



Intelligent Decision-Support Quality-Gate Framework for Manufacturing-Stage Power Transformer Control: A Thematic Review

Alibek Adilbekov¹, Alexandr Kashevkin¹, Luigi Carlo De Jesus², Roben Antalan Juanatas³, Sergey Latypov¹, Pavel Petrov^{1*}, Sayat Moldakhmetov¹

¹ Department of Power Engineering and Radio Electronics, M. Kozybayev North Kazakhstan University, Pushkin str., 86, Petropavlovsk, Republic of Kazakhstan, 150001

² Department of Computer, Electronics, and Electrical Engineering, De La Salle University, Manila, Philippines; E-mail: luigi_dejesus@dlsu.edu.ph

³ College of Computing and Information Technologies, National University Manila, Philippines; E-mail: rajuanatas@national-u.edu.ph

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ABSTRACT

Manufacturing-stage defects in power transformers can remain latent until they develop into dielectric, thermal, mechanical, or chemical failures after commissioning. Existing diagnostic literature often treats factory tests as separate technical procedures, which limits the traceability of evidence used for release, retest, hold, or rework decisions. This study develops an intelligent decision-support quality-gate framework that organizes manufacturing-stage diagnostic information into auditable factory actions. A thematic review was combined with Python-assisted bibliographic mapping of a 146-record corpus, multi-label coding, analysis of 125 retained sources and 12 international standards, row-level evidence synthesis, and a demonstrative normalized-risk scenario. The synthesis shows that routine electrical and dielectric tests provide the minimum acceptance baseline, while hidden local defects require complementary partial-discharge, frequency-response, dissolved-gas, oil-chemistry, thermal, acoustic, vibration, visual, and data-fusion evidence. Standards define mandatory gates, whereas manufacturer-calibrated thresholds and explainable inference rules are needed to manage borderline or conflicting indicators. The proposed framework separates data acquisition, information integration, decision inference, and audit-trail functions, linking each defect origin and diagnostic indicator to its method, standard basis, confidence, and prescribed action. It therefore converts heterogeneous diagnostic records into a transparent intelligent decision-support process for manufacturing quality control. Validation with real factory datasets remains necessary before the framework can be used as a production release authority.

1. Introduction

The manufacturing stage is the last controllable point at which many transformer defects can be detected before the unit becomes an operational risk. Defects introduced during conductor winding, insulation handling, drying, clamping, tank assembly, oil processing, and final testing may not immediately appear as catastrophic failures. Instead, they may appear as weak diagnostic indicators such as partial-discharge inception, abnormal dielectric losses, winding-response deviations, unusual gas generation, local heating, or abnormal vibroacoustic behavior. Broad transformer diagnostic reviews provide strong coverage of methods and failure mechanisms [1-4], but they often emphasize

in-service monitoring and maintenance rather than manufacturing-stage quality gates.

The objective of this article is therefore to conduct a thematic review of methods and systems for the control of power transformers at the manufacturing stage. The review focuses on identifying manufacturing defects before commissioning, comparing traditional and modern diagnostic methods, and justifying the need for an integrated approach to factory quality control. The paper systematizes typical transformer defects, diagnostic indicators of their occurrence, and detection methods including electrical tests, partial discharge measurement, FRA/SFRA, DGA, thermal imaging, acoustic, vibration, visual/infrared, and intelligent diagnostic methods.

The article is positioned at the intersection of intelligent decision making, information science, and manufacturing quality control. Its practical focus is not only whether a diagnostic method can detect a defect, but how heterogeneous evidence can be structured, interpreted, and preserved in an information system that supports a manufacturer in deciding whether a transformer should pass, be retested, be held for engineering review, or be reworked. This decision-centered framing connects transformer diagnostics with intelligent decision support, operational efficiency, process control, rework avoidance, and traceability.

This article contributes to intelligent manufacturing decision support in five connected ways. It distinguishes factory control from general in-service diagnostics, describes the evidence base through a transparent CSV-based bibliographic and thematic mapping procedure, links claims to differentiated citation clusters, makes the principal synthesis tables traceable through row-level citations, and introduces a demonstrative quality-gate inference example with manufacturer-configurable thresholds rather than unsupported universal limits.

Accordingly, the study is guided by the following research question: how can manufacturing-stage transformer diagnostics be organized as a traceable quality-control system rather than as a collection of separate tests? The article contributes by combining literature synthesis, standards mapping, bibliographic data analysis, and a demonstrative quality-gate example into one applied decision framework.

This article explicitly differentiates its contribution from the existing review literature. Mwinisin et al. provide a broad review of electrical diagnostic methods, instrumentation, and research challenges [1]. Aj et al. and Fofana and Hadjadj focus on failure causes, monitoring, diagnostic features, and design-related aspects of transformer reliability [3, 4]. Costa et al. emphasize monitoring and failure investigation for large power transformers [2], while Abdugaffar Ugli et al. review failure types and causative factors [5]. Jou et al. are closer to industrial practice, but their contribution is a productivity-improvement simulation in a transformer manufacturing company rather than a multi-method diagnostic quality-gate framework [6].

The present paper differs in four ways. First, it treats manufacturing-stage control as the unit of analysis rather than post-commissioning maintenance. Second, it organizes methods around defect origin, diagnostic indicator, and factory decision. Third, it integrates IEC/IEEE standards as explicit quality gates. Fourth, it adds an applied numerical decision-logic example that links multiple diagnostic signals to pass, hold, retest, and rework actions. The novelty is therefore not the invention

of a new sensor, but the synthesis of diagnostic evidence into a traceable manufacturing decision framework. Table 1 positions this contribution explicitly against prior reviews and manufacturing studies.

Table 1 Positioning of the intelligent quality-gate framework relative to prior reviews and manufacturing studies

Prior work	Main emphasis	Remaining gap addressed here
Mwinisin et al. [1]	Comprehensive electrical diagnosis methods and instrumentation	Does not center the review on manufacturing-stage quality-gate decisions
Costa et al. [2]	Monitoring and failure investigation of large transformers	Focused more on investigation/monitoring than production-stage release decisions
Aj et al. [3]	Failure causes and diagnostic methods	Less emphasis on pre-commissioning production defects and factory workflow
Fofana and Hadjadj [4]	Diagnostics, monitoring, and design features	Broader reliability focus rather than a manufacturing-control framework
Abdugaffar Ugli et al. [5]	Failure types and causative factors	Limited traceable mapping from defect indicators to factory decisions
Jou et al. [6]	Manufacturing productivity simulation case study	Does not integrate electrical, chemical, mechanical, thermal, and intelligent diagnostics

2. Methodology

The review was conducted as a thematic review with a transparent bibliographic and coding procedure. The method was designed to be replicable: the source corpus was defined, records were mapped by year and DOI availability, thematic labels were assigned from titles and abstracts, and the synthesis was organized around manufacturing defect themes, diagnostic indicators, methods, standards, and quality-control decisions. The evidence base consisted of a bibliographic CSV corpus containing 146 records. Python analysis of the corpus showed that 145 records contained DOI metadata, the publication years ranged from 1999 to 2025, and 93 records were published from 2021 onward. The CSV was used for bibliographic mapping and thematic coding, while the final reference set retained 125 sources, including recent DOI-verified publications and IEC/IEEE standards. This statement is intentionally bounded: the article does not claim a full meta-analysis of diagnostic performance because the available literature reports heterogeneous transformer ratings, test setups, defect simulations, thresholds, and data formats. **Fig. 1** shows the publication-year distribution of the corpus, while **Table 2** summarizes the evidence elements and their screening and coding roles.

Table 2 Evidence base and screening/coding role

Evidence element	Evidence value	Purpose in the manuscript
CSV bibliographic corpus	146 records; 145 records with DOI metadata	Real-data basis for bibliographic and thematic mapping
Recent records in the CSV	93 records from 2021-2025	Shows that the source base is sufficiently current for a modern review
Final cited literature set	125 references	Detailed synthesis and standards integration
Standards stream	12 IEC/IEEE standards	Normative quality-gate basis for factory testing
Quantitative application	Demonstrative numerical quality-gate scenario	Shows decision logic without claiming proprietary factory measurements

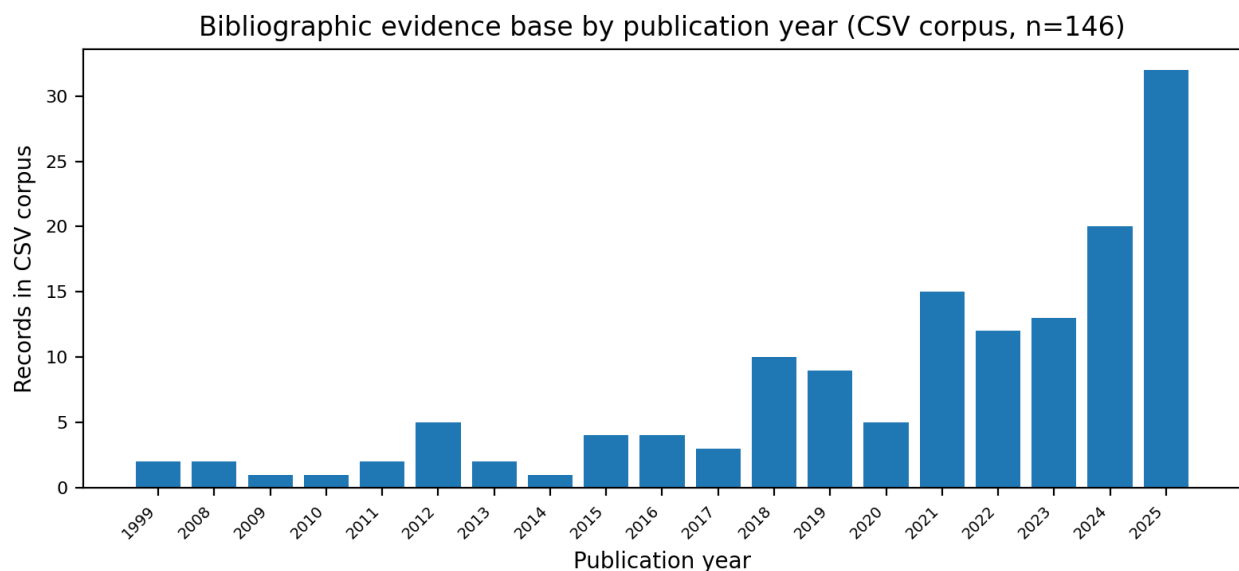


Fig. 1. Publication-year distribution of the CSV corpus used for the real-data bibliographic mapping

The coding was conducted at three levels. First, records were mapped by year, source type, DOI availability, and publication venue. Second, title and abstract keywords were used to assign sources to non-exclusive diagnostic themes. Third, representative sources were selected for detailed synthesis when they directly supported manufacturing-stage defect detection, factory acceptance testing, diagnostic indicators, method limitations, or standards-based quality gates. The thematic counts in **Fig. 2** are multi-label counts. A single article may appear in more than one theme, for example when a paper discusses both DGA and machine learning or both winding deformation and FRA. This approach is more suitable for a thematic review than mutually exclusive classification because manufacturing-stage defects are not isolated by method boundaries. The axis labels in the

figure therefore report the number of theme assignments, not the number of unique papers in mutually exclusive groups.

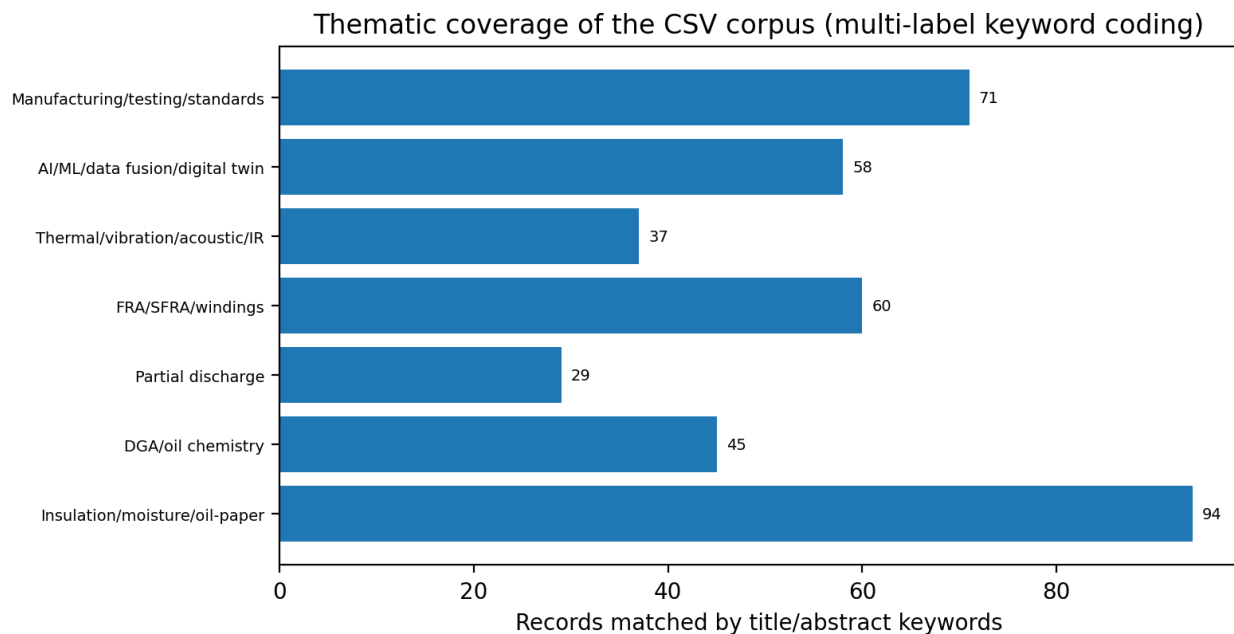


Fig. 2. Thematic coverage of the CSV corpus using multi-label title/abstract keyword coding. Counts are non-exclusive because one article may address more than one diagnostic theme

For the demonstrative decision example, a normalized risk indicator was used to show how heterogeneous diagnostic variables can be compared without implying universal factory limits. The illustrative normalization is defined in Eq. (1).

$$R_i = x_i / \tau_i \quad (1)$$

where R_i is the normalized risk value for indicator i , x_i is the measured or coded indicator value, and τ_i is a factory-configured action threshold. The equation is used only for decision-logic illustration and does not replace standard-specific acceptance rules or manufacturer specifications.

3. Results and Discussion

3.1 Manufacturing Defects and Standards-Based Quality Gates

Manufacturing defects are not merely final-test failures. They are process deviations that may produce measurable electrical, chemical, thermal, mechanical, or visual signatures before commissioning. Insulation-related defects can arise from insufficient drying, contamination, voids, moisture exchange between oil and cellulose, or poor handling of pressboard and paper. Insulation-related manufacturing quality is strongly influenced by pressboard processing, drying, oil-paper chemistry, and long-term ageing mechanisms. Industrial pressboard manufacturing/testing procedures, insulation-system reviews, moisture-detection studies, and chemical markers such as methanol, ethanol, n-butanol, and oil ageing indicators support this theme [7-19].

Winding and mechanical defects can originate from winding errors, insufficient clamping, axial/radial displacement, insulation material deformation, or short-circuit mechanical vulnerability. These

defects are particularly relevant for manufacturing because mechanical integrity must be established before shipment, and FRA/SFRA traces provide a baseline for future comparison [20-23].

Electrical-contact and magnetic-core problems may appear as abnormal winding resistance, load loss, no-load loss, temperature rise, local heating, or sound/vibration deviation. Routine and type tests described by IEC 60076-1 and IEEE C57.12.90 provide the basic factory test structure, while IEC 60076-2 and IEC 60076-10 connect thermal and sound measurements to acceptance practice [24-27].

Latent dielectric defects are particularly important because they may pass simple resistance checks yet produce partial discharge under high-voltage stress. IEC 60076-3 defines the dielectric-test context for transformers, while IEC 60270 specifies charge-based partial-discharge measurement principles; UHF, acoustic, optical, and hybrid PD methods extend the detection and localization capability beyond conventional apparent-charge measurement [28-32]. Table 3 consolidates these manufacturing-defect themes together with their diagnostic indicators, detection methods, and traceable sources.

Table 3 Traceable manufacturing-defect, indicator, method, and source matrix

Manufacturing defect theme	Typical diagnostic indicators	Primary detection methods	Traceable sources
Insufficient drying or moisture contamination in oil-paper insulation	High moisture index, abnormal dielectric response, reduced insulation resistance, increased dielectric losses, chemical markers in oil	Insulation resistance, polarization index, capacitance/tan delta, dielectric response, oil tests, moisture/chemical marker analysis	[7–19, 33–37]
Voids, contamination, sharp edges, or local insulation weakness	PD inception, phase-resolved PD patterns, apparent charge, UHF/acoustic/optical emissions	IEC 60270 PD measurement, UHF sensors, acoustic localization, optical sensing, PRPD analysis	[28–32, 38–47]
Winding deformation, displacement, or inter-turn weakness	Deviation from reference FRA/SFRA trace, abnormal short-circuit impedance, anomalous resistance/ratio results	FRA/SFRA, winding resistance, ratio test, short-circuit impedance, inter-turn transient tests	[20–24, 48–63]
Oil contamination, early thermal/electrical fault chemistry, or abnormal gassing	DGA gas concentration and rate, gas ratios, severity index, stray-gassing pattern	DGA, oil quality supervision, gas-rate monitoring, fuzzy/ML-assisted DGA interpretation	[64–87]

Manufacturing defect theme	Typical diagnostic indicators	Primary detection methods	Traceable sources
Core, contacts, tank, cooling, and assembly defects	No-load/load-loss abnormality, hot spots, leakage, unusual sound, vibration, visual nonconformity	Routine electrical tests, temperature-rise tests, thermal imaging, acoustic/vibration analysis, visual inspection	[24–27, 88–94]
Complex multi-symptom defects requiring decision support	Conflicting or weak indicators across PD, FRA, DGA, thermal, visual, and process history	Data fusion, digital twin, explainable ML, IoT-based monitoring, rule-based quality gates	[95–119]

Standards should not be treated as background citations only; in a manufacturing-stage article they define the minimum quality gates through which diagnostic evidence is interpreted. IEC 60076-1 provides the general transformer requirements and test framework, while IEEE C57.12.90 provides detailed test-code procedures for liquid-immersed distribution, power, and regulating transformers [24, 26]. These two documents are the foundation for routine and type tests, including winding resistance, voltage ratio, polarity/phase relation, losses, impedance, dielectric tests, and temperature-related procedures.

IEC 60076-2 and IEEE C57.100 support the thermal dimension of quality control. IEC 60076-2 addresses temperature rise for liquid-immersed transformers, whereas IEEE C57.100 concerns thermal evaluation of insulation systems [27, 120]. In manufacturing control, these standards support decisions on thermal design conformity, cooling performance, insulation-system qualification, and post-test engineering review when thermal indicators disagree with electrical tests.

IEC 60076-3 and IEC 60270 are essential for dielectric and partial-discharge quality gates. IEC 60076-3 establishes insulation levels, dielectric tests, and external clearances, while IEC 60270 specifies charge-based PD measurements [28, 32]. IEC 60076-18 supports FRA/SFRA measurement for establishing a reference signature before delivery, and IEC 60076-5 connects winding mechanical integrity to short-circuit withstand capability [23, 63]. For oil-based diagnostics, IEC 60599 and IEEE C57.104 guide DGA interpretation, while IEC 60422 covers mineral insulating-oil supervision [33, 80, 84].

In practical factory control, IEC 60076-1 and IEEE C57.12.90 define the general routine/type-test baseline; IEC 60076-2 and IEEE C57.100 support thermal-rise and insulation-system evaluation; IEC 60076-3 and IEC 60270 frame dielectric and partial-discharge testing; IEC 60076-5 and IEC 60076-18 support short-circuit withstand and frequency-response baselines; IEC 60076-10 supports sound-level measurement; and IEC 60599, IEC 60422, and IEEE C57.104 support oil, gas, and oil-paper interpretation. These standards are therefore treated as quality gates rather than as background documents only [23-28, 32, 33, 63, 80, 84, 120].

3.2 Thematic Review of Diagnostic Method Groups

Traditional factory tests remain the first screening layer because they are standardized, repeatable, and directly linked to acceptance documentation. Winding resistance and ratio tests support detection of conductor discontinuity, tap-changer connection errors, and contact problems under IEEE C57.12.90 [24]. Insulation resistance, capacitance, and dielectric-loss measurements reveal broad insulation degradation or moisture-sensitive behavior, but they are not sufficient to localize voids or small local defects; moisture-specific studies show why dielectric response and oil-paper moisture interpretation are needed for deeper assessment [8, 10, 37]. Temperature-rise and thermal-evaluation documents add design and insulation-life relevance to the electrical test results, including IEC temperature-rise testing, IEEE thermal evaluation of insulation systems, and recommended practice for temperature-rise tests beyond nameplate loading [27, 120-122].

Partial discharge is the principal indicator of local dielectric weakness under electrical stress. The conventional apparent-charge measurement is grounded in IEC 60270 and should be interpreted within the dielectric-test framework of IEC 60076-3 [28, 32]. Review studies summarize PD mechanisms, PRPD interpretation, and transformer-specific challenges such as noise, propagation paths, and defect-source classification [31, 41].

Modern PD extensions improve manufacturing-stage localization and source discrimination. UHF methods are useful because transformer tanks can act as electromagnetic cavities and UHF sensors can be embedded or externally mounted for sensitive detection [40, 47]. Acoustic and fiber-optic sensors support localization by time-of-arrival, array-based processing, or optical sensing [30, 38, 39, 46]. Factory acceptance decision-support research shows that PD data can be translated into a release/hold recommendation, but the threshold must be connected to contractual requirements, insulation design, and test voltage rather than treated as a universal number [43, 44].

FRA/SFRA is central to manufacturing-stage control because it can establish a reference signature before shipment. IEC 60076-18 standardizes the measurement of frequency response, while review studies describe its sensitivity to winding displacement, deformation, clamping changes, and connection variations [20, 21, 23].

Interpretation remains the main limitation. Statistical indices, clustering, SVM, morphology-based features, and deep learning have been proposed to improve interpretation of FRA curves [22, 48, 51, 54, 56, 58]. However, for factory release, the most defensible procedure is not to rely on a single global index. The method should compare phase-to-phase similarity, reference trace similarity, sub-band deviations, and engineering knowledge of the active part. The factory baseline then becomes a long-term asset for transport damage assessment and future in-service diagnostics [20, 23, 49, 52, 57, 59, 62].

DGA is often associated with in-service condition monitoring, but it also matters in manufacturing when oil processing, heating, drying, vacuuming, or high-voltage tests produce abnormal gassing. IEC 60599 and IEEE C57.104 define DGA interpretation logic, while IEC 60422 supports oil quality supervision [33, 80, 84]. Classical DGA reviews establish gas-generation mechanisms and ratio-based interpretation methods [65, 86].

The weakness of DGA in the factory context is that a new transformer may have limited gas history. Therefore, absolute gas levels, gas production rate during tests, oil processing history, and possible stray-gassing behavior must be interpreted together [73, 74]. Intelligent DGA models can improve pattern recognition, but the literature warns that incomplete data, class imbalance, and explainability remain practical barriers [64, 68, 79, 117]. Moisture and oil-paper studies add another manufacturing-specific layer because insufficient drying or moisture re-entry may degrade dielectric strength even before commissioning [8, 35, 37].

Thermal, acoustic, vibration, and visual/infrared methods form a complementary layer rather than a replacement for electrical tests. Thermal imaging can reveal local hot spots caused by high-resistance connections, cooling-path problems, abnormal magnetic losses, or assembly defects [90, 92, 93]. Vibration and acoustic signatures are useful for detecting mechanical looseness, core vibration, abnormal magnetostriction behavior, and PD-related acoustic emissions [88, 89, 91, 94]. IEC 60076-10 makes sound-level measurement a standards-based factory gate, while IEC 60076-2 connects thermal testing to transformer design conformity [25, 27].

The main limitation is observability. A defect that does not produce a thermal or acoustic manifestation during the test may remain invisible to these methods. Therefore, these methods are strongest when applied as confirmatory or localization tools after electrical, PD, DGA, or FRA indicators have already raised a concern. For oil-paper problems, thermal evidence should also be interpreted together with moisture and chemical-marker information because insulation ageing and drying quality may be visible in oil/pressboard indicators before a clear external hot spot is observed [12, 14, 15, 17, 18].

Intelligent diagnostics are increasingly proposed for DGA interpretation, PD classification, FRA pattern analysis, visual inspection, and multi-source fusion. Digital twins and IoT-based systems can connect production-test data, sensor data, and design parameters in a common decision environment [103, 113, 114]. Recent studies show growing use of deep learning, synthetic-data balancing, feature explainability, multi-modal fusion, and physics-informed models for transformer fault diagnosis [71, 76, 77, 95, 96, 98-100, 105, 106, 108, 114, 115, 118].

For manufacturing control, the value of intelligent diagnostics is not only classification accuracy; it is traceable decision support. A useful model must explain which indicator triggered a hold/rework recommendation, whether the input data are within the model validity domain, and whether the decision is consistent with standards and engineering experience. This is why the proposed framework combines rules, standards, and model outputs rather than treating machine learning as a standalone release authority [68, 79, 97, 104, 112, 117].

3.3 Comparative Synthesis of Diagnostic Methods

The comparative synthesis in **Table 4** avoids uncited generalizations by providing row-level source support. The table should be read as a practical selection matrix: traditional tests are standardized and mandatory, PD and FRA/SFRA are strong for hidden dielectric and mechanical defects, DGA and oil chemistry are powerful but history-dependent, thermal/acoustic/vibration methods are confirmatory and localization-oriented, and AI/fusion methods are promising when validated against

factory data.

Table 4 Comparative synthesis of manufacturing-stage diagnostic method groups with row-level citations

Method group	Strongest manufacturing role	Main limitation	Best decision use	Row-level support
Traditional electrical and dielectric tests	Baseline acceptance, conformity check, documentation	Limited localization of hidden or early local defects	Pass/retest gate; trigger deeper investigation when inconsistent	[24, 26, 27, 32, 120–122]
Partial discharge measurement	Detection of local insulation weakness before commissioning	Noise sensitivity and need for expert interpretation/localization	Hold/rework gate for dielectric defects; confirm with UHF/acoustic/optical methods	[28–31, 38–47]
FRA/SFRA	Detection and baseline documentation of winding mechanical integrity	No universal interpretation threshold across designs	Hold/review gate for winding displacement or transport vulnerability	[20–23, 48, 49, 51, 52, 54–59, 61, 62]
DGA/oil/moisture chemistry	Chemical evidence of thermal/electrical activity and oil-paper condition	Weak history in new units; risk of false interpretation without context	Engineering review gate after thermal, dielectric, or oil-processing events	[7–12, 14–18, 33–37, 65–70, 72–74, 79–87]
Thermal imaging/IR	Localization of hot spots in contacts, connections, core regions, cooling paths	Requires loading or thermal manifestation	Confirmatory gate for local heating and assembly defects	[24, 27, 90, 92, 93]
Acoustic/vibration/sound	Mechanical and vibroacoustic anomaly screening; PD acoustic localization	Sensitive to background noise and operating condition	Localization and confirmatory gate for core, clamping, and PD sources	[25, 29, 30, 39, 88, 89, 91, 94]

Method group	Strongest manufacturing role	Main limitation	Best decision use	Row-level support
Intelligent diagnostics/fusion	Combining weak evidence across methods into a transparent risk score	Requires validated data, calibration, explainability, and governance	Decision-support layer, not standalone release authority	[71, 76, 77, 95–119]

3.4 Quantitative Benchmarking and Factory-Configurable Decision Variables

Quantitative decision variables are necessary when a review is intended to support manufacturing decisions rather than only summarize diagnostic principles. The article does not present proprietary factory data; however, a manufacturing-oriented review should still define which measurable variables enter the quality decision. **Table 5** gives examples of variables, units, and action logic. Numerical action levels are shown as factory-configurable examples where universal limits are not appropriate. Actual acceptance criteria must be defined by the applicable standard, purchase specification, transformer rating, insulation design, and manufacturer practice.

Table 5 Quantitative variables and demonstrative quality-gate scenario for integrated factory decision-making

Diagnostic layer	Measurable variable or example result	Factory-configurable action logic	Source basis / status
Electrical routine tests	Winding resistance deviation, voltage ratio deviation, no-load/load losses, impedance	Pass if within specified tolerance; hold if phase/tap deviation or loss/impedance inconsistency cannot be explained	[24, 26]
Dielectric/PD test	Apparent charge in pC, background noise level, PD inception/extinction behavior, PRPD pattern	Example: pass if below contract/standard acceptance level; hold if sustained PD exceeds agreed pC level or pattern suggests internal insulation defect	[28, 31, 32, 41, 44]
FRA/SFRA	Trace similarity, sub-band correlation, resonance-frequency shift, magnitude deviation	Example: pass if phase/reference similarity remains high; hold if correlation falls below factory-configured limit or localized resonance shift appears	[20–23]

Diagnostic layer	Measurable variable or example result	Factory-configurable action logic	Source basis / status
DGA/oil chemistry	Gas concentration in ppm, gas rate, gas ratios, severity index, moisture/oil quality indicators	Example: hold if post-test gas generation or moisture indicators exceed baseline trend or DGA interpretation indicates thermal/electrical activity	[33, 65–70, 72–74, 79–87]
Thermal/IR	Hot-spot temperature, temperature rise, Delta T between similar connections/phases	Example: hold if Delta T is persistent under comparable loading or inconsistent with temperature-rise design expectation	[24, 27, 90, 92, 93, 120]
Vibration/acoustic/sound	Sound level, dominant frequency components, RMS vibration, acoustic source location	Example: hold if sound/vibration exceeds specified gate or correlates with suspected core/clamping/PD source	[25, 88, 89, 91, 94]
AI/fusion model	Probability score, anomaly score, confidence, feature attribution	Example: advisory only unless model validation, calibration, and traceability are documented; use as decision-support layer	[95–100, 102, 104–106, 108, 112–115, 117, 118]
Routine electrical tests	Resistance, ratio, and losses within specified tolerance	All mandatory routine-test tolerances satisfied; interpretation: No immediate electrical rejection; action: Continue to deeper diagnostic gate	Demonstrative example; not proprietary measured data
Partial discharge	Sustained PD above agreed apparent-charge level during dielectric test	PD must remain below contract/standard acceptance criterion and stable after noise rejection; interpretation: Local dielectric weakness suspected; action: Hold for localization and engineering review	Demonstrative example; not proprietary measured data

Diagnostic layer	Measurable variable or example result	Factory-configurable action logic	Source basis / status
FRA/SFRA	Phase-reference similarity score 0.82 in one sub-band	Factory example: similarity <0.90 triggers hold; 0.90-0.95 triggers review; >0.95 passes; interpretation: Possible winding displacement or clamping anomaly; action: Compare with design/ref phase and inspect active part if confirmed	Demonstrative example; not proprietary measured data
DGA/oil chemistry	Moderate gas-risk score 0.68 after test sequence	Factory example: risk >0.60 requires engineering review when combined with PD/thermal evidence; interpretation: Chemical evidence alone is not decisive but supports concern; action: Repeat oil sampling and review processing/test history	Demonstrative example; not proprietary measured data
Thermal imaging	Local Delta T exceeds comparable-phase reference during loading	Factory example: persistent normalized Delta T >1.0 relative to action threshold requires hold; interpretation: Possible contact/core/cooling defect; action: Inspect connection/core/cooling path	Demonstrative example; not proprietary measured data
Integrated decision	Three independent evidence layers exceed review/hold logic	Two or more independent hold indicators move decision from retest to rework review; interpretation: Multi-evidence defect risk is high enough to prevent release; action: Hold unit; localize; correct; repeat affected tests	Demonstrative example; not proprietary measured data

3.5 Demonstrative Intelligent Quality-Gate Application

To avoid overstating empirical claims, this section is explicitly framed as a conceptual decision-logic example. It is not presented as a proprietary factory dataset. The purpose is to show how a manufacturer can convert multi-method diagnostic evidence into an auditable quality decision. The numerical values and thresholds are examples that must be recalibrated for a specific transformer rating, insulation system, test voltage, purchase specification, and factory practice. The example assumes that a transformer has completed routine electrical tests and then shows suspicious dielectric behavior during high-voltage testing. A traditional pass/fail approach may be inconclusive if a single method is borderline. The integrated approach therefore combines PD, FRA/SFRA, DGA,

thermal imaging, and moisture-related indicators into a hold/rework decision.

The numerical values in **Table 5** are illustrative and factory-configurable; they are not universal standard limits or proprietary measured data. They demonstrate how a manufacturer can document pass, retest, hold, or rework logic after calibration to transformer rating, insulation design, purchase specification, and factory acceptance procedure. The practical conclusion from the example is that a factory decision should not be made from a single weak signal. PD evidence is strong for dielectric defects, FRA evidence is strong for mechanical displacement, DGA evidence is supportive when gas history is limited, and thermal/acoustic/visual evidence helps localize the issue. The integrated gate converts these signals into an auditable decision: release only when mandatory tests pass and no independent high-risk indicator remains unresolved; retest when the indicator is likely procedural or noisy; hold when one critical or several moderate indicators appear; rework when the defect source is localized or repeatable. The numerical values in the following table are illustrative and factory-configurable; they are not universal standard limits and are not proprietary measured data. **Fig. 3** illustrates the resulting normalized risk values, where values above 1.0 exceed the configured action threshold.

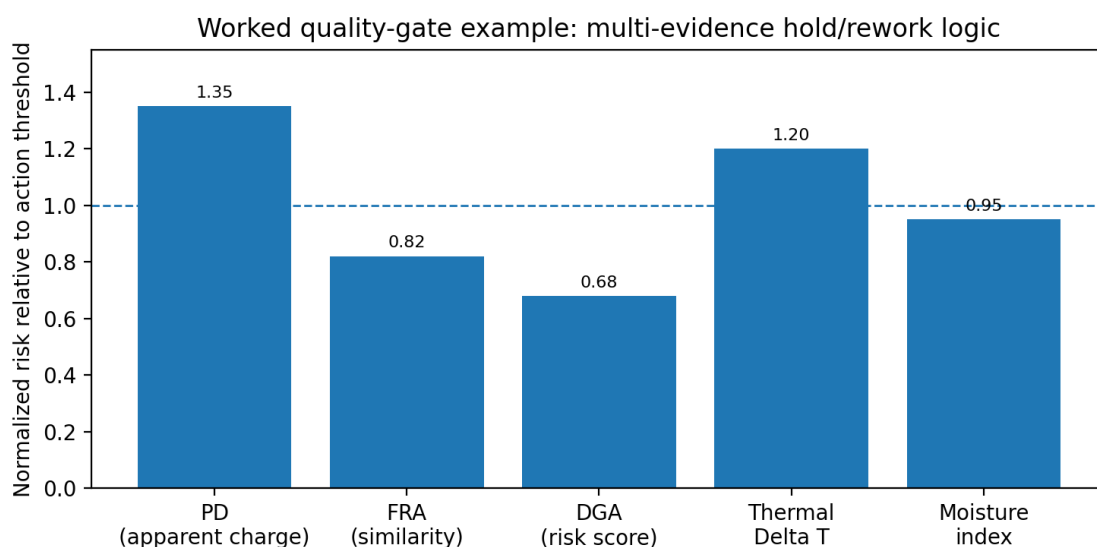


Fig. 3. Demonstrative normalized risk values for a multi-evidence factory quality-gate decision.
Values above 1.0 exceed the configured action threshold

3.6 Integrated Intelligent Decision-Support and Information Framework

The proposed intelligent decision-support framework has four layers. Layer 1 is mandatory standardized testing: general transformer requirements [26], temperature-rise and thermal-evaluation tests [27, 120], dielectric and partial-discharge testing [28, 32], short-circuit withstand and frequency-response baseline recording [23, 63], sound-level testing [25], oil and dissolved-gas interpretation and oil supervision [33, 80, 84], and IEEE routine and type factory-test procedures [24]. Layer 2 is defect-indicator mapping: every abnormal result is linked to a plausible manufacturing origin such as drying, insulation handling, winding displacement, clamping, connection quality, oil processing, or tank and cooling assembly. Layer 3 is multi-method confirmation: a suspicious

indicator is confirmed or rejected using a second method from a different physical domain. Layer 4 is the explainable quality decision: pass, retest, hold, rework, or release with a monitoring recommendation.

This layered framework is important because each diagnostic method observes a different physical manifestation. PD observes local dielectric stress, FRA observes network-response changes, DGA observes chemical decomposition, thermal imaging observes heat generation, acoustic/vibration methods observe mechanical or discharge-generated waves, and AI/fusion models observe cross-domain patterns. A manufacturing-quality system is strongest when it records these signals together rather than storing them as isolated test reports.

Viewed as an information-science architecture, the framework separates four functions: diagnostic data acquisition, cross-method information integration, standards- and rule-based decision inference, and preservation of an auditable action record. The resulting information object for each transformer contains the measured indicator, source method, applicable standard, configured threshold, confidence or uncertainty, confirming evidence, responsible reviewer, and final disposition. This structure allows intelligent models to contribute evidence without becoming an unaccountable release authority.

3.7 Research Gaps and Future Directions

The first gap is the absence of open manufacturing-stage datasets. Many AI and fusion studies use in-service, simulated, or laboratory datasets, while actual factory acceptance data are commercially sensitive. This limits independent validation and makes reported model performance difficult to transfer into factory release decisions [68, 71, 76, 77, 79, 95, 98, 100, 108, 114]. The second gap is threshold transferability. PD limits, FRA similarity indices, DGA severity levels, and thermal Delta T values depend on transformer design, rating, insulation system, test voltage, sensor location, loading condition, and factory practice. Therefore, future work should report not only method accuracy but also calibration context, uncertainty, and false-hold/false-release consequences [21, 23, 28, 31, 44]. The third gap is traceability between manufacturing process history and diagnostic signatures. Future research should connect winding process parameters, drying logs, oil-processing records, active-part assembly data, and test outcomes. Such linkage would make the diagnostic framework more empirical and better aligned with industrial technology-management research. In addition, power transformers increasingly operate in converter-fed environments supplied by multilevel inverters and renewable-generation interfaces, which impose additional dielectric and harmonic stresses that manufacturing-stage qualification should anticipate [123-125].

3.8 Practical Recommendations for Manufacturers

For manufacturers, the most practical implication is to treat diagnostic evidence as a cumulative quality record rather than as a set of isolated test results. Each transformer should have a diagnostic passport that combines routine electrical tests, PD results, FRA/SFRA baseline traces, oil and DGA records, thermal and sound measurements, vibration or acoustic observations, and visual inspection evidence. Standards should define the mandatory acceptance baseline, while factory-calibrated review thresholds should guide hold, retest, rework, and release decisions for PD, FRA, DGA, thermal,

acoustic, and vibration indicators. Each abnormal indicator should be linked to a probable manufacturing origin, a confirming method, an engineering decision, and a corrective action so that the quality decision remains auditable. AI and data-fusion outputs should be used as advisory tools unless they have been validated on comparable transformer designs and factory test conditions. The first production units of a design can be used to build method-specific baselines, and future progress will depend on shared but anonymized benchmark datasets that allow manufacturing-stage diagnostic frameworks to be evaluated quantitatively.

3.9 Limitations

The main limitation is that the paper uses bibliographic metadata and literature synthesis rather than proprietary factory measurement data. The Python-assisted analysis of the CSV corpus is a real bibliographic-data component, while the quality-gate case is explicitly demonstrative. The framework therefore provides a structured and traceable applied decision logic, but it should be validated using real factory datasets before being claimed as a tested industrial implementation.

A second limitation is that quantitative thresholds in transformer diagnostics are not universally transferable. Where the literature and standards do not define a single universal action level, the article identifies the relevant variable and gives factory-configurable example logic rather than presenting unverified limits as standards.

4. Conclusions

This thematic review shows that manufacturing-stage transformer control requires more than routine pass/fail testing. Traditional electrical and dielectric tests provide a necessary baseline, but hidden insulation, winding, oil-paper, thermal, mechanical, and assembly defects require complementary PD, FRA/SFRA, DGA, thermal, acoustic, vibration, visual, and intelligent diagnostic methods. The bibliographic mapping, traceable synthesis tables, novelty positioning, quantitative decision variables, and applied quality-gate example show how these methods can be organized as an integrated manufacturing quality-control system rather than as independent diagnostic tools.

The main practical contribution is an intelligent, traceable framework that links defect origin, diagnostic indicator, detection method, standard basis, evidence confidence, and factory action. This structure operationalizes information integration and explainable decision support by converting heterogeneous diagnostic records into auditable release, retest, hold, or rework recommendations. The next research step is validation using real transformer factory datasets, including measured partial-discharge levels, frequency-response traces, dissolved-gas trends, thermal images, vibration and sound data, and documented rework outcomes.

Author Contributions

Conceptualization, Alibek Adilbekov and Pavel Petrov; methodology, Alibek Adilbekov, Luigi Carlo De Jesus, and Sayat Moldakhmetov; formal analysis, Luigi Carlo De Jesus and Pavel Petrov; investigation, Alibek Adilbekov, Alexandr Kashevkin, and Luigi Carlo De Jesus; data curation, Alibek Adilbekov and Roben Antalan Juanatas; validation, Alibek Adilbekov, Alexandr Kashevkin, Roben Antalan Juanatas, and Sergey Latypov; visualization, Luigi Carlo De Jesus; resources, Sergey Latypov and Sayat

Moldakhmetov; writing-original draft preparation, Alibek Adilbekov and Luigi Carlo De Jesus; writing-review and editing, Roben Antalan Juanatas, Alexandr Kashevkin, Sergey Latypov, Pavel Petrov, and Sayat Moldakhmetov; supervision, Pavel Petrov and Sayat Moldakhmetov; project administration, Pavel Petrov. All authors have read and agreed to the published version of the manuscript.

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The bibliographic data supporting the findings of this review are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Use of Artificial Intelligence

The authors declare limited use of ChatGPT Edu (GPT-5.5) for grammar checking and language refinement only. The authors reviewed and approved the final manuscript and remain fully responsible for its content, analysis, interpretations, and conclusions.

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