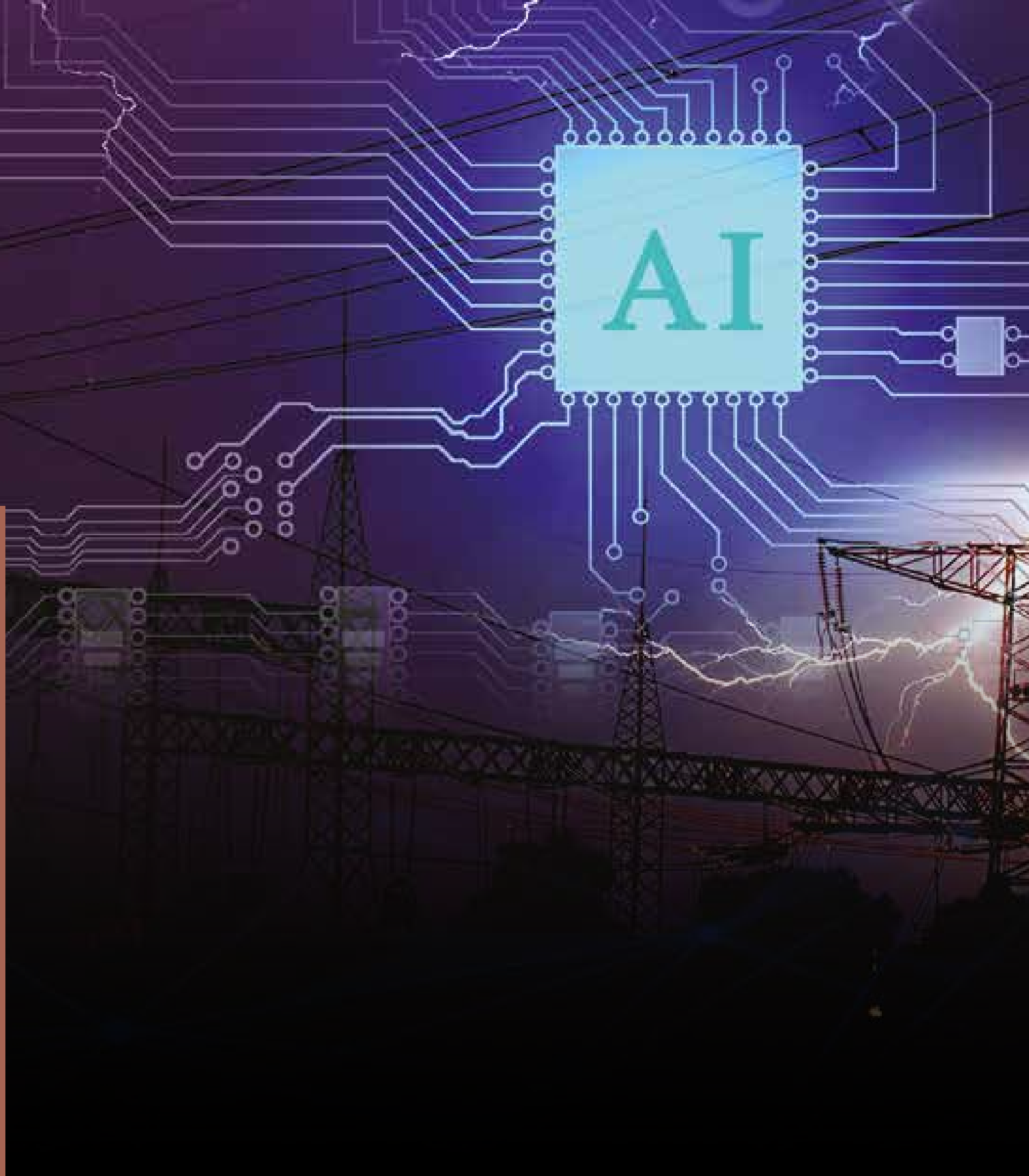
An intelligent system for condition assessment of power transformers



ABSTRACT

Health index (HI) approach has been adopted widely as a tool that assists the asset managers to prioritise their plans and actions. However, the conventional computation of HI, which is based on scoring and ranking, has several drawbacks. In this work, the fuzzy logic approach is utilised to build up an intelligent HI system to assess the condition of power transformers based on oil quality and DGA results.

KEYWORDS

fuzzy logic, health index, power transformers, predictive maintenance

Mohamed KHALIL

Fuzzy logic is utilised to build up an intelligent model for evaluating the health index of power transformers; fuzzy logic is based on a network of *if-then* rules that are constructed using the experience of experts

1. Introduction

The continuous demand for optimising the lifetime cost of transformers through informed decisions has led to adopting condition monitoring tools in addition to the traditional offline testing methods. Many utilities have migrated from the conventional time-based to condition-based maintenance. The outcome of the current diagnostic methods, online and offline, is large volumes of accumulated data. As a result, the use of quantitative indicators, such as health index (HI), is gaining wide popularity, especially when it comes to prioritising maintenance and replacement activities.

HI is an approach that combines all the information of a transformer in order to provide a single quantitative index that expresses the overall condition based on the measured data. The available data can be online, from condition monitoring systems, operational, offline, visual inspection, etc.

Several methods are developed to convert the existing diagnostic data into a HI. For instance, binary logistic regression is used in [1] for this purpose. The input data are classified into categories, healthy or unhealthy. Weights, assigned to each input, are calculated using the maximum likelihood criterion. Another approach is introduced in [2-5] to calculate the HI using the weighting average such that:

Fuzzy logic has a continuous band between logical true (1) and false (0) level; this degree of true or false is determined by the membership functions

$$AHI = \frac{\sum_i^n S_i \times W_i}{\sum_i^n W_i} \tag{1}$$

where n is the number of diagnostic tests, *S* is the score of each test measurement, and *W* is the allocated weight given to each diagnostic test. In [6], the weighting sum is used instead to calculate the HI.

Despite the simplicity of weighting methods, the determination of the weight factors for the diagnostic tests is based on the experience of experts, which differs from one person to another. In addition, setting a sharp threshold of diagnostic measurements for scoring is very difficult. In practice, there can be overlaps of scores; exact measurand does not exist due to the unavoidable imperfection involved in the measurement process [7]. Moreover, from experience, the traditional weighting average method may omit the influence of a bad diagnostic test result on the overall health condition.

To address these challenges, artificial intelligence (AI) methods have been applied to calculate HI as alternative approaches. For example, artificial neural network (ANN) [8] and adaptive neuro-fuzzy inference system (ANFIS) [9] are used to evaluate the HI of transformers. However, their practical application in electric utilities is scarce due to the challenges associated with symbolic reasoning and preparing large amounts of hand-crafted, structured training data.

In this article, fuzzy logic is utilised to build up an intelligent model for evaluating the HI of power transformers. On the contrary to ANN and ANFIS, fuzzy logic is based on a network of *if-then* rules that are constructed using the experience of experts. It does not need training data to learn, and it has a sophisticated capability to process the rules for all possible scenarios and form an accurate decision. Also, fuzzy logic does not apply sharp thresholds between the grades of the input data, since imprecision and fuzziness are the core of the fuzzy set theory.

2. Oil analysis in the condition assessment of power transformers

Conventionally, the primary areas of concern for electric utilities are oil quality and DGA results. Because oil sampling is the most practical way in the field to diagnose the condition of transformers while they are in-service, the scope of this work is focused on oil quality and DGA results. However, the proposed fuzzy logic model can be extended similarly to include all the possible factors that impact the condition of transformers.

2.1 DGA

The analysis of dissolved gases in transformer's oil gives general information on the condition of the transformer and identifies unusual events, such as incipient faults. Gases, such as methane (CH_4), ethane (C_2H_4), hydrogen (H_2), ethylene (C_2H_6), acetylene (C_2H_2), carbon monoxide (CO), and carbon dioxide (CO_2), are analysed to determine the types and the severity of each fault.

2.2 Oil quality

Oil quality tests focus on the condition of oil and paper insulation. For oil, there are several parameters that are usually monitored, such as break down voltage (BDV), acidity, water content, interfacial tension (IFT) and furanic compounds, such as 2-FAL.

3. Fuzzy logic approach

Fig. 1 shows the architecture of the fuzzy logic process. It consists of three stages.

3.1 Fuzzification

The truth of any statement in fuzzy logic

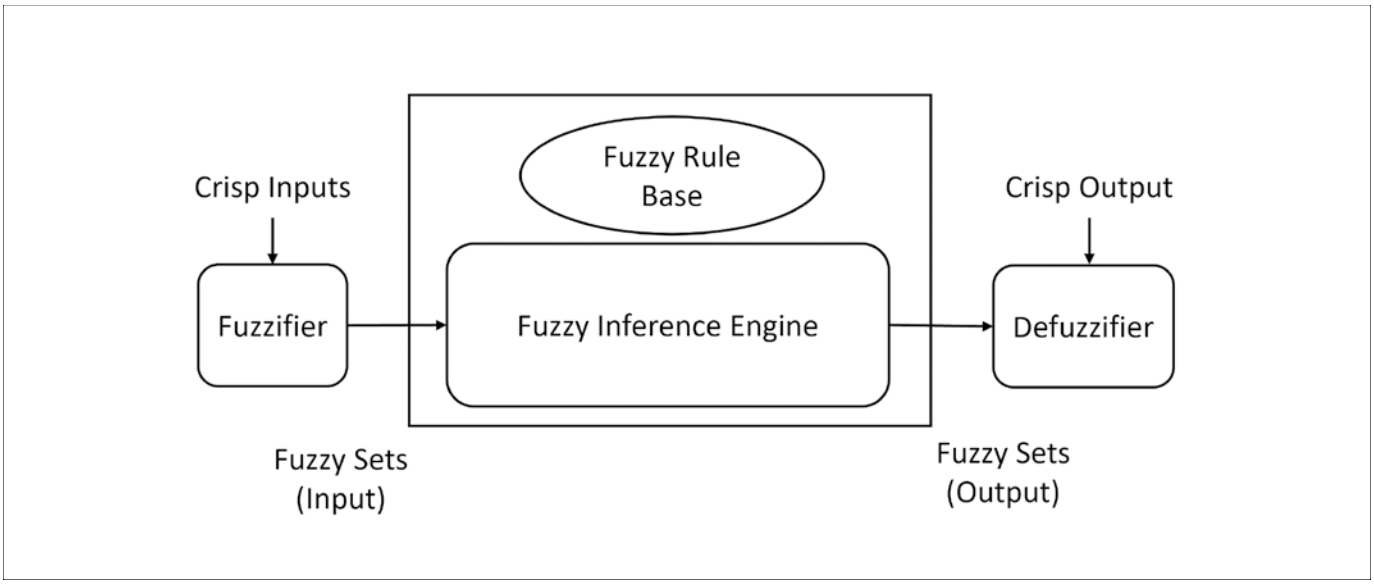


Figure 1. Block diagram of the fuzzy logic process

is just a matter of degree. This degree of truth is determined by generating membership functions (MF). MF is a curve or a straight line that defines how a given input is mapped to a degree of membership between 0 and 1 of the fuzzy sets. It can be triangular, trapezoidal, sigmoidal, or Gaussian. The MF used in this work is the trapezoidal one, as shown in Fig. 2, because of its simplicity. It is expressed as:

$$A = \begin{cases} 0, & x \leq a \\ \frac{x - a}{c_1 - a}, & a \leq x \leq c_1 \\ 1, & c_1 \leq x \leq c_2 \\ \frac{b - x}{b - c_2}, & c_2 \leq x \leq b \\ 0, & x \geq b \end{cases} \tag{2}$$

where x is the input parameter. If x lies between the centres of the trapezoidal c_1 and c_2, then the corresponding MF achieves the maximum degree of membership of 1. On the other hand, if the input is between a and c_1, or b and c_2, then the degree of membership is less than 1. This is the case when the measurand of a diagnostic test lies near to the thresholds.

In this stage, the MFs convert the inputs from precise to fuzzy form between 0 and 1.

Measured values are used as inputs to calculate the output values of the fuzzy membership functions; those output values are then combined to calculate the fuzzy values using logical operations like AND, OR, MIN, or MAX

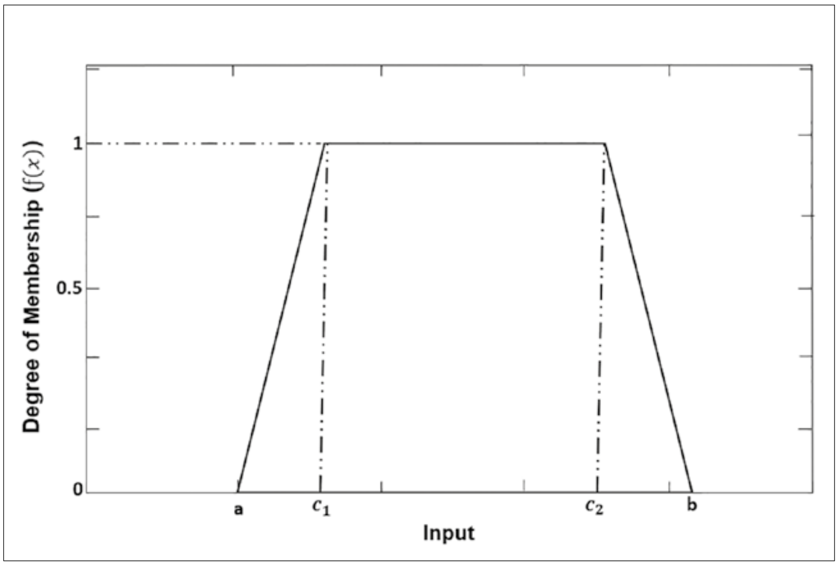


Figure 2. Trapezoidal MF

3.2 Fuzzy rules and fuzzy inference engine

In this work, Mamdani fuzzy inference system is used. It is described in the XY–plane as:

$$\mu_{(a \to b)}(x,y) = \min\,[\mu_a(x), \mu_b(y)] \quad \forall_x \in X, \forall_y \in Y \tag{3}$$

where $\mu_a\ (x)$ is the membership function of the fuzzy set a defined in the universe X, $\mu_b\ (y)$ is the membership function of the fuzzy set b defined in universe Y, and $\mu_{(a \to b)}\ (x,y)$ is the fuzzy implication in the XY-plane. The min $(\mu_a\ (x), \mu_b\ (y))$ takes the minimum of the two (or more) membership values when the fuzzy rules are fired.

Meanwhile, fuzzy rules are a set of knowledge-based linguistic rules, developed by the knowledge of test data interpretation and its impact on the condition of transformers. For instance, some of the implemented rules for arcing in the oil of transformers are as follows:

1. *If (C_2H_2 is very high) and (H_2 is very high), then (arcing is very high)*

2. *If (C_2H_2 is very high) and (H_2 is high), then (arcing is very high)*

3. *If (C_2H_2 is medium) and (H_2 is high), then (arcing is high)*

4. *If (C_2H_2 is low) and (H_2 is medium), then (arcing is medium).*

In this stage, the results of the rules are combined to form the final value, a fuzzy value.

3.3 Defuzzification

This is the stage of converting the fuzzy output into a precise quantitative value. In this work, defuzzification using the centroid method is performed. It determines the centre of gravity Z_0 of the area bound by the truncated output MFs, such that:

$$Z_0 = \frac{\int z.\mu(z)dz}{\int \mu(z)dz} \tag{4}$$

Where z is the output variable and $\mu(z)$ is the degree of membership of the truncated output MF.

4. Adopting fuzzy logic in the condition assessment of transformers

The proposed HI modelling, based on the oil results, is shown in Fig. 3.
In the proposed architecture, the HI of the transformer is divided into three main failure profiles: prognostic index (PI), oil quality index (OQI), and dissolved gas analysis index (DGAI). The score of each failure profile is evaluated based on the scores of the associated failure modes.

4.1 DGA Index (DGAI)

DGAI is based on the results of the levels of gases in the oil. The level of each gas is subsequently fuzzified into four MFs (fuzzy sets), namely, low, medium, high, and very high (VHigh), respectively. As an example, the MF of H_2 is shown in Fig. 4.

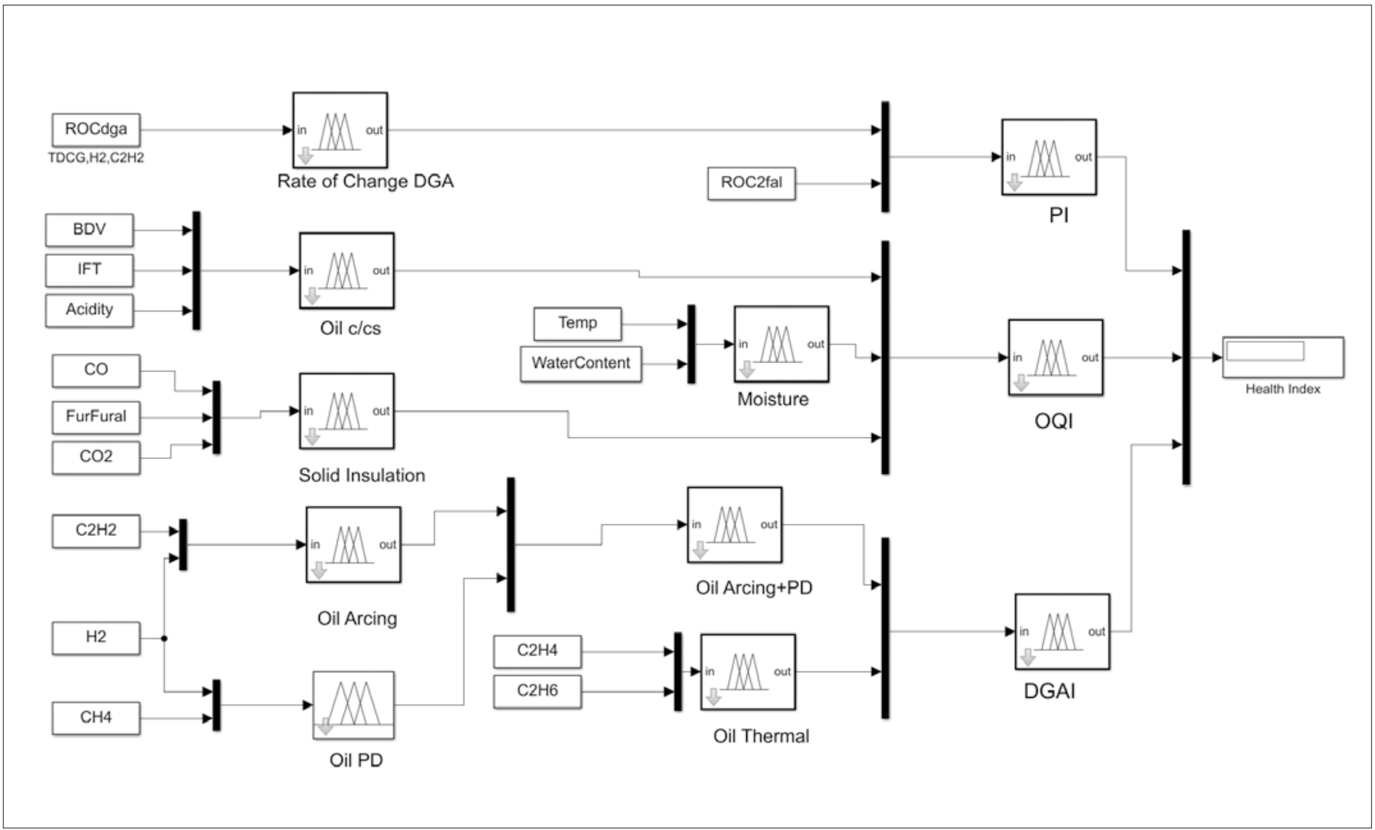


Figure 3. The fuzzy logic architecture of HI evaluation

Defuzzification is converting the fuzzy output into a precise quantitative value which can be the transformer's health index, for example

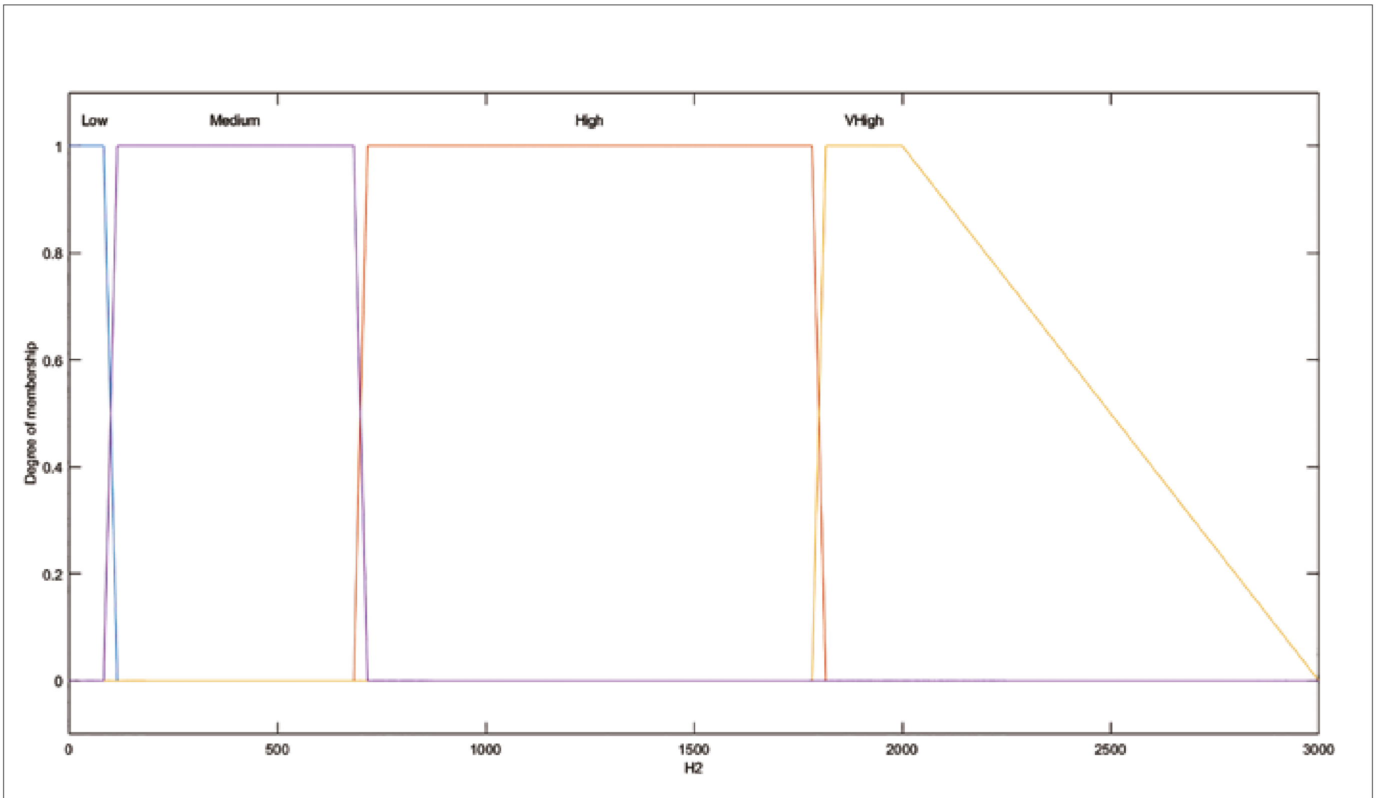


Figure 4. MF of H_2 gas

Table 1. Limits values of gas concentration MFS

	Low				Medium				High				VHigh			
Gas	a	c_1	c_2	b	a	c_1	c_2	b	a	c_1	c_2	b	a	c_1	c_2	b
H_2	0	0	95	105	95	105	695	705	695	705	1790	1810	1790	1810	2000	3000
C_2H_2	0	0	1	3	1	3	8	10	8	10	32	38	32	38	100	1000
CH_4	0	0	118	122	118	122	396	403	396	403	994	1004	994	1004	3000	5000
C_2H_4	0	0	45	55	45	55	95	105	95	105	195	205	195	205	300	1000
C_2H_6	0	0	60	70	60	70	95	105	95	105	145	155	145	155	400	1000
CO	0	0	345	355	345	355	565	575	565	575	1390	1420	1390	1420	2000	3000
CO_2	0	0	2470	2520	2470	2520	3970	4020	3970	4020	9900	10100	10050	10100	10100	50000

In this example, health index is estimated based on the prognostic index, oil quality index, and dissolved gas analysis index, which all are modelled using fuzzy logic techniques

The lower and upper limits and the two centres for each of the seven MFs for each input gas concentration are given in Table 1. The lower and upper limits were selected in accordance with IEEE Std C57.10-2008 [12].

DGAI index is composed of two main modules oil arcing and PD, and oil thermal, as shown in Fig. 5. Due to the ther-

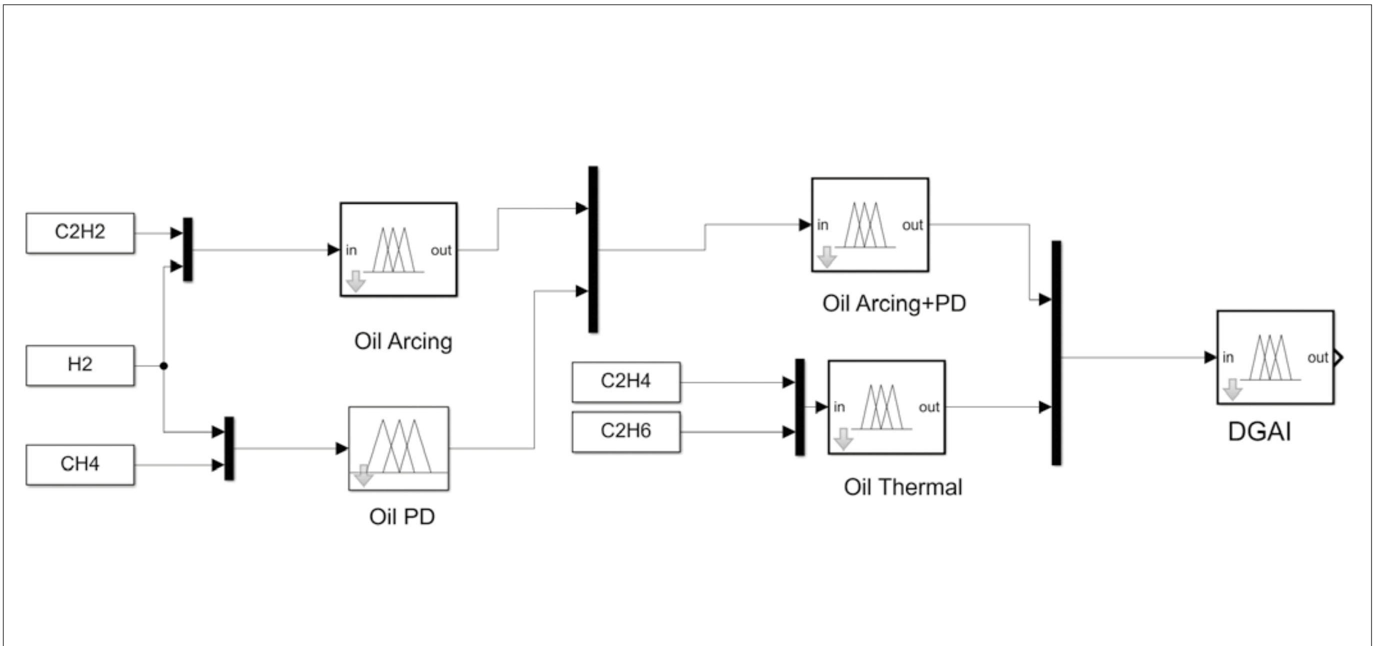


Figure 5. DGAI module

DGAI index is estimated using fuzzy logic techniques and measurement data of dissolved gases concentrations

mal effect, the transformer's oil decomposes and generates ethylene and ethane as principal gases. Therefore, one module was created for both ethylene and ethane to represent this failure mode 'oil thermal'.

On the one hand, the presence of hydrogen and acetylene in the oil may indicate arcing. Based on transformer diagnostic and test data interpretation technique, fuzzy rules are developed for the oil arcing sub-module, as shown in Fig. 6. The three-dimensional curve plotted in Fig. 7, shows the oil arcing output score, z-axis, which is based on the values of hydrogen, acetylene, their corresponding membership functions, and the predefined fuzzy rules of the oil arcing sub-module. The oil arcing output score is divided into four categories: very high (yellow), high (green), medium (light blue), and low (dark blue).

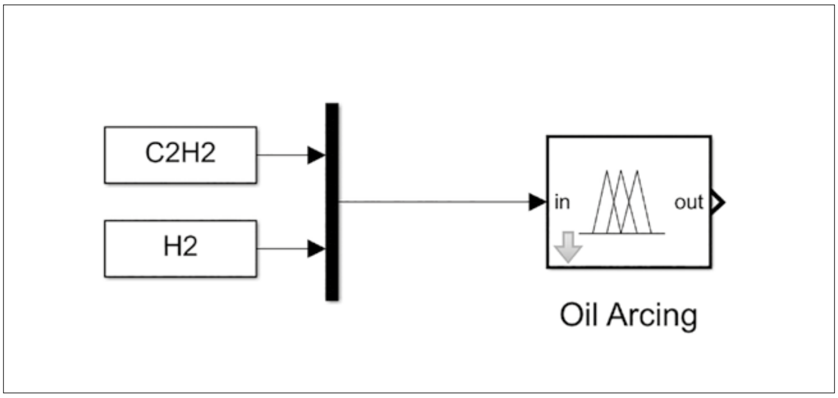


Figure 6. Oil arcing sub-module

On the other hand, partial discharge (PD) activity in a transformer produces a high level of hydrogen and a considerable level of methane gases. An individual sub-module for 'oil PD' is designed and combined with the sub-module 'oil-arcing' mode so that the output score of both sub-modules reflects the 'oil-arcing and PD' failure module.

4.2 Prognostic index (PI)

The inputs to the PI module, shown in Fig. 8, are data that change with respect to time. The monotony increase of the input values gives an indication of the deterioration of the transformer's condition. MFs are developed for the daily generated ppm of TDCG, hydrogen and acetylene. The fuzzy inference system of the inputs is indicated in Fig. 9 showing 29 out of the implemented 64 fuzzy rules. These rules cover all the possible scenarios of the input data and the associated output score. For example, when the daily rate of change (ROC) of C_2H_2 = 2.3, H2 = 2.3, and TDCG = 9.79, rule 25 is fired and the output score of 'ROC DGA' module, shown in Fig. 8, is 87.5.

In addition, MFs are created to include the ROC of 2FAL for thermally upgraded paper, in ppm per year, such that the output score of ROC of DGA sub-module and ROC of furfural are inputs to PI profile.

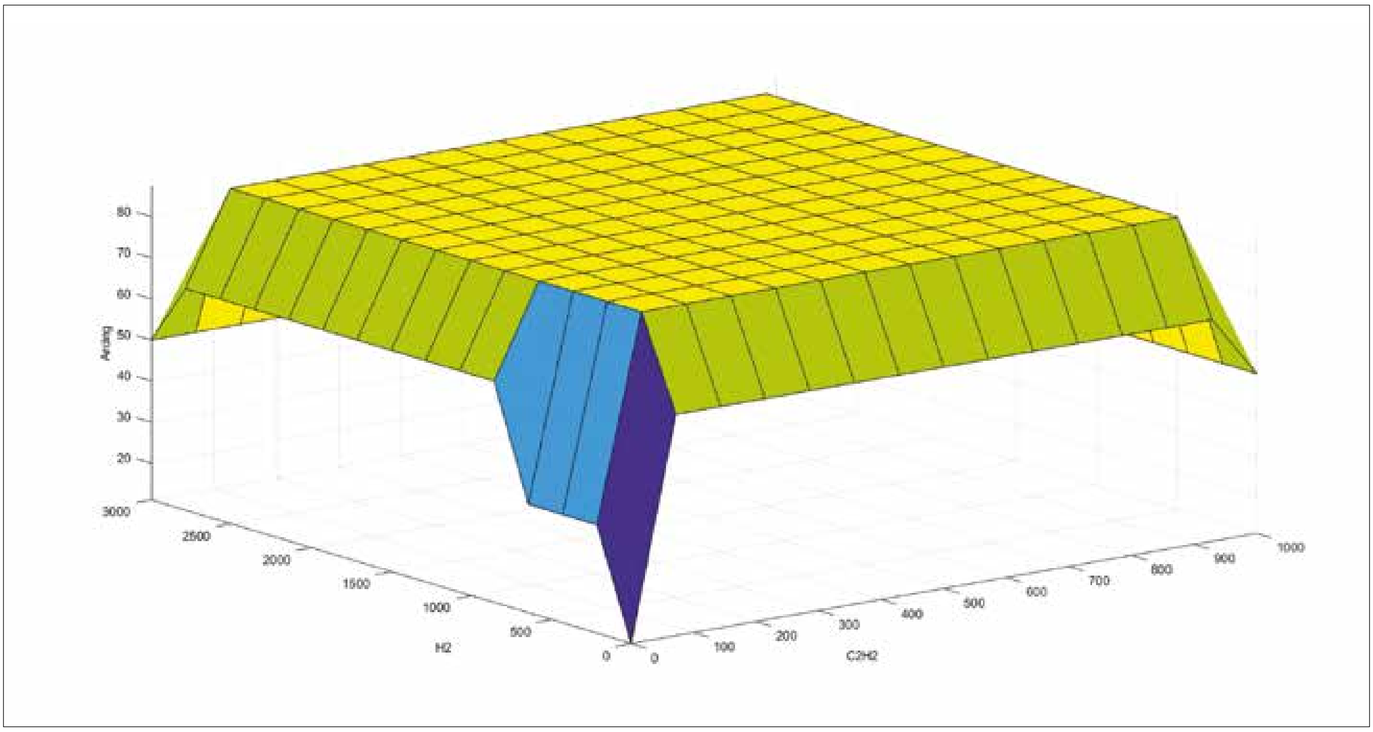


Figure 7. Scoring of oil arcing sub-mode based on H_2 and C_2H_2

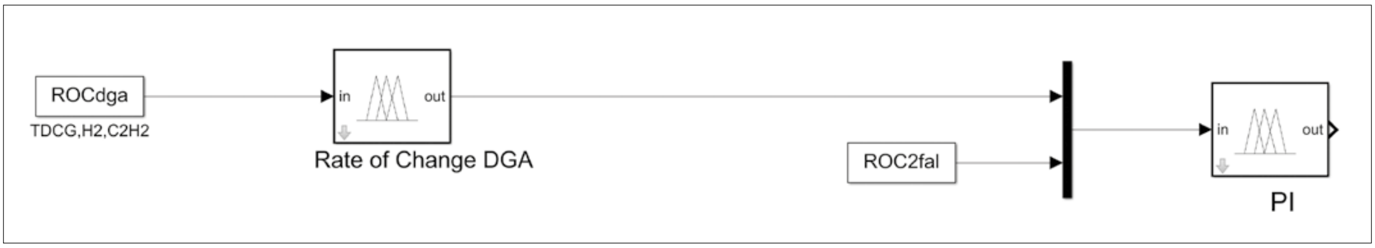


Figure 8. PI profile

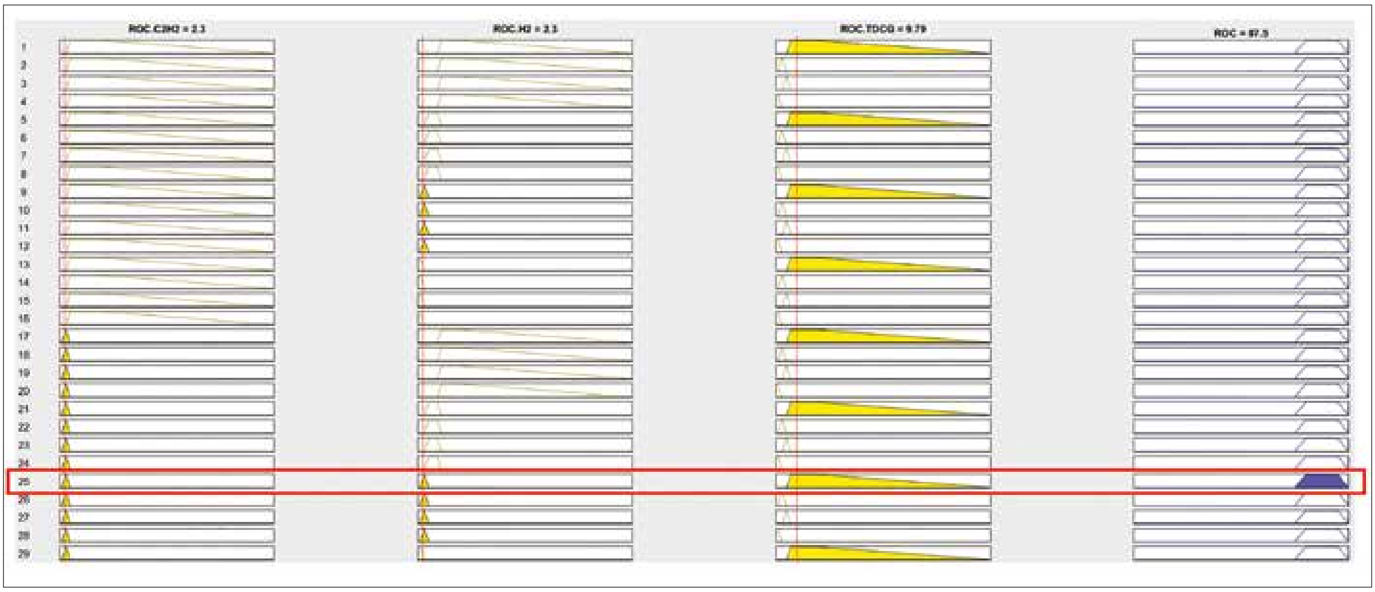


Figure 9. Fuzzy inference rules of ROC DGA module

4.3 Oil quality index (OQI)

OQI is a combination of three modules for moisture, oil characteristics, and solid insulation, as shown in Fig. 10. MFs are developed for the input data: break down voltage (BDV), acidity, interfacial tension (IFT), water content, oil temperature, CO, CO_2, and the absolute value of 2FAL. Since the water content values, in ppm, are dependent on oil temperature, a separate module for the moisture is used with its own implemented fuzzy rules, and the output of moisture module is the input to OQI.

The output score of 'oil characteristics' module is based on the three inputs of BDV, acidity, and IFT. The BDV test is one of the prominent diagnostic tests. This test gives an indication of contaminants, such as oil degradation products and water. The acidity in the oil deteriorates the dielectric properties of paper insulation and accelerates the oxidation process in the oil. An increase in the acidity of the oil in a transformer gives an indication of the rate of degradation of the oil with sludge. The output of 'oil characteristics' module is an input of OQI module.

Similarly, the 'solid insulation' module output is dependent on CO and CO_2 gas levels in addition to the absolute value of 2FAL in the oil.

Conclusion

The fuzzy logic method is utilised to build up an intelligent system to evaluate the condition of power transformers based on oil data. Hundreds of fuzzy rules are developed in the proposed model to mimic the behaviour of an oil transformer expert and generate a reliable HI. The proposed model can be a useful tool to make decisions and prioritise maintenance plans of power transformers.

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Prognostic index is estimated using the measured rate of change of dissolved gasses in time, combined with fuzzy logic model

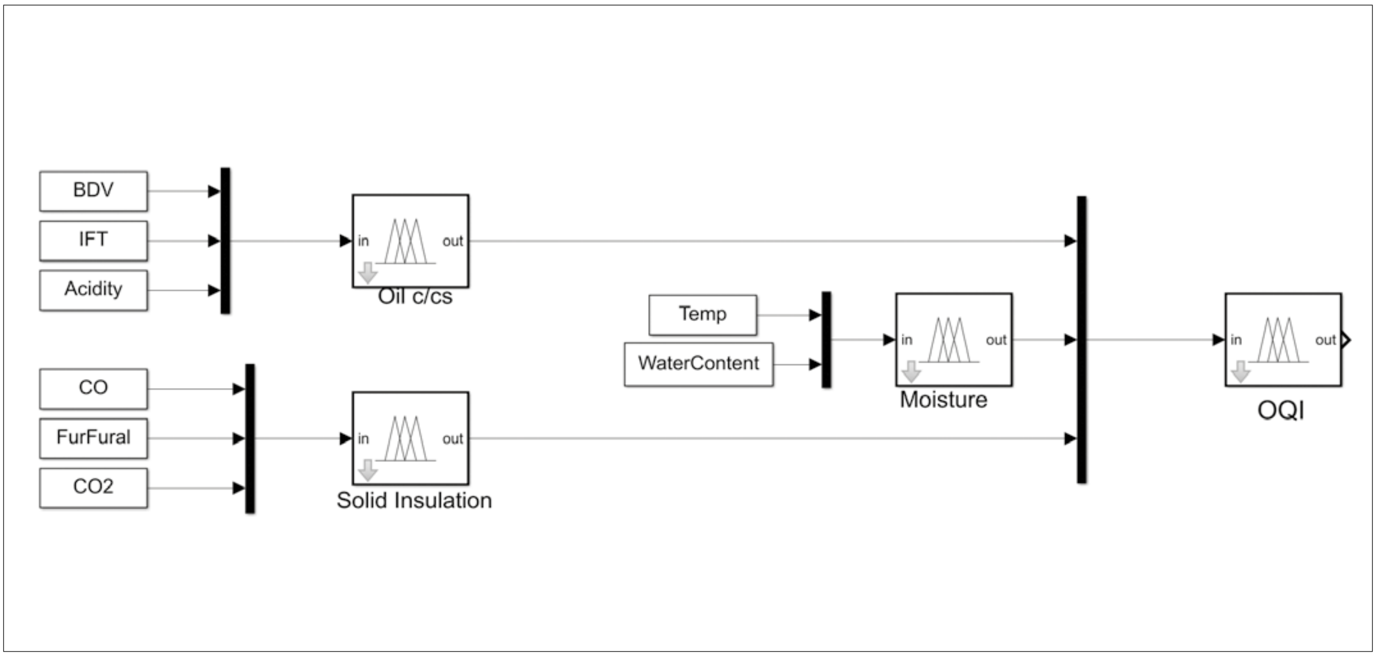

Figure 10. Fuzzy logic - oil quality index

Oil quality index is estimated using the fuzzy logic model, which uses measurement data such as break down voltage, acidity, interfacial tension, water content, oil temperature, CO, CO_2, etc.

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Author

Mohamed Khalil is a Technical Application Engineer at Doble Engineering, focusing on Doble's enterprise asset management solutions. He received his M.Sc. degree in Electrical Engineering and his doctorate degree in Reliability Engineering from Politecnico di Milano, Italy. His fields of interests are reliability evaluation of electrical systems, failure modes and criticality analysis. He was appointed in IEEE Instrumentation and Measurement Administrative Committee and was a guest editor of IEEE Instrumentation and Measurement Magazine. Mohamed is currently an invited technical reviewer in a number of IEEE conferences.