IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 13 July 2024, accepted 6 August 2024, date of publication 9 August 2024, date of current version 20 August 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3441523

TOPICAL REVIEW

Emerging Trends in Power Transformer Maintenance and Diagnostics: A Scoping Review of Asset Management Methodologies, Condition Assessment Techniques, and Oil Analysis

GABRIELA S. RÊMA[1,2], BENEDITO D. BONATTO[1], (Senior Member, IEEE), ANTONIO C. S. DE LIMA[3], AND ANDRÉ T. DE CARVALHO[4]

[1]Electrical Engineering Graduate Program - Institute of Electrical Systems and Energy (ISEE), Federal University of Itajubá (UNIFEI), Itajubá, Minas Gerais 37500-903, Brazil
[2]Companhia de Transmissão de Energia Elétrica Paulista (ISA CTEEP), São Paulo 04794-000, Brazil
[3]Electrical Engineering Program (PEE), Federal University of Rio de Janeiro (COPPE/UFRJ), Rio de Janeiro 21941-911, Brazil
[4]Centro de Pesquisas de Energia Elétrica (CEPEL), Rio de Janeiro 21941-911, Brazil

Corresponding author: Gabriela S. Rêma (gabrielarema@unifei.edu.br)

This work was supported in part by the UNIFEI—Federal University of Itajuba; in part by the UNICAMP—Universidade Estadual de Campinas; in part by the CAPES—Coordenação de Aperfeiçoamento de Pessoal de Nível Superior, Brazil—Finance Code 001; in part by the CNPq—National Council for Scientific and Technological Development, Brazil; in part by the FAPEMIG—Fundação de Amparo à Pesquisa do Estado de Minas Gerais under Grant APQ-03609-17; in part by the INERGE—Instituto Nacional de Energia Elétrica; in part by the CPTEn—São Paulo Center for Energy Transition Studies under Grant 2021/11380-5; in part by the FAPESP—São Paulo Research Foundation; and in part by FAPEMIG under Grant APQ-02845-2021.

ABSTRACT The present study undertakes a scoping review of research on the methodologies and techniques used for the maintenance and condition assessment of power transformers, which are the main asset in the electrical power transmission sector. It addresses articles on asset management, monitoring and diagnostics, oil analysis, and insulation moisture, with these articles originating from twenty-five countries and being published in journals in the last fifteen years, with more than half of them published in the last five years. The aim of this research is to map the literature linked to the topic in a broader and more exploratory manner and to identify any existing gaps in knowledge. Guidelines such as eligibility criteria, sources of evidence, data charting, and result summaries are described. This study finds that data analysis methodologies related to identifying failures and aiding decision-making can add value to power transformer asset management and this scoping review was the basis for the development of an inedited methodology to aid decision-making regarding investments in the maintenance of power transformers.

INDEX TERMS Asset management, condition assessment, diagnostic techniques, oil analysis, power transformers.

I. INTRODUCTION

Worldwide, electric power transmission companies are facing a challenge involving the end of the regulatory useful life of various pieces of equipment [1]. In Brazil, the current scenario in the energy transmission sector involves a large number of assets that are depreciated from a regulatory perspective. This context can bring risks to the system, impact sectoral planning, and affect the capacity to support the energy transition.

The power transformer is the main asset in the electrical energy transmission sector. Ensuring a consistent electricity supply mandates paying considerable attention to transformer maintenance. To optimize the power transformer's lifespan and reliability, it is paramount to monitor and address any internal or external aging or damage that may occur [2]. The Figure 1 shows a power transformer installed in a substation.

The associate editor coordinating the review of this manuscript and approving it for publication was Arpan Kumar Pradhan.

FIGURE 1. Power transformer installed in a substation.

Failures in electrical network equipment result in substantial expenses for power utilities. Therefore, employing assessment techniques is essential for effectively diagnosing and estimating the true operational status of such equipment. Efficient diagnoses enable the management of this asset chain, aiming to strike the optimal balance between investments, maintenance costs, and operational performance [3].

Many studies related to the asset management and condition assessment of power transformers have been conducted. However, given the technical and economic infeasibility of renewing all depreciated assets from a regulatory standpoint, the need for an assertive risk management analysis and a reliable assessment of the physical useful life of assets, especially power transformers, is emphasized. The scoping review method was chosen with the aim of mapping the literature linked to the topic in a broader and more exploratory manner and to identify any existing gaps in knowledge.

In 2008, the Conseil International des Grands Réseaux Électriques (CIGRÉ) formed Working Group A2.37 Transformer Reliability and published the resulting Transformer Reliability Survey material [4], with contributions from 58 concessionaires from 21 countries. A total of 964 failures occurring in transformers were examined, with 799 occurring in transmission substation transformers and 165 occurring in power plant step-up transformers. The mode describes the nature of the failure. The failure modes in the study were classified as follows: (a) dielectric—primarily related to partial discharge (PD) and flashover; (b) electrical—open circuit, short circuit, and failure in electrical contacts; (c) thermal—overheating and hotspot; (d) chemical—oil contamination and corrosion; and (e) mechanical—bending, breakage, displacement, and loosening. Dielectric failures account for the majority of failures in transmission substation transformers. Within the Brazilian electrical sector, the study was conducted with data from 3198 transformers and reactors from voltage classes starting at 138 kV. The information came from thirteen concessionaires in the country, representing more than 70% of the installed capacity in Brazil. It was found that dielectric failures accounted for more than 45% of the total failures. Table 1 shows the classification of the failure modes that occur in power transformers according to concessionaires.

TABLE 1. Classification of failure modes occurring in power transformers according to concessionaires [4].

Failure modes	964 failures in 21 countries	799 failures in transmission substations	165 failures in power plants	Brazilian concessionaires
Dielectric	36.62 %	38.30 %	28.48 %	45.14 %
Mechanical	20.02 %	22.15 %	9.70 %	26.29 %
Electrical	16.49 %	18.02 %	9.09 %	-
Thermal	10.89 %	6.51 %	32.12 %	15.43 %
Chemical	3.32 %	2.88 %	5.45 %	7.43 %
Unknown	12.66 %	12.14 %	15.15 %	5.71 %

Given these data, this scoping review focuses on previous studies that evaluate, in addition to asset management methodologies and condition assessment techniques, assessments of transformer dielectrics, involving the analysis of insulating oil and moisture in the insulation.

II. SCOPING REVIEW METHODOLOGY

This scoping review was prepared following the guidelines provided by the PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) protocol [5].

To identify potentially relevant articles, the bibliographic databases of the publishers Elsevier, IEEE, and Multidisciplinary Digital Publishing Institute (MDPI) were searched from October 2023 to June 2024. The complete electronic search strategy for the Elsevier database used keywords, subject areas, and article type as selection filters. The keywords used were power transformers, asset management, condition-based maintenance, failure analysis, moisture, and oil samples; the selected subject areas were energy, engineering, computer science, and materials science; and the chosen article types were review articles and research articles.

A. ELIGIBILITY CRITERIA

To be included in this review, papers needed to address the topics of asset management and condition assessment of power transformers. To select articles, the following keywords were used: power transformer, asset management, condition-based maintenance or condition monitoring, and failure analysis.

Considering that dielectric failure is the main failure mode in transmission substation transformers in Brazil and worldwide [4], articles specifically addressing oil analysis and insulation moisture were also examined, as insulating oil has dielectric and cooling functions in power transformers. Physicochemical and gas chromatography tests are carried

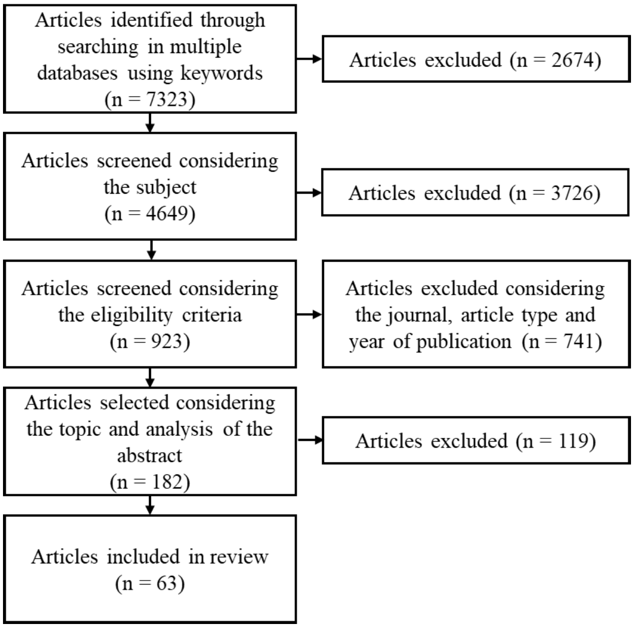

FIGURE 2. Flow diagram illustrating the selection of sources of evidence.

out on the equipment's insulating oil to confirm that operating conditions are adequate and to analyze dissolved gases, respectively. Water content is one of the properties evaluated in physical–chemical tests. The keywords oil analysis, oil samples, and moisture were included.

Peer-reviewed journal papers were included if they were published in the period of 2009–2023 and in journals classified as Qualis CAPES Engineering IV A1 and A2, with the aim of mapping recent publications subjected to rigorous reviews.

Another eligibility criterion was the article type: review articles and research articles were included, with the aim of including articles that provide a solid foundation on the topic and insights and guidance for further investigation.

B. SELECTION OF SOURCES OF EVIDENCE

After identifying articles by conducting a search by keywords and subject, articles were selected using the eligibility criteria. In the next stage of selecting sources of evidence, the topics, titles, and abstracts were evaluated. Finally, an evaluation was carried out on the full text of all publications identified in our searches for potentially relevant publications. Figure 2 shows a flow diagram that illustrates the steps taken to select sources of evidence and the number of articles selected per step.

C. DATA CHARTING

The 63 articles included in this review are related to transformer asset management and condition assessment. After reading and analysis, it was deemed possible to classify them into subtopics, as some articles address the topic more broadly, while others specifically address diagnostic techniques and/or failure analyses. Table 2 shows the subtopic classification of the articles, considering the specificity of each work.

TABLE 2. Classification of articles among the subtopics.

Subtopics	Number of articles
Asset management and condition assessment methodologies	10
Monitoring and diagnostic techniques and methods	22
Oil analysis	16
Moisture in insulation	15

Articles related to transformer design, engineering optimization, and new technologies linked to manufacturing were not considered. Regarding articles related to sustainability it was considered only papers focusing on analysis that seeks better efficiency in the performance of power transformers articles focusing on specific environmental characteristics were not selected.

III. SYNTHESIS

In the following sections, a synthesis of the articles is presented, focusing on their methodology, evaluated data, and contributions. At the end of each section, there is a table that summarizes the main subjects covered in each article, particularly the monitoring techniques, data analysis methods, and condition assessment methodologies and models.

A. ASSET MANAGEMENT AND CONDITION ASSESSMENT METHODOLOGIES

Abu-Elanien and Salama [6] and Velasquez-Contreras et al. [7] addressed about the monitoring techniques Dissolved Gas Analysis (DGA) and Frequency Response Analysis (FRA). Abu-Elanien and Salama also evaluate thermal analysis, vibration analysis, PD, and Recovery Voltage Measurement (RVM). Regarding the criteria for assessing the end-of-life physical condition of the equipment, the authors highlighted the degree of polymerization, maintained tensile strength, furanic compounds and addressed economic aging models considering linear depreciation and accelerated depreciation [6]. Velasquez-Contreras et al. developed the General Asset Management Model for an Electric Utility (GAMMEU), an integrated approach for managing power transformer assets within an electric utility company environment. The authors introduced a novel method to characterize the deterioration process of power transformers using the Multi-State Condition (MSC) Model and a methodology based on Hidden Markov Chains in order to estimate the failure rate using DGA tests. Anomaly detection modeling is carried out using oil temperature data and neural networks, and decision trees are employed as classifiers to evaluate FRA measurements of the transformers. An approach for maintenance scheduling was proposed using asset prioritization diagrams to support decision-making [7].

Soni and Mehta [2] presented a comprehensive review of the methods used for assessing the condition of power transformers, highlighting useful practices for evaluating the Health Index (HI), extending the lifecycle, and predicting failures. The following methods are addressed by the authors: DGA, oil analysis, FRA, RVM, PD testing, thermography testing, transformer turns ratio test, dielectric dissipation factor, winding resistance, core ground resistance, and insulation resistance calculation.

Murugan and Ramasamy [8], Koziel et al. [9], Gorginpour et al. [10], Balanta et al. [11], and Biçen and Aras [12] proposed condition assessment methodologies of power transformers. Koziel et al. proposed a data quality management framework and emphasized the need to consider and quantify data quality for efficient asset management decisions [9] as Biçen and Aras introduced an intelligent asset management system for power transformers that enables a simultaneous and holistic evaluation of multiple input parameters for more accurate diagnostics, and it was based on a Failure-Sensitive Matrix (FSM) [12].

Murugan and Ramasamy developed statistical analysis of failures based on voltage level, geographic zone, and transformer components [8] while Gorginpour et al. were based on the degree of polymerization and developed a Machine Learning (ML) algorithm with temperature, humidity, and daily scheduling data [10] and the method developed by Balanta et al. consider the insulation system degradation, risk index, consequence factor (CF), and economic impact [11]. The model proposed by Murugan and Ramasamy was based on a failure analysis of power transformers from two electric utility companies in Tamil Nadu, India, considering 196 failure cases from 2009 to 2013 [8] while the method developed by Gorginpour et al. was validated using data from damaged transformers in Bushehr, Iran, with a predicted useful life accuracy error of less than 10% [10].

Jin et al. [13] and Jin, Kim, and Abu-Siada [14] addressed about DGA, PD, and vibration analysis. The authors also addressed the temperature measurement [13] and presented about the methods based on temperature and paper degradation value, and insulation system degradation [14]. The article underscores the importance of understanding the characteristics of each technique to design effective condition monitoring systems and anticipates the development of more comprehensive systems that not only report on the transformer's condition but also provide guidance for asset management and estimates of remaining useful life [13]. Regarding reliability assessments, the authors highlighted the use of the HI and the combination of inspection and monitoring data as an important tool [14].

Table 3 shows the main topics covered and the respective references.

B. MONITORING AND DIAGNOSTIC TECHNIQUES AND METHODS

Soni and Mehta [15] proposed an approach to identify the health indices of power transformers from the following tests: dielectric strength, acidity, breakdown voltage, DGA, furan compounds, the dielectric dissipation factor, the presence of moisture, interfacial tension, coil DC resistance, and tangent delta. The authors utilize three mathematical analyses: Piecewise Linear Equations, the Analytic Hierarchy Process for weighting factors, and a residual analysis for curve fitting. Data from 100 transformers (20 healthy, 60 partially damaged, and 20 with high probability of failure) were analyzed [15]. And Wong et al. [16] proposed the use of computational intelligence models through the analysis of techniques DGA, FRA, PD, Polarization and Depolarization Current (PDC) measurement, RVM, Infrared Thermography (IRT), and a furan analysis (FA) [16].

Ma et al. [17], Guillen et al. [18], Didouche et al. [19], Sekatane and Bokoro [20], Beura et al. [21], and Liu et al. [22] addressed about PD measurement and analysis methods.

Ma et al. addressed statistical learning techniques and highlighted the development of an algorithm based on a Support Vector Machine (SVM). To acquire knowledge about the statistical dependence between historical data and equipment conditions, data from PD in components collected from transformers were used [17]. Guillen et al. developed an algorithm to PD location in transformer windings. The authors used discrete wavelets transform (DWT) and the Kullback–Leibler (KL) divergence [18]. Didouche et al. proposed a numerical localization method based on the Newton-Raphson iterative method which use mainly the finite elements method. This proposal reduces the number of sensors required for PD measurement [19].

Sekatane and Bokoro investigated the use of time reversal (TR) and the integration with convolution neural networks (CNNs) for diagnosing PD in power transformers [20] and Beura et al. use Dijkstra's algorithm with additional line-of-sight propagation algorithms to determine the paths of the electromagnetic waves generated by PD sources. According to the authors, this algorithm can circumvent the time-consuming and computationally intensive process of simulating or collecting experimental data for an Artificial Intelligence (AI)-based system of partial discharges in power transformers [21]. Liu et al. developed an ultrasonic detection system based on Fabry–Perot optical fiber sensor. The system employs a directional cross-localization method built on the multiple signal classification (MUSIC) algorithm to precisely pinpoint dual PD sources into the transformer interior [22].

Senobari et al. [23] and Seifi et al. [24] discussed about FRA as a method for assessing and detecting faults in transformers. Senobari et al. realized a literature review regarding the topic and highlighted points such as the development of methods independent of the transformer structure and mathematical and statistical understanding of FRA comparison indices [23]. And Seifi et al. proposed the Sweep Reflection Coefficient (SRC) method, using FRA, for the early detection of inter-turn faults and mechanical faults in the winding. The proposal was validated in distribution transformers, with localization errors of less than 5% for ground resistance faults and less than 15% for other types of faults [24].

Velásquez and Lara [25], Medina et al. [26], and Costa et al. [27] analyzed condition and diagnostic data using neural networks, Fuzzy logic, and linear regressions, respectively. In the implementation of the neural network, three layers and fourteen neurons in the hidden layer were used, and a backpropagation algorithm was employed to predict the lifetime parameter of reactors. The proposed methodology was validated on power reactors from the Red de Energía del Perú (REP) through statistical tests, with a confidence level of 98.5% [25]. Medina et al. developed a Fuzzy Inference System (FIS)-based approach to estimate the risk index of power transformers. Three FISs were used and tested on a fleet of 15 transformers: the HI, the CF, and the combination of both systems. The HI was calculated based on physical–chemical tests, considering the degree of polymerization. The failure CF was determined considering technical and operational parameters: load, oil volume, proximity to buildings, and penalties for asset unavailability. The third FIS combined the HI and CF to estimate the transformer's risk index [26]. Costa et al. proposed a model using linear regressions and temperature parameters based on environmental and historical data, along with gas concentration information [27].

Da Silva et al. [3] presented the development of a methodology to estimate the health of power transformers through a new diagnostic factor based on a historical average daily load curve and the identification of insulation conditions. And Zhou et al. [28] proposed a fault diagnosis model for power transformers based on a Probabilistic Neural Network (PNN) and optimized using an improved Gray Wolf Optimizer (GWO) algorithm. The methodology proposed by Da Silva et al. was applied and validated using data oil sample and electrical quantities from 204 power transformers in operation and its advantages include reducing the time needed to obtain results, allowing for the monitoring of solid transformer insulation degradation in 24-hour cycles [3]. The methodology proposed by Da Silva et al. used 555 real fault samples from the Jiangxi Power Supply Company [28].

Huang et al. [29] proposed an unsupervised clustering method Entropy-Weighted K-means (EW-Kmeans) and the classical two-parameter Weibull model to assess the average failures of different groups of transformers. The methodology was validated in a distribution transformer park of the Chongqing Electric Power Company in China [29]. Islam et al. [30] presented the implementation of an intelligent framework based on a Multilayer Perceptron (MLP) generative model and a logistic regression classifier with the aim of assessing the condition of power transformers. This methodology was valid with data from 608 real transformers [30].

Wang et al. [31] proposed a new integrated multi-level and multi-parameter diagnostic method based on the integration of fault information. The method was validated using data from 628 fault samples from transformers across China [31]. Building upon the root cause analyses, in 2019 [32], the authors developed a systematic approach including traditional methods, Principal Component Analysis (PCA), data mining, and causal mapping. A total of 279 reactors in high-voltage systems in Latin America were analyzed, with the forecast of an additional 134 units in the coming years, and the methodology was validated in a case study on a 500 kV reactor [32].

Murugan and Ramasamy [33] proposed a practical approach based on statistical analysis to transformer maintenance using failure data and the HI, aiming to prevent failures and reduce the maintenance costs of this equipment. The article analyzes 343 failures in distribution and power transformer components, with voltage classes ranging from 33 kV to 400 kV, over 11 years at the Tamil Nadu Electric Utility (TNEU) in India. A case study involving the calculation of the HI for seven power transformers was presented to validate the methodology [33]. Ariannik et al. [34] presented the development of a lifespan estimation model for distribution transformers based on the degree of polymerization, considering the following variables: ambient temperature, load factor, and moisture content of the paper insulation. The calculation of the hot-spot temperature and a dynamic analysis of the polymerization degree profile were performed with variations in the operational conditions, and the optimal time to implement reductions in the paper insulation moisture content was suggested [34]. And Liu et al. [35] proposed an algorithm for monitoring abnormal conditions in distribution transformers using the Spearman correlation coefficient and the t-Statistics test. The authors developed a data acquisition system and utilized phase current data from transformers. The algorithm was validated based on nine cases of real data from the power distribution system of Zhejiang, China [35].

Table 4 shows the main topics covered and the respective references.

C. OIL ANALYSIS

The developments proposed by Chen et al. [36], Abu-Siada and Islam [37], Abu-Siada et al. [38], Cui et al. [39], Tra et al. [40], Rajesh et al. [41], Velásquez and Lara [42], Aizpurua et al. [43], Bustamante et al. [44], Ward et al. [45], Menezes et al. [46], Soni and Mehta [47], [48], and Malik et al. [49] were based on DGA data. In addition to DGA, Velásquez and Lara used data from corrosive sulfur, and physical–chemical and electrical tests [38] while Aizpurua et al. evaluated oil quality, and solid insulation [43] and Ward et al. also addressed PD data [45]. Bustamante et al. discussed about DGA continuous online [44]. Soni and Mehta proposed methods using moisture content, furan compounds, and interfacial tension [47] and thermal stability, acidity, water content, breakdown voltage, and viscosity [48].

Vrsaljko et al. [50] did not use DGA data, the authors proposed the use of High-Performance Liquid Chromatography (HPLC) to determine the contents of phenol, m-cresol, and o-cresol in transformer oil. They confirmed that phenol, m-cresol, and o-cresol were not present in new oils, indicating their presence as a result of insulation material degradation. Therefore, the detection of these compounds serves as an

TABLE 3. Main subjects covered in each article on the subtopic of asset management and condition assessment methodologies.

Reference Index	Monitoring techniques	Condition assessment methodologies/models
[2]	Dissolved Gas Analysis (DGA), Frequency Response Analysis (FRA), Recovery Voltage Measurement (RVM), partial discharge (PD), thermography testing, transformer turns ratio test, dielectric dissipation factor, winding resistance, core ground resistance, and insulation resistance calculation.	
[6]	Thermal analysis, vibration analysis, PD, DGA, RVM, and FRA.	Degree of polymerization, maintained tensile strength, and furanic compounds.
[7]	DGA, oil temperature measurement and FRA.	Multi-State Condition (MSC), Hidden Markov Chains, neural networks, and decision trees.
[8]		Statistical analysis of failures based on voltage level, geographic zone, and transformer components.
[9]		Data quality management framework.
[10]		Degree of polymerization and Machine Learning (ML) algorithm based on temperature, humidity, and daily scheduling.
[11]		Insulation system degradation, risk index, consequence factor (CF), and economic impact.
[12]		Failure-Sensitive Matrix (FSM).
[13]	DGA, PD, vibration analysis, and temperature measurement.	
[14]	DGA, PD, and vibration analysis.	Methods based on temperature and paper degradation value, and insulation system degradation.

additional diagnostic tool to assess the normal or abnormal condition of transformer insulation, and elevated concentrations suggest equipment overheating [50].

Fuzzy logic was used by the authors in data analysis algorithms [38], [47], [48], [49]. Soni and Mehta proposed a combined approach using a Fuzzy Logic Controller (FLC) and Fuzzy C-Means (FCM) [47] and, in addition to Fuzzy Logic, clustering, and conditional probability [48].

The following methods have also been covered by the authors: Wavelet [36]; Gene Expression Programming (GEP) [37]; MLP Neural Networks [38]; Bayesian Particle Filtering [43]; ML classifiers: the J48 decision tree and random forest transformation with k-means, correlation-based feature selection, and PCA [51], and Computational Intelligence-based Decision Trees [43].

Cui et al. [39] and Tra et al. [40] proposed over-sampling methods with the aim of improving the diagnosis of the power transformer condition. The authors worked with oil analysis data, and the proposals were motivated by the fact that the nature of the data was not favorable for generalizing AI models.

Both works used the Synthetic Minority Over-Sampling Technique (SMOTE), referred to by Cui et al. [39] as SMOTEBoost and by Tra et al. [40] as ASMOTE (Adaptive SMOTE), in their adaptive approach. To validate the effectiveness of the methods, SVM and k-Nearest Neighbor (kNN) classification algorithms were used by both authors. Cui et al. [39] also used decision trees and radial basis function networks, while Tra et al. [40] also used the MLP. In 2023, Rajesh et al. [41] proposed the use of the ADASYN (Adaptive Synthetic Sampling Approach) technique, also a variant of the SMOTE. The authors used 4580 DGA samples from operational transformers to train the ML models.

The method proposed by Chen et al. was validated in a total of 700 oil samples and the five proposed approaches out-perform the accuracy and efficiency of the conventional backpropagation neural network method [36]. The approach using GEP, proposed by Abu-Siada and Islam, combines

Roger's ratio method, the IEEE method, and the CO/CO_2 ratio for interpreting the results and the critical classification of the transformer. Analyses are conducted on 338 oil samples collected from transformers with different classifications and lifespans [37], while the method proposed by Abu-Siada et al. was based on data from 2000 oil samples from different transformers, and the agreement of the method with real failures was tested on 70 samples with known failures [38].

Velásquez and Lara analyzed failures in 61 transformers and a preliminary correlation study between sulfurinduced corrosion and PD activity was performed [42] and the proposal developed by Aizpurua et al. was validated using data from a nuclear power plant [43].

The proposed approach by Soni and Mehta was applied to data from 200 transformers. Different oil analysis techniques were analyzed: (a) Duval Triangle, (b) Gouda's Three-Ratio Method (GTRT), (c) paper degradation based on the degree of polymerization and furans, and (d) insulation degradation based on moisture content and interfacial tension [47]. In the same year, the authors published [48] about the implementation of alternative fluids to replace mineral oil in transformers, citing environmental concerns, scarcity, the high costs of petroleum resources, and disposal issues.

Table 5 shows the main topics covered and the respective references.

D. MOISTURE IN INSULATION

Velásquez and Lara [52], Liu et al. [53], Liu et al. [54], Zukowski et al. [55], Hernandez and Ramirez [56], and Vatsa and Hati [57] addressed about the application of Frequency-Domain Spectroscopy (FDS) for the early detection of moisture in power transformer. The technique detects the degradation of the paper layer due to moisture.

Velásquez and Lara presented a study on the application of FDS in bushings. The results of the technique and the conductivity associated with temperature changes in this layer is reflected in the characteristics of the dissipation factor and the capacitance of the bushing [52]. Liu et al. used the FDS with the algorithm-enhanced backpropagation neural network (AdaBoost) [53]. Liu et al. discussed conventional dielectric response measurement techniques in oil-immersed power transformers, such as RVM, FDS, and polarization-depolarization current (PDC). The authors proposed the use of Grey Relational Analysis (GRA) to assess insulation condition by analyzing various dielectric response data [54], while Zukowski et al. proposed an accurate way to determine the standard characteristics for the conductivity of paper impregnated with insulating oil and containing moisture. The authors used direct and alternating current conductivity frequencies obtained by FDS [55]. Hernandez and Ramirez proposed an approach based on vector fitting (VF), a rational approximation, to find positive real parameters for the extended Debye model (EDM) using FDS data [56] and Vatsa and Hati developed a deep learning-based aging assessment technique combining FDS and squeeze-and-excitation-enabled convolutional neural network (SE-CNN) [57].

Singh et al. [58] and Arsad et al. [59] discussed the presence of moisture in the insulation by analyzing it with other physico-chemical tests. Meanwhile, Przybylek [60] proposed an alternative measurement method to determine the moisture content in oil and Koch et al. [61] developed an analysis relating moisture through water saturation while Medina et al. [62] discussed about the solid insulation degradation. Singh et al. presented a study on the influence of the age of transformers in operation on insulating oil, based on the following oil properties: moisture, dielectric strength, resistivity, the dissipation factor (tangent delta), interfacial tension, and flash point. They analyzed samples from 10 transformers in operation, with power ratings ranging from 16 to 20 MVA, manufactured between 1991 and 1997, installed in various substations in Punjab, India [58]. Medina et al. used arithmetic Brownian Motion algorithms to estimate paper moisture. The method involved a holistic approach to assess the aging of solid insulation [62] while Przybylek discussed methods for measuring moisture in liquid dielectrics, presenting the pros and cons of existing techniques and exploring the viability of Near-Infrared Spectroscopy (NIR) for this purpose [60].

Suleiman et al. [63], Liao et al. [64], Tu et al. [65], and Villarroela et al. [66] discussed about alternative insulators and the relationship with moisture. Suleiman et al. [63] discussed the effect of moisture on the dielectric strength and physicochemical structure of biodegradable palm-based insulating oils, used as alternatives to mineral oil. The Fourier Transform Infrared (FTIR) technique was employed to analyze the molecular structure changes in the oils at different moisture levels. Liao et al. investigated the effects of thermal aging on moisture equilibrium curves of a mineral oil–paper insulation system and a new paper–oil insulation system more resistant to aging [64] and Tu et al. [65] conducted an analysis of the moisture variation in oil and solid insulation during thermal aging for three types of papers [65]. Villarroela et al. [66] presented an analysis of moisture dynamics in transformers insulated with natural esters and highlighted the growing use of these liquids as insulation in transformers, aligned with the search for greater sustainability and clean energy [66].

Table 6 shows the main topics covered and the respective references.

IV. RESULTS AND DISCUSSIONS

This section presents information from the sources of evidence and a synthesis and discussion of the results.

The subtopics covered in this scoping review are related to asset management of power transformers. Asset management covers the entire life cycle of the equipment. The Operation and Maintenance stage, the largest part of the asset's useful life, includes Maintenance Management, which includes preventive, corrective and predictive maintenance. Figure 3 represents the hierarchical relationship between the asset management and the types of maintenance, and Figure 4 represents the hierarchy between subtopics of the articles.

TABLE 4. Main subjects covered in each article on the subtopic of monitoring and diagnostic techniques and methods.

Reference Index	Monitoring techniques	Condition assessment methodologies/models
[3]	An analysis data from oil samples and electrical quantities.	Models based on the historical average daily load curve.
[15]	The dielectric strength, acidity, breakdown voltage, DGA, furan compounds, dielectric dissipation factor, presence of moisture, interfacial tension, coil direct current (DC) resistance, and tangent delta.	Multi-Criteria Decision Making (MCDM) and Piecewise Linear Equations, Analytic Hierarchy Process for weighting factors, and residual analysis.
[16]	DGA, FRA, PD, Polarization and Depolarization Current (PDC) measurement, RVM, Infrared Thermography (IRT), and a furan analysis (FA).	
[17]	PD.	Support Vector Machine (SVM) based ML algorithm.
[18]	PD.	Discrete wavelets transform (DWT) and Kullback–Leibler (KL).
[19]	PD.	The Newton-Raphson iterative method based on finite elements method.
[20]	PD.	The time reversal (TR) and integration with convolution neural networks (CNNs).
[21]	PD.	Dijkstra's algorithm.
[22]	PD.	Sensor: Fabry–Perot optical fiber. Algortimo: directional cross-localization based on the multiple signal classification (MUSIC).
[23]	FRA.	
[24]	FRA.	Sweep Reflection Coefficient (SRC).
[25]		Neural networks.
[26]	Physical–chemical tests.	Models: Fuzzy logic. Data: degree of polymerization, load, oil volume, proximity to buildings, and penalties for asset unavailability
[27]		Models: linear regressions. Data: temperature parameters and gas concentration information.
[28]		Probabilistic Neural Network (PNN) and Gray Wolf Optimizer (GWO).

TABLE 4. *(Continued.)* **Main subjects covered in each article on the subtopic of monitoring and diagnostic techniques and methods.**

Reference Index	Monitoring techniques	Condition assessment methodologies/models
[29]		Unsupervised clustering method of Entropy-Weighted K-means (EW-Kmeans) and the classical two-parameter Weibull model. Data: degree of polymerization.
[30]		Multilayer Perceptron (MLP) generative model and logistic regression classifier.
[31]	A comparative evaluation of the reliability of seven fault diagnostic methods in transformers, with emphasis on DGA.	Integrated multi-level and multi-parameter diagnostic method based on the integration of fault information.
[32]	An analysis based on data on mechanical, electrical, physical, and chemical dimensions.	Principal Component Analysis (PCA), data mining, and causal mapping.
[33]		A statistical analysis of failure data and identification of failure causes through maintenance records, direct observations in the repair yard, and consultations with experts.
[34]		The degree of polymerization, considering the variables ambient temperature, load factor, and moisture content of the paper insulation.
[35]		Spearman correlation coefficient and the t-Statistics test.

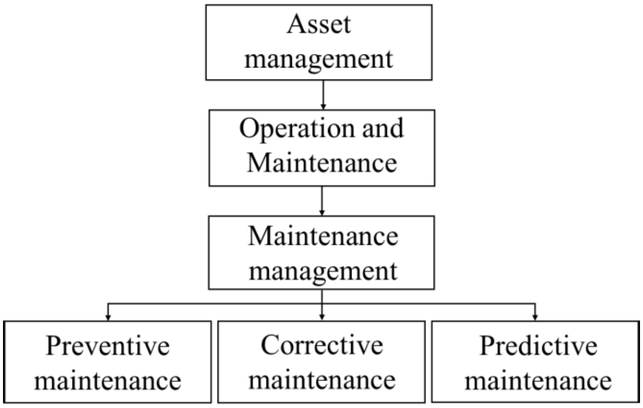

FIGURE 3. Hierarchical relationship between the asset management and the types of maintenance.

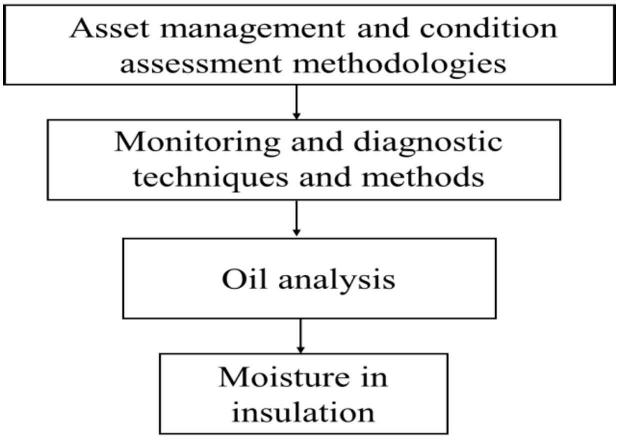

FIGURE 4. Hierarchical relationship between the subtopics of the articles.

Table 7 shows the reference, subtopic, journal, year, and country of each source of evidence.

Articles [2], [6], [7], [8], [9], [10], [11], [12], [13], and [14] addressed the importance of effective asset management

TABLE 5. Main subjects covered in each article on the subtopic of oil analysis.

Reference Index	Monitoring techniques	Condition assessment methodologies/models
[36]	DGA	Wavelet.
[37]	DGA	Gene Expression Programming (GEP).
[38]	DGA	Fuzzy logic.
[39]	DGA	SMOTE (Synthetic Minority Over-sampling Technique), SVM and k-Nearest Neighbor (kNN), and decision trees and radial basis function networks.
[40]	DGA	ASMOTE (Adaptive SMOTE), SVM and (kNN), and MLP.
[41]	DGA	ADASYN (Adaptive Synthetic Sampling Approach).
[42]	DGA, corrosive sulfur, and physical–chemical and electrical tests.	Data mining and MLP neural networks.
[43]	DGA, oil quality, and solid insulation.	Bayesian Particle Filtering.
[44]	DGA online contínuo.	
[45]	DGA and PD.	
[46]	DGA	Computational intelligence based decision trees.
[47]	DGA, moisture content, furan compounds, and interfacial tension	Degree of polymerization, Fuzzy Logic Controller (FLC), and Fuzzy C-Means (FCM).
[48]	Thermal stability, acidity, water content, DGA, dissolved gases, breakdown voltage, viscosity, and accelerated aging.	Fuzzy logic, clustering, and conditional probability.
[49]	DGA	Fuzzy logic, clustering, and conditional probability.
[50]	High-Performance Liquid Chromatography (HPLC) to determine phenol, m-cresol, and o-cresol contents in transformer oil.	
[51]		ML J48 decision tree and random forest, transformation with k-means, correlation-based feature selection, and PCA.

for power transformers, focusing on monitoring techniques, condition assessments, and maintenance optimization. Models and methodologies were proposed to enhance reliability, reduce maintenance costs, and predict failures. Furthermore,

TABLE 6. Main subjects covered in each article on the subtopic of moisture in insulation.

Reference Index	Diagnosis of moisture level	Condition assessment
[52]	The early detection of moisture in power transformer bushings.	Technique: Frequency-Domain Spectroscopy (FDS).
[53]	A prediction of moisture content.	Technique: FDS. Algorithms: Enhanced backpropagation neural network (Ada-Boost) and ML.
[54]	A combination of techniques for evaluating dielectric response data.	Technique: RVM, FDS, and polarization-depolarization current (PDC). Analysis: Grey Relational Analysis (GRA).
[55]	A way of determining the standard characteristics for the conductivity of paper impregnated with insulating oil and containing moisture.	Technique: FDS.
[56]	An approximation of moisture content.	Technique: FDS. Analysis: Vector fitting (VF) and extended Debye model (EDM).
[57]	A technique to assess the aging status of paper.	Technique: FDS. Analysis: neural network.
[58]	Transformer age analysis and physicochemical tests on oil.	Oil properties analyzed: moisture, dielectric strength, resistivity, the dis-sipation factor (tangent delta), interfacial tension, and flash point.
[59]	Th methods for detecting and quantifying moisture in oil.	Oil properties analyzed: breakdown voltage and moisture. Analysis: accuracy, measurement time, and cost.
[60]	An alternative method to the Karl Fischer Titration (KFT).	Technique: Near-Infrared Spectroscopy (NIR)
[61]	The determination of moisture in oil and cellulose in power transformer.	Analysis: water saturation and representations of the isotherms
[62]	A method to estimate solid insulation degradation in power transformers.	Oil properties analyzed: temperature and moisture. Algorithm: Arithmetic Brownian Motion.
[63]	The effect of moisture on alternative insulating oils compared to mineral oil.	Technique: Fourier Transform Infrared (FTIR). Analysis: molecular structure changes in the oils at different moisture levels.
[64]	The effects of thermal aging on moisture equilibrium curves for mineral oil–paper insulation and proposal of a new paper–oil insulation system more resistant to aging.	Analysis: effects of moisture distribution based on the absorption capacity of oil and paper and the degree of polymerization.
[65]	The moisture variation in oil and solid insulation during thermal aging for three types of papers.	Oil properties analyzed: temperature and moisture. Analysis: saturated solubility and breakdown of molecular chains.
[66]	An analysis of moisture dynamics in transformers insulated with natural esters.	Oil properties analyzed: temperature and moisture

TABLE 7. Information from each source of evidence.

Reference Index	Reference	Subtopic	Journal	Year	Country
[2]	Soni and Mehta	*A*	*Engineering Failure Analysis*	2021	India
[3]	Da Silva et al.	*B*	*Engineering Failure Analysis*	2021	Brazil
[6]	Abu-Elanien and Salama	*A*	*Electric Power Systems Research*	2010	Canada
[7]	Velasquez-Contreras, Sanz-Bobi, and Arellano	*A*	*Electric Power Systems Research*	2011	Spain
[8]	Murugan and Ramasamy	*A*	*Engineering Failure Analysis*	2015	India
[9]	Koziel et al.	*A*	*Applied Energy*	2021	Sweden
[10]	Gorginpour, Ghimatgar and Toulab	*A*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2022	Iran
[11]	Balanta et al.	*A*	*Energies*	2023	Argentina
[12]	Biçen and Aras	*A*	*Engineering Failure Analysis*	2023	Australia
[13]	Jin et al.	*A*	*Energies*	2022	Australia
[14]	Jin, Kim, and Abu-Siada	*A*	*Engineering Failure Analysis*	2023	Turkey
[15]	Soni and Mehta	*B*	*Engineering Failure Analysis*	2022	India
[16]	Wong et al.	*B*	*Applied Soft Computing*	2022	Malaysia
[17]	Ma, Saha, and Ekanayake	*B*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2012	Australia
[18]	Guillen et al.	*B*	*Electric Power Systems Research*	2016	Mexico
[19]	Didouche et al.	*B*	*Electric Power Systems Research*	2022	Algeria
[20]	Sekatane and Bokoro	*B*	*Energies*	2023	South Africa
[21]	Beura, Wolters and Tenbohlen	*B*	*Sensors*	2024	Germany
[22]	Liu et al.	*B*	*Energies*	2024	China
[23]	Senobari, Sadeha and Borsi	*B*	*Electric Power Systems Research*	2018	Iran
[24]	Seifi et al.	*B*	*International Journal of Electrical Power & Energy Systems*	2022	Germany
[25]	Velásquez and Lara	*B*	*Engineering Failure Analysis*	2018	Peru
[26]	Medina et al.	*B*	*Electric Power Systems Research*	2022	Argentina
[27]	Costa, Silva, and Branco	*B*	*Energies*	2022	Portugal
[28]	Zhou et al.	*B*	*Energies*	2021	China
[29]	Huang et al.	*B*	*Reliability Engineering & System Safety*	2023	China
[30]	Islam et al.	*B*	*Electric Power Systems Research*	2023	Bangladesh
[31]	Wang et al.	*B*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2013	China
[32]	Velásquez and Lara	*B*	*Engineering Failure Analysis*	2019	Peru
[33]	Murugan and Ramasamy	*B*	*Engineering Failure Analysis*	2019	India
[34]	Ariannik, Razi-Kazemi, and Lehtonen	*B*	*Reliability Engineering & System Safety*	2020	Iran
[35]	Liu et al.	*B*	*IEEE Transactions on Power Delivery*	2019	China
[36]	Chen et al.	*C*	*IEEE Transactions on Power Delivery*	2009	China
[37]	Abu-Siada and Islam	*C*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2012	Australia
[38]	Abu-Siada, Hmood, and Islam	*C*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2013	Australia
[39]	Cui, Ma, and Saha	*C*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2014	Australia
[40]	Tra, Duong, and Kim	*C*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2019	South Korea
[41]	Rajesh et al.	*C*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2023	India

TABLE 7. ***(Continued.)*** **Information from each source of evidence.**

Reference Index	Reference	Subtopic	Journal	Year	Country
[42]	Velásquez and Lara	*C*	*Engineering Failure Analysis*	2018	Peru
[43]	Aizpurua et al.	*C*	*Applied Soft Computing*	2019	Spain
[44]	Bustamante et al.	*C*	*Sensors*	2019	Spain
[45]	Ward et al.	*C*	*Sensors*	2021	Egypt
[46]	Menezes et al.	*C*	*IEEE Transactions on Power Delivery*	2022	Brazil
[47]	Soni and Mehta	*C*	*Electric Power Systems Research*	2023	India
[48]	Soni and Mehta	*C*	*Electric Power Systems Research*	2023	India
[49]	Malik, Sharma, and Naayagi	*C*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2023	Singapore
[50]	Vrsaljko, Haramija, and Hadzi-Skerlev	*C*	*Electric Power Systems Research*	2012	Croatia
[51]	Senoussaoui, Brahami, and Fofana	*C*	*Energies*	2021	Algeria
[52]	Velásquez and Lara	*D*	*Engineering Failure Analysis*	2018	Peru
[53]	Liu et al.	*D*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2022	China
[54]	Liu et al.	*D*	*Energies*	2017	China
[55]	Zukowski et al.	*D*	*Energies*	2021	Poland
[56]	Hernandez and Ramirez	*D*	*Energies*	2022	Mexico
[57]	Vatsa and Hati	*D*	*Engineering Applications of Artificial Intelligence,*	2024	India
[58]	Singh, Sood, and Verma	*D*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2012	India
[59]	Arsad et al.	*D*	*Energies*	2023	Malaysia
[60]	Przybylek	*D*	*Energies*	2022	Poland
[61]	Koch, Tenbohlen, and Stirl	*D*	*IEEE Transactions on Power Delivery*	2010	Germany
[62]	Medina et al.	*D*	*Electric Power Systems Research*	2017	Ecuador
[63]	Suleiman et al.	*D*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2014	Malaysia
[64]	Liao et al.	*D*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2015	China
[65]	Tu et al.	*D*	*IEEE Transactions on Dielectrics and Electrical Insulation*	2016	China
[66]	Villarroela, Burgos, and García	*D*	*International Journal of Electrical Power & Energy Systems*	2021	United Kingdom

there is a consensus on the importance of integrating diagnostic algorithms, monitoring techniques, and AI for fault prediction, with an emphasis on DGA and HI assessments.

Articles [3], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], and [35] addressed a variety of methodologies and techniques for diagnosing faults and estimating the lifespan of power transformers. The authors highlighted the importance of DGA, PDs, statistical learning, online and offline diagnostic methods, lifespan models, and continuous monitoring techniques. Additionally, they emphasized the need for more accurate and efficient methods to ensure the reliability and operational safety of transformers, contributing to the optimization of maintenance strategies and the extension of the lifespan of this essential piece of equipment for power supply.

Articles [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], and [51] discussed the techniques and methodologies used for diagnosing faults in power transformers, with an emphasis on insulating oil analysis and a particular focus on dissolved gases. The approaches included the use of statistical methods, AI techniques such as neural networks and Fuzzy logic, and physicochemical analyses. There is a search to find more effective and accurate methods, often combining multiple techniques to enhance result reliability.

Articles [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], and [66] addressed the issue of moisture in power transformers, exploring different aspects related to its impact on the performance and integrity of insulation systems. The authors discussed methods for assessing moisture, the effects of thermal aging on insulating materials,

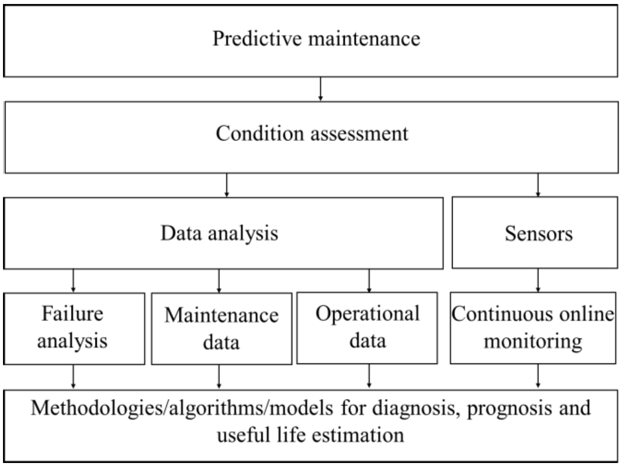

FIGURE 5. Hierarchical relationship between the predictive maintenance and the data analysis methodologies.

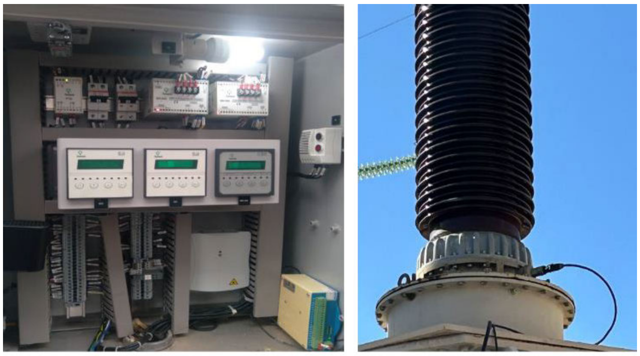
(a) (b)

FIGURE 6. Continuous online monitoring of bushings installed on a power transformer in the field: (a) Monitoring system; (b) Bushing sensor.

the influence of moisture on the properties of insulating oils, and sustainable alternatives to traditional mineral oils. Additionally, there is an emphasis on the importance of the early detection and monitoring of moisture, highlighting the need for precise and efficient techniques to ensure the safe and reliable operation of transformers.

V. CONCLUSION

This study aimed to provide a foundation for new research and investigations by conducting an unprecedented review on the subject, examining recent works published in twenty-five countries worldwide. One of the key research results is the finding that the data analysis methodologies related to identifying failures and aiding decision-making can add value to asset management, especially considering the aging of the transmission sector's infrastructure, the impracticality of replacing all depreciated assets from a regulatory perspective, the challenges posed by the system, including support for energy transition, and developments and advances in relation to smart grids.

(a) (b)

FIGURE 7. Online DGA installed on a power transformer in the field: (a) Monitoring system; (b) Monitoring system and transformer view.

Another important research result is the finding of the opportunity and importance of developing algorithms related to the evaluation of transformer insulating oil. This knowledge still largely depends on assessments by experts. The analysis of the physical–chemical results of the oil, in addition to the already well-explored DGA, is an important line of research.

This research also found the importance of applying statistical tools prior to the application of AI algorithms. With the possibility of using diverse data from transformers, the prioritization of variables prior to applying predictive models can result in better performance.

Given these findings, this scoping review was the basis for the development of an inedited methodology, to be presented in a future article, to aid decision-making regarding investments in the maintenance of power transformers that aims to evaluate the predictive power of variable categories in relation to binary output, considering characteristics equipment techniques and the water content in the oil.

As potential new technologies and future development trends highlighted continuous online monitoring of the condition of power transformers and the application of data analysis tools and algorithms that contribute to better equipment assessment. Failure analysis, evaluation of maintenance data, equipment operating data and continuous online monitoring are important for the development of methodologies for diagnosis, prognosis of assets and estimation of their useful life. Figure 5 represents the hierarchy between these subjects and Figure 6 shows continuous online monitoring of bushings installed on a power transformer in the field.

Another future development trend is the processing of signals and data analysis of partial discharges, especially for online measurements. Online DGA measurement is also a technology with potential for further developments and analyses. Figure 7 shows a pilot installation of online DGA installed on a power transformer in the field. Condition assessment methodologies, especially using AI, and definition of standardized failure modes also present opportunities for development and impact better management of power transformer assets.

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GABRIELA S. RÊMA received the master's degree from UNIFEI, in 2018, a scholarship from CNPq. She is currently pursuing the Ph.D. degree with the Electrical Engineering Program, Federal University of Itajubá—UNIFEI. She was a Researcher with the Centro de Pesquisas de Energia Elétrica (CEPEL) (2017–2023) and a Substitute Professor with the Institute of Systems Engineering and Information Technologies (IESTI), UNIFEI, and FER/AEDB (2016–2017). She is also an Engineer with the Companhia de Transmissão de Energia Elétrica Paulista—ISA CTEEP. She is also an Electrical Engineer with an emphasis on electronics with the Faculty of Engineering of Resende (FER/AEDB), in 2015; a Scholarship Holder with Prouni; a Technician in telecommunications with the Escola Técnica Pandiá Calógeras (ETPC), in 2010; and a Scholarship Holder with ETPC. Works in the areas of high voltage equipment, monitoring and analysis of the condition of transmission assets, maintenance management based on reliability and condition of assets, frequency response, and electromagnetic transients and simulation and modeling of electrical equipment.

BENEDITO D. BONATTO (Senior Member, IEEE) received the bachelor's degree in electrical engineering from the Federal University of Itajuba, in 1991, the master's degree in electrical engineering from the State University of Campinas, in 1995, and the Doctorate (Ph.D.) degree in electrical and computer engineering from the EMTP—Electromagnetics Transients Program, in 2001, under the supervision of Dr.-Ing. Hermann W. Dommel. He was with a Post-Doctorate (Visiting Associate Professor) with the Power and I2Sim Group, Department of Electrical and Computer Engineering, The University of British Columbia (UBC), in 2013, under the leadership of Prof. José R. Martí, Vancouver, BC, Canada; a Post-Doctorate (Visiting Associate Professor) with the EPSEVG—Escola Politècnica Superior d'Enginyeria de Vilanova i la Geltrú, UPC—Universitat Politècnica de Catalunya BARCELONATECH, Vilanova i la Geltrú, Barcelona, Spain, under the leadership of Prof. Miguel Castilla, in 2019; and a Post-Doctorate (Invited Visiting Professor) with the Faculty of Electrical and Computing Engineering, The State University of Campinas (UNICAMP), Research Groups, under the leadership of Prof. Walmir Freitas Filho and Luiz Carlos Pereira da Silva (CPTEn), Campinas, São Paulo, Brazil, in 2022. He is currently a Full Professor with the Federal University of Itajuba (UNIFEI), Brazil. He has experience in electrical engineering, in industries and power companies, acting on the following subjects: smart grids, electric power quality (PQ), electromagnetic transients (EMTP) in electrical power systems, technical and economic regulation in electricity markets, electricity work safety, and engineering education. He is a Sponsored Researcher by CNPq-Brasil.

ANTONIO C. S. DE LIMA received the bachelor's, master's, and Doctor degrees in electrical engineering from the Federal University of Rio de Janeiro, in 1994, 1997, and 1999, respectively. He is currently a Full Professor with the Federal University of Rio de Janeiro and the Department Head of the Graduate Department of Electrical Engineering, COPPE/UFRJ. He has experience in the area of electrical engineering. His main research interests include electric power transmission and distribution, modeling of power equipment and wideband modeling of overhead transmission lines, underground and subsea cables, solution of electric networks, and applied electromagnetism.

ANDRÉ T. DE CARVALHO received the Graduate degree in electrical engineering from the Federal University of Rio de Janeiro, in 2001, the Master of Science degree from the University of São Paulo, in 2005, and the Doctor of Science degree from the Federal University of Rio de Janeiro, in 2014. From 2001 to 2006, he was a Collaborating Researcher with the Centro de Pesquisas de Energia Elétrica (CEPEL). In 2006, he was admitted through a public competition as a Researcher with CEPEL. He is currently the Head of the Asset Management Technology Department, CEPEL. His main professional and research interests include virtual instrumentation, embedded systems, digital signal processing, and predictive diagnosis of electrical equipment.

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