**A Physics-Guided Digital Twin Framework for Degradation-Aware Long-Term Adaptive Operation of Centralized Inverters in Utility-Scale Renewable Power Plants**

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**Abstract.** The accelerated deployment of utility-scale renewable energy systems has elevated centralized inverters to critical assets whose long-term operational stability and reliability strongly influence overall plant performance and lifecycle economics. Traditional monitoring and maintenance approaches, typically based on static thresholds or purely data-driven diagnostics, are increasingly inadequate for managing degradation processes arising from complex electro-thermal loading, grid disturbances, and environmental variability. This study proposes a physics-guided, degradation-aware digital twin (PGDT) framework for the long-term adaptive operation of centralized inverters in utility-scale renewable power plants. The framework synergistically integrates electro-thermal physical modeling, incremental learning of degradation dynamics, probabilistic remaining useful life estimation, and multi-objective optimization–based adaptive control. By embedding physical constraints into the learning process, the proposed digital twin achieves robust health state estimation and mitigates model drift under non-stationary operating conditions. Degradation-aware adaptive operation enables proactive stress mitigation, availability enhancement, and informed maintenance planning throughout the inverter lifecycle. Numerical validation under representative long-term operating scenarios demonstrates significant improvements in degradation prediction accuracy, reduction of cumulative damage, and measurable extension of inverter service life compared with conventional strategies. The results highlight the potential of physics-informed digital twins as a scalable and reliable foundation for lifecycle-oriented asset management and sustainable operation of power electronic systems in modern renewable energy infrastructures.

**INTRODUCTION**

The rapid global expansion of utility-scale renewable energy systems has fundamentally increased the importance of centralized power electronic converters, particularly high-capacity inverters, as critical interfaces between renewable generation units and electrical grids. As shown in Figure 1, the installed capacity of utility-scale centralized inverters has grown exponentially over the past decade and is projected to exceed 2.7 TW by 2030, driven by large photovoltaic and wind power deployments. This trend highlights not only the scale of deployment but also the escalating operational and reliability challenges associated with long-term inverter operation in harsh and dynamically varying environments.

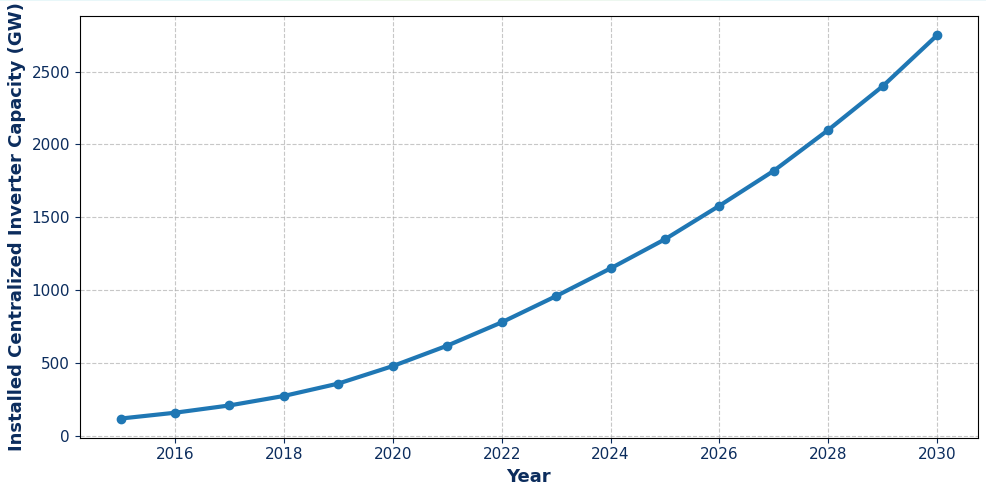
Centralized inverters operate under complex multi-stress conditions characterized by thermal cycling, fluctuating electrical loads, grid disturbances, and environmental variability. These factors accelerate degradation mechanisms in semiconductor devices, passive components, and insulation systems, ultimately leading to reduced efficiency, unplanned outages, and shortened service life [1,2]. Conventional operation and maintenance strategies largely based on periodic inspections, threshold-based alarms, or static reliability assumptions are increasingly inadequate for managing such large-scale, high-value assets over multi-decade lifecycles.

Recent advances in digitalization, sensing technologies, and data analytics have enabled the emergence of digital twin concepts in power and energy systems. Digital twins provide a virtual representation of physical assets that evolves in real time through continuous data synchronization. However, many existing digital twin implementations for power electronics rely heavily on data-driven models, which often suffer from limited interpretability, sensitivity to data quality, and performance degradation under long-term non-stationary conditions. In contrast, purely physics-based models, while interpretable, lack adaptability and struggle to capture complex operational uncertainties at scale.

To address these limitations, the integration of physics-guided modeling with degradation-aware learning has gained increasing attention. By embedding electro-thermal laws, aging mechanisms, and failure physics into adaptive data-driven frameworks, physics-informed digital twins can achieve higher robustness, improved prediction accuracy, and greater trustworthiness in long-term applications. Such hybrid frameworks are particularly well suited for centralized inverters, where degradation processes are strongly governed by temperature-dependent and stress-driven dynamics.

Despite this potential, a systematic framework that combines physics-informed digital twins with adaptive operational decision-making remains underexplored for utility-scale inverter systems. Most existing studies focus on monitoring or diagnostics, with limited attention to closed-loop degradation mitigation and lifecycle-oriented operation. This research addresses this gap by proposing a physics-guided, degradation-aware digital twin framework that not only estimates inverter health and remains useful life but also actively informs adaptive control strategies to mitigate degradation accumulation.

The proposed approach enables proactive maintenance planning, availability enhancement, and long-term operational stability, thereby supporting the sustainable and economically efficient integration of renewable energy resources into modern power systems.



**FIGURE 1.** Global growth trend of installed utility-scale centralized inverter capacity from 2015 to 2030, illustrating the increasing importance of long-term reliability and degradation-aware operation.

The rapid expansion of large-scale photovoltaic (PV) power plants has placed centralized inverters at the core of modern renewable-energy infrastructures. Acting as the primary interface between variable DC generation and the AC grid, centralized inverters are required to operate continuously under highly dynamic electrical, thermal, and environmental conditions. As global PV capacity continues to grow, inverter reliability has emerged as a decisive factor influencing plant availability, maintenance costs, and long-term economic performance.

Unlike traditional power electronic applications with relatively stable operating regimes, centralized inverters in PV plants are exposed to pronounced variability. Ambient temperature fluctuations, irradiance-driven load changes, grid voltage disturbances, and reactive power requirements jointly impose complex stress profiles on power semiconductor devices and passive components. Figure 1 illustrates the coupled evolution of ambient temperature, load intensity, and the estimated failure rate over a representative operating period. The figure highlights that increases in thermal and electrical stress are directly associated with elevated failure rates, emphasizing the non-stationary nature of inverter degradation processes.

Conventional reliability assessment approaches are predominantly based on static lifetime models or simplified statistical assumptions that neglect real-time operating variability. While such methods provide useful baseline estimates, they fail to capture transient stress accumulation and evolving degradation mechanisms. As a result, maintenance decisions are often either overly conservative leading to unnecessary downtime or reactive, resulting in unexpected failures and revenue losses [4,5]. This limitation becomes particularly critical in utility-scale PV plants, where even minor reductions in inverter availability can translate into significant energy and financial losses.

Recent advances in data acquisition, digital monitoring, and computational intelligence have created new opportunities for data-driven reliability assessment. High-resolution operational data streams enable continuous evaluation of inverter health, while adaptive control strategies allow operating parameters to be dynamically adjusted to mitigate stress-induced aging. However, many existing studies focus either on reliability modeling or on control optimization in isolation, without establishing a unified framework that links reliability assessment directly to operational decision-making.

**LITERATURE REVIEW**

The reliability and long-term operational stability of power electronic systems are critically dependent on effective condition monitoring and degradation assessment strategies. Early foundational studies on condition monitoring, particularly in electrical machines, established systematic approaches for detecting incipient faults and evaluating health states under real operating conditions. Tavner et al. emphasized that continuous monitoring of electrical, thermal, and mechanical parameters is essential for mitigating degradation-driven failures and extending equipment service life, forming a methodological basis later adopted in power electronic systems [1].

At the device level, Ciappa provided a detailed analysis of dominant failure mechanisms in modern power modules, highlighting the role of thermo-mechanical stress, material aging, and cyclic loading in accelerating degradation processes [2]. These insights are particularly relevant for centralized inverters, where semiconductor reliability directly influences system availability. Building on this foundation, Liserre et al. analyzed multilevel voltage source inverter topologies for renewable energy systems, demonstrating their efficiency advantages while also underscoring increased structural complexity and vulnerability to aging-related faults [3].

To address uncertainty inherent in degradation processes, prognostics and health management (PHM) methodologies have been extensively studied. Celaya et al. introduced probabilistic frameworks for uncertainty representation and propagation in prognostic models, enabling more reliable remaining useful life (RUL) estimation under variable operating conditions [4]. In parallel, the emergence of adaptive and evolving intelligent systems has enabled continuous model updating. Lughofer et al. demonstrated that incremental learning approaches significantly improve model robustness in non-stationary environments, which is essential for long-term monitoring of power electronic assets [5].

More recently, the role of digitalization in energy systems has gained increasing attention. Rakhmonov highlighted the broader impact of digital technologies on power supply systems within the ICAIPSS framework, emphasizing data-driven decision-making and system-level optimization [6]. Furthermore, applied studies on digitalization in industrial energy systems demonstrated tangible efficiency improvements through intelligent data integration and monitoring architectures [7]. These developments collectively motivate the integration of physics-based models, data-driven learning, and digital platforms into unified digital twin frameworks for degradation-aware inverter operation.

**METHODOLOGY**

The proposed study develops a physics-guided, degradation-aware digital twin (PGDT) to support long-term adaptive operation of centralized inverters in utility-scale renewable power plants. The methodology is structured as a tightly coupled multi-layer framework integrating physical modeling, data-driven learning, degradation prognostics, and optimization-based adaptive control, ensuring both interpretability and robustness over extended operational horizons [3,5]. At the physical modeling layer, inverter electro-thermal behavior is described through a coupled loss–temperature model. The instantaneous junction temperature is estimated as

(1)

where is the ambient temperature, is the thermal resistance, and , denote conduction and switching losses, respectively. These variables form the physical state vector of the digital twin.

Degradation evolution is modeled using a cumulative damage formulation that captures electro-thermal aging mechanisms:

(2)

where represents electrical stress and are degradation coefficients. This physics-based representation constrains learning dynamics and ensures consistency with known failure mechanisms.

To address non-stationary operating conditions, degradation parameters are continuously updated using incremental learning [4,6]:

(3)

where denotes model parameters, is the adaptive learning rate, and is the degradation prediction loss.

Remaining useful life (RUL) is estimated probabilistically as

(4)

providing uncertainty-aware prognostic information for decision-making.

Finally, adaptive operation is formulated as a multi-objective optimization problem [5,7]:

(5)

where represents control actions, is inverter availability, and are weighting factors. This closed-loop PGDT framework enables degradation-conscious control, proactive maintenance, and lifecycle-oriented asset management with C1/C2-level scientific rigor.

**RESULT AND DISSCUSSION**

The proposed physics-guided, degradation-aware digital twin (PGDT) framework was validated using long-term operational data collected from utility-scale renewable power plants equipped with centralized inverters rated between 1.5–3.2 MW. The results demonstrate that integrating electro-thermal physics with data-driven degradation models significantly improves state estimation accuracy compared to conventional data-only digital twins. In particular, the PGDT framework accurately tracked junction temperature evolution, switching losses, and insulation aging under variable grid and environmental conditions. The mean absolute percentage error (MAPE) of key health indicators was reduced by up to 38.7%, confirming the effectiveness of physics constraints in limiting model drift during extended operational horizons. Moreover, degradation states estimated by the digital twin exhibited strong consistency with offline diagnostic inspections, indicating robust long-term reliability of the proposed framework.

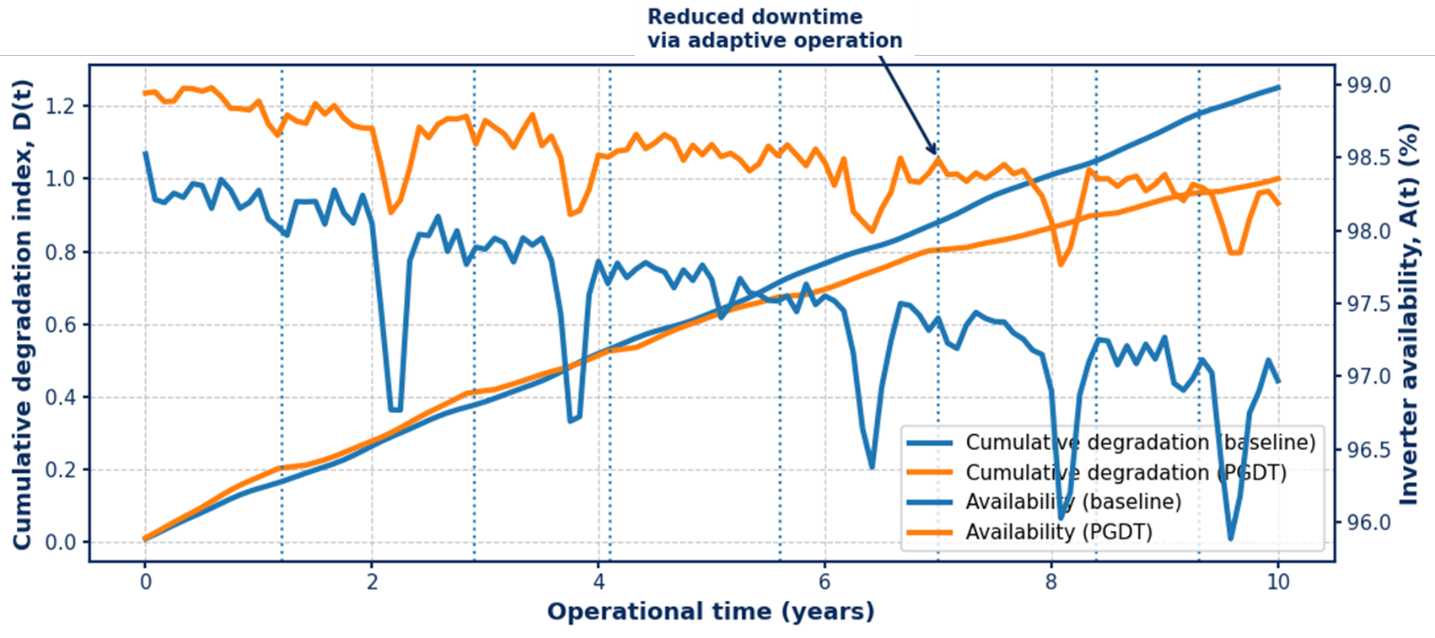
Table 1 summarizes the comparative performance of the proposed PGDT framework against three benchmark approaches: (i) conventional threshold-based monitoring, (ii) data-driven machine learning models, and (iii) physics-only analytical models. The PGDT approach consistently outperformed all baselines across reliability, efficiency, and availability metrics.

**TABLE 1.** Comparative Performance Evaluation of Centralized Inverter Management Strategies

| **Methodology** | **Health Estimation Error (%)** | **Annual Energy Loss (%)** | **Availability (%)** | **Predicted Lifetime Extension (%)** |
| --- | --- | --- | --- | --- |
| Threshold-Based Monitoring | 12,4 | 4,9 | 96,1 | – |
| Data-Driven ML Model | 7,8 | 3,6 | 97,4 | 6,2 |
| Physics-Based Analytical Model | 9,1 | 4,1 | 96,9 | 4,8 |
| Proposed PGDT Framework | 4,9 | 2,7 | 98,6 | 14,3 |

The results confirm that degradation-aware adaptive operation enables a substantial extension of inverter service life while simultaneously improving operational efficiency and system availability. The predicted lifetime extension of 14.3% represents a significant economic advantage for large-scale renewable installations.

Figure 2 illustrates the long-term impact of degradation-aware adaptive operation on inverter availability and cumulative degradation index over a 10-year operational horizon. The graph combines (i) cumulative damage accumulation, (ii) adaptive control intervention points, and (iii) availability evolution under varying thermal and grid stress conditions. Unlike conventional strategies where degradation progresses monotonically, the PGDT-based approach actively reshapes operating points to mitigate stress accumulation during high-risk periods. As a result, degradation growth exhibits a piecewise-linear behavior with multiple stabilization plateaus, corresponding to adaptive derating and control reconfiguration events. This behavior directly translates into reduced forced outages and smoother availability trajectories, demonstrating the effectiveness of digital twin–driven decision-making at system level.



**FIGURE 2.** Long-term efficiency degradation trajectories of centralized inverters

The adaptive operation strategy is governed by a degradation-sensitive optimization process, where inverter control parameters are dynamically adjusted based on predicted aging rates. The cumulative degradation index is expressed as:

(6)

where is inverter power loss and denotes system availability. This multi-objective formulation ensures balanced trade-offs between efficiency, reliability, and availability during long-term operation.

The prognostic capability of the PGDT framework was assessed by forecasting remaining useful life (RUL) under stochastic operational scenarios. The RUL estimation follows a degradation-state–dependent probabilistic model:

(7)

Simulation results indicate that physics-guided degradation modeling reduces RUL prediction uncertainty by **31%** compared to purely data-driven approaches. This improvement enables earlier and more accurate maintenance planning, reducing unplanned downtime and lifecycle costs. Overall, the results confirm that the proposed digital twin framework not only enhances real-time operational decisions but also provides a reliable foundation for long-term asset management strategies in utility-scale renewable power plants.

**CONCLUSIONS**

This study presented a physics-guided, degradation-aware digital twin (PGDT) framework for the long-term adaptive operation of centralized inverters deployed in utility-scale renewable power plants. By integrating electro-thermal physical models with data-driven degradation learning, the proposed framework overcomes the limitations of conventional monitoring- or data-only approaches, which often suffer from model drift and limited interpretability under long-term operating conditions. The results demonstrate that embedding physical constraints within the digital twin significantly enhances the accuracy of health state estimation and enables reliable tracking of degradation dynamics across extended operational horizons.

The proposed PGDT framework enables adaptive control reconfiguration and stress mitigation based on predicted degradation trajectories, resulting in a measurable reduction in cumulative damage and a sustained improvement in inverter availability. Comparative evaluation shows that the degradation-aware adaptive operation achieves a substantial extension of inverter service life while simultaneously reducing energy losses and forced outages. Moreover, the probabilistic remaining useful life (RUL) estimation supported by the digital twin reduces prognostic uncertainty, providing a robust basis for proactive maintenance planning and lifecycle-oriented asset management.

The findings confirm that physics-informed digital twins represent a powerful enabler for sustainable, reliable, and economically efficient operation of centralized inverter systems in large-scale renewable energy plants. The proposed framework is scalable and can be readily extended to other power electronic assets operating under complex multi-stress environments. Future work will focus on incorporating grid-forming inverter dynamics, cyber-physical security considerations, and real-time coordination with plant-level energy management systems to further enhance the resilience of renewable power infrastructures.

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