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NEW TOOLS FOR ENHANCED DIAGNOSTICS OF DGA DATA

SUMMARY

In the last decade there has been a significant change in the way transformers are viewed. Their importance together with their obvious value to the network has been enhanced and recognized, especially in light of the ageing fleet worldwide. At the other end of the spectrum, new transformers are now being designed and built to tighter tolerances as a result of competitive market conditions, with the knock-on effect that these “modern” devices do not appear to provide the same stability and longevity as those that were entering service in the 1970s and 1980s.

Against this backdrop, the advent of transformer monitoring has emerged and continues to develop at a rapid pace. Although still considered an emerging component of asset management practice, online DGA is rapidly gaining acceptance and recognition as one of the most powerful tools in protection against asset failures. While other transformer monitoring technologies abound, many of them now online, such as partial discharge, these products collectively combine to enable the move to condition based monitoring of transformer assets.

As online DGA monitors have evolved new products and technologies are reaching the market at an ever increasing rate. However, the quiet revolution is in the analysis of the data. As more and more monitors are installed, so the burden of data analysis becomes increasingly large. New ways of extracting value from this data required. One important approach is the use of Artificial Neural Networks (ANN) for DGA data analysis. Additionally, with the recognition that data from monitors must be easily transferred into meaningful information for the end-user, diagnostic tools, such as the Duval Triangle, have evolved where the addition of Triangles 4 and 5 brings significantly more value to previously mined data.

The mute question in this paper relates to whether or not existing online monitoring hardware has sufficient accuracy and repeatability of measurement to be of use with these more advanced diagnostic tools.

Key words: DGA, Online Monitoring, TOAN, Duval Triangles, Artificial Neural Networks

1. INTRODUCTION

1.1. A Brief History on Online DGA

Prior to the emergence of online DGA monitoring, the traditional technique, still widely used today, is manual oil sampling and laboratory DGA. It is subject to a wide range of quality control measures, laid out in standards, which define procedures for obtaining and analysing an oil sample. A manual oil sample extraction would typically occur every 6 or 12 months depending on the critical nature of the transformer. Weekly sampling is a requirement under certain imminent fault conditions. The manual sample is used for other parameters associated within transformers, however, the DGA inaccuracy is well documented elsewhere and so renders the data useful for trending only.

The market conditions that have driven the evolution of online DGA relate, to a large extent in the changing structure of the electricity supply industry – liberalised and privatised markets. Many specialists with deep subject matter expertise in the area of transformers were retiring or leaving the industry as a consequence. While this has raised the number of consultants, it also left those remaining with a general lack of expertise coincident with assets which were getting older and more prone to failure.

The earliest online DGA monitors can be traced back to around 1990 – these single-gas monitors were primarily sensitive to hydrogen in oil. Some of these devices showed some cross sensitivity to other gases, meaning that the user did not always have a clear picture of the nature of the gas been reported. There were issues with measuring hydrogen. Hydrogen is the most insoluble of all the gases-in-oil, and as such has a propensity to escape from the oil. Further, hydrogen can be created in fairly large quantities due to heating within the transformer, where no fault has occurred - known as stray gassing, and can also be created in large quantities due to galvanic interaction [1]. So, by itself, the measurement of hydrogen only provides alarms related to possible fault conditions within the transformer.

The early part of this century saw the introduction of multi-gas online DGA devices as a means of determining the health of the transformer asset both in terms of discreet gas measurement, the trending of gases and most importantly the ability to diagnose a developing fault in real time. At this time IEC and IEEE call for 7 specific diagnostic gases to be measured as incipient fault gases. These gases are: Carbon Monoxide (CO), Carbon Dioxide (CO_2), Hydrogen (H_2), Methane (CH_4), Ethane (C_2H_6), Ethylene (C_2H_4) and Acetylene (C_2H_2). No specific specifications have so far emerged in support of required measurement technologies, required accuracies, repeatability or frequency of sampling although both standards do allude to performance levels best suited. While Gas Chromatography is the default technology for performing DGA in the laboratory and has been successfully employed for online monitoring, several manufacturers have chosen alternative approaches for example Infrared Spectroscopy. While Infra-red technology is employed successfully for trending in many locations one possible issue of concern is that infra-red systems may not align to laboratories with a reasonable level of confidence. Gas chromatography has the ability and requirement to field calibrate providing for a more obvious possibility of alignment to the laboratory based analysis. It can also be argued that these technologies do not provide as good a job of discriminating gases from each other as gas chromatography can.

As the market for online DGA gains market penetration, novel solid state sensors and other high-tech technologies are now emerging. It remains to be seen if any of these newer technologies will evolve to offer a higher accuracy/cost relationship than exists at present. However, with the industry moving towards conditioned based monitoring, the emphasis in real customer value resides more with interpretation of data.

2. ENHANCED DIAGNOSTICS

2.1. Artificial Neural Networks

Artificial neural networks are a computational model based on the structure of the human brain and have been used for over 50 years in weather and stock forecasting as well as process controls. ANNs are excellent classifiers for use in pattern recognition tasks where the relationship between input and output is complex and so are well suited to “big data” analytical problems. This is so with the large volumes of data in the form of alarms, frequency of analysis, and ppm changes of multiple gases reported by online DGA monitors. ANNs are taught the particular process they are analysing through a database of examples. The artificial neural network will incrementally change its internal connections between its’ ‘neurons’ based on previous ‘experience’. Provided the database that the artificial neural networks has been taught is sufficiently representative, then they will be able to correctly classify new unseen data from previous experience [2].

Used as part of an Expert System, an ANN is made up of a network of nodes and weighted connections. Each node sums the input from several weighted connections and applies a transfer function. The resulting value at each node is then propagated to nodes through outgoing weighted connections. These nodes are arranged in layers – the input nodes receive supplied data and each succeeding layer receiving weighted outputs from the preceding layer as it’s input. The first and last layers are called the input and output layers. Between these is the hidden layer or layers. So, the ANN learns through adjustments to the connection weights based on the error found at the output of the network. During the learning phase each set of data presented to the ANN includes known outputs and inputs and the generated output can be compared to the expected output. The weights are adjusted backwards (back propagated) through the ANN network until the error is minimized for a specific set of data [2].

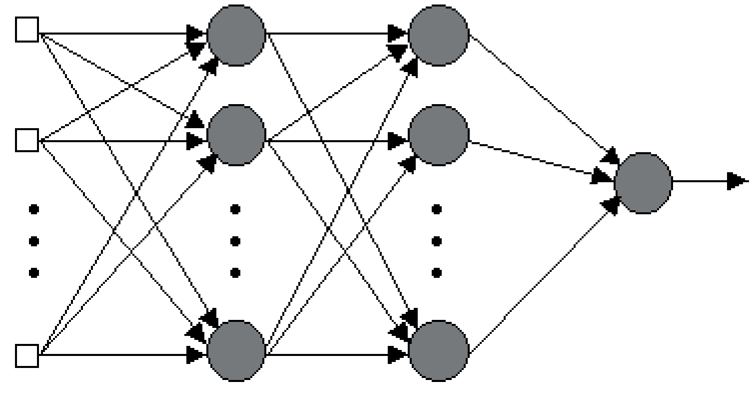


Fig. 1 –Example of an Artificial Neural Network structure

The example presented here of the use of an ANN used by Arizona Public Service (APS) company. It is a component as they of their Transformer Oil Analysis and Notification (TOAN) expert system where multiple ANNs are used.

The development of TOAN stemmed from the fact that APS has over 170 Serveron 8-gas on-line monitors on their system. Each monitor was sampling the transformer oil every 4 hours and reporting data on individual gas concentrations for Carbon Monoxide (CO), Carbon Dioxide ($CO_{2)}$, Hydrogen (H_2), Methane (CH_4), Ethane (C_2H_6), Ethylene(C_2H_4), Acetylene(C_2H_2), Oxygen(O_2). Clearly the volume of data obtained from these monitors was huge, at over 350,000 samples annually with most of the data being repetitive. APS considered that what they needed was to develop or acquire an analysis engine employing highly accurate algorithms that would also allow them to incorporate an exception based reporting system. This would serve to alert on fault type and severity levels and not alarm again until these values got progressively worse. Their research into ANNs took them to some studies done in a dissertation by Zhenyuan Wang at Virginia Polytechnic (VT). Wang had developed an analysis system using ANNs, running in parallel with a rules based expert system and referred to as ANNEPS [4]. They had attempted to use traditional diagnostic tools such as seen below in Table 1. with the following success rates had being reported:

Table 1 – Conventional Fault Type Prediction.

Diagnostic Method	Success %	Error %	Not identifiable %
Doenenburg Ratio	22.9	65.2	11.9
Rogers Ratio	24.8	12.4	62.8
IEC 599	42.8	24.8	32.4

Following training on a database of transformer failure autopsies testing of the ANNEPS engine showed the following success in recognizing five different fault types. These were Overheating (OH), Overheating oil (OHO), Low energy discharge or arcing (LED), High energy discharge or Arcing(HEDA) and Cellulose Decomposition(CD).

Table 2. Testing accuracy of ANNEPS

Fault Type	Success
OH	99%
OHO	98.6%
LED	98.6%
HEDA	98.6%
CD	97.6%

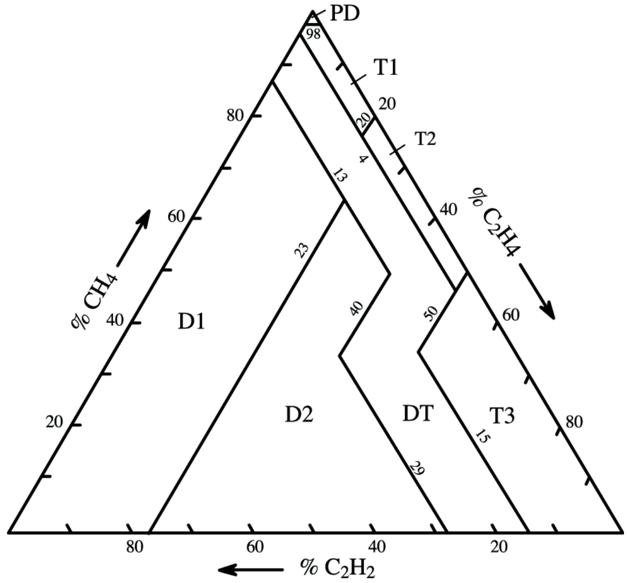
The initial observations were that the ANN represented the significant improvement in accuracy that APS were looking and this served as the basis for the TOAN project. There were modifications to the ANNEPS which APS implemented to improve its accuracy and flexibility. These included adaptation of the ANN to suit internal policy, a modification to the fuzzy logic models used to finalise maintenance recommendations, a change to 4 fault types: (Overheating (OH), Low energy discharge (LED), High energy discharge or arcing (HEDA) and Cellulose degradation (CD) and incorporating 6 levels of severity [6]. Added to that was a notification engine and also the incorporation of improved algorithms such as Piecewise Linear Approximation (PLA) and harmonic regression [7]. These stabilized gassing rate measurements by eliminating the harmonic effects, of time, temperate and transformer loading on gas generation. Harmonic regression is also able to provide better predictions, with a degree of certainty, on the values of dissolved gases. Later research by APS on the capabilities of TOAN revealed that these algorithms, when applied to CO and CO_2 gas concentrations show an excellent correlation to the degree of polymerisation to the point where online DGA data could be used to determine insulation ageing [4].

The key to TOANs success rate in diagnosing faults lies in both the power of the ANN and also the database used to train the system. This database is laboratory GC based and as such it was natural that the Serveron gas chromatography systems would be the optimum technology to feed in to this system. Any other non-chromatography online monitors would require some type of alignment to the TOAN database with a resulting level of uncertainty been introduced into the diagnosis. Given that all historical laboratory DGA results are gas chromatography based this is likely to be a continuing issue for the newer technologies

It is worth pointing out, and perfectly illustrates the achievement that is TOAN that its chief architect Don Lamontagne (and APS CEO Donald Branch) accepted the prestigious Edison Electric Institute Award in 2008 on behalf of APS for his team's work on TOAN.

2.2. Duval Triangle

Dr Michel Duval, a senior researcher at Hydro Quebec's Institute of Research is well known for his Duval Triangle. His research into DGA results stem from personal detailed investigations of over 200 transformer failures and autopsies. The Initial Duval Triangle was developed empirically; the fault zones in the Triangle are based on observed failures matched to laboratory gas chromatography based DGA data [5]. Duval identified that DGA data from just three gases could be mapped to a coordinate within a triangle and that this DGA data correctly matched the root cause of these failures to a very high success rate. The three gases are Methane (CH_4), Ethylene (C_2H_4) and Acetylene (C_2H_2) – as a rough estimate Methane begins to accumulate at about 150°C, Ethylene at around 350°C and Acetylene at around 700°C. The calculation is based on plotting the relative percentages of each of the three gases on a scale of 0-100%. Additionally the Triangle is divided into 6 zones which are defined in Fig. 2. These zones define certain fault conditions



T1 –Thermal Fault ≤300˚C
T2 – Thermal Fault ≥300˚C <700˚C
T3 –Thermal Fault >700˚C
D1 – Discharge, Low Energy
D2 – Discharge, High Energy
DT – Combination of Thermal Fault and High Energy
PD- Partial Discharge

Fig. 2 Duval Triangle 1

As described by Dr. Duval T1, 2 and 3 define thermal faults in different temperature ranges [5]. T1 is for thermal faults of < 300˚C normally due to overloading, blocked oil ducts or insufficient cooling evidenced by paper turning brown at around 200˚C or perhaps carbonised at around 300˚C. T2 is for thermal faults between 300˚C and less than 700˚C and generally associated with defective contacts, defective welds and circulating currents – evidenced by carbonisation of paper and formation of carbon particles in the oil. Finally T3 is for thermal faults in excess of 700˚C and is exemplified by large circulating currents in oil in the tank and core and evidenced by carbon particles in the oil, metal discolouration(at 800˚C) and possible fusion of metal at over 1000˚C.

PD is a partial discharge of the corona type and may show discharge in gas bubbles or voids trapped in paper. It is generally evidenced by poor drying and poor oil impregnation.

D1 is for low energy discharge induced by PD of the sparking type inducing carbonized penetration in in paper and evidenced by low energy arcing inducing surface tracking of paper and particles in oil.

D2 defines discharge of the high energy variety and is evidenced by high energy arcing and flashover. This results is extensive damage to paper, large formation of carbonised particles in oil, possible metal fusion and tripping of equipment and alarms.

Faults in paper are considered more dangerous than those in oil because the paper is normally found in the HV area(windings, barriers) and is irreversible.

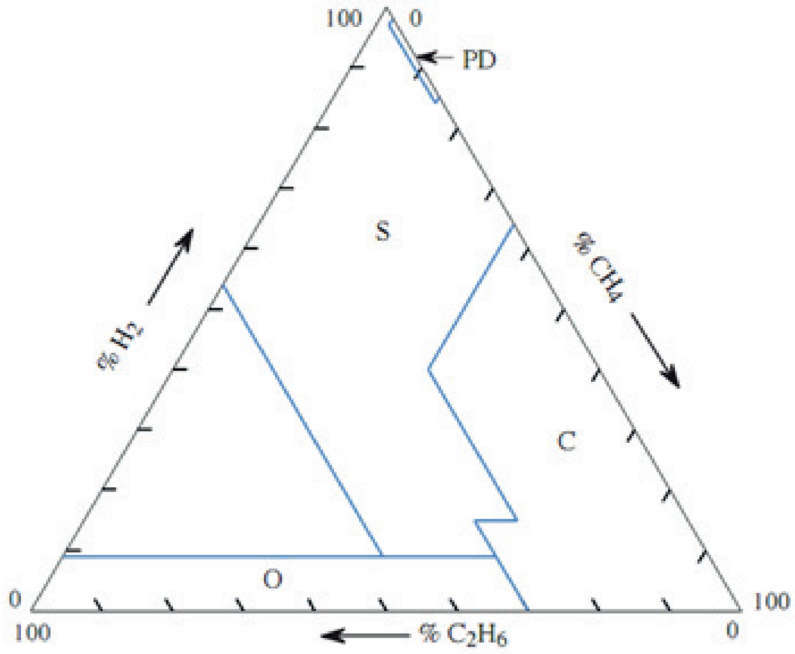
In 2008 Dr.Duval proposed an enhanced version of the traditional triangle with the introduction of 4 more triangles that further refined the ability of DGA to accurately identify a wide range of faults. Based on the same laboratory gas chromatography DGA results used to develop Triangle 1, Dr.Duval presented the following triangles:

- Triangle 2 for oil type Load Tap Changer
- Triangle 3 for Non-Mineral Oils
- Triangle 4 and 5 for low temperature faults in transformers

Considering Triangle 4 and 5, this is essentially an enhancement to the traditional Triangle 1 method. Dr Duval states that Triangle 1 is most useful for determination of a general type of fault occurring in a transformer, as described earlier. However limitations in Triangle 1 related to results being close to boundary conditions and the result of stray gassing which leads to some uncertainty. This uncertainty is removed with the inclusion of Triangle 4 and 5 which characterise low temperature faults. Employing the so called low energy gases Hydrogen (H_2), Methane (CH_4) and Ethane (C_2H_6), Triangle 4 differentiates between stray gassing and true faults.

Triangle 5 further refines the interpretation of results from Triangle 4 employing the so called temperature gases; Ethylene (C_2H_4), Methane (CH_4), and Ethane (C_2H_6). It can be used to confirm fault attributes which are still uncertain from Triangle 4

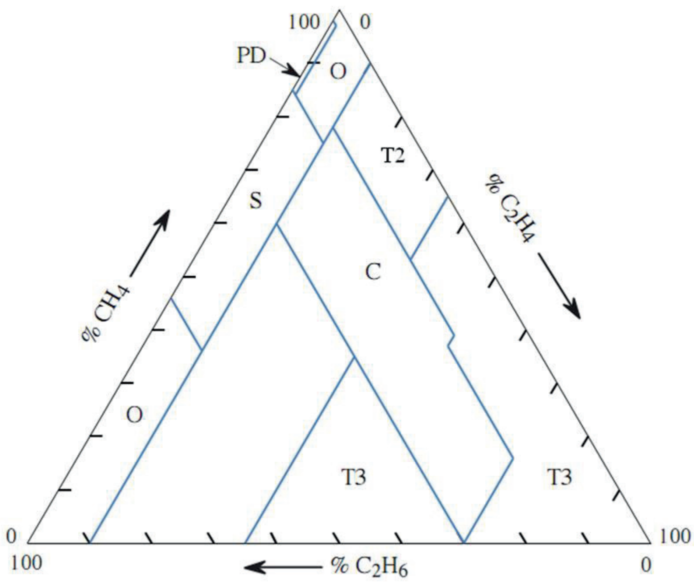
Both Triangles 4 and 5 are illustrated below



PD = Corona partial discharges
S = Stray gassing of mineral oil (T < 200°C)
C = Hot spots with carbonization of paper (T > 300°C)

O = Overheating (T < 250°C)
N/D = Not determined

Fig. 3: Duval Triangle 4



PD = Corona partial discharges
S = Stray gassing of mineral oil (T< 200°C)
C = Hot Spot with carbonization of paper (T > 300°C)

O = Overheating (T < 250°C)
T2 = Thermal faults of high temperature 300 < T < 700° C
T3 = Thermal faults of very high temperature T > 700° C
N/D = Not determined

Fig. 4 – Duval Triangle 5

Given the coordinated nature of each triangle it can be easily understood that only accurate results will provide the correct location. One can consider the effect of uncertainty in results by how the target area expands and so the level of uncertainty in diagnosis expands as errors are introduced into the measurement. For this reason accuracy of DGA is critically to the successful deploying of each of the triangles both the original Duval Triangle and these refined versions.

2.3. Case Study

One of the main benefits of using online DGA is the ability to identify rapidly developing faults and their consequential gas development. In this instance we see the development of Ethylene(C2H4) and Methane exponentially and a significant change in Acetylene, rising from below 1ppm to over 12ppm in a matter of a few weeks. The rapid increases are correlated to the load.

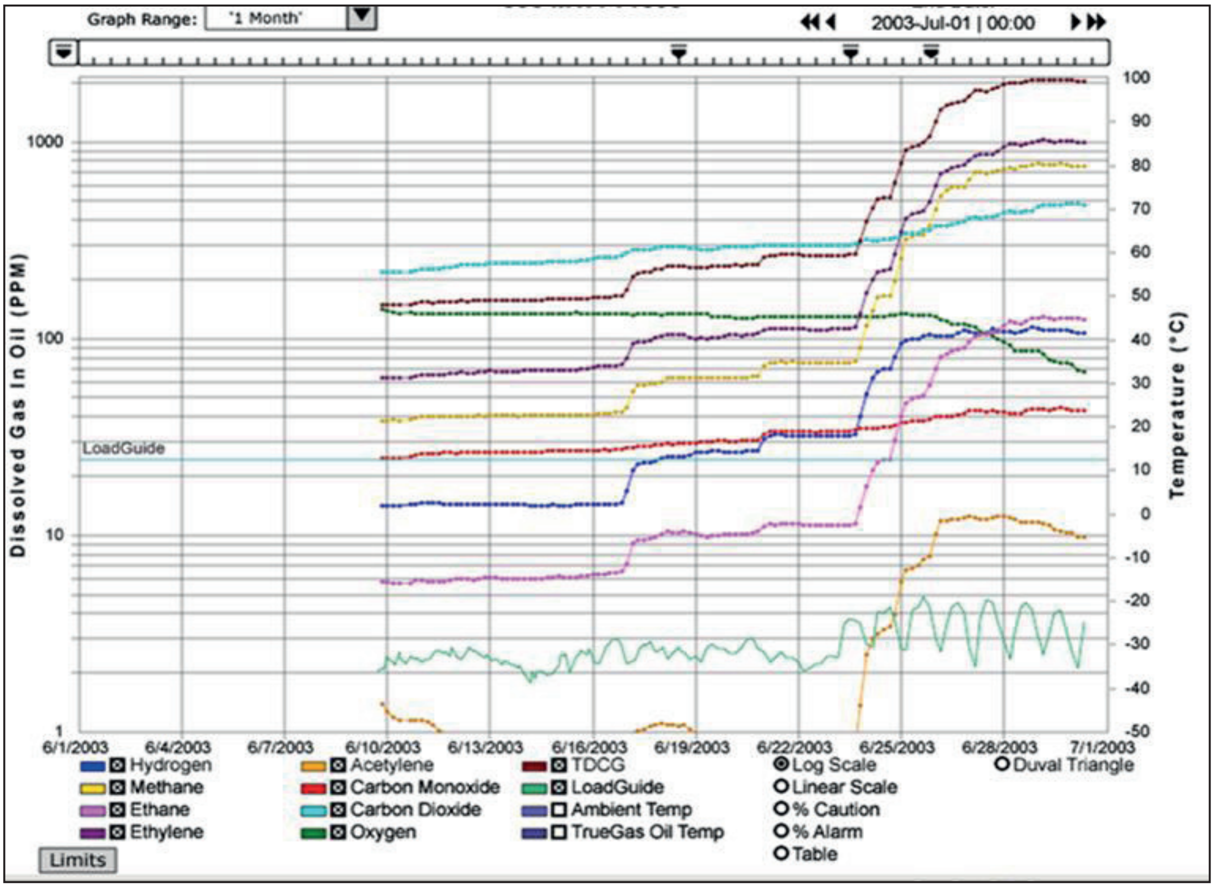


Fig.5. Gassing evolution.

As can be seen in the Duval Triangle in Fig.6 below, the gas sample accumulations are in the T3 area of the triangle thereby suggesting a thermal fault in oil.

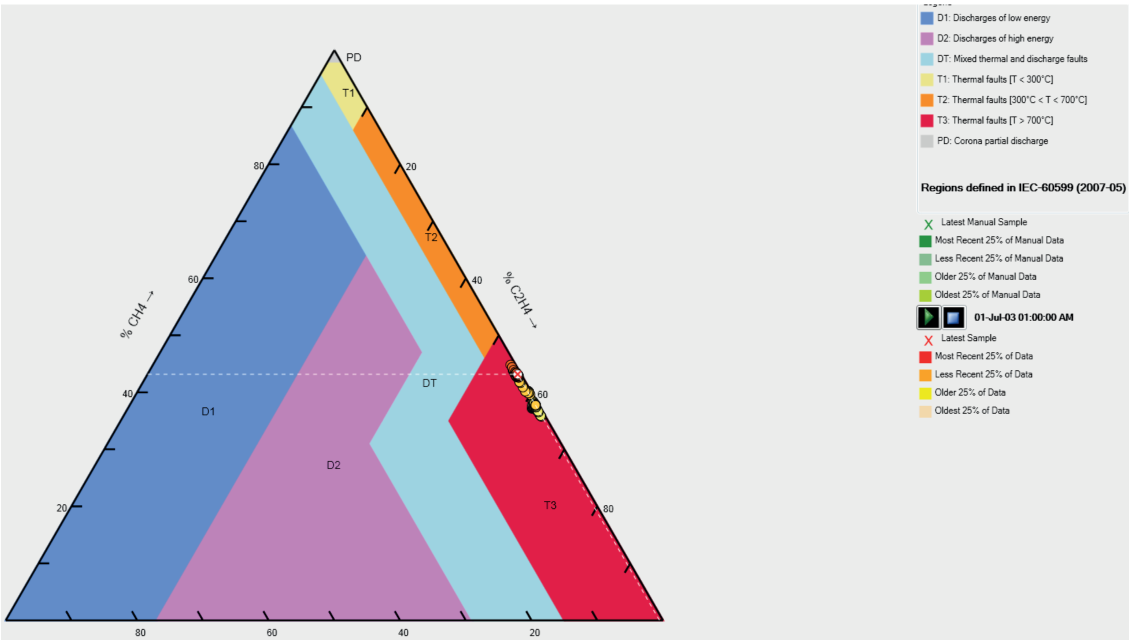


Fig 6. Triangle 1 showing T3 condition

The same data is put through TOAN and as can be seen in Fig.7 below, this fault condition is identified as being most severe (condition 1) and points to OHO (overheating oil) with a recommendation in the notification for immediate attention and a possible removal from service.

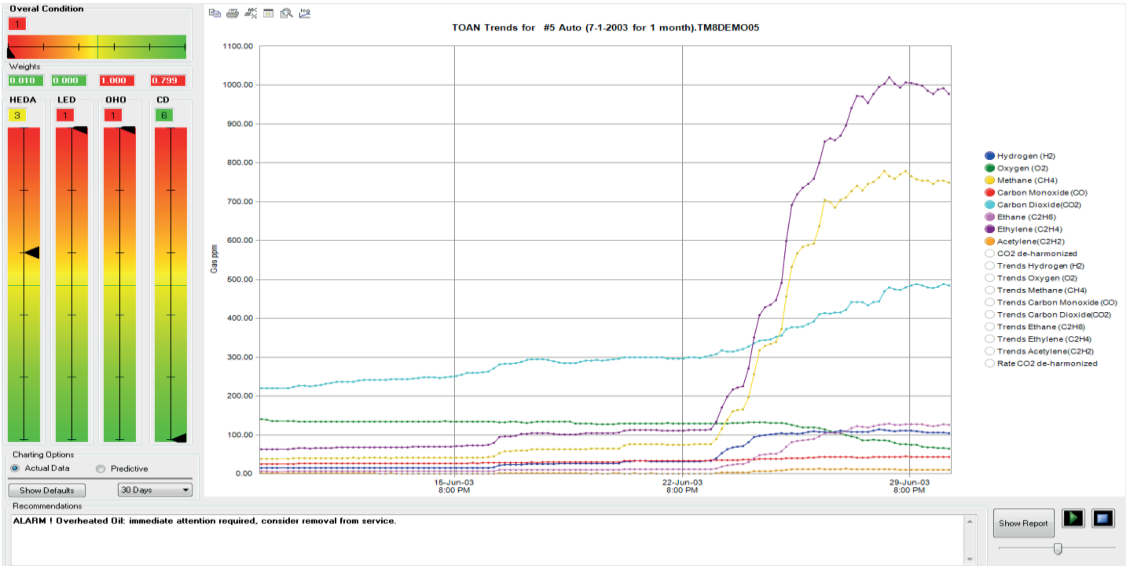


Fig.7. Representation of TOAN

The Duval Triangle is showing ppm of gases while the TOAN is actually identifying a fault condition.

3. CONCLUSION

It can be seen that diagnostic methods are emerging that are much more sophisticated than the traditional and often unreliable ratio based systems. However, accuracy and repeatability are critical both in terms of identifying the location in graphic diagnostic tools such as the Duval Triangle and for modeling such as ANNs. As such tools develop we are also seeing another leap, through TOAN, possibly representing the most significant change in DGA diagnostics in the last decade. Apart from the ability to identify a specific fault condition, the prospects of being able to identify on-line ageing of insulation adds another dimension in the monitoring of these assets.

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