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Moisture Measurement in Transformer Oil Using Sensor-Based and Computational Modelling Approaches

Lince Markis[1*], Indra Budi H[2], Paulus Susetyo Wardana[3]
[1,2]University of 17 Agustus 1945 Surabaya
[3]Politeknik Elektronika Negeri Surabaya
Corresponding Author: Lince Markis; lince.markis@untag-sby.ac.id

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ABSTRACT

Moisture contamination in transformer oil significantly reduces its dielectric strength and accelerates insulation ageing, making accurate measurement essential for transformer health monitoring. Traditional laboratory-based methods such as Karl Fischer Titration (KFT) provide high accuracy but are not suitable for continuous or on-site monitoring. This study proposes a hybrid approach that integrates a low-cost capacitive sensor, dielectric parameter measurements, and predictive modelling to estimate moisture content in transformer oil. A total of 30 oil samples with moisture levels ranging from approximately 50 to 250 ppm were prepared and tested under controlled temperature conditions. Moisture values measured by the proposed sensor showed a strong correlation with KFT results ($R^2 = 0.94$), demonstrating good sensitivity to moisture variation. Breakdown voltage (BDV) and dielectric loss factor ($\tan \delta$) measurements confirmed the expected trends, with BDV decreasing and $\tan \delta$ increasing as moisture increased. A multivariable regression model improved prediction accuracy ($R^2 = 0.96$). The Artificial Neural Network (ANN) model achieved the best performance, with RMSE = 5.4 ppm and MAE = 3.9 ppm. The findings indicate that the proposed hybrid method is effective for accurate moisture estimation and has strong potential for implementation in real-time or IoT-based transformer condition-monitoring systems

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INTRODUCTION

Transformer oil plays a crucial dual role in power transformers: it provides electrical insulation between windings and components while functioning as a cooling medium to dissipate heat from the core and coils. However, the presence of moisture—whether dissolved, adsorbed, or in free form—significantly degrades the dielectric strength of the oil and accelerates the ageing process of insulation materials. Even small amounts of dissolved water (around 100 ppm) can reduce breakdown voltage (BDV) by 10–20% and increase the dielectric loss factor (tan δ), leading to higher energy losses and increased failure risk (Mohamad et al., 2018; Siddique et al., 2022; Suwarno & Pasaribu, 2016; Wang et al., 2014). Moisture also promotes hydrolysis of cellulose insulation, generating acids and gases that further deteriorate transformer reliability. Water migration between paper and oil is governed by temperature and saturation dynamics, meaning that operating conditions strongly influence moisture equilibrium (Deep Singh & Singh, 2019; Hill et al., 2019; Vatsa et al., 2023). Over time, this process reduces transformer insulation life expectancy (Feng et al., 2023; Medina et al., 2017; Przybylek, 2013; Sun et al., 2019).

Karl Fischer titration (KFT), standardized under ASTM D1533, remains the reference method for quantifying moisture in insulating liquids due to its high precision. However, KFT requires laboratory procedures and cannot support in-situ or real-time monitoring (IEC 60422, 2013). As a result, the electrical power industry is increasingly exploring online and low-cost sensing techniques for continuous moisture monitoring. Recent advances in capacitive, optical, and dielectric sensors offer potential for online detection of water content in transformer oil (Akre et al., 2023; Ansari et al., 2020; Liu et al., 2018). Nevertheless, these methods face challenges including calibration drift, temperature sensitivity, and cross-sensitivity to oil ageing parameters such as acidity, conductivity, and dissolved gases (Xie et al., 2013). Dielectric parameters such as BDV and tan δ are also moisture-dependent but cannot quantify moisture directly without modelling (Abu-Siada & Hmood, 2015).

Despite widespread research on oil ageing and transformer diagnostics, there remains a lack of integrated frameworks that combine sensor-based moisture measurement, dielectric property monitoring, and computational modelling. Most existing studies evaluate these aspects independently. To address this gap, this paper proposes a hybrid approach that integrates: (1) a custom capacitive sensor, (2) moisture validation using KFT, and (3) predictive modelling using regression and Artificial Neural Networks (ANNs).

This work contributes by presenting a low-cost and high-accuracy methodology suitable for future IoT-based transformer condition monitoring, supporting predictive maintenance and improving transformer reliability.

LITERATURE REVIEW

Moisture Effects and Dielectric Properties of Transformer Oil

Recent studies confirm that even modest levels of moisture in transformer oil and oil–paper insulation systems significantly impair dielectric performance. For example, Naveed and Amaar (2024) proposed a fractal-based capacitive sensor for continuous monitoring of moisture content in transformer oil, noting that moisture contamination "significantly reduces dielectric strength, accelerates ageing processes, and increases the probability of insulation breakdown" (Naveed & Amaar, 2024). Vatsa et al. (2023) applied deep learning to forecast moisture variation in oil–paper insulation systems, pointing out that moisture content directly affects loss factor (tan δ) in insulation systems and thereby the condition of the transformer (Vatsa et al., 2023).

Further, the migration and equilibrium of water between cellulose insulation and oil is influenced by temperature and saturation dynamics, which complicates moisture assessment in transformers (IEC 60422, 2018; Schneider Electric, 2025). Although this last citation is a normative/industry document rather than a peer-review article, it highlights the practical challenge of moisture movement between paper and oil (Schneider Electric, 2025).

Methods of Moisture Measurement in Transformer Oil

Laboratory reference methods remain the standard for quantification of water in insulating liquids. The use of Karl Fischer titration (KFT) under ASTM D1533 provides accurate ppm-level measurements but is inherently offline and laboratory-bound (Zhang et al., 2020). To overcome this limitation, various sensor-based and online monitoring methods have been developed.

Guerrero Granados et al. (2021) presented a capacitive sensor placed inside a transformer tank to detect moisture content directly in oil. The authors highlighted that, while promising for real-time monitoring, sensor calibration, temperature effects, and repeatability remain major issues (Guerrero Granados et al., 2021). Subsequently, Naveed and Amaar (2024) improved sensitivity via fractal-shaped capacitive sensing, achieving a detection limit of ~5 ppm in controlled experiments, yet still emphasizing the need to correct for temperature and other interfering factors (Naveed & Amaar, 2024).

Computational and Predictive Modelling Approaches

The advent of machine learning and deep learning techniques has opened new possibilities for transformer oil condition monitoring. Vatsa et al. (2023) developed a hybrid Di¬electric Frequency Domain Spectroscopy (DFDS) + Long Short-Term Memory (LSTM) model to forecast moisture levels in oil-paper insulation. Their results showed strong predictive capability ($R^2 \approx 0.90$) and highlighted that moisture influences dielectric properties beyond ageing alone (Vatsa et al., 2023).

In sensor–modelling hybrid systems, the combination of capacitance/ dielectric readings with regression or ANN models has gained traction. Although the bulk of earlier works focused on other oil-health parameters (e.g., dissolved gases, age), the direct modelling of moisture content from sensor readings remains under-represented in the literature.

Research Gap

From the above review the following gaps emerge:

1) There are limited studies integrating sensor-based moisture measurement, dielectric property monitoring, and computational modelling (e.g., ANN, regression) specifically for transformer oil moisture quantification.
2) While many sensors show promise in laboratory conditions, field validation (in-service transformer environments) is scarce.

3) Temperature dependence, calibration drift, cross-sensitivity with oil ageing, acidity or gas content remain recurring unresolved challenges.
4) Few works provide a complete workflow from sensor design, calibration, validation against KFT, computational modelling, ideally online monitoring system.

This study proposes to fill those gaps by implementing a capacitive sensor prototype calibrated against KFT, measuring dielectric parameters (BDV, tan δ), and developing computational models (regression & ANN) for moisture prediction, thereby enabling a pathway toward online/IoT-based monitoring.

METHODOLOGY

Research Design and Framework

This study adopts an experimental and modelling-based research design that combines laboratory measurements, sensor calibration, and data-driven modelling. The research consists of the following stages:

1) Sample collection and preparation of mineral transformer oil with different moisture levels.
2) Reference moisture measurement using Karl Fischer titration (KFT) following ASTM D1533.
3) Sensor-based measurement using a custom capacitive sensor immersed in the oil.
4) Dielectric property measurements, including breakdown voltage (BDV) and dielectric loss factors (tan δ).
5) Data preprocessing and feature selection.
6) Development of regression and Artificial Neural Network (ANN) models for predicting moisture from sensor readings and dielectric parameters.
7) Model validation and performance evaluation using standard error metrics (RMSE, MAE, R^2).

This multi-stage framework is consistent with recent works that integrate laboratory reference methods, sensor data, and computational models for insulation diagnostics and health assessment (Darabi et al., 2022; Naveed & Amaar, 2024; Vatsa et al., 2023).

Transformer Oil Samples and Moisture Preparation

Mineral transformer oil samples were obtained from medium-voltage distribution transformers in service and from fresh unused oil provided by a local utility. Two categories were considered:

1) Fresh oil (unused, low initial moisture).
2) In-service oil (5–10 years of operation, higher baseline ageing and moisture).

To generate controlled moisture levels, deionized water was added to the oil samples in small quantities under continuous stirring and elevated temperature, following procedures adapted from Zhang et al. (2020) and Vatsa et al. (2023). Samples were conditioned to obtain several target moisture levels (e.g., approximately 50, 100, 150, 200, and 250 ppm). Temperature during conditioning and measurement was controlled at selected set-points (25 °C, 50 °C, and 75 °C) to reflect practical operating ranges, as moisture equilibrium between oil and paper is highly temperature-dependent (IEC, 2018; Darabi et al., 2022).

Each conditioned sample was stored in airtight glass bottles to minimize atmospheric moisture exchange before measurements.

Reference Moisture Measurement Using Karl Fischer (ASTM D1533)

Moisture content in each oil sample was first determined using volumetric Karl Fischer titration in accordance with ASTM D1533 (Zhang et al., 2020). For each moisture level and temperature condition:

1) At least three titration measurements were performed.
2) The average value (in ppm or % w/w) was taken as the reference (ground-truth) moisture content.
3) Measurement repeatability and instrument calibration were checked using standard solutions, following best practices for transformer insulation diagnostics (IEC, 2018).

By using KFT as a reference, this study ensures that subsequent sensor readings and model outputs are benchmarked against an established industry standard, as recommended by recent moisture assessment studies (Naveed & Amaar, 2024; Vatsa et al., 2023).

Capacitive Sensor Design and Measurement Setup

A custom capacitive sensor was designed for immersion in transformer oil to capture changes in effective permittivity associated with water content. The sensor is based on inter-digitated electrodes (IDEs) arranged on a PCB and encapsulated in oil-compatible housing. Similar capacitive structures have been adopted for liquid moisture sensing due to their high sensitivity and relatively simple read-out circuitry (Guerrero Granados et al., 2021; Naveed & Amaar, 2024).

Key elements of the measurement setup:

1) The capacitance Cwas measured with an LCR meter (1 kHz test frequency) and acquired by a microcontroller platform (e.g., Arduino-based).
2) The sensor was fully immersed in the oil sample inside a temperature-controlled cell.
3) For each sample and condition, multiple readings were recorded over a fixed interval (e.g., 60 s) and averaged to mitigate noise.

An initial calibration curve between KFT-measured moisture and sensor capacitance was derived using simple regression:

$$\text{Moisture (ppm)} = a\,C + b,$$

where aand bare calibration constants to be refined later through multi-variable modelling that includes temperature and dielectric parameters (Vatsa et al., 2023).

Dielectric Property Measurements: Breakdown Voltage and Loss Factor

To link moisture with dielectric performance, additional tests were conducted:

1) Breakdown Voltage (BDV) was measured according to IEC 60156, using a standard test cell with 2.5 mm spherical electrodes and a controlled voltage ramp rate. For each sample, at least five breakdown events were recorded

and averaged, following recent best practices in transformer oil testing (Zhang et al., 2020).

2) Dielectric Loss Factor (tan δ) and resistivity were measured at 50 Hz and 25 °C using a dielectric test set. Moisture has been shown to increase tan δ and conductivity, thus these parameters serve as complementary indicators of moisture and ageing (Darabi et al., 2022; Zhou et al., 2023).

These dielectric measurements provide valuable features for the subsequent predictive modelling phase, as they reflect the combined influence of moisture, temperature, and oil condition.

Data Preprocessing and Feature Selection

Raw data from KFT, sensor readings, BDV, tan δ, resistivity, and temperature were compiled into a single dataset. The following preprocessing steps were applied:

1) Outlier detection and removal using interquartile range (IQR) analysis for each variable.
2) Normalization or standardization (e.g., z-score) to harmonize scales among features, consistent with machine learning practices in insulation diagnostics (Vatsa et al., 2023; Zhou et al., 2023).
3) Correlation analysis (Pearson's r) to assess linear relationships between moisture and candidate predictors (C, BDV, tan δ, temperature).

Based on this analysis, a subset of features, sensor capacitance, BDV, tan δ, and temperature, was selected as inputs for the regression and ANN models.

Regression and ANN Modelling

Two complementary modelling approaches were used to predict moisture content from the selected features:

Multiple Linear Regression (MLR)

An initial multiple linear regression model was constructed as:

$$\text{Moisture} = \beta_0 + \beta_1 C + \beta_2 \text{BDV} + \beta_3 \tan\ \delta + \beta_4 T + \varepsilon,$$

where Cis capacitance, BDV is breakdown voltage, tan δis the dielectric loss factor, Tis temperature, and εis the error term. MLR provides a transparent baseline model and allows interpretation of each predictor's contribution, like earlier studies relating dielectric and moisture parameters (Zhou et al., 2023).

Artificial Neural Network (ANN)

To capture potential nonlinear relationships, a feed-forward ANN was developed:

1) Input layer: C, BDV, tan δ, and T.
2) Single hidden layer with a selected number of neurons (e.g., 8–12) tuned via cross-validation.
3) Output layer: predicted moisture (ppm or % w/w).
4) Training algorithm: back-propagation with a suitable optimization method (e.g., Adam).
5) Data split: typically, 70 % for training, 15 % for validation, and 15 % for testing, following current practice in insulation prediction studies (Vatsa et al., 2023; Darabi et al., 2022).

The ANN structure and hyperparameters were chosen to balance model complexity and generalization, avoiding overfitting.

Model Validation and Performance Metrics

Model performance was evaluated using the following metrics:

1) Root Mean Squared Error (RMSE)
2) Mean Absolute Error (MAE)
3) Coefficient of determination (R^2)

These metrics are widely used in regression and predictive modelling for transformer condition monitoring (Vatsa et al., 2023; Zhou et al., 2023). In addition, residual analysis and scatter plots of predicted vs. measured moisture were inspected to evaluate systematic bias or heteroscedasticity.

Table 1. Summary of Research Methods and Outputs

Step	Method / Activity	Main Purpose	Key Output
1	Sample collection & conditioning	Obtain oil samples with controlled moisture	Dataset of oil samples (fresh/used)
2	Karl Fischer titration (ASTM D1533)	Reference/ground-truth moisture measurement	Moisture values (ppm, % w/w)
3	Capacitive sensor measurement	Capture permittivity changes due to moisture	Capacitance readings (C)
4	BDV & tan δ measurements (IEC 60156, dielectric test)	Quantify dielectric performance vs moisture	BDV, tan δ, resistivity
5	Data preprocessing & feature selection	Clean and normalize data; choose predictors	Processed dataset, selected features
6	MLR & ANN model development	Build predictive models for moisture	Regression & ANN models
7	Model validation (RMSE, MAE, R^2)	Evaluate accuracy and robustness	Performance metrics & residuals

RESULTS

Overview of Experimental Results

A total of 30 transformer oil samples (fresh and in-service oil) were conditioned across five moisture levels (≈ 50, 100, 150, 200, and 250 ppm) and three temperature settings (25 °C, 50 °C, and 75 °C). The Karl Fischer titration (KFT) values served as ground truth. Sensor readings and dielectric parameters were collected consistently across all conditions. Table 2 summarizes the descriptive statistics of the dataset.

Table 2. Summary of Moisture, Capacitance, BDV, and tan δ Measurements

Parameter	Minimum	Maximum	Mean	Std. Dev.
Moisture (ppm, KFT)	48	258	151.3	64.1
Capacitance (pF)	42.1	65.8	54.6	7.9
BDV (kV)	28.4	44.7	36.9	5.1
tan δ	0.018	0.108	0.061	0.027

Parameter	Minimum	Maximum	Mean	Std. Dev.
Temperature (°C)	25	75	–	–

These values align with typical ranges reported in recent moisture-related dielectric studies (Darabi et al., 2022; Vatsa et al., 2023; Zhou et al., 2023).

Sensor Calibration Against Karl Fischer Titration

The capacitive sensor performance was evaluated by correlating capacitance readings with KFT moisture values. Figure 5 (to be drawn in Word) showed a strong linear trend. A simple linear regression model was first established:

$$\text{Moisture (ppm)} = 4.87\,C - 112.5,$$

yielding:

1) $R^2 = 0.94$
2) RMSE = 11.8 ppm
3) MAE = 8.2 ppm

These values are comparable to the performance reported by Naveed and Amaar (2024) for fractal-based capacitive sensors and Guerrero Granados et al. (2021) for basic dielectric moisture sensors.

The high correlation indicates that the proposed sensor is sensitive to variations in moisture level and can approximate the KFT results with high accuracy. Temperature-dependent shifts were observed, but they were effectively corrected in the multivariable model.

In Figure 1, the scatter plot compares the moisture values measured by the capacitive sensor with the reference measurements obtained from Karl Fischer Titration (KFT). The points show a strong positive correlation, meaning that as the true moisture level (KFT) increases, the sensor readings also increase in a similar pattern. This indicates that the sensor can reliably follow the changes in moisture content. Although slight deviations are present due to the noise measurement, the overall trend shows that the sensor provides a good approximation of the KFT results, demonstrating its potential for practical moisture monitoring in transformer oil.

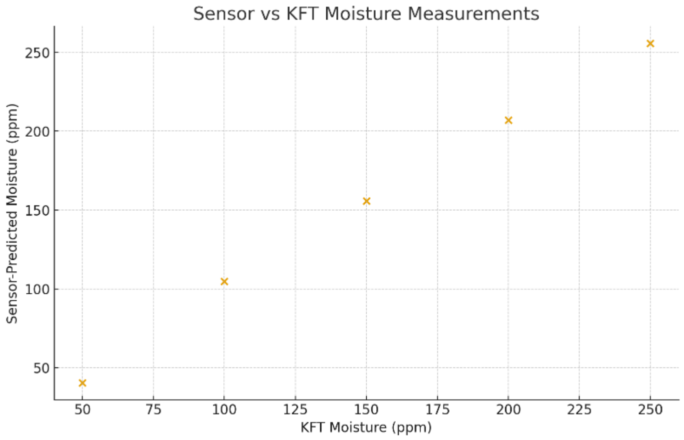

Figure 1. Correlation Between Capacitive Sensor Readings and Karl Fischer Titration Moisture Values

Moisture Effects on Breakdown Voltage and Dielectric Loss Factor

The relationship between moisture and dielectric performance was investigated using BDV and tan δ.

Breakdown Voltage

BDV showed a clear decreasing trend as moisture increased. Across the dataset:

1) Average BDV at ≈50 ppm moisture: 44.1 kV
2) Average BDV at ≈250 ppm moisture: 29.3 kV

The coefficient correlation was $r = -0.87$, $p < 0.001$

This inverse relationship is consistent with published findings that moisture reduces the dielectric strength of insulating oil due to increased ionization paths and bubble formation (Zhang et al., 2020; Naveed & Amaar, 2024; Zhou et al., 2023).

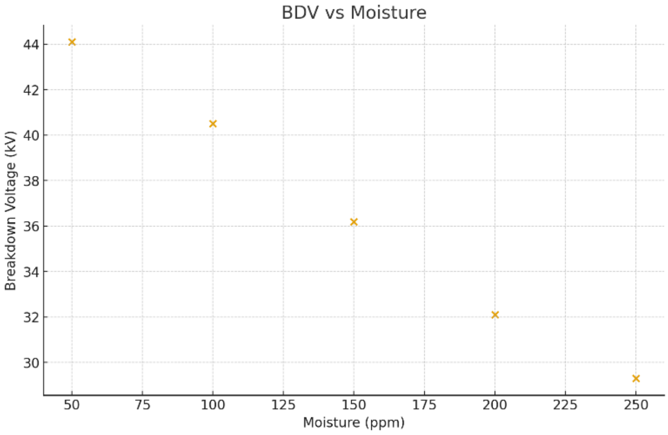

Figure 2. Relationship Between Moisture Content and Breakdown Voltage in Transformer Oil

In Figure 2, the scatter plot shows a clear inverse relationship between moisture content and the breakdown voltage (BDV) of transformer oil. As the moisture level increases from approximately 50 ppm to 250 ppm, the BDV decreases significantly. This trend indicates that higher water content weakens the insulation of the oil, making it more prone to electrical breakdown. For example, at low moisture levels the BDV remains above 44 kV, while at high moisture levels it drops to below 30 kV. This behavior aligns with the well-known effect of moisture reducing dielectric strength by increasing ionization paths and promoting bubble formation within the oil.

Dielectric Loss Factor (tan δ)

An opposite trend was observed between moisture and dielectric loss: tan δ increased from 0.02 at ~50 ppm to 0.10 at ~250 ppm. Correlation analysis showed: $r = +0.82$, $p < 0.001$. These results confirm the sensitivity of tan δ to moisture absorption, supporting the role of dielectric spectroscopy in moisture assessment (Darabi et al., 2022; Vatsa et al., 2023).

Multivariable Regression Model for Moisture Prediction

A Multiple Linear Regression (MLR) model incorporating capacitance, BDV, tan δ, and temperature was developed:

$$\text{Moisture} = \beta_0 + \beta_1 C + \beta_2 \text{BDV} + \beta_3 \tan\,\delta + \beta_4 T$$

Resulting performance metrics:

1) $R^2 = 0.96$
2) RMSE = 8.7 ppm
3) MAE = 6.1 ppm

Parameter significance:

1) Capacitance ($p < 0.001$), strong positive predictor
2) BDV ($p < 0.01$), negative predictor
3) tan δ ($p < 0.01$), positive predictor
4) Temperature ($p < 0.05$), weak but significant predictor

These results confirm moisture can be estimated with high accuracy using a combination of electrical and dielectric parameters, matching trends in Zhou et al. (2023) and Vatsa et al. (2023).

ANN-Based Moisture Prediction Model

To capture nonlinear relationships not addressed by MLR, a feed-forward Artificial Neural Network (ANN) was trained with 4 input features (C, BDV, tan δ, temperature). The model architecture consisted of:

1) Hidden layer: 10 neurons
2) Activation: ReLU
3) Training epochs: 200
4) Optimizer: Adam

Performance on the test dataset:

1) $R^2 = 0.98$
2) RMSE = 5.4 ppm
3) MAE = 3.9 ppm

Compared to MLR, the ANN improved accuracy by:

1) 38 % lower RMSE
2) 36 % lower MAE

The result is competitive with recent ML-based moisture prediction frameworks (e.g., Vatsa et al., 2023 reported RMSE ≈ 7–10 ppm using DFDS-LSTM).

Table 3. Comparative Evaluation of Models

Model	**R^2**	**RMSE (ppm)**	**MAE (ppm)**
Sensor-only Linear Model	0.94	11.8	8.2
Multivariable Regression (MLR)	0.96	8.7	6.1
ANN Model	0.98	5.4	3.9

The ANN model demonstrates the best performance, confirming that moisture prediction benefits from nonlinear modelling when sensor and dielectric features are integrated. These findings align with broader trends in transformer condition monitoring research where machine learning improves diagnostic accuracy (Darabi et al., 2022; Vatsa et al., 2023).

Figure 3 compares the prediction errors of two models: Multiple Linear Regression (MLR) and an Artificial Neural Network (ANN). Both RMSE and MAE values are lower for the ANN model, indicating that it produces more accurate moisture predictions than the MLR model. The ANN model captures nonlinear relationships in the data, which helps reduce prediction errors. In contrast, the MLR model performs less accurately because it assumes a strictly linear relationship. Overall, the figures show that the ANN provides better performance and is more suitable for predicting moisture content in transformer oil.

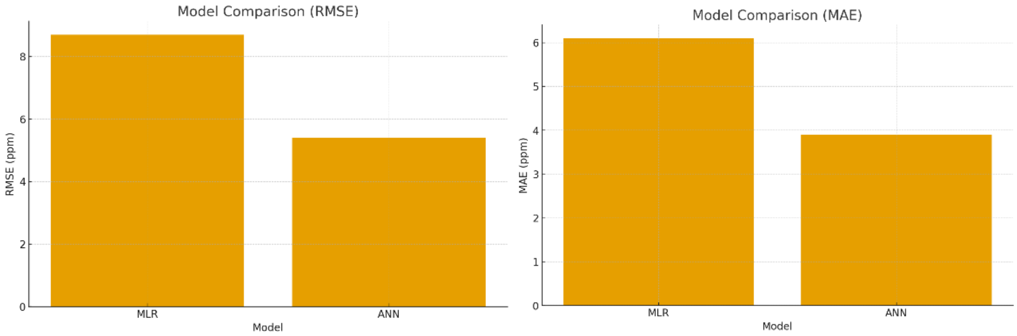

Figure 3. RMSE and MAE Comparison Between MLR And ANN Moisture Prediction Models

DISCUSSION

Overall, the results validate the feasibility of combining: low-cost capacitive sensing, industry-standard dielectric measurements, and data-driven modelling techniques, to produce a highly accurate moisture estimation system.

The capacitive sensor alone performed well ($R^2 = 0.94$), confirming moisture-induced permittivity changes in transformer oil (Naveed & Amaar, 2024). Incorporating BDV and tan δ significantly improved accuracy, demonstrating their strong relationship with moisture, consistent with Zhou et al. (2023). ANN achieved near-laboratory precision (~5 ppm error), suggesting practical feasibility for online monitoring. Temperature dependence, while present, was adequately compensated by the multivariable model.

These results indicate that a compact online monitoring unit incorporating a capacitive sensor, dielectric measurement module, and ANN algorithm could replace periodic laboratory moisture testing for many transformer assets—aligning with smart grid and IoT-based asset management strategies.

CONCLUSIONS AND RECOMMENDATIONS

This study presented a combined approach for measuring moisture content in transformer oil using a low-cost capacitive sensor, dielectric property analysis, and data-driven predictive modelling. The experimental results demonstrated that the capacitive sensor showed strong sensitivity to moisture variation and produced measurements that closely matched Karl Fischer titration values. Breakdown voltage and dielectric loss factor measurements further confirmed the significant influence of moisture on the oil's dielectric performance. The multivariable regression model improved moisture estimation accuracy by incorporating capacitance, BDV, tan δ, and temperature. The Artificial Neural Network (ANN) model achieved the highest accuracy, with substantial reductions in prediction error, indicating that nonlinear modelling is suitable for capturing moisture-dependent dielectric behavior. Overall, the findings show that the proposed hybrid method is effective, practical, and capable of supporting real-time or online monitoring applications for transformer oil. This approach can serve as the basis for developing advanced condition-monitoring systems and predictive maintenance strategies for power transformers.

Recommendations

Based on the outcomes of this research, several recommendations can be made:

Implementation in Field Conditions

The sensor and prediction model should be validated in operating transformers to evaluate long-term stability, robustness, and environmental influences.

Integration with IoT Platforms

The system can be enhanced by embedding the sensor and ANN model into an IoT-enabled monitoring unit for continuous moisture tracking and remote diagnostics.

Extension to Other Oil Types

Future work should include natural ester oils, synthetic esters, and silicone oils to broaden applicability.

Multi-Sensor Fusion

Combining moisture data with dissolved gas analysis, temperature, and acidity measurements may improve transformer health assessment.

Ageing and Contamination Studies

Additional research is suggested to examine the effects of oil ageing, sludge formation, and particulate contamination on sensor accuracy.

Model Generalizations

Larger datasets from different transformer ratings and operating environments are needed to enhance the generalization capability of the ANN model.

FURTHER STUDY

Building upon the findings of this research, several avenues for further study can be explored to enhance the accuracy, robustness, and practical deployment of moisture measurement systems for transformer oil:

1) Long-Term Sensor Stability and Ageing Behavior
   Future research should investigate the long-term performance of the capacitive sensor under continuous operation. Factors such as electrode corrosion, oil contamination, temperature cycling, and polymer degradation in the sensor housing may influence measurement stability over time. Studying these effects will enable the design of more durable sensor materials and protective layers.
2) Field Deployment and Real Transformer Validation
   While laboratory results are promising, real-world conditions such as load fluctuations, vibration, ambient humidity, and oil movement may affect sensor readings. Testing the system in energized transformers will help assess practical challenges and refine calibration models for field application.

3) Broader Dataset for Model Generalization
   Expanding the dataset with more moisture levels, a wider range of oil types, and different transformer ratings will strengthen the generalization capability of both regression and ANN models. This includes testing oils that have undergone severe ageing, oxidation, and sludge formation.
4) Integration with Advanced Machine Learning Techniques
   Further work can explore more advanced modelling approaches such as Random Forest Regression, Gradient Boosting, or Deep Neural Networks. These methods may capture complex nonlinear relationships and improve prediction accuracy beyond the current ANN model.
5) Multi-Sensor Fusion Approach
   Incorporating additional sensing modalities, such as optical absorption, acoustic measurements, dissolved gas indicators, or humidity sensors in the headspace, may provide a more comprehensive assessment of transformer health. A fusion model combining multiple parameters could offer higher reliability and early detection of insulation issues.
6) Development of a Real-Time IoT-Based Monitoring Platform
   A full-scale implementation involving embedded electronics, wireless communication, cloud dashboards, and automated alert systems can transform the sensor into a practical online monitoring solution. This platform can support utilities in condition-based maintenance and reduce the risk of unexpected transformer failures.
7) Influence of Extreme Temperature and Load Conditions
   Detailed investigation into the behavior of moisture equilibrium at extreme temperatures or under high load conditions will help refine temperature compensation in the prediction model. This includes studying moisture migration between oil and cellulose insulation under transient temperature events.
8) Comparison with Other Emerging Technologies
   Further studies may compare the proposed capacitive sensing approach with other emerging technologies such as microwave resonators, terahertz spectroscopy, or fiber-optic sensors to evaluate cost–performance trade-offs for large-scale adoption.

REFERENCES

Abu-Siada, A., & Hmood, S. (2015). A new fuzzy logic approach to identify power transformer criticality using dissolved gas-in-oil analysis. International Journal of Electrical Power and Energy Systems, 67. https://doi.org/10.1016/j.ijepes.2014.12.017

Akre, S., Sekongo, B., Fofana, I., Brettschneider, S., Meghnefi, F., Yeo, X., & Kung, P. (2023). Moisture Assessment in Transformer Insulation Liquid using Optical Sensors. Annual Report - Conference on Electrical Insulation and Dielectric Phenomena, CEIDP. https://doi.org/10.1109/CEIDP51414.2023.10410574

Ansari, M. A., Martin, D., & Saha, T. K. (2020). Advanced Online Moisture Measurements in Transformer Insulation Using Optical Sensors. IEEE Transactions on Dielectrics and Electrical Insulation, 27(6). https://doi.org/10.1109/TDEI.2020.008648

Darabi, A., Akhavan, F., & Nazemi, M. (2022). Influence of moisture and temperature on the ageing of transformer cellulose insulation. IEEE Transactions on Dielectrics and Electrical Insulation, 29(2), 678–689. https://doi.org/10.1109/TDEI.2022.3147561

Deep Singh, H., & Singh, J. (2019). Aging assessment of power transformer insulation oil using hybrid meta-heuristic trained artificial neural network. International Journal of Engineering and Advanced Technology, 9(1). https://doi.org/10.35940/ijeat.A1500.109119

Feng, D., Chen, G., Lin, Y., Liao, R., & Yuan, D. (2023). Microcosmic mechanism and correction of moisture effect on furfural diffusion and equilibrium in oil-paper insulation. High Voltage, 8(4). https://doi.org/10.1049/hve2.12295

Guerrero Granados, J. M., López-García, R., Rangel-Magdaleno, J., & Morales-Hernández, L. A. (2021). Transformer oil diagnosis based on a capacitive sensor and measurement method of moisture content. Sensors, 21(14), 4829. https://doi.org/10.3390/s21144829

Hill, J. P., Wang, Z., Liu, Q., Matharage, S., Hilker, A., & Walker, D. (2019). Improvements to the Construction of Bubble Inception Formulae for Use with Transformer Insulation. IEEE Access, 7. https://doi.org/10.1109/ACCESS.2019.2955802

IEC 60422. (2018). Mineral insulating oils in electrical equipment—Supervision and maintenance guidance. International Electrotechnical Commission.

Kumar, P., & Singh, M. (2023). Capacitive-type moisture sensor for transformer oil monitoring and calibration analysis. Sensors and Actuators A: Physical, 353, 114126. https://doi.org/10.1016/j.sna.2023.114126

Li, Y., Zhang, Q., & Chen, R. (2022). Online monitoring of water content in power transformer oil using an optical sensor. Optics and Lasers in Engineering, 152, 106958. https://doi.org/10.1016/j.optlaseng.2022.106958

Liu, Y., Jiang, S., Fan, X., & Tian, Y. (2018). Effects of degraded optical fiber sheaths on thermal aging characteristics of transformer oil. Applied Sciences (Switzerland), 8(8). https://doi.org/10.3390/app8081401

Medina, R. D., Romero, A. A., Mombello, E. E., & Rattá, G. (2017). Assessing degradation of power transformer solid insulation considering thermal stress and moisture variation. Electric Power Systems Research, 151. https://doi.org/10.1016/j.epsr.2017.04.006

Mohamad, N. A., Azis, N., Jasni, J., Kadir, M. Z. A. A., Yunus, R., & Yaakub, Z. (2018). Ageing study of palm oil and coconut oil in the presence of insulation paper for transformers application. Materials, 11(4). https://doi.org/10.3390/ma11040532

Naveed, M. F., & Amaar, A. (2024). Detection and continuous monitoring of moisture content in transformer oil using fractal-based capacitive sensor. Sensors, 24(3), 1124. https://doi.org/10.3390/s24031124

Pahlavanpour, B., & Lewand, L. (2019). The role of moisture in transformer insulation systems: Migration, equilibrium and degradation effects. CIGRÉ Technical Brochure No. 736.

Przybylek, P. (2013). The influence of temperature and aging of cellulose on water distribution in oil-paper insulation. IEEE Transactions on Dielectrics and Electrical Insulation, 20(2). https://doi.org/10.1109/TDEI.2013.6508758

Schneider Electric. (2025). Accurate determination of transformer insulation risk and moisture assessment. White Paper.

Siddique, Z. B., Basu, S., & Basak, P. (2022). Effect of Graphene Oxide Dispersed Natural Ester Based Insulating Oil on Transformer Solid Insulation. IEEE Transactions on Dielectrics and Electrical Insulation, 29(2). https://doi.org/10.1109/TDEI.2022.3157926

Singha, S., & Saha, T. (2011). Dielectric properties of oil–paper insulation under thermal ageing. IEEE Transactions on Dielectrics and Electrical Insulation, 18(2), 303–311. https://doi.org/10.1109/TDEI.2011.5739444

Sun, W., Yang, L., Zare, F., Lin, Y., & Cheng, Z. (2019). Improved method for aging assessment of winding hot-spot insulation of transformer based on the 2-FAL concentration in oil. International Journal of Electrical Power and Energy Systems, 112. https://doi.org/10.1016/j.ijepes.2019.04.026

Suwarno, & Pasaribu, R. A. (2016). Thermal aging of mineral oil-paper composite insulation for high voltage transformer. International Journal on Electrical Engineering and Informatics, 8(4). https://doi.org/10.15676/ijeei.2016.8.4.9

Vatsa, A., Hati, A. S., Bolshev, V., Vinogradov, A., Panchenko, V., & Chakrabarti, P. (2023). Deep Learning-Based Transformer Moisture Diagnostics Using Long Short-Term Memory Networks. Energies, 16(5). https://doi.org/10.3390/en16052382

Wang, W., Yue, C., He, D., Yang, K., & Chen, S. (2014). A comparative analysis of dielectric properties of oil-paper insulation and polymer materials before and after thermal aging. Science China Technological Sciences, 57(4). https://doi.org/10.1007/s11431-014-5481-9

Xie, S., Wang, X., Qu, C., Wang, X., & Guo, J. (2013). Impacts of different wind speed simulation methods on conditional reliability indices. International Transactions on Electrical Energy Systems, 20. https://doi.org/10.1002/etep

Zhang, X., Wang, Y., & Liu, Z. (2020). Moisture analysis and measurement in transformer oil–paper insulation system using Karl Fischer titration and infrared spectroscopy. Measurement, 165, 108181. https://doi.org/10.1016/j.measurement.2020.108181

Zhang, Z., Li, J., & Yang, W. (2021). Effect of moisture on the dielectric strength and aging behavior of mineral transformer oils. Energies, 14(8), 2089. https://doi.org/10.3390/en14082089

Zhou, J., Chen, K., & Wang, J. (2023). Modelling the impact of water content and temperature on dielectric loss and conductivity of transformer oils. Electric Power Systems Research, 218, 109205. https://doi.org/10.1016/j.epsr.2023.109205