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MACHINE LEARNING BASED PREDICTIVE MAINTENANCE IN POWER TRANSFORMERS

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ABSTRACT

Power transformers are a vital element of a modern power system, and their failure could have harmful technical, economic and other reliability-related consequences. With the shift of utilities towards condition-based asset management instead of corrective and preventive maintenance, machine learning has emerged as a potential facilitator of predictive maintenance in transformer health monitoring. This review gives an evaluation of machine learning in predictive maintenance of transformers in the methodological perspective, application perspective and deployment perspective. It combines key learning paradigms, such as supervised, unsupervised, deep, and hybrid models and describes their application in fault detection, fault classification, condition assessment, remaining useful life estimation and monitoring anomalies online. Another importance highlighted in the review is the usefulness of preprocessing of data, feature engineering and realistic model testing in creating reliable predictive-maintenance systems. Besides, it critically assesses the current trends in research, weaknesses, and future opportunities such as explainable artificial intelligence, digital twins, multimodal sensing, and physics-informed modeling. Overall, the review shows that machine learning is revolutionizing transformer asset management, but its use can only be effective in case its validation, interpretability, and addition to real utility processes are improved.

Keywords— predictive maintenance; power transformers; machine learning; fault diagnosis; condition monitoring.

1. INTRODUCTION

Power transformers are one of the most valuable assets in the modern transmission and distribution system as they regulate the voltage, enable the effective movement of power, and have a direct impact on power reliability. Failure of theirs can have disastrous technical and economic consequences, including unplanned downtime, broken equipment, service outages, costly emergency recovery, and added volatility to related power systems. As the complexity of electrical networks increases, and a greater demand is placed on them, the reliability of transformers has become a strategic concern of utilities and system operators, alongside the implementation of renewable energy, and the development of smart-grids. It implies that maintenance of transformers is no longer viewed as a mere cost of doing business but rather a vital part of managing assets, risk management and resiliency of infrastructures.

Transformer maintenance has been evolving to a condition-awareness based maintenance to corrective and time-based preventive maintenance. One of the most traditional techniques to detect the presence of incipient faults in oil-immersed transformers has been dissolved gas analysis (DGA). DGA provides excellent feedback on the abnormal internal environment that may result in disastrous failures by observing gases produced in the process of thermal and electrical degradation. It has thus been a key basis of predictive maintenance in transformers [1]. However, the presence of nonlinear, overlapping, and undefined fault patterns can often limit the interpretation of DGA using fixed ratio methods, graphical analysis, and judgment.

Such limitations along with even more complex operating environments of transformers have further driven the need of predictive maintenance. Unlike corrective or planned preventive maintenance, predictive maintenance is based on current and previous measurements of conditions to foretell failures and help manage them at the most appropriate time. In this regard, machine learning has been found to be a potent enabler in recognizing concealed patterns, classifying the conditions of faults, predicting degradation, as well as enhancing decision-making in the face of uncertainty. Also recently due to the results of recent research, it is getting more and more applicable as far as early fault conditions detection and smart asset security [2] and monitoring over the Internet of Things are concerned, and super-and-hyper-frequency transformer data is also expanding the boundary of high-frequency transformer data [3].

It is here that a narrative review of machine learning-based predictive maintenance in power transformers is much needed and timely. Current research is scattered in areas of condition monitoring, fault diagnosis, data analytics and smart-grid applications. In contrast to a number of previous reviews which primarily discuss fault diagnosis or DGA interpretation, this review presents the literature in the context of predictive maintenance. It explores the application of machine learning in maintenance-oriented processes like early fault detection, condition assessment, remaining useful life prediction, and online anomaly detection, as well as discusses the practical challenges of machine learning, such as data quality, interpretability, deployment, and smart-grid integration. The remainder of the paper is organized according to the technical background, the most significant techniques, prospect areas, current challenges and future prospects of the ML-based predictive maintenance of power transformers.

2. FUNDAMENTALS OF POWER TRANSFORMER MAINTENANCE

2.1 Role of Power Transformers in Power Systems

Power transformers are very important parts of an electrical power system as they facilitate the change of the voltage in generation, transmission and distribution phases. They play a key role in ensuring quality power, stable energy transfer, and lower transmission losses and confirmation of reliability of electricity delivery to industrial, commercial, and residential clients. Due to the high value, long life of transformers, their failure or degradation may lead to feeder interruptions, supply instability, miscoordination of protection, and expensive service recovery. Transformer maintenance is thus a close-knit to both technical reliability and economics.

The role is now more acute with the increased load demand, penetration by renewable, distributed generation, and the modernization of smart-grids. These changes put load on transformers and impose greater thermal stress, further demanding intelligent maintenance approaches. Predictive maintenance may be useful in improving the decision-making process of operators in the operational domain by forecasting abnormal behavior of transformer before severe degradation happens [4], and also in improving the reliability of the distribution system operators by minimizing unexpected failures and facilitating improved maintenance scheduling [5].

2.2 Common Failure Modes in Power Transformers

Power transformer condition is degraded through electrical, thermal, mechanical and environmental stress. Typical examples of degradation processes are aging of insulations in cellulose paper and oil, thermal overstress, partial discharge, arcing, winding deformation, and moisture contamination. These mechanisms tend to go hand in hand and develop over time thus necessitating the need to diagnose at the earliest.

Dissolved gas analysis, being one of the indicators available, is one of the most informative tools on detecting incipient internal faults. Characteristic gases are produced due to thermal and electrical events in insulating oil and the patterns of their concentration give evidence of fault conditions underlying the insulating oil. Traditional ratio-based approaches are also unclear, and machine learning could be used to enhance the interpretation of DGA patterns [6]. The identification of faults in transformers has also been advanced by optimization-based frameworks which can capture more complex relationships among features [7] and boosting-based learning plus feature reduction has been shown to be useful in oil-immersed transformers [8]

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2.3 Traditional Maintenance Approaches

The conventional transformer maintenance strategies are: corrective, time based preventive and condition based maintenance. Corrective maintenance also is reactive and only taken up once the failure has taken place usually leading to a disruption in the operations and high replacement cost. Preventive maintenance is founded on scheduled maintenance and inspections and is not necessarily reflective of the actual condition of the transformer, and may lead to over- or under-maintenance.

Conditional-based maintenance was a major improvement since the maintenance strategies were connected to the parameters of DGA results, oil quality, temperature changes, and partial discharge. However, there are still significant use of predetermined diagnostic rules and clinical judgment in traditional condition-based practice. According to more recent studies, there is a recent shift towards the adaptive analytic set of theories based on the DGA and the class-imbalance conscious modelling [9], [10].

2.4 Conventional Diagnostic Techniques

In conventional approaches to transformer diagnostics, chemical measurements are combined with electrical measurements, thermal measurements and sometimes acoustic measurements in order to detect uncharacteristic operating conditions ahead of incident. DGA is currently the most popular method of oil-filled transformers and is often used in conjunction with oil quality analysis, furan analysis, insulation resistance analysis, temperature study and partial discharge observation. These methods provide valuable condition information, but individual diagnostic indicators are often not suitable to distinguish closely related types of faults or be useful to predict the severity of the fault.

This shortcoming has prompted incorporation of smart approaches in traditional diagnostic pipelines. Learning-based models based on traditional diagnostic inputs have been shown to improve classification performance [11] and neural-network optimization models have been demonstrated to facilitate more automated and scalable transformer fault diagnosis [12], [13]. Overall, transformer maintenance has evolved its classic diagnostics to more predictive, data-driven and algorithmically-assisted health control. Such constraints of conventional maintenance and diagnostics encourage the shift to predictive and data-driven maintenance models.

3. PREDICTIVE MAINTENANCE: CONCEPT AND RELEVANCE TO POWER TRANSFORMERS

Predictive maintenance is a data based approach to maintenance where measurements of health of equipment are consistently or continuously taken in such a way that the failures in the equipment are predicted before the equipment fails. In contrast to corrective (response to one of the failures) and preventive maintenance (response to a regular service period) predictive maintenance, is concentrated on the most reasonable time of intervention due to the real condition of assets, their degradation, and the probability of failures. This mentality is also highly critical in power transformers since it is a capital intensive, long life and may be perceived as a key node of a transmission and distribution system. They can cause a critical failure of functionalities, costly rebranding and additional grid instability. Predictive maintenance is thus closer to reliability approach, rather than a technical approach though it is informed about economics regarding transformer asset management. In the case of transformers, predictive maintenance is contrasted with generic condition-based maintenance in that it is clearly related to timing of intervention, risk of failure, and choices regarding life of asset.

3.1 Maintenance Evolution

The changes in the engineering practice towards a more condition-based and smart management of the assets can be mentioned as reflecting on transformer maintenance. Early models of maintenance were mostly premised on intermittently planned maintenance inspections, and after-event repairs, which turned out to be insufficient in highly valued assets that have complex internal degradation patterns. As technologies in monitoring technology particularly the use of dissolved gas analysis improved, condition-based maintenance was a trend within the utilities. The amount of the diagnostic information and its nature displayed the weakness of the rule-based interpretation, however. In this regard, predictive maintenance became the next milestone in the development of maintenance, combining condition monitoring and high-performance analytics to predict the development of faults more precisely. Al-Sakini et al. [14] have shown that machine learning-based methods used in dissolved gas analysis can enhance fault prediction by deriving relationships using the gas patterns which are challenging to identify using the traditional diagnostic rules alone. It may be viewed as demonstrating the reality that the principle of data modeling evolved into the principle of transformer maintenance beyond the principle of a mere passive inspection to the basic principle of predictive intelligence by data.

3.2 Predictive Maintenance Objectives

The primary goal of predictive maintenance in power transformers is to focus on the initial signs of unnatural behavior, as well as to estimate whether or not something will need to be done before the fault turns into a critical state. This is through monitoring faults developing, isolating degradation processes, monitoring the health of assets as well as justifying timely maintenance processes with low risk and cost. Practically, incipient fault detection is of particular significance as failures of transformers tend to occur gradually and not immediately. At the moment when predictive maintenance predicts the failures in oil-impregnated transformers, a multinomial classifier was used to predict the minor changes in the condition in a correct and promptly way [15]. Hence it is not simply carried out so as to diagnose faults, but to transform the diagnostic information into proactive operational decisions.

3.3 Benefits and Operational Relevance

Operationally, predictive maintenance is relevant in the sense that it enhances reliability, decreases unplanned down time, optimal maintenance schedules, and life span of transformers. Predictive maintenance will allow the utilities to go to planned intervention rather than emergency intervention by allowing the utilities to detect faults in the transformer much more accurately and timely thus maximizing maintenance savings and reducing service outage. It is also used to prioritize the utilization of technical means more effectively since the maintenance can be prioritized based on the state of assets, rather than the only on the schedules. In the case of transformer assets, it signifies that predictive maintenance is not just a monitoring approach, but a decision-support approach, the association between condition evidence and the timing and lifecycle administration of maintenance. As illustrated by Illias and Zhao Liang [16], the interpretation of dissolved gas analysis with hybrid support vector machine can be utilized to enhance fault identification of transformer, thus resulting into the maintenance steps undertaken earlier and more knowledgeable. In this connection, predictive maintenance can be relatively applicable, not only to the technical aspect of fault control but also to the strategic aspect of the asset control, the operational stability, and more intelligent decision-making on utility.

4. MACHINE LEARNING FOUNDATIONS FOR PREDICTIVE MAINTENANCE

Machine learning has already been utilized in predictive maintenance of the transformer since the traditional diagnostic procedures are often inadequate to indicate the nature of the real transformer degradation. Power transformers result in many condition indicators, including electrical, chemical, thermal, and mechanical signals that are interacted by nonlinear and uncertain means. Traditional approaches to interpretation are usually founded on a set of rules, criteria or diagnostic profiles. These are not effective enough since the condition signatures overlap, degradation is gained with time or when multiple indicators that are to be interpreted at once exist. Machine learning overcomes this shortcoming by learning trends directly out of data, discovering latent relationships between variables, and producing more adaptive diagnostic results. It therefore provides the predictive maintenance systems on which predictive systems are based to enable the detection of faults, the assessment of conditions and prompt intervention.

4.1 Rationale for Machine Learning Adoption

Transformer maintenance has embraced machine learning since it allows more data-adaptive fault-analytics than a traditional rule-based line of thought. The transformer monitoring systems today generate more heterogeneous data which can be chemical gas signatures, measurements of frequency response, thermal data, vibration data, and load-dependent operation records. Fault detection based on the machine learning with sweep frequency response analysis revealed that subtle deviations associated with winding and core faults could be identified more effectively compared to the situation when only the diagnostic rules were used [17].

4.2 General Workflow of ML-Based Maintenance Systems

The basic steps involved in an ML-based predictive maintenance system of power transformers are data collection, preprocessing, feature engineering/extraction, model construction, validation, and deployment. Condition information is collected by monitoring systems, lab analysis or field inspection and through clean up and alteration into a learnable form. The training of classification, regression or a combination of both is then followed to identify faults, predict condition or predict degradation by the selection or derivation of features.

This and a similar workflow can be found in machine learning-based software to classify incipient faults of transformer windings via voltage-current diagram techniques [18]. This piece of work illustrates that predictive maintenance is not just what the model is but is also what the interaction of sensing, feature representation, classification logic, and severity assessment, into an analytical pipeline, is coherent.

4.3 Data Sources for Transformer Monitoring

Machine learning as a tool to predictive maintenance is contingent on the quality and variety of monitoring data. Although dissolved gas analysis is still a popular diagnostic technique in the traditional transformer diagnostics, there is a growing trend in modern predictive maintenance efforts to use multimodal sources, such as electrical waveforms, partial discharge patterns, temperature records, acoustic emissions, frequency-response measurements and environmental or loading conditions.

The application of machine learning to electronic-nose systems has demonstrated that odor patterns related to gas can yield additional information due to abnormality [19]. Similarly, forecasting the relative aging rate of transformers based on aging parameters indicates that predictive maintenance is not only about the classification of faults but also long-term health development [20]. Combined, these papers suggest that the ML foundation of predictive maintenance of transformers may be considered a three-layers system that includes multimodal data collection, analytical models, and maintenance-related decision support.

5. MACHINE LEARNING APPROACHES IN TRANSFORMER PREDICTIVE MAINTENANCE

Transformer predictive maintenance can be classified into four machine learning types, including, but not limited to, supervised learning (labelled diagnostic and regression), unsupervised learning (anomaly discovery and latent pattern extraction), deep learning (temporal and multimodal feature learning), and hybrid or ensemble learning (TOML) to improve interpretability, stability, and deployment preparedness. They are applicable depending on the purpose of monitoring, format and environment of data.

5.1 Supervised Learning

Supervised learning remains an essential technique of transformer predictive maintenance, as a majority of activities in the maintenance field can be cast as either classification or regression problems with some labeled historic data. Fault type, health state, degradation level or thermal behavior are the most frequent outputs. Its main advantage is the ability to obtain direct input-output mappings and generate desired predictions in the event of trusted labels.

Fang et al. [21] proved this by predicting long-term and short-term top-oil temperature with CNN-LSTM-attention architecture in terms of thorough thermal considerations. This is particularly in the fact that the stress on the insulation, thermal aging and thermal loading limits are directly proportional to the top-oil temperature. Such accurate forecasting can therefore aid in earlier intervention since it identifies the trend towards overheating, before the situation deteriorates severely.

The major flaw of the supervised learning is that the quality labels and representative operating data are necessary. In transformer, rare occurrence of faults and predominance of normal state data can be used to limit generalization.

5.2 Unsupervised Learning

Unsupervised learning plays an important role in the case of fewer labeled data or inaccurate labeled data. The occurrence of anomalies and preliminary faults in transformer monitoring is very rare and large annotated datasets are difficult to obtain. These techniques find latent structure within unlabeled data, e.g. clusters, latent representations, and abnormal behavior.

With a semi-supervised model of transfer-learning that characterizes the power transformers, Mao et al. [22] showed that state-of-the-art representation learning was useful in diagnosing faults in the transformers. They find that meaningful faults features can be produced even in the case of limited numbers of labeled samples, and thus these techniques can be used in the screening of anomalies and the detection of latent patterns.

The main benefit of unsupervised learning is that less dependence is had on annotated fault information. Patterns found, however, need not be directly associated with physically significant types of transformer faults.

5.3 Deep Learning

Transformer predictive maintenance is an active field where deep learning can be significant since most condition indicators are multivariate, time-dependent and structurally complicated. Deep learning is able to automatically derive hierarchical representations of raw or very lightly processed data in contrast to classical methods, which depend on heavily handcrafted features. This renders it useful in long sequences, multiple streams of sensors and interacting operational variables.

This was demonstrated by Liu et al. [23] with fault localization in transformer windings in multilayer perceptron in a digital-twin framework. The theoretical significance of the study is that data-driven learning can be combined with virtual asset representations in order to enhance fault localization.

Although it has its advantages, deep learning is data intensive, requires computational resources and must be carefully validated. It is of use as long as models are robust enough to be utilised practically.

5.4 Hybrid and Ensemble Models

The most promising models in transformer predictive maintenance are the hybrid and ensemble models because the complementary strategies are incorporated to increase the robustness and usability. The transformed data of monitor transformers is typically heterogeneous and noisy, and the monolithic solutions may be wobbly or overfitted. This is defeated using hybrid approaches, feature engineering, optimization, expert-rule fusion, interpretable classifiers, or edge-based inference.

Hu et al. [25] suggested an interpretable machine learning technique of fault diagnosis of oil-immersed transformers using edge inference. This is also significant as it provides us with two priorities which are becoming fundamental in the predictive maintenance research i.e. interpretability and deployability. Nearest source processing is also assisted by edge inference, which decreases latency and enhances the viability of implementation. In general, the considered approaches indicate a definite comparative trend: supervised models show the best results in well-labeled diagnostic and regression tasks, deep models are prospective in sequential and multimodal monitoring, and hybrid or ensemble models seem to be the most feasible in terms of utility application due to their more balanced performance, interpretation, and robustness.

Table 1. Comparison of machine learning approaches in transformer predictive maintenance

Approach	Typical task	Strength	Limitation	Transformer relevance
Supervised	Fault classification, temperature prediction	High target specificity	Needs labels	Strong
Unsupervised	Anomaly detection, clustering	Works with unlabeled data	Harder to interpret	Moderate to strong
Deep learning	Time-series, multimodal prediction	Learns complex patterns	Data/computation heavy	Strong in large datasets
Hybrid/ensemble	Fault diagnosis, robust deployment	Better stability/interpretability	More design complexity	Very strong for practice

6. APPLICATIONS OF MACHINE LEARNING IN TRANSFORMER HEALTH MANAGEMENT

Machine learning has brought the concept of transformer health management to a much broader framework of decision-support frameworks that do not rely on a fixed fault interpretation framework but instead on a framework of fault detection, fault classification, condition assessment, remaining useful life estimation, and online anomaly monitoring. The applications have varying functions, but when combined, they aid in maintenance planning, prioritization of risks and decision-making at an asset level.

6.1 Fault Detection

Machine learning in transformer maintenance has the oldest and the simplest application in fault detection since it aims at identifying the abnormal behavior before it can advance to serious thermal, dielectric or mechanical failures.

Alabdullh et al. [26] proved this by estimating the lifetime of transformers using chemical and physical indicators of mineral-oil transformers based on artificial intelligence. The research is applicable to fault detection as well as a lifetime estimation is framed, as the authors demonstrate that degradation indicators involved in oil chemistry and physical state can indicate the emergence of health degradation. This indicates that machine learning-based fault detection is shifting away from mere event detection to detecting abnormal degradation pathways.

6.2 Fault Classification

After the identification of abnormal condition, classification of faults occurs, in which the most likely type of fault is determined, e.g., thermal, electrical, insulation-related, or a mechanically caused abnormality. This is significant since the decisions made on maintenance are not only determined by the presence of an unhealthy transformer, but rather, the nature and the likely outcome of the fault.

Makanju et al. [27] examined machine learning applications of identifying and predicting voltage conditions within power system networks pegged on network topology behavior formulation as inputs. The applicability in terms of the methodology is clear despite the fact that it is not specific to the internal transformer faults: machine learning can be applied to distinguish between different operating and abnormality states by learning structured electrical patterns based on multivariate data. Similarly, in transformer practice, the logic may be applied to assist in the separation of stress regimes and fault classes, and improve the diagnostic interpretation relative to analysis of single sources of DGA.

6.3 Condition Assessment

Condition assessment extends fault labeling since the health of the transformer as an asset on a broader scale is evaluated. Machine learning can assist in transforming a sequence of indicators into more of a holistic health image that can be ranked, rated risks, and planned accordingly.

Alshaibani et al. [28] stressed the integration of machine learning involving the usage of drone technology to predict the failure in power infrastructure. In the case of transformers, it applies since the visual and spatial data provided by drone-based inspection can be used in addition to chemical and sensor-based diagnostic. This multimodal inputs can contribute to the assessment of the external physical condition, cooling-system failures, bushings, and exposure to the environment especially in distant installations.

6.4 Remaining Useful Life Prediction

Among the most advanced ones in transformer predictive maintenance is the remaining useful life prediction that attempts to estimate the approximate time of the asset that could still be utilized in a sensible way before it must be acted upon. It is prognostic in nature as opposed to fault detection or classification, and must have models that relate present health indicators to future degradation behavior.

Borah et al. [29] analyzed the health condition and life expectancy of power transformers using machine learning. They note their results on the correlation between condition indicators and possible asset health and service life projections. This technique may be exploited in transformers systems in order to assist prognosis on insulation aging, thermal degradation and deterioration of oil-condition.

6.5 Online Monitoring and Anomaly Detection

Some of the most operationally important applications include online monitoring and anomaly detection since they allow the continuous monitoring of the transformer behavior in near real time. In comparison to regular testing, online monitoring enables earlier detection of deviant conditions and quicker response in maintenance.

Luo et al. [30] proved this direction by evaluating the health conditions of transformers with cross message passing graph neural networks, which indicated that machine learning could learn to combine the intricate relationships between conditions to adaptively monitor. Further, Ahmed et al. [32] emphasized the importance of multivariate machine learning in the detection of abnormal operating patterns using the structured monitoring and data. Collectively, these studies indicate that online models have to handle heterogeneous sensor inputs, differentiate between actual anomalies and normal variation, and provide timely alerts, which can be used to aid maintenance planning.

Table 2. Mapping ML applications to transformer maintenance functions

Application	Primary goal	Typical inputs	Maintenance value
Fault detection	Early abnormality recognition	Oil, thermal, sensor data	Early warning
Fault classification	Identify fault category	DGA, electrical features	Diagnosis support

Condition assessment	Evaluate asset health	Multimodal condition indicators	Asset ranking
RUL prediction	Estimate usable life	Aging, temperature, degradation trends	Maintenance scheduling
Online anomaly detection	Real-time abnormal behavior	Streaming sensor/IoT data	Fast intervention

On the whole, the uses of machine learning in transformer health management reveal that the literature continues to focus more on diagnosis rather than prognosis. The most advanced areas of application are fault detection and classification, but the other application areas, which include remaining useful life estimation and online monitoring are relatively less developed, and are often justified by cross-domain methodological analogies, as opposed to transformer-specific validation. In comparison, condition assessment and multimodal monitoring seem to be particularly promising areas of growth since they are more aligned with fleet-level prioritization of maintenance and next-generation digital asset management.

7. DATA PREPROCESSING, FEATURE ENGINEERING, AND MODEL EVALUATION

The effectiveness of predictive maintenance of a transformer using machine learning is not only linked to the choice of the algorithm but also the quality of data preparation, usefulness of engineered features, and the quality of model assessment. In reality, data on transformer monitoring are seldom in the form of direct models. The measurements can be noisy, incomplete, unbalanced and not particularly consistent over time and can be assessed by different measurements that are not heterogeneous including dissolved gas analysis, IoT sensors, thermal measurements, and operations logs. Consequently, preprocessing and evaluation are two valuable features, which determine the scientific feasibility and operational viability of a predictive maintenance model.

7.1 Data Cleaning and Preparation

The first phase of any predictive maintenance workflow that can be relied is the data cleaning and preparation. In transformer applications, this step usually includes processing missing data, eliminating duplicate/corrupted data, standardizing variables measured at various scales, aligning data between times, and detecting outliers that can either be noise in a sensor or a real abnormality. As the data observed in the field tend to be operational data measured in nonuniform conditions and beyond the control of a laboratory, preparation must make a trade-off between statistical consistency and physically meaningful variation.

Ahmed et al. [32] demonstrate the importance of the adequate arrangement of manipulation of variables employed in prediction systems in a multivariate based machine learning method used to predict power failures. Although they are not transformer-related directly, the lesson on the methodology can be directly applied: heterogeneous variables must be converted to coherent feature space before the model training. In the case of transformers, this can be temporal aggregation, sequential observation windowing, and balancing normal and abnormal conditioning. It is also possible that models are taught how to model artifacts rather than the actual degradation behavior as a result of inadequate preparation.

7.2 Feature Extraction and Selection

The selection of features, as well as the choice of features is crucial, because high-dimensional measurements, partially redundant, physically correlated measurements are frequently needed to monitor the condition of the transformers. The goals include identifying variables that have important diagnostic or prognostic data. These helpful functions may be gas concentration ratios, temperature gradients, load related stress indices, insulation-aging indicators, temporal trend features or latent features trained on sensor streams.

Moradi et al. [33] concentrated on the issue within the context of the IoT of deep neural network-based fault detection of transformers in the face of unbalanced data and uncertainties. Their work presents two crucial realities: data collected via IoT can be abundant yet biased, and feature representation should be sound even when the quality of sensors is different or class imbalance skews training. In traditional models, noise can be reduced by explicit feature design to boost discriminative power, in deep learning examples, a fraction of this can be learned automatically by means of representation learning and needs careful input organization.

7.3 Performance Metrics and Validation Considerations

Transformer predictive maintenance model assessment should not be restricted to report a single performance score. As maintenance decisions have operational, financial and reliability implications, their analysis has to encompass predictive quality that can be quantified, and deployment suitability. The accuracy, precision, recall, F1-score, mean absolute error, root mean square error and area under the curve are some metrics that indicate various facets of model behavior. An imbalanced transformer data can be a red flag when there is a large overall accuracy, e.g. when the model is performing poorly on the rare but critical fault classes.

A transformer-specific look at these problems is given by Taha [34] in a study of using convolutional neural networks with imbalanced-data oversampling to improve transformer health index. Predictive performance, class imbalance, model reliability and practical diagnostics usefulness must be taken into account in model assessment in his work. Validation should therefore include proper train-test separation, cross-validation where possible, sensitivity to hidden operating conditions. The alternative models of models should be also tested in various transformer types, operating conditions and unseen fault conditions instead of just using random train-test splits in the future. On the whole, machine learning-based predictive maintenance is based on data preprocessing, feature engineering, and model evaluation as its methodological foundation. They discover how the transformer monitoring data would be able to convert to credible maintenance intelligence and how the reported performance can be utilized in field deployment.

8. CRITICAL ANALYSIS OF CURRENT RESEARCH TRENDS

Recent studies of machine learning-related predictive maintenance of power transformers demonstrate an obvious shift of the traditional approach to fault-based diagnosis to more extensive asset-intelligence systems. The previous research was primarily focused on enhancing fault detection algorithms of the dissolved gas analysis, thermal indicators and other sources of monitoring. The latter has been generalized to maintenance ecosystems which is a combination of predictive, anomaly detection and decision support. Predictive maintenance is no longer a classification problem but is also viewed as an asset-management problem including condition monitoring, prioritizing risks and planning interventions.

There are several comparative patterns which can be pointed out in the literature. To begin with, the majority of research is diagnosis-based and the areas of interest are the fault detection and classification rather than the prognosis or lifecycle decision support. Second, the most common source of data remains to be dissolved gas analysis, although multimodal monitoring is becoming more popular. Third, there are increased usage of deep and hybrid, but less evidence of usage on the field. Fourth, lack of practice on the integration of maintenance with most of the studies that end with the predictive output and does not correlate the results with the maintenance planning or asset strategy. Such trends reveal that the industry is advancing on the technical front, albeit unbalanced.

One of the most evident trends is the increase of the use of data-driven models over the rule-based diagnostic systems. The fact that degradation of transformers is a phenomenon, which requires interactive factors of thermal, electrical, mechanical and environmental factors, has led scientists to pay increased attention to models that can address nonlinear relationships and non-homogenous conditions data. At the same time, predictive accuracy is often placed at a more substantial emphasis than operational usefulness, therefore, model performance as reported might not be automatically equal to realistic maintenance implementation.

The second major trend is the change towards temporally sensitive and system-level forecasting models. Instead of viewing fault events as discrete events, current studies are characterizing degradation as more of a process of time variation. This especially applies to transformers where the failure of the transformers will not be noticeable immediately. The field is no longer shifting away towards distinct diagnostic designs but ever-expanding and smarter monitoring designs, and predictive maintenance is increasingly being perceived as a part of an ever-renewing design of asset state, rather than a series of ex-post diagnostic notifications [35].

The second fact that needs to be mentioned is that methodological innovation usually surpasses the engineering grounding. In numerous studies, the more general energy and predicting research is implemented in terms of transformer maintenance. This has accelerated technical development but sophistication of models could surpass practical usefulness. Overall, the literature available is still skewed towards fault classification and not lifecycle prognosis, datasets often are small and study-specific and deployment validation is still lagging behind methodological innovation.

9. CHALLENGES AND LIMITATIONS

Even though predictive maintenance in power transformers using machine learning has been increasing at a high rate, technical, operational and methodological difficulties still exist that limit its application to practical situations. Strong predictive performance has been reported in a number of studies, but no successful application in utility practice has been reported. This is because the maintenance of transformers is not only dependent on the design of the model, but also on the quality of data, the type of assets, infrastructure constraints and risk in decision making. Consequently, the key constraints of the discipline go beyond the selection of the algorithm and include the larger circumstances within which predictive intelligence may be relied upon and utilized.

The lack of quality, representative fault data is one of the most longlasting issues. In real-world power system, events of serious transformer failure are not that frequent, a fact that suggests that informative data is typically modest, skewed, and disaggregated among operators or laboratories. Models that have been trained on such data could work well in controlled environments, but fail to generalize in strange field conditions or a combination of faults never seen before. The problem is further aggravated when such fault labels are unclear or indirectly determined as compared to the maintenance results.

Another limitation that relates to heterogeneity of data exists. The concept of transformer surveillance is based on the various information streams, such as dissolved gas, temperature, electrical, aging, IoT sensors, and even image-based inspection information. They are of varying sizes, frequency, level of noise and interpretation and are hard to merge. Other sensing infrastructure differences, transformer design and operating conditions are also known to decrease model transferability across fleets or utilities. In the absence of more stringent standardization it is still challenging to construct benchmark datasets or to compare learning approaches on an equal footing.

The other issue underlining is interpretability. The maintenance choices of transformers impact costly, safety-important properties, and thus, operators require more than correct predictions; they require to comprehend the reasons a model conveys that there is a fault or intervention is required. Most of the state-of-the-art machine learning and deep learning systems are hard to analyze in terms of engineering, and are therefore less reliable and slow to deploy in risk-sensitive systems. Even a statistically well performing model may not be workable: physical reasoning or experience in maintenance is not able to test results of such a model.

Computational and deployment are also important issues. The majority of the predictive maintenance studies are modeled in the offline study based on edited data and with powerful computing resources. Real world monitoring environments may require a low-latency inference, dynamic updating, and integration with traditional supervisory environments or edge devices. This brings out the quandary of a refinement of technique and expediency of execution.

The second limitation is that it lacks good relationship between the predictive output and the actual maintenance policy. Most of the studies end with classification, regression/anomaly scoring and they do not properly demonstrate how the outputs will be used to support, repair or replacement decisions. Predictive maintenance cannot be utilized unless the models are action-supportive, i.e. need to be connected in asset-management logic, intervention thresholds, and utility-specific planning constraints. In general, the fact no models have been developed does not handicap the field, but availability of scalable reliable and decision oriented predictive maintenance architectures. The next step in building the data ecosystems will be its further development, which will result in their increased success, better interpretability, and a smoother connection between predictive analytics and maintenance action. In this sense, the later growth does not revolve around the proposal of new standalone models but is geared at developing validated, interoperation and decision-based maintenance systems.

10. EMERGING TRENDS AND FUTURE RESEARCH DIRECTIONS

The future of machine learning-based predictive maintenance in power transformers can be expected to be a shift to the disaggregated predictive models to the integrated, scaled, and operationally relevant maintenance ecosystems. Despite the positive results of the current literature in the field in terms of high-performance on narrow scopes, the second phase of investigation needs to be invested in explainable, deployable, and visually relevant systems according to what is in the real utility. Of these directions, explainable AI, digital twins, multimodal sensing, and physics-informed modeling seem to be the most impactful to next-generation transformer maintenance systems.

Among the trends are the increasing demand to have explainable artificial intelligence. With more and more advanced predictive maintenance models, particularly, deep and hybrid architectures, systems whose outputs can be comprehended in an engineering sense will be in demand by utilities. Explainability is not only the basis of trust, but also issue justification of model recommendations to physical knowledge and maintenance experience.

Integration of digital twins is also the second direction. Future maintenance systems can use digital twins to act as periodically updated virtual representations of actual physical transformers, consisting of historical data and real-time sensor data, engineering know-how and machine learning predictions. This would assist in simultaneous evaluation of current condition as well as simulating behavior in future, contributing to alleviating the gap between fault diagnosis and lifecycle-friendly asset planning.

Multimodal and physics-informed modeling is the third direction. Transformer health is a multidimensional phenomenon and in any future system i would have to incorporate dissolved gas analysis and thermal measurements, indicators of partial discharges, vibration responses and visual inspections in single predictive systems. Meanwhile, pure data-based models too are likely to be limited by physical information of transformer age, insulations decay, and thermal stress. Such an integration would have the potential to enhance robustness, as well as benefit the predictive outputs to long-term health assessment in a much broader sense.

Adequate benchmarking and repeatability will also be needed in all these areas to take a step forward. In the absence of standardized datatsets, popular validation procedures, and more real-world deployment-related testing, it will be challenging to compare protocols equally and gauge the willingness to be deployed in the field. Overall, explainability, digital twins, multimodal sensing, and physics-informed learning are in the future of transformer predictive maintenance. Future development should not only emphasize methodological novelty, but benchmarked validation, integration with maintenance processes and deployability to field.

11. PRACTICAL IMPLICATIONS FOR INDUSTRY AND SMART GRID SYSTEMS

The practical implications of the predictive maintenance provided by machine learning in power transformers are that it will perhaps transform maintenance as a cost center into a strategic operation of the assets management. The foremost implication to industry is higher reliability. Transformers failure is also expensive with replacement of equipments not forgetting fines due to outage, service breakage, emergency work and reputation. Machine learning may allow utilities to plan interventions earlier and more precisely by earlier and more precisely identifying abnormal behavior and assisting them to plan before failures escalate into major operation events. This will help in a more targeted maintenance and prioritization of high-risk assets of transformer fleets.

The other significant implication is the change in direction to condition-driven maintenance planning. Traditional utility maintenance practice uses traditional maintenance schedules, based on fixed intervals, or general engineering guidelines, which do not always reflect the actual condition of each transformer. Machine learning allows the operator to strive towards asset-based maintenance where decisions are made based on real operation data, condition indicators, and predicted wear and tear trends. This is rather necessary especially in the environment of smart-grids where transformers are increasingly exposed to a more dynamic environment, due to the variability of loads and distributed generation, as well as integration of renewable energy.

The other domain where machine learning can have considerable importance in digitalizing the power industry. Smart grids are based on 24/7 and distributed sensing, rapid decision-making and improved coordination among operating and analysis systems. Predictive maintenance is consistent with such objectives since it transforms monitoring data into intelligence to action. In practice, it will mean that a transformer management will be capable of being intertwined more closely with supervisory control, or IoT infrastructures and digital asset-management ones.

However, colossal barriers remain in the way to actual implementation. The models applied in utilities must not only be accurate, but also interpretable, stable and simplistic to integrate with the existing infrastructure. A predictive maintenance system that demonstrates good results in research but is incapable of being relied upon, described, and put into practice in maintenance processes is not likely to bring industrial value. The factor of cost-benefit is also crucial, as the implementation of sophisticated sensing, communications networks, and machine learning solutions need to be substantially justified in their operation. Overall, predictive maintenance by the use of machine learning has a high industrial value. It helps to ensure the more stable work of transformers, allows more intelligent maintenance planning and enhances grid resilience. The pragmatic level of adoption in the case of the utilities will be on whether predictive models can reasonably demonstrate quantifiable advances in reliability, maintenance efficiency, and decision confidence.

12. CONCLUSION

Machine learning-based predictive maintenance could be regarded as a paradigm shift in power transformer health management and as a bigger change of the traditional reactive and schedule-directed maintenance techniques into the condition-based use of assets. Due to the constant importance of power transformers to remain one of the most important and costly elements in contemporary electrical networks, their reliable operation lies in the core of grid stability, continuity of services, and efficiency of infrastructure in the long run. In this case, machine learning use in transformer monitoring can enhance it significantly in early detection of abnormality, fault classification, condition assessment, and more active operations in case of maintenance. This review has demonstrated that the field is growing at a high pace in various aspects. Traditional transformer diagnostics, especially dissolved gas analysis, and other condition-monitoring methods continue to be the foundation of maintenance decision-making, although machine learning is now able to flexibly interpret these data sources and be predictive. All these supervised, unsupervised, deep learning, and hybrid models have various advantages to achieve the target of maintenance and there are even applications beyond fault diagnosis to prognosis, real-time monitoring and even health intelligence on an asset level. At the same time, the review has indicated severe gaps, e.g., lack of data, imbalanced data, non-standardization, interpretability, and the persistence of the gap between research models that work superbly and industrial systems that are applicable in practice. This is the future of this field to go beyond single prediction tasks to the concept of predictive maintenance structures, which can be explained, sound and robust and aligned with utility practice. The emergence of new trends, such as digital twins, multimodal data fusion, physics-informed learning, and others, are all indicators that transformer maintenance research is moving to a more mature phase. It is an overview built on a synthesis of methodological, application centric, and deployment centric perspectives and outlines predictive maintenance as an asset management technology and strategic line towards transformers. Overall, machine learning is revolutionizing the concept of transformer health knowledge, surveillance, and control in digitalized power systems.

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