ONLINE RISK MONITORING OF NUCLEAR POWER PLANTS: SYSTEM AND ITS COMPONENTS ORDERING BASED ON COST IMPORTANCE

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In the nuclear industry, risk monitors are intended to provide a point-in-time estimate of the system risk given the current plant configuration. The health information (operating condition) of plant components is not considered. Hence, there is a need to develop an enabling approach to solidify risk monitors to provide time and condition-dependent risk by integrating traditional probabilistic risk assessment models with prognostics and health management techniques. This lays the foundation for online risk monitors. To achieve online risk monitors, one of the crucial steps is system components selection. This paper will focus evaluation of system components based on risk- and cost-based importance measures. Traditionally, importance measures like Fussell-Vesely, risk reduction worth, risk achievement worth, partial derivative, Birnbaum importance, and others are applied to identify the role of components in the risk of a nuclear power plant. Existing importance measures have paid little attention to the costs incurred by maintaining a system (including diagnosis, repair, or replacement based on prognosis analysis) within a given time period. However, cost-effective analysis is critically important in an increasingly competitive energy market. Different types of costs will be considered for evaluating system components in this paper. The initial outcome of component ordering based on cost is illustrated on simplified system architecture. And model validation via MATLAB® simulation is also presented. This paper provides an aid to systematic identification of system components based on cost importance in addition to risk-based importance measures.

I. INTRODUCTION

The application of traditional probabilistic risk assessment (PRA) methodology to evaluate risk associated with structures, systems, and components (SSCs) in the nuclear industry and in other industries is well established (Refs. 1, 2, and 3). PRA methodology (also known as probabilistic safety assessment) plays a significant role in quantitative decision-making by finding design and operational vulnerabilities. In particular, it has been widely used as the core methodology for risk-informed applications. Even though traditional PRA seeks realistic results, the assessment is based on Boolean logic (i.e., SSCs have only two states: operational and failure), time-independent failure information (i.e., failure information is collected in time snapshots and not on a continuous basis), and assumption that system/components are non-repairable. As a result, traditional PRA in its present form has some limitations. These are (1) it is not capable of handling time evolving scenarios (e.g., fault tree analysis [FTA] and event tree analysis are static in nature); (2) it does not include system/component degradation or aging information in risk analysis (i.e., no intermediate state analysis); (3) conservative risk estimate; and (4) inability to handle uncertainty due to change in reliability of components/system due to operational or external factors.

The limitations of traditional PRA methodology are addressed to a certain level by several extensions of fault trees (Ref. 4). Dynamic fault trees are best known, but extended fault trees, repairable fault trees, fuzzy fault trees, state-event fault trees are popular as well. Despite several fault tree extensions in the nuclear industry, risk is a point-in-time estimate of a system under investigation for a current plant configuration (scenario). The information on plant components health and partial failures (also referred as degraded states) is not explicitly considered.

In recent years, researchers have explored the concept of utilizing condition monitoring in PRA (Refs. 5, 6, 7, and 8). The progress reported in the literature on this topic of research updates the probability of failure based on time- and condition-information of passive structures. However, the reported research is still based on Boolean PRA. The intermediate states, referred to as partial failures, are not considered. For example, consider a simple system as shown in Fig. 1. The top event for the example in Fig. 1 is no flow of water to reactor, (i.e., $T = C \vee (A \wedge B)$). The top event (T) is independent of current state of the reactor and current operating health state of components (valve and pumps). The well-known failure modes for valve and pumps are used to analyze the top event in traditional PRA. Consider a scenario where the valve expected to be fully closed but is NOT; instead, it is partially open due to unknown reasons (referred to as partial failure in this paper). The questions now are: How would you account this real-time information that the valve is partially open in PRA? How would FTA change? Similarly, there could be evolving partial failure modes (degradation) associated with pumps based on operating conditions and should be taken into consideration in traditional PRA. How do uncertainties associated with partial failure modes propagate to the top event? How to estimate those uncertainties? What is economic impact? Fig. 1 illustrates a simple system in which these questions are associated.

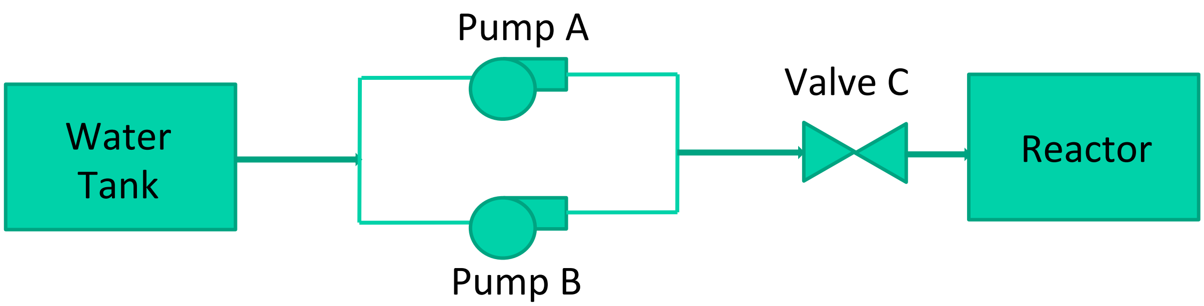

Fig. 1. An example of a simple system.

Researchers at Idaho National Laboratory (INL) are currently working on a research project to seek answers for the above concerns. One of the research objectives presented in this paper is component importance considering cost (in addition to risk). In reliability engineering, risk importance measures are often used to determine which components of the system are the biggest contributors to the overall system risk measures. In nuclear power plants, risk importance measures are used to rank components for risk-informed in-service inspection (Ref. 9). Different risk importance measures are established and used in the nuclear industry (Ref. 10). Existing importance measures have paid little attention to the costs incurred by manipulating a system and its components in a given time period. In the current energy market, for the nuclear industry to be competitive when compared to other clean energy industries, it would be unrealistic to evaluate the importance of system and its components to improve their reliability without considering the cost.

The rest of the paper is organized as follows: Section II presents brief overview of the online risk monitoring research. Different importance measures utilized in the nuclear industry are presented in Section III. Section IV discuss components importance considering cost, modeling assumptions, and model development. Section V presents a case study and compares the finding with the research presented in Ref. 11. Finally, Section VI summarizes the initial findings and discusses the path forward.

II. BRIEF OVERVIEW OF THE ONLINE RISK MONITORING RESEARCH

Online risk monitoring research is currently in progress at INL. The research is focusing on developing and enabling an approach to solidify risk monitors to provide time- and condition-dependent risk estimates. The approach was adapted to achieve online risk estimates and integrated traditional PRA methodologies and prognostic and health management (PHM) research, as shown in Fig. 2. Mathematically interpret it as a transition from $\{0,1\}$ to $[0,1]$. In $\{0,1\}$ only Boolean states are considered, whereas in $[0,1]$ all the possible states between 0 and 1 (including 0 and 1) are considered.

To achieve the research vision, systematic integration of PHM framework with PRA is essential to alleviate the conservatism in the traditional PRA.

The PHM framework envisages online monitoring of precursor and feature extraction towards predicting degradation trend and the life of the component. The evaluation of remaining useful life for the monitored component or system and the use of insights from this evaluation is a crucial part of online risk-based/risk-informed applications. A prognostics-based approach, as an extension of a condition-monitoring approach, can address the surveillance and monitoring requirements of new as well as old nuclear plants (Ref. 6); its benefit analysis is presented in Ref. 12. Implementing a PHM framework requires three crucial steps:

1. Selecting the SSCs for monitoring
2. Developing a diagnostic model enabling early detection of degradation in selected SSCs
3. Developing a prognostic model to estimate expected remaining useful life.

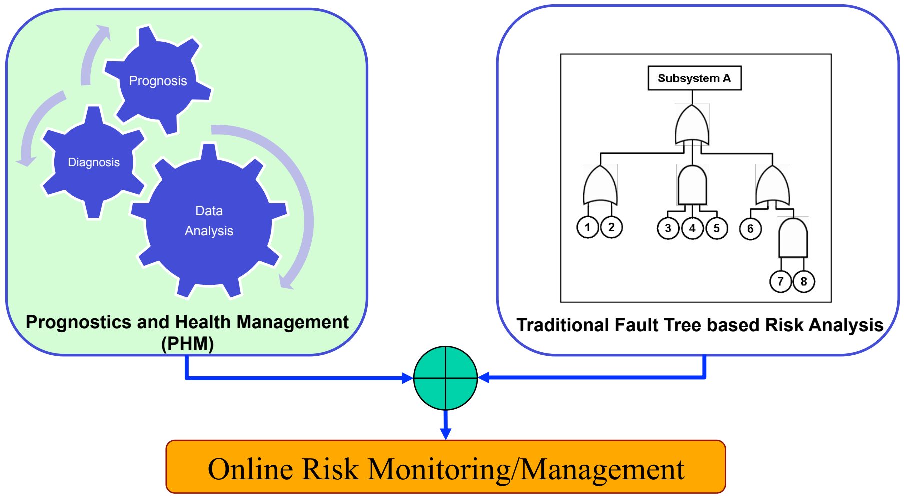

Fig. 2. A schematic representation of research vision to achieve online risk monitoring.

III. IMPORTANCE MEASURES

Importance measure plays a critical role in prioritizing component importance in a system. The commonly used importance measures in nuclear industry are broadly categorized as risk significant and safety significant (Ref. 10). An extensive review of different importance measures and their applications is available in Ref. 10. The application of importance measures assumes that a component/system is non-repairable and has binary states (i.e., operating and failed). During the literature review, three importance measures (Barlow-Proscha measure [Ref. 13], Natvig measure [Ref. 14], and Joint Importance measure [Ref. 15]) were identified that could be extended to repairable systems with non-binary states. These measures are under investigation as part of the current research. With too much emphasis on risk and safety significance importance measures, little attention is paid to the cost incurred to maintain a system and its components within a given time period. This led to the investigation in component importance when considering cost.

IV. COMPONENT IMPORTANCE CONSIDERING COST

Following the discussion on importance measures in the previous section, risk has been the primary metric in prioritization/ranking of component significance in a system and optimization of inspection frequency (Refs. 9 and 16). In the current energy competitive market, it is important to consider cost when determining component importance for inspection or maintenance or for implementation of PHM technologies.

Ref. 11 showed that the importance of a component depends on the cost of maintaining this component in a given time internal $(0,t)$ and proposed a new importance measure that takes different costs into consideration. These costs are:

- Cost 1 (C_1): Costs of improving component reliability. In a system, the cost of improving the reliabilities of different components is likely to be different in interval $(0,t)$.
- Cost 2 (C_2): Costs due to component failure. If a component fails, it needs to be repaired or replaced. This incurs costs.
- Cost 3 (C_3): Cost of system failure. A system is usually designed and installed for completing a specific function. If a system fails, it can cause losses, such as loss of lives, damage to health, release of hazardous materials or other detrimental effects to the environment, or economic losses including repair or replacement of directly damaged structures as well as repair of collateral damage.

Ref. 11 in their analysis considered the operation of system and its component in binary state (i.e., functioning or failed). Also, they ignored the cost C_1 and considered only C_2 and C_3 to enable comparison between the Birnbaum importance measure and cost importance measure based on binary operational states. However, in practice, the system and its components are repairable before failure, thereby improving component reliability. For such system and components, the cost C_1 should be incorporated in the cost importance. In this paper, cost-based importance measure framework of Ref. 11 is utilized and modified to include cost C_1. The cost C_1 for each component in a system is expressed in terms of reliability as:

$$C_{1,k} = f(R_k(t)) \qquad (1)$$

where $R_k(t)$ is the reliability of the $k-$th component and $C_{1,k}$ is the cost of improving the reliability of the $k-$th component.

IV.A. Modeling Assumptions

In this paper, following assumptions are made.

1. A system is composed of k components. At time $t=0$, all components are new.
2. The system and its components are repairable.
3. The behaviors of the components in the system are mutually statistically independent.
4. Compared to the operating time, repair times are negligible.
5. For each component in a system, the maximum and minimum reliability is same and predefined (i.e., $R_k^{\max} = R^{\max} = 0.95$ and $R_k^{\min} = R^{\min} = 0.1$).
6. The reliability of each component is constant for initial m cycles. Here, each cycle interval is 18 months.
7. After m cycles, component reliability drops and component is repaired. After each repair, component reliability returns to maximum achievable reliability value for n cycles.
8. After $m+n$ cycles, the component reliability decrease and component is repaired. After each repair, component reliability does not return to maximum achievable reliability value. Instead returns to a reliability value in the interval $[R^{\max}, R^{\min}]$.
9. Component is considered failed when $R_k(t) < R^{\min}$. This definition of failure is different from the one considered in Ref. 11.
10. The degradation rate (λ) of each component in a system is mutually statistically independent. The reliability of each component is:

    $$R_k(t) = e^{-\lambda_k t} \qquad (2)$$

    Here λ_k is the degradation rate of $k-$th component.
11. In simulation evaluation, the degradation is modeled as a Bernoulli distribution.

IV.B. Cost Model Formulation

Based on cost definitions and assumptions, a function expression for the cost C_1 in terms of reliability is developed in this section. The reliability of each component in a system changes over time interval $(0,t)$ (i.e., $R_k(t) \in [R_k^{\min}, R_k^{\max}]$). A four-parameter model is presented in this paper, which is defined as:

$$C_{1,k} = a_k \cdot G(t) + b \qquad (3)$$

where a_k is the maximum cost incurred in improving reliability of the $k-$th component, which includes be labor hour, instrumentation cost, administrative cost, and system downtime cost; b is the fixed cost that is incurred every operational cycle as a result of scheduled/planned maintenance and includes the cost of any PHM implementation on the $k-$th component; and $G(t)$ is the dimensionless quantity that represents the normalized survival function of the $k-$th component and has value in [0,1]. $G(t)$ is expressed as:

$$G_k(t)=\frac{R_k^{\max}-R_k(t)}{R_k^{\max}-R_k^{\min}} \qquad (4)$$

In cost estimation of a_k, it is assumed that the system downtime does not impact the operation of the plant because a backup system would be engaged so that reactor operation is not impacted. However, at this point, probability of failure the overall system increases. Substitute Eq. (4) into Eq. (3), to obtain:

$$C_{1,k}=a_k\cdot\frac{R_k^{\max}-R_k(t)}{R_k^{\max}-R_k^{\min}}+b \qquad (5)$$

The model in Eq. (5) has the following characteristics:

1. If $R_k(t)=R_k^{\max}$, $C_{1,k}=b$. This implies that the component is at its maximum achievable reliability; thereby no additional cost of improving component reliability is required. The minimum cost will be incurred due to scheduled maintenance activities (as expected).
2. If $R_k(t)=R_k^{\min}$, $C_{1,k}=a_k+b$. This implies that the component is at its minimum reliability (close to failure based on modified definition used in this paper, see Assumption 9 above); thereby the cost associated with improving component reliability at that instance of time would be high. It is also a decision point, whether to repair or replace the component.
3. As the value of $R_k(t)$ monotonically decreases, the value of $C_{1,k}$ monotonically increases as shown in Fig. 3.

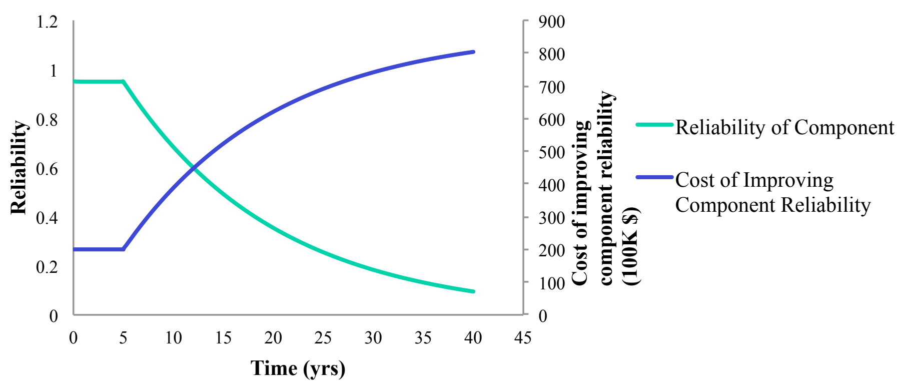

Fig. 3. Characteristic of the model in Eq. (5).

Given the expression for $C_{1,k}$, the costs $C_{2,k}$ and C_3 (as described in Ref. 11) is combined to obtain a cumulative cost in the interval $(0,t)$. Note, that the definition of $C_{1,k}$ in this paper is as per Assumption 9. The cost-based ordering of components achieved with $C_{1,k}$ (in this paper) and without $C_{1,k}$ (as in Ref. 11) is compared on series-parallel system architecture.

V. MODEL VALIDATION

In this section, cost model $C_{1,k}$ is validated by performing a MATLAB® simulation for a given scenario, and by comparing the cost-based ordering of components achieved by including $C_{1,k}$ in the cumulative cost with the ordering report in Ref. 11.

V.A. Scenario-based Cost $C_{1,k}$ Model Validation via MATLAB® Simulation

Based on assumptions in Section IV and parameter values in Table 1, a scenario is developed for model validation. In this scenario, the component reliability remains constant for $m = 6$ cycles. Here each cycle interval is 18 months. After m cycles, the component degradation rate λ is constant 15% for next $n = 5$ cycles, thereby reducing component reliability. The component is repaired and it recovers completely such that $R_k(t) = R_k^{\max}$. After $m + n$ cycles (i.e., after 11 cycles combined) the component degradation is random and is uniformly distributed between 5% and 25%. The component is repaired, but the recovery is partial such that $R_k(t) < R_k^{\max}$. The time duration in the simulation is 22 cycles (equivalent to 39 years and 6 months) or until $R_k(t) < R_k^{\min}$. If $R_k(t) < R_k^{\min}$ is achieved before 22 cycles, the simulation is terminated. The simulation was performed 1000 times to compute the expected value of the reliability and cost with respective standard deviations, as shown in Fig. 4, for the main shaft of the system architecture shown in Fig. 5. From Fig. 4, observe that the cost $C_{1,k}$ model is in agreement with the mean simulated cost.

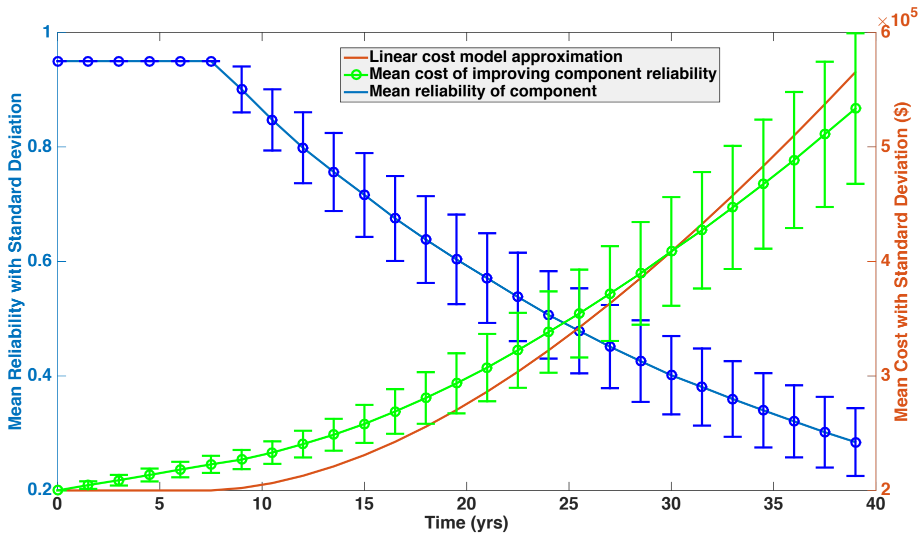

Fig. 4. Mean reliability and cummulative cost versus cost model for main shaft.

TABLE I. Cost data and parameter values for scenario-based model validation.

$a_{MainShaft}$ ($)	b ($)	$R_k^{\min}$	$R_k^{\min}$	$\lambda_{MainShaft}$ after 11 cycles
45887	200000	0.1	0.95	$U \sim [0.15, 0.25]$

V.B. Comparison of Cumulative Cost with and without $C_{1,k}$ in Component Importance Ranking

The system architecture in Fig. 5 is representative of a 600-KW wind turbine. For evaluation purpose, the system architecture, cost data, and failure rate as reported in Ref. 17 are used (see Table II). For details on cumulative cost computation without $C_{1,k}$, see Ref. 11. The component ordering based on cost without $C_{1,k}$ in Ref. 11 and with $C_{1,k}$ (in this paper) is presented in Table III. From Table III, observe that the component ordering based on cost has changed with and without $C_{1,k}$. From cost perspective main observations from Table III include (i) without $C_{1,k}$, the gearbox was the most important component as per Ref. 11, and with $C_{1,k}$, the main shaft is the most important component; and (ii) with or without $C_{1,k}$, the bearing is still the least important component. Observation (ii) is as expected because Bearings A and B are in parallel and both bearings have to fail to cause system failure, whereas other components are in a series and if any one component fails, the system failure occurs.

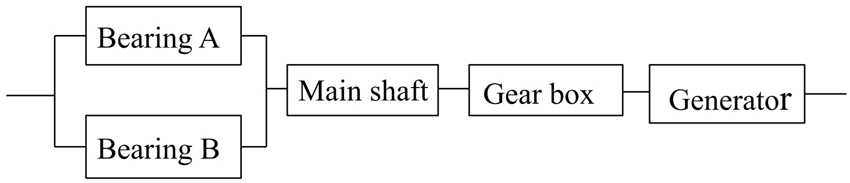

Fig. 5. Series-parallel system architecture (Ref. 11).

TABLE II. Cost Data and Parameter Values for Model Comparison (Ref. 17).

Component	Gear Box	Bearing	Generator	Main Shaft
Cost ($)	70062	55548	65128	45887
Probability of failure	0.3835	0.2104	0.5460	0.632

TABLE III. Comparison of component ordering based on cost.

	Without $C_{1,k}$ (Ref. 11)	With $C_{1,k}$
Component Ordering	Gear box > Generator > Main shaft > Bearing	Main Shaft > Generator > Gear Box > Bearing

VI. CONCLUSIONS AND PATH FORWARD

This paper presented a brief overview of an ongoing research effort at INL in the area of online risk monitoring. The paper focused on one of the research objectives of component ordering based on cost importance instead on only risk importance. A simple four-parameter cost model as function of reliability was developed. This cost model was able to capture the cost of improving component reliability with operational time. This cost was included with two additional costs to obtain cumulative cost. The four-parameter cost model was validated via a scenario based MATLAB® simulation. The impact of cumulative cost on component ordering with and without the four-parameter cost model was performed and compared with the results reported in Ref. 11.

As part of future research, the model needs to be evaluated on a complex interconnected nuclear system with cost and failure data.

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DISCLAIMER

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