

Physics-Digital Twin Based Synthetic Data Generation and AI Predictive Maintenance Technology for Non-Destructive Testing of Small Modular Reactors (SMR)

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1. Introduction

Nuclear power plants operate for decades under high-temperature, high-pressure, and radiation environments, so gradual degradation of structural components is unavoidable and must be detected before it develops into a safety-significant event. In the Davis-Besse (2002) and San Onofre (2013) cases [1,2], undetected or misjudged degradation of reactor and steam generator components was the direct precursor to the incident, underscoring that reliable, consistent inspection is as critical to safety as the physical integrity of the component.

Steam generator tubes, which form the boundary between the radioactive primary loop and the non-radioactive secondary loop, are currently inspected using eddy current testing (ECT) and the internal rotary inspection system (IRIS) technique. In both methods, signal acquisition is automated, but interpretation still depends on the visual judgment of certified Level II/III inspectors, resulting in inter-inspector variability. AI-based interpretation of ECT and IRIS signals offers a systematic solution to this limitation, providing consistent, reproducible results while reducing interpretation time. However, existing AI-based non-destructive testing (NDT) models have limited applicability to i-SMRs (innovative-small modular reactors), since they were developed for conventional large PWRs whose reactor configuration differs substantially from the compact, naturally circulated, helical-tube design of i-SMRs as can be seen in Figure 1.

대형원전 (PWR)		VS	i-SMR (170MW _e)	
운전 방식	100% 정상 출력 / 일정 부하 부하 변동 큼		가변 출력 / Load-following 부하 변동 큼 · 피로 누적 가속	
전열관 구조	직관 또는 관안된 U배열 곡률 반경 R > 500mm		나선형 (스프레이팅) 곡면 연속 나선 구조 곡률 반경 R < 100mm · 경첩 제한 없이	
보유 데이터	2,200만 건 / 40년 누적 AI 학습·검증 가능		0 건 / 운전 시작 0년 AI 학습 데이터 부족	
정기점검 주기	약 18개월 주기 원수원 위험 관리 기준		24개월 이상 목표 대형 원전 안전관리 요구	

Fig. 1. Comparison of conventional PWRs and i-SMRs.

Developing SMR-specific NDT is therefore urgent, since gaps in inspection-signal physics, degradation data, and regulatory standards must be closed before the planned 2028 i-SMR licensing review. Establishing a validated, explainable inspection framework in advance

is essential for demonstrating safety and supporting the development of SMR-specific inspection standards.

To address these challenges, this project establishes an integrated framework combining a 0.1-mm-precision physics-based digital twin, CIVA-based ECT/IRIS signal simulation, and physics-informed AI. The digital twin incorporates i-SMR tube geometry, Alloy 690 properties, and operating conditions, while approximately 22 million field inspection records are used to adapt simulated noise profiles and improve synthetic-to-real consistency. By embedding defect-growth equations in the AI loss function and constructing more than 50,000 degradation scenarios, the project generates physically admissible training data despite the absence of i-SMR operating history. The resulting SMR-specific model is intended to improve defect detection, enable remaining-useful-life prediction, provide explainable-AI evidence, and support the development of licensing-oriented inspection standards. This paper presents the framework of an ongoing project; therefore, the models, figures, and quantitative performance values presented herein represent preliminary developments rather than final project outcomes.

2. Methods

2.1 Physics-Based Digital Twin Construction

The i-SMR helical steam generator tube geometry (outer diameter, wall thickness, helix pitch, and bend radius) is reconstructed as a parametric 3D CAD model with 0.1 mm dimensional precision. Electromagnetic properties (electrical conductivity, permeability) and acoustic properties (longitudinal/shear wave velocity, attenuation coefficient) of the Alloy 690 tube material are measured under representative operating conditions (300°C, 150 bar) and embedded as inputs to the CIVA simulation environment, which serves as the common starting point for all subsequent synthetic data generation.



Fig. 2. Workflow for constructing a 0.1 mm precision 3D digital twin of an i-SMR steam generator tube.

2.2 Defect Growth Mechanism Modeling and Scenario Library

Representative degradation mechanisms (DMs) for Alloy 690 tubing under i-SMR service conditions are selected and modeled: pitting corrosion following Butler-Volmer reaction kinetics, stress corrosion cracking (SCC) following a Paris-law-type growth relation ($da/dt = C \cdot \Delta K^n$), and fretting wear following an Archard-type wear relation ($V = k \cdot F \cdot d/H$). Each mechanism is integrated over a 60-year design life to produce a five-level severity classification, and stochastic sampling of the calibrated growth-law coefficients yields a library of over 50,000 defect growth scenario combinations that serve as ground truth for synthetic signal generation.

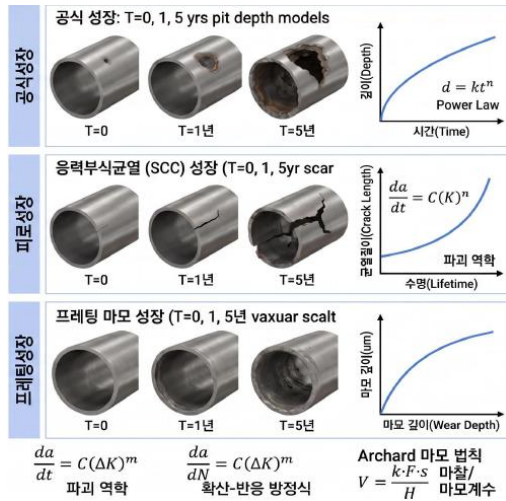


Fig. 3. Physics-based time-evolution models of pitting corrosion, stress corrosion cracking, and fretting wear in Alloy 690 steam generator tubes.

2.3 Physically-Valid Synthetic ECT/IRIS Signal Generation

Defect geometries sampled from the scenario library are implanted into the defect-free digital twin and processed through CIVA — which solves Maxwell's equations for eddy-current response and the acoustic wave equation for ultrasonic response — to generate physically valid ECT and IRIS signals. Three characteristic field-noise components (probe lift-off variation, probe wobble, and electronic noise), statistically extracted from the 22 million real inspection records held by the consortium, are superimposed on the simulated signals to close the simulation-to-real domain gap, and the resulting synthetic-to-measured signal agreement is verified against mock-up specimens.

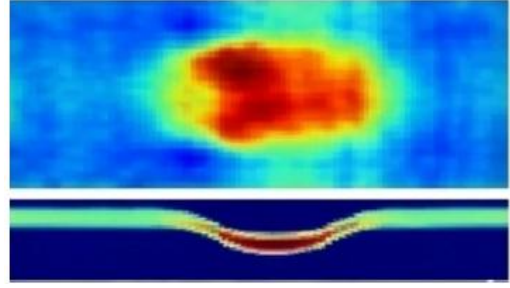


Fig. 4. Example of simulated IRIS scan outputs for a wall-thinning defect.

2.4 Physics-Informed AI Diagnostic Model

A physics-informed neural architecture is trained with a composite loss combining a data-driven term, a physics-consistency term derived from the governing growth equations, and a distribution-consistency term against real inspection data, which constrains the model to output only physically admissible defect states. The model is trained on the blended synthetic-and-real dataset and evaluated on independent synthetic, mixed, and real-data blind test sets, with explainable-AI (XAI) output intended to support ASME Section XI — compliant regulatory submission [3]. The proposed workflow will use CPU-based batch computing for CIVA simulations and GPU acceleration for AI training. An initial configuration of at least 32 CPU cores, 128 GB RAM, several TB of storage, and a GPU with at least 24 GB VRAM is expected to support pilot-scale analysis.

3. Conclusions

This project proposes a physics-digital twin and physics-informed AI framework to resolve the structural data gap that currently prevents large-reactor NDT AI technology from being transferred to next-generation integral SMRs. The framework generates a physically valid, field-noise-adapted synthetic dataset spanning more than 50,000 defect growth scenarios for Alloy 690 helical steam generator tubing. By further constraining the diagnostic AI model with governing degradation physics, it provides an explainable, standard-compliant route to automated i-SMR steam generator inspection ahead of the 2028 standard design certification milestone. In year one, the defect growth models and initial synthetic scenario library established by this consortium will form the foundation for physics-informed AI model development.

4. Acknowledgment

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REFERENCES

- [1] Davis, C. B., & Commission, N. R. (1987). *Davis-Besse uncertainty study*.
- [2] Latorre, V., & Victor, R. (1980). *Technical evaluation of the susceptibility of safety-related systems*

to flooding caused by the failure of non-category 1 systems for the San Onofre Nuclear Power Plant, Unit 1.

[3] Bush, S. (1989). *Wall thinning in nuclear piping: Status and ASME Section XI activities.*