# Survey on Prognostics Techniques for Updating Initiating Event Frequency in PSA

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## 1. Introduction

Recently, the concerns on regulation for Nuclear Power Plants (NPPs) have been increasing because of Fukushima disaster and increasing operating years of NPPs. In order to deal with these concerns, conventional Probabilistic Safety Assessment (PSA) makes more exquisite and accurate and expands the applications [1, 2]. One of the applications using PSA is a risk monitor [3]. The risk monitoring is real-time analysis tool to decide real-time risk based on real state of components and systems. In order to utilize more effective, the methodologies that manipulate the data from Prognostics was suggested. Generally, Prognostic comprehensively includes not only prognostic but also monitoring and diagnostic. The prognostic method must need condition monitoring. In case of applying PHM to a PSA model, the latest condition of NPPs can be identified more clearly. For reducing the conservatism and uncertainties, we suggested the concept that updates the initiating event frequency in a PSA model by using Bayesian approach [4] which is one of the prognostics techniques before. From previous research, the possibility that PSA is updated by using data more correctly was found.

In reliability theory, the Bathtub curve divides three parts (infant failure, constant & random failure, ware-out failure). Infant failure and ware-out failure are rapidly decreasing or increasing and constant & random failure keeps the constant. The component of NPPs is used within constant & random failure rate interval in the Bathtub curves. However, constant & random failure has some random changes and the beginning of the ware-out failure is not convinced clearly. Prognostic can predict random changes in constant & random failure rate and the beginning of the ware-out failure. However, there is concern about applying prognostic to assure quality of prognostic. In order to assure prognostic, prognostic had been approved for regulation about the helicopter rotor [5].

Thus, in this paper, on-line monitoring (OLM) acceptance criteria indicated by US Nuclear Regulatory Commission (NRC) to support the applicability of prognostic are summarized [6]. As mentioned above, because prognostic include the monitoring data, OLM acceptance criteria support to apply prognostic. The concept how to use prognostic in the PSA and enabling prognostic techniques is described.

## 2. Background

In this section, the OLM acceptance criteria from NRC are explained to support the applicability of PHM. And the concept of prognostic in PSA is explained.

### *2.1 OLM Acceptance Criteria*

In 1998, the Electric Power Research Institute (EPRI) submitted Topical Report (TR) 104965, this report demonstrated a non-intrusive method for monitoring the performance of instrument channels and extending calibration intervals required by technical specifications (TS). NRC staff concluded that the generic concept of OLM for tracking instrument performance was issued. However, they also listed 14 requirements that must be addressed by plant specific license amendment. These 14 requirements can be considered the acceptance criteria for OLM [6].

1. Implementation of the on-line monitoring technique shall confirm that the impact on plant safety of the deficiencies inherent in the on-line monitoring technique on plant safety will be insignificant, and that all uncertainties associated with the process parameter estimate have been quantitatively bounded and accounted for either in the on-line monitoring acceptance criteria or in the applicable set-point and uncertainty calculations.
2. Instrument channels monitoring processes that are always at the low or high end of an instrument's calibrated span during normal plant operation shall be excluded from the on-line monitoring program.
3. The algorithm used for on-line monitoring shall be able to distinguish between the process variable drift and the instrument drift and shall be able to compensate for uncertainties introduced by unstable process, sensor locations, non-simultaneous measurements, and noisy signals.
4. For instruments that were not included in the EPRI drift study, the value of the allowance or penalty to compensate for single-point monitoring must be determined by using the instrument's historical calibration data and by analyzing the instrument performance over its range for all modes of operation, including startup, shutdown, and plant trips.
5. Calculations for the acceptance criteria defining the proposed three zones of deviation ("acceptable", "needs calibration", and

"inoperable") should be done in a manner consistent with the plant-specific safety-related instrumentation set-point methodology so that using on-line monitoring technique to monitor instrument performance and extend its calibration interval will not invalidate the set-point calculation assumptions and the safety analysis assumptions.

6. For any algorithm used, the maximum acceptable value of deviation (MAVD) shall be such that accepting the deviation in the monitored value anywhere in the zone between Process parameter Estimate (PE) and MAVD will provide high confidence (level of 95%/O/95%o).
7. The instrument shall meet all requirements of the above requirement 6 for the acceptable band or acceptable region.
8. The maximum value of the channel deviation beyond which the instrument is declared "inoperable" shall be listed in the technical specifications. It could be called "allowable deviation value for on-line monitoring" (ADVOLM). The ADVOLM shall be established by the instrument uncertainty analysis.
9. Calculations defining alarm set-point (if any), acceptable band, the identifying the monitored instrument as needing to be calibrated earlier than its next scheduled calibration, shall be performed to ensure that all safety analysis assumptions and assumptions of the associated set-point calculation are satisfied and the calculated limits for the monitored process variables specified by, 10CFR50.36 are not violated.
10. The plant specific submittal shall confirm that the proposed on-line monitoring system will be consistent with the plant's licensing basis, and that there continues to be a coordinated defense in-depth against instrument failure.
11. Adequate isolation and independence, as required by Regulatory Guide 1.75, GDC 21, GDC 22, IEEE Std. 279 or IEEE Std. 603, and IEE Std. 384, shall be maintained between the on-line monitoring devices and Class 1E instruments being monitored.
12. (a) QA requirements as delineated in 10CFR Part 50, Appendix B, shall be applicable to all engineering and design activities related to on-line monitoring, including design and implementation of the on line system, (b) The plant-specific QA requirements shall be applicable to the selected on-line monitoring methodology, its algorithm, and the associated software.
13. All equipment (except software) used for collection shall meet the requirements of 10CFR Part 50, Appendix B, Criterion XII, "Control of Measuring and Test Equipment.
14. Before declaring the on-line monitoring system operable for the first time, and just before each performance of the scheduled surveillance using an on-line monitoring technique, a full-features functional test, using simulated input signals of known and traceable accuracy, should be conducted to verify that the algorithm and its software perform all required functions within acceptable limits of accuracy. All applicable features shall be tested.

Because prognostic includes monitoring data, OLM acceptance criteria support to apply prognostic. Thus, to use prognostic for updating initiating event of PSA also follows OLM acceptance criteria.

### *2.2 Prognostics in PSA*

The event tree was basically made to include each accident scenario and correlation of systems. The frequency of an end state of a specific accident scenario is calculated by the combination of the event. The event tree consisting of initiating event and sequence event uses frequency or failure probability.

The values of frequency or failure probability are obtained through statistical analysis from diverse information. The prognostic can contribute to this statistical analysis by getting frequency and failure probability.

In the Fig. 1, the conventional failure distribution is a reliability-based distribution. The reliability-based distribution can be obtained from traditional time-to-failure analysis. The transition from a reliability-based distribution to a condition-based distribution can be done by prognostic techniques with the observation of condition indicators. The condition-based distribution characterizes the lifetime of a specific system or components operating in components operating in that system specific environment. In Fig. 1, the monitoring of condition indicators updates the condition-dependent model and the condition prognostic supports the time-dependent model [4].

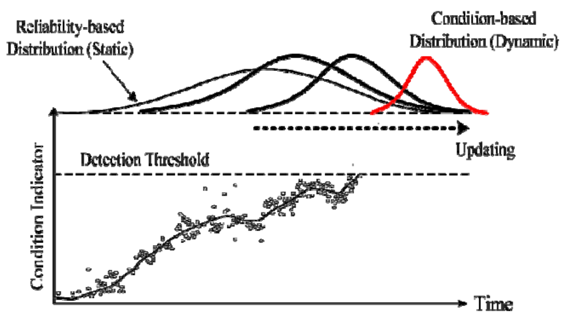


Figure. 1. The transition of failure distribution using prognostic

Conventionally, statistical analysis in Level 1 PSA has used reliability-based distributions. As see in Fig. 2, we replace reliability-based distributions with condition-based distributions using the prognostic to event tree and fault tree.

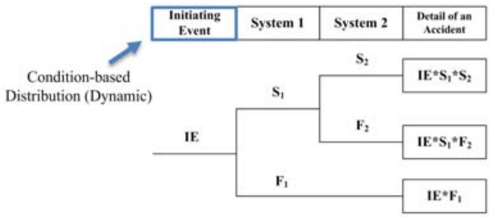


Figure. 2. The concept of integrating PHM and PSA

### 3. Enabling Prognostic Techniques

The prognostic utilizes the information from monitoring and diagnostic. Generally, monitoring, diagnostic and prognostic call Prognostic and Health Management (PHM). In this paper, prognostic are more explained to support previous research as mentioned above. The figure 1 shows the concept of PHM system and related representative algorithms [7, 8].

In the Fig. 3, 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. These methods include Artificial Neural Network (ANN), Auto-Associate Kernel Regression (AAKR), Multivariate State Estimation Technique (MSET), Sequential Probability Ratio Test (SPRT), Error Uncertainty Limit Method (EULM), and Statistical Quality Control (SQC).

The Diagnostic is those identifies and diagnose the cause of an anomaly in the system or process. The diagnostic method includes k-Nearest Neighbor (kNN), Principal Component Analysis (PCA) and Fuzzy application.

Finally, the prognostic estimates the time remaining to run the system or process within specified tolerances, in order word, estimate Remaining Useful Life (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.

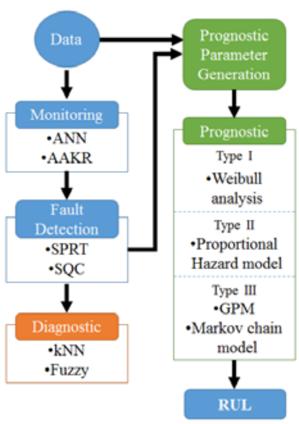


Figure. 3. The concept of PHM system and related algorithms

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. Fig. 4 shows prognostic algorithm categorization [8].

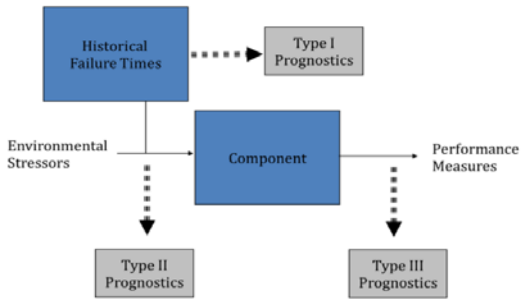


Figure. 4. The prognostic algorithm categorization

Type I prognostic, or reliability-based, is traditional time-to-failure analysis. These methods consider historical time to failure data which are used to model the failure distribution. They estimate the life of an average component under average usage conditions. These methods may be applied if no data specific to the current system is available. Examples of Type I prognostic include Weibull analysis, exponential or normal distribution analysis, and non-parametric distribution analysis. An apparent shortcoming of these methods is the absence of consideration for operating conditions and environment in making RUL estimates.

Type II prognostic, or stress-based, consider the environmental stresses (temperature, load, vibration, etc.) on the component. This type of prognostic characterizes the lifetime of an average system or component operating in specific environment. These methods required environmental effects that drive the failure modes must be measurable. Type II methods include simple regression analysis, Markov Chain model, and the proportional hazards model. Because Type II prognostic neglect unit-to-unit variance, they have are deficient.

Type III prognostic, or degradation-based, also consider measured or inferred component degradation. They estimate the life of a specific component under specific usage and degradation conditions. For Type III, degradation severity must be related to a measurable parameter such as tread depth or bearing vibration level or temperature. Extrapolation of a General Path Model (GPM) or a particle filter model is the most common empirical Type III method. Additional Type III methods include a degradation-based formulation of the Markov Chain model and the shock model.

As mentioned above, more accurate failure rate and distribution are generated by using more information from Type I to Type III. Figure 3 representative transition of distribution by utilizing data from components and system. In the Figure 3, the monitoring data updates reliability-base distribution and prognoses RUL after detection threshold.

*3.1 Type I Prognostic*

Type I prognostic characterize the expected lifetime of the average component operating in historically average conditions. The major assumption is that future components will operate in similar conditions and degrade in similar ways to those seen in the past. This method is generally the least accurate and precise for predicting RUL of specific devices. Components that have not failed are called censored data and that information is also used to predict the failure density. Example parametric models include exponential, normal, log-normal, and Weibull.

Probably the most common parametric model is the Weibull distribution. This model is used because it is flexible enough to model a variety of failure rate profiles. The failure rate is modeled with two parameters. The Eq. 1 shows failure rate of Weibull model.

$$\lambda(t) = \frac{\beta}{\theta}\left(\frac{t}{\theta}\right)^{\beta-1} \qquad \text{Eq. 1}$$

where $\beta$ is shape parameter
$\theta$ is characteristic life

*3.2 Type II Prognostic*

The Type II prognostic estimates the lifetime of the average component in a specific environment. The major assumption is that components operating in similar conditions will degrade in similar ways and unit to unit variation is not significant. Type II can be applied if stressor variables are measureable. The simplest class of methods for Type II prognostic is failure-time, linear regression models. These methods use prior observations of explanatory variables such as temperature, load, voltage, etc. and the response variable, which is usually the failure time, to model relationship between the stressors and life of a component.

In this paper, proportional hazards model which the type II algorithm is explained. The proportional hazards model is a technique that merges failure time data and stress data. The model uses environmental condition information termed covariates ($z_j$), to modify a baseline hazard rate ($\lambda_0(t)$) to form a new hazard rate as see the Eq. 2.

$$\lambda(t;z) = \lambda_0(t)\exp\left(\sum_{j=1}^{q}\beta_j z_j\right) \qquad \text{Eq. 2}$$

where $\lambda_0(t)$ is an arbitrary baseline hazard or function
$z_j$ is a multiplicative factor, explanatory variable or covariate
$\beta_j$ is a model parameter

*3.3 Type III Prognostic*

The Type III prognostic estimates the lifetime of the specific operating environment. Type III algorithms track the degradation as a function of time and predict when the total damage will exceed a predefined threshold that defines failure. Type III prognostic uses degradation that measures to form a prognostic prediction. The degradation measure does not have to be a directly measured parameter. It could be a function of several measured variable that provide a quantitative measure of degradation.

Many Type III prognostic models track the degradation as a function of time and predict when the total damage will exceed a predefined threshold that defines failure. Cumulative degradation is defined to be irreversible accumulation of degradation in components under cyclical loadings. Typically, Markov Chain-based models, Shock models and GPM can calculate cumulative degradation model. Markov Chain-based model and GPM model are explained in this paper.

*3.3.1 Markov chain based model*

Markov chain model is used in many stochastic simulations and also can be used as Type II or Type III prognostic model. Markov chain model is developed to study transition or stochastic matrices. The strength of Markov chain model can analyze long range sequential state predictions without previous state. Thus, Markov chain model is possible to track cumulative degradation and to generate possible future degradation paths.

The Type III case is when one is able to directly observe a numerical quantity characterizing the component's ability to function in accordance with its specifications. Markov model explain the equipment degradation as a transition of states. The states can be the environmental conditions that cause degradation. Fig 5 shows the result of cumulative degradation model by using Markov chain model.

*3.3.2 General Path Model (GPM)*

The GPM was originally proposed as a statistical method for using degradation measures to estimate a failure distribution for censored data. Degradation paths were extrapolated to find estimated failure times and then the distribution was estimated. The observed degradation path is explained by Eq. 3. And, Eq.4 indicates Time-to-Failure (TTF) distribution.

$$y_i = \eta(t, \varphi, \Theta_i) + \varepsilon \qquad \text{Eq. 3}$$

where y is the observed degradation
η is the actual degradation
ε is the measurement error
φ is population characteristics
$\Theta_i$ is individual unit characteristics

$$\Pr\{T \le t\} = F_T(t, \varphi, G_\Theta(\cdot), D, \eta) \qquad \text{Eq. 4}$$

where $G_\Theta$ is the distribution of $\Theta_i$
D is the critical threshold

Using the Eq. 4, GPM parameter is estimated. However, it is difficult to estimate GPM parameter, directly. Thus, in order to estimate GPM parameter, Two-step parameter estimation is used to fit the non-linear degradation model

## 4. Conclusions

In this paper, in order to investigate the applicability of prognostic methods in updating quantitative data in a PSA model, the OLM acceptance criteria from NUREG, the concept of how to using prognostic in PSA, and the enabling prognostic techniques are suggested.

The prognostic has the motivation that improved the predictive capabilities using existing monitoring systems, data, and information will enable more accurate equipment risk assessment for improved decision-making. From using prognostic, needless and unplanned maintenance through optimized, environmental impacts can be reduced and safety can be improved through more accurate failure rate.

## 5. Acknowledgement

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