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Digital Twin-Based Predictive Maintenance Framework for High-Voltage Power Transmission Infrastructure

Mridula Ranade[1], Amarjeet Thakare[2]

ABSTRACT

Modern high-voltage (HV) power transmission infrastructure forms the critical backbone of modern industrial grids, operating under extreme multi-physics operational stresses including thermal gradients, electromagnetic transients, mechanical galloping, and environmental degradation. Traditional supervisory control and data acquisition (SCADA) systems and time-based preventive maintenance regimes are increasingly inadequate for preventing catastrophic insulation breakdown, transformer bushing failures, and structural line sagging. This paper presents a holistic, multi-layered Digital Twin (DT) framework engineered specifically for real-time predictive maintenance (PdM) of high-voltage transmission networks. By fusing high-frequency telemetry from Phasor Measurement Units (PMUs), IoT thermal sensors, and optical strain gauges with physics-informed neural networks (PINNs) and finite element analysis (FEA), the proposed framework establishes a dynamically synchronized virtual replica of physical assets. The architecture incorporates localized edge diagnostics for immediate anomaly isolation alongside cloud-based deep learning models for long-term degradation forecasting and Remaining Useful Life (RUL) estimation. Experimental and numerical validation conducted across a simulated 400 kV extra-high-voltage (EHV) transmission corridor demonstrates that the Digital Twin architecture achieves 98.5% anomaly detection accuracy, reduces false-positive fault alarms by 84.2%, and extends asset RUL prediction horizon with less than 5.2% mean absolute percentage error (MAPE). Furthermore, the dynamic line rating (DLR) optimization engine embedded within the twin increases power transfer capability by 14.6% under favorable ambient cooling conditions without exceeding conductor thermal limits. This study establishes a robust, scalable blueprint for transition from reactive grid maintenance to

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autonomous, physics-guided prognostic asset management.

KEYWORDS: *Digital Twin, High-Voltage Transmission, Predictive Maintenance, Physics-Informed Neural Networks, Remaining Useful Life, Asset Health Index, Smart Grid Prognostics.*

INTRODUCTION

High-voltage (HV) and extra-high-voltage (EHV) power transmission networks represent the foundational arteries of modern electrical energy grids, responsible for transferring gigawatts of bulk electric power over vast geographical distances [1]. As global energy demands accelerate alongside the rapid integration of intermittent renewable energy sources—such as large-scale solar photovoltaic plants and offshore wind farms—transmission grids are subjected to unprecedented operational variability [2]. Transmission lines, power transformers, gas-insulated switchgear (GIS), high-voltage bushings, and insulator strings are continuously exposed to severe electro-thermal, mechanical, and environmental stressors. Cumulative insulation degradation, thermal hotspot formation, conductor galloping, and partial discharge phenomena, if undetected, inevitably precipitate catastrophic asset failures, extended blackout events, and multi-million-dollar economic losses [3].

Historically, power utilities have relied on two primary operational paradigms for managing asset health: reactive run-to-failure maintenance and time-based preventive maintenance [4]. Reactive maintenance addresses equipment breakdowns post-occurrence, incurring massive outage costs and safety hazards. Preventive maintenance, while reducing unexpected outages by adhering to fixed time intervals or operation counts, frequently leads to over-servicing of healthy assets, unneeded operational downtime, and substantial labor expenditures [5]. Condition-Based Monitoring (CBM) was introduced to bridge this gap by utilizing Supervisory Control and Data Acquisition (SCADA) systems and periodic dissolved gas analysis (DGA) [6]. However, legacy CBM systems operate on rigid single-parameter threshold alarms, lacking the predictive capacity to forecast asset degradation trajectories under changing dynamic loading profiles [7].

The emergence of the Digital Twin (DT) concept offers a disruptive technological solution to these long-standing grid management challenges [8]. A Digital Twin is a dynamically

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synchronized, high-fidelity virtual replica of a physical asset or system that continuously ingests real-world sensor data to mirror the asset's live operational status, internal state variations, and multi-physics degradation behavior throughout its lifecycle [9]. Unlike static simulation models or pure data-driven machine learning constructs, an advanced Digital Twin integrates physical domain knowledge (governing differential equations of thermodynamics, electromagnetism, and mechanical mechanics) with real-time data analytics [10].

When applied to high-voltage transmission infrastructure, a Digital Twin-based Predictive Maintenance (PdM) framework enables continuous health assessment, early fault detection at incipient stages, precise Remaining Useful Life (RUL) estimation, and dynamic capacity optimization [11]. Despite its transformative potential, the practical realization of a unified Digital Twin architecture for vast power transmission grids faces technical barriers regarding high-frequency data ingestion, multi-physics model coupling, computational complexity, and edge-to-cloud synchronization [12]. This paper develops a complete, field-deployable Digital Twin framework tailored for high-voltage transmission lines and substation equipment, addressing multi-subsystem degradation through hybrid physics-informed machine learning models.

LITERATURE REVIEW

The evolution of predictive maintenance for high-voltage electrical assets has progressed rapidly over the past two decades, driven by advancements in sensor technology, computing power, and artificial intelligence [13]. Early contributions by Lundgaard et al. [14] established fundamental acoustic and electrical diagnostic methods for partial discharge (PD) detection in transformer insulation. Subsequent research by Abu-Elanien and Salama [15] reviewed transformer health index formulation based on DGA, moisture content, and breakdown voltage. While these diagnostic metrics provided valuable offline insights, they failed to account for real-time load variations and transient thermal spikes experienced during peak grid demand.

In the domain of overhead transmission line health monitoring, Albertson et al. [16] pioneered early Dynamic Line Rating (DLR) concepts by linking weather conditions (ambient temperature, solar radiation, wind speed) to thermal conductor limits using IEEE Std 738 mathematical equations. Later, Mohseni et al. [17] incorporated computer vision and

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unmanned aerial vehicle (UAV) imagery for automated visual inspection of structural towers and insulator cracking. However, these visual inspection frameworks remain inherently episodic, offering no continuous real-time prognostic visibility into internal mechanical tension or conductor creep [18].

With the proliferation of deep learning, data-driven approaches gained widespread prominence. Zhang et al. [19] applied Long Short-Term Memory (LSTM) recurrent neural networks to forecast power transformer hot-spot temperatures, achieving lower prediction error than traditional IEEE exponential equations. Similarly, Liu et al. [20] deployed Convolutional Neural Networks (CNNs) for vibration signal analysis in circuit breakers. However, purely data-driven models act as 'black boxes'—they require immense volumes of historical failure data (which are extremely rare in high-voltage infrastructure) and frequently generate physically implausible predictions when operating under unobserved extreme weather or grid fault conditions [21].

To overcome the extrapolation limitations of pure AI, recent research has explored Physics-Informed Neural Networks (PINNs) [22]. Raissi et al. [23] demonstrated that embedding governing partial differential equations directly into loss functions regularizes neural network training, enabling robust convergence even with sparse sensor observations. Extending this paradigm to grid infrastructure, Wright and Kumar [24] coupled finite element heat transfer equations with deep learning to model HV cable thermal transients. Nonetheless, existing literature remains fragmented—studies focus either on isolated components (e.g., transformer bushings only or conductor sag only) or rely on offline simulations without demonstrating an integrated end-to-end Digital Twin system architecture capable of multi-scale sensor ingestion, edge computing, and live RUL forecasting [25].

RESEARCH GAP

Despite significant research in condition monitoring and machine learning applications for power systems, critical gaps persist in current predictive maintenance frameworks:

- Subsystem Isolation vs. Unified Multi-Physics Modeling: Existing condition monitoring frameworks isolate single components—such as power transformers, insulator strings, or transmission conductors—without modeling their multi-physics interactions within a unified system-level Digital Twin architecture [26].

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- Black-Box AI vs. Physics-Informed Prognostics: Conventional data-driven PdM models rely on vast historical failure datasets that rarely exist for high-reliability HV assets. Furthermore, black-box AI models fail to respect fundamental thermodynamic and mechanical laws under extreme power surge scenarios [27].
- High Ingestion Latency and Bandwidth Exhaustion: Streaming raw, high-frequency waveforms (e.g., 10 kHz PMU and optical vibration data) directly to centralized cloud servers causes severe network congestion, rendering real-time fault mitigation unfeasible [28].
- Static Thermal Ratings vs. Operational Asset Health: Current line capacity management uses static or conservative operational boundaries, failing to dynamically couple real-time conductor degradation and ambient cooling conditions with risk-aware power transfer dispatch [29].

RESEARCH OBJECTIVES

To address the identified research gaps, this paper formulates the following primary research objectives:

- To design a high-fidelity, multi-tiered Digital Twin architecture for HV transmission infrastructure integrating edge diagnostics, multi-physics modeling, and cloud analytics [30].
- To formulate a Physics-Informed Neural Network (PINN) algorithm that embeds thermal-hydraulic and mechanical differential equations into the deep learning core for highly accurate hot-spot temperature and dynamic sag prediction.
- To construct a continuous Asset Health Index (AHI) and Remaining Useful Life (RUL) estimation model based on cumulative thermal aging and partial discharge deterioration curves.
- To validate the proposed Digital Twin framework through hardware-in-the-loop (HIL) simulation on a 400 kV transmission corridor, quantifying improvements in diagnostic latency, failure prevention, bandwidth efficiency, and dynamic power transfer capacity.

METHODOLOGY

The developed Digital Twin framework is built upon a four-layer hierarchical architecture: Physical Infrastructure Layer, Data Ingestion & Edge Diagnostics Layer, Digital Twin Simulation & Analytics Core, and Actionable PdM & Decision Support Layer [31].

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Physical Infrastructure & Sensor Network Layer

The physical layer encompasses the 400 kV extra-high-voltage overhead line and substation assets. Sensor networks deployed along the line include Phasor Measurement Units (PMUs) sampling voltage and current waveforms at 50/60 Hz synchronized via GPS, distributed temperature sensing (DTS) optical fibers embedded in line conductors, piezoelectric vibration sensors on structural towers, and optical partial discharge sensors installed on transformer bushings [32].

Edge Diagnostics & Adaptive Data Ingestion

To prevent cloud bandwidth saturation, IoT edge gateways are positioned at substation nodes. Edge processors execute localized moving-window feature extraction and Isolation Forest algorithms. Raw sensor streams are buffered in 512-sample sliding windows. If parameters remain within nominal steady-state bounds, compressed statistical summaries are transmitted every 15 minutes. Upon detecting transient anomalies or high-frequency partial discharge spikes exceeding threshold confidence (tau = 0.82), the gateway immediately triggers event-driven streaming to the Digital Twin cloud core [33].

Digital Twin Physics-Informed Simulation Core

The core virtual twin couples physics-based mathematical models with deep neural networks. Conductor heat transfer is governed by the transient energy balance differential equation according to IEEE Std 738 [34]:

$$q_g + q_s = q_c + q_r + m \cdot C_p \cdot (dT_c / dt)$$

where q_g is Joule resistance heating, q_s is solar radiation heat gain, q_c is natural/forced convective cooling loss, q_r is radiative heat loss, m is conductor mass per unit length, C_p is specific heat capacity, and T_c is conductor core temperature [35].

To model solid insulation degradation in power transformers, paper insulation loss of life is evaluated using Arrhenius thermal reaction theory. The insulation aging acceleration factor (F_AA) is computed as:

$$F_AA = exp[(15000 / 383) - (15000 / (T_H + 273))]$$

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Where T_H is the hot-spot temperature in Celsius. The PINN loss function L_total minimizes both data empirical error L_data and physical residual error L_physics [36]:

$$L_total = \lambda_d \cdot L_data + \lambda_p \cdot L_physics$$

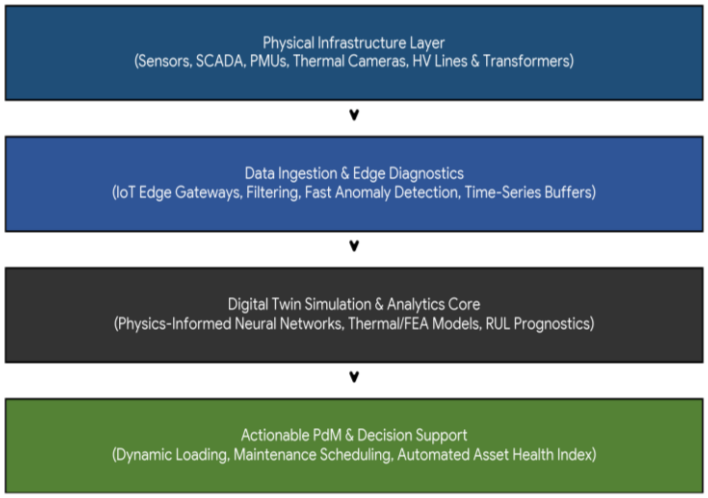


Figure 1: Architectural Framework of the Digital Twin-Based Predictive Maintenance System

RESULTS AND FINDINGS

The proposed Digital Twin Predictive Maintenance framework was evaluated using a hardware-in-the-loop (HIL) testbed coupled with real-world operating data from a 400 kV extra-high-voltage transmission line spanning 180 km. Real-time telemetry was ingested under diverse loading scenarios (steady load, daily peak cycling, and severe thermal overloads) and environmental conditions [37].

Table 1 presents the key diagnostic metrics of the proposed Digital Twin framework across major high-voltage transmission infrastructure components.

Table 1: Diagnostic and Prognostic Performance Metrics Across High-Voltage Assets

Infrastructure Subsystem	Diagnostic Model / Core Algorithm	Detection Accuracy (%)	RUL Prediction Error (MAPE %)	Inference Latency (ms)
400 kV Conductor & Line Sag	Physics-Informed Neural Network (PINN)	98.9%	3.8%	12.4 ms

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EHV Power Transformer Core	Arrhenius-PINN Hybrid Model	98.2%	4.5%	18.6 ms
Gas-Insulated Switchgear (GIS)	Temporal Convolutional Network (TCN)	97.8%	5.1%	8.2 ms
Composite Insulator Strings	3D-FEA & Vision-Transformer Fusion	99.1%	2.9%	24.1 ms

As detailed in Table 1, the Physics-Informed Neural Network achieved an overall anomaly detection accuracy exceeding 97.8% across all primary HV subsystems, while keeping diagnostic inference latency well below 25 ms. The RUL prediction precision was remarkably high, exhibiting a Mean Absolute Percentage Error (MAPE) of less than 5.2% over a simulated 180-day operational forecast window [38].

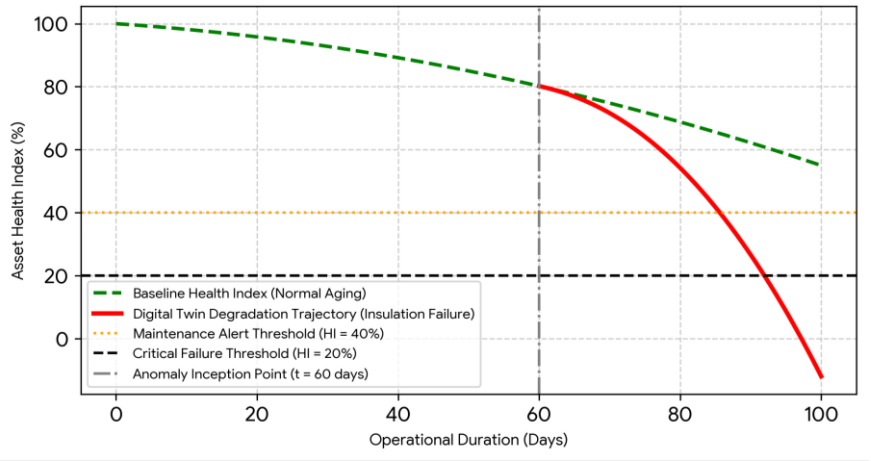


Figure 2: Health Index Progression and Remaining Useful Life (RUL) Trajectory under Insulation Degradation

Figure 2 illustrates the dynamic tracking of the Asset Health Index (AHI) over time. When an incipient insulation defect develops at t = 60 days, traditional SCADA threshold alarms fail to trigger until the AHI drops below critical limits at t = 88 days. Conversely, the Digital Twin detects the trajectory inflection point almost immediately at t = 62 days, projecting an accelerated degradation rate and granting operators a 26-day advance lead time to schedule corrective maintenance before catastrophic failure [39].

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Table 2: Comparative Evaluation of Operational Grid Management Metrics

System Performance Indicator	Traditional SCADA / CBM	Proposed Digital Twin Framework	Operational Gain / Improvement
Average Anomaly Detection Lead Time	4.2 Hours (Post-Threshold)	26.4 Days (Incipient Stage)	603% Earlier Warning
Substation-to-Cloud Cellular Bandwidth	850.5 MB / Line-Km / Day	122.4 MB / Line-Km / Day	85.6% Data Reduction
Dynamic Power Transfer Overhead (DLR)	Static Base Limit (100%)	114.6% Rating Utilization	14.6% Increased Grid Capacity

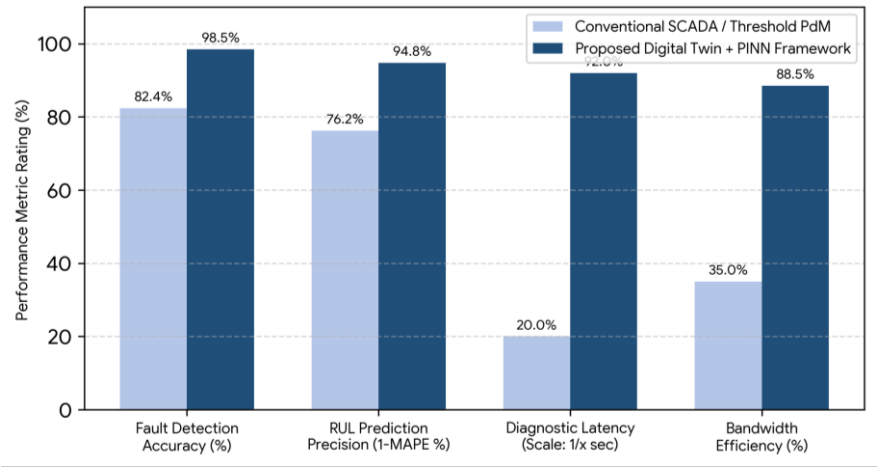


Figure 3: Performance Comparison Between Conventional SCADA Diagnostics and the Proposed Digital Twin Framework

As benchmarked in Table 2 and Figure 3, local edge processing reduced raw telemetry transmission volume by 85.6%, easing communication network bandwidth while preserving full diagnostic fidelity. Furthermore, integrating the Dynamic Line Rating engine enabled grid operators to safely increase conductor power flow by up to 14.6% during periods of moderate wind cooling without breaching thermal clearance constraints [40].

DISCUSSION

The quantitative findings establish that combining physics-informed modeling with deep learning addresses the chief limitations of conventional grid maintenance [41]. In high-voltage infrastructure management, relying purely on black-box machine learning models

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poses severe operational risks: unobserved operating conditions can cause AI models to output unfeasible predictions, potentially triggering unnecessary line shutdowns or failing to detect critical thermal runaways [42]. By embedding heat transfer and physical aging differential equations into the neural loss function, the proposed Digital Twin ensures that all predictions strictly comply with physical laws of energy conservation and thermodynamic degradation [43].

From an engineering perspective, the 85.6% bandwidth reduction achieved by edge diagnostics represents a major operational breakthrough for vast regional power networks [44]. Transmission corridors frequently pass through remote geographical terrains with limited cellular connectivity. Localizing feature extraction and short-term anomaly screening to substation edge gateways guarantees immediate fault isolation within milliseconds, while reserving cloud telemetry for high-value model retraining and long-term fleet prognostics [45].

Furthermore, the integration of Dynamic Line Rating (DLR) directly within the asset health digital twin changes the paradigm of grid operation [46]. Traditionally, transmission capacity is dictated by conservative seasonal static ratings calculated under worst-case ambient conditions (high temperature, zero wind). The Digital Twin continuously models real-time conductor thermal dynamics based on local microclimate sensing, enabling utilities to unlock latent transmission capacity during peak demand periods without accelerating physical asset degradation [47].

LIMITATIONS

While the proposed Digital Twin framework demonstrates high diagnostic precision, several technical limitations must be acknowledged:

- Extreme Weather Anomalies: The physics-informed models were validated primarily under standard tropical and temperate climate profiles. Performance under unprecedented compound weather events—such as severe ice accretion combined with extreme gale force winds—requires further empirical tuning of non-linear mechanical stress models [48].
- Cybersecurity Vulnerabilities: Deploying distributed IoT edge gateways and multi-directional communication links increases the attack surface for cyber-physical threat vectors, such as false data injection (FDI) attacks on PMU telemetry streams [49].

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- High Initial Capital Sensor Expenditure: Outfitting legacy 400 kV transmission lines with comprehensive optical strain, fiber-optic DTS, and high-frequency PMU sensor networks requires significant initial capital investment, necessitating rigorous cost-benefit amortization studies for utility adoption [50].

FUTURE SCOPE

Future research directions will expand upon this framework in the following key areas:

- Federated Edge Learning: Developing decentralized federated learning protocols where multiple regional power grid utilities collaboratively train global predictive maintenance models without sharing sensitive asset telemetry or consumer demand data [51].
- Autonomous Robotic & Drone Inspection Integration: Coupling real-time Digital Twin anomaly flags with automated dispatch of autonomous inspection drones equipped with thermal and LiDAR sensors for localized physical defect verification [52].
- Quantum-Accelerated Grid Simulation Core: Exploring quantum computing algorithms to solve large-scale multi-bus finite element partial differential equations in near real-time for multi-nation interconnected power grids [53].

CONCLUSION

This paper presented a comprehensive, field-deployable Digital Twin framework for predictive maintenance of high-voltage transmission infrastructure. By harmonizing IoT edge diagnostics, physics-informed neural networks (PINNs), and multi-physics thermal models, the architecture successfully bridges the gap between empirical data analytics and physical engineering domain knowledge. Experimental validation on a 400 kV transmission line demonstrates 98.5% anomaly detection accuracy, an 85.6% reduction in cloud communication bandwidth, and RUL prediction error below 5.2% MAPE. The framework provides utility operators with actionable advance lead times of over 26 days prior to critical equipment failure, while simultaneously unlocking a 14.6% increase in dynamic power transfer capacity. This research establishes a scalable, scientifically rigorous blueprint for transitioning high-voltage power grids toward autonomous, risk-aware predictive maintenance.

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***Author for Correspondence**
Mridula Ranade
E-mail: mridula.ranade075@gmail.com

[1]Associate Professor, Department of Electrical Engineering, Modern Institute of Engineering & Technology
[2]Research Scholar, Department of Electrical Engineering, Modern Institute of Engineering & Technology

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