

Physics-informed Multi-fidelity Digital Twins for Prognostics and Health Management of Complex Engineering Systems

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ABSTRACT

Scalable and reliable prognostics and health management (PHM) has become increasingly important for safety-critical applications operating under dynamic environments. However, existing PHM digital twins often suffer from expensive high-fidelity modeling, limited scalability for large-scale systems, and lack of adaptability under evolving degradation behaviors. This research develops a unified physics-informed digital twin framework integrating multi-fidelity learning, physics-informed machine learning, and adaptive uncertainty-aware prognostics for complex multi-physics engineering systems. The proposed framework enables data-efficient diagnosis through multi-fidelity digital twins, mesh-free thermal-state monitoring through physics-informed spatial learning, and adaptive remaining useful life prediction through online state estimation and model adaptation. Preliminary studies on wet clutch systems, battery packs, and Hall thrusters demonstrate improved prediction accuracy, reduced dependence on high-fidelity data, and robust prognostics under dynamic operating environments.

Keywords: physics-informed machine learning, digital twin, prognostics and health management, multi-fidelity modeling

1. INTRODUCTION AND MOTIVATION

Modern engineering systems increasingly operate under safety- and reliability-critical conditions. Failures in these systems can lead to severe operational and economic consequences, motivating growing interest in prognostics and health management (PHM) technologies for predictive maintenance, operational reliability, and lifecycle management (Hu et al., 2022). Accurate failure diagnosis, state-of-health (SOH) monitoring, degradation tracking, and remaining useful life (RUL) prediction have therefore become essential to improve system safety, reduce maintenance cost, and en-

hance operational efficiency in next-generation engineering applications (Vrignat et al., 2022).

In recent years, digital twins have emerged as a promising PHM paradigm by integrating physics-based modeling, in-situ sensing, and data-driven learning to provide virtual representations, supporting diagnosis, condition monitoring, and prognostics throughout the system lifecycle (Wang et al., 2025). The integration of physics-informed machine learning further enables scalable PHM by combining governing physics with operational data (Xu et al., 2023).

This research develops a unified physics-informed digital twin framework integrating multi-fidelity learning, physics-informed spatial monitoring, and adaptive uncertainty-aware prognostics for complex engineering systems. The proposed framework aims to improve data efficiency, physical consistency, scalability, and online adaptability for diagnosis, thermal health monitoring, and RUL prediction across complex multi-physics applications.

2. RESEARCH GAPS

Despite recent advances in PHM-oriented digital twins, several fundamental research gaps remain in current frameworks:

- **Data scarcity and expensive high-fidelity modeling:** High-fidelity simulations and degradation testing are expensive, while purely data-driven methods require large amounts of labeled degradation data and often struggle to generalize under varying operating conditions.
- **Limited scalability of spatial digital twins:** Existing spatial learning frameworks are often discretization-dependent and struggle to efficiently model large-scale systems with continuous spatial dynamics and strong multi-component interactions.
- **Lack of adaptability and uncertainty awareness:** Most existing digital twins remain static after offline learning and cannot effectively adapt to environmen-

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tal variations, operational uncertainties, and evolving degradation behaviors during online deployment.

These limitations motivate the development of a unified physics-informed multi-fidelity digital twin framework for scalable, data-efficient, and uncertainty-aware PHM under limited data and dynamic operating conditions.

3. UNIFIED PHYSICS-INFORMED DIGITAL TWIN FRAMEWORK FOR PHM

As illustrated in Fig. 1, the proposed framework integrates three tightly coupled research thrusts: (1) multi-fidelity digital twins for data-efficient diagnosis, (2) physics-informed spatial digital twins for thermal health monitoring, and (3) adaptive digital twins for uncertainty-aware prognostics through online state estimation and adaptive model update.

3.1. Thrust 1: Multi-fidelity Digital Twins for Data-efficient Diagnosis

Accurate fault diagnosis requires large amounts of failure data, which are often scarce in practical PHM applications due to limited fault occurrence (Li et al., 2024). Although high-fidelity simulations can serve as an alternative, their computational cost remains prohibitive for large-scale deployment. These challenges become particularly critical in wet clutch systems, where long-term operation introduces worn or missing clutch plates, leading to abnormal hydraulic response and degraded engagement performance (Xue et al., 2022). Strongly coupled fluid-structure interaction (FSI) and localized contact dynamics further complicate scalable and data-efficient diagnosis.

This thrust develops a physics-guided multi-fidelity digital twin framework, as shown in Fig. 1(a), for data-efficient diagnosis of complex engineering systems under limited high-fidelity data. Multi-fidelity FSI simulations for wet clutch are first established, where high-fidelity simulations utilize contact-pair formulations to resolve localized contact-induced pressure evolution, whereas low-fidelity simulations employ simplified spring-damper contact approximations to efficiently capture global transient hydraulic dynamics. Building upon the resulting physical representations, a multi-fidelity Fourier deep compositional neural operator (MF-FDCON) is further developed for diagnosis-oriented digital twin construction. Fourier feature mapping is adopted to represent transient hydraulic pressure evolution. To address nonlinear fidelity discrepancies induced by different contact representations, a two-stage training strategy is further developed: the entire FDCON is first pretrained using large amount of low-fidelity data to learn global hydraulic dynamics as a physics-guided prior, followed by fine-tuning of the feature fusion module using limited high-fidelity data to efficiently capture localized nonlinear fidelity discrepancies.

Preliminary studies on wet clutch missing-plate failure re-

sponse prediction (Fig. 2) show that the proposed framework accurately reconstructs transient hydraulic responses under varying operating conditions. MF-FDCON achieves prediction errors below 1%, outperforming baseline machine learning models and residual-based multi-fidelity neural operators in both prediction accuracy and extrapolation capability. In addition, high-fidelity data requirements are reduced to one-fourth of conventional strategies while overall simulation time is reduced by nearly one-third, demonstrating the potential of physics-guided digital twins for scalable and data-efficient modeling of complex multi-physics engineering systems under sparse-data conditions. Future work will focus on inverse diagnosis, sparse-sensor state reconstruction, and robust diagnosis under noisy observations.

3.2. Thrust 2: Physics-informed Spatial Digital Twins for Thermal Health Monitoring

Thermal health monitoring requires accurate prediction of spatial temperature distributions to prevent thermal-induced degradation, abnormal hot spots, and catastrophic failures (Kabirzadeh et al., 2025; Jiang, Jiang, & Wang, 2026). However, direct measurement of full thermal fields is often impractical due to sparse sensing and instrumentation constraints, while reduced-order models and grid-based surrogates struggle to reconstruct continuous temperature fields. These challenges become particularly critical in large-scale battery packs, where thermal behavior strongly depends on complex cell layouts and nonuniform heat transfer interactions, posing significant challenges for scalable thermal-state monitoring (Kumar et al., 2023; Jiang, Liu, et al., 2025).

This thrust develops a physics-informed spatial digital twin framework, as shown in Fig. 1(b), for scalable thermal health monitoring of large-scale engineering systems. A physics-informed cross-attention operator network (PI-CAON) with hard-constrained Fourier features is developed to enable mesh-free and resolution-independent heat map prediction under varying battery layouts without relying on labeled thermal data (Jiang, Jiang, Liu, & Wang, 2026). Fourier feature embeddings capture multi-scale thermal behaviors and sharp temperature gradients near cell-grease interfaces. To improve physical consistency and training stability, hard-constrained Fourier embeddings are further developed to automatically enforce Neumann boundary conditions through network architecture design instead of soft penalty constraints. A stacked cross-attention mechanism models inter-cell thermal interactions and layout-dependent spatial correlations in large-scale battery packs. Heat-transfer physics is embedded into the loss function through automatic differentiation, enabling fully physics-informed and label-free thermal field learning.

Preliminary studies on large-scale battery systems (Fig. 3) show that PI-CAON predicts heat maps with maximum errors

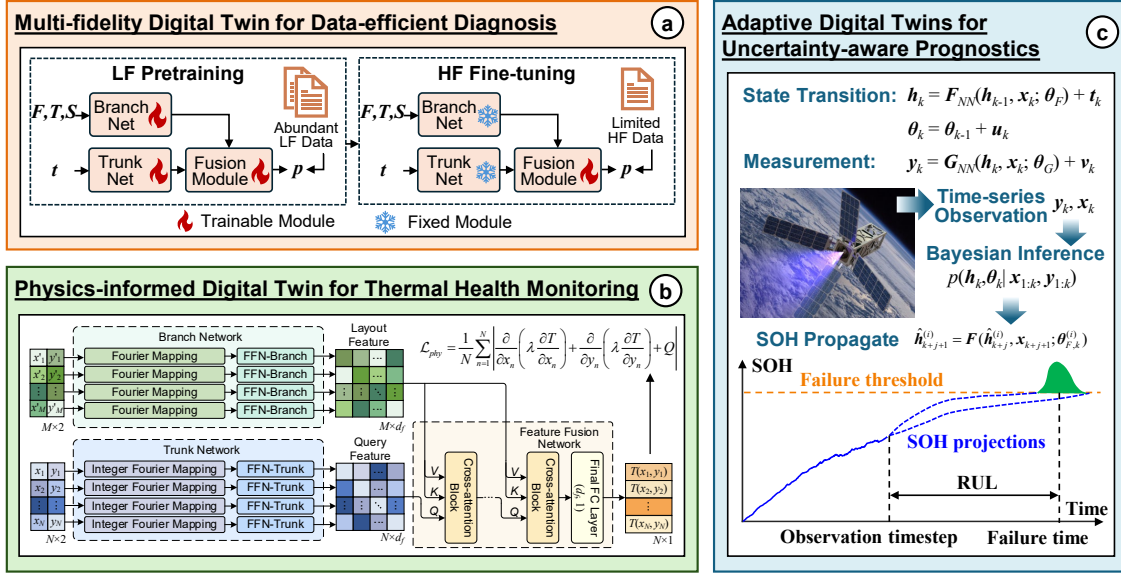


Figure 1. Physics-informed multi-fidelity digital twin framework for PHM of complex engineering systems.

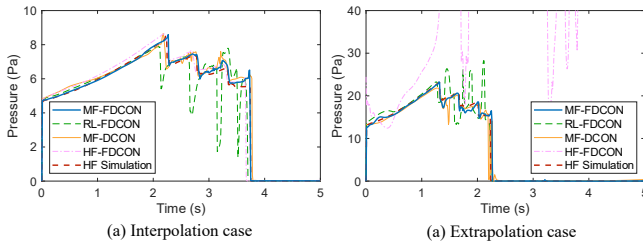


Figure 2. Wet clutch hydraulic pressure prediction for missing-plate failure by MF-FDCON.

below 0.03°C (2% of the temperature range), outperforming baseline neural operators and grid-based surrogates (Jiang, Jiang, Liu, & Wang, 2026; Liu et al., 2025). By enabling fully label-free thermal field learning, the proposed framework reduces overall training time by 10% compared with conventional data-driven workflows. In addition, it enables continuous mesh-free thermal-state prediction at arbitrary spatial locations while eliminating discretization-induced errors associated with grid-based representations. These results demonstrate the potential of physics-informed spatial digital twins for scalable and data-efficient thermal health monitoring of complex engineering systems under limited sensing conditions. Future work will focus on online thermal-state estimation, sparse-sensor thermal reconstruction, and thermal runaway anomaly detection.

3.3. Thrust 3: Adaptive Digital Twins for Uncertainty-aware Prognostics

PHM of failure-critical systems requires accurate degradation and RUL estimation for maintenance decision-making. However, degradation behavior is often influenced by environmen-

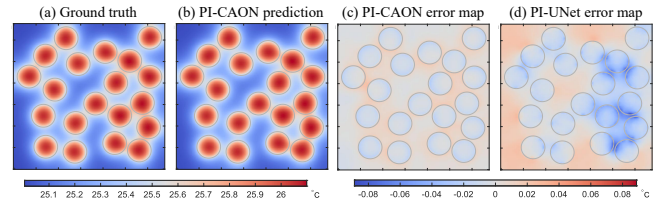


Figure 3. Battery pack thermal prediction by PI-CAON (Jiang, Jiang, Liu, & Wang, 2026).

tal variability and unit-to-unit inconsistency, making reliable prognostics highly challenging. In many systems, SOH must be inferred from indirect observations. Although physics-based simulations provide interpretable degradation mechanisms and lifecycle data, their computational cost remains prohibitive for long-term online prognostics. These challenges become particularly critical in Hall thrusters, where ion-sputtering-induced discharge channel wall erosion gradually alters plasma dynamics and thrust performance during long-duration cislunar missions (Brown & Walker, 2020).

This thrust develops an adaptive digital twin framework, as shown in Fig. 1(c), for uncertainty-aware prognostics of complex engineering systems. A multi-fidelity Hall thruster degradation model is first developed by integrating low-fidelity 1D fluid-based plasma simulations with high-fidelity 2D particle-in-cell (PIC) simulations to efficiently generate physics-consistent degradation data (Jiang, Leeming, Rovey, & Wang, 2025). Specifically, the radial-to-axial ion flux relationships from PIC simulations are utilized to calibrate the low-fidelity plasma solver. Building upon the resulting degradation datasets, an adaptive self-cognizant dynamic system (ASDS) is further developed for online SOH estimation and

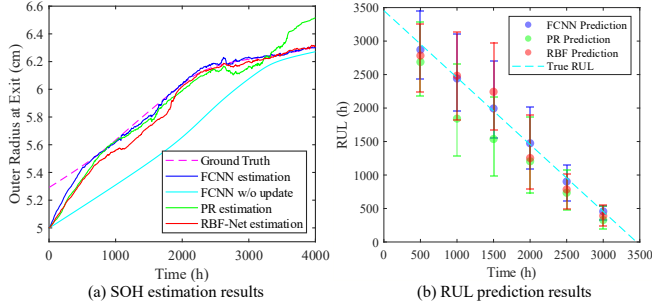


Figure 4. Hall thruster prognostic results by ASDS (Jiang, Leeming, et al., 2026).

RUL prediction. The degradation dynamics is formulated within a state-space framework, where fully connected neural networks are employed to model degradation evolution and measurement functions. To improve adaptability under varying environmental conditions, particle filtering is further integrated to simultaneously update SOH and neural network parameters during online deployment. By propagating the particle ensemble through the updated degradation dynamics, the proposed framework enables uncertainty-aware RUL prediction together with probabilistic confidence bounds for risk-informed prognostics.

Preliminary studies on Hall thruster erosion prognostics (Fig. 4) show accurate degradation tracking and RUL prediction under varying environmental conditions (Jiang, Leeming, et al., 2026). By integrating high-fidelity plasma information into the low-fidelity simulation framework, the proposed multi-fidelity physics-based modeling reduces full life-cycle degradation simulation time from two weeks to six hours while preserving physically consistent erosion behavior. The adaptive online update framework further achieves SOH estimation errors below 3% with online estimation and model update latency of 0.15 s. In addition, the proposed ASDS achieves RUL prediction errors below 5%, outperforming conventional regression-based and static neural network baselines in both prediction accuracy and uncertainty confidence under environmental variability. These results demonstrate the potential of adaptive digital twins for scalable and uncertainty-aware prognostics under dynamic operating and environmental environments. Future work will focus on direct SOH sensing, adaptive prognostics under varying operating conditions, and time-dependent degradation modeling.

4. EXPECTED RESEARCH CONTRIBUTIONS

This research contributes to physics-informed PHM through advances in multi-fidelity learning, mesh-free spatial monitoring, and adaptive uncertainty-aware prognostics for complex multi-physics engineering systems. The expected contributions are summarized as follows:

- **Physics-informed multi-fidelity PHM:** A unified multi-fidelity learning framework that integrates low- and high-fidelity physics representations to reduce dependence on expensive simulations and labeled degradation data.
- **Mesh-free thermal health monitoring:** A physics-informed spatial learning framework with resolution-independent thermal field prediction and hard-constrained physics embedding for scalable thermal-state monitoring under sparse sensing conditions.
- **Adaptive uncertainty-aware prognostics:** An adaptive prognostic framework integrating online state estimation, model adaptation, and probabilistic inference for robust RUL prediction under environmental variability and evolving degradation behaviors.
- **Generalizable PHM digital twins:** A unified digital twin paradigm integrating physics consistency, scalability, data efficiency, and uncertainty awareness for complex multi-physics engineering systems.

5. CONCLUSION

This research proposes a unified physics-informed digital twin framework for scalable, data-efficient, and uncertainty-aware PHM of next-generation multi-physics engineering systems. By integrating multi-fidelity modeling, physics-informed machine learning, and adaptive online updating, the proposed research addresses critical challenges associated with data limitation, expensive high-fidelity simulations, sparse sensing conditions, and evolving operational environments. Preliminary studies on wet clutches, large-scale battery packs, and Hall thrusters demonstrate improved prediction accuracy, lower dependence on high-fidelity data, high-fidelity thermal-state monitoring, and robust uncertainty-aware prognostics under dynamic conditions.

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