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Boosting Digital Transformation

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Probabilistic Estimation of Health Indicators of Complex Systems

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1. Scientific Context

Estimating the health of complex industrial systems with Digital Twins (DT)

- Utilizing sensor data to monitor industrial systems
- Probabilistic estimation of health indicators (HI)



 Combining invariant characteristics and learned information from measured data

Considering the physics governing system operation



2. Challenges and objectives

Fig. 3. Overview of the Expected Architecture

4. Case study





CX2 Battery Degradation & PyBaMM Simulator [9-10]

Railroad degradation

Safran Turbofan engine

- Assessing real-world applicability
- Managing intricate, real-world scenarios
- Pinpointing and mitigating uncertainty sources
- Evaluating and enhancing performance

5. Expected results



3. Proposed research method

- Unified domain agnostic framework to predict and create HIs
- Gaussian approximation for quantification in aleatoric & epistemic uncertainties
- Benchmarked on RUL estimation
- Interpretable degradation maps





6. Future work

for the FD001 dataset. [1]

- Physics Informed Neural Networks (PINNs)
- Domain adaptation between simulation and real datasets
- Feature selection for HI creation
- Reinforcement learning approaches
- Identify current challenges in the literature and the industry
- Explore HIs created by data-driven methods
- Propose an AI pipeline architecture to model both HIs with uncertainties: aleatoric and epistemic
- Investigate learning methods: supervised, unsupervised, reinforcement
- Incorporate physics-informed methods

7. References

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