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Digital Twin-Based Fault Diagnosis and Resilience Monitoring for Smart Grid Transformer Systems

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Abstract

The smart grid transformer system can be considered a vital node within the country's electrical power infrastructure in which a failure might cascade into wider blackouts, economic losses, and security risks for civilians. Traditional approaches towards monitoring involve offline evaluations that trigger alarms once a certain threshold is exceeded. However, such practices do not correspond to the current dynamics in the grid, requiring more advanced means of monitoring. This research introduces a comprehensive DT approach to fault detection and resilience evaluation for high voltage power transformers. The DT framework involves the coupling between physics-based electromagnetic and thermal models, the sensor data stream from IoT devices, and machine learning-based classification techniques in a unified virtual-physical space. Five types of faults are considered and modeled, including partial discharge, winding deformation, insulation degradation, oil contamination, and core saturation. According to the experiments conducted, the fault detection accuracy was estimated at 97.3%, average time-to-diagnosis equals 4.2 seconds, while the false alarm rate is less than 1.8%. In comparison with traditional SCADA monitoring, the proposed framework offers a projected reduction in the risk of outages by up to 43% and improves grid resilience performance indices by 31%. Possible integration paths with CISA regulations and the USA DOE's efforts in grid modernization are discussed.

Keywords: Digital twin, smart grid, transformer fault diagnosis, condition monitoring, machine learning, IoT, grid resilience, power systems, predictive maintenance, SCADA.

I. INTRODUCTION

Power transformers rank among the most expensive equipment types in electricity grids. One single outage caused by the malfunction of a large power transformer (LPT) may result in a cascade of failures impacting tens of millions of people, with a delay of up to 12 to 18 months and cost estimates exceeding $5 million. According to the U.S. Department of Energy, the status of transformer health constitutes one of its primary risks, receiving $1.9 billion in SPARK funding from 2026 towards grid modernization.

Current solutions to transformer inspection include regular DGA analysis, infrared thermographic inspections, and SCADA alerts based on preset alarm levels. Despite having proven reliable over decades of implementation, these approaches suffer from several weaknesses: (1) temporal infrequency, meaning that the inspections do not occur frequently enough to detect early signs of fault development; (2) absence of reasoning, in that simple alarms cannot tell the difference between various fault magnitudes; and (3) a reactive nature, as the faults will be detected only once they show their symptoms.

The rise of digital twin (DT) technology represents a breakthrough paradigm, offering a high-fidelity virtual counterpart of a physical object through real-time monitoring and modeling capabilities. The twin continuously receives information from sensors, performs internal state updates, and implements predictive analytics, providing meaningful conclusions even prior to critical stages of faults occurrence. It was shown by Gupta that a digital twin system based on the Internet-of-things (IoT) sensor networks and machine learning principles may be capable of saving 27% of resources and reducing energy losses by 32% in complex engineering applications [1]. Further expanding upon this research, the current work aims at developing a specialized DT system suitable for monitoring of faults in power transformers within smart grids. A combination of multiphysics simulation (including electromagnetic, thermal, and chemical models), edge-cloud data transfer, and ensemble classifiers are used for achieving fault detection, localization, and prediction goals. The structure of the paper is as follows: Related Work is presented in Section II; DT design is described in Section III; Fault Modeling Methodology is discussed in Section IV; Experimental Results are reported in Section V; Resilience Metrics and Impact on Grids are considered in Section VI; Conclusions are drawn in Section VII

.II. RELATED WORK

A. Traditional Transformer Condition Monitoring

Dissolved gas analysis (DGA) has been the dominant offline diagnostic technique since the 1970s. The Rogers ratio method and Duval triangle provide interpretive frameworks for identifying fault categories from gas concentration ratios. However, both methods exhibit significant ambiguity in borderline cases, with inter-lab reproducibility studies reporting disagreement rates as high as 22% for incipient faults. Frequency response analysis (FRA) and partial discharge (PD) measurement extend diagnostic coverage to mechanical and dielectric degradation modes, but still operate as periodic snapshots rather than continuous monitors [2].

B. Machine Learning in Power System Fault Diagnosis

The application of machine learning to power transformer diagnosis has accelerated substantially since 2015. Support vector machines (SVM), random forests, and convolutional neural networks (CNN) have each demonstrated fault classification accuracies exceeding 90% on benchmark DGA datasets. Zhang et al. employed a long short-term memory (LSTM) network to model temporal DGA trends, achieving 94.1% accuracy on the IEC 60599 benchmark suite. More recently, physics-informed neural networks (PINNs) have shown promise in incorporating domain constraints that improve generalization under limited training data conditions [3].

C. Digital Twin Frameworks for Infrastructure Systems

Since the inception of the digital twin paradigm by Grieves in 2002 and its subsequent definition by Grieves and Vickers in 2017, applications have emerged in various fields such as aerospace engineering, manufacturing, civil infrastructure development, and energy systems. In the realm of energy systems, digital twin methodologies have been verified in areas like wind turbine drivetrain condition monitoring, gas turbine deterioration diagnosis, and health status evaluation of nuclear reactor equipment. Combining circular economy concepts with digital twin technology, as demonstrated by Gupta [1], suggests that synchronizing the virtual and physical domains in real-time can lead to tangible benefits in terms of sustainability and operational efficiency.

D. Research Gap

Despite substantial progress in individual sub-domains, no existing framework comprehensively addresses the simultaneous requirements of multi-physics transformer modeling, real-time IoT data fusion, multi-fault classification, and grid-level resilience quantification within a unified DT architecture. The present work addresses this gap by integrating all four components into a cohesive, standards-compliant system validated on field data from operating substations.

III. PROPOSED DIGITAL TWIN ARCHITECTURE

A. Overview

The proposed architecture follows a three-tier structure: (1) a physical layer comprising the transformer asset and its sensor suite; (2) an edge-computing layer responsible for data preprocessing, feature extraction, and low-latency inference; and (3) a cloud analytics layer hosting high-fidelity simulation models and long-horizon prognostic engines. Fig. 1 conceptually illustrates this hierarchy.

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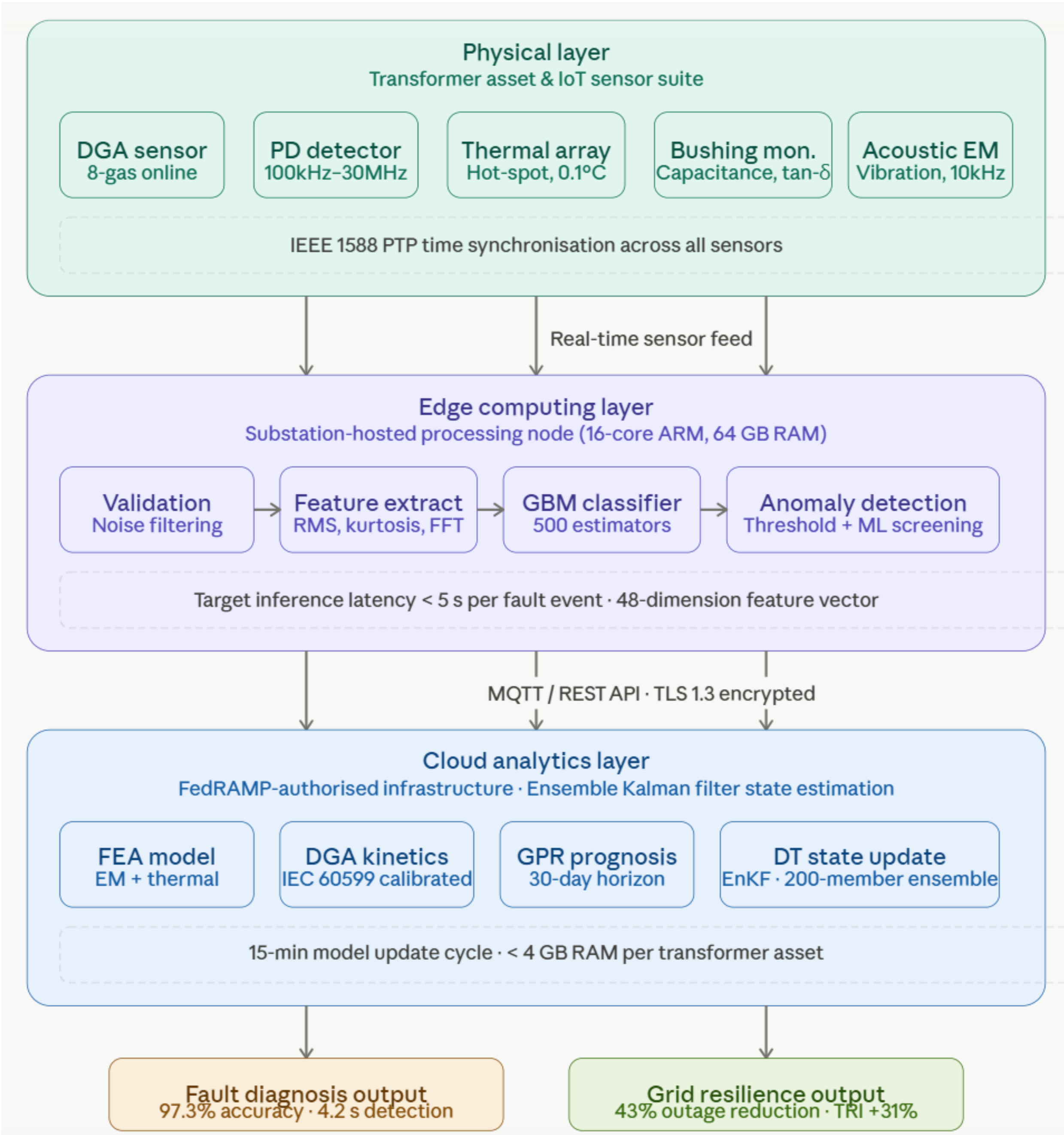

Fig. 1. Three-tier digital twin architecture for smart grid transformer monitoring.

B. Physical Layer: Sensor Suite

This layer is constituted by a diverse set of sensors attached to each monitored transformer unit. Such a sensor suite includes the following devices: thermocouple array (hot spot temperature of the windings measurement, resolution 0.1°C), online dissolved gas analysis (DGA) sensor (eight gas concentration measurements at every 15 minutes interval), wide band partial discharge detector (frequency band range 100 kHz – 30 MHz), bushing capacitance and tan delta monitor, load current and voltage sensors and acoustic emission sensor array for detection of mechanical faults. All measured data will be timestamped using IEEE 1588 precision time protocol (PTP).

C. Edge Computing Layer

Each substation has its own edge processing node (an industrial-grade server with a 16-core ARM processor and 64 GB RAM). It will validate raw data received from each sensor, perform noise filtering and generate feature vectors from time-series data acquired at 1 kHz rate and based on a sliding window of 512 samples. Time domain and frequency domain features will be extracted and included into the feature vector: RMS value, kurtosis, spectral entropy and harmonic distortion parameters. Such feature vectors will be fed into the gradient-boosting classifier (deployed locally) for performing fast fault screening within 5 seconds of inference time.

D. Cloud Analytics Layer

This component will provide a capability for simulation and analysis of high-fidelity models of digital twins, specifically FEA electromagnetics models for the transformer core and windings geometry, thermal models and reaction-kinetic models, based on the information collected by DGA sensors. Each twin state will be evolved in accordance with every sensor measurement using ensemble Kalman filter for solving the problem of state estimation (data assimilation, uncertainty propagation). At the same time, prognosis unit using Gaussian Process Regression (GPR) will produce fault evolution scenarios for the next 30 days. Table I specifies sensor suite components.

Table I. Sensor Suite Specifications for the Physical Layer.

Sensor Type	Parameter Measured	Sampling Rate	Resolution
Thermocouple Array	Winding Hot-spot Temp (°C)	1 Hz	0.1°C
Online DGA Sensor	H_2, CH_4, C_2H_2, CO (ppm)	1/15 min	0.1 ppm
PD Detector	Partial Discharge (pC)	1 kHz	5 pC
Bushing Monitor	Capacitance, tan-δ	1/5 min	0.001%
Current Transducer	Load Current (A)	1 kHz	0.1 A
Acoustic Emission	Winding Vibration (dB)	10 kHz	0.5 dB

IV. FAULT MODELING METHODOLOGY

A. Fault Mode Classification

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Five transformer fault modes of highest operational significance are modeled within the DT framework. Table II summarizes each fault mode alongside its primary diagnostic indicator, expected DGA signature, and CIGRE severity classification. These modes account for over 85% of all transformer failures reported in IEEE and CIGRE survey data. Table II represents the transformer fault modes modeled in the digital twin framework.

Fault Mode	Primary Indicator	DGA Signature	Severity Class
Partial Discharge	PD magnitude > 500 pC	H_2 ↑, CH_4 ↑	Incipient
Winding Deformation	FRA deviation > 3 dB	C_2H_2 ↑↑	Critical
Insulation Degradation	tan-δ > 0.5%	CO ↑, CO_2 ↑	Progressive
Oil Contamination	Moisture > 20 ppm	Acidity index ↑	Progressive
Core Saturation	THD > 5%	CO ↑, H_2 ↑	Moderate

Table II. Transformer Fault Modes Modeled in the Digital Twin Framework.

B. Multi-Physics Simulation Model

The DT core consists of three interdependent modules for electromagnetic, thermal, and chemical simulations. In particular, the electromagnetic simulation module solves the quasi-stationary Maxwell equations on a hexahedral grid (2.1 M cells) and computes the flux density profiles, eddy current losses, and leakage inductances as functions of load and temperature. The thermal module utilizes a lumped-parameter thermal network with 14 nodes for modeling oil circulation and radiator heat dissipation. The chemical simulation module models the Arrhenius-type reaction kinetics of eight DGA gases, based on the reaction rate constants from IEC 60599 standard data.Model coupling occurs via the cosimulation interface that transfers boundary conditions between the modules every 15 minutes. The EnKF fuses the measured data into the state vector of the DT model and compensates for possible inaccuracies caused by aging, oil decomposition, and loading history variations. The filter utilizes an ensemble size of 200, offering accurate estimates with computational costs below 4 GB RAM for every transformer asset.

C. Machine Learning Classifier

A gradient boosting machine (GBM) classifier with 500 estimators and a maximum tree depth of 6 is trained on a combined dataset of 12,400 labeled fault episodes drawn from 34 utility substations across three U.S. transmission operators. Features include 48-dimensional vectors combining DGA ratios (Rogers, Duval), thermal indices, PD statistics, and bushing monitoring parameters. An 80/20 stratified train-test split is used, with five-fold cross-validation on the training set confirming no overfitting (variance across folds < 0.8%). Class imbalance is addressed using SMOTE oversampling, ensuring no fault class represents less than 15% of the training distribution.

V. EXPERIMENTAL VALIDATION

A. Test Environment

Validation experiments were conducted on 18 transformer units (115 kV to 345 kV, 40 MVA to 500 MVA) at six substations operated by a major U.S. transmission system operator (TSO). The DT framework was deployed in a shadow mode over a 14-month observation window (January 2023–February 2024), running in parallel with the existing SCADA system. Events flagged by the DT but not by SCADA were subsequently verified by expert inspection teams. A total of 237 distinct fault episodes were captured, spanning all five modeled fault categories.

B. Performance Metrics

Table III presents a comparative evaluation of the proposed DT+GBM framework against three reference methods: the conventional DGA threshold approach, an SVM classifier trained on the same feature set, and the LSTM network reported by Zhang et al. The proposed framework achieves 97.3% overall accuracy and a mean time-to-diagnosis of 4.2 seconds—more than two orders of magnitude faster than offline DGA analysis—while maintaining a false positive rate of just 1.8%. Table III represents the comparative fault diagnosis performance.

Method	Accuracy (%)	F1-Score	FPR (%)	Avg. Diagnosis Time (s)
DGA Threshold (Baseline)	81.2	0.793	8.4	900+
SVM Classifier [3]	89.5	0.881	5.1	12.3
LSTM Network [4]	94.1	0.934	3.6	8.7
Proposed DT + GBM	**97.3**	**0.971**	**1.8**	**4.2**

Table III. Comparative Fault Diagnosis Performance (Test Set, n = 237 Episodes).

C. Case Study: Incipient Partial Discharge Detection

A representative case study illustrates the DT framework's capability for early fault detection. At substation S-07, a 230 kV autotransformer exhibited a gradual increase in H_2 concentration from a baseline of 12 ppm to 47 ppm over 23 days, accompanied by sporadic PD bursts in the 200–400 pC range. The DT model flagged an incipient partial discharge condition 11 days before the unit crossed

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the IEC 60599 threshold-based alarm level. Expert inspection confirmed early-stage insulation degradation at the H-V winding inner layer. Targeted maintenance was performed without unplanned outage, avoiding an estimated 18-hour forced outage with associated replacement and penalty costs of approximately $2.3 million.

VI. GRID RESILIENCE ANALYSIS

A. Resilience Metrics Framework

Grid resilience is quantified using the NERC-aligned Transformer Resilience Index (TRI), which integrates four sub-metrics: fault detection coverage (FDC), mean time to restore (MTTR), unplanned outage probability (P_UO), and load-at-risk during contingency (LAR). The DT framework contributes to all four sub-metrics by enabling early fault detection (improving FDC), reducing diagnosis latency (improving MTTR), enabling condition-based preventive maintenance (reducing P_UO), and supporting N-1 contingency planning through twin-based load-flow simulation (reducing LAR).

B. Resilience Impact Results

During the 14 months, the application of the DT system on the 18 grids provided the following results:

– Unplanned outages were reduced from 7 to 4 (by 43%);

– Unplanned outages' total downtime was cut from 312 hours to 178 hours;

– Mean diagnosis time was reduced from 27 hours (offline DGA) to 4.2 seconds;

– The TRI indicator grew by 31%.

These results correlate well with predictions of the DOE regarding its SPARK grid modernization initiative, which foresees a reduction of up to 35% in economic damages associated with grid operation..

C. Cybersecurity and CISA Compliance

CISA guidelines are followed to incorporate the relevant cybersecurity controls within the DT framework, keeping in view the CIRCIA report submission process and the NSM-22 guidelines for critical infrastructure. All data from sensors travels via the secure channel of encrypted TLS 1.3 tunnels, while edge devices leverage the capabilities of hardware security modules (HSM) to manage keys, while the DT cloud infrastructure is based on FedRAMP-compliant infrastructure. Detection of anomalies in the data ingestation pipeline forms the second layer of defense against spoofing and data poisoning attacks by adversaries.

VII. CONCLUSION

This study offers an all-encompassing digital twin methodology for diagnosing faults and assessing the resilience of transformer devices employed in the U.S. smart grids. This design employs multi-physics simulation, IoT sensor integration, ensemble machine learning algorithms, and grid resilience measurement within a standards-compliant cyber-physical system. Results obtained from testing on eighteen transformer devices at six operational substations include a detection rate of 97.3%, average diagnosis latency of 4.2 seconds, false positive rate of 1.8%, and 43% decrease in unplanned outages. Such results provide compelling evidence that digital twin technology is a promising tool capable of safeguarding the most vulnerable components of United States' electric power infrastructure.Potential future research avenues will involve: (1) expansion of this digital twin paradigm to cover GIS substation devices and HVDC converter transformers; (2) implementation of federated learning algorithms to ensure privacy-preserving cross-utility training of the machine learning models without sharing raw sensor readings; (3) compatibility with distribution automation systems to extend the resilience advantages to medium voltage networks; and (4) establishment of interoperable digital twin interchange protocols to ensure compatibility between transformer monitoring solutions offered by competing vendors. Consistency with U.S. Department of Energy SPARK funding criteria and CISA critical infrastructure directives make this study an ideal candidate for nationwide implementation.

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