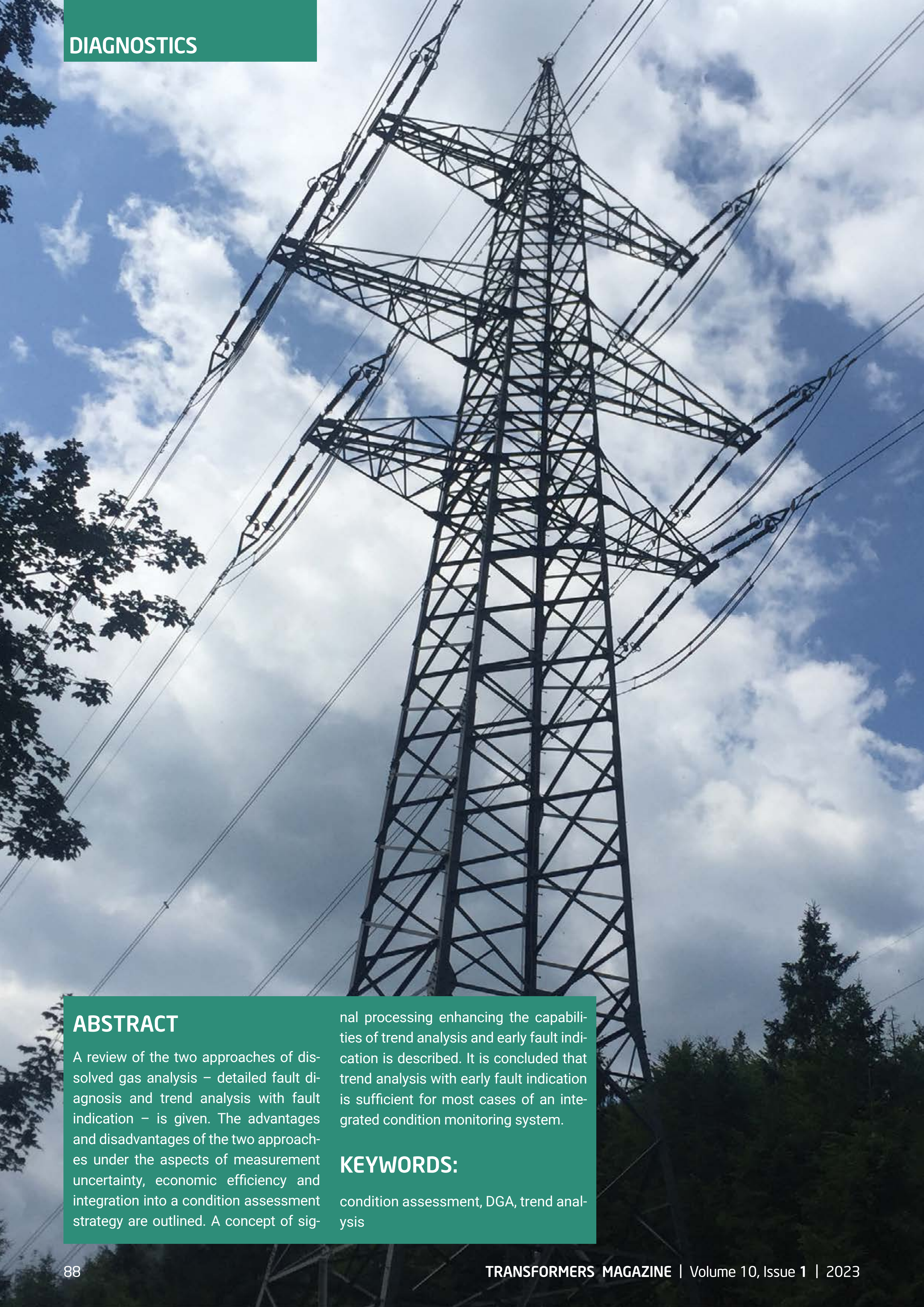


ABSTRACT

A review of the two approaches of dissolved gas analysis – detailed fault diagnosis and trend analysis with fault indication – is given. The advantages and disadvantages of the two approaches under the aspects of measurement uncertainty, economic efficiency and integration into a condition assessment strategy are outlined. A concept of signal processing enhancing the capabilities of trend analysis and early fault indication is described. It is concluded that trend analysis with early fault indication is sufficient for most cases of an integrated condition monitoring system.

KEYWORDS:

condition assessment, DGA, trend analysis

More and more online DGA systems appeared on the market of various types – starting from the sum gas sensor system to multi-gas sensor systems

Dissolved gas analysis: Early fault indication and trend analysis

Why DGA trend analysis is sufficient for transformer active part monitoring

1. Introduction

Evaluation of electrical equipment is an essential but complex process for any asset operator to ensure both operational safety and economic efficiency. As described in detail in CIGRÉ TB 761 [1], the condition of the individual components of the transformer system must be assessed with regard to the following aspects

- replacement
- safety
- maintenance
- refurbishment / upgrading and
- oil treatment

This information is condensed, usually in the form of condition indices, and presented for the entire fleet of equipment for decision-making. Over the last 30 years, a very useful method for condition assessment has been the analysis of dissolved gases in insulating oil. This has been used to evaluate the condition of the active part of a transformer, the tap changer, and the bushings (see Fig. 1 [1]).

Interpretation of the gas patterns for mineral oil-based insulating oils is described, for instance, in [2, 3], for ester-based insulating oils in [4]. These interpretation approaches found their way into relevant standards [5, 6]. After the establishment of the method in laboratories, more and more online DGA systems appeared on the market of various types – starting from the sum gas sensor system to multi-gas sensor systems with 8, 9 or more gases [7, 8]. Essentially, available online DGA systems can be divided into two categories:

a. Systems for fault indication and trend analysis.
b. Systems for fault diagnosis as described in [5, 6].

So, which are more suitable online DGA systems? As is often the case, it depends.

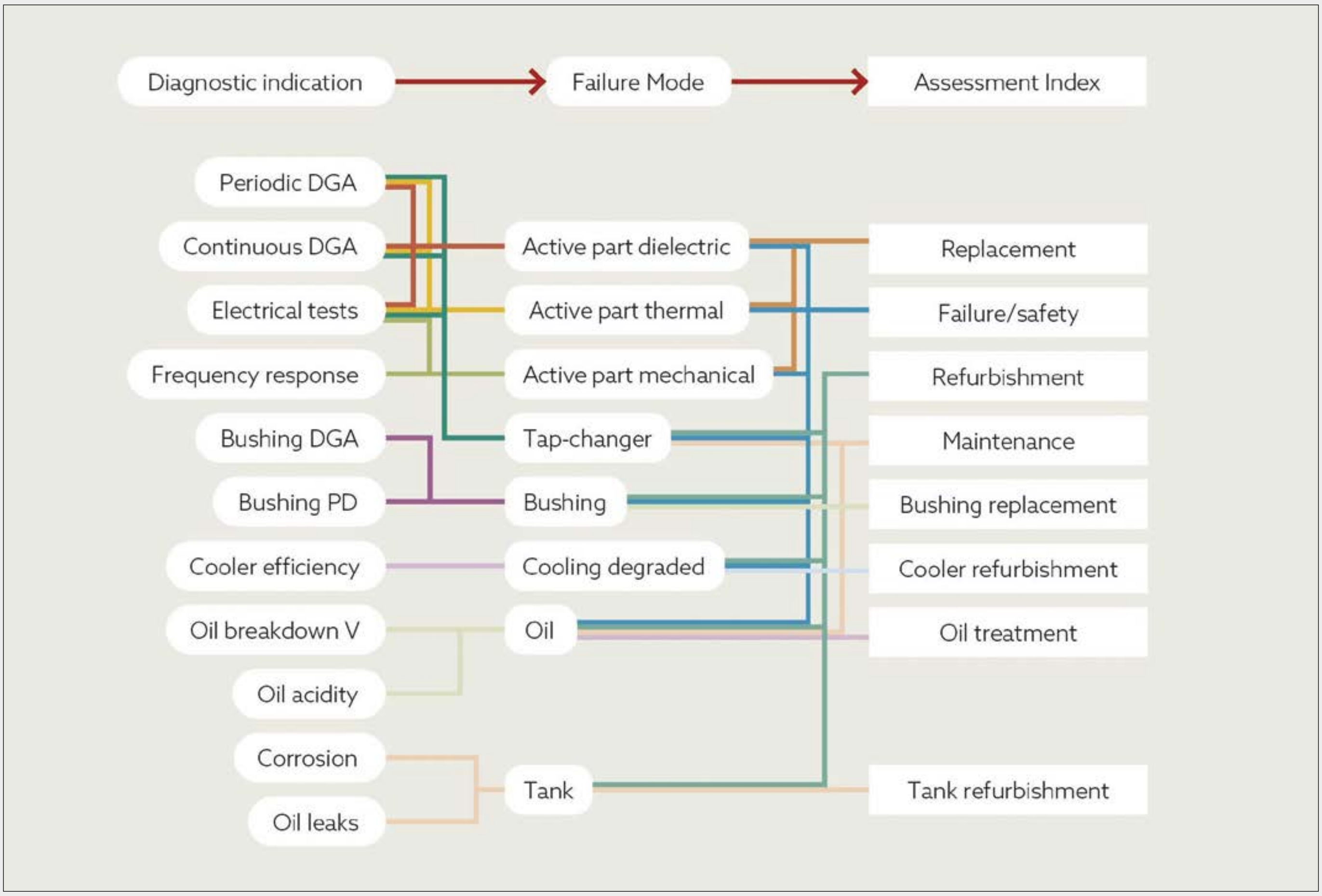


Figure 1. Relationships between diagnostic methods, failure modes, and assessment indices [1]

Trend analysis with early fault indication is sufficient for most applications of monitoring transformers, tap changers and other electrical equipment

Table 1. Required gas components for the formation of the gas ratios according to different interpretation

Interpretation according to	Gas components								
	H_2	O_2	N_2	CO	CO_2	CH_4	C_2H_6	C_2H_4	C_2H_2
Rogers	X					X	X	X	X
Doernenburg	X					X	X	X	X
Duval triangle						X		X	X
Duval pentagon	X					X	X	X	X
CO_2 / CO				X	X				
O_2 / N_2		X	X						
IEC 60599	X					X	X	X	X

2. Fault diagnosis

Fault diagnosis is the interpretation of gas patterns according to the methods described in [5, 6]. Usually, gas concentrations are related to each other and assigned to corresponding fault classes. To form different gas ratios, the respective gas components are required, as listed in Table 1.

Basically, faults are divided into the following classes according to IEC 60599 [5]:

- PD Partial Discharge
- D1 Low energy discharges
- D2 High energy discharges
- T1 Thermal fault with T < 300 °C
- T2 Thermal fault 300 °C <= T < 700 °C
- T3 Thermal fault 700 °C <= T

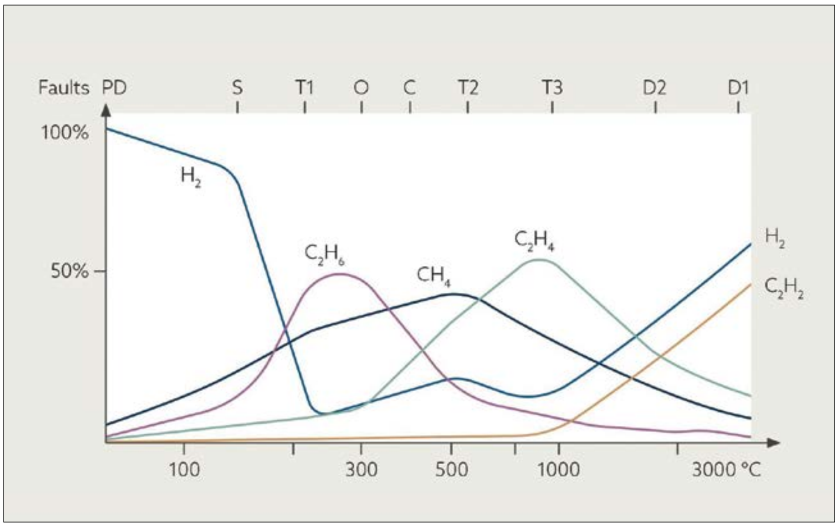


Figure 2. Gas formation pattern as a function of temperature [3]

These classical interpretation approaches show several problems:

- There is – except for Rogers' gas ratios – no normal range. The gas ratios always indicate a fault.
- The interpretation should be applied only when certain limit concentrations of the gases are exceeded.
- The superposition of different types of faults, which is often the case, is not correctly detected [9].

In recent years, attempts have been made to counteract these disadvantages and improve the reliability of the interpretation results by applying statistical methods from the Artificial Intelligence (AI) toolbox [9-12].

For fault diagnosis, multi-gas online DGA systems are used, which can usually detect > 4 gases and are based on principles of optical spectroscopy (IR or photoacoustic spectroscopy) or gas chromatography.

3. Trend analysis with fault indication

Fault indication and trend analysis focus on the relative change of a few gas concentrations. The aim here is to obtain an early indication of deviations from a normal or desired operation. Fault classification, as described in the previous chapter, is not the focus. If a corresponding indication is obtained, appropriate measures can be initiated promptly, such as oil sampling with subsequent analysis of various parameters or electrical measurements on-site.

If we look at the development of various gases as a function of temperature and assign them to the typical fault classes, as shown in Fig. 2, we can see:

- Hydrogen is present in varying proportions over the entire temperature range.
- The proportion of hydrogen increases sharply during high-energy events (very high temperatures).
- The proportion of acetylene increases sharply during high-energy events (very high temperatures).
- Methane is present in appreciable proportions early in thermally induced faults.

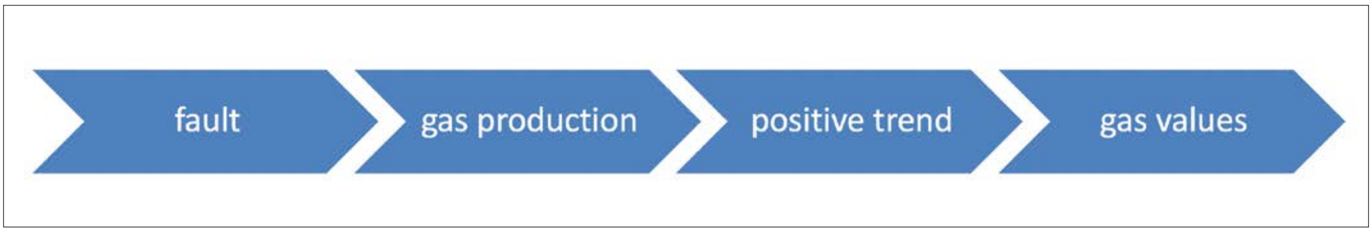
Furthermore, the present proportions of carbon monoxide and carbon dioxide indicate possible degradation reactions of the insulating paper, with carbon monoxide forming the precursor to carbon dioxide during paper degradation.

Thus, even with only a few gases, trend analysis and an early fault indication can be carried out. As shown in Fig. 2, a DGA system detecting the gases hydrogen and carbon monoxide, as well as oil moisture, can be used for reliable early fault indication and trend analysis. In combination with an extraction unit based on membrane technology, such systems are usually robustly designed and inexpensive and thus quite suitable for fleet monitoring. The monitoring approach here is rather the large-scale monitoring of the equipment to get a continuous overview of its condition and its development rather than the detailed fault diagnosis of a few critical pieces of equipment.

In combination with the mathematical approach to signal processing described below, the "fault activity indicator" can be used to further improve early fault indication and trend analysis.

3.1 Fault activity indicator

Both absolute gas values and their trends are indicators of fault activity. Looking at this from a causal perspective, a fault leads to gas production, gas production leads to a positive trend, and in the long term, the trend leads to higher gas values.



We propose the fault activity indicator that can be used for earlier fault detection, which is based on the control systems theory, in particular on the lead-lag compensators due to their simplicity and ease of implementation

Considering trends instead of values is a good idea since faults can be recognized earlier. But analyzing trends alone has its disadvantages. After a while, an equilibrium gas level will be reached due to gas evaporation, especially if the transformer is not sealed. In that case, the trend will become small. Also, estimating the trend based on noisy data results in either noisy trends or slow reaction times, depending on the used time base. A human looking at time series plots of absolute gas values will always intuitively recognize this, but the current automated solutions are lacking.

We propose the fault activity indicator. It is based on the insight that these problems are similar in structure to problems faced by control systems engineers: The values measured (gas levels) are different from the values of interest (gas production). Noise creates additional issues.

Control systems theory has multiple ways to deal with these concerns. We chose lead-lag compensators due to their simplicity and ease of implementation. The evaporation dynamics of a transformer tank represent a lag element. They can therefore be compensated by a lead element. The remaining lag element of the lead-lag compensator is then used to provide noise rejection.

Implementation is quite simple, as a lead-lag compensator can be described by two first-order differential equations. Some exemplary results of an implementation in Python are shown in Fig. 3.

a. The gas production was low at the beginning. On day 100, a fault occurs, increasing the gas production to 1 ppm per day.
b. The constant production creates a positive slope, also starting at day 100. Due to evaporation, the slope peters out after a while.
c. Reality is not smooth. To simulate this, additive and multiplicative noise are added.
d. Trends are estimated using ordinary least squares, using a rolling 25-day window. The result is quite noisy and sensitive to outliers. As the system nears a steady state, the trend decreases again.
e. The trend estimation is repeated using a 50-day window. Noise is decreased.
f. The fault activity indicator is used to estimate gas production. The light blue area represents the uncertainty due to the transformer evaporation time constant. If the actual time constant is known, the dark blue curve is achieved.

As can be seen, the fault activity indicator tracks the theoretical gas production. It behaves similarly to the rolling 50-day trend at first, but then it stays up. This is useful for automated diagnostics systems since the fault activity indicator can simply be checked against a single threshold with meaningful results without the drawbacks of doing the same with absolute values or trends.

4. Measurement uncertainty

Every chemical and physical analysis is subject to errors. The sum of all errors in

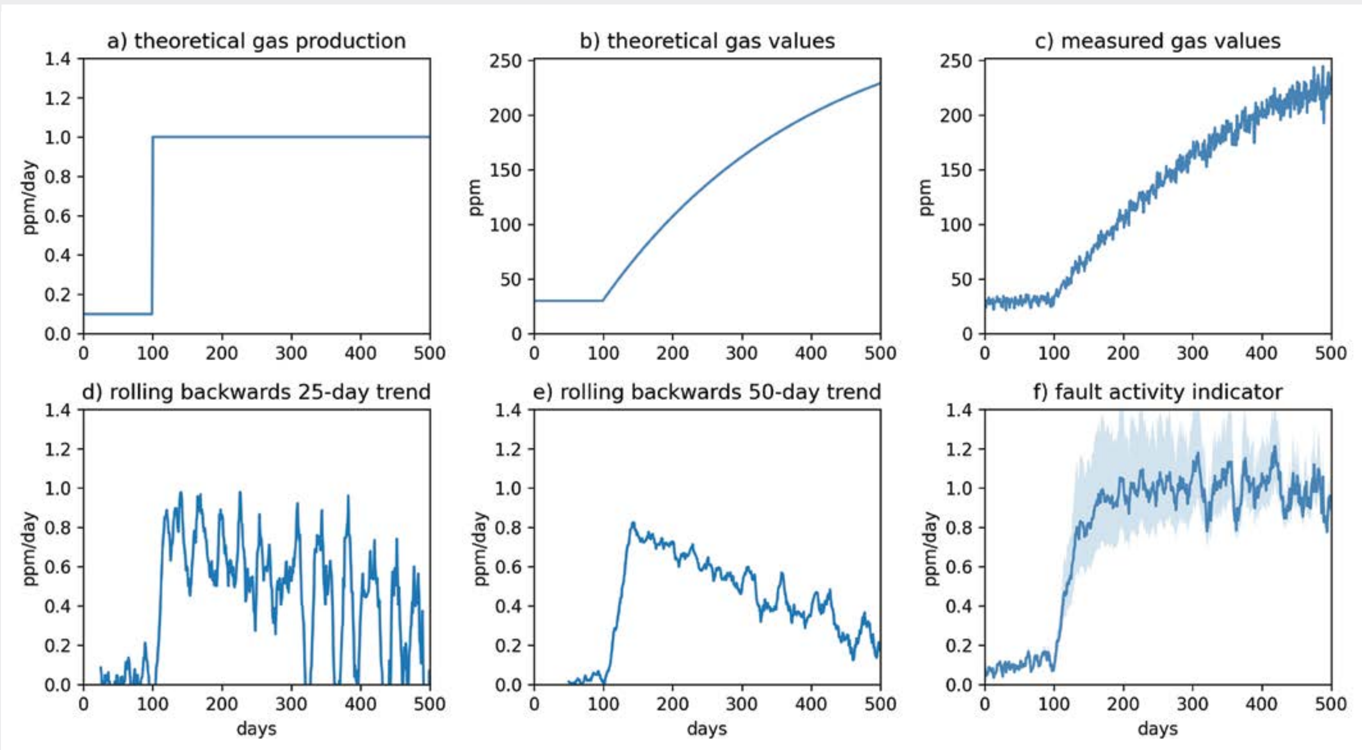


Figure 3. Implementation of different trending algorithms

the entire analytical procedure, starting with sampling, through sample preparation to the actual detection of the target variable, results in the so-called combined measurement uncertainty [13–17]. The measurement uncertainty consists of a random (variance) and a systematic (bias) error component.

The random errors determine the noise of the measurement signal. Random or statistical errors can only be minimized to a certain degree by increasing the number of measurements and averaging individual measurement values.

Systematic errors have a constant direction if the environment also stays the same. Measures can be taken to minimize systematic errors, such as describing the procedure precisely or performing correction calculations.

Fig. 4 shows the different measurement uncertainties:

The information about measurement uncertainty on data sheets of DGA systems is quite diverse, and the figures are not directly comparable, therefore caution is advised when comparing different systems

a) upper left: spread around the true value (low bias) and good repeatability (low variance).
b) upper right: spread around the true value (low bias) but poor repeatability (high variance).
c) bottom left: spread around a point different from the true value (high bias) and good repeatability (low variance).
d) bottom right: spread around a point different from the true value (high bias) but poor repeatability (high variance).

So what measurement uncertainty is sufficient for the applications of online DGA systems? The simplest answer to this is, of course – as low as possible. However, reducing the measurement uncertainty to a minimum goes hand in hand with a high technical effort and thus with high costs (corresponding to a) in Fig. 4). This is shown in simplified form in Fig. 5.

Thus, a compromise between economic and analytical requirements must always be found for analyzer systems, and this also applies to DGA systems.

Considering the measurement uncertainties of gas chromatographic analysis

Figure 4. Uncertainty levels

The practice has shown that the total measurement uncertainty under repeatability conditions through all individual steps of the analysis procedure of online DGA systems ranges between 15 %–20 %

according to IEC 60567 [18] as determined in interlaboratory tests [19] among laboratories, the following can be observed.

1. Depending on the gas component, the relative standard deviation, which corresponds to the measurement uncertainty under repeatability conditions, is between 9 % and 20 % (this corresponds to b) of Fig. 4 under the assumption that the mean value represents the true value).
2. Depending on the gas component, the relative reproducibility, which corresponds to the measurement uncertainty under reproducibility conditions, is between 26 % and 41 %.

The practice has shown that the total measurement uncertainty under repeatability conditions through all individual steps of the analysis procedure of online DGA systems ranges between 15 %–20 %. If measurement data from an online DGA system in the field is compared with data from laboratory analyses, the measurement uncertainty under reproducibility conditions must be used.

Caution should be exercised when comparing data on the measurement uncertainty of the various analyzer systems available on the market. In most cases, the data are not directly comparable with each other. Sometimes the information is given only concerning the actual detection unit, and the gas extraction is not taken into account. Other times, the specifications apply only to defined ambient conditions, i.e., certain oil and ambient temperatures. The data must therefore be critically scrutinized and, if necessary, adjusted by employing suitable calculations. The combined measurement uncertainty for the comparison of analyzer systems should always be used as the relevant variable in practice.

For early fault indication and trend analysis, our own field experience to date shows that a total measurement uncertainty in the range of 15 %–20 % is sufficient. This can also be justified by the observation that DGA values tend to be lognormal-distributed – it's more about the order of magnitude than about exact values. Most important for such systems is a satisfactory repeatability and a bias towards the true value; this means a systematic error could be accepted (this corresponds to c) of Fig. 4).

Conclusion

DGA is the most worthwhile and accepted method for condition assessment of transformers, tap changers and bushings. Its parameters can be measured with online systems in comparison to many other parameters. Today, there is no real alternative for continuous monitoring of electrical equipment. Additional methods should be conducted to get a complete picture for the decision of replacing, refurbishing, or repairing electrical equipment. These include things like electrical measurements, laboratory analyses, or temperature measurements. The operator has to evaluate the role of DGA as a part of a broader assessment strategy. This is the basis for choosing the right DGA concept and system. In many cases, early fault indication and trend analysis of a few key gases like hydrogen and carbon monoxide are sufficient for powerful and cost-efficient monitoring. The results can then be contextualized by considering additional operating parameters and environmental conditions to get a better picture of the situation.

DGA systems for trending should be robust and easy to handle. A suitable gas extraction method to fulfil these requirements can be found in the membrane technology, especially in a form that is stable against pressure fluctuations and vacuum. Gas sensors with long lifetimes and low sensitivity towards ambient influences should be used. It is very convenient for the user when an oil-sampling unit is integrated into the system. This ensures that the oil inside the transformer has the same properties as the oil that is seen by the DGA system. Relative measurement uncertainty in the range of 15 % to 20 % is sufficient for this application. In combination with intelligent algorithms like fault activity indicators which use signal processing and data evaluation, it is possible to develop systems with enhanced stability and early warning capabilities. These less-complex systems, in comparison to multi-gas DGA systems, are a good compromise between costs, measurement uncertainty and measurement time (see Fig. 3) and therefore seem suitable for fleet monitoring.

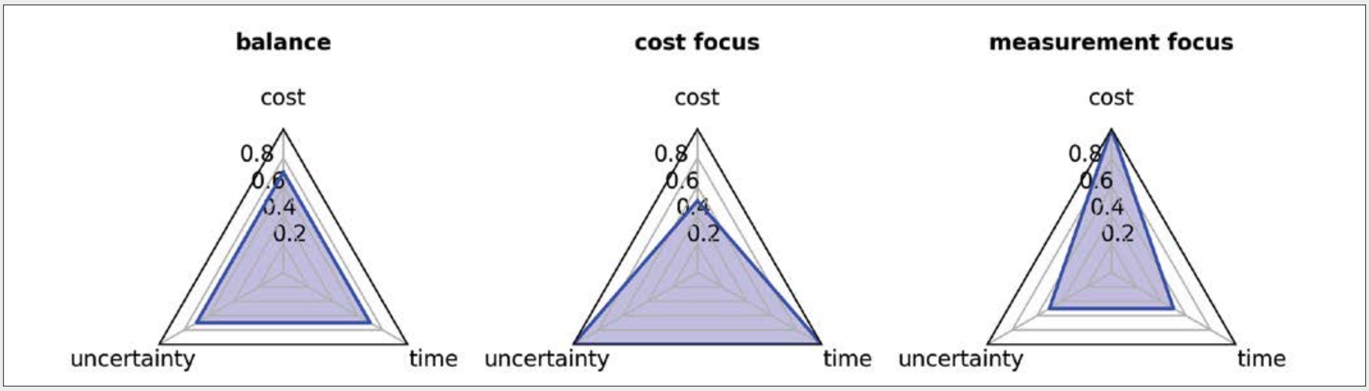


Figure 5. Relationship between costs, measurement uncertainty and measurement time for analyzer systems

More expensive – and more accurate – multi-gas DGA systems are suitable for detailed fault diagnosis or critical transformers. They need expertise or a supporting expertise system and a re-calibration on a regular basis to ensure reliable results.

In combination with intelligent algorithms like fault activity indicators which use signal processing and data evaluation, it is possible to develop systems with enhanced stability and early warning capabilities

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