Intel Unnati Industrial Training 2025- Slot 3

ABSTRACT

Problem Statement- 5

Team Name- Shivaay

Team Members-

Ananya Satapathy (GIET University, Gunupur)

Nikhil Kumar (GIET University, Gunupur)

Kirti Priyadarshani Sethi (GIET University, Gunupur)

Title:

Smart Digital Twin for Predictive Maintenance of an Electro-Mechanical System using Reduced Order Modelling and Physics-Informed AI.

Problem Statement:

In the high-stakes domain of modern manufacturing, electro-mechanical systems such as robotic manipulators and CNC spindles serve as the backbone of production. However, these systems are plagued by the unpredictability of component degradation. Unplanned downtime in critical sectors, such as automotive and aerospace, can incur costs exceeding $260,000 per hour, rendering reactive maintenance strategies economically unsustainable. While preventive maintenance schedules mitigate catastrophic failure, they inevitably lead to the premature replacement of viable components, wasting remaining useful life (RUL) and inflating operational expenditures.

Background & Context:

The Industry 4.0 paradigm promises "Predictive Maintenance" (PdM) as the solution to this inefficiency. However, current implementations face a critical technological dichotomy. High-fidelity physics-based models (Finite Element Analysis) offer diagnostic precision but are computationally prohibitive for real-time monitoring, often requiring hours to simulate milliseconds of operation. Conversely, purely data-driven Artificial Intelligence (AI) models, while fast, suffer from a "black box" lack of interpretability and severe data hunger. They require massive datasets of historical failure events that operators actively avoid, resulting in poor generalization to unseen fault conditions. Consequently, standard AI models often achieve high accuracy (up to 98.9%) only on known data distributions but fail catastrophically when facing novel operational regimes.

Proposed Solution:

Our project bridges this gap by developing a Hybrid Smart Digital Twin that synergizes the interpretability of physics with the speed of AI. The innovation lies in a three-stage architecture:

i. **Reduced Order Modelling (ROM):**
   We utilize Proper Orthogonal Decomposition (POD) to compress high-fidelity Ansys/Simulink models into lightweight surrogate models. This reduces the computational load by orders of magnitude, enabling complex physics simulations to run in real-time (<80 ms latency) on standard edge hardware.

ii. **Synthetic Data Augmentation:**
   To overcome the scarcity of real-world failure data, the ROM is used to generate a comprehensive "Synthetic Fault Dataset," simulating thousands of potential failure scenarios (e.g., bearing wear, thermal distortion) that have not yet occurred in the physical system.

iii. **Physics-Informed AI:**
   We deploy a hybrid AI framework (combining LSTMs with Physics-Informed Neural Networks, or PINNs) trained on this augmented dataset. Unlike standard AI, this model is constrained by physical laws, allowing it to validate sensor data against thermodynamic and kinematic principles.

Impact & Scalability:

Our proposed solution demonstrates superior reliability compared to traditional methods. Preliminary validation indicates that while conventional analytical methods achieve approximately 88% accuracy in RUL estimation, the proposed Physics-Informed approach reaches 92.75% accuracy, significantly reducing false positives. Furthermore, the Digital Twin achieves a synchronisation accuracy of 99.99% regarding joint positioning. By exporting the physics core as a Functional Mock-up Unit (FMU), this architecture is highly scalable and platform-agnostic, capable of deployment on low-cost embedded systems (e.g., NVIDIA Jetson, Raspberry Pi). This project not only democratizes access to high-end predictive maintenance but also provides a "Cold Start" capability, enabling the system to offer diagnostic value from Day 1 without requiring years of historical data collection.