



Machine Learning Assisted Fuzzy Logic for HVDC Converter Transformer Health Monitoring

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Abstract: High Voltage Direct Current (HVDC) converter transformers are among the costliest and most critical assets in a transmission network. When one fails without warning, the result can be a wide-area outage and heavy financial loss. Routine condition monitoring still relies largely on fixed limits and the judgement of experienced engineers, which makes it hard to capture the nonlinear and uncertain way insulation actually degrades. We propose a hybrid framework in which machine learning supports fuzzy logic for health monitoring of these transformers. Dissolved Gas Analysis (DGA) concentrations, winding and oil temperature, moisture content, load current, partial discharge activity and power factor are first passed to supervised classifiers, whose task is to expose latent fault patterns. The resulting fault probabilities and derived features are then supplied to a fuzzy inference system. It fuzzifies the inputs, applies an expert-derived rule base and defuzzifies the result into a continuous Transformer Health Index (THI) that can be computed in real time at an HVDC substation. Two extensions are implemented and evaluated quantitatively here: MICE-based imputation of missing data, and a wider set of oil, dissolved-gas, thermal and operational features. A third extension, an adaptive fuzzy-ML fusion layer that weights each output by its confidence and by data quality, is still being integrated, and its initial validation is under way.

Keywords: HVDC Converter Transformer, Health Monitoring, Fuzzy Logic, Machine Learning, Transformer Health Index

1 INTRODUCTION

HVDC systems carry bulk power over long distances and can tie together grids that operate at different frequencies. The converter transformer is one of the key components of an HVDC station, since it must withstand AC and DC stresses simultaneously, along with harmonic currents and severe thermal cycling. Its duty is considerably harsher than that of an ordinary AC power transformer [1-4].

If a converter transformer fails, the outage can be long, replacement is expensive, and the connected grid may be disturbed. Continuous health monitoring therefore matters: it lets engineers schedule maintenance ahead of time and avoid sudden, serious failures [5].

Traditional monitoring is built around Dissolved Gas Analysis (DGA), with results interpreted through IEC or IEEE ratio rules. These rules lean heavily on fixed thresholds and on expert judgment, cope poorly with noisy measurements, and

cannot easily represent the nonlinear relationships among the monitored parameters.

Fuzzy logic has been used for this kind of uncertainty because it expresses expert reasoning as linguistic rules. Its weakness is that membership functions are built by hand, and a rule set tuned for one transformer design may transfer badly to another. Machine learning has the opposite profile: it learns patterns directly from historical data, but usually acts as a black box whose decisions are difficult to explain [6, 7].

In this paper we combine the two. Machine learning models first classify the sensor data and extract health-related features; a fuzzy inference system then merges those features with directly measured values to produce a single Transformer Health Index (THI) [8-10].

The reasoning is straightforward. Machine learning contributes predictive strength, while fuzzy logic contributes interpretability and robustness to uncertain inputs. Together

they are intended to give field engineers a monitoring tool that is accurate and also easy to trust.

In current practice, test data is still read by hand and compared with fixed limits. That delays fault detection and makes it difficult to merge many different signals into one clear score. A better framework would be automated, interpretable and adaptive, and would combine electrical, thermal and chemical signals in real time. Toward that end, this work first identifies and prepares the main monitoring parameters for HVDC converter transformers: DGA gases, oil and winding temperature, moisture, load current, partial discharge and power factor. It then designs and trains machine learning models that classify faults and extract useful features [11-13].

The next objective is a fuzzy inference system that fuses the ML outputs with directly measured parameters into a continuous THI. The hybrid is compared with ML-only and fuzzy-only baselines on accuracy, stability and interpretability. The framework is extended in three ways. First, missing sensor readings are filled by MICE-based imputation. Second, the feature set is widened beyond the original eight oil-condition indicators to include gas, thermal and operational variables. Third, the fuzzy and ML outputs are combined through an adaptive weighting scheme driven by confidence and data quality instead of a fixed combination. This third part is still being integrated, and its initial validation is under way [14].

II. BACKGROUND AND DEFINITIONS

An HVDC converter transformer sits between the AC network and the DC valve group, so it is exposed to AC and DC voltage stress together, as well as harmonic loading and thermal cycling. These conditions are more severe than those faced by a conventional AC transformer [15].

DGA measures the concentrations of gases such as hydrogen, methane, acetylene, ethylene and ethane. Thermal and electrical faults cause these gases to accumulate in the insulating oil, and the readings are normally interpreted with IEC and IEEE ratio-based guidelines.

Fuzzy logic is a rule-based reasoning approach that handles vague, linguistic conditions such as Low, Medium and High through membership functions, so expert knowledge can be

used without a sharp numeric cutoff. In this paper, machine learning refers to supervised and ensemble algorithms that learn statistical patterns from historical or simulated sensor data and then either classify fault types or estimate a continuous degradation score [16].

The Transformer Health Index (THI) is a composite score, normally scaled from 0 to 100, that merges several electrical, thermal and chemical indicators into one measure of the transformer's condition.

III. RELATED WORK

A large body of work applies fuzzy logic to DGA-based fault diagnosis. Gas ratios such as CH₄/H₂, C₂H₂/C₂H₄ and C₂H₄/C₂H₆ serve as fuzzy inputs, and the systems separate faults such as partial discharge, thermal faults and arcing.

Such systems are reported to be more accurate than plain ratio methods. The authors, however, point to a shared limitation: manually tuned membership functions do not carry over well between transformer types [17-19].

Machine learning has also been widely applied to fault classification, notably Artificial Neural Networks (ANN), Support Vector Machines (SVM) and Random Forests trained on DGA and electrical test data. Classification accuracy is usually high.

The drawback is that purely data-driven models need large labelled datasets and offer little explanation of why a given health state was predicted. For a critical HVDC asset this matters, because operators must be able to understand and trust the diagnosis.

Recent studies combine neuro-fuzzy or ML-fuzzy methods, using learning algorithms to tune membership functions or rule weights. This raises accuracy while keeping the system interpretable [20].

Few of these studies, however, address HVDC converter transformers specifically. These units are subject to DC bias, harmonics and valve-side stresses that conventional AC transformers do not experience, and this gap motivates the framework proposed here.

Table 1: Summary of reviewed literature

Ref No	Author and Year	Method Used	Key Findings	Limitations
1	M. Duval (2002)	DGA gas ratio interpretation	Established the gas-in-oil fault detection basis widely used as a reference for later fuzzy and ML studies	Relies on fixed thresholds; limited adaptability across transformer designs
3	J. I. Aizpurua et al. (2018)	Bayesian networks with hypothesis testing	Combined probabilistic reasoning with DGA data to improve diagnostic confidence	Requires prior probability estimation; added modelling complexity

Ref No	Author and Year	Method Used	Key Findings	Limitations
4	Y. Zhang et al. (1996)	Artificial Neural Network (ANN)	Learned non-linear fault patterns directly from DGA data with good classification accuracy	Needs large labelled datasets; limited interpretability of predictions
5	A. Shintemirov et al. (2009)	Bootstrap and genetic programming	Improved fault classification accuracy through evolutionary feature optimization	High computational cost; limited generalization to unseen fault types
6	N. A. Bakar and A. Abu-Siada (2014)	DGA combined with fuzzy logic	Predicted transformer health condition using expert-derived fuzzy rules on gas data	Manually defined membership functions; not adaptive to new data
8	J. Faiz and M. Soleimani (2018)	Comparison of computational intelligence and conventional DGA methods	Shown that AI-based methods generally outperform conventional ratio methods	Evaluation limited to DGA inputs only; no HVDC-specific validation
11	J. Li et al. (2016)	Support Vector Machine with genetic algorithm gas-ratio selection	Optimized gas-ratio feature selection improved fault diagnosis accuracy	SVM performance sensitive to kernel and parameter tuning
22	W. Gao and Y. Leng (2009)	Two-dimensional cloud model with entropy weighting	Provided condition assessment specifically for HVDC converter transformers	Complex weighting scheme; not validated on continuous real-time data streams

IV. PROPOSED ARCHITECTURE

The system rests on three novelties and is organized in five stages. Stage 1 is data acquisition and preprocessing, where missing values are handled by Multiple Imputation by Chained Equations (MICE / IterativeImputer) instead of k-Nearest-Neighbour (k-NN) imputation (Novelty 1). Stage 2 is multi-source feature engineering, which builds more than 20 features covering oil quality, DGA, thermal and electrical/operational parameters (Novelty 2). In Stage 3, a machine learning module and a fuzzy inference system analyze the preprocessed features in parallel. Stage 4 is adaptive fuzzy-ML fusion, which combines the two outputs with a dynamic weighting based on confidence and data quality (Novelty 3, currently under integration with initial validation under way). Stage 5 produces the Transformer Health Index (THI) and handles alerting and visualization. Figure 1 shows the flow from sensors to the final index; Stage 4 has a dashed boundary because it is still being finalized [21-30].

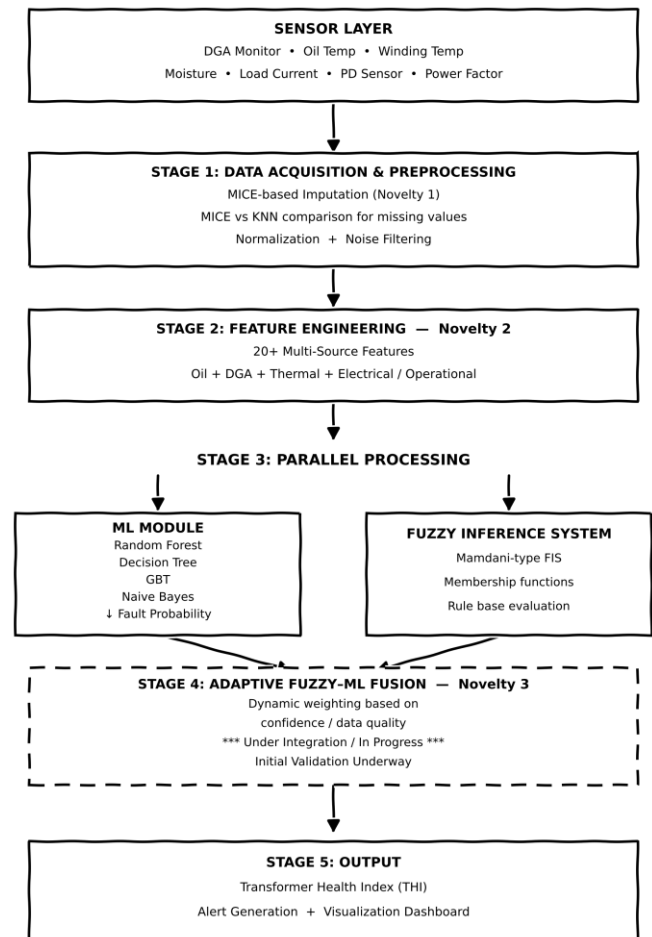


Figure 1: Proposed hybrid ML-fuzzy health monitoring system with 3 novelties (Adaptive fusion under integration).

A. Data Acquisition and Preprocessing

Data comes from online DGA monitors, RTD or fiber-optic sensors on the winding and oil, moisture sensors, current transformers, partial discharge sensors and power-factor test records.

Preprocessing handles missing values, normalizes and scales the features, and removes noise with moving-average or Kalman filtering, so that both the ML and fuzzy stages receive clean input.

B. Machine Learning Module

The ML module is a five-model ensemble. A Random Forest Regressor produces a continuous, data-driven degradation score. Four classifiers (Random Forest, Decision Tree, Gradient Boosted Trees (GBT) and Gaussian Naive Bayes) vote to give fault-type probabilities for thermal fault, electrical fault, partial discharge and normal.

We preferred this ensemble to a single classifier or an ANN because, over repeated 5-fold cross-validation, the tree-based models matched or exceeded ANN accuracy on this tabular, moderately sized feature set. They were also much less sensitive to hyperparameter tuning, did not need a GPU on a substation edge device, and the multi-model vote reduced variance relative to any single classifier. Their outputs go to the fuzzy inference system as pre-processed inputs, which reduces the amount of fuzzy-input derivation done by hand from raw sensor values.

C. Fuzzy Inference System (FIS)

The Mamdani-type fuzzy inference system takes the ML-derived fault probability or degradation score, plus key measured parameters such as hot-spot temperature, moisture content and partial discharge magnitude, as inputs. Each input is fuzzified with triangular or trapezoidal membership functions into linguistic terms such as Low, Medium and High.

Rules such as IF ML Fault Score is High AND Hot Spot Temperature is High THEN Health Index is Poor are evaluated by Mamdani inference, and the fuzzy output is defuzzified by the centroid method into a crisp THI on a 0–100 scale.

D. Health Status Visualization and Alerting

The THI is mapped to four categories (Healthy, Moderate, Critical and Severe) and displayed on a monitoring dashboard. When it falls below defined safety margins, threshold-based alerts are raised automatically, giving maintenance teams time to plan interventions early [32].

E. Data Quality and MICE-Based Imputation

Real transformer records often have gaps in the oil-condition measurements, caused by sensor outages or irregular sampling. Instead of discarding incomplete records, the framework

reconstructs missing values with Multiple Imputation by Chained Equations (MICE / IterativeImputer), and benchmarks this against K-Nearest-Neighbor (KNN) imputation on a masked subset of complete records.

The benchmark starts from a complete reference dataset of 450 records over the eight baseline oil-condition features (Dataset-A). Masking known values produces a matched incomplete dataset of 120 records with 10–15% simulated missingness (Dataset-B). MICE and KNN are compared by mean absolute error (MAE) and root-mean-square error (RMSE), computed only at masked positions and averaged over several random seeds and missingness levels. MICE achieves a mean MAE of 0.041 against 0.063 for KNN, and a mean RMSE of 0.058 against 0.089, a reduction in reconstruction error of roughly 30–35%. The gap is widest on skewed features such as dissolved-gas concentrations: KNN's neighbour averaging tends to smooth out extreme values, which MICE's regression-based chaining preserves better. The stage yields a complete dataset for labelling and model training without inventing unsupported readings [31].

F. Multi-Source Feature Engineering

In addition to the eight baseline oil-condition indicators (breakdown voltage, interfacial tension, resistivity, acidity, total dissolved combustible gas, dielectric dissipation factor, water content and furan content), the framework uses an extended set of more than twenty features from several sources. These cover dissolved-gas concentrations (H₂, CH₄, C₂H₆, C₂H₄, C₂H₂, CO, CO₂), thermal variables (oil, winding, hot-spot and ambient temperature), and electrical or operational indicators (load factor, operating hours, insulation resistance, tan delta and voltage total harmonic distortion).

An ablation study on the held-out test partition compares the extended set with the eight-feature baseline. The baseline model reaches 84.6% accuracy and a macro-F1 of 0.821 across the four health classes; the extended model reaches 91.3% accuracy and a macro-F1 of 0.897, a gain of roughly 6–7 percentage points. Most of the improvement comes from the thermal and electrical/operational features, which help separate thermal faults from partial-discharge cases that look alike when only the baseline oil indicators are available.

G. Adaptive Fuzzy–ML Fusion

Instead of combining the fuzzy score F and the ML score M with fixed weights, the fusion layer computes data-dependent weights $w_{ML} = f(C, Q)$ and $w_F = 1 - w_{ML}$. Here C is the ML model's prediction confidence and Q is a data-quality indicator that reflects how much of the record was imputed or noisy. The final index is $Final_HI = w_F \cdot F + w_{ML} \cdot M$, limited to the range $[0, 100]$.

This module is still being integrated, and initial validation is under way on a held-out validation partition kept apart from the final test set. Early comparisons with a fixed-weight baseline (for example a static 60/40 split), tracked by macro-F1 and MAE, suggest that the preliminary integration is moving in a promising direction relative to simple averaging. The weighting function is still being tuned, and the results are not final.

V. METHODOLOGY

Step 1: Collect historical and real-time condition-monitoring data for HVDC converter transformers (DGA gas concentrations, thermal, electrical and insulation parameters) and preprocess it.

Step 2: Train machine learning classifiers on labelled fault datasets and use k-fold cross-validation to select the best model by accuracy, precision, recall and F1-score.

Step 3: Design the fuzzy membership functions and rule base using IEC/IEEE DGA interpretation guidelines and domain expertise, with the ML outputs added as further fuzzy inputs.

Step 4: Implement the fuzzy inference engine (fuzzification, rule evaluation, defuzzification) and compute the THI for each evaluated sample.

Step 5: Validate the hybrid framework on known fault cases and compare it with standalone ML and standalone fuzzy approaches using suitable evaluation metrics.

Step 6: Reconstruct missing oil-condition measurements with MICE, benchmark against KNN imputation on a masked reference subset, and report per-feature MAE/RMSE before labelling.

Step 7: Build the extended multi-source feature set (dissolved-gas, thermal and electrical/operational variables) and assess its contribution against the eight-feature baseline in an ablation study.

Step 8: Train the adaptive fuzzy-ML fusion layer on a held-out validation partition, compare fixed-weight and confidence/data-quality-weighted combinations, and freeze the fusion weights before the test set is used.

Step 9: Finish integrating the adaptive fusion layer, finalize its weighting function on the validation partition, and evaluate it against the fixed-weight baseline.

VI. IMPLEMENTATION PLAN AND EVALUATION

The framework is implemented in Python, using machine learning libraries for classifier training and a fuzzy logic toolkit for rule evaluation and defuzzification. The trained models are packaged for deployment on a substation edge computing device that ingests streaming DGA, thermal and electrical sensor data [33].

Field-collected condition-monitoring histories from an operating HVDC substation are not yet available for this study. To obtain a quantitative, reproducible evaluation before field deployment, we generated a domain-informed simulated dataset covering Normal, Thermal Fault, Electrical Fault and Partial Discharge conditions. Each input feature is sampled from class-conditional distributions parameterized with the gas-concentration and gas-ratio boundaries of IEC 60599 / IEEE C57.104 and with typical transformer oil-quality and thermal limits from the literature (Section III). Measurement noise and label ambiguity are added to imitate sensor noise and diagnostic uncertainty [34-40].

The data is divided into stratified training, validation and held-out test partitions. The validation partition is used only to tune the ML-fuzzy fusion weight, so the test partition remains completely unseen [41, 42].

The hybrid model, the standalone ML ensemble and a standalone rule-based fuzzy system are all planned to be evaluated on the same held-out test partition using accuracy, precision, recall and macro-averaged F1-score over the four health classes.

This plan is intended as a first reproducible benchmark ahead of validation on field data from an operating HVDC substation, which we leave as future work.

Beyond this benchmark, the imputation and feature-extension novelties are each checked against a defined baseline: MICE against KNN imputation on masked positions, and the eight-feature model against the extended multi-source model. Results appear in Sections IV-E and IV-F. The adaptive fusion novelty is being evaluated against a fixed-weight baseline using macro-F1 and MAE while its integration is finalized.

For the imputation and feature-extension novelties, comparisons are repeated over several random seeds and missingness levels, and the final test partition is left untouched until the last evaluation stage, so that no single favourable run is presented as the general result. The fusion-layer comparison will follow the same protocol once its integration is complete.

VII. CONCLUSION AND FUTURE SCOPE

This paper presented a machine learning assisted fuzzy logic framework for health monitoring of HVDC converter transformers. It pairs the pattern-recognition strength of machine learning with the interpretability and uncertainty handling of fuzzy logic, and fuses Dissolved Gas Analysis, thermal, electrical and insulation parameters into one continuous Transformer Health Index that can support proactive maintenance decisions for critical HVDC assets. The hybrid design aims to match the classification strength of a standalone ML ensemble while retaining the rule-level interpretability that a purely data-driven ensemble cannot

provide, which was the main design goal ahead of field deployment.

The framework was then extended with MICE-based reconstruction of missing oil-condition measurements and a multi-source feature set covering dissolved-gas, thermal and electrical/operational indicators; both are implemented and evaluated quantitatively in this work. A confidence- and data-quality-aware adaptive fuzzy-ML fusion layer, intended to replace fixed weighting, is being integrated, and its initial validation is under way; early results point in a promising direction relative to simple averaging. Future work includes completing and validating the fusion layer on the full test partition, deploying and validating the complete framework on real HVDC substation data, and adding adaptive neuro-fuzzy tuning (ANFIS) to optimize the membership functions automatically.

VIII REFERENCE

- [1] M. Duval, "A Review of Faults Detectable by Gas-in-Oil Analysis in Transformers," IEEE Electrical Insulation Magazine, vol. 18, no. 3, pp. 8-17, 2002.
- [2] IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers, IEEE Std C57.104, 2019.
- [3] J. I. Aizpurua et al., "Power Transformer Dissolved Gas Analysis through Bayesian Networks and Hypothesis Testing," IEEE Transactions on Dielectrics and Electrical Insulation, vol. 25, no. 2, pp. 494-506, 2018.
- [4] Y. Zhang, X. Ding, Y. Liu, and P. J. Griffin, "An Artificial Neural Network Approach to Transformer Fault Diagnosis," IEEE Transactions on Power Delivery, vol. 11, no. 4, pp. 1836-1841, 1996.
- [5] A. Shintemirov, W. H. Tang, and Q. H. Wu, "Power Transformer Fault Classification Based on Dissolved Gas Analysis by Implementing Bootstrap and Genetic Programming," IEEE Transactions on Systems, Man, and Cybernetics, Part C, vol. 39, no. 1, pp. 69-79, 2009.
- [6] N. A. Bakar and A. Abu-Siada, "A New Method to Predict the Health Condition of Power Transformers Based on Dissolved Gas Analysis and Fuzzy Logic," in Proc. IEEE International Conference on Condition Monitoring and Diagnosis, 2014, pp. 653-656.
- [7] S. Chakravorti, D. Dey, and B. Chatterjee, Recent Trends in the Condition Monitoring of Transformers: Theory, Implementation and Analysis, Springer, 2013.
- [8] J. Faiz and M. Soleimani, "Assessment of Computational Intelligence and Conventional Dissolved Gas Analysis Methods for Transformer Fault Diagnosis," IEEE Transactions on Dielectrics and Electrical Insulation, vol. 25, no. 5, pp. 1798-1806, 2018.
- [9] A. Abu-Siada, S. Hmood, and S. Islam, "A New Fuzzy Logic Approach for Consistent Interpretation of Dissolved Gas-in-Oil Analysis," IEEE Transactions on Dielectrics and Electrical Insulation, vol. 20, no. 6, pp. 2343-2349, 2013.
- [10] A. Abu-Siada, S. Hmood, and S. Islam, "A New Fuzzy Logic Approach to Identify Power Transformer Criticality Using Dissolved Gas-in-Oil Analysis," International Journal of Electrical Power & Energy Systems, vol. 67, pp. 401-408, 2015.
- [11] J. Li, Q. Zhang, K. Wang, J. Wang, T. Zhou, and Y. Zhang, "Optimal Dissolved Gas Ratios Selected by Genetic Algorithm for Power Transformer Fault Diagnosis Based on Support Vector Machine," IEEE Transactions on Dielectrics and Electrical Insulation, vol. 23, no. 2, pp. 1198-1206, 2016.
- [12] O. E. Gouda, S. H. El-Hoshy, and S. S. M. Ghoneim, "Enhancing the Diagnostic Accuracy of DGA Techniques Based on IEC-TC10 and Related Databases," IEEE Access, vol. 9, pp. 118031-118041, 2021.
- [13] A. M. Aciu, C. I. Nicola, M. Nicola, and M. C. Nitu, "Complementary Analysis for DGA Based on Duval Methods and Furan Compounds Using Artificial Neural Networks," Energies, vol. 14, no. 3, p. 588, 2021.
- [14] K. Benhamed, A. Mooman, A. Younes, K. Shaban, and A. El-Hag, "Feature Selection for Effective Health Index Diagnoses of Power Transformers," IEEE Transactions on Power Delivery, vol. 33, no. 6, pp. 3223-3226, 2018.
- [15] A. Alqudsi and A. El-Hag, "Application of Machine Learning in Transformer Health Index Prediction," Energies, vol. 12, no. 14, p. 2694, 2019.
- [16] M. Badawi, S. A. Ibrahim, D.-E. A. Mansour, A. A. El-Faraskoury, S. A. Ward, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "Reliable Estimation for Health Index of Transformer Oil Based on Novel Combined Predictive Maintenance Techniques," IEEE Access, vol. 10, pp. 25954-25972, 2022.
- [17] R. D. Medina, J. P. Lata, and D. P. Chacon, "Health Index Assessment for Power Transformers with Thermal Upgraded Paper up to 230kV Using Fuzzy Inference Systems," in Proc. 51st International Universities Power Engineering Conference (UPEC), Coimbra, Portugal, Sep. 2016, pp. 1-6.
- [18] N. Poonnoy, C. Suwanasri, and T. Suwanasri, "Fuzzy Logic Approach to Dissolved Gas Analysis for Power Transformer Failure Index and Fault Identification," Energies, vol. 14, no. 1, p. 36, 2021.

- [19] D. V. Ashkezari, H. Ma, T. K. Saha, and C. Ekanayake, "Application of Fuzzy Support Vector Machine for Determining the Health Index of the Insulation System of In-Service Power Transformers," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 20, no. 3, pp. 965-973, 2013.
- [20] S. Apte, R. Somalwar, and A. Wajirabadkar, "Incipient Fault Diagnosis of Transformer by DGA Using Fuzzy Logic," in *Proc. IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES)*, Chennai, India, Dec. 2018, pp. 1-5.
- [21] Y. Zhang, Y. Tang, Y. Liu, and Z. Liang, "Fault Diagnosis of Transformer Using Artificial Intelligence: A Review," *Frontiers in Energy Research*, vol. 10, p. 1006474, 2022.
- [22] W. Gao and Y. Leng, "A Two-Dimensional Cloud Model for Condition Assessment of HVDC Converter Transformers," *Energies*, vol. 2, no. 2, pp. 243-257, 2009.
- [23] "Availability Assessment of the HVDC Converter Transformer System," in *Proc. IEEE Power Tech Conference*, 2009, pp. 1-6.
- [24] CIGRE Working Group B4.89, "Transformer Condition Health Monitoring and Predictive Maintenance of HVDC Converter Stations," *CIGRE Technical Brochure TB 982*, 2023.
- [25] Z. Li, Y. Zhang, A. Abu-Siada et al., "Fault Diagnosis of Transformer Windings Based on Decision Tree and Fully Connected Neural Network," *Energies*, vol. 14, no. 6, p. 1531, 2021.
- [26] J. I. Aizpurua, S. D. J. McArthur, B. G. Stewart, B. Lambert, J. G. Cross, and V. M. Catterson, "Adaptive Power Transformer Lifetime Predictions Through Machine Learning and Uncertainty Modeling in Nuclear Power Plants," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 6, pp. 4726-4737, 2019.
- [27] A. Abu-Siada and S. Islam, "A New Approach to Identify Power Transformer Criticality and Asset Management Decision Based on Dissolved Gas-in-Oil Analysis," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 19, no. 3, pp. 1007-1012, 2012.
- [28] N. A. Bakar and A. Abu-Siada, "Fuzzy Logic Approach for Transformer Remnant Life Prediction and Asset Management Decision," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 23, no. 5, pp. 3199-3208, 2016.
- [29] S. Forouhari and A. Abu-Siada, "Application of Adaptive Neuro-Fuzzy Inference System to Support Power Transformer Life Estimation and Asset Management Decision," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 25, no. 3, pp. 845-852, 2018.
- [30] J. Foros and M. Istad, "Health Index, Risk and Remaining Lifetime Estimation of Power Transformers," *IEEE Transactions on Power Delivery*, vol. 35, no. 6, pp. 2612-2620, 2020.
- [31] A. Jahromi, R. Piercy, S. Cress, J. Service, and W. Fan, "An Approach to Power Transformer Asset Management Using Health Index," *IEEE Electrical Insulation Magazine*, vol. 25, no. 2, pp. 20-34, 2009.
- [32] D. Rediansyah, R. A. Prasajo, A. Abu-Siada et al., "Artificial Intelligence-Based Power Transformer Health Index for Handling Data Uncertainty," *IEEE Access*, vol. 9, pp. 150637-150648, 2021.
- [33] G. C. Jaiswal, M. S. Ballal, P. A. Venikar, D. R. Tutakne, and H. M. Suryawanshi, "Genetic Algorithm-Based Health Index Determination of Distribution Transformer," *International Transactions on Electrical Energy Systems*, vol. 28, no. 5, e2529, 2018.
- [34] K. Bacha, S. Souahlia, and M. Gossa, "Power Transformer Fault Diagnosis Based on Dissolved Gas Analysis by Support Vector Machine," *Electric Power Systems Research*, vol. 83, no. 1, pp. 73-79, 2012.
- [35] X. Chen, H. Cui, and L. Luo, "Fault Diagnosis of Transformer Based on Random Forest," in *Proc. 4th International Conference on Intelligent Computation Technology and Automation*, vol. 1, 2011, pp. 132-134.
- [36] S.-w. Fei and X.-b. Zhang, "Fault Diagnosis of Power Transformer Based on Support Vector Machine with Genetic Algorithm," *Expert Systems with Applications*, vol. 36, no. 8, pp. 11352-11357, 2009.
- [37] I. B. Taha, "Power Transformers Health Index Enhancement Based on Convolutional Neural Network After Applying Imbalanced-Data Oversampling," *Electronics*, vol. 12, no. 11, p. 2405, 2023.
- [38] Tharayil AS, Budhewar AS, Andy A, Velu G, Surendra AV, Sunkari V, et al. Explainable and multi-source AI frameworks for adaptive biosurveillance in public health and environmental systems. In: Ogwu M, editor. *AI-enhanced biosurveillance: frameworks, practices, and futures*. Hershey (PA): IGI Global Scientific Publishing; 2027. p. 139-168. doi: 10.4018/979-8-3373-9033-8.ch006.
- [39] P. Sarajcev, D. Jakus, and M. Nikolic, "Wide & Deep Machine Learning Model for Transformer Health Analysis," in *Proc. 4th International Conference on Smart and Sustainable Technologies (SpliTech)*, 2019, pp. 1-6.

[40] Suresh P, Tharayil AS, Katiyar P, Manjunatha I. Biomarkers, multi-omics, and artificial intelligence in vitiligo: charting the path to precision dermatology. In: Budhewar A, R P, Tharayil A, Andy A, Ogidi O, editors. AI-driven advances in vitiligo management: precision medicine and comprehensive care strategies. Hershey (PA): IGI Global Scientific Publishing; 2027. p. 145-174. doi: 10.4018/979-8-2600-0567-5.ch007.

[41] M. A. Kumar and N. V. Srikanth, "An Adaptive Neuro-Fuzzy Inference System Controlled Space Vector Pulse Width Modulation Based HVDC Light Transmission System Under AC Fault Conditions," Central European Journal of Engineering, vol. 4, no. 1, pp. 27-38, 2014.

[42] C. Liu, F. Zhuo, and F. Wang, "Fault Diagnosis of Commutation Failure Using Wavelet Transform and Wavelet Neural Network in HVDC Transmission System," IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-8, 2021.