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Power Transformer Fault Detection And Classification By Coupling Conventional And Machine Learning Methods

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Power transformers are one of a power system's most essential and costly assets. Failure of a transformer may lead to high repair costs or irreversible internal damage. Furthermore, failures can result in power supply interruption, causing loss of profit for utilities and electrical energy shortages for consumers. Therefore, high importance is given to monitoring the transformers' health, detecting, and classifying faults at an early stage, and taking the necessary maintenance actions. Traditionally, conventional methods (known as rule-based) have been used for transformer health assessment using Dissolved Gas Analysis (DGA) data, which includes 5 key gases. These methods include the Duval Triangle (Duval and dePabla, 2001), Duval Pentagon, Doernenburg Ratios, Rogers Ratios, IEC Ratio Method (IRM), and Mulier, Schlliesing, and Soldner (MSS) method. The Duval triangle is the most widely used method and is characterized by higher accuracy compared to the other methods (Wajid, Rehman et al. 2023). However, the Duval triangle only classifies the faults, given that a DGA sample is already classified as faulty (IEEE 2017). Other methods, such as Rogers Ratios, IEC method, and MSC, can perform both fault detection and fault classification; however, these methods are not accurate (Wajid et al., 2023).

Inspired by the limitations of rule-based methods, such as low accuracy and inconsistencies in results (Kim et al., 2020), the research community has paid much attention to machine learning (ML) methods in recent years. ML methods such as support vector machine, decision trees, and artificial neural networks are frequently used for transformer health diagnostics with DGA data (Zhang et al., 2020). Most ML implementations are faced with the problem of small datasets, a lack of public datasets, and often a lack of knowledge on the transformer state of health (labels) associated with the DGA samples. Therefore, often the results, such as the reported accuracy and the applicability of trained models to new datasets are difficult to validate.

Here, we combine rule-based methods and machine learning to develop models for simultaneous fault detection and classification with satisfactory accuracy. We utilize the following four steps to train a model:

1. Dataset preparation: we utilize a dataset of 10,000 DGA samples from different power grid components, including power transformers (with and without online tap changers (OLCT)), measurement transformers, and bushings. After preprocessing, we are left with 3,500 DGA samples of power transformers at all voltage levels from Switzerland. These samples only include power transforms for which a clear separation between the OLTC and the transformer winding compartments is evident. We will refer to this dataset as a training dataset. In addition, we utilize 85 recent samples from the Swiss very high voltage power transformers, which are used as a test dataset. For both datasets, we do not have the true status of the transformer (healthy, suspicious, faulty, and the type of fault for the latter).
2. Fault detection using statistical approaches: The conventional approaches use reference values (limits) that are statistically determined. Typically, the 90^{th} and the 95^{th} percentile of the gas concentrations in a dataset are used to determine the status of a transformer (IEEE 2017). Here, we designate the status as healthy (if all gas concentrations are below the 90^{th} percentile), suspicious (if at least one gas concentration is between the 90^{th} and 95^{th} percentile), and faulty (if at least one gas concentration is above the 95^{th} percentile). We calculate the

percentiles using 3500 samples and use them as reference values. We refer to this approach as Approach 1. Furthermore, we use the approach described in (IEEE 2017), including the percentiles, which are calculated with DGA samples from North America. We refer to this approach as Approach 2.

3. Fault classification using rule-based methods: The DGA samples that are detected as faulty in Step 2, undergo fault classification with Duval Triangle, Duval pentagon, Doernenburg ratios, Rogers Ratios, IRM, and MSS. The methods have different accuracy expectation, and the literature has shown different performance on different datasets. Therefore, we compare all, and take the label that is identified by most.

4. Fault classification and detection using machine learning: Step 2 and Step 3 allow us to perform fault detection and fault classification. We use these labels to train an ML model that simultaneously preforms fault detection and classification. We have tested a large set of machine learning methods: Decision trees, Naive Bayes Classifiers, Support Vector Machines, Ensemble classifiers (Boosted Trees, Bagged Trees, RUSBoosted Trees), and Artificial Neural Networks. The best (high accuracy) models are obtained with an Optimizable ensemble of Bagged trees.

Figure 1 shows the classification of the faulty DGA samples, which are identified with Approach 1. We observe that for both datasets the highest concentration of samples is in the thermal fault category (T1-3).

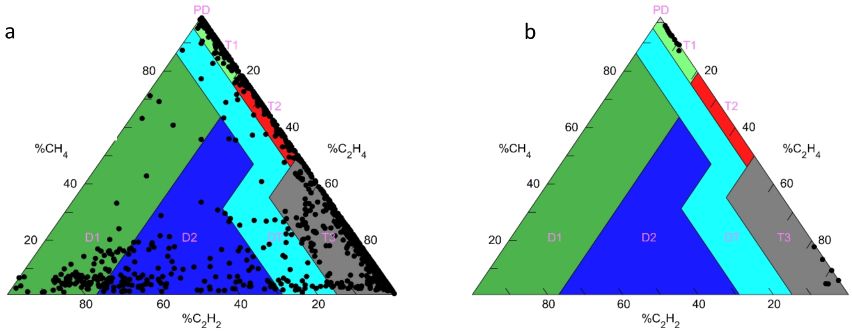

Fig 1. Fault classification of the DGA samples: (a) the training dataset; (b) the test dataset. T1-thermal fault 1, T2-thermal fault 2, T3-thermal fault 3, PD-partial discharge, D1-dischare 1, D2-dischare 2, DT-combination of thermal and discharge faults.

We have trained two models, i.e., a separate model (Models 1 and 2) is trained with the labels obtained from the conventional fault detection methods (Approaches 1 and 2, see Step 2 in Methodology). The models are trained on the training dataset and applied to the test dataset. The classification accuracy of Model 1 is 100 %, while Model 2 underperforms, with accuracy of 64 %. The reasons for the underperformance of the latter model could be simply due to the difference in the percentiles used. The detection of the faulty and healthy transformers with Approach 2 is based on data from North America (IEEE, 2017). In fact, the standard (IEEE, 2017) encourages the use of local data if available to calculate the reference values.

In this work, the true labels used in training are not known but estimated with conventional approaches. Therefore, in future work, we aim to account for the uncertainty in the labels when training an ML model. The uncertainty in the measured DGA data will be considered in addition.

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