Physics-Informed Intelligent Prognostic and Diagnostic Framework for Nuclear Power Plant Safety System Signal Processors

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1. Introduction

The global nuclear energy sector is currently undergoing a major transition. Although approximately 440 commercial pressurized water reactors (PWRs) and boiling water reactors (BWRs) remain in operation worldwide, more than 80 small modular reactor (SMR) concepts were under active development across OECD Nuclear Energy Agency (NEA) member countries as of 2024 [1,2]. These SMR concepts, which range from integral pressurized water reactor (iPWR) designs such as SMART and NuScale to gas-cooled and molten-salt reactors, are widely expected to reach commercial deployment in the 2030s [3].

Both conventional nuclear power plants (NPPs) and SMRs depend on safety-grade instrumentation and control (I&C) systems, particularly digital signal processors responsible for reactor protection and process monitoring functions [4,5]. Compared with large conventional plants, however, SMRs present additional operational and maintenance challenges. Their compact integral layouts restrict physical accessibility, and many designs pursue semi-autonomous or remotely supervised operation with reduced onsite staffing [6]. Under these conditions, online fault diagnostics and prognostics for I&C components become increasingly important, not only for large PWRs undergoing long-term operation to 60–80 years, but also for SMRs from the outset of deployment.

Safety-grade signal processors are vulnerable to degradation induced by thermal, radiation, and humidity stresses. For thermally activated degradation, the Arrhenius equation provides a well-established physics-of-failure basis [7,8]. Meanwhile, the Extended Kalman Filter (EKF) offers an effective recursive estimation framework for nonlinear systems and has been applied to prognostic problems involving nuclear power plant components [9,10]. Based on these considerations, this paper proposes a physics-informed intelligent prognostic and diagnostic framework that couples an EKF-based prognostic core with a hierarchical AI-agent orchestration architecture.

2. Methods and Results

2.1 Arrhenius Physics-of-Failure Model

The thermally activated degradation rate follows the Arrhenius equation [7]:

$$r(T) = A\exp\left(-\frac{E_a}{k_B T}\right) \tag{1}$$

where *A [h^-1]* is the pre-exponential factor, E_a [eV] is the activation energy, k_B =8.617 × 10^{-5} eV/K is the Boltzmann constant, and T [K] is the absolute temperature. The degradation index evolves as:

$$D_{k+1} = D_k + r(T_k)\Delta t + w_k \tag{2}$$

Failure is assumed D_{th} = 0.80 when. For accelerated life testing (ALT), the acceleration factor is given by:

$$AF = \exp\left[\frac{E_a}{k_B}\left(\frac{1}{T_{use}} - \frac{1}{T_{stress}}\right)\right] \tag{3}$$

Although E_a is an intrinsic material property representing the energy barrier of the underlying degradation mechanism, the degradation rate varies exponentially with temperature through the Arrhenius term. At the reference operating temperature of 45 °C (318.15 K) with E_a = 0.85 eV, a 10 °C rise to 55 °C increases the degradation rate by AF_{10} = exp[(E_a/k_B)(1/318.15 - 1/328.15)] approx. 1.78, while a 20 °C rise to 65 °C yields AF_{20} approx. 3.18. Because the Remaining Useful Life (RUL) is inversely proportional to the degradation rate, these increases directly reduce the predicted RUL. This strong exponential temperature sensitivity highlights the importance of accurate real-time temperature monitoring in nuclear I&C environments. Because individual system may deviate from nominal E_a values due to manufacturing tolerances or prior aging history, augmenting E_a as an online-identifiable EKF state (Section 2.2) enables component-specific RUL estimation rather than relying on generic constants tabulated in MIL-HDBK-217F [5].

2.2 State-Space Formulation

E_a is augmented into the state vector $x = [D, E_a]^{T}$ for online identification. The Jacobian for EKF linearization is F = partial f / partial x, with the critical element:

$$F_{12} = -\frac{A\Delta t}{k_B T_k}\exp\left(-\frac{E_a}{k_B T_k}\right) \tag{4}$$

The term F_{12} represents the sensitivity of the degradation evolution to the activation energy, enabling online identification of component-specific degradation kinetics.

2.3 EKF Algorithm

The EKF alternates predict/update steps with Joseph-form covariance update for numerical stability. Table 1 summarizes the full algorithm. Table 1 presents the recursive EKF formulation used to estimate degradation state and activation energy while maintaining numerical stability.

Table 1. EKF Algorithm for Arrhenius Degradation Estimation

Step	Operation	Expression
Initialize	State vector	$x_0 = [0, E_{a0}]^T$, $P_0 = \text{diag}([1e^{-6}, 0.01])$
Predict state	$\hat{x}(k\|k-1)$	$x_p = f(x(k-1), T(k))$
Predict covariance	$P(k\|k-1)$	$P_p = F\,P\,F^T + Q$
Kalman gain	K_k	$K = P_p H^T (H P_p H^T + R)^{-1}$
Update state	$\hat{x}(k)$	$x = x_p + K(z_k - Hx_p)$
Update covariance	Covariance	$P = (I - KH)P_p(I - KH)^T + K\,R\,K^T$
Output	$\hat{D}$, $\hat{E}_a$, RUL	RUL = $(D\_th - \hat{D}) / r(\bar{T}, \hat{E}_a)$

2.4 RUL Prediction

Under a stationary future temperature $\bar{T}$, the RUL with a 95% confidence bound is expressed as:

$$RUL = \frac{D_{th} - \hat{D}}{r(\bar{T}, \hat{E}_a)}, \quad RUL_{95} = RUL - 1.645\sigma_{RUL} \tag{5}$$

2.5 Intelligent diagnostic agent Framework & Monitoring Flow

"Intelligent diagnostic agent" here denotes an architectural pattern (not a specific AI algorithm) structuring autonomous sensing, diagnosis, decision-making, and reporting into a coherent pipeline [8,11]. Fig. 1 shows the overall physics-informed intelligent prognostic and diagnostic monitoring cycle executed at each Δt = 1 min interval.

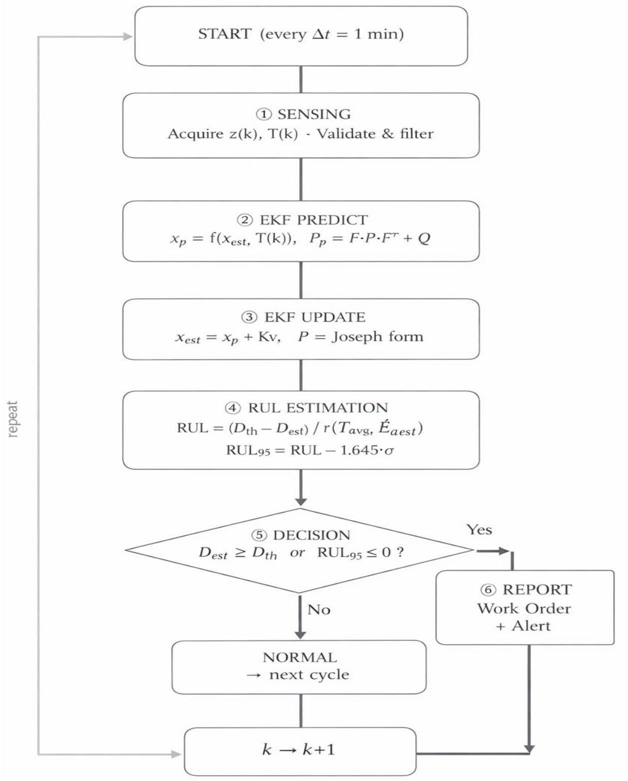

Fig. 1. overall algorithm flow of Physics-Informed Intelligent Prognostic and Diagnostic.

2.6 SMR Applicability

SMRs present three Prognostics and Health Management (PHM) challenges addressed by physics-informed intelligent prognostic and diagnostic: (1) integral designs limit in-situ sensor access, making model-based *Ea* inference valuable; (2) reduced staffing requires autonomous explainable diagnostics; (3) absence of field degradation databases motivates online Ea identification. The modular agent architecture supports deployment on existing DCS platforms [11].

3. Simulation Validation

3.1 Setup for Simulation

A virtual electrolytic capacitor was simulated with A = 2.5×10^{-4} h^{-1}, E_a = 0.85 eV, D_{th} = 0.80. A 1,000-day field profile at 45°C ± 8°C was applied, with EKF initialized at biased $\hat{E}_{a,0}$ = 0.748 eV (−12%). Accelerated life testing at 85/105/125°C validated the Arrhenius model via acceleration factors AF = 31.9, 137.5, and 511.7, respectively.

3.2 EKF Results

Fig. 2 demonstrates EKF performance under a 1-minute measurement interval a practically achievable sampling rate for signal processors. With high-frequency data, the EKF maintains tight uncertainty bounds throughout the 1,000 days monitoring period and simultaneously converges the online *Ea* estimate from the initial biased value ($\hat{E}a,0$ = 0.748 eV, −12%) toward the true material value (0.85 eV) within the first few hundred days. Beyond the observation cutoff at Day 799, the intelligent diagnostic agent projects the EKF estimation based on Arrhenius model forward to predict failure at Day 889, providing a 90 days advance warning with quantified 95% confidence bounds.

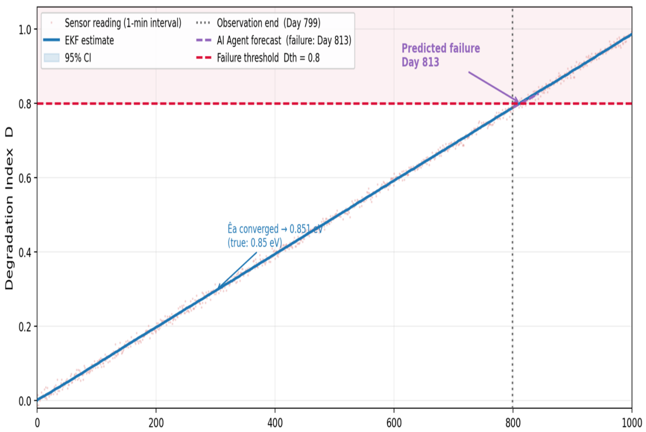

Fig. 2. EKF degradation estimation (1-min interval)

3.3 Fault Diagnosis

Fig. 3 illustrates intelligent diagnostic agent anomaly detection. At Day 300, an overload shock causes D to deviate abruptly from the expected normal trajectory. The Kalman filter innovation immediately exceeds the 3σ threshold, triggering an intelligent diagnostic agent alert and transitioning system status from NORMAL to WARNING. The causal chain from anomaly to alert is directly readable from the two-panel figure.

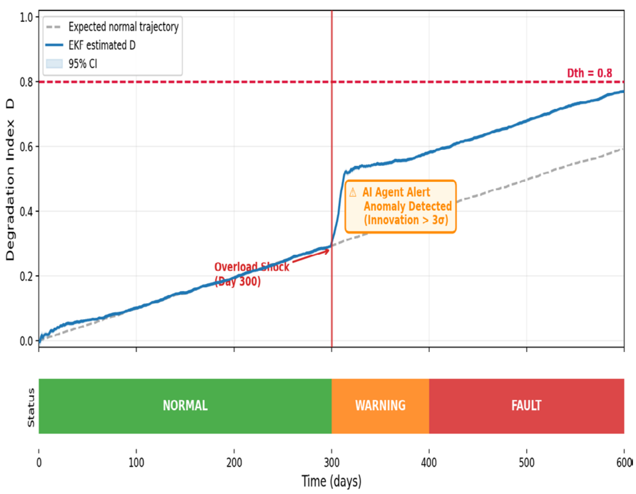

Fig. 3. intelligent diagnostic agent anomaly detection via Kalman filter estimation.

3.4 intelligent diagnostic agent Predictive Scenario Analysis

A critical advantage of the EKF based on Arrhenius formulation is the ability to forecast failure timing under hypothetical future environments without any additional measurement data. As demonstrated in Fig. 2, the intelligent diagnostic agent uses the EKF posterior state ($\hat{D}$, $\hat{E}a$, covariance P) established up to the observation cutoff at Day 799 to project degradation trajectories forward in time under multiple temperature scenarios.

Using the converged EKF estimate ($\hat{D} \approx 0.72$, $\hat{E}a \approx 0.85$ eV at Day 799), the intelligent diagnostic agent applies Arrhenius acceleration kinetics to generate scenario-specific RUL forecasts: (1) baseline at 45°C yields failure at Day 889 (RUL ≈ 90 days); (2) a moderate rise to 55°C ($AF_{10} \approx 1.78\times$) compresses RUL to approximately 51 days; (3) a severe excursion to 65°C ($AF_{20} \approx 3.18\times$) further reduces RUL to approximately 28 days. This scenario-driven output exemplifies the operational value of physics-informed intelligent prognostic and diagnostic: the intelligent diagnostic agent converts a temperature forecast into a quantified, actionable maintenance timeline directly readable from the probabilistic forecast envelope shown in Fig. 2 requiring no human intervention.

4. Conclusions

The physics informed intelligent prognostic and diagnostic framework contributes: (1) a rigorous EKF formulation based on Arrhenius physical model enabling simultaneous degradation index D estimation and online activation energy Ea identification with uncertainty bounded RUL; and (2) a hierarchical intelligent diagnostic agent architecture clarified as a framework pattern, not an AI algorithm for autonomous diagnostic pipelines. For SMRs, online Ea identification addresses limited degradation databases, and the modular architecture supports autonomous operation scenarios.

While the Arrhenius model is well-validated per IEEE Std 323 and IEC 61709 for thermally activated degradation, actual nuclear I&C environments subject signal processors to simultaneous multi-stress conditions, including radiation-induced damage (total ionizing dose, displacement damage) and mechanical fatigue from thermal cycling. These additional degradation pathways are not captured by the single-mechanism Arrhenius formulation. Accordingly, future work will extend the physics-informed intelligent prognostic and diagnostic state-space formulation to incorporate multi-physics degradation pathways together with hardware in the loop validation by using the actual test data.

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