Transactions of the Korean Nuclear Society Autumn Meeting
Gyeongju, Korea, October 27-28, 2016

Research status of Prognostics and Health Management in Nuclear Power Plants

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1. Introduction

Recently, the concerns of Nuclear Power Plants (NPPs) safety and reliability have increasing because of Fukushima disaster and NPPs increasing operating years. Operational experience has shown that greater situational awareness of the state of safety-critical nuclear plant System, Structure, and Components (SSCs) is necessary, particularly as they age due to exposure to harsh service conditions. While replacement of a subset of components is possible, and may even be economically attractive, it may be economically prohibitive to replace several of the lager components, including the reactor pressure vessel and primary piping. Thus, characterization, management, and mitigation of aging-related degradation in these critical passive components becomes important to maintain safety margins.

In order to deal with these problem above mentioned, thus, it is necessary to develop Prognostics and health Management (PHM) technology. The key technology in PHM is to detect degradation and anomalies and to determine Remaining Useful Life (RUL) and Probability of Failure (POF) of SSCs. The prognostics results can be used to manage the evolving health and condition of nuclear plant SSCs [1]. The prognostics information is used in a Probabilistic Safety Assessment (PSA) model to assess the risk significance of the degradation and the corresponding reduced safety margin [2]. In this paper, the algorithms of PHM for NPPs, the review of the state of the art in PHM for nuclear industry was summarized.

2. Method and Algorithms for PHM

In this section some of the techniques used to model for PHM are described. The PHM consist of three parts; monitoring, diagnostics, and prognostics. The figure 1 shows the concept of PHM system and related representative algorithms. In the figure 1, the monitoring and detection is that monitor signals or features that can be related to the operating state of a component, process, or system and detect a deviation from nominal behavior. The Diagnostic is that identify and diagnose the cause of an anomaly in the system or process. The prognostics estimate the time remaining to run the system or process within specified tolerances, in order word, estimate RUL. The RUL is that amount of time, in terms of operating hours, cycles, or other measures the component will continue to meets its design specification.

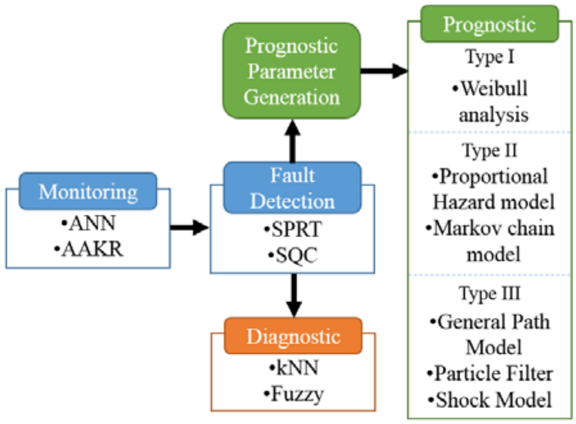

Fig. 1. The concept of PHM system and representative algorithms

Table 1. Application area and several classes for diagnostics (D) and prognostics (P)

Diagnostic/Prognostic Technology for:	**AP[(a)]**	**A[(b)]**	**I[(c)]**	**No[(d)]**
Basic Machinery (motors, pumps, generators, etc.)	D&P			
Complex Machinery (helicopter gearboxes, etc.)	D&P			
Metal Structures	D	P		
Composite Structures		D	P	
Electronic Power Supplies (low power.)	D	P		
Avionics and Controls Electronics	D	P		
Medium Power Electronics (radar, etc.)	D	P		
High Power Electronics (electric propulsion, etc.)	D	P		
Instrument Re-calibration -monitoring (NPPs)	D			P
Active Components – NPPs	D		P	
Passive Components – NPPs			D	P

(a)AP=Technology currently available and proven effective
(b)A=Technology currently available, but V&V not completed
(c)I=Technology in process, but not completely ready for V&V
(d)No= No significant technology development in place

Table 1 summarized the state of maturity of diagnostic and prognostics analysis for a variety of application spaces: the final three entries summarize the state of maturity in the nuclear power industry, which lags behind other industries and applications [3, 4]. The following sections briefly introduce algorithms and approaches for each of the key modules in the PHM system: monitoring and detection, diagnostics and prognostics.

2.1 Monitoring

The monitoring module consist of two parts: the monitoring and fault detection. The monitoring describes a suite of activities for estimating system state and providing early warning of anomalous behavior. The monitoring module can be considered an error correction routine; the model gives its best estimate of the true value of the system variables. The fault detection is compared to the data collected form the system to generate a time-series of residuals. Residual characterize system deviation from normal behavior and can be used to determine if the system is operating in an abnormal state. The monitoring method is the Artificial Neural Network (ANN) and Auto-associative Kernel Regression. The fault detection method is Sequential Probability Ratio Test (SPRT) and Statistical Quality Chart (SQC) that is based on SPRT.

2.2 Diagnostics

The Diagnostic is that identify and diagnose the cause of an anomaly in the system or process. Thus, diagnostics may express fault classification and fault identification. Fault classification locates the fault to a specific component or area of a structure. Fault identification determines the root cause of the fault. Often, these analyses are completed in concert with each other; when an anomaly is detected, the diagnostics system typically determines both the location and cause of the fault given the available fault symptoms. A variety of traditional and advanced classification algorithms have been applied to fault diagnostics, including expert system, k-Nearest neighbors (kNN), fuzzy approach, clustering, etc.

2.3 Prognostics

The prognostics estimate the time remaining to run the system or process within specified tolerances, in order word, estimate RUL. The RUL is that amount of time, in terms of operating hours, cycles, or other measures the component will continue to meets its design specification. A variety of prognostic algorithms have been developed or application to specific situation or specific classes of systems. These algorithms are chosen depending on the type and quality of data available and the assumptions inherent in the algorithm that can validly be made about the system. These prognostic algorithms can be categorized according to type of information used to make prognostic estimate [5]. Type I prognostic is traditional time-to-failure analysis and reliability-based. These methods consider historical time to failure data which are used to model the failure distribution (Weibull analysis). Type II, or stressor-based, prognostics address this shortcoming by incorporating operational and environmental condition data to estimate RUL. This type of prognostics characterizes the lifetime of an average system or component operating in a specific environment (Proportional Hazard model, Markov chain model). The final class of algorithms, Type III or degradation-based prognostics, characterize the lifetime of a specific unit or system operating in its specific environment (General Path Model, particle filter).

3. PHM Applications

For the sensors, monitoring techniques have been proposed to assess the calibration of sensors using data collected during plant operation [6]. In 2000, the U.S.NRC accepted the generic concept of monitoring for sensor calibration assessment and calibration interval extension [7]. However, no U.S. plant successfully obtained the license amendment necessary to implement calibration interval extension. The Sizewell BNPP in the United Kingdom does employ monitoring for sensor calibration.

Motors was applied for monitoring and diagnostics. Induction motors are commonly monitored online through vibration testing, electrical signature analysis, and temperature monitoring. Motor Current Signature Analysis (MCSA) monitors specific frequencies for sign of impending anomalies and faults [8, 9, and 10]. In addition, vibration monitoring can detect and diagnose mechanical issues. Deployed motor monitoring systems do not currently extend to prognostics of motor life.

The Reactor Coolant Pump (RCP) have received significant research attention for fault detection and diagnostics. The degradation and failure of RCPs and casing are commonly monitored through the RCP Vibration Monitoring System (RCPVMS) [11, 12]. As an alternative to the current RCPVMSs, developed a SPRT-based fault detection and diagnostic system.

For the valve, there are a verity of type of valve, thus a review of monitoring and diagnostic method for check valves was performed. Several studies have looked at using acoustic emission signals for valve health monitoring [13]. A check valve monitoring system using ultrasonic transducers coupled to a pipe was developed and patented. The remote testing methods that rely on accurate first principle models of the induction machine in the Motor Operate Valve (MOV) and an online valve diagnostic monitoring system was patented [14]. In addition, monitoring and diagnostic system applied to a turbine control valve during transient operation.

Recent work has focused on developing monitoring and diagnostics for Control Rod and Element Drive Mechanisms (CEDMs). The enhancement of the Digital Rod Position Indication (DRPI) resulted in single step accuracy; in-situ health assessment of the coil, cable, connectors, and power supply. The DRPI data can be used for performance testing, anomaly detection, and diagnostics for the CEDMs [15].

The passive SSCs can be further divided totally passive system (pipes, reactor vessel, etc.) and semi-passive (heat exchanger). The reason of divided that may be monitored through performance assessments and process parameters. These semi-passive components can be monitored and prognosed in much the same way that active components are considered. Passive structures require alternate data collection methods that typically interrogate the structure and record responses. Thus, the research for the passive SSCs is ongoing. On the other hands, monitoring, diagnostics, and prognostic have been performed [16, 17].

4. Summary

The summary of applications of PHM for NPPs as table 2. In the table 2, the target PHM for NPPs categorized active and passive SSCs and express status of maturity of each technology.

Table 2. The Application of active and passive SSCs in NPPs

Component	Monitoring	Diagnostics	Prognostics
Sensor	***	*	*
Motor	***	**	*
Pump	***	***	*
Valve	***	**	*
CEDM	***	**	*
Heat Exchanger	**	*	**
Passive Structure	**	*	*

***: Technology available for NPPs

** : Technology available further qualifications are required for specific applications

* : Technology in R&D domain, feasibility demonstrated

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