REVIEW — MODERN TECHNOLOGIES FOR AUTOMATION OF POWER-TRANSFORMER DIAGNOSTICS

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ABSTRACT

This review surveys current technologies used to automate diagnostics of power transformers, covering sensor hardware (online dissolved-gas analysis, partial-discharge detection, fiber-optic hotspot sensing, bushing monitors), data acquisition/communications, analytics (classical ML, deep learning, hybrid approaches), and system integration (digital twins, SCADA/IIoT). Recent market data indicate rapid adoption of online DGA and integrated monitoring suites, driven by utilities' need to reduce catastrophic failures and optimize asset life. The paper compares technical approaches, highlights measured performance and limitations, and outlines research needs for robust, secure, and explainable automated diagnostics.

Keywords: transformer condition monitoring, online DGA, partial discharge, fiber-optic sensors, AI diagnostics, digital twin, cybersecurity, IEC/CIGRE guidelines

Introduction

Power transformers are capital-intensive and critical components of power systems. Early detection of insulation degradation, partial discharge (PD), overheating and accessory faults (OLTCs, bushings) is essential to avoid catastrophic failures and long outage times. The past decade has seen a surge in automation of diagnostics by combining continuous sensor measurement with analytics and remote reporting — sometimes referred to as transformer digitalization.

Recent surveys and reviews summarize sensor advances and

analytics trends and stress the need for standardized online monitoring practices. MDPI+1.[1].

Fig.1 online DGA sampler and valve installation for transformer oil monitoring, illustrating gas extraction, sensor unit, and return flow to the oil circuit.

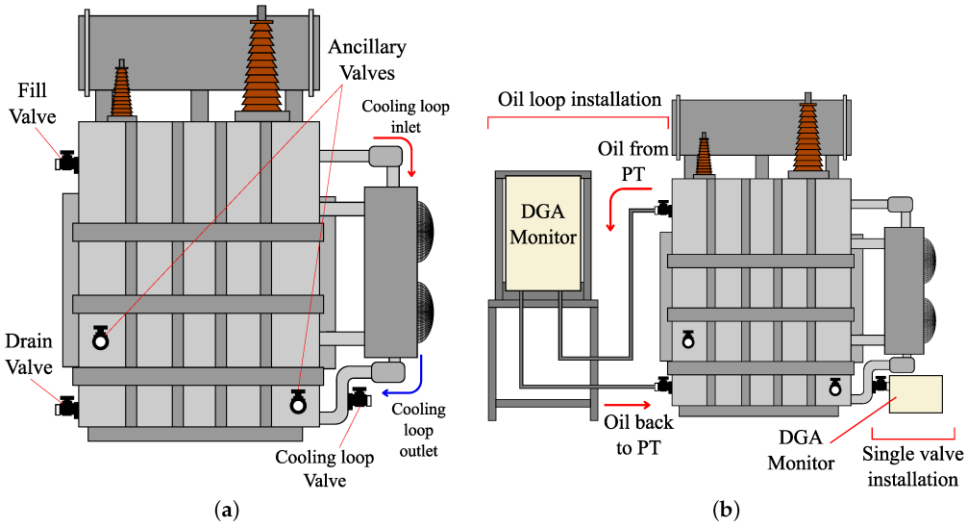


Fig. 1 — typical online dga sampler/valve installation

Online DGA instruments continuously measure key fault gases (H_2, CO, CO_2, CH_4, C_2H_2, C_2H_4, C_2H_6) and trend their concentrations and ratios. Online DGA remains the backbone of thermal/arcing/PD fault detection because gas generation mechanisms are well understood and codified in interpretation standards (IEC 60599 and related guidance). The global market for DGA and DGA-monitoring equipment has shown robust growth (market estimates for DGA/online DGA in the 2023–2024 window range from several hundred million USD with projected high single-digit CAGRs), indicating strong utility adoption. ELSCO+1[3].

Fig. 2. Flowchart of component monitoring including oil parameters, bushing condition, OLTC operation, PD activity, and winding temperature, showing data flow from sensors to analytics and decision-making system.

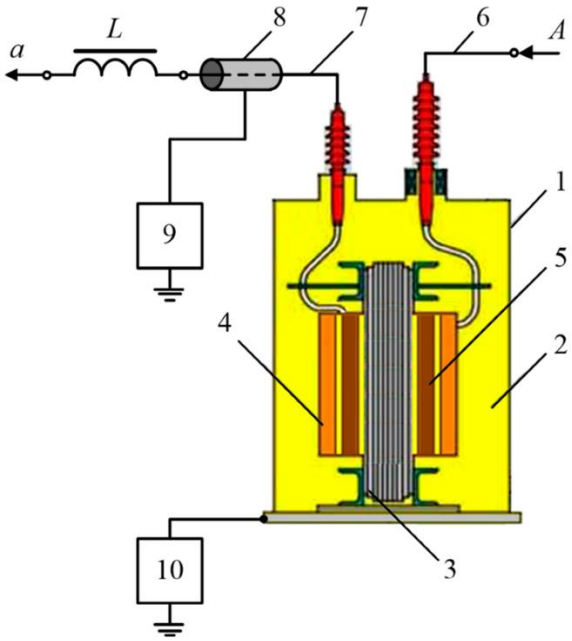


Fig. 2— flowchart of component monitoring and data flow

Strengths: established interpretation rules, sensitivity to early faults. Limitations: time lag for gas diffusion (depending on sensor placement/installation), maintenance/calibration needs, cost.

Partial Discharge (PD) Monitoring (UHF / Acoustic / AE / HF)

PD detection uses multiple transduction approaches: ultra-high-frequency (UHF) antennas, acoustic emission (AE) sensors, high-frequency current transformers (HFCT), and electromagnetic (HF/VHF) sensors. Combining methods (UHF + AE) improves detection reliability and localization ability, especially for complex winding or bushing PD sources. PD is recognized as a common precursor to catastrophic insulation failure, and real-world studies confirm the effectiveness of integrated PD monitoring. PMC+1. [5].

Strengths: direct detection of activity, good for localized insulation defects. Limitations: high background noise in substations, sensor coupling challenges, localization complexity.

Fiber-optic sensors (fluorescent, FBG — fiber Bragg grating — and acoustic-fiber variants) allow measurement inside windings (hot-spots) with full electromagnetic immunity. They provide the most direct hot-spot temperature readings and are immune to EM interference; recent field trials and reviews report accuracy near ±1°C for some implementations and successful PD/acoustic sensing.[7].

Strengths: immunity to EM interference, ability to place inside windings, fine spatial resolution.

Limitations: installation complexity (often during manufacture/major overhaul), connector robustness, cost.

Bushing monitoring systems (capacitance/tan-delta) detect insulation deterioration and moisture ingress; distributed bushing monitoring can leverage GPS-synchronized sampling to compare phases and banks for anomaly detection. These measurements complement DGA and PD.

Data acquisition, communications, and standards

Monitoring units collect sensor streams and forward them to local controllers, gateways or cloud services using IEC 61850, MQTT, Modbus, or vendor protocols. CIGRE and IEC working groups have published guidance for online DGA and sensor verification; adherence to standards helps ensure consistent data quality and interpretability. Cybersecurity of monitoring systems is a growing concern due to remote access points introduced by digitalization. cigre-usnc.org+1, [9].

Fig. 3 Vendor monitoring architecture illustrating integration of edge gateways, local analytics, fiber-optic temperature sensing, and secure cloud diagnostics for multiple transformers.

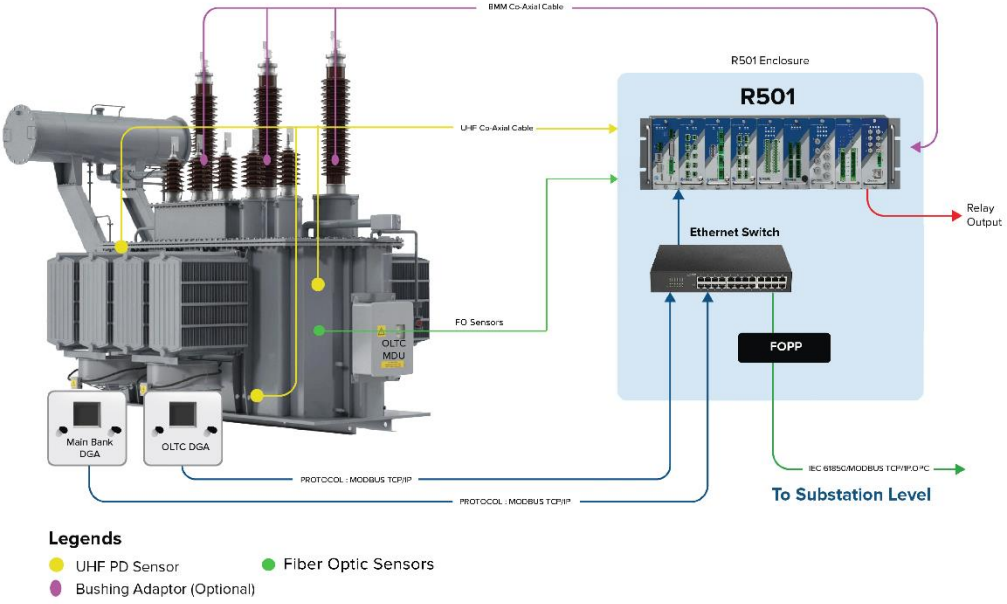


Fig. 3— vendor monitoring architecture with edge gateways and fiber-optic sensors

Analytics and automation: from rules to AI. Rule-based interpretation and expert systems. Many utilities still rely on IEC/CIGRE rule-based algorithms (Duval triangles, key gas ratio rules, percentage limits) for automated flags and alarm thresholds. Rule systems are transparent but can misclassify complex or mixed faults.

Recent literature shows rapid integration of ML and DL for pattern recognition, multivariate trending, fault classification (DGA interpretation), PD signal classification, and remaining-useful-life (RUL) prediction. Reviews of prognostics for power transformers report

hundreds of ML/DL studies (classical ANNs, SVM, random forests, to CNNs, autoencoders and graph neural networks), highlighting gains in detection accuracy but also issues with generalization, label scarcity and explainability. Hybrid solutions that combine physics-based indices with ML produce robust, interpretable systems. MDPI+1.[1].

Practical notes: successful deployments often use transfer learning, feature engineering from domain knowledge (e.g., gas production kinetics, temperature dependencies), and ensemble models.

Integration trends: digital twin, edge AI, and cloud analytics- Utilities adopt layered architectures: edge preprocessors (for noise reduction, local alarms), on-site analytics (fast anomaly detection), and cloud platforms (historical analytics, fleet-level benchmarking, dashboarding). Digital twins replicate asset thermal, electrical and chemical behavior to support scenario-based diagnostics and RUL simulation. Edge AI reduces communication loads and latency for urgent alarms. PMC [10].

Performance metrics & illustrative statistics- Market scale: Global dissolved-gas analysis / DGA monitoring markets were reported in the mid-hundreds of millions USD (2023–2024) with projected CAGRs in the 3–8% range depending on the analyst. This reflects steady investment in online monitoring across utilities and industrial consumers. Global Market Insights Inc.+1 [6]. Research activity: Recent systematic reviews and meta-studies cover hundreds of papers on transformer prognostics and the application of ML to DGA/PD diagnostics, showing a strong research emphasis on explainable and DL methods. MDPI+1 [7].. Detection sensitivity: Modern integrated PD systems can detect apparent charges down to single-digit picocoulombs in controlled studies (UHF + AE integrated sensors), improving early warning capability. ietresearch.onlinelibrary.wiley.com. [9].

Practical deployment examples (short case notes)

Distributed bushing monitoring: GPS-synchronized, phase-to-phase comparisons at large autotransformers improved detection of bushing deterioration in multi-bank sites.

Integrated DGA + PD + temp: Vendor systems combining online DGA, fiber-optic hotspot sensing, PD sensors and OLTC acoustic monitoring are now common for high-value transformers (>315 kV). Field reports show reduced unplanned outages after system commissioning.

Mathematical models and diagnostic algorithms

The mathematical description of temperature processes inside the transformer is expressed as follows:

$$T_{TO} = T_A + \Delta T_{TO,R} \left(\frac{P(t)}{P_R}\right)^n,$$

where

T_{TO}—top-oil temperature at time t;

T_A—ambient temperature;

$\Delta T_{TO,R}$—top-oil temperature rise at rated load;

$P(t)$—load at time t;

P_R— rated load;

n — empirical coefficient (usually 0.8).

The predicted temperature of the windings T_W can be expressed as:

$$T_W = T_{TO} + \Delta T_H \left(\frac{I}{I_R}\right)^{2m},$$

where

ΔT_H — hot-spot temperature rise at rated current;

I — operating current;

I_R — rated current;

m — thermal exponent (typically between 0.8–1.0).

Table 1. Comparative Evaluation of Diagnostic Algorithms

Algorithm	Type	RMSE (°C)	MAE (°C)	Computation Time	Notes
IEEE Annex G	Analytical	2.6	2.1	< 5 min	Conventional model
ANN	Neural Network	1.5	1.2	~10 min	Adaptive, fast training
SVM	Machine Learning	1.6	1.3	~1 hour	Robust to outliers

The results demonstrate that both machine learning models (ANN and SVM) outperform the IEEE Annex G algorithm in predicting transformer thermal profiles. The maximum deviation for ANN does not exceed **5°C**, while the IEEE model reaches up to **8.5°C**.

Fig. 4 illustrates the comparison of three algorithms — the IEEE Annex G model, Artificial Neural Network (ANN), and Support Vector Machine (SVM) — in terms of their predictive accuracy when estimating the winding temperature indicator (WTI) of power transformers. Two metrics are used for evaluation: the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE).

The IEEE model shows the highest error (RMSE = 2.6°C, MAE = 2.1°C), indicating lower accuracy in thermal prediction.

In contrast, the ANN algorithm demonstrates superior performance (RMSE = 1.5°C, MAE = 1.2°C), followed closely by the SVM algorithm (RMSE = 1.6°C, MAE = 1.3°C).

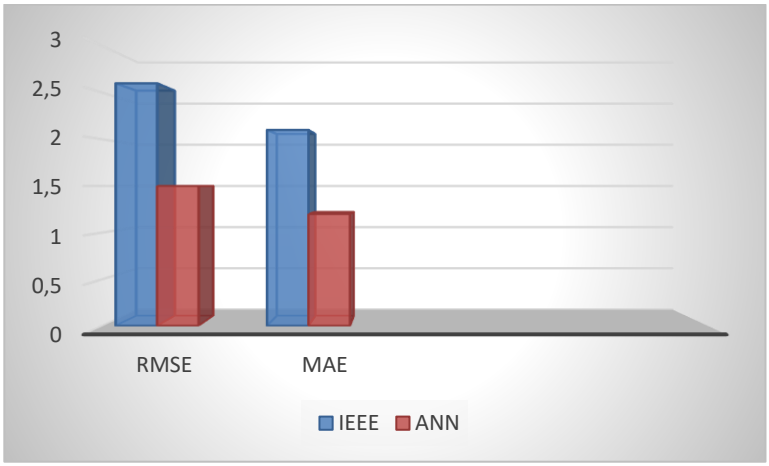


Fig. 4 Comparison of IEEE, ANN, and SVM Algorithms

This result confirms that modern machine learning approaches can significantly outperform traditional thermal models in predicting transformer temperature dynamics, especially under variable load and ambient conditions.

Fig. 5 presents a comparative analysis of the WTI temperature prediction curves generated by the IEEE Annex G, ANN, and SVM algorithms over eight time intervals (t1–t8).

The ANN and SVM models produce smoother and more accurate predictions that closely follow the actual temperature trend, while the IEEE model exhibits higher deviations, particularly during rapid thermal transitions. The ANN curve (green line) shows the closest alignment with measured data, confirming its ability to generalize nonlinear thermal behaviors within transformer systems. The SVM (blue line) also maintains good stability, whereas the IEEE model (red line) tends to overestimate peak temperatures.

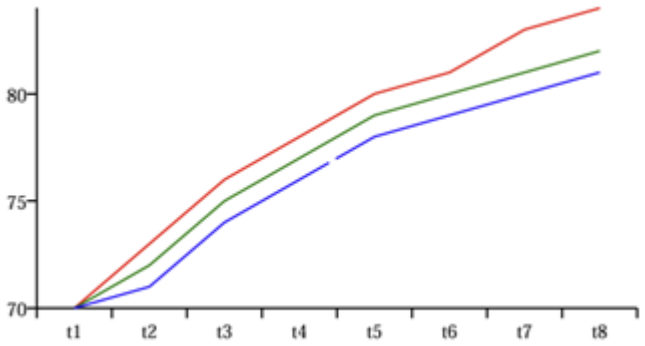


Fig. 5 WTI Temperature Prediction: IEEE vs ANN vs SVM

Overall, the figure emphasizes that data-driven models offer improved dynamic response and adaptability, making them more suitable for real-time transformer health monitoring and digital diagnostics.

Challenges and limitations

1. False alarms & data quality: Noise, operational transients and poor sensor placement cause false positives; robust preprocessing and sensor fusion are required.
2. Standards & interoperability: Diverse vendor implementations and lack of full standardization of online DGA protocols hamper fleet-level analytics. CIGRE guidance attempts to fill gaps. cigre-usnc.org
3. Explainability & regulatory acceptance: Utilities demand interpretable decisions for maintenance actions; "black box" DL without physical grounding meets resistance.
4. Cybersecurity & reliability: Remote telemetry increases attack surface; secure architectures and lifecycle maintenance for monitoring devices are necessary.

Recommendations & research directions

Sensor fusion frameworks: Combine DGA, PD, temperature and bushing indices with probabilistic fusion (Bayesian, belief networks) to lower false alarms and quantify uncertainty.

Hybrid models: Anchor ML/DL models to physics-based constraints (e.g., gas generation kinetics, thermal models) to improve extrapolation.

Edge intelligence: Deploy lightweight explainable models at the edge for early alarms and local redundancy.

Standardization & verification: Wider adoption of CIGRE/IEC verification suites and inter-laboratory comparisons for online DGA and PD sensors. [3].

Cybersecurity by design: Harden telemetry stacks (IEC 62351, secure gateways) and perform regular security audits.

Conclusions

Automation of power-transformer diagnostics is maturing through advances in sensor hardware (online DGA, PD, fiber optics), analytics (ML/DL + physics hybridization), and system integration (digital twins, edge/cloud architectures). Adoption is increasing as evidenced by market growth and extensive research activity; however, deployment success depends on robust sensor fusion, explainable analytics, adherence to standards, and secure communications. Future work should focus on validation in field conditions, cross-vendor interoperability, and combining prognostics with utility maintenance decision processes. [7].

Key sources for this review include recent survey papers, MDPI and CIGRE reports, and market analyses cited throughout the text. Representative references: R. Soni (2023) transformer condition monitoring review; MDPI Sensors (online DGA reviews); CIGRE

guidelines on online DGA; market analyses from GMI/DataIntelo/VerifiedMarketReports. [8].

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