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Physics-Informed Intelligent Prognostic and Diagnostic Framework

for Nuclear Power Plant Safety System Signal Processors

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ABSTRACT

We propose a Physics-Informed Intelligent Prognostic and Diagnostic (**PIIM**) framework that couples an **Extended Kalman Filter (EKF)** with the Arrhenius physics-of-failure model to estimate the degradation index ***D*** and identify the activation energy ***E$_a$*** online for nuclear safety-grade signal processors. A hierarchical intelligent diagnostic agent — clarified as an *architectural pattern* rather than a specific AI algorithm — converts EKF output into uncertainty-bounded RUL with autonomous reporting. Validated on a 1,000-day virtual capacitor profile, the framework converges $\hat{E}_a$ from a −12% biased prior, predicts failure at Day 889 with 90-day advance warning, and detects an injected Day-300 overload shock via 3σ innovation. Multi-temperature scenario analysis (45 / 55 / 65°C) yields directly actionable maintenance timelines.

Keywords *Signal Processor · Physical Model · Extended Kalman Filter · Intelligent Agent · RUL · Prognostic · Diagnostic · SMR*

1 Introduction

~440 PWRs / BWRs in operation worldwide

> 80 SMR concepts under development (NEA, 2024)

2030s Expected commercial SMR deployment

Why online PHM for I&C signal processors?

- Safety-grade I&C is core to reactor protection in both NPPs and SMRs
- Subject to thermal, radiation, and humidity-induced degradation
- Large PWRs target 60–80 year long-term operation
- SMRs need reliable PHM from deployment outset

2 Arrhenius Physics-of-Failure

Degradation rate

$$r(T) = A \cdot \exp(-E_a / k_B T) \quad (1)$$

State evolution

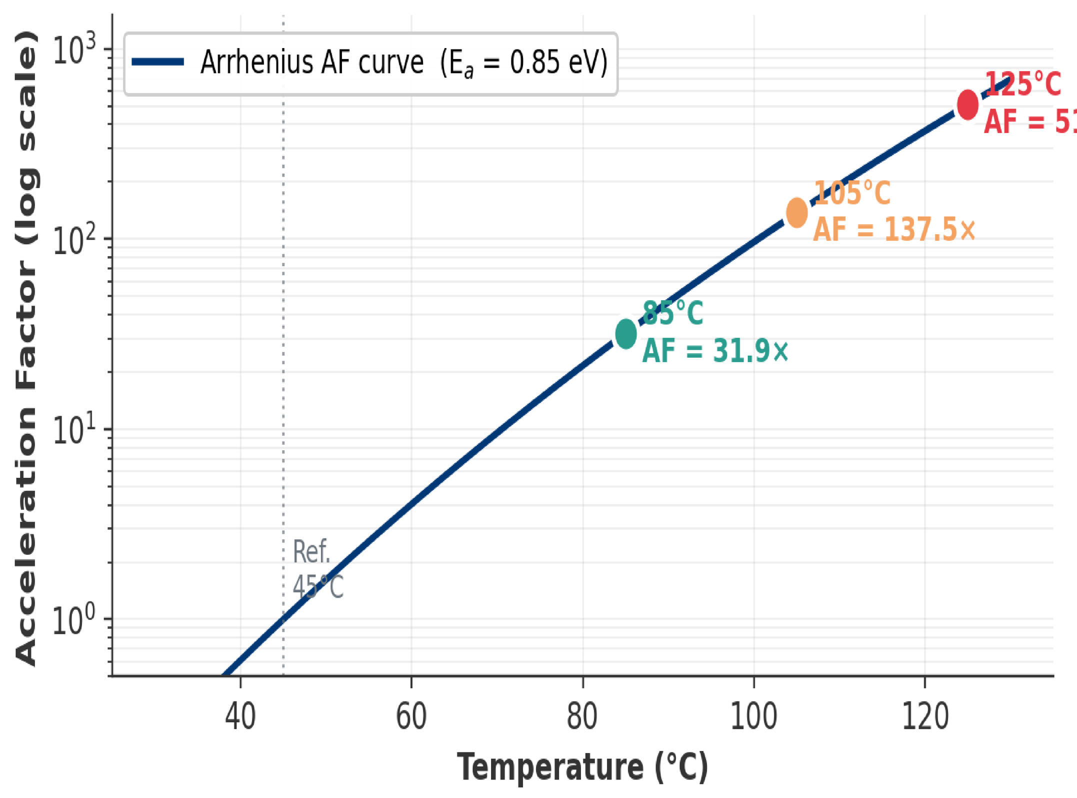
$$D_{k+1} = D_k + r(T_k)\cdot\Delta t + w_k \quad (2)$$

Acceleration factor (ALT)

$$AF = \exp[(E_a / k_B) \cdot (1/T_{use} - 1/T_{ss})] \quad (3)$$

Failure threshold: **D_{th} = 0.80**

Arrhenius Acceleration — ALT Validation Points



Temperature Sensitivity (ref. 45°C, E$_a$ = 0.85 eV)

+10°C → **AF$_{10}$ ≈ 1.78×** , +20°C → **AF$_{20}$ ≈ 3.18×**

RUL ∝ 1 / r(T) → strong exponential temperature sensitivity

3 EKF State-Space Formulation

Augmented State Vector

$$x = [\,D,\ E_a\,]^T$$

Enables simultaneous degradation estimation + component-specific E$_a$ identification

Critical Jacobian Element (Eq. 4)

$$F_{12} = -(A\cdot\Delta t / k_B\cdot T_k) \cdot \exp(-E_a / k_B\cdot T_k)$$

Sensitivity of D-evolution to activation energy

Table 1. EKF Algorithm (Joseph-form covariance update)

Step	Operation	Expression
Initialize	x_0, P_0	$x_0 = [0, E_{a,0}]^T$, $P_0 = \mathrm{diag}([1\times10^{-6}, 0.01])$
Predict	$\hat{x}(k\|k-1)$	$x_p = f(\,x(k-1), T(k)\,)$
	$P(k\|k-1)$	$P_p = F\cdot P\cdot F^T + Q$
Update	K_k	$K = P_p\cdot H^T \cdot (H\cdot P_p\cdot H^T + R)^{-1}$
	$\hat{x}(k)$	$x = x_p + K \cdot (z_k - H\cdot x_p)$
	P	$P = (I - KH)\cdot P_p\cdot(I - KH)^T + K\cdot R\cdot K^T$
Output	$\hat{D}$, $\hat{E}_a$, RUL	$RUL = (D_{th} - \hat{D}) / r(\hat{T}, \hat{E}_a)$

RUL with 95% Confidence Bound

$$RUL = (D_{th} - \hat{D}) / r(\hat{T}, \hat{E}_a) \qquad RUL_{95} = RUL - 1.645\cdot\sigma_{RUL}$$

4 PIIM Framework Architecture

Intelligent Diagnostic Agent — Δt = 1 min monitoring cycle

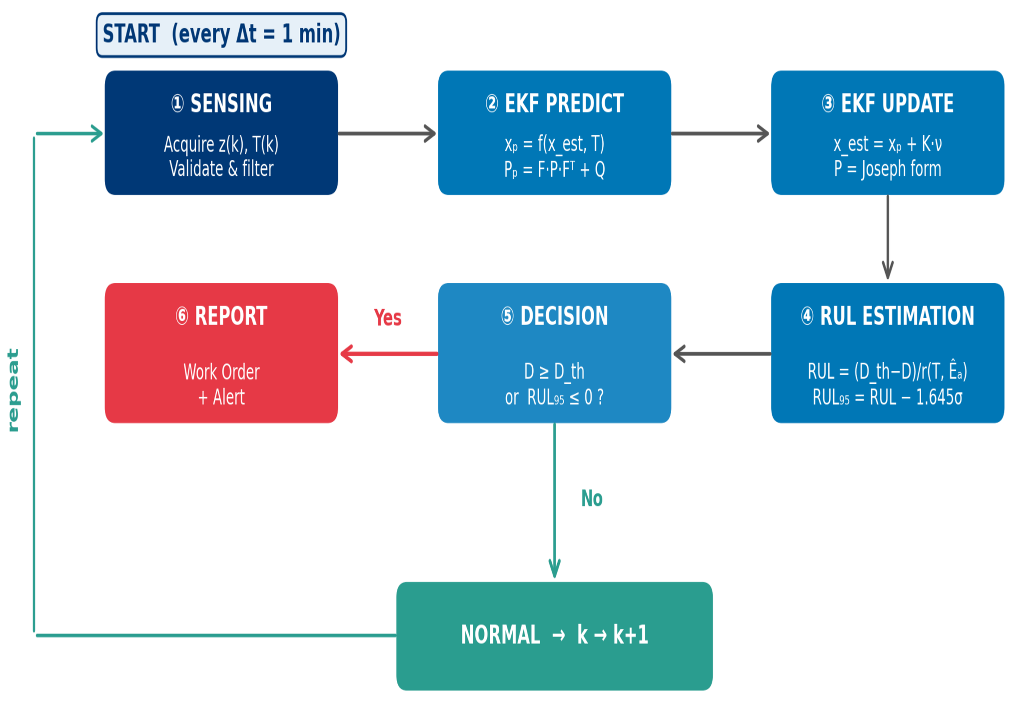


Fig. 1. Overall algorithm flow of PIIM.

Note "Intelligent diagnostic agent" denotes an **architectural pattern** structuring autonomous sensing, diagnosis, decision-making, and reporting — not a specific AI algorithm.

5 Simulation & Validation

Parameters

A	2.5×10^{-4} h^{-1}
E$_a$ (true)	0.85 eV
D_th	0.80
Profile	1,000 d @ 45±8°C
Δt	1 minute
$\hat{E}_{a,0}$	0.748 eV (−12%)
Cutoff	Day 799

ALT Acceleration Factors

85°C	AF = 31.9×
105°C	AF = 137.5×
125°C	AF = 511.7×

6 EKF Results

Tight uncertainty bounds + 90-day advance failure warning

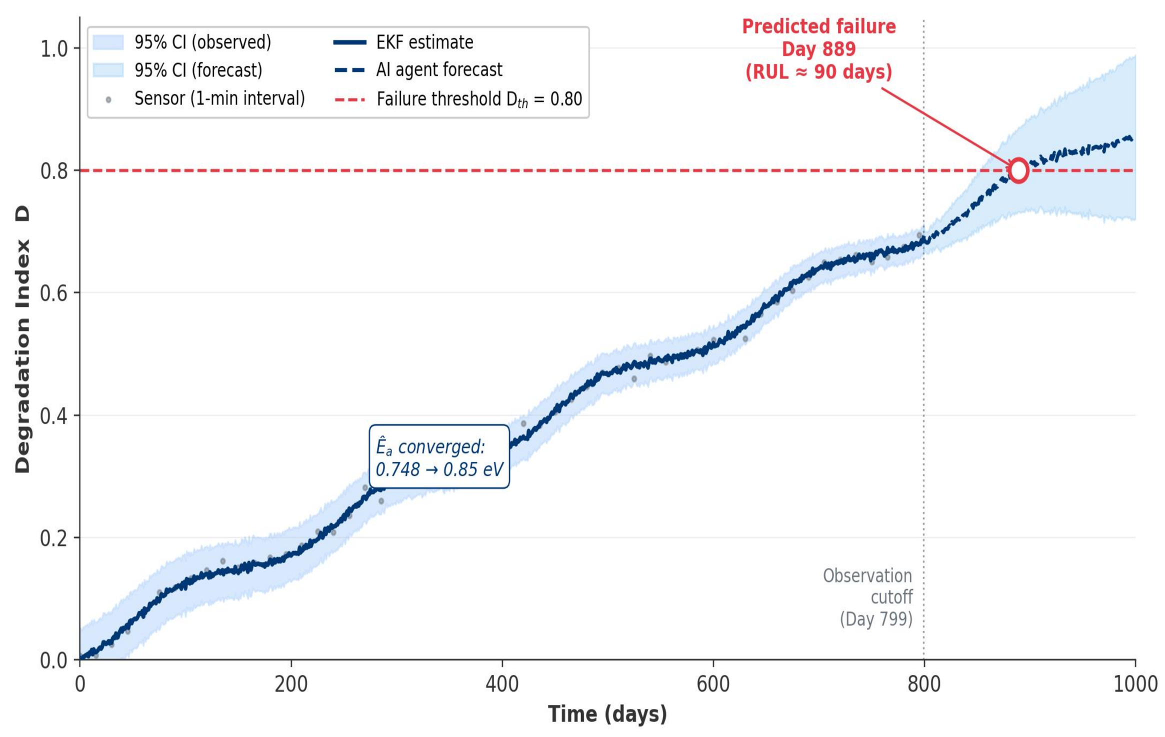


Fig. 2. EKF degradation estimation (1-min interval) with 95% CI and forecast.

KEY RESULTS

Ê$_a$ convergence	0.748 → 0.85 eV
Predicted failure	Day 889
Advance warning	≈ 90 days

Fault Diagnosis — Day 300 Overload Shock Detection

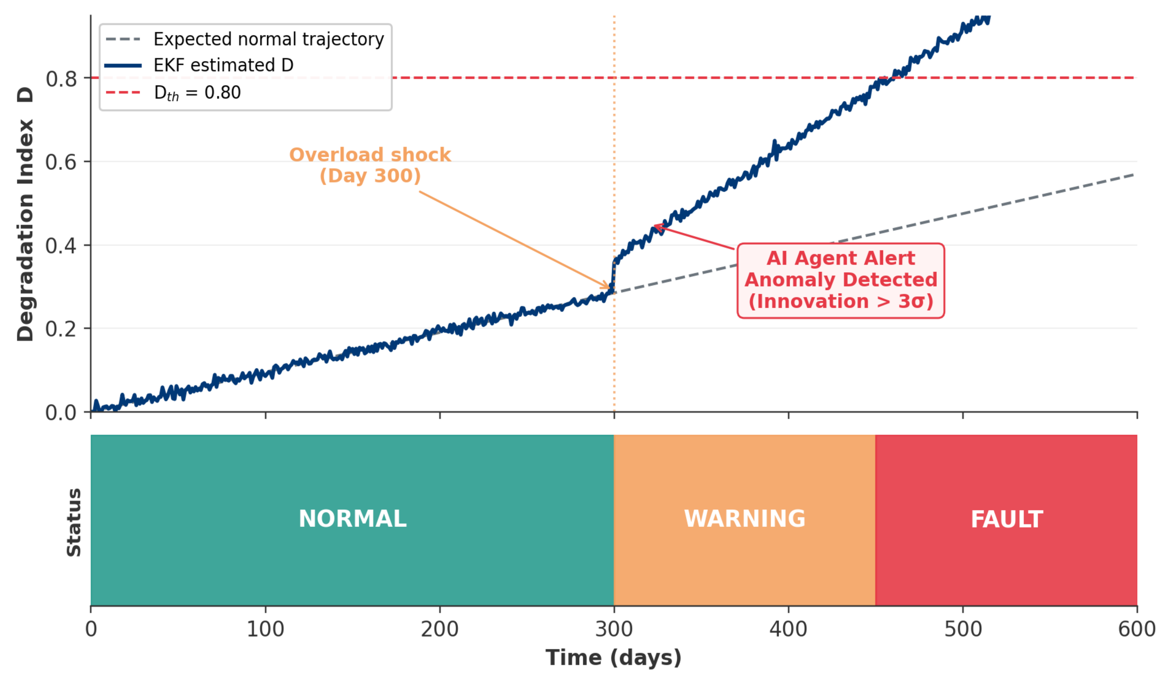
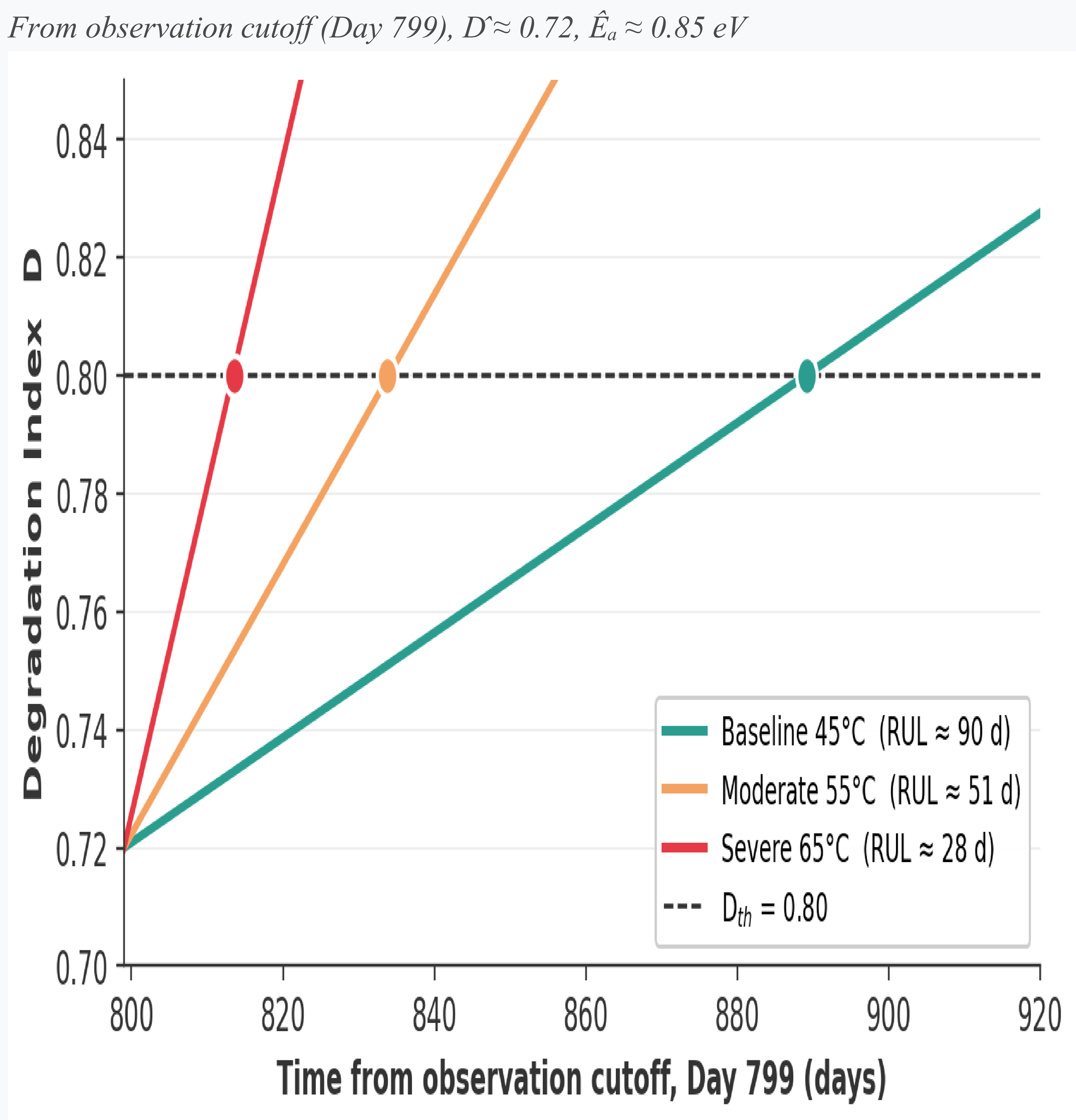


Fig. 3. Anomaly detection via Kalman-filter innovation > 3σ.

7 Predictive Scenarios

From observation cutoff (Day 799), $\hat{D}$ ≈ 0.72, Ê$_a$ ≈ 0.85 eV



8 SMR Applicability

① CHALLENGE
Limited Sensor Access
→ ***Model-based E$_a$ inference***

② CHALLENGE
Reduced Staffing
→ ***Autonomous explainable agent***

③ CHALLENGE
Absent Field Database
→ ***Online E$_a$ identification***

9 Conclusions

C1 Rigorous EKF formulation
Arrhenius-based simultaneous D estimation + online E$_a$ identification with uncertainty-bounded RUL.

C2 Hierarchical agent architecture
Framework pattern (not AI algorithm) for autonomous sensing-diagnosis-decision-reporting.

C3 SMR applicability
Adapts to limited field DBs; modular agent supports DCS deployment.

FUTURE WORK Multi-physics extension (radiation TID + thermal-cycling fatigue) · HiL validation with actual signal-processor data

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