of monitoring and surveillance methods used in a plant. If a plant is in the design stage, metrics may include the requirements for monitoring and health management. Provisions can then be made throughout the design stage for implementation of prognostic program. However, in the operating plants the existing sensors/provisions, and new sensors will determine the level and scope of prognostic. Generally, the state of the art in the current generation of plants facilitates the online monitoring of important safety parameters and condition monitoring and surveillance. Such programs are not fully automated, however; the diagnosis is performed in off-line mode for most systems. There are closed feedback loops wherein corrective actions are automatic. These feedback loops ensure the maintenance of plant parameters within set limits. These metrics help to determine the specifications and the scope of the prognostic requirements. The available literature on NPPs does not appear to provide information on application of prognostic based on online life and reliability prediction.

5.1.4 Subject

For complex systems such as NPPs most of the systems require an interdisciplinary approach to implement prognostic program. However, particular disciplines may require a unique focus. For example, prognostics for reactor protection channels and structural components such as reactor blocks will differ with respect to degradation mechanisms, the time window available, and the monitoring and sensor requirements. Hence, even though the broad framework may remain the same, the specifics will vary by applications.

5.1.5 Level of Implementation

The level of implementation metric is derived/adopted from the procedure developed by Gu et al., keeping in mind the NPP requirements. In this reference, various levels have been presented for the implementation of prognostics of electronic systems. For complex systems such as NPPs, there are different prognostic levels. Level 0 is the component level, which includes items such as fuel assembly, feeder, bearing, motor, control and power cables, alternator, pipeline, battery, relay, micro-processor chip, switch, and electronic cards. Level 1 includes the assembly of components of a particular class, such as mechanical, electrical, electrical, or nuclear and associated connections that perform a basic function. Examples include pumps with connected piping up to suction and discharge and the suction strainer, a compressor with sub-components such as coolers and associated connections, diesel generators with support systems, and power supply modules, amplifier modules, and function generators. Level 2 includes those systems that are activated only on demand from the plant control system. They can also be referred to as safety support systems such as class III electrical power supply, class II control supply, and class I power supply systems. Level 3 systems include those systems that are required to be operational when the reactor is in operational state, including the main coolant system, class IV power supply systems, feed water systems, regulation systems, and process water systems. The structural systems, such as the reactor vessel and reactor shielding components, reactor pile, and containment building, that are basically passive in nature but require a structural approach for health monitoring are categorized as level 4. These categories are based on the broad characterization of component functional requirements and their place in a system, whether as an independent unit, sub-block, block, major function, or assembly of functions to deliver an objective function.

5.1.6 Risk Assessment Approach

Most NPPs have a level 1 PRA implemented, considering the internal initiating of events for full power conditions. Even though risk-based applications require shutdown or a low power operation PRA, the availability of a full-power PRA can be considered for initiating a PHM implementation program. Apart from this, Failure Modes, Effects, and Criticality Analysis (FMECA) forms an integral part of PHM implementation. It is recommended that a comprehensive FMECA program should be initiated, keeping in mind the focus of prognostic implementation.

5.1.7 Existing Maintenance Health Management Strategies

This metric determines the current maintenance strategy, an important reference for building a PHM program. Typically, most nuclear plants use preventive maintenance as the major approach for health management. However, condition monitoring, in-service inspection, and scheduled test and maintenance are the general features for health management. The available literature shows that in some NPPs and industrial systems, reliability-centered maintenance, risk-based in-service inspection, and risk-based technical specification optimizations are also used (IAEA, 1993). The available framework is important, as the data generated on the maintenance and health of these systems and pieces of equipment form the fundamental part of the data-driven approach for prognostics. Along with inputs from risk models, these data and insights will help to identify and prioritize the prognostic program.

5.1.8 Stakeholders

Though stakeholders are not a metric, they affect which agency is interested in prognostic applications. The designers would like to have a prognostic program for identified systems or as part of a design policy for systems that they feel will determine the life of the plant. These could be in-core components or structures that form an integral part of systems such as reactor vessels, pile blocks, storage pool linings, or containment, or it could be some safety or process system for which it is important to track performance. For operational agency, it could be certain aspects of the plant that affect plant availability, such as performance of the strainer, check valves, and certain pipelines and bearings, which require continuous monitoring and remaining life assessment such that repair and replacement of these components can be scheduled to improve plant availability. Regulatory agencies want to track the performance of a system where the changes have been implemented. Here the role of prognostics is to provide feedback on the remaining useful life or performance monitoring of a system for a specified period of time or for an extended duration to ensure that safety has not been compromised.

5.1.9 Approach for Implementation

The approach to prognostics implementation is governed by many factors, including the objective or purpose of prognostics, the level of detail required the availability of data, and plant constraints. For argument's sake, if a prognostic program requires performance monitoring as part of a risk-informed or risk-based approach, then the focus will be on monitoring the performance metrics of the system under regulatory review. If a prognostics program is being designed for a new plant where the objective is to strengthen the safety function, then the task should include the prognostic specifications in the design phase and keep provisions not only for online monitoring but also for the implementation and management of the health of the plant. If prognostics is being implemented as part of a life extension strategy, then it must be noted that the focus should be on structural remaining life assessment. As a rule, NPPs require close monitoring of structural health, particularly where safety is the major metric, even if it has not entered the aging phase.

5.1.10 Tools and Methods

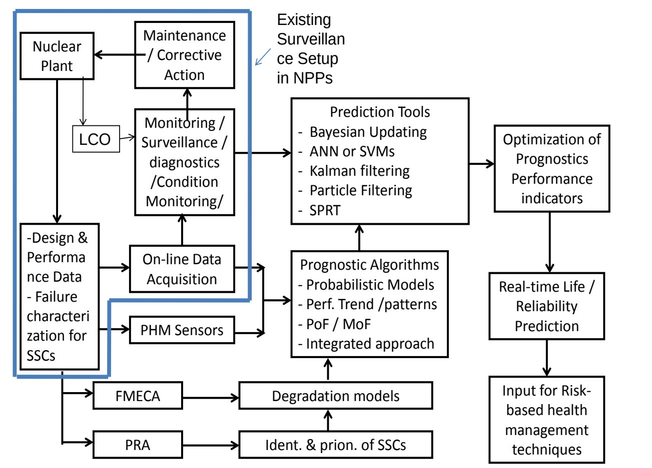
Prognostic tools and methods are identified only when FMECA has been performed, precursors have been identified, and the broad approaches, including data-driven and PoF-based, have been evaluated, keeping in mind the requirements of applications. However, detailed studies, literature searches, or required meetings with consultants may present issues associated with selection of prognostic algorithms, the availability of sensors, the availability or limitations of degradation models, and approaches that will be required for feature extraction, deriving useful data and information from a host of complex data and signatures collected from experiments.

5.1.11 Cost-benefit Studies

The available literature shows that cost-benefit evaluation can be used to demonstrate the net benefit of the implementation of PHM results (Wood and Goodman, 2006). In the context of nuclear plants, benefits need not be in terms of monitory gain; they could be in terms of safety improvement, life extension, or lessening the burden on the operating staff.

4. PROGNOSTIC FRAMEWORK FOR NUCLEAR PLANTS

Major elements of prognostics implementation include monitoring system performance through noise analysis, detecting changes by trending, understanding and identifying root causes of failure, prognostics, and health management (Vichare and Pecht, 2006). Even though there will be variation in the tools and methods, the level of accuracy required when the prognostics is implemented for



Legend: PRA: Probabilistic Risk Assessment; FMECA: Failure Modes, Effects, and Criticality Analysis; SSCs: Systems Structures and Components; LCO: Limiting Condition for Operations; SPRT: Sequential Probability Ratio Test.

Figure 4. Prognostics framework for NPPs.

mechanical, structural, or electrical systems, will remain the same.

6.1 Existing Set-up

Traditionally, online monitoring and maintenance, including surveillance of passive and structural systems, as well as maintenance of active components form an integral part of NPP operations, as shown in Figure 4. The existing approach is shown within the boundary drawn on left side of the Fig. 4. The monitoring provisions exist at the component, system, and plant level. These monitoring provisions are limited to process parameter values and an equipment status display, which indicates various states of reactor operation including transient states. However, condition monitoring and surveillance for many systems is performed in an off-line mode as part of plant policy for selected equipment. Even though condition-monitoring approaches have matured and are being used in the health management, the prognostic quotient in terms of the prediction of remaining life is low. One of the major reasons for this is complexity in terms of material characterization, such as irradiation-induced degradation of core components and structures (Bond et al., 2008). Apart from this, the nuclear industry operates on conservative criteria; hence, strict regulations for design and operation dictate that uncertainty in real-time assessment should be as low as possible. However, in the present situation, advances made in other application areas (such as space, aircraft, and civil) can be implemented in NPPs by incorporating adequate provisions for some identified systems, which can provide insight into the application of prognostics in a graded manner as well as into safety critical systems.

Figure 4 shows the framework for PHM for NPPs. The proposed approach, while utilizing the data and information that is available in the traditional approach, envisages development of prognostic sensor systems to monitor the identified precursor parameters. The data available through the sensors are mapped on the prognostic algorithms to track deviation and therefore provide information on incipient faults. Here, the role of intelligent tools like Support Vector Machine or Bayesian estimation or Sequential Probability Ratio Technique is to predict the prognostic distance such that action can be taken well before the situation results into safety or availability consequences.

The following subsection deals with major aspects of prognostic implementation which are relevant to NPPs.

6.2 Prognostic Approaches

6.2.1 Probabilistic or Reliability-based Approach

This approach is used extensively to predict the life and reliability of components, be they mechanical, electrical, or electronic components. Even though this is considered to be an approximate approach, the advantage of this method is that uncertainty characterization comes naturally. Often the Weibull distribution is utilized extensively. Other distributions, such as exponential and log-normal distribution, are also common as a life prediction model (Yates et al., 2006; Modarres, Kiminskiy and Krivstov, 2010). The weakness of this approach is that the predictions are based on the past performance data of equipment and components. This implies that the prediction does not account for changed component operational and environmental loads. For example, for a given component in a component database, the failure rate estimations are based on an operational environment where the average temperature and relative humidity is 28^{o}C and 65%, respectively. The condition for which the failure rate estimation is required to work is a ground benign environment of 22^{o}C and humidity of 55%. These environmental conditions are bound to affect the failure rate—in this case, reduction in failure rate. Certain external factors such as vibration and seismic shocks adversely affect the life and performance of a component. If these aspects are not factored into the estimates based on historical data, then the estimates tend to be either optimistic or conservative, depending on the severity levels of the component in the database compared to the component for which failure rates are being estimated. If a given component experiences less vibration and seismic shock than a component with a failure rate estimate based on higher vibration and shocks, then the failure rate estimates will not be accurate. Often these types of situations involving application of PHM approach in real-life situations are handled by providing uncertainty bounds.

This approach involves prediction of the mean life of a component along with its upper and lower uncertainty bounds. A wide uncertainty bound indicates that the prediction is based on limited data sets, that reliance on such estimates should be lower, and that these estimates should be used as an indicator. In such situations, precursor-monitoring techniques such as vibration or temperature monitoring of the components represent an effective strategy for prognostics. The Bayesian model features probabilistic estimates that form a priori and has data coming from the precursor monitoring that can be used as evidence for updating the strategy for prediction (Yates and Mosleh, 2006). So, even though the approach is primarily probabilistic in nature, trend monitoring is used to improve the prediction capability.

6.2.2 Physics-of-Failure-based Approach

The physics of failure (PoF) approach deals with the application of first principle models to understand the various failure mechanisms and thereby predict the remaining useful life and reliability of components. In other words, this approach is based on the development and application of scientific models that predict the life of component. In this approach, unlike statistical approaches for reliability estimation, past performance data is not required (White and Bernstein, 2010). The predictions are based on the component characteristics, such as material properties, geometrical attributes, and activation energy for applicable degradation processes for given environmental, operational, and environmental stressors. Accelerated life testing is central to the PoF approach. PoF enables the identification of dominant failure modes and mechanisms, and thereby precursors for monitoring the health of the component. Failure Modes, Effects, and Criticality Analysis (FMECA) form the cornerstone of this approach to identify and prioritize the applicable degradation mechanisms. Identification of precursors is an important part of this approach. The precursors are the parameters that can be monitored using the available sensors (Patil, Das, Pecht, Celaya and Goebel, 2009). Precursor monitoring provides advanced information about the underlying degradation mechanism.

The PoF model can be expressed in general form as:

$$t_{50} = f(x_1, x_2, x_3.......) \qquad [1]$$

where t_{50} is the median life and x_i is the parameter of the model. The commonly known PoF model for life prediction is the Arrhenius model, which is expressed as follows:

$$t_{50} = A\exp\left[\frac{E_a}{kT}\right] \qquad [2]$$

where A is a process constant, E_a is the activation energy of the process in eV (electron volt), k=Boltzmann’s constant= 8.617*10^{-5} eV/K, and T is the temperature in Kelvin.

There are many more models available to predict life, such as the Eyring model. The limitation of these models is that they only recognize temperature as an environmental stress.

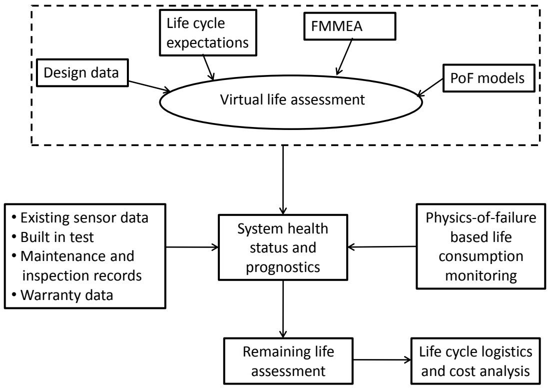


Figure 5. CALCE Physics of Failure Based Approach for Prognostics (Pecht and Gu, 2009).

In real life, there are many environmental and operational stresses.

These models also fail to account for the geometrical and other material mechanical design features such as material finishes and materials of the mating parts. Overall, the challenge translates into assessment of the accurate prediction of activation energy for a given case.

These limitations have led to further research into developing PoF models that take under consideration the various stresses associated with each component in reliability modeling. This became possible with a basic understanding of the physics of degradation of materials under various stresses. Accordingly, accelerated life testing has become central to PoF modeling. Root cause analysis is performed to understand the degradation mechanisms responsible for failure. Figure 5 shows the framework of PoF approach developed at Center for Advanced Life Cycle Engineering (CALCE), University of Maryland, USA (Pecht, 1996).

This figure shows that information about the component, including physical specifications, geometry, construction materials, operating environment (including temperature, humidity, and vibration), and operational stresses (current, voltage, and electric field) forms the main input for modeling.

One of the notable and significant features of the PoF approach is the development and application of canaries (Dasgupta, Doraisami, Azarian, Osterman, Mathew and Pecht, 2010). Canaries are miniature versions of the subject electronic component, which is designed to fail early. This early failure predicts the impending failure of the subject component. The available literature provides examples of the application of canaries for prognostics (Pecht, 2008). It is very important to note that the word “canary” was coined very recently for incorporating a “weak link” or “weak device” into electronic systems. However, the concept of weak link has been used in mechanical and electrical systems to protect major failure in these systems due to over stresses. In electrical systems the “fuse” protects the electronic or electrical system by cutting of power when electrical stresses reach above the pre-designed levels. Similarly, when mechanical components, such as fuel elements that are incorporated with tension members or pins which are designed to fail, before permanent damage occurs to the reactor structural components or in the fuel itself due to over stressing during fuel handling. This weak link concept, coupled with the present knowledge base and further R&D on prediction of remaining life, provides a promising approach to developing canaries for mechanical and electrical systems.

The PoF approach is particularly suited for assessing electronic component reliability. Even though this approach is in the research and development stage, there are many models available for electronic components. The state of the art in micro-electronic reliability shows that greater advances have been made for reliability modeling of micro-electronic components compared to power electronic components.

6.2.3 Mechanics of Failure (MoF) Approach

The root cause failure analysis of mechanical components and structures may differ from the RCA of electronic components. In mechanical components, the RCA often deals with the macro-level. In a few cases the micro-level of investigations is necessary for understanding failure mechanisms, unlike for electronic components, which require developing models and methods that function at the micro- and at nano-levels. RCA of mechanical components may not always require high precision lab facilities, tools, methods, and software. Often, the stress-strength reliability model with prediction capability and within reasonable uncertainty bands may provide satisfactory insights into failure modes and mechanisms. In fact, the failure modes of mechanical components include failed to open, leakage, failure on demand, and blockage. These failure modes can be verified by visual examination, unlike electronic components, where often the information about failure mode is not directly available or based on failure symptoms.

Another important feature included in MoF is a detailed investigation through corrosion-related modeling. These models and investigations deal with various materials, weld joints, environments, stresses (stress corrosion cracking), finishes, and provisions of protection against corrosion.

The failure surface characterization at the macro or micro level, often part of any RCA for mechanical components, provides reasonable results. Apart from this modeling and simulation, using the finite element approach at the macro-level can provide satisfactory inputs. Generally, an accelerated test approach does not form part of the RCA of mechanical components, unlike electronic components where accelerated life testing forms the bottom line. Even though mechanical components can also be modeled using the PoF approach, the nature of prediction and level of treatment required to model mechanical components and structures require the problem to be handled at the macro-level rather than the micro-level. Hence, this paper proposes a collection of tools and methods through an approach called mechanics of failure (MoF) to predict the life of mechanical and structural components. Here, the stress-strain relationship forms the fundamental approach to reliability and life prediction.

Even though this approach is best suited to tackle one of the main bottlenecks of risk-based approach, namely, assessment of the safety margin, the data and the models available so far often form a limitation to predict reasonably accurate safety margins. Accelerated testing methods, probabilistic fracture mechanics approach, damage mechanics, strength of material methods, finite element analysis, and failure analysis methods form the major elements of the MoF approach. Reliability methods are used as part of the MoF approach for making statistical estimates of life. The major degradation mechanisms that are evaluated in this approach include mechanical wear, creep, corrosion, and catastrophic failure. As with the PoF approach, MoF also utilizes root cause failure analysis models for understanding underlying failure or degradation mechanisms. The work performed by Mathew et al. provides a structural analysis of a structural board for NASA and appears to bring out, in a way, the essence of the MoF approach (Mathew, Das, Osterman, and Pecht, 2006). There are many studies in the literature where the objective is to base the prognostics on two major degradation mechanisms—temperature and vibration (Pecht, 2010). Of course, when the application is designed for nuclear core components, irradiation-induced degradation often becomes the leading parameter (IAEA, 1998).

6.2.4 Symptom or Data-based Approach

Generally, this approach is referred as the data-driven approach. This section deals with a data-driven approach, except that here a distinction between various data forms an input for prognostics. For example, a trend monitoring of operational and environmental parameters through on–line instrumentation may provide information about some precursor. A pattern comprising the status of a finite set of alarms as “registered as 1” and “cleared as 0” is another representation of data. A probabilistic distribution of time to failure based of individual components provides time to failure estimates of the systems being monitored. Input can be in the form of linguistic variables in place of a numerical value. All these require different approaches.

The term “symptom-based approach” is used in this paper to extend the context of input data and information used in prediction, particularly for nuclear plant applications. As mentioned above, often information is not available in the form of a numerical value or in the form of binary values (0/1 or yes/no). Instead the information about the model parameters comes from experts in linguistic expressions. This information is not suitable for use as input; however, the information cannot be ignored, as it provides much stronger input for prediction or estimation of remaining useful life. In such instances, treating expert opening, which can be considered imprecise information, using fuzzy algorithms can provide one with improved assessment of imprecise parameters (Chen and Vachtsevanos, 2012).

Second, the reason to have provision for some information is that establishing a pattern is important, as often, instead of a single parameter, a pattern can provide more data and information. For example, a comparative value of three parallel components seeing the same operational and environmental stresses may form a pattern, which may provide an effective mechanism to assess the health of the component and thereby provide an effective input for predicting the remaining life. The only issue is that even this information could be expressed in terms of linguistic variables and will require the fuzzy approach to address the challenge.

This background is an obvious reason to formulate the data and information in two ways: trend monitoring using precursor symptoms and a pattern-driven knowledge-based approach.

6.2.4.1 Trend Monitoring

Trend monitoring is a natural extension of the condition-based approach to diagnostics. Often pump bearing temperature, vibration reading, or a pump shaft that has run out of measurements forms part of a condition-monitoring program in nuclear plants. An expert can predict the time when a piece of equipment will need to be shutdown. This practice is common in industrial environments in general and nuclear plants in particular. In these cases, pump bearing vibration, temperature, and shaft run-out act as precursors for the prediction.

To extend this approach to a prognostic regime, it is required that the deviations be tracked or monitored in online mode, that the failure criteria and associated uncertainty band be assessed for the component in question, that the future operational and environmental loading be used to assess the remaining useful life, that the prognostic distance, which can come from the maintenance logs, be assessed, that the uncertainty in RUL estimates be assessed; and that the degradation rate and alarm be predicted online as soon as the prediction upper estimates overlap with the lower bound of the failure criteria.

There are many examples of models and methods that have been developed for prognostics and health assessment of check-valves or loose part monitoring in nuclear plants. This approach is particularly useful when the degradation profile is well understood. This means that this approach is more applicable to micro-electronic components where adequate accumulated operational experience on degradation trend is available. The availability of a PoF approach to the modeling of micro-electronic systems is testimony to this observation.

However, when it comes to power electronic components, one can only claim that work on the application of a PoF model for these systems has been initiated (Yin, Hua, Mussalam, Baily and Johnson, 2010; Patil, Das and Pecht, 2012) but still is not as developed as micro-electronic systems. In the absence of the proper understanding of the degradation process, the current strategy to overcome this limitation is to uprate the system by providing the extra margins in design.

6.2.4.2 Pattern-driven Knowledge-based Approach

This approach does not require description of the system or component through basic models, but only requires patterns comprising component and system specific historical data and information. It provides an efficient and effective mechanism where the input/output relation cannot be defined through well-defined scientific models. However, it establishes that there is a one-to-one relationship between a set of input patterns and corresponding states in a system. One example is the alarm/trip pattern in a reactor, which can be associated with a discrete reactor state. When number of patterns or vectors each comprising a set of alarms uniquely define a given reactor state, then this approach can effectively be used for reactor status and condition monitoring. The advantage of this approach is that it can operate successfully even with missing primary data to form a precursor for predictions. As it operates on clusters of data and often derives data it can use to predict with reasonable assurance. The applications include nuclear plant transient identification, prediction reactivity, and health monitoring in rotating machines. This approach has often been implemented using artificial neural networks (ANNs) (Varde, Verma and Sankar, 1998; Lee et. al., 2005), neuro fuzzy systems (Chen, Zhang, Vachtsevanos and Orchard, 2011), support vector machines (Abe, 2010), or sequential probability ratio techniques (Coble et al., 2010). When ANN tools are used, the approach involves training the ANN with various patterns, including healthy patterns and various failure patterns for specific components.

Another example is application of ANN for health prediction for check valves (Lee, Lee and Kim, 2005), (Uhrig, 1994). The ANN is trained with historical data on the failure of the check valve involving the hinge pin, dish, stopper pin, or dash pot. These patterns, along with healthy patterns, are used to train the ANN. Validation and verification of the algorithm is carried out by testing the ANN response for new and existing patterns, for which it has been trained, plus unlearned patterns. The recall tests are often carried out with additional patterns having noise, missing data, or fuzzy data to ensure that the prognostic model is robust and that repeatability is high. During the course of prognosis, if the ANN algorithm comes across a new pattern that was not there in the database, there is a provision to train the ANN for this new condition. This new pattern then becomes part of a pattern-knowledge-based library for prognostics.

It may be noted that the approaches listed above fall in the category of intelligent methods. The objective is to extract the features specific to a given input pattern. Here, the main issue is to determine which approach should be used for arriving at a given solution. Often, this decision comes from assessing the nature and complexity of the level of details that are expected in the solution space. This often requires performance evaluation of the approaches under consideration (Varde et. al, 1998).

6.2.5 Integrated Approach.

The prognostics approach followed for electronic components often uses what is called a fusion approach to enhance the prediction capability of the prognostics approach. General experience has been that often one approach may not be adequate to provide the desired results. Hence, the trend-driven approach is integrated with the PoF approach. While the PoF approach prides fundamental requirements for prognostic models, the database approach complements the model with a knowledge base that has already been developed for various failure modes.

An integrated approach is also beneficial where the available data is inadequate to implement prognostics. To improve the prediction accuracy and precision, it is often necessary to use Bayesian updating to incorporate new data for prediction (Modarres et al., 2010). Hence, the probabilistic approach is used in conjunction with online precursor trends to update estimates with new data available from online sensors. While the trend monitoring identifies the deviation from the normal operation of equipment, the probabilistic model with uncertainty bands will provide an estimate of the prognostic distance—a performance metric crucial for fixing the deficiency either through repair or replacement. The prognostic distance also prompts the plant manager to plan the action in advance such that plant availability and safety can be optimized.

6.3 Material Degradation and PHM Requirements

Nuclear power plants include PWR, BWR and other designs such as Canadian deuterium reactor (Candu), pressurized heavy water reactors (PHWR), and gas-cooled reactors. The accumulated operating experience works out to be 10,750 reactor years, considering an average operating experience of 25 years. Logs of failure history of components provide indicators for degradation trends. Prognostic applications require research and development to fuse the historical data with the available PoF models, considering intrinsic and extrinsic parameters, to gain improved understanding of the degradation of SSCs. It may be noted that non-destructive evaluation or testing (NDE or NDT) forms a major component of the surveillance of SSCs in NPPs (Baskaran, 2000). With respect to the aging or degradation of SSCs, degradation is a slow and gradual process and the prognostics used to track trends exists only after a period of 30 years (Bond, 2008a). This means that the pre-service inspection (PSI) data collected during the plant licensing phase forms a template or reference for future trend monitoring.

However, often the information may not be adequate to provide support of the estimation of remaining useful life or to determine the failure criteria for a given material application. This is why there is an overwhelming desire to have a proactive approach to the management of material degradation in nuclear plants in general and aged plants in particular (Bond, 2008a; Bond, 2008b). The incentive for the operating organization is to support the case for life extension while for regulators it provides flexibility for oversight and monitoring to generate feedback. Hence, monitoring as part of the implementation of PHM strategy backed up by degradation models forms a vital element for remaining useful life prediction (Meyer, Ramuhalli and Bond, 2011).

For a prognostic strategy to be effective, it is important to have the reference signatures of the systems during the initial stages of operation. This makes it prudent that all the condition monitoring and surveillance applications, like leak-before-break, coolant channel health monitoring, installation of coupons (to assess corrosion in strategic location for in-core or out-of-core components), in-service-inspection, bearing signatures, and cable insulation strength be seen as prognostic applications. As the life of components depends on lifetime loading and variation in environmental, electrical and mechanical stresses, (this includes the effect of external events and new combined phenomenon), it is important that PoF and MoF models account for degradation history to predict life.

6.4 Prediction and Learning Machines and Tools

There are a host of approaches for prediction, including probabilistic and statistical approaches. Examples of probabilistic methods include regression modeling, Bayesian updating (Guan et al., 2011; Modarres et al., 2010), principal component analysis and sequential probability ratio tests (Coble, 2010). The intelligent methods or machine learning approaches form an important element in prognostics. The common approaches employed for prediction and machine learning are artificial neural networks (ANNs) (Varde et al., 1998), neuro-fuzzy models (Chen et al., 2010; Chen et al. 2011), Kalman filters (Heimes, 2008), particle filters (Chen, Vachtsevanos, and Orchard, 2010), and support vector machines (Abe, 2010). The selection and application of a given approach is based on the nature of the predictions to be made. For example, ANN tools are used when the prediction is based on symptoms and not an actual model of the system. The Bayesian approach is used where the prior knowledge predictions are based on new evidence or data. Probabilistic approaches are the traditional methods for estimating time to failure as an indicator of remaining life. Support vector machines are used where predictions are to be based on the clustering of data and information to form patterns.

6.5 Limitation of Prognostic Methods

Even though prognostics has evolved into a relatively new paradigm with applications in areas such as space, aircraft, and structural engineering, the development and deployment of prognostics in NPPs is very limited (Shafto et al.,). There are certain issues that need to be addressed through research and development efforts.

Major challenges to the implementation of prognostics include sensors and associated networks, PoF and damage models and failure criteria, uncertainty characterization, and organizational frameworks. The availability of sensors in general and the development of an integrated sensor network can be considered one bottleneck in the implementation of prognostics. This is particularly true for electronic components, as this application requires miniaturization of the sensors such that newly developed sensors and networks can fulfill the requirements of an application. Keeping in view the enhanced performance of prognostics for future applications, wireless sensor networks (WSNs), along with utilization of miniaturized sensors such as Pt-100 for online temperature measurement, provide with an effective technique for the implementation of prognostics for electronic components (Puccinelli and Haenggi, 2005), (Lin, Wang, and Sun, 2004).

The designers of newly built plants have to take a proactive approach for making prognostics provisions. This requires focused efforts on preparing design specifications based on safety and availability studies that identify not only components and processes that require PHM, but also selecting a PHM approach depending on failure mechanisms. For instance, if prognostic provisions are required for certain in-core components, suitable provisions should be made right before the start of construction activity. For existing plants, plant constraints will dictate the level of prognostics to be implemented. However, when life extension is being explored for the new plants, implementation of prognostics tools and methods can provide valuable insights into tracking aging mechanisms as well as help in assessing performance of systems in on-line mode or at periodic intervals. Keeping in mind advances in wireless sensor network (WSN) applications, the pros-and -cons of this technology should be evaluated. On the one hand, while there is immense potential for WSN technology, there are some limitations, which include, a) lower speed, b) requirement of power supply to the node, c) more complex to configure and d) the performance of the node is easily affected by surroundings like walls, microwaves, large distances due to signal attenuation, etc. (Bhattacharya, Kim and Pal, 2010).

In the nuclear industry the principles of defense in depth ensures the implementation of redundant and diverse electronic channels; however, the common cause failure (CCFs) aspects require special attention. The effect of any degradation or failure mode, induced by material, environmental, operational parameters needs to be analyzed, particularly for assessing its CCF impact as part of PHM implementation (IAEA, 2009). For developing the PoF model for electronic protection channels, the potential failure due to whisker growth, electromigration induced shorting of parallel metallization, coupling of the redundant path due to field effects and solder joint failure requires special CCF considerations.

Similarly, for developing degradation models for in-core structural components as part of PHM implementation requires not only the monitoring provisions that include special sensors but also considerations and development of irradiation induced degradation and growth models. The prediction accuracy of these models will require assessment of change in material property in dynamic manner with the fluence it has seen in the reactor core (IAEA, 1999; Dharmaraju et al., 2008). When implemented, these models are expected to provide input for a risk-based approach (Samal, 2010).

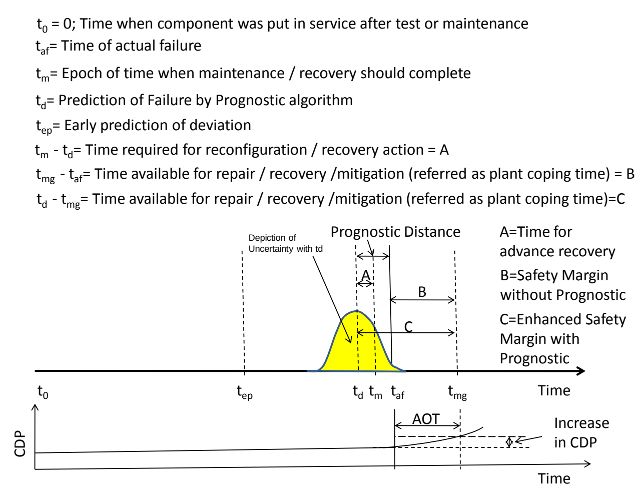
Often if the PoF models/damage models are available it is challenging to define the failure criteria and the uncertainty associated with these definitions. The lack of knowledge related to failure criteria is often addressed by conservative assumptions. Here, the role of prognostics becomes crucial, as the online signal can be used with the available data and models to characterize the incipient failures.

There are two types of uncertainties that need to be addressed in prognostics: aleatory and epistemic. Aleatory uncertainty, which is inherent in nature and cannot be reduced, arises from data and models. Epistemic uncertainty is uncertainty, which is reduced by acquiring additional knowledge or data. The integrated approach is a typical example of reducing epistemic uncertainty. Reducing uncertainty in PHM becomes more important from the point of estimating prognostic distance. At a higher level, it affects the accuracy of the assessment of the safety margin as part of risk-based applications. Other approaches to model or reduce uncertainty involve updating the prior data with new evidence using well-known techniques such as Bayesian updating, Kalman filtering, constrained optimization, and particle filtering.

In spite of the above developments, the accuracy of uncertainty assessment is a lingering issue. Other non-parametric methods that are expected to reduce subjectivity in uncertainty assessment are being developed. One method is the imprecise probability based approach. However, there are limited applications of this approach. Further R&D in this area may provide a new approach to uncertainty modeling and analysis.PHM is a resource-intensive application. Hence, organizational will to implement and operate a PHM program is a pre-requisite. Whether it is for routine health management of components in support of surveillance or life extension studies for new plants, the involvement of not only implementation-level staff but also plant management is an important factor in the success of the PHM approach (Pecht, 2010). The availability of a PoF or damage model is one of the major challenges to the initiation and implementation of a PHM program in a nuclear plant. Even though limited application up to condition monitoring has found wider applications in the nuclear sector, full potential of prognostics can be realized only after the damage model for mechanical and structural engineering components and PoF models for power and micro-electronics and electrical components.

5. PERFORMANCE CRITERIA

Performance criteria or metrics determine the adequacy of a prognostic approach for a given application (Saxena et al., 2010). Extensive work has been reported to define the appropriate performance metrics for a given application to improve the performance of prognostics and health management and condition monitoring approaches (Wheeler et al., 2010; Saxena et al., 2010; Pecht, 2009; Feldman et al., 2010; Coble and Hines, 2008). As the literature shows, there are three major performance indicators to determine the efficiency and effectiveness of PHM applications: prognostic distance (PD), accuracy, and precision.



Legends: CDP: Core Damage Probability
AOT: Allowable outage time

Figure 6. Depiction of features of prognostics and performance criteria.

5.1. Prognostic Distance

The time between the predicted time of incipient failure and actual component failure is called the prognostic distance. This definition has been derived from the concept of prognostic distance used in canaries (Wang, Luo, and Pecht, 2011). This indicator can be better understood by the following assumptions and observations: 1) assume that the time t_{af} is the actual time to failure of a component involving a particular failure mechanism, 2) t_m is the time for completion of the recovery of a component, assuming that the time for actual failure is known, 3) the time when the prognostic model detects and confirms the degradation trend as positive is t_d, 4) the prognostic algorithm has the built-in capacity to predict uncertainty in the remaining life estimate and degradation parameter assessment, and 5) the success of metrics is determined by how far in advance it predicts the deviation such that an adequate time window is available for the replacement or recovery action such that availability and safety functions are ensured. However, the prediction should not be so early that it results in a loss of component life or premature replacement. Fig. 6 depicts the condition for optimum prognostics.

7.2 Accuracy: Accuracy means the correctness of the remaining life estimates. As can be seen in Figure 6, the correctness of the prediction of time determines the accuracy of prediction.

7.3 Precision:

Precision accounts for the uncertainty estimates in remaining life prediction. The width of the uncertainty band determines the precision of the estimates. A shorter band has higher precision, and a wider band has lower precision.

Other parameters that are of interest to risk-based applications include assessment of the safety margin for the case or scenario being evolved. Figure 6 also shows the increased safety margin made available by the prognostic algorithm. The increase in core damage probability (CDP) is depicted by the lower time vs CDP plot. The plant technical specification defines the allowable outage time. It can be seen that by keeping a safety related system or component, the core damage probability increases while the process of prognostics is dynamic in nature, the efficiency and effectiveness of this process, from the risk evaluation point of view, is determined by how effectively the process addresses performance trending and follow-up activities. This increase is linear with time. This aspect extends the role of a prognostic algorithm to monitoring and comparing the performance of the subject case or component to ensure that it meets the performance criteria set or recommended by the regulator. The algorithm then produces documentary evidence, providing the estimates of assessment of safety margin, characterization of uncertainty, critical parameter trends, and projected life of the new modifications. These indicators are of particular interest to risk-based applications.

6. CONCLUSIONS AND RECOMMENDATIONS

There is increasing use of condition monitoring in support of operation and maintenance of nuclear plants. The diagnostic and prognostic approach can be used as part of a risk-based approach. A risk-based approach can support the prognostics program. Looking at the publications in the areas of mechanical and structural engineering, it can be argued that a prognostics framework for nuclear plants can be established by adopting the models and methods developed for space, aircraft, and civil engineering systems for core components where radiation-induced degradation may not play much of a role in dictating the remaining useful life. For core components, a limited knowledge base is available that can be utilized with certain uncertainty bounds.

We have proposed a new paradigm called the mechanics of failure as part of prognostics implementation for risk-based applications. The MoF approach to a large extent operates in the manner of a PoF approach; the only difference is that most of the times MoF deals with macro- or micro-level analysis tools and methods. It has been argued that although PoF is more suitable for the modeling and analysis of electronic and power electronic components, MoF works for structural systems and components in nuclear systems, such as pressure vessels, coolant channels, pumps, valves, pipes, and heat exchangers. For example let us take the case of implementation of prognostics as part of risk-based in-service inspection programme. Here, tools like probabilistic fracture mechanics, finite element methods, irradiation induced degradation when dealt at macro level as part of MoF approach forms an effective strategy to implement prognostics for addressing issues related to management of safety issues. As in NPPs the ISI program deals with relatively large components and volumes where, a PoF approach may not be effective.

Prognostics can be applied to new plants by making the complete monitoring and surveillance and maintenance management process more effective through the prediction of fault and degradation trends, such that adequate time is available for recovery and repair actions. This aspect is important as it works for both safety and availability improvement. For existing or older plants with constraints imposed by design, layout, or operational limitations, this approach is expected to be very effective for life extension studies that are carried out as part of aging studies and performance monitoring after the changes and modifications have been incorporated. As can be seen, all of these gains go further towards consolidating the risk-based approach.

Advances in any field and their application to real-life situations are normally judged by the availability of codes and standards. Even though there are many standards and codes for surveillance and condition monitoring, there are hardly any standards on prognostics and health management. In this direction, the development of the first IEEE prognostics and health management standard for electronics is at an advanced stage and appears to be undergoing review (IEEE). The availability of this standard will mark a significant step: it will channelize the knowledge base available in advanced labs for system applications to industry. As far as the nuclear industry is concerned, this will be a clear incentive to develop prognostics for electronics in reactor controls and protection.

Based on the review of the status of existing surveillance and monitoring programs and the potential role that prognostics can play as part of the IRBE in NPPs, we make the following recommendations:

A prognostics approach brings in the element of dynamics into the existing risk-based approach. Hence there is a strong argument in favor of initiating a prognostics-based health management program in NPPs. The current knowledge of prognostics is such that extensive research and development is required, particularly for power electronic systems and electrical systems, such that accurate prediction of remaining useful life can be developed.

The development of PoF and MoF models require elaborate life test set-ups and material characterization facilities. Apart from this, the study of irradiation-induced degradation requires research reactor test facilities. The available resources can be networked in a coordinated manner to support this development work. There should be provision in the operating reactor organization to communicate data and insights on failure to a prognostics laboratory on the one hand while providing prognostic solutions for real-time issues on the other.

Even though the prognostic approach for estimating the life and reliability of the components in new and old plants remains similar, the emphasis in new plants is to develop a host of prognostic performance metrics for the identified components while for old plant prognostics must support inspection, testing, and condition monitoring. Development efforts should adopt the prognostic systems that have been developed in other fields, such as navigation, aircraft, space, and infrastructure systems, so that the program is more effective in terms of deliverables.

Nuclear research labs generally have a reasonable infrastructure for developing prognostic sensors and associated systems. Hence, early identification of sensor requirements is important for the success of prognostic programs.

Work should start on the development of codes and standards for prognostics and health management for nuclear components and systems.

Keeping in mind the benefits that can be realized through the implementation of a risk-based prognostic program, this paper argues a case for setting up centers of excellence to facilitate research and development on prognostics for engineering systems in complex systems such as nuclear power plant. This is required as the prognostic and health management approach has the potential to benefit existing plants entering the aging zone and new plants where a target life of more than 90 years can be met with online prognostics that enable degradation monitoring of critical systems and components.

REFERENCES

Abe Shigeo, (2010). *Support vector machines for pattern classification - advances in computer vision and pattern recognition.* Second Edition, Springer.

Andonov, A., Apostolov, K., Kostov, M., A. Iliev, Stefanov, D., Varbanov, G., (2011). Structural health monitoring of VVER-1000 containment structure. Transactions, *SMiRT 21*, New Delhi, India

Baskaran S., (2000). Role of NDE in residual life assessment of power plant components. *NDT.net*, Vol. 5 No. 07.

Bhambra J.K., Nayagam S., Jennions I., (2011). Electronic prognostics and health management of aircraft avionics using digital power convertors. 2011 *Annual Conference of the Prognostics and Health Management Society*.

Bhattacharya, D., Kim T., and Pal S., (2010). A comparative study of wireless sensor networks and their routing protocols. *Sensors, 10, 10506-10523; doi:10.3390/s101210506*, ISSN 1424-8220.

Bond L.J., Doctor. S.R. and Taylor, T.T., (2008a). Proactive management of materials degradation – a review of principles and programs. *PNNL-17779, Pacific Northwest National Laboratory, U.S. Department of Energy, Richland, Washington*.

Bond L.J., Taylor, T.T., Doctor S.R., Hull Amy B., and Malik S. N., (2008b). Proactive management of materials degradation for nuclear power plant systems. *2008 International Conference on Prognostics and Health Management*.

Chatterjee, K, and Nodarres, M., (2012). A probabilistic physics-of-failure approach to prediction of steam generator tube rupture frequency. *Nuclear Engineering and Science*, Vol. 170, Number 2, pp. 136-150.

Chen Chaochao, Brown D., Sconyers Chris, Zhang Bin, Vachtsevanos George, Orchard M.E. (2012). An integrated architecture for fault diagnosis and failure prognosis of complex engineering systems. *Expert Systems with Applications 39 9031–9040*.

Chen Chaochao, Pech Michael, (2012). Prognostics of lithium-ion batteries using model-based and data-driven methods. *Prognostics and System Health Management Conference* (PHM-2012 Beijing).

Chen Chaochao, Vachtsevanos George (2012). Bearing condition prediction considering uncertainty: an interval type-2 fuzzy neural network approach. *Robotics and Computer-Integrated Manufacturing* 28 509–516.

Chen Chaochao, Vachtsevanos George, and Orchard Marcos E. (2010). Machine remaining useful life prediction based on adaptive neuro-fuzzy and high-order particle filtering. *Annual Conference of the Prognostics and Health Management Society*.

Chen Chaochao, Zhang Bin, Vachtsevanos George, and Orchard Marcos (2011). “Machine condition prediction based on adaptive neuro–fuzzy and high-order particle filtering. *IEEE Transactions on Industrial Electronics*, Vol. 58, No. 9, 4353.

Coble J.B. and Hines J.H., (2008). Prognostic algorithm categorization with PHM challenge application. *2008 Int. Conf. on Prognostics and Health Management*.

Coble, J., and J.W. Hines, (2010). Application of failure prognostics to the IRIS plant., *Seventh American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation, Control, and Human-Machine Interface Technologies NPIC and HMIT 2010*, Las Vegas, NV, Nov. 7-11.

Coble, Jamie, Humberstone Matt, and Hines J. Wes, (2010). Adaptive Monitoring, Fault Detection and Diagnostics, and Prognostics System for the IRIS Nuclear Plant. *Annual Conference of the Prognostics and Health Management Society*, Portland, Oregon, USA.

Coble, JB, Ramuhalli, P, Bond, LJ, Hines, JW, and Upadhyay, BR, (July 2012). Prognostics and health management in nuclear power plants: a review of technologies and applications. *PNNL-21515*, Contract DE-AC05-76RL01830, Pacific Northwest National laboratory, Richland, Washington.

Coppe A., Haftka R.T., Kim Nam-Ho, and Bes C. (2008). “A statistical model for estimating probability of crack detection. *2008 Int. Conf. on Prognostics and Health Management*.

Dasgupta Abhijit, Doraiswami Ravi, Azarian Michael, Michael Osterman, Sony Mathew, and Michael Pecht, (2010). The use of “canaries” for adaptive health management of electronic systems. ADAPTIVE 2010 : *The Second International Conference on Adaptive and Self-Adaptive Systems and Applications*, IARIA, 2010 ISBN: 978-1-61208-109-0.

Dharmaraju, N. and Rama Rao, A. (2008). Review article: Dynamic Analysis of Coolant Channel and Its Internals of Indian 540MWe PHWR Reactor. *Hindawi Publishing Corporation - Science and Technology of Nuclear Installations*, Volume 2008, Article ID 764301, 7 pages, doi:10.1155/2008/764301.

Gregor, F and Chokie, Alan (2006). Ageing management and life extension in the US nuclear power industry. *CGI Report 06:23, Prepared for the Petroleum Safety Authority Norway, Chokie Group International Inc, USA.*

Feldman Alexander, et. al., (2010). Empirical Evaluation of Diagnostic Algorithm Performance Using Generic Framework. *International Journal of Prognostics and Health Management*”, 002, (ISSN 2153-2648).

Gu Jie, Vichare Nikhil, Tracy T. and Pecht, M. Prognostics implementation methods for electronics. http://www.prognostics.umd.edu/calcepapers/07_Jie_PrognosticsImplemntationmethodElectronics_RAMS.pdf.

Guan X., Liu Y., Jha R., Saxena A., Celaya J, Geobel K., (2011). Comparison of two probabilistic fatigue damage assessment approaches using prognostic performance metrics. *International Journal of Prognostics and Health Management*, 005, (ISSN 2153-2648).

Hashemian, H.M. On-line Monitoring and Calibration Techniques in Nuclear Power Plants. *IAEA-CN-164-7S05*, IAEA, Vienna. http://www-pub.iaea.org/MTCD/publications/PDF/P1500_CD_Web/htm/pdf/topic7/7S05_H.Hashemian.pdf.

Heimes F.O., (2008). Recurrent neural networks for remaining useful life estimation. *2008 Int. Conf. on Prognostics and Health Management*.

Heng Aiwina, Zhang Sheng, Tan, Andi CC, and Mathew Joseph, (2009). Review – Rotating machinery prognostics: state of the art, challenges and opportunities. *Mechanical Systems and Signal Processing*, 23, 724-739. Doi:10.1016/j.ymssp.2008.06.09.

http: //standards.ieee.org/develop/wg/PHM.html.

Hyers, R.W., McGowan, J.G., Sullivan, K.L, Manwell, J.F., and Syrett, B.C., (2006). Condition monitoring and prognosis of utility scale wind turbines, *Energy Materials*, Vol. 1, No. 3, 187.

IEEE Standard Association, Draft of “P-1856 – *Standard framework for prognostics and health management of electronic systems*, IEEE Reliability Society,

International Atomic Energy Agency (1993). Risk based optimization of technical specifications for operation of nuclear power plant. *IAEA-TECDOC-729*, IAEA, Vienna.

International Atomic Energy Agency (1995). Management of research reactor ageing . *IAEA-TECDOC-792*, IAEA, Vienna.

International Atomic Energy Agency (1999). Assessment and management of ageing of major nuclear power plant components important to safety : CANDU pressure tubes. *IAEA-TECDOC-1037*, IAEA, Vienna.

International Atomic Energy Agency (1999). Living probabilistic safety assessment (LPSA). *IAEA-TECDOC-1106*, IAEA, Vienna.

International Atomic Energy Agency (2009a). Protecting against common cause failures in digital I&C systems of nuclear power plants, *IAEA-Nuclear Energy Series* No NP-T-1.5, IAEA, Vienna.

International Atomic Energy Agency (2009b). Proactive management of ageing for nuclear power plants, *IAEA-Safety Report Series No. 62*, IAEA, Vienna.

International Atomic Energy Agency, (1998). "Assessment and management of ageing of major nuclear power plant components important to safety: CANDU pressure tubes. *IAEA-TECDOC-1037*, IAEA, Vienna.

International Atomic Energy Agency (2010). Risk informed in-service inspection of piping systems of nuclear power plants: process, status, issues and development. *IAEA nuclear energy series no. NP-T- IAEA*, Vienna.

Kadak, Andrew C., Matsuo,Toshihiro, (2007). "The nuclear industry's transition to risk-informed regulation and operation in the United States. *Reliability Engineering and System Safety* 92 609–618.

Kalgren P.W, et. al., (2010). Application of prognostic health management in digital electronic systems. *International Journal of Prognostics and Health Management*, 002, (ISSN 2153-2648). 1-4222-0525-4/07 2007, IEEE Paper 1326 Version 3.

Klein R., Rudyk E., Masad E., and Issacharoff M., (2011). Model based approach for identification of gears and bearings failure modes. *International Journal of Prognostics and Health Management", 009*, (ISSN 2153-2648).

Lee Min-Rae, Lee Joon-Hyun and Kim Jung-Teak, (2005). Condition monitoring of a nuclear power plant check valve based on acoustic emission and a neural network. Jr. of Pressure vessel Tech., issue 3, Volume 127.

Lee, WW, Nguyen, LT, and Selvaduray, (2000). Solder joint fatigue models: review and applicability to chip scale packages. *Microelectronics reliability*, 40, 231-244.

Lin R., Wang Z., and Sun Y., (2004). "Wireless sensor network solutions for real-time monitoring of nuclear power plants., *Proc. 5th World Congress on Intelligent Controls and Automation*, Vol 4, pp. 3663 – 3667.

Mathew Sony, Das Diganta, Osterman Michael, Michael Pech, (2006). Prognostics assessment of aluminum support structure on a printed circuit board. *ASME Journal of Electronic Packaging*, , Vol. 128 / 339.

Meyer, Ryan, Ramuhalli Pradeep, Bond L.J., (2011). Developing effective online monitoring technologies to manager service degradation of nuclear power plants. *IEEE PHM Conference*, Denver, Colorado, USA, 20-23, , Denver.

Mishra S., Ganesan S., Pecht, M, and Xie Jingsong,(2004). Life consumption monitoring for electronics prognostics. *2004 IEEE Aerospace Conference Proceedings*.

Modarres M., Kaminskiy M. and Valiliy Kristov, (2010) *"Reliability engineering and risk analysis – a practical guide"* (Second Edition), CRC Press.

Nuclear Energy Agency, (2005). CSNI Technical Opinion paper No *7 on Living PSA* and its Use in the Nuclear Safety Decision-making Process /No 8 on Development and Use of Risk Monitors at Nuclear Power Plants. *NEA 4411*, Organization for Economic Co-Operation and Development, Paris.

Patil Nishad, Das Diganta, and Pecht Michael (2012). A prognostic approach for non-punch through and field stop igbts. *Microelectronics Reliability*.

Patil Nishad, Das, Diganta and Pecht Michael, Jose Celaya and Goebel Kai, (2009). Precursor parameter identification for insulated gate bipolar transistor (IGBT) prognostics. *IEEE Transactions on Reliability*, Vol. 58, No. 2, pp. 271-276.

Pecht, M.G., (2008) *"Prognostics and health management of electronics"*, Wiley and Sons.

Pecht, Michael and Dasgupta, Abhijit, (1996). Physics-of-failure: an approach to reliable product development, *IEEE - 95* IRW FINAL REPORT.

Pecht, M. and Gu, Jie, (2009). Physics-of-failure-based prognostics for electronic products. *Transaction of the Institute of Measurements and Control, 31, 309-322.*

Pecht, Michael, (2009). Prognostics and Health Management. *Encyclopedia of Structural Health Monitoring*, Ed. Boller Christian, Chang Fu-Kuo and Fujino Y.; John Wiley and Sons, Ltd.

Pecht, Michael G. (2010) *"Prognostics and health monitoring in complex engineering systems: methods and applications"*, IEICE Fundamental Reviews Vol. 3 No. 4.

Puccinelli D., Haenggi M., (2005). Wireless sensor networks : application and challenges of ubiquitous sensing. Feature Article, *IEEE Circuits and Systems*, Third Edition.

Samul, MK, Dutta, BK, and Kushwaha, (2010). A probabilistic approach to evaluate creep and fatigue damage in critical components. *Transaction of Indian Institute of Metals*, Vol. 63, Issues 2-3, pp. 595-600.

Saxena A., et. al. (2010). Metrics for Offline Evaluation of Prognostic Performance. *International Journal of Prognostics and Health Management"*, Vol 1(1) 001, (ISSN 2153-2648).

Saxena A., Simon D., (2008). Damage propagation modeling for aircraft engine run-to-failure simulation. *2008 Int. Conf. on Prognostics and Health Management*.

Saxena, A., "Prognostics Performance Evaluation", National Aeronautics and Space Administration web-site: http://ti.arc.nasa.gov/tech/dash/pcoe/prognostics-performance-evaluation/metrics/algorithm-performance/.

Sinha, R.K., Sinha, S.K., Madhusoodhan, K., (2008). Fitness for service assessment of coolant channels of Indian PHWRs. *Journal of Nuclear Materials*, Vol. 383, Issue 1-2, pages 14-21.

Tantawy A., Koutsoukos X., and Biswas G., (2008). Aircraft ac generators: hybrid system modeling and simulation. *2008 Int. Conf. on Prognostics and Health Management*.

Tsu-Mu Kao, (2007) "*Risk-Informed Regulation and Applications in Taiwan"* International Journal of Performability Engineering Volume 3, Number 1, - Paper 5 - pp. 47 – 59.

U.S. Nuclear Regulatory Commission, **(**2002). Regulatory guide 1.182 - assessing and managing risk before maintenance activities at nuclear power plants**.** *Office of nuclear regulatory research*, Washington.

Uhrig, R.E., (1994). Application of artificial neural network in industrial technology. *Proc. of the 1994 IEEE International Industrial Technology Conference*.

Varde, P.V. Sankar S. and Verma, A.K., (1998). An operator support system for research reactor operations and fault diagnosis through a connectionist framework and PSA based knowledge based systems. *Reliability Engineering and System Safety*, 60, 53 – 69.

Varghese, Joy P., Verma, V.S., Rajput, C.D., Ramamurthy, K., (2010). "En-Masse Coolant Channel Replacement in Indian PHWR. Energy Procedia *00 000-000.*

Vichare, N.M. and Pech M.G.,*(*2006). Prognostics and Health Management of Electronics. *IEEE transactions on components and packaging technologies*, V:29, 1.

Wang, W., Luo S., and Pecht, M.G. Economic design of the mean prognostic distance for canary-equipped electronic systems. *Microelectronics Reliability, 52 (2012) 1086-1091*.

Wheeler K.R., Kurtpglu T., and Poll S.D., (2010). A Survey of Health Management User Objectives in Aerospace Systems Related to Diagnostic and Prognostic Metrics. *International Journal of Prognostics and Health Management*", 003, (ISSN 2153-2648).

White M., Bernstein, (2010). Microelectronics reliability: physics-of-failure based modeling and life time evaluation. *NASA Electronic Parts and Packaging (NEPP) Program Office of Safety and Mission Assurance*, NASA EBS: 939904.01.11.10, Jet Propulsion Lab, 4800 Oak Grove Drive, Pasadena, CA.

Wood S.M., Goodman L.D., (2006). Return-on-investment (roi) for electronic prognostics in high reliability telecom applications. *1-4244-0431-2/06, IEEE, Pg 229*.

Wu KT, et. al., (2011). Engine oil condition monitoring using high temperature integrated ultrasonic transducers. *International Journal of Prognostics and Health Management*, 010, (ISSN 2153-2648).

Yates, S.W., Mosleh, M., (2006). A Bayesian approach to reliability demonstration for aerospace systems. *Proc. IEEE Explore, Reliability and Maintainability Symposium*, 611-617.

Ye Hua, Basaran, C., Hopkins, DC, (2006). Experimental damage mechanics of micro / power electronics solder joints under electric current stresses. International Journal of Damage Mechanics, Vol. 15, doi:10.1177/105678906054311.

Yin Chunyan, Lu Hua, MUSALLAM M., Bailey C. and Johnson C. Mark, (2008). Prognostic reliability analysis of power electronics modules. 2nd Electronics System integration Technology Conference, Greenwich, UK.

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