The application of artificial intelligence methods for the interpretation of dissolved gas analysis results in transformer oil

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***Abstract*— The growing complexity of power grids driven by the integration of renewable energy sources, electric vehicles, and climate change has increased the importance of reliable maintenance of power transformers (PT). Transformer failures can severely impact electricity generation, transmission, and distribution. Accurate condition assessment, especially through Dissolved Gas Analysis (DGA) of transformer oil, is crucial for early fault detection. This paper presents an overview of recent developments in the application of artificial intelligence (AI) methods for interpreting DGA results to improve diagnostic accuracy. Various supervised, unsupervised, and hybrid approaches are analyzed, with a focus on their capabilities, advantages, and limitations. The paper also discusses two representative case studies from the literature to illustrate the practical implementation and effectiveness of AI-based diagnostics. AI significantly enhances the reliability and automation of transformer condition monitoring, particularly in borderline or uncertain cases, thereby promoting the adoption of web-based and e-commerce preventive maintenance solutions.**

Keywords*— *power transformers, diagnostic, DGA, artificial intelligence, machine learning, supervised learning, unsupervised learning, fuzzy logic, electrical network

I. Introduction

Power transformers (PTs) play a key role in the power system, not only in the generation, but also in the transmission and distribution of electricity. These are large, expensive, and strategically important assets with long procurement and replacement times. Their failure can lead to reduced production, transmission and distribution capacity or to the failure of the electrical network [1].

In recent years, due to the emergence of renewable energy sources, small power producers, electric vehicles, data centers and the impact of climate change, the number of PTs has increased and the structure of the power grid has become more complex. These modern challenges have further emphasized the need for efficient monitoring and maintenance strategies of power transformers to ensure the reliable and continuous operation of power systems. Consequently, accurate condition assessment and fault prediction for transformers are becoming increasingly important to support maintenance, planning, exploitation and optimize asset management. The complexity of determining and predicting the operating condition requires the use of complex artificial intelligence algorithms [2].

One of the key elements of diagnostic and prediction of the state of PT is testing the transformer oil. It is particularly important because of the possibility of oil sampling from transformers in operation. The most important method for diagnostic testing of oil in terms of assessing the operational readiness of the transformer is the dissolved gas analysis (DGA) of transformer oil, which provides indicators of emerging failures, as well as types of failures. Considering the cases when it is necessary to analyze a large number of samples, artificial intelligence (AI) methods are an effective tool for automating and improving the diagnostic process. The power of AI methods is especially evident in cases where the test results are in the border areas of the states defined by the standard, and in that case the combination of historical data and AI methods can contribute to a more reliable determination of the operating condition of the transformer. In such cases, manual diagnosis can be ambiguous and prone to human error. To address this issue, artificial intelligence (AI) techniques, such as machine learning, fuzzy logic, neural networks, and hybrid approaches have emerged as powerful tools for automating the diagnostic process and enhancing the reliability of transformer condition assessment [3-5].

This paper provides an insight into the current state of technology in diagnosing the operating condition of transformers using artificial intelligence methods to interpret the results of DGA of transformer oil. The paper presents an analysis of the latest developments in this field, including the use of supervised machine learning algorithms, unsupervised machine learning, hybrid approaches and fuzzy logic. The review also summarizes and classifies existing research contributions based on the type of artificial intelligence algorithms used and the datasets involved in the analysis. The paper also includes brief explanations of the most commonly used artificial intelligence methods.

In addition to the general overview, the paper presents an analysis of two representative studies that demonstrate the practical application of artificial intelligence techniques in transformer fault diagnosis using DGA. These examples were selected to illustrate the potential of integrating artificial intelligence into transformer monitoring systems.

A brief overview of currently available web-based and e-commerce solutions supporting transformer oil DGA interpretation is also provided.

The goal of this work is to highlight the growing relevance of AI-assisted DGA diagnostics, to identify gaps in the current literature, and to serve as a foundation for future research and development in this evolving field.

II. Dissolved Gas Analysis

Gas chromatography (GC) is a standardized and widely used technique for diagnosing the condition of power transformers. This method enables the detection and quantification of gases generated as a result of thermal and electrical stresses within the transformer, most commonly in the insulating oil. Dissolved Gas Analysis (DGA) is employed for the early detection of potential faults, thereby significantly reducing the risk of costly failures and unplanned outages [6].

During normal transformer operation, insulating materials (oil and paper insulation) gradually age and degrade due to thermal and electrical stresses. As a result of oil decomposition and cellulose degradation under operating conditions, the following gases are generated: hydrogen and hydrocarbon gases (methane, acetylene, ethylene, and ethane), along with carbon monoxide and carbon dioxide. In addition to these, oxygen and nitrogen from the external environment are also present.

The presence and concentration of these gases, as well as their mutual ratios, provide diagnostic information about the type and severity of internal faults, such as localized overheating, electrical discharges, arcing, and thermal degradation of the cellulose insulation.

Methods for analyzing gas chromatography results are based on a straightforward principle: a specific type of fault generates characteristic gases in certain quantities. For instance, elevated levels of acetylene indicate electrical arcing, whereas a dominance of carbon oxides suggests thermal degradation of paper insulation. It is important to interpret the results within context: transformer type, age, voltage level, and operating conditions significantly affect typical gas concentrations. Therefore, monitoring gas concentration trends over time is recommended, rather than relying solely on a single measurement.

Faults that may occur can generally be classified into two main groups: electrical and thermal. Typical electrical faults include: partial discharges (code PD), low-energy electrical discharges (D1), and high-energy electrical discharges (D2). Thermal faults are categorized based on temperature range into three groups: T1 (up to 300 °C), T2 (300 °C to 700 °C), and T3 (above 700 °C) [7].

Based on various databases of gas chromatography analyses of faulty transformers, where fault types were confirmed through factory inspections, several diagnostic methods have been developed. These methods rely on calculating the ratios of specific gas pairs to identify fault types. Depending on which gas ratios are applied, multiple interpretation techniques are available for evaluating DGA results, including [7-9]:

- the IEC 60599:2022,
- the Duval Triangle,
- the Duval Pentagon,
- Rogers' Ratios,
- the Logarithmic Nomograph Method,
- the Doernenburg Method,
- the Key Gas Method.

These interpretation DGA methods are called classical DGA methods in the literature.

Each of these methods has its own advantages and areas of applicability, and they are often used in combination to improve diagnostic accuracy, especially in borderline or ambiguous cases. The Table I is presented that compares these methods based on criteria such as the number of gases analyzed and fault coverage.

TABLE I. DGA INTERPRETION METHODS

Method	Number of Gases Analyzed	Fault Coverage	Brief Description / Notes
IEC 60599:2022	6	All fault types	Standardized approach, widely accepted
Duval Triangle	3	Common faults (electrical, thermal)	Simple graphical tool, easy to use
Duval Pentagon	5	Broader range of faults	Extension of Duval Triangle for better fault distinction
Rogers' Ratios	5	Major electrical and thermal faults	Calculation of gas ratio values
Logarithmic Nomograph	5	Thermal and electrical faults	Uses logarithmic gas ratios for interpretation
Doernenburg Method	6	Various fault types	More complex, uses a larger number of gases and criteria
Key Gas Method	1-2	Specific faults	Focuses on individual indicator gases

The interpretation of DGA results is based on absolute gas concentrations, statistical analysis of historical gas chromatography tests, gas generation rates, and characteristic ratios of gases dissolved in the oil. The IEC and IEEE standards define concentration thresholds for individual gases dissolved in transformer oil that are typical for normal transformer operation under standard conditions. Typical values largely depend on the transformer type, voltage level, and operating conditions. Therefore, it is appropriate to establish typical gas concentration values for different transformer populations [10]. Any significant deviation from these typical values may indicate abnormal transformer operation or the presence of a fault.

The basic gas ratios most commonly used in fault diagnosis and employed by interpretation methods are:

$$R_1 = \frac{C_2H_2}{C_2H_4},\ R_2 = \frac{CH_4}{H_2} \text{ and } R_3 = \frac{C_2H_4}{C_2H_6} \tag{1}$$

Gas chromatography remains an indispensable diagnostic method in the maintenance and monitoring of power transformers. The integration of artificial intelligence in processing these data enables a higher level of automation, accuracy, and reliability in fault diagnosis. Although challenges remain regarding the validation and interpretation of AI models, industry trends clearly indicate that the role of artificial intelligence in preventive maintenance will become increasingly important as part of a broader strategy for smart management of power systems.

III. REVIEW OF MACHINE LEARNING METHODS APPLIED TO DISSOLVED GAS ANALYSIS (DGA) OF TRANSFORMER OILS

This chapter presents machine learning methods applied to dissolved gas analysis (DGA) of transformer oils. The methods included were identified through a literature search of papers published in journals and conference proceedings. The final criteria for selecting the papers were that they focus on the application of machine learning or fuzzy logic to transformer DGA, they were published in reputable journals and conferences, and that they were published in English. The following repositories were used for the search: IEEE Xplore, MDPI, ResearchGate, ScienceDirect, Scientific Reports, Springer Link, and The Institute of Engineering and Technology [4-5].

Machine learning is commonly categorized into three types: supervised learning, unsupervised learning, and reinforcement learning.

Supervised learning algorithms are used when both the test results and their interpretations are known and available for model training. Unsupervised learning algorithms are applied when the test results are known, but the interpretation of those results is not available.

Algorithms from the field of supervised machine learning identified during the search are presented in Table II, while those from the field of unsupervised learning are shown in Table III.

TABLE II. SUPERVISED MACHINE LEARNING ALGORITHMS APPLIED TO DGA

Algorithm	Description
Support Vector Machine (SVM)	Effective for classifying fault types based on gas levels
Artificial Neural Networks (ANN)	Used for detecting and classifying transformer faults
Decision Tree (DT)	Interpretable model for condition classification
Random Forest (RF)	Ensemble method that improves classification accuracy
K-Nearest Neighbors (KNN)	Simple method for classification based on similarity
Gradient Boosting (XGBoost, LightGBM)	Accurate and robust fault prediction method
Logistic Regression	Used for binary classification (e.g., fault / no fault)
Naive Bayes	Classifying transformer fault types, especially in cases with limited training samples due to its simplicity and efficiency
Convolutional Neural Networks (CNN)	Extract patterns from gas concentration vectors and classify transformer fault types with high accuracy
Recurrent Neural Networks (RNN)	Model time-series DGA data and capture temporal patterns in gas concentrations for fault prediction.

TABLE III. UNSUPERVISED MACHINE LEARNING ALGORITHMS APPLIED TO DGA

Algorithm	Description
K-Means Clustering	Groups DGA samples into clusters based on gas concentration similarity. Helps identify potential fault categories.
Fuzzy C-Means (FCM)	Allows each sample to belong to multiple clusters with different degrees of membership, useful when fault types are overlapping.
Hierarchical Clustering	Builds a tree (dendrogram) showing how DGA samples are grouped, useful for visual exploration of similarities.
Principal Component Analysis (PCA)	Reduces dimensionality of DGA data and reveals key gas combinations that distinguish different transformer states.
Self-Organizing Maps (SOM)	Visualization and clustering of high-dimensional DGA data
DBSCAN (Density-Based Spatial Clustering of Applications with Noise)	Detects clusters based on data density and isolates outliers; useful for identifying rare or novel fault conditions.
Autoencoders	Used to detect anomalies in gas patterns by measuring reconstruction error.

Of the methods listed, CNN, RNN, and Autoencoders are categorized as deep learning techniques.

Reinforcement learning algorithms are not typically used in DGA analysis due to the nature of the problem, which involves classification or regression tasks. Reinforcement learning is designed for scenarios where learning occurs through interaction with the environment. Applying it to transformer diagnostics would require simulating a large number of fault scenarios on real transformers, which is impractical, hazardous, and costly. However, this limitation could potentially be addressed by implementing a digital twin model, allowing for realistic interaction and fault simulation in a virtual environment.

Fuzzy logic is among the artificial intelligence techniques applied in DGA analysis, particularly for handling uncertainty and imprecise gas concentration thresholds.

A hybrid approach can be applied to the evaluation of DGA results and transformer fault detection, combining multiple artificial intelligence algorithms to improve diagnostic accuracy and robustness. For example, the integration of fuzzy logic with artificial neural networks (Fuzzy-ANN) enables better handling of uncertainty in gas measurements, while combining Decision Trees with Support Vector Machines (DT-SVM) can improve classification performance by leveraging the interpretability of tree-based models and the generalization capabilities of SVMs

The presented artificial intelligence algorithms rely on classical methods for interpreting DGA results, which were described in the previous chapter.

IV. Review of Machine Learning Method Applications in DGA

Artificial intelligence methods have been used for more than three decades as a tool for transformer diagnostics based on DGA. During this period, several hundred papers have been published in journals and presented at conferences.

A total of 28 papers were analyzed based on the criteria presented in the previous section [11-38]. An overview of the use of artificial intelligence methods in the reviewed papers is presented in Table IV.

TABLE IV. Review of papers and machine learning algorithms for transformer fault diagnosis based on DGA

Algorithm	Papers
Support Vector Machine (SVM)	[14], [16], [17], [20], [21], [22], [24], [27], [29], [32], [33], [37]
Artificial Neural Networks (ANN)	[13], [21], [27], [28], [31], [34], [35], [38]
Decision Tree (DT)	[20], [21], [22], [24]
Random Forest (RF)	[21], [23], [24]
K-Nearest Neighbors (KNN)	[16], [20], [21], [22]
Gradient Boosting (XGBoost, LightGBM)	
Logistic Regression	[26]
Naive Bayes	[21], [38]
Convolutional Neural Networks (CNN)	[15], [19]
Recurrent Neural Networks (RNN)	
K-Means Clustering	[12]
Fuzzy C-Means (FCM)	[30]
Hierarchical Clustering	
Principal Component Analysis (PCA)	
Self-Organizing Maps (SOM)	
DBSCAN (Density-Based Spatial Clustering of Applications with Noise)	[25]
Autoencoders	
Fuzzy logic	[11], [17], [18], [36]

Figure 1 provides a graphical representation with percentages, indicating that SVM (43%) and ANN (29%) are the most frequently used methods. Six algorithms were not used in any of the reviewed papers.

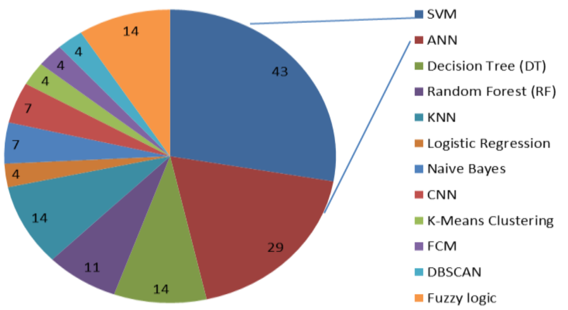

Fig. 1. Machine learning algorithms for transformer fault diagnosis based on DGA

In the application of supervised machine learning methods to Dissolved Gas Analysis (DGA), classical diagnostic techniques such as the IEC, Rogers, and Duval methods are often utilized for data labeling, model validation, and the selection of relevant input features—particularly gas ratios that are characteristic of each method.

In unsupervised machine learning approaches applied to DGA, classical diagnostic methods such as Duval, IEC, and Rogers are not used for labeling but can serve as valuable tools for selecting input features (e.g., key gas ratios) and interpreting the resulting clusters. These methods help to associate formed clusters with known fault types, thus enhancing the interpretability and practical relevance of the unsupervised models.

An overview of the DGA interpretation methods utilized by machine learning algorithms is provided in this work and summarized in Table V.

TABLE V. Review of papers and use of DGA interpretation methods in machine learning applications

DGA method	Papers
IEC 60599:2022	[11], [12], [13], [14], [15], [18], [19], [23], [25], [26], [27], [29], [30], [32], [33], [34], [35], [36], [37], [38]
Rogers	[11], [12], [14], [15], [18], [21], [23], [26], [27], [29], [32], [35], [36]
Doernenburg	[11], [13], [14], [21], [23], [29], [36]
Key gases	[18], [33], [36]
Nomograph	
Duval	[12], [13], [15], [16], [20], [21], [22], [23], [27], [28], [31], [32], [33], [35], [36], [38]

Figure 2 provides a graphical representation with percentages, indicating that IEC 60599:2022 (71%) and Duval (57%) are the most frequently used methods. It can be observed that the Nomograph method was not used in any of the analyzed papers.

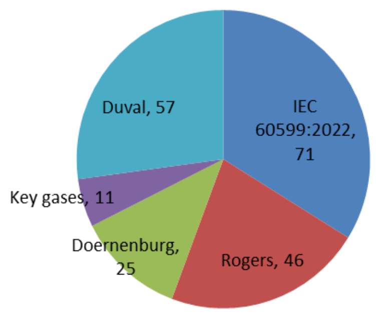

Fig. 2. Use of DGA interpretation methods in machine learning applications

Several papers have employed a hybrid approach utilizing multiple artificial intelligence techniques to diagnose transformer faults based on DGA. For example, Support Vector Machine (SVM), Decision Tree (DT), and K-Nearest Neighbors (KNN) algorithms were used together as part of a hybrid approach [20].

The following chapters present two representative studies that demonstrate the practical application of artificial intelligence techniques in transformer fault diagnosis using DGA.

A. *Example 1 of an AI application in transformer fault diagnosis based on DGA*

One of the earliest studies applying AI to DGA is the paper "An expert system for transformer fault diagnosis using dissolved gas analysis" [18], which presents an expert system for diagnosing the condition of power transformers based on the analysis of gases dissolved in oil.

Fuzzy logic is used as an artificial intelligence method. It is an AI technique designed to handle uncertainty and imprecision, and is particularly useful in decision-making systems. In developing and evaluating the expert system, the authors used a dataset provided by the Taiwan Power Company (TPC). After sampling and determining the concentration of dissolved gases, the system evaluates whether any gas exceeds the critical threshold defined by TPC. If no gas exceeds the limit, the diagnostic process ends; otherwise, the expert system is activated.

Within the expert system, the Rogers ratio method, the IEC 60599 method, and the Key Gas method are implemented. In cases where standard diagnostic criteria do not yield a conclusive result, a fuzzy modification of the IEC 60599 criteria is applied.

The expert system consists of four components: working memory, knowledge base, inference engine, and user interface. The system also incorporates the concept of fuzzy sets. The working memory contains the data to be interpreted, while the knowledge base includes a collection of facts used as the foundation for decision-making. The production rules are structured in IF-THEN format. The inference engine employs both backward chaining and forward chaining techniques to search the knowledge base.

During the evaluation of the expert system, samples from 101 transformers were tested. The results produced by the expert system were compared with the actual conditions determined by experts in the TPC laboratory. The results are presented in the Table VI.

TABLE VI. EXPERT SYSTEM EVALUATION

Voltage level [kV]		69	161	345	
Trans. units		36	31	34	Total 101
Samples		95	80	84	Accuracy
No fault	Total	21	17	29	100%
	Success	21	17	29	
Thermal fault	Total	58	42	47	93.9%
	Success	57	37	43	
Electrical fault	Total	16	21	8	84.4%
	Success	14	17	7	
				Total accuracy	93.8

B. *Example 2 of an AI application in transformer fault diagnosis based on DGA*

In the study described in [21], six machine learning algorithms were used to evaluate the results of DGA: random forest (RF), backpropagation neural network (BPNN), K-nearest neighbors (KNN), support vector machine (SVM), decision tree (DT), and Naive Bayes (NB).

The machine learning algorithms were implemented on a dataset of 628 samples, with 502 samples used as the training set and 126 as the testing set.

Three classical methods were used for the evaluation of the results: Duval triangle method (DTM), the Doernenburg ratio method (DRM), and the Rogers ratio method (RRM). The results are presented in Table VII.

TABLE VII. MACHINE LEARNING METHODS' PERFORMANCE EVALUATION RESULTS

ML algorithm	**Accuracy – DTM [%]**	**Accuracy – DRM [%]**	**Accuracy – RRM [%]**
RF	95.2	100	99.4
BPNN	69.8	49.2	60.1
KNN	81.7	89.7	94
SVM	78.6	54.8	47.3
DT	86.5	100	99.4
NB	74.5	93.7	80

The best accuracy in transformer fault detection obtained random forest algorithm. The conclusion in the paper was that the results of RF were the best for the three types of evaluation because this method relies on generating a good number of solutions and selects the best among them, which distinguishes it from other methods of machine learning.

V. WEB-BASED AND E-COMMERCE SOLUTIONS

In addition to numerous research studies on the application of artificial intelligence in DGA-based transformer diagnostics, several web-based and commercial solutions have also been developed. These practical solutions differ in scope, accessibility, and intended application. Table VIII summarizes the key platforms, their features, and access models.

TABLE VIII. OVERVIEW OF AVAILABLE WEB-BASED AND E-COMMERCE SOLUTIONS FOR TRANSFORMER OIL DGA INTERPRETATION

Name	**Description**
Camlin DGA Matrix	Free, web-based application for manual data interpretation using multiple standard diagnostic methods (Duval, Rogers, Doernenburg) [39].
Delta-X TOA (Transformer Oil Analyst)	Commercial software solution (on-prem/cloud) for transformer oil analysis and risk evaluation [40].
Doble INSIDEVIEW	Monitoring and diagnostic platform for managing transformer oil test results [41].
Weidmann MY DGA	Online diagnostic service with optional expert report validation [42].
GE Vernova – Kelman Transport X²	Portable DGA analyzer with on-site diagnostics and web-accessible data features [43].
Hitachi Energy – CoreSense M10	Online multi-gas DGA analyzer with real-time web access and condition monitoring capabilities [44].

The solutions presented in the Table VIII illustrate a wide range of commercial and web-based approaches to DGA interpretation. While platforms like Camlin DGA Matrix offer accessible manual tools based on standard methods, they lack automation and integration capabilities. More advanced systems such as Doble INSIDEVIEW and Delta-X TOA provide powerful diagnostics, but are enterprise-oriented, closed, and tied to commercial licenses. Devices like Hitachi CoreSense and GE Kelman deliver real-time insights, yet depend on proprietary hardware.

These limitations highlight the need for an open, lightweight, and flexible solution that can provide automated, on-demand transformer diagnostics that would be suitable for both large utilities and smaller operators.

VI. Conclusion

This paper provides an overview of the application of machine learning methods for the interpretation of DGA results. A total of 28 papers from reputable sources were reviewed in survey.

In practical applications, Support Vector Machines (SVM) and Artificial Neural Networks (ANN) are the most frequently employed machine learning algorithms, while the IEC 60599:2022 and Duval methods are the predominant techniques for interpreting DGA data. Furthermore, this overview identifies algorithms and methods that have not been applied in any of the reviewed papers. Such insights are valuable for future research, as they highlight commonly used approaches and reveal areas with limited or no prior application where further investigation could be conducted.

Within the field of machine learning algorithms for transformer fault diagnosis based on DGA, only algorithms from supervised and unsupervised learning have been applied so far. Reinforcement learning algorithms have not yet been utilized in this domain. However, they hold potential for future application, particularly through the use of digital twin models of power transformers. Recent progress in the development of such digital twin models may enable the application of reinforcement learning techniques in future research.

The paper also discussed two representative studies from the literature that demonstrated the practical application of artificial intelligence methods in transformer fault diagnosis.

Future research may include an analysis of the dataset sources used for training, validation, and testing of machine learning algorithms, as well as the accuracy of these algorithms in transformer fault diagnosis. Additionally, hybrid algorithms may be of interest for further analysis to determine which individual algorithms can constitute them and whether this leads to an increase in fault detection accuracy.

The authors observe that, based on the current landscape of available solutions and digital diagnostics trends, there is a clearly defined market niche for an open, accessible, and adaptable e-commerce platform for transformer oil DGA interpretation. Such a platform would enable fast and standardized "one-click" diagnostics without the need for specialized infrastructure or proprietary software.

Acknowledgment

This work was supported in part by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia under the Contract on the realization and financing of the scientific research work of Research and Innovation Organizations in 2025.

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