

# Enhancing transformer reliability with multi-modal sensor-based monitoring

## ABSTRACT

Multi-modal sensor-based system gives assets managers a clear picture of the health of transformer. By integrating multiple types of sensors with effective data fusion algorithms, it enables a more comprehensive evaluation of transformer health. Compared to single-sensor approaches, this method offers improved fault detection, health analysis, and operational reliability. Experimental results validate its accuracy, while case studies and in-field measurements demon-

strate its effectiveness in supporting transformer asset management. The integration of AI and machine learning (ML) with expert knowledge further strengthens data-driven decision-making, offering improved predictive maintenance and smarter transformer fleet management.

## KEYWORDS:

power transformer, condition monitoring, multi-modal sensors, data fusion, predictive maintenance

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## 1. Introduction

Power transformers are among the most critical assets in electricity grids. During their operation, they are continuously exposed to thermal, mechanical, and electrical stresses, which gradually cause degradation of their components and increase the probability of failure. Some common failure modes in transformers include insulation breakdown, winding deformation, OLTC malfunction, and bushing failures. CIGRE surveys reported that for transformers with on-load tap changers (OLTCs), 40% of their failures were caused by OLTCs and 19% by windings, while for transformers without OLTCs, 26% of their failures were due to windings and 33% were due to terminals [1]. A South African study found that out of 188 transformer failures, 56 were attributed to insulation aging [2]. The IMIA WG 33(03) survey of 94 transformer failures revealed that 24 failures were attributed to insulation aging [3]. Together, these studies highlight con-

sistent failure patterns across different regions. CIGRE WG05 published an international study which provides a comprehensive analysis on transformer failure offering broader insight on failure statistics, while the South African analysis is a regional study reflecting local operating conditions, fleet age profiles, and maintenance practices. This study helps us to identify the common failure modes, but the exact proportions may vary with geography and loading conditions. This means the figures from this study can be indicative trends rather than universally applicable values.

With many utilities operating aging fleets of transformers, a comprehensive condition assessment of in-service transformers has become more critical. To ensure reliable operation, it is therefore essential to implement continuous condition monitoring of transformers and subsequently provide reliable transformer health indicators for informed transformer asset management decisions.

Asset owners have been supporting the development of a range of techniques to monitor the condition of their transformers, including offline and online methods. Offline methods take key measurements typically during routine inspections, periodic testing, or even after outages. Some examples include dissolved gas analysis (DGA) to detect thermal and discharge faults, high-performance liquid chromatography to measure 2-furfuraldehyde to assess the condition of transformer solid insulation, polarization/depolarization currents (PDC) and frequency domain spectroscopy (FDS) to estimate aging and moisture content in transformer oil-paper insulation systems, and frequency response analysis (FRA) to detect deformations in core and winding [4]. In contrast, online condition monitoring methods perform continuous sensor-based measurements, eliminating the need for planned inspections or scheduled events. Some examples include temperature and moisture measurements, partial discharge (PD) detection, and vibration measurements to provide insights into the health status of transformer's oil-paper insulation system, core, and windings. Online monitoring detects real time events and long-term trends that offline tests can miss, enabling earlier intervention and reducing false positives. However, offline monitoring remains crucial for confirmatory diagnostics of transformer health.

An effective transformer condition assessment strategy based on online sensor-based measurements can enhance visibility into transformer health, enabling utilities to achieve operational efficiency and develop informed plans for transformer fleet management. However, due to the complex internal construction of transformers, a reliable condition

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Table 1. Comparison of online and offline measurements

Feature	Online monitoring	Offline testing
State	In service	Outage required
Data type	Time-series data	Discrete snapshot
Primary objective	Trending and alarming	Diagnosis and condition assessment
Key advantage	Captures transients and rapid fault evolution, enables early intervention	Allows for comprehensive electrical testing and high-accuracy analysis
Key limitation	Sensor reliability; high installation and maintenance cost	Blind spots between test; requires downtime

assessment cannot be achieved using a single measurement method. A practical approach is to implement an intelligent diagnostic framework supported by the data fusion of multi-modal sensors.

This article examines the effectiveness of a multi-modal sensor-based system, which can measure moisture, temperature, vibration, and PD (Sensor A). The temperature and moisture measurement results (denoted as Sensor A) are compared with a traditional capacitive moisture sensor (Sensor B). The data and information fusion process, which integrates measurements from different types of sensing modalities to produce a comprehensive health index of the transformer, is presented in this article. The multi-modal sensor-based system will support more effective transformer asset management. Fusing multiple sensors into one modality can reduce false alarms by cross-validating signals, so operations teams can spend less time chasing false alarms. The system produces a ranked based risk score for each transformer, which enables prioritisation

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for inspection and planned intervention rather than going directly with the reactive approach.

### 2. Multi-modal sensor-based transformer condition monitoring system

In the multi-modal sensor-based system, several types of sensors are deployed to capture different physical phenomena associated with transformer health. Whereas single-sensor installations typically place accelerometers on the tank near the core or bushings, acoustic sensors near the conservator or tap changer, and thermal sensors on radia-

tors or bushings, a multi-modal sensor unit can be mounted at the drain valve, allowing multiple measurements to be collected from a single access point. Unlike single-parameter monitoring, the multi-modal sensor-based system can provide a holistic view of transformer condition, enable cross-validation of anomalies, and improve prediction accuracy. Figure 1 illustrates the structure of the multi-modal sensor-based system for power transformer condition assessment.

The multi-modal sensor-based system consists of several components [5]. The first component, shown at the bottom of Figure 1, includes sensor measurements such as moisture, vibration, tempera-



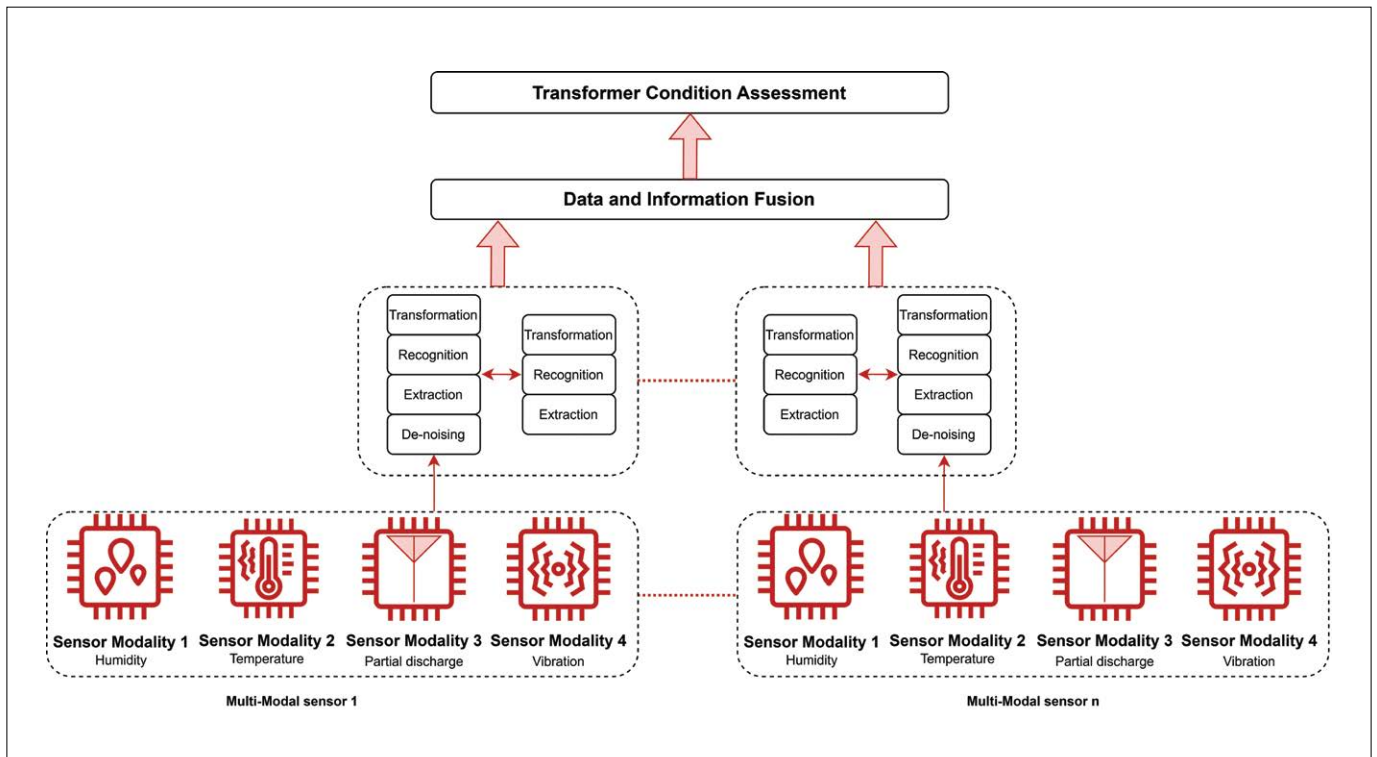


Figure 1. Intelligent asset management framework for power transformers using multi-modal sensing

## By combining the results of different measurements, the overall dynamic operating condition of a transformer can be evaluated

ture, and PD. Data acquisition hardware collects signals from sensors and transmits them for further processing.

For condition monitoring of a transformer in a substation environment, interference and noise may jeopardize the sensor-acquired signals, which can affect sensitivity and reliability. Therefore, the second component shown in Figure 1 employs a set of signal processing algorithms to mitigate noise effects in the raw measurement data. Although modern systems make it easy to gather and store raw data, the data may still contain errors, redundancy, or be incomplete. Hence, the third component in Figure 1, feature extraction is developed. It selects representative characteristics from the raw data to provide concise information suitable for further analysis.

The fourth component in Figure 1, pattern recognition algorithms, classifies different types of faults and evaluate the transformer's health. These algorithms can also learn from the historical data to

identify correlations between measurements and transformer health conditions, ultimately aiding in the condition assessment of the transformer.

Finally, by combining the results of different measurements, the overall dynamic operating condition of a transformer can be evaluated. A data and information fusion component integrates pattern recognition results from individual measurements to estimate the likelihood of various fault types associated with the transformer.

In short, sensors stream raw signals to a data acquisition device that performs initial filtering, noise suppression, and feature extraction to reduce bandwidth and latency. Pre-processed features are transmitted securely to cloud where Bayesian fusion and machine-learning models combine evidence across all modalities to produce a probabilistic health index and ranked maintenance recommendations. Decision outputs (alarms, risk scores, inspection priorities)

are returned to operators and the asset management system for action.

### 2.1 Moisture measurement for transformer oil and cellulose insulation system

The service life of a power transformer largely depends on the aging state of its solid insulation, which consists mainly of cellulose-based paper and pressboard. Moisture is widely recognized as one of the most detrimental factors affecting cellulose insulation, as it significantly accelerates aging processes and degrades both dielectric and mechanical properties [4]. Consequently, accurate estimation of the moisture content within cellulose insulation is of critical importance for transformer condition assessment and asset management.

Asset managers have used direct moisture measurement techniques, such as dielectric response measurements (PDC and FDS) to estimate the moisture content in the cellulose insulation of transformers. However, these measurements require the transformer to be disconnected from the grid. In addition, the transformer temperature may not remain constant throughout the measurement, which may affect the final moisture estimation.

Capacitive-based moisture sensors have also been used to measure the relative humidity % (RH) of water in the oil which is then combined with other data to evaluate the moisture levels in the cellulose insulation. Existing research works indicate that the sensors utilising the capacitive principle are well-suited for moisture monitoring due to their linear sensitivity across a broad humidity range and thermal stability [6]. The moisture content in cellulose insulation is typically estimated by measuring the moisture concentration in the insulating oil and subsequently applying oil paper moisture equilibrium curves [7]. However, changes in temperature can affect the moisture distribution between oil and paper, so the measurement of oil temperature is also necessary during moisture measurement. Continuous monitoring of moisture in the insulating oil, together with temperature variations, enables improved estimation of the cellulose insulation moisture levels [8].

## 2.2 Vibration measurement for monitoring transformer mechanical integrity

Vibration signatures reveal mechanical looseness, winding movement, and clamping pressure changes. These are early indicators of structural faults that can lead to failure of a transformer if not addressed. Within transformers, vibrations are generated from the core and windings. For core vibrations, this is due to magnetostriction, and for the wind-

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ings, this is caused by the interaction of the winding's leakage magnetic flux with that of the other winding or the core. Vibration monitoring involves tracking key areas within the transformer for changes in vibration patterns. These key areas include the core, windings, clamping pressure structure, OLTC, and bushings [9], [10]. To establish baseline vibration signatures, laboratory experiments are conducted, in which the test transformers are subjected to different controlled mechanical stresses. Baselines are determined by measuring vibration under nominal conditions and determining the normal ranges of key parameters. The key parameters include dominant harmonic amplitudes (100 Hz, 200 Hz), total vibration energy, and harmonic distortion. These baseline values are then used to track the changes on key parameters

over time. During field measurements, transformer vibration signals under varying load conditions are captured and analysed, enabling the recognition of abnormal structural faults, such as changes to the clamping system [11]. Signal processing techniques such as Fast Fourier Transform (FFT), wavelet analysis, and principal component analysis are used for vibration signal analysis. Piezoelectric accelerometers are a suitable choice to monitor transformer vibrations given their high accuracy. Additionally, tri-axis piezoelectric accelerometers allow for vibrations along the x, y, and z axes to be captured, enabling more advanced assessments, such as detecting changes in radial clamping pressure.

Figure 2 shows the typical vibration spectra captured from an in-field trans-

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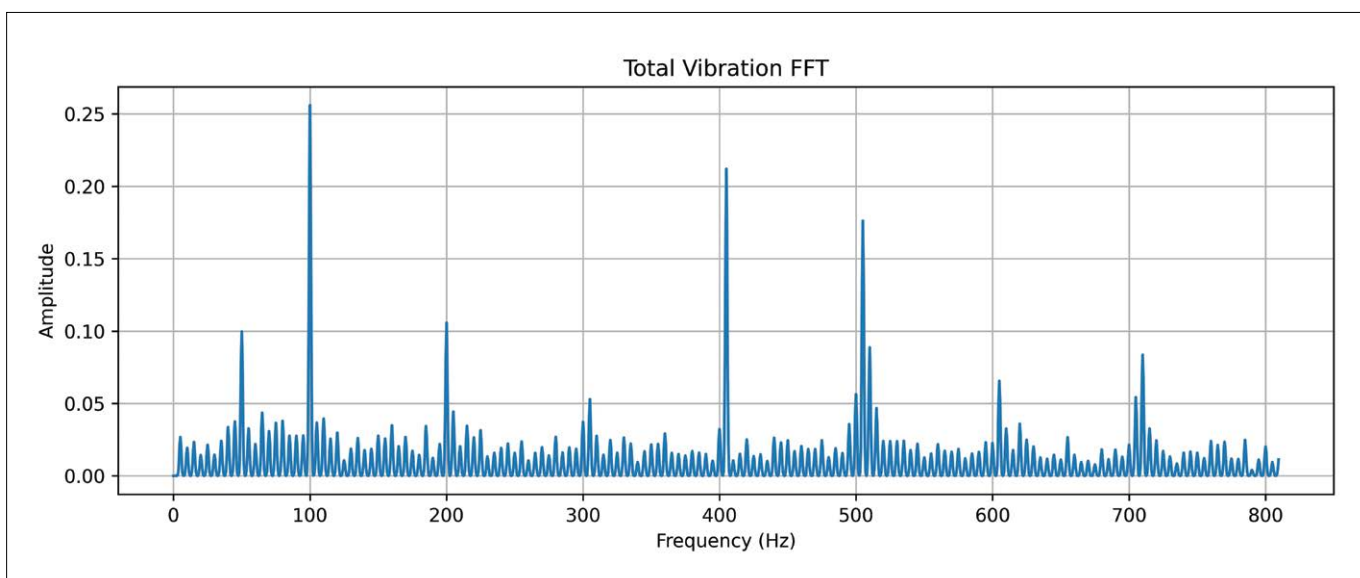


Figure 2. Vibration measurement by sensor A

## Though it may not immediately cause a complete insulation failure, continuous PD activity can progressively damage a transformer’s insulation system, accelerate aging and potentially lead to a catastrophic breakdown

former. The figure highlights the sensor’s capability in detecting the vibrations, given the sharp peaks observed at the expected vibration harmonics (twice the power frequency).

### 2.3 Temperature measurement

Continuous temperature monitoring is essential for assessing transformer condition since the elevating temperature can increase the rate of insulation degradation. Furthermore, moisture dynamics within transformer insulation are strongly dependent on temperature [12]. Accurate assessment of the moisture level in cellulose insulation is therefore essential. Continuous temperature monitoring can also provide valuable information regarding transformer loading conditions and the effectiveness of the cooling system.

Figure 3 shows the moisture, temperature, and water content in oil measured

by multi-modal Sensor (Sensor A) and a conventional benchmark sensor (Sensor B). The graph shows that the measurements from the multi-modal sensor A are in line with the conventional benchmark sensor.

### 3. Partial discharge detection and localization in transformer

PD is the localized breakdown that only partially bridges the insulation between two energized conductors in high-voltage (HV) equipment [13]. Though it may not immediately cause a complete insulation failure, continuous PD activity can progressively damage a transformer’s insulation system, accelerate aging and potentially lead to a catastrophic breakdown [14]. As PD is an early sign of insulation degradation, PD detection has become a valuable tool for insu-

lation condition monitoring, offering early detection of defects, types of defects, and assessment of deterioration trends. Different PD sources, such as cracks and voids in solid insulation, air bubbles and free water in oil, and floating conductive particles in oil, can create distinct discharge patterns, which can be analysed to reveal the underlying fault.

PD detection can be conducted through electrical, acoustic, high frequency and ultra-high frequency (UHF) methods. The UHF method has been gaining popularity because it can be deployed for online PD measurement. Though the acoustic method can also be deployed for online PD measurement, it is susceptible to environmental interference and noise and may not provide reliable measurement results [12]. The UHF method has the merits of its applicability in noisy environments. This is because it can be installed into an in-operation transformer’s oil drain valve and acquire PD signals with high signal-to-noise (SNR) ratio. Various machine learning algorithms can be applied to classify types of PD sources. In addition, other than the transformer oil valve, multiple UHF sensors can be installed at other locations on the transformer tank to identify the location of PD sources within the transformer. Figure 4 shows the PD signal acquired and processed by Sensor A adopted in the multi-modal sensor-based system in Figure 1. The PD signals are depicted in both the dB level above the noise floor and the PD prevalence (%). The two metrics are used together to determine the level of PD signal magnitude and the frequency of PD occurrence.

### 4. Data and information fusion for transformer condition assessment

The data and information fusion component in the multi-modal sensor-based

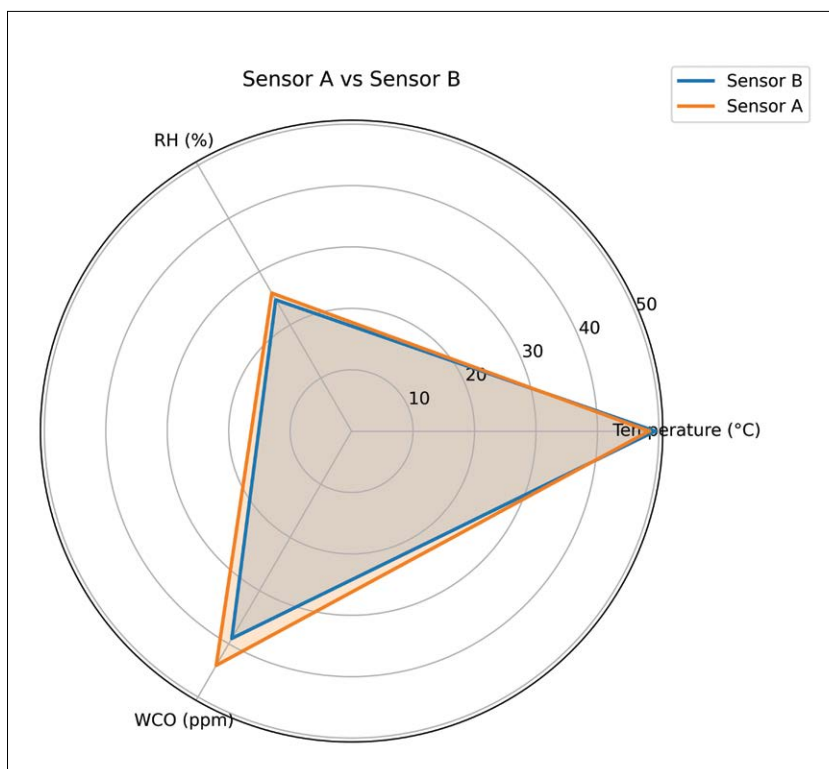


Figure 3. Moisture, temperature, and water content measured by Sensors A and B

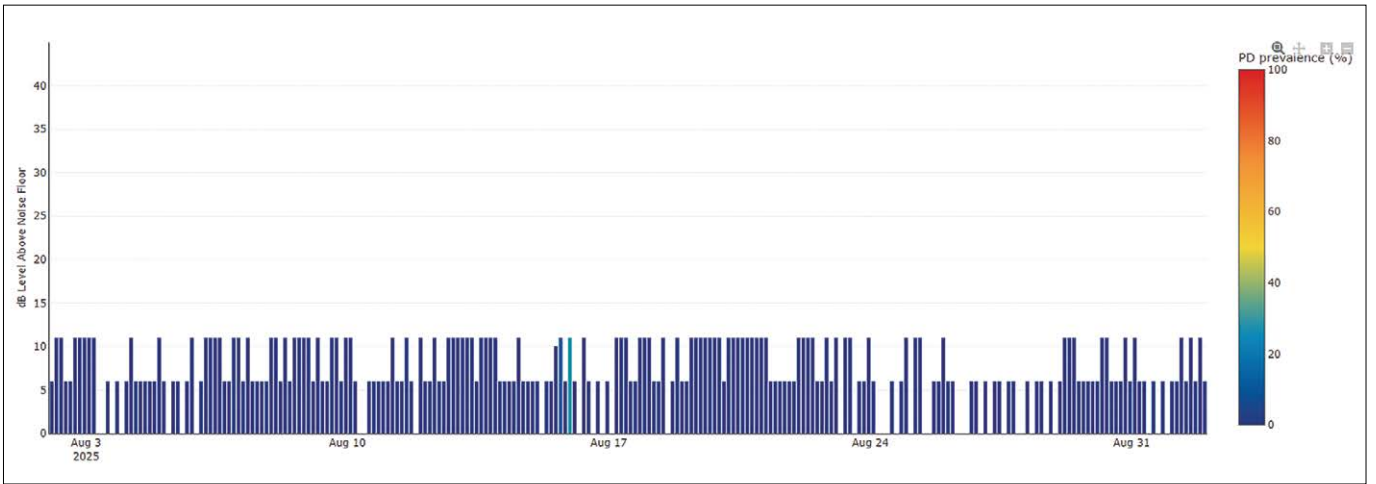


Figure 4. PD pulse measured by Sensor A

system (illustrated in Figure 1) integrates moisture, vibration, temperature, and UHF PD measurements and provide composite health indices to reflect the overall condition of the transformer. This technique combines all available data and information obtained from these sensor-based measurements, maintenance records, failure statistics, and expert knowledge.

Machine learning algorithms are employed in the data and information fusion component to explore the correlations between monitoring data and the health of transformer [15]. Figure 5 provides an example of employing Bayesian information fusion and hierarchical Bayesian belief networks for data and information fusion and the derivation of a probabilistic health

index of transformer [15]. The system begins with an existing estimate of the asset's condition, evaluates how likely each new measurement is given that estimate, and updates the health score accordingly. With every new observation the model updates and refines both the central estimate and its uncertainty. This approach gradually increases the confidence in diagnostic as well as

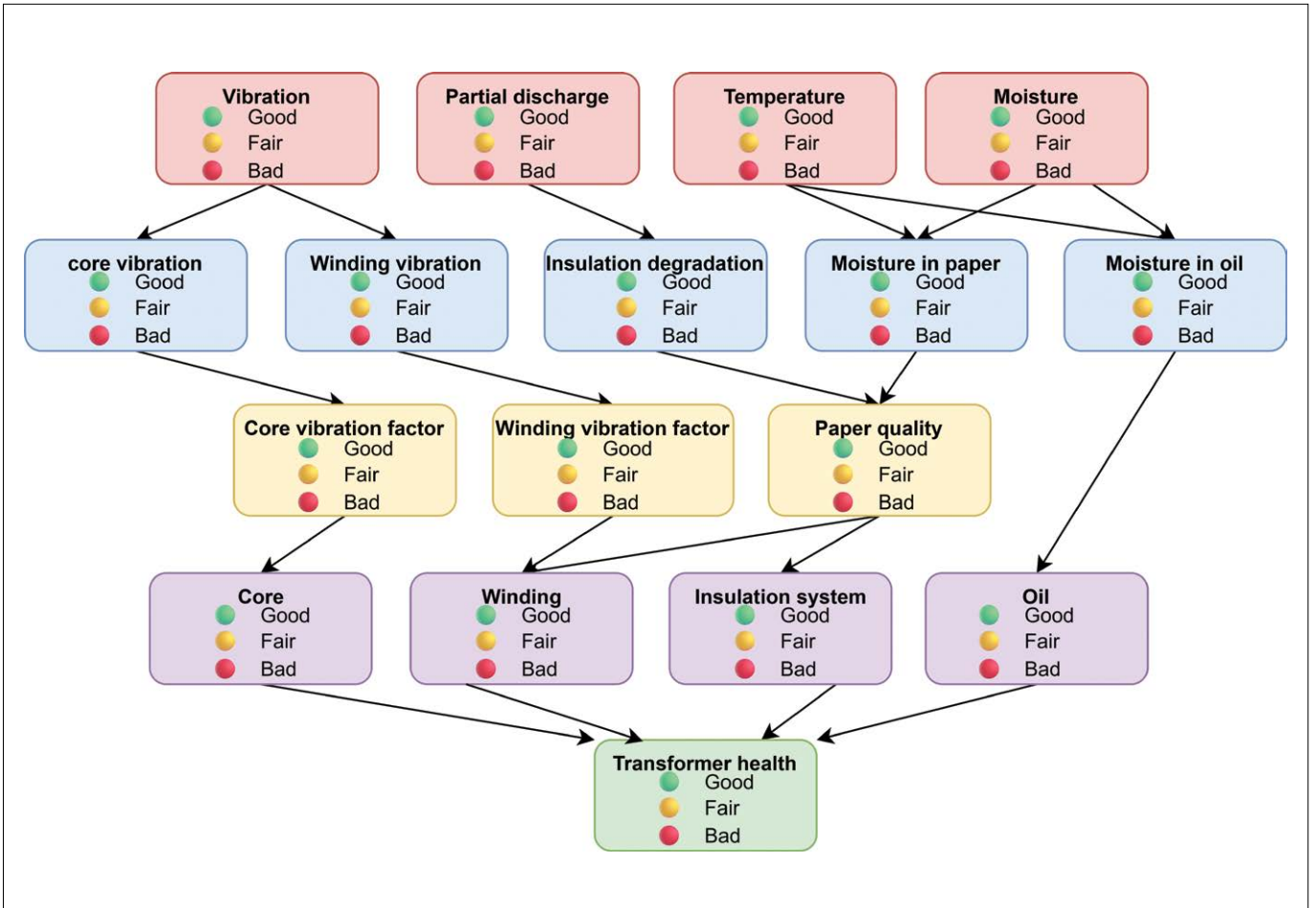


Figure 14. Distribution of calculated data for one winding (losses are presented as value of total losses in each conductor)

# Cloud-based platforms and edge computing enable advanced analytics and remote condition monitoring of transformers for utility operation managers

identifying faulty signals. If one sensor is noisy or ambiguous, other modalities adjust the overall fault probability reducing false alarms and strengthening confidence in online monitoring. Con-

fidence weights based on sensor calibration and historical accuracy should be included in the fusion process. Laboratory validations prove the reliability of the algorithms, whereas field trials

illustrate their scalability and adaptability to various transformers. Cloud-based platforms and edge computing enable advanced analytics and remote condition monitoring of transformers for utility operation managers.

## Authors



**Chandima Ekanayake** received his B.Sc. Eng (Hons) in 1999 from the University of Peradeniya, Sri Lanka PhD from Chalmers University of Technology, Sweden, in 2006. He is currently an Associate Professor attached to School of Electrical Engineering and Computer Science in The University of Queensland.

His research focuses on instrumentation for condition monitoring & protection of power system assets and developing ageing models based on laboratory and field measurements to quantify the ageing of assets due to multi-factor ageing mechanisms. This work targets to increase the reliability and efficiency of electricity supply.

Chandima is senior member of IEEE and Fellow of Engineers Australia. He is an active IEEE volunteer and held many volunteer positions including the Chair of IEEE PES/DEIS Queensland and Chair of IEEE Queensland and Sri Lanka section. Currently he is serving as the Deputy Director of Australasian Transformer Innovation Centre. Chandima is a member of CIGRE Australian Panels A2 and B1. His research work is closely associated with the Australian electricity supply industry.



**Dr Hui Ma** received his B. Eng and M. Eng from Xi'an Jiaotong University (China), M. Eng (research) from Nanyang Technological University, Singapore, and PhD from the University of Adelaide, Australia. He has been working at the University of Queensland, Australia since 2008. From 1997 to 2003, Dr Ma was an engineer in Singapore and made contribution to the

design, development and deployment of the Intelligent Self-recovery and Automated Cargo Inventory Control System for Singapore Airline SuperHub 2.

Dr. Ma's current research and development work is associated with Australian electricity supply industry. His research is centred on Electrical Asset Management including (1) modelling, sensing, and signal processing to improve the visibility of electricity networks and assets condition; and (2) data mining with uncertain reasoning for various applications of electricity networks with high penetration of renewables.

Dr Hui Ma is an editor for IEEE Transactions on Power Delivery and a member of IEEE Smart Grid Steering Committee. He is also a member of CIGRE Australian Panel D1.

## 5. Conclusion and future works

In conclusion, the multi-modal sensor system improves diagnostic confidence by combining moisture, temperature, vibration, and PD data into a unified platform. The system's architecture, sensor integration, and data fusion process were discussed, demonstrating how combining multiple sensing modalities enhances diagnostic reliability and improves failure mode coverage. Continued refinement of calibration, fusion algorithms, and AI-based analytics will further strengthen predictive maintenance capabilities and support smarter, more resilient transformer asset management.

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## Authors



**Abhinav Bhattarai** received a B.E. degree in Electrical Engineering from Tribhuvan University, Nepal, in 2019, and the M.E. degree in Electrical Power Engineering from Kathmandu University, Nepal, in 2023. He worked as a Researcher at Kathmandu University, where his work focused on power transformer condition monitoring, with particular emphasis on partial discharge detection. He is currently pursuing the Ph.D. degree at The University of Queensland, Australia. His research interests include digital twins for power transformers, transformer condition monitoring, fault detection, and finite-element-based modelling.



**Anuradha Abeysekera** received his Bachelor of Science in Engineering (Honours) from the University of Peradeniya in 2015. After graduation, he joined the industry as a transformer design engineer at LTL Transformers (Pvt) Ltd. Subsequently, he worked as an electrical engineer at the Ceylon Electricity Board and pursued his Master of Science in Engineering at the University of Peradeniya. He is now pursuing his PhD at the University of Queensland and is investigating the impact of current and voltage harmonics on transformer insulation. His research interests include harmonic resonance, insulation ageing, and transformer condition monitoring.



**Weibin He** (Student Member, IEEE) received a B.A.Sc in 2018 from the University of Toronto, Canada, and a M. Eng in 2024 from the University of Queensland, Australia. He is currently pursuing a Ph.D. degree in the School of Electrical Engineering and Computer Science at the University of Queensland, Australia. His research interests include arc faults in renewable energy systems.