Edge AI-Driven Predictive Maintenance Framework for Smart Electrical Grids Using IoT Sensor Networks

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***Abstract*— This paper presents a power-systems-centric predictive maintenance framework for smart electrical grid infrastructure that integrates IoT multi-modal sensor measurements with edge AI inference. Grounded in classical electrical fault theory — including symmetrical component analysis, transformer equivalent circuit modelling, and IEC protection relay standards — the framework employs real-time monitoring of current, voltage, temperature, vibration, and power quality parameters across three voltage levels (132 kV, 33 kV, 11 kV). A lightweight LSTM-CNN model quantized via TensorFlow Lite is deployed on edge nodes at substation level, achieving 97.3% fault detection accuracy with a latency of 11.4 ms. Federated Averaging with differential privacy enables distributed model updates without exposing raw grid telemetry. Validation on the EPRI Smart Grid Dataset demonstrates 97.1% bandwidth reduction versus cloud-only approaches and full offline operational capability. The proposed framework bridges IEC 61850 communication standards, classical power system protection, and modern edge intelligence to deliver practical, standards-compliant predictive maintenance for next-generation smart grids.**

Index Terms*— *Smart grid protection; transformer monitoring; symmetrical components; predictive maintenance; IEC 61850; edge computing; IoT sensors; federated learning; fault detection.

I. INTRODUCTION

Modern power grids operate across multiple voltage transformation levels, integrating generation, transmission, and distribution assets that must remain highly reliable. Global electricity demand growth, increased penetration of renewable energy, and the transition to smart grid architectures impose stringent requirements on fault detection, equipment health monitoring, and maintenance scheduling [1].

Power transformers, circuit breakers, and distribution feeders are among the most critical — and most failure-prone — assets in the grid. A single unplanned transformer outage can affect tens of thousands of consumers and incur replacement costs exceeding US$1 million per unit [2]. Traditional preventive maintenance relies on fixed inspection intervals derived from manufacturer guidelines rather than real-time asset condition, resulting in either excessive maintenance expenditure or under-maintenance leading to catastrophic failure.

Condition-Based Monitoring (CBM) using IoT sensors offers continuous visibility into asset health. However, raw sensor data volumes at transmission substations can exceed 50 GB per day per site, making centralised cloud-based analytics bandwidth-prohibitive. Edge computing is therefore an architectural necessity for large-scale smart grid monitoring [3].

This paper adopts a fundamentally electrical engineering perspective. The key contributions are:

1) Electrical fault modelling for four dominant grid failure modes using symmetrical component theory and IEC protection standards.

2) Multi-modal IoT sensor network designed per IEC 60044, IEC 60270, and IEC 61000 standards for comprehensive grid asset monitoring.

3) Edge-deployed LSTM-CNN fault classifier with INT8 quantization, validated against IEC 61850-7-2 communication constraints.
4) Federated learning for privacy-preserving, distributed model updates across geographically dispersed substations.

II. POWER SYSTEM FAULT ANALYSIS

A. Symmetrical Component Decomposition

For an unbalanced three-phase power system, Fortescue's theorem decomposes phase quantities into positive-sequence (1), negative-sequence (2), and zero-sequence (0) components. For phase voltages Va, Vb, Vc:

$$[V_1, V_2, V_0]^T = (1/3) \cdot A^{-1} [Va, Vb, Vc]^T \quad (1)$$

where the transformation matrix A is:

$$A = [[1,1,1],[1,a,a^2],[1,a^2,a]], \quad a = e^{\wedge}(j2\pi/3) \quad (2)$$

Per IEC 61000-4-30, a negative-sequence voltage ratio exceeding 0.02 p.u. constitutes a reportable imbalance:

$$VRR = |V_2|/|V_1| \times 100\% \geq 2.0\% \;\Rightarrow\; \text{Phase Imbalance} \quad (3)$$

B. Transformer Thermal Fault Model

The IEC 60076-7 thermal model governs transformer insulation ageing. The hot-spot temperature θ^h is:

$$\theta^h(t) = \theta^a + \Delta\theta L + \Delta\theta he \quad (4)$$

$$\Delta\theta L = \Delta\theta LR \cdot [(K^2R + 1)/(R + 1)]^n \quad (5)$$

The equivalent ageing acceleration factor FaΘ quantifies insulation degradation rate:

$$Fa\Theta = \exp[(15000/383) - (15000/(\theta^h+273))] \quad (6)$$

A sustained thermal rate exceeding 15°C/hr triggers a Critical fault alert.

C. Impedance-Based Fault Detection

The apparent impedance seen by the protective relay is:

$$Zapp = Vr / Ir = x \cdot ZL + If/(Ir) \cdot Zf \quad (7)$$

$$|Zapp| = \sqrt{(R^2app + X^2app)} < Zthresh \;\Rightarrow\; \text{Fault Zone} \quad (8)$$

D. Total Harmonic Distortion and Power Factor

$$THDI = \sqrt{(\Sigma_{n=2}^{N} I_n^2)} / I_1 \times 100\% \quad (9)$$

$$DPF = \cos(\varphi_1) = P / (V_1 \cdot I_1) \quad (10)$$

Per IEC 61000-4-7, THDI exceeding 8% constitutes a warning-level event.

E. Differential Protection for Transformer Faults

$$Idiff = |I_1 - n \cdot I_2| \quad (11)$$

$$\text{Operate: } Idiff > kbias \cdot Iop + krstrt \cdot Irst \quad (12)$$

CT sensors S_1 and S_2 measure primary and secondary currents enabling (11) at the edge node in real time.

III. IOT SENSOR NETWORK ARCHITECTURE

Fig. 1 illustrates the smart grid single-line diagram with IoT sensor placements across three voltage levels. Table I summarises the six sensor types deployed, their measurement ranges, sampling rates, and governing IEC standards.

Fig. 1. Smart electrical grid single-line diagram showing 132 kV transmission bus, three 33/11 kV substations, circuit breakers, power transformers, and IoT sensor node placements.

TABLE I- *IoT Sensor Specifications and Governing IEC Standards*

Sensor Type	Range	Accuracy	Sampling Rate	Monitored Parameter / IEC Standard
Current Transformer (CT)	0–10 kA	±0.2%	1 kHz	Load current, fault current — IEC 60044-1
Potential Transformer (PT)	0–15 kV	±0.1%	1 kHz	Bus voltage, sag/swell — IEC 60044-2
RTD Temp. Sensor (Pt-100)	−40 to 200°C	±0.1°C	1 Hz	Winding/core temp., thermal aging — IEC 60068
MEMS Vibration (3-axis)	±16 g	±0.01 g	4 kHz	Mechanical fault, partial discharge — IEC 60270
Power Quality Analyser	THD 0–100%	±0.5%	10 kHz	Harmonic distortion, power factor — IEC 61000-4-7
SCADA/PMU	GPS sync	±1 µs	50/60 Hz	Synchrophasor, freq. deviation — IEEE C37.118

The sensor network topology follows IEC 61850-9-2 process bus architecture. All sensor data is timestamped using IEEE C37.118.1 synchrophasor GPS synchronisation (±1 μs accuracy) to enable inter-substation correlation analysis.

Measured quantities are converted to p.u. before feature extraction:

$$V_{p.u.} = V_{measured} / V_{base}, \quad I_{p.u.} = I_{measured} / I_{base} \quad (13)$$

IV. TRANSFORMER EQUIVALENT CIRCUIT AND FAULT MODELLING

The IEEE/IEC transformer equivalent circuit referred to the primary side is the foundation for fault signature analysis. Fig. 2 shows the complete circuit including winding resistances R_1, R_2', leakage reactances jX_1, jX_2', shunt core branch ($R_c \parallel jX_m$), and fault impedance Z_f.

$$R_2' = n^2 R_2, \quad X_2' = n^2 X_2, \quad n = N_1/N_2 \quad (14)$$

$$Z_{sc} = R_{sc} + jX_{sc} = (R_1 + R_2') + j(X_1 + X_2') \quad (15)$$

A fault with impedance Z_f at position x p.u. from the primary terminal produces:

$$I_f = V_1 / (Z_{sc} + x \cdot Z_L + Z_f) \quad (16)$$

$$R_c = |V_1|^2 / P_c, \quad X_m = |V_1|^2 / Q_c \quad (17)$$

A significant increase in core loss P_c indicates core insulation deterioration or partial discharge.

Fig. 2. Transformer equivalent circuit (referred to primary) with fault injection impedance Zf, IoT sensor positions, and detected fault types F_1–F_4.

Fig. 3. Three-phase phasor diagrams for (a) healthy balanced and (b) faulty phase imbalance condition showing negative-sequence component V_2 and $\Delta\varphi = 20°$.

V. FAULT DETECTION CRITERIA AND THRESHOLDS

Table II summarises the five fault types, their primary electrical feature, detection threshold, governing IEC standard, and severity classification (W=Warning, C=Critical, E=Emergency).

The percentage biased differential protection characteristic is:

$$I_{diff} > k_1 \cdot I_{op} + k_2 \quad (\text{for } I_{op} > I_{op,min}) \quad (18)$$

where $k_1 = 0.2$ and $k_2 = 0.1$ In. The relay coordination margin per IEC 60255-151:

$$CTI = t_2 - t_1 \geq 0.3 \text{ s} \quad (\text{Coordination Time Interval}) \quad (19)$$

The edge AI framework complements relay protection: relays operate within <100 ms for emergency faults, while the AI model provides a 1–24 hour predictive warning horizon for incipient faults.

TABLE II- *Fault Detection Criteria, IEC Standards, and Severity Classification*

Fault Type	Feature	Threshold	IEC Ref.	Sev.
Transformer Overload	$\lvert I\rvert/I_{rated}$	>1.25 p.u.	IEC 60076	C
Insulation Fault	$\Delta T/\Delta t$	>15°C/hr	IEC 60270	C
Phase Imbalance	$\lvert V_2\rvert/\lvert V_1\rvert$	>0.02 p.u.	IEC 61000	W
Harmonic Distortion	THD_I	>8%	IEC 61000-4-7	W
Inter-turn Fault	diff. I	>5% I_nom	IEC 60255	E

VI. EDGE AI INFERENCE METHODOLOGY

The AI inference layer is the predictive analytics complement to the electrical protection hardware described above.

A. Feature Extraction from Electrical Measurements

Per-window (W = 256 samples) electrical features are extracted. The RMS current and voltage per phase are:

$$I_{RMS} = \sqrt{(1/N) \textstyle\sum_n i_n^2} \quad (20)$$

$$V_{RMS} = \sqrt{(1/N) \textstyle\sum_n v_n^2} \quad (21)$$

The apparent, active, and reactive power per IEC 61557-12:

$$S = V_{RMS} \cdot I_{RMS}, \quad P = (1/N)\textstyle\sum_n v_n i_n, \quad Q = \sqrt{S^2 - P^2} \quad (22)$$

FFT-derived harmonic magnitudes I_n (n = 1…100) are computed via the Cooley-Tukey radix-2 algorithm.

B. LSTM-CNN Model Architecture

The hybrid model: Input(256×6) → Conv1D(32,k=5) → BN → MaxPool → Conv1D(64,k=3) → MaxPool → BiLSTM(128) → Dropout(0.3) → Dense(64,ReLU) → Softmax(5). Quantized to INT8 via TensorFlow Lite (4.7 MB → 1.2 MB, latency 38 ms → 11.4 ms, accuracy loss 0.6%).

C. EWMA Fault Alert

$St = \alpha \cdot pt + (1 - \alpha) \cdot St_{-1}, \ \ \alpha = 0.15$ (23)

Alert if $St > \theta = 0.72$ for ≥ 3 consecutive windows (24)

D. Federated Learning

FedAvg with Gaussian differential privacy ($\sigma = 0.01$) updates the global model every 24 hours:

$w^* = \Sigma k\ (nk/n)\ wk, \ \ n = \Sigma k\ nk$ (25)

Only gradient tensors — not raw sensor data — are transmitted, ensuring compliance with IEC 62351 grid cybersecurity requirements.

VII. EXPERIMENTAL RESULTS

Experiments used the EPRI Smart Grid Sensor Dataset (14 months, 38 substations, 220,000 labelled windows, 5 fault classes). Edge hardware: NVIDIA Jetson Nano (128-core Maxwell, 4 GB LPDDR4). Table III compares the proposed framework against cloud-only, edge-only, and fog-only architectures.

The proposed framework achieves 97.3% accuracy and F1 = 0.965, surpassing all baselines. Inference latency of 10–18 ms satisfies the sub-50 ms requirement for Zone-1 relay coordination alerting (see (19)). Bandwidth is reduced by 97.1% versus cloud-only. The EWMA alert mechanism reduces FPR to 1.8%.

Ablation results confirm: (i) symmetrical component features contribute +1.4% accuracy over raw time-domain features; (ii) federated learning contributes +0.9%; (iii) the thermal model feature FaΘ from (6) improves insulation fault precision by 3.2%.

Fig. 4. Edge AI inference pipeline from IoT sensor acquisition through signal processing, feature extraction, LSTM-CNN fault classification, and EWMA alert generation.

TABLE III- *Performance Comparison Across Deployment Architectures*

Metric	Cloud	Edge	Fog	Proposed
Accuracy (%)	94.1	95.8	95.2	97.3
Latency (ms)	350–900	8–15	40–80	10–18
F1-Score	0.932	0.947	0.941	0.965
BW (MB/hr)	1200	12	85	35
FPR (%)	4.2	2.3	2.9	1.8
Offline Ops.	No	Yes	Part.	Yes
Power (W)	N/A	3.2	18	4.1

VIII. DISCUSSION AND LIMITATIONS

The presented results demonstrate that electrical-theory-grounded feature engineering significantly outperforms purely data-driven approaches for smart grid fault detection. By encoding domain knowledge — symmetrical component ratios, transformer thermal model state, differential protection criteria — as explicit input features, the LSTM-CNN model converges faster and generalises better to rare fault conditions.

Practical deployment considerations include: (i) CT and PT secondary burden must be within rated limits when sharing measurement channels with IoT gateways; additional burden analysis per IEC 60044 is required per site. (ii) The INT8 quantization scheme introduces rounding error; fixed-point arithmetic verification per IEC 61010-1 should be performed for safety-critical relay supplementary functions. (iii) Asynchronous federated learning protocols are needed for substations in islanded or storm-damaged grid segments.

Future work will investigate: (i) relay auto-setting based on edge AI fault trajectory prediction; (ii) integration with IEC 61968/61970 Common Information Model

(CIM) for interoperability with Energy Management Systems (EMS); (iii) hardware-in-the-loop (HIL) testing on a real-time digital simulator (RTDS) with IEC 61850 GOOSE messaging; (iv) cable fault location using travelling-wave reflection analysis.

IX. CONCLUSION

This paper presented an electrically-grounded Edge AI Predictive Maintenance framework for smart electrical grids. Beginning from classical power system fault theory — symmetrical components (1)–(3), transformer thermal modelling (4)–(6), impedance-based protection (7)–(8), THD analysis (9)–(10), and differential protection (11)–(12) — the framework defines precise, IEC-standard-compliant electrical fault signatures monitored continuously by a six-modality IoT sensor network.

A compact LSTM-CNN model deployed on edge hardware achieves 97.3% fault detection accuracy at 11.4 ms latency with only 1.8% false positive rate, operating within IEC 61850 communication constraints. The federated learning mechanism enables collaborative model improvement without compromising grid data privacy per IEC 62351.

The framework's primary contribution to the power engineering community is the principled translation of decades of electrical fault theory into practical, real-time, AI-augmented condition monitoring that is directly deployable in existing IEC 61850 substation automation environments.

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