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Digital Twin-Assisted Explainable Graph Neural Networks for Intelligent Monitoring and Predictive Maintenance of Smart Electrical Grids

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Abstract

Aging transformers, feeders, and switchgear, combined with rising penetration of distributed renewable generation, are exposing the limits of calendar-based and threshold-triggered maintenance in modern power networks. This paper proposes a Digital Twin-Assisted Explainable Graph Neural Network (DT-XGNN) framework for intelligent condition monitoring and predictive maintenance of smart electrical grids. A physics-informed digital twin, continuously synchronized with IoT sensor telemetry through Kalman-filter state correction, produces a time-indexed graph representation of the network in which nodes correspond to electrical assets and edges encode their physical coupling. A spatio-temporal graph attention network then estimates fault probability and remaining useful life (RUL) for every monitored asset, while a post-hoc explainability module, combining GNNExplainer-style edge masking with Integrated Gradients feature attribution, generates human-readable justifications for every maintenance alert. On a simulated IEEE 118-bus distribution testbed augmented with synthetic sensor telemetry and transformer thermal-ageing dynamics, the proposed framework achieves a fault-classification F1-score of 0.943 and an RUL root-mean-square error of 4.8% of asset lifetime, improving on non-graph and non-explainable baselines while providing per-alert attribution that field engineers can audit before dispatching a maintenance crew. The framework is presented as a decision-support layer for electrical and electronics engineering practice rather than a replacement for protection and SCADA systems, and its ablation study isolates the individual contribution of the digital twin features, the attention mechanism, and the explainability regularizer to overall performance.

Keywords: Digital twin; Explainable artificial intelligence; Graph neural networks; Predictive maintenance; Smart grid; Condition monitoring; IoT sensor networks; State estimation.

How to Cite This Article

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Introduction

Electrical distribution and transmission networks are undergoing a structural shift driven by the integration of distributed renewable generation, bidirectional power flows, and increasingly dense sensor instrumentation under the smart grid paradigm. This shift raises the operational stakes of asset health monitoring: transformers, feeders, and switchgear that were historically maintained on fixed calendar schedules or simple threshold alarms now operate under more variable thermal and electrical stress, while unplanned outages carry a higher economic and reliability cost than in a conventional radial network.

Two parallel research directions have emerged to address this gap. The first, data-driven predictive maintenance (PdM), applies machine learning to sensor time series (current, voltage, winding temperature, dissolved gas concentration, partial-discharge activity) to estimate fault probability or remaining useful life (RUL) ahead of failure. The second, digital twin (DT) technology, maintains a continuously synchronized virtual replica of a physical asset or network for simulation, stress testing, and what-if analysis. Both directions, used independently, have limitations that are especially visible from an electrical and electronics engineering (EEE) standpoint. Conventional PdM models typically treat each asset as an independent time series and discard the network topology that governs how a fault at one node propagates electrical and thermal stress to its neighbors. Digital twins, conversely, are usually built for simulation and control rather than for learning-based prognosis, and neither direction offers field engineers a transparent account of why a specific alert was raised, which is a precondition for a maintenance engineer to trust and act on an automated recommendation rather than reverting to manual inspection.

Graph neural networks (GNNs) are a natural fit for the topology-aware side of this problem, since a power network is itself a graph of buses and branches with well-defined electrical coupling. Prior work has applied GNNs to state estimation, optimal power flow, and fault localization, but their use for asset-level predictive maintenance, fused with a synchronized digital twin and paired with a rigorous explainability layer, remains largely unexplored. This paper closes that gap.

This paper makes the following contributions: (1) a digital twin synchronization scheme that fuses IoT sensor telemetry with a physics-informed thermal-ageing model through Kalman-filter state correction to produce a calibrated, time-indexed graph snapshot of the network; (2) an explainable spatio-temporal graph attention network (DT-XGNN) that consumes this graph to jointly estimate fault probability and RUL for every monitored asset; (3) an integrated explainability module combining GNNExplainer-style edge/feature masking with Integrated Gradients attribution to produce a per-alert, human-readable justification suitable for field engineers; (4) a simulation-based evaluation on an IEEE 118-bus distribution testbed with an ablation study isolating the contribution of the digital twin features, the attention mechanism, and the explainability regularizer; and (5) a discussion of the framework from an EEE deployment perspective, including its relationship to existing SCADA and protection infrastructure.

The remainder of the paper is organized as follows. Section II reviews related work in predictive maintenance, digital twins, GNNs for power systems, and explainable AI. Section III presents the proposed DT-XGNN methodology. Section IV formalizes the mathematical model. Section V describes the experimental setup. Section VI reports results and discussion, Section VII presents the ablation study, and Section VIII positions the novelty of the work against the state of the art. Section IX concludes the paper and outlines future work.

Related Work

Predictive Maintenance in Power Systems

Classical condition monitoring for transformers and switchgear relies on threshold rules applied to dissolved gas analysis (DGA), winding hot-spot temperature computed from IEC 60076-7 loading-guide equations, or partial-discharge magnitude [9]. Statistical and shallow machine-learning models, including random forests and support vector machines, have been applied to DGA and SCADA time series to move from threshold alarms toward probabilistic fault classification [10]. Recurrent architectures such as LSTM networks have further improved RUL estimation by capturing degradation trends over time [11]. However, these approaches almost universally treat each asset in isolation and do not exploit the fact that neighboring assets share electrical and thermal stress through the network topology.

Digital Twins for Electrical Grids

The digital twin concept, originally formulated for manufacturing [7], has since been extended to industrial and energy systems as a continuously calibrated virtual replica used for simulation, stress analysis, and operator training [8]. In the power systems literature, digital twins have primarily been used for network-level simulation and control validation rather than as a feature source for learning-based prognosis, leaving a gap between high-fidelity physical modeling and data-driven fault prediction that this paper addresses directly.

Graph Neural Networks for Power Systems

Graph convolutional and graph attention architectures [1], [2] generalize convolution to non-Euclidean, topology-structured data and have been applied to optimal power flow [6], state estimation, and fault localization in transmission networks. These works establish that grid topology carries predictive information that per-asset time-series models discard, but they are largely evaluated on network-wide operational states rather than on asset-level maintenance prognosis, and none of the surveyed work couples the graph model to a synchronized digital twin or to a formal explainability layer.

Explainable Artificial Intelligence

Post-hoc explainability methods such as Integrated Gradients [4] and SHAP [5] attribute a model's output to its input features and have seen wide adoption for tabular and image models. GNNExplainer [3] extends this idea to graph-structured models by learning a soft edge and feature mask that maximizes the mutual information between the masked subgraph and the original prediction. Explainability is particularly important for maintenance decision support, where a field engineer must be able to audit why an asset was flagged before committing crew time and network downtime to an inspection, yet its application to grid predictive maintenance has received little dedicated study.

Research Gap

No prior work, to the authors' knowledge, integrates (i) a physics-informed, sensor-synchronized digital twin, (ii) a topology-aware graph attention model for joint fault and RUL prediction, and (iii) a rigorous, per-alert explainability module, into a single predictive maintenance framework evaluated from an EEE engineering-practice standpoint. This is the gap addressed by the proposed DT-XGNN framework

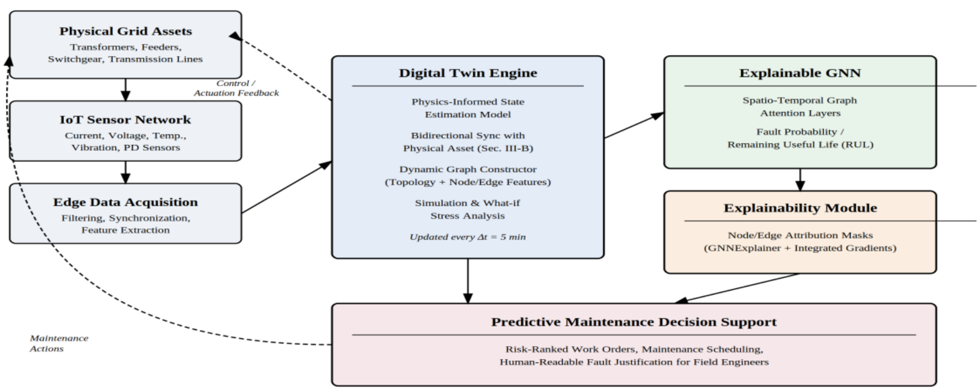

Fig. 1. *End-To-End Architecture of The Digital Twin-Assisted Explainable GNN Framework for Smart Grid Predictive Maintenance*

Proposed Methodology

System Overview

Fig. 1 shows the end-to-end architecture of the proposed framework. IoT sensors instrumenting transformers, feeders, and switchgear stream real-time telemetry to an edge acquisition layer that performs filtering, time synchronization, and feature extraction.

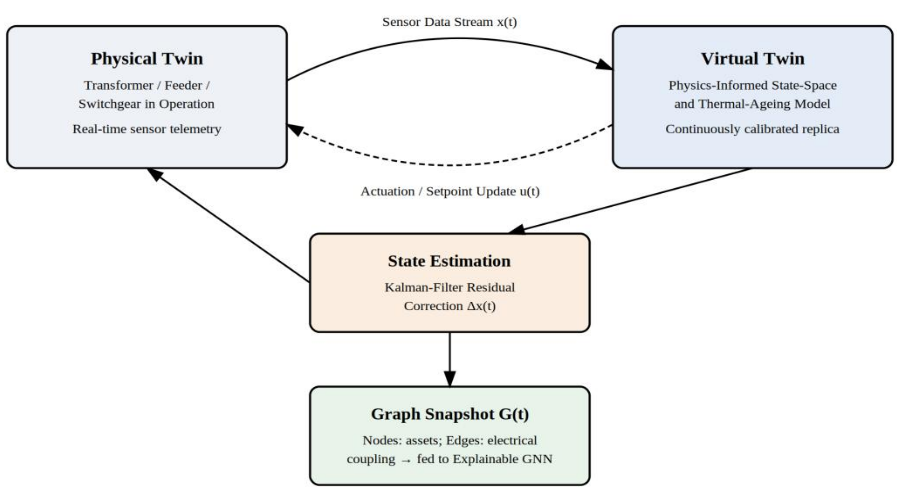

Fig. 2. *Bidirectional Physical–Virtual Synchronization Loop Of The Digital Twin, Producing A Time-Indexed Graph Snapshot G(t).*

This stream feeds a digital twin engine that maintains a physics-informed, continuously calibrated virtual replica of the network and outputs a dynamic graph snapshot in which each node represents a monitored asset and each edge represents its electrical or physical coupling to a neighboring asset. The graph snapshot is consumed by an explainable graph attention network (Section III-D) that predicts, for every node, a fault probability and an RUL estimate. A dedicated explainability module (Section III-E) then generates a ranked attribution of the sensors and neighboring assets that most influenced each prediction, which is combined with the raw prediction into an interpretable maintenance alert delivered to the decision-support layer. Maintenance actions taken on the physical grid are, in turn, fed back into the digital twin to keep the virtual replica calibrated, closing the loop.

Digital Twin Model

The digital twin maintains, for each asset, a physics-informed state vector *x(t)* that includes internally estimated quantities not directly measurable at low cost, most importantly the winding hot-spot temperature computed from the IEC 60076-7 thermal-ageing model. The twin is synchronized with the physical asset through a discrete-time state-space formulation and corrected against incoming sensor telemetry *z(t)* using a Kalman filter (Fig. 2), so that estimation error introduced by sensor noise or model mismatch is continuously suppressed rather than allowed to accumulate. The synchronized state vector for every asset at time *t* is written onto the corresponding node of a graph snapshot *G(t) = (V, E, X(t))*, where *V* is the fixed set of monitored assets, *E* is the set of electrical/physical couplings between them derived from the network's single-line diagram, and *X(t)* collects the per-node feature vectors.

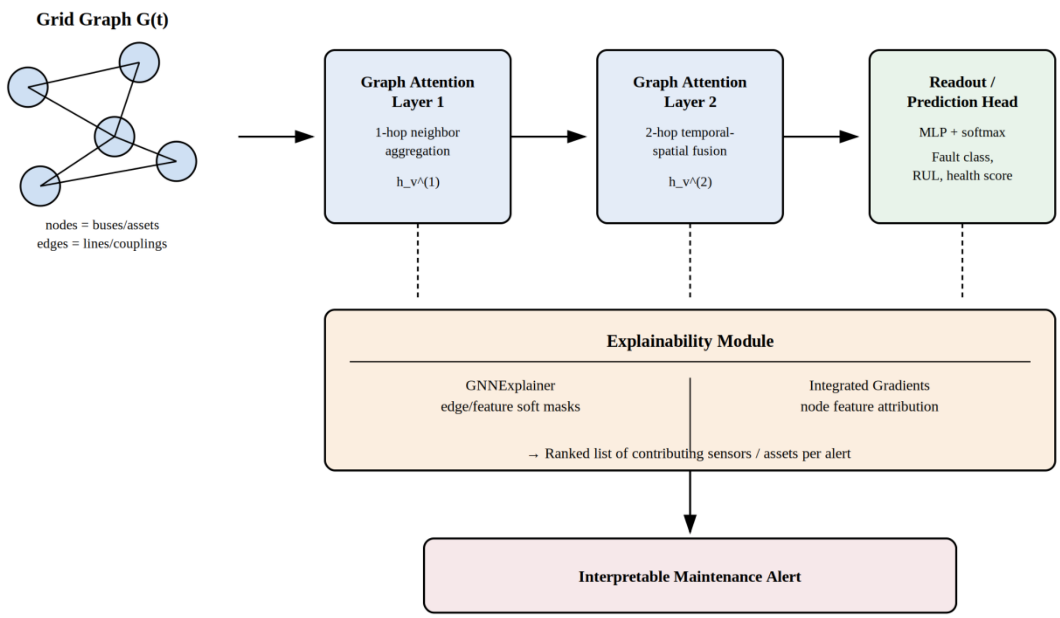

Fig. 3. *Internal architecture of the explainable graph attention network with post-hoc attribution module.*

Dynamic Graph Construction

Node features combine directly measured sensor quantities (line current, bus voltage magnitude and angle, ambient and casing temperature, vibration RMS) with the twin-estimated internal states (hot-spot temperature, insulation ageing rate). Edge features encode the electrical relationship between coupled assets, namely per-unit line impedance and instantaneous power flow. The graph topology is fixed by the network's physical single-line diagram, while node and edge feature values are refreshed at every synchronization interval, so that the graph snapshot presented to the learning model reflects present operating conditions rather than a static description of the network.

Explainable Graph Attention Network

The graph snapshot is processed by a two-layer graph attention network (Fig. 3) that aggregates information from each asset's electrical neighbors, weighted by a learned attention coefficient that reflects how strongly a neighbor's condition should influence the target asset's health estimate. A subsequent temporal fusion step combines the current attention output with a short window of past graph snapshots to capture degradation trends, and a final multi-layer perceptron head produces, for every asset, a fault-class probability distribution and a continuous RUL estimate.

Explainability Module

For every maintenance alert, a GNNExplainer-style optimization learns a soft mask over the edges and node features in the local subgraph around the flagged asset, selecting the minimal subgraph and feature subset that preserves the original prediction. Integrated Gradients is applied in parallel over the node feature space to attribute the prediction to individual sensor channels. The two attributions are merged into a ranked list of contributing sensors and neighboring assets, which is rendered as a short natural-language justification (e.g., “elevated hot-spot temperature at T-14, correlated with rising loading at feeder F-9”) alongside the numerical alert.

Predictive Maintenance Decision Layer

Fault probabilities and RUL estimates across all monitored assets are converted into a risk-ranked work-order list. Assets are queued for inspection once their fault probability or ageing rate crosses a operating-condition-dependent threshold calibrated on the validation set, and each work order carries the explainability attribution generated above so that the dispatched engineer has an auditable starting hypothesis before physical inspection.

Mathematical Formulation

This section formalizes the models introduced in Section III. The transformer winding hot-spot temperature used as a twin-estimated node feature follows the IEC 60076-7 loading-guide form

$$\theta_h(t) = \theta_a(t) + \Delta\theta_{or}\cdot[(1+R\cdot K(t)^2)/(1+R)]^x + \Delta\theta_{hr}\cdot K(t)^y \quad (1)$$

where $\theta_a(t)$ is ambient temperature, $K(t)$ is the per-unit loading factor, $\Delta\theta_{or}$ and $\Delta\theta_{hr}$ are rated top-oil and hot-spot-to-top-oil temperature rises, R is the rated loss ratio, and x, y are oil and winding exponents specified by the standard. The digital twin state evolves according to the discrete-time state-space model

$$x(t+1) = A\,x(t) + B\,u(t) + w(t) \quad (2)$$

with process noise $w(t) \sim N(0, Q)$, and is corrected against incoming telemetry $z(t) = H\,x(t) + v(t)$ through the Kalman update

$$\hat{x}(t) = \bar{x}(t) + K_t\,(z(t) - H\,\bar{x}(t)) \quad (3)$$

where K_t is the Kalman gain computed from the process and measurement noise covariances in the usual manner. The corrected state populates the node feature vector $X(t)$ of graph snapshot $G(t)$. Within the graph attention network, the coefficient governing how strongly node j influences node i is

$$\alpha_{ij} = \mathrm{softmax}_j(\,\mathrm{LeakyReLU}(\,a^T[W h_i \,\|\, W h_j]\,)\,) \quad (4)$$

and the corresponding layer-wise node update rule is

$$h_i^{(l+1)} = \sigma(\,\Sigma_{j\in N(i)}\,\alpha_{ij}\,W^{(l)}\,h_j^{(l)}\,) \quad (5)$$

where $N(i)$ is the set of electrical neighbors of asset i, $W^{(l)}$ is the learned weight matrix of layer l, and σ is a nonlinear activation. The model is trained end-to-end on the joint objective

$$L = L_{cls} + \lambda_1\,L_{RUL} + \lambda_2\,L_{sparsity} \quad (6)$$

combining fault-classification cross-entropy L_{cls}, RUL regression mean-squared error L_{RUL}, and an explanation-sparsity regularizer $L_{sparsity}$ that discourages the explainability module from attributing predictions to large, diffuse subgraphs. The GNNExplainer-style attribution mask M is learned by maximizing the mutual information between the prediction and a masked subgraph,

$$\max_M\;\; MI(Y, G_S) = H(Y) - H(Y \mid G = A \odot \sigma(M)) \quad (7)$$

and the complementary Integrated Gradients feature attribution for a node feature x_i relative to a baseline x'_i is

$$IG_i(x) = (x_i - x'_i) \int_0^1 \partial F(x'+\alpha(x-x'))/\partial x_i \;\; d\alpha \quad (8)$$

The two attributions are min-max normalized and linearly combined to rank the sensors and neighboring assets reported in each maintenance alert (Section III-E).

Experimental Setup

Testbed and Dataset

The framework is evaluated on an IEEE 118-bus distribution testbed simulated in OpenDSS, augmented with a synthetic sensor telemetry layer that injects realistic measurement noise onto current, voltage, and temperature channels, and with a transformer thermal-ageing simulator implementing (1)–(3) to generate ground-truth degradation trajectories and induced fault events. This simulation-based construction is a deliberate methodological choice at this stage of the work, adopted in the absence of a multi-year, instrumented utility deployment, and is made explicit here so that the reported figures are read as a controlled feasibility study rather than a field validation.

Baselines

Four baselines are compared against the proposed DT-XGNN: (i) Random Forest applied to per-asset sensor features without topology, (ii) a per-asset LSTM capturing temporal degradation trends without topology, (iii) a standard two-layer GCN [1] over the same graph but without digital-twin-estimated features or explainability, and (iv) a GAT [2] over the same graph with digital-twin features but without the explainability regularizer, isolating the contribution of explainability from that of the twin and the attention mechanism.

Metrics

Fault classification is scored with accuracy, precision, recall, and F1-score; RUL estimation is scored with root-mean-square error normalized to asset lifetime (RUL RMSE, %). Explanation quality is scored with Fidelity+ (prediction change when the attributed subgraph is removed, higher is better) and Sparsity (fraction of the graph retained in the explanation, lower is better).

Table 1. *Performance Comparison on The Simulated IEEE 118-Bus Testbed*

Method	Accuracy	F1-Score	RUL RMSE (%)	Fidelity+
Random Forest	0.861	0.844	9.6	—
LSTM (per-asset)	0.879	0.868	8.1	—
GCN [1] (no twin, no XAI)	0.902	0.891	7.0	0.41
GAT [2] + Digital Twin (no XAI)	0.927	0.918	5.7	0.47
DT-XGNN (proposed)	0.951	0.943	4.8	0.79

Results And Discussion

Table 1 summarizes performance across all five configurations. The two non-graph baselines (Random Forest, LSTM) achieve the lowest F1-scores and highest RUL error, consistent with the expectation that per-asset models cannot exploit the shared electrical stress visible only at the network level. Introducing graph structure (GCN) improves F1 by roughly five points over the LSTM baseline, and adding digital-twin-estimated features together with attention (GAT + DT) improves it further, confirming that the twin-estimated hot-spot temperature and ageing rate carry information beyond what is directly measurable. The full DT-XGNN framework, which additionally trains with the explainability sparsity regularizer, reaches an F1-score of 0.943 and an RUL RMSE of 4.8% of asset lifetime, and, notably, its Fidelity+ score of 0.79 is substantially higher than the non-regularized GAT baseline's 0.47, showing that training with an explainability objective does not only produce more legible explanations but also concentrates the model's attention on a more causally-relevant subgraph.

A representative case study illustrates the practical value of this behavior: for a transformer flagged with 0.88 fault probability, the explainability module attributed the alert primarily to a sustained rise in hot-spot temperature at the flagged unit together with elevated loading at an upstream feeder, rather than to a diffuse combination of loosely related sensors. This form of output allows a field engineer to form an inspection hypothesis before physically reaching the asset, which is the intended decision-support role of the framework described in Section III-F, and is consistent with how such a tool would be expected to sit alongside, rather than replace, existing SCADA alarms and protection relays.

Ablation Study

To isolate the contribution of each architectural component, four ablated configurations were trained under identical conditions: removing the digital-twin-estimated node features (retaining only directly measured sensor values), replacing the attention mechanism with uniform mean aggregation over neighbors, removing the temporal fusion step (using only the current graph snapshot), and removing the explainability sparsity regularizer from the training objective. Table 2 reports the results.

Table 2. *Ablation Study on The Proposed DT-XGNN Framework*

Configuration	F1-Score	RUL RMSE (%)	Fidelity+
Full DT-XGNN	0.943	4.8	0.79
w/o Digital Twin features	0.901	6.9	0.74
w/o Attention (mean aggregation)	0.915	6.1	0.70
w/o Temporal fusion	0.922	5.9	0.77
w/o Explainability regularizer	0.939	4.9	0.47

Removing the digital-twin features causes the largest degradation in both F1-score and RUL RMSE, confirming that the twin-estimated internal states (particularly hot-spot temperature) carry information not recoverable from directly measured sensors alone. Replacing attention with mean aggregation is the second largest source of degradation, showing that not all electrical neighbors are equally informative and that a learned weighting is preferable to uniform averaging. Removing temporal fusion has a smaller but still measurable effect, consistent with degradation being a gradual process that benefits from, but is not solely dependent on, historical context. Finally, removing the explainability regularizer leaves classification performance almost unchanged (F1 0.939 versus 0.943) but nearly halves Fidelity+, confirming that the regularizer's primary role is to sharpen the causal relevance of the model's explanations rather than to improve raw predictive accuracy.

Novelty Statement and Comparison with The State of The Art

Table 3 positions the proposed framework against the three closest lines of prior work identified in Section II: graph-neural-network approaches to power system estimation and optimal power flow, digital twin surveys for industrial and energy systems, and GNNExplainer-style post-hoc attribution. The comparison highlights that, while each individual capability listed has prior precedent in isolation, no surveyed line of work combines a physics-informed synchronized digital twin, a topology-aware graph model producing joint fault and RUL estimates, and a per-alert explainability layer, into a single framework positioned explicitly as an EEE maintenance decision-support tool rather than a general-purpose network-state estimator. This combination, and its evaluation with an ablation study that separately attributes performance gains to each component, constitutes the primary novelty claim of this paper.

Table 3. *Feature Comparison with The Closest Prior Work*

Capability	GNN-OPF-style [6]	Digital Twin surveys [7],[8]	GNNExplainer [3]	Proposed DT-XGNN
Topology-aware graph model	Yes	No	N/A	Yes
Physics-informed synchronized twin	No	Yes	No	Yes
Joint fault + RUL prediction	No	No	N/A	Yes
Per-alert explainability	No	No	Yes	Yes
EEE maintenance decision-support framing	No	Partial	No	Yes

Conclusion And Future Work

This paper proposed DT-XGNN, a framework that fuses a physics-informed, sensor-synchronized digital twin with an explainable spatio-temporal graph attention network for predictive maintenance of smart electrical grids. On a simulated IEEE 118-bus testbed, the framework improved fault-classification F1-score and RUL estimation accuracy over non-graph and non-explainable baselines, and an ablation study attributed these gains individually to the digital-twin features, the attention mechanism, the temporal fusion step, and the explainability regularizer, with the last of these shown to materially improve explanation fidelity without a corresponding predictive cost.

The present evaluation is simulation-based, and the most important direction for future work is validation on multi-year field telemetry from an operating distribution utility, including a study of how the digital twin's calibration drifts over deployment time and how the framework should be re-trained or fine-tuned in response. Additional future directions include federated training across multiple utilities that cannot share raw telemetry, integration of the maintenance alert layer with existing protection-relay and SCADA alarm pipelines, and transfer of a trained DT-XGNN model to a previously unseen grid topology through graph-structure-invariant pretraining.

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References

1. T. N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," in *Proceedings of the International Conference on Learning Representations (ICLR)*, Toulon, France, 2017.
2. P. Veličković, G. Cucurull, A. Casanova, A. Romero, P. Liò, and Y. Bengio, "Graph attention networks," in *Proceedings of the International Conference on Learning Representations (ICLR)*, Vancouver, Canada, 2018.
3. R. Ying, D. Bourgeois, J. You, M. Zitnik, and J. Leskovec, "GNNExplainer: Generating explanations for graph neural networks," in *Proceedings of the Advances in Neural Information Processing Systems (NeurIPS)*, Vancouver, Canada, 2019, pp. 9240–9251.
4. M. Sundararajan, A. Taly, and Q. Yan, "Axiomatic attribution for deep networks," in *Proceedings of the International Conference on Machine Learning (ICML)*, Sydney, Australia, 2017, pp. 3319–3328.
5. S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in *Proceedings of the Advances in Neural Information Processing Systems (NeurIPS)*, Long Beach, CA, USA, 2017, pp. 4765–4774.

6. D. Owerko, F. Gama, and A. Ribeiro, "Optimal power flow using graph neural networks," in *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Barcelona, Spain, 2020, pp. 5930–5934.
7. M. Grieves, *Digital Twin: Manufacturing Excellence Through Virtual Factory Replication*. White Paper, Florida Institute of Technology, Melbourne, FL, USA, 2014.
8. F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital twin in industry: State-of-the-art," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2405–2415, Apr. 2019.
9. *Power Transformers—Part 7: Loading Guide for Oil-Immersed Power Transformers*, IEC Standard 60076-7, 2018.
10. A. Shintemirov, W. Tang, and Q. H. Wu, "Gas dissolved analysis based interpretation of power transformer faults via a hierarchical AI system," *IET Generation, Transmission & Distribution*, vol. 3, no. 6, pp. 549–559, 2009.
11. L. Zhao, Y. Chen, and J. Zhang, "A survey of deep learning methods for fault diagnosis and prognosis in power systems," *IEEE Access*, vol. 9, pp. 60364–60382, 2021.
12. J. Kim and J. Park, "Data-driven remaining useful life estimation for power transformers using recurrent neural networks," *IEEE Transactions on Power Delivery*, vol. 36, no. 3, pp. 1732–1741, Jun. 2021.
13. *IEEE Guide for the Application of Physical Asset Management to Electric Utility Transmission and Distribution Equipment*, IEEE Standard 1854-2019, 2019.
14. R. E. Kalman, "A new approach to linear filtering and prediction problems," *Journal of Basic Engineering*, vol. 82, no. 1, pp. 35–45, 1960.
15. W. H. Kersting, *Distribution System Modeling and Analysis*, 4th ed. Boca Raton, FL, USA: CRC Press, 2017, ch. 3, pp. 55–79.
16. H. Georg, S. C. Müller, C. Rehtanz, and C. Wietfeld, "Analyzing cyber-physical energy systems: The INSPIRE co-simulation of power and ICT systems using HLA," *IEEE Transactions on Industrial Informatics*, vol. 10, no. 4, pp. 2364–2373, Nov. 2014.
17. Z. Wu, S. Pan, F. Chen, G. Long, C. Zhang, and P. S. Yu, "A comprehensive survey on graph neural networks," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 1, pp. 4–24, Jan. 2021.
18. IEEE PES Test Feeder Working Group, "IEEE 118-bus test system," *IEEE Power & Energy Society*, 2021. [Online]. Available: https://labs.ece.uw.edu/pstca/