Piotr S. SZCZEPANIAK
Institute of Information Technology, Technical University of Lodz
Lodz, Poland

ADVANCES IN DGA-BASED IAGNOSIS OF POWER TRANSFORMERS – SELECTED TECHNIQUES

Key words

Intelligent data analysis, clustering, classification, diagnosis of power transformers.

Summary

To a large extent, the chromatographic data obtained by measurements on power transformers reflect the state of a power transformer and allow the assessment of possible faults. The distribution of real learning data is not even approximately uniform and makes the partitioning of decision space difficult. The purpose of this paper is to present the results of the application of an IEC-based classifier and a number of novel methods.

1. Introduction to DGA-based diagnosis

It is of great importance to ensure proper and fault-free operation of transformers in a power grid. The permanent examination of transformers' technical condition is here the solution. One of the methods applied to diagnose technical condition of transformers is DGA – the analysis of the concentration of gases dissolved in transformer oil. Based on their own experience, different countries have worked out different transformer diagnostic methods based on DGA results. The diagnosis is based on the results collected in the past during the inspection of a large number of power transformers of the same size. The measurement data used in the presented research come from small and medium size transformer units.

The classic methods presently used for diagnoses are based on rigid mathematical dependencies. There also exists an internationally acknowledged standard – IEC (International Electrotechnical Commission, 1978) that uses three variables *(x, y, z)* defined by the following ratios:

$$x = \frac{C_2H_2}{C_2H_4} \qquad y = \frac{CH_4}{H_2} \qquad z = \frac{C_2H_4}{C_2H_6} \tag{1}$$

where H_2, CH_4, C_2H_2, C_2H_4, and C_2H_6 denote the amount of hydrogen, methane, acetylene, ethylene, and ethane in a gas under examination (in ppm units – parts per one million), respectively. The IEC-code and all the classic methods are based on knowledge and experience and are constructed as rigid classification rules. Recently, the use of soft computing technology (M. Rudnicki, et al., 1999; Sasiak, 2002; Szczepaniak and Cholajda, 1998; Szczepaniak, 2000) and *k*-NN have also been considered (Szczepaniak and Kłosiński, 2010).

In the following investigation, the diagnosis is performed on these IEC variables and that every triple enables assumptions to be drawn about the technical condition of the examined transformer. Following the IEC code, it has also been assumed that there are nine classes describing the state of the transformer.

Apart from variables (*x, y, z*), which reflect the DGA results for the transformer under examination, all data (placed in a database) contain additional information about the technical condition of the transformer. This information is obtained from a human-expert who usually makes the diagnosis by inspection of the transformer. This enables classification of a point (or, generally speaking, an object) described by the triple (*x, y, z*) – Fig. 1. It has been assumed that there are ten classes (according to IEC code), namely:

No fault,
Partial discharge of low energy,
Partial discharge of high energy,
Disruptive discharge of low energy,
Disruptive discharge of high energy,
Overheating below 150°C,
Overheating between 150°C and 300°C,
Overheating between 300oC and 700°C,
Overheating over 700°C, and
Unidentified.

Consequently, every triple enables assumptions to be drawn about the technical condition of the examined transformer. The intervals of quotient values are coded with three integers {0,1,2}, see Table 1.

Table 1. IEC coding

quotient value	$\frac{C_2H_2}{C_2H_4}$	$\frac{CH_4}{H_2}$	$\frac{C_2H_4}{C_2H_6}$
[0; 0,1)	0	1	0
[0,1; 1)	1	0	0
[1; 3)	1	2	1
Value > 3	2	2	2

Table 2. Classification according to IEC

No	Transformer's condition	$\frac{C_2H_2}{C_2H_4}$	$\frac{CH_4}{H_2}$	$\frac{C_2H_4}{C_2H_6}$
1	No fault	0	0	0
2	Partial discharge of low energy	0	1	0
3	Partial discharge of high energy	1	1	0
4	Disruptive discharge of low energy	1 or 2	0	1 or 2 *)
5	Disruptive discharge of high energy	1	0	2
6	Overheating below 150°C	0	0	1
7	Overheating (150 °C, 300°C]	0	2	0
8	Overheating (300 °C, 700°C]	0	2	1
9	Overheating 700 °C	0	2	2
10	Unidentified fault	Code other than those listed above		

According to IEC, there are nine classes (Table 2) that are well defined from the engineering point of view and one class that contains ambiguous cases.

The expert knowledge shown in the table can also be represented in the form of logic rules:

$$\begin{gathered}\text{If } \mathit{code}\ \{d_x\ , d_y\ , d_z\ \} \\ \text{then } \mathit{the\ transformer's\ condition}\end{gathered} \tag{2}$$

These are the rules of crisp logic, which are unambiguous and mutually exclusive.

Visually, IEC system divides the three-dimensional decision space into a number of disjoint spaces. (Fig.1), with the largest volume being occupied by the space of unidentified transformer's conditions.

*) Code „102" is usually interpreted as „full discharge of high energy", whereas „full discharge of low energy" is associated with one of the three codes: {101}, {201} or {202}.

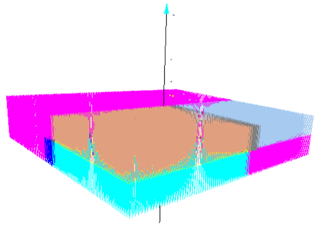

Fig. 1. Visualisation of the IEC classification

To sum up, every triple (x, y, z) or every triple shown in the table depicting DGA results for the examined transformer can be assigned an additional value describing (in a coded or linguistic way) the transformer's technical condition. This value, determined by inspection of a switched off transformer or an expert's opinion, is in fact a diagnosis of the transformer's condition.

The approach presented in this paper is as follows. With a sufficiently great number of representative results for a series of transformers, it should be possible to find regions related to the above nine classes or to generate a number of logic rules. The examination of a new DGA result would then be straightforward. So far the IEC, as well as every other national system of classification**,** has offered an arbitrary division of the space. In the presented approach, the determination of regions related to the nine classes of diagnosis depends on the real results of previous examinations performed on transformers working in real conditions.

1. Fuzzy controllers

The diagnosis can be made by a fuzzy controller making use of the rules resulting from fuzziness introduced in the IEC code.

Real data frequently differ from the IEC classification. Thus, it is purposeful to replace IEC intervals with suitably defined fuzzy sets. For example, the fuzzy set "0" corresponds to the interval <0;0.1) of the IEC code, etc. The fuzzy sets chosen should be flexible and easily modifiable by suitable changes of their parameters.

Note that the faults that can be identified by the IEC code can be divided into three mutually independent groups as shown in Fig. 2. An essential element of the system shown in this figure is a fuzzy controller that takes values calculated from (1) as input and gives an appropriate real number on each output. The number contains information about a fault identified by the controller and a certainty degree of the diagnosis. In the next step, suitable fuzzy sets (values of the linguistic variables "partial discharge," "disruptive discharge," and "overheating") to which the number received from the controller belongs with the highest degree are found. The very value of this membership degree is the certainty of the answer acquired.

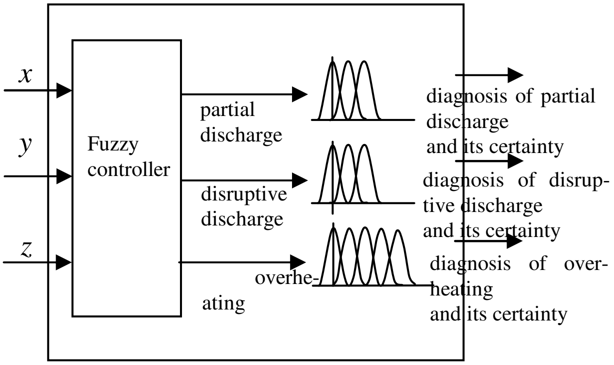

Fig. 2. Operation scheme of the fuzzy diagnostic system

In accordance with (1), the controller must have three inputs and three outputs. The outputs are mutually independent; therefore, the controller can be presented as three fuzzy controllers with common inputs and a scalar output (the first to detect existence of partial discharge, the second for detection of disruptive discharge, and the third one to identify overheating). The controllers applied in the system presented here can make use of a generalised *modus ponens* inference rule together with fuzzification of *singleton* type, Larsen's rule for the fuzzy implication and *centre average defuzzification*. Following information about the nature of the problem, component controllers may be of two types of structures, namely, basic or simplified.

The controller of the basic type is based on rules of the form

$$R^{(k)}: \textbf{IF } (x \text{ is } A_1^{\,k} \textbf{ AND } y \text{ is } A_2^{\,k} \textbf{ AND } z \text{ is } A_3^{\,k})$$

$$\textbf{THEN } (\mathrm{y} \text{ is } B^{k})$$

For a controller of this type, each rule has a separate group of fuzzy sets in the premises of the rules.

In the construction of controllers of the simplified type, additional information about the number of different types of fuzzy sets in the premises of the rules is exploited. It must be assumed here that in all inference rules the sets denoted by the symbol "0" are "similar" to one another and can be replaced by one set, and the same reasoning is valid for sets "1" and "2". Analogous simplification is applied to the linguistic values standing for the system's answers.

To train the controller, the system can exploit a genetic algorithm (Szczepaniak, 2000).

2. Application of adaptive logic networks

Subsequently, we apply Pedrycz's neurons (Pedrycz, 1993, 1995, 1998; Pedrycz and Szczepaniak, 2001) that perform logic operations. Two types of the neurons are used, namely, OR and AND. The OR neurons compare their weights w_i with inputs x_i using t-norm (AND) and then expose the indirect results obtained in this way to s-norm (OR). The AND neurons work conversely: they expose the weights and inputs to s-norm (OR) and the indirect results to t-norm (AND). The processing that occurs in neuron OR can be written as follows:

$$y = \mathop{\mathrm{S}}_{i=1}^{n} (w_i \ \mathrm{t}\ x_i) \tag{3}$$

Whereas, the processing that occurs in neuron AND as

$$y = \mathop{\mathrm{T}}_{i=1}^{n} (w_i \ \mathrm{s}\ x_i) \tag{4}$$

where S and T denote generalised norms.

The processing elements of the network used in the following are aggregative OR and AND logic neurons, which perform the mapping $[0,1]^K \rightarrow [0,1]$, using t- and s-norms. Their functions are as defined in Pedrycz (1993, 1995, and 1998):

$$\text{OR neuron} \quad y = \mathop{\mathrm{S}}_{i=1}^{n} (w_i \ \mathrm{t}\ x_i) \tag{4}$$

$$\text{AND neuron} \quad y = \mathop{\mathrm{T}}_{i=1}^{n} (w_i \ \mathrm{s}\ x_i) \tag{5}$$

The frequently used special cases of the norms are as follows:

$$\begin{aligned} \mathrm{s}(x,w) &= \max(x,w) = x \vee w \\ \mathrm{t}(x,w) &= \min(x,w) = x \wedge w \end{aligned} \tag{6}$$

and

$$\begin{aligned} \mathrm{s}(x,w) &= x + w - x \cdot w \\ \mathrm{t}(x,w) &= x \cdot w \end{aligned} \tag{7}$$

What we mean by logic processors here are the three-layered networks consisting of Pedrycz's neurons (Pedrycz, 1993, 1995, 1998; Pedrycz and Szczepaniak, 2001). They represent a logic rule consisting of simple expressions (inputs), negative expressions connected with conjunctions, and alternatives. Each of the three layers consists of the same type of neurons. The input layer is a table of values (no processing occurs in it); and for a single rule, the output layer is a single neuron. There are two architectures of such networks, which are equivalent, because a logic rule written as an alternative of conjunctions can be transformed into a conjunction of alternatives, and visa versa.

Again, every triple (x, y, z) or every triple of numbers from the table showing the DGA results for a transformer can be assigned an additional value describing (in a coded or linguistic way) the transformer's technical condition. This value, determined by inspection of a switched off transformer or an expert's opinion, is in fact a diagnosis of the transformer's condition.

Having a sufficiently large database for a given class of transformers, we can create an expert system for diagnosing this class of transformers, that is, an intelligent classifier that is able to classify new data (x, y, z) on the basis of learning patterns collected in that database. This could provide greater flexibility and the ability to adjust the classifier to the type of transformer than in the case of an IEC code.

Pedrycz's networks are designed to process fuzzy quantities or Boolean data. Thus, there are two ways of coding:

1) Converting all the values x, y, z to interval [0, 1] according to

$$x_p^{nowy} = \frac{x_p - \min\{x_p\}}{\max\{x_p\} - \min\{x_p\}}, \qquad p = 1, ..., P$$

   where P is the number of learning objects.

2) Transformation into binary data (there are different ways to do the transformation).

In other words, our aim is to build a classification system, similar to the IEC method, which would be able to obtain knowledge by learning from many various cases. We could also compare the artificially extracted knowledge with the knowledge and experience of engineers contained in the IEC. Of course, such comparisons can be made between other standards of transformer fault classifications.

Generally, the three-layer (input-hidden-output) OR-AND – networks, and AND-OR – networks are sufficient topologies for the stated task. Here, the first one has been chosen. The input layer consists of $2K$ nodes which distribute both the direct x_{ij} and complementary signals to all the neurons of the hidden layer (i = 1, 2,..., N; j = 1, 2,..., K). The hidden layer contains AND-neurons, whose outputs are aggregated by the only OR element of the output layer. The initial number of hidden neurons depends on a chosen learning strategy.

One OR-*many* AND networks were used – one for each class. They were taught by reducing the redundant structure (the gradient adaptation of weights and the deletion of needless connections and neurons). Obviously, the rules obtained for the same data with different learning parameters can slightly differ.

The logic processor proved to be a good tool for example-based rule creation. It can even deal with difficult data; although, it is not always capable of finding the solution on the initial run. It can also quite successfully optimise the rules it generates, but the optimisation is more successful if continuous norms are applied. However, these are more difficult to use and require more computations.

The experiments with the logic processor have shown that this tool, because of its limitations, is not able to successfully retrieve knowledge from any real data, since real data requires digitising and division into a small number of ranges, which results in the loss of part of information. Division into a large number of ranges can, in turn, complicate the problem by generating rules that are difficult to use (numerous single expressions, i.e., network inputs).

The experimental results indicate that IEC is not entirely reliable. It is worth mentioning that the number of data (including the real data before coding) was small for some categories, so the attempts of developing a code better than IEC may not be successful. Nevertheless, the network is able to generate a set of rules based on the information it receives. With a sufficient amount of data, we could try to create a code that would more faithfully represent the data about the condition of the class of transformers under examination.

3. Determination of regions by learning

In the novel propositions, the determination of regions related to the nine classes of diagnosis depends on the real results of previous examinations performed on transformers working in real conditions.

To find the regions, diverse approaches can be considered. Below are some examples of recently verified approaches: the classic *k*-NN method, svm-based classifier, and fuzzy classification.

A simple but effective method is *k*-NN based partition of the space (Szczepaniak and Kłosiński, 2010). Comparison of *k*-NN (correctness of the diagnosis about 50% for $k = 7$) with IEC-classifier (correctness of about 70%) clearly shows that it is worth searching for new partition methods of the decision space (x, y, z) of the results of the chromatography of gases dissolved in transformer oil.

For determination of regions, the fuzzy set theory can successfully be applied. (For details see Cholajda and Szczepaniak, 1998; Szczepaniak and

Cholajda, 1998; Rudnicki, et al. 1999). With every region a number of fuzzy "if-then" rules can be correlated, and then the classification of a new data can be performed. The main drawback of this technique is that the number of rules can be large. However, it is possible to attain a significant reduction in calculations needed to classify a new object if, under the condition that classification correctness is kept for the greatest possible number of known database objects, the number of rules used for classification could be reduced. To achieve this aim, the genetic algorithm can be applied. The requirement is that objects from the database are as correctly classified as possible.

The method called "support vector machines" – SVM (or alternatively "maximal margin classifier") also enables the creation of an expert system for the technical condition diagnosis of transformer oil. One can notice the difference. While IEC leaves most of the feature space unrecognised, the SVM classifier introduces classification in the whole space by extrapolating the rules learnt from the training patterns.

The SVM method enables one to create a classifier which is capable of introducing feature space separation that is about 15–20% more accurate than the standard IEC approach (the results will be published in the near future).

Summary

Partitioning of the decision space of the ratios calculated for chromatographic data obtained by measurements on power transformers is a difficult task, because the data is not distributed uniformly and frequently is not separable. This is the reason why classic methods of clustering are of limited use. Thus, classification performed by systems learning from this data is not entirely accurate. To eliminate these difficulties, researchers have been working on applying soft computing methods. Among those methods are artificial neural networks, logic networks, fuzzy systems, and support vector machines. Intelligent approaches show their capability to perform better or at least not worse than classic methods. This paper offers a survey of the mentioned applications. For details, the listed references are recommended.

Acknowledgement

The author would like to express his gratitude to Mr P. Cholajda (Systems Research Institute, PAS) and Mr M. Kłosinski (Technical University of Lodz) for performing a part of computations.

References

1. Cholajda P., Szczepaniak P.S. (1998): Zastosowanie algorytmu genetycznego do interpretacji wyników analizy chromatograficznej gazów

w transformatorach. Materiały III Krajowej Konferencji Naukowo--Technicznej nt. Diagnostyka Procesów Przemysłowych, Jurata/Gdańsk.
2. International Electrotechnical Commission, Interpretation of the Analysis of Gases in Transformers and other Oil-Filled Electrical Equipment in Service. Geneva, 1978 (see also: http://www.iec.org).
3. Pedrycz W. (1993): Fuzzy neural networks and neurocomputations. Fuzzy Sets and Systems, vol. 56, 1–28.
4. Pedrycz W. (1995): Fuzzy sets engineering. CRC Press, Boca Raton.
5. Pedrycz W. (1998): Computational intelligence: an introduction. CRC Press.
6. Pedrycz W., Szczepaniak P.S. (2001): Digital Systems Design through Learning. In: New Learning Paradigms in Soft Computing, L.C.Jain and J. Kacprzyk (Eds.), Physica Verlag, c/o Springer-Verlag, Heidelberg, New York.
7. Rudnicki M., Szczepaniak P., and Cholajda P., Genetic algorithm as a tool for solving electrical engineering problems. In: K.Miettinen, P.Neittaanmä ki, and J.Périaux (Eds.), Evolutionary Algorithms in Engineering and Computer Science, Chapter 13, pp. 261–281.
8. Sasiak K. (2002): Sieci neuronowe i logika rozmyta w diagnostyce technicznej. Praca dyplomowa magisterska, Instytut Informatyki, Politechnika Łódzka, Łódź.
9. Szczepaniak, P. and Cholajda P., Genetic interpretation of DGA results in power transformers. Proc. Int. Conf. SSCC'98: Advances in Systems, Signals, Control and Computers, Durban, South Africa, 1998, vol. II, pp. 216–220.
10. Szczepaniak P.S., Fuzzy and Genetic Approach to Diagnosis of Power Transformers. Preprints of the 4th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes, Budapest, Hungary, 2000, vol. 1, pp. 428–433.
11. Szczepaniak P.S., Sasiak K.: Zastosowanie adaptacyjnych sieci logicznych do diagnostyki transformatorów. Pomiary, automatyka, kontrola. **9**(2005), pp. 206–209.
12. Szczepaniak P.S., Kłosiński M.: DGA-based Diagnosis of Power Transformers – IEC Standard versus k-Nearest Neighbours. IEEE Region 8 SIBIRCON-2010, Proceedings of 2010 IEEE Region 8 Int. Conference on Computational Technologies in Electrical and Electronic Engineering, Irkutsk Listvyanka, Russia, 2010, pp. 740–743.

Reviewers:
Dariusz UCIŃSKI
Anna TIMOFIEJCZUK

Postępy w diagnostyce transformatorów w oparciu o wyniki analizy chromatograficznej rozpuszczonych w oleju gazów – przegląd zastosowań nowych metod

Słowa kluczowe

Diagnostyka transformatorów, analiza chromatograficzna gazów, obliczenia inteligentne, standard IEC.

Streszczenie

Jak wiadomo, wyniki analizy chromatograficznej gazów rozpuszczonych w oleju transformatorowym (*Dissolved Gas Analysis* – DGA) mogą być użyte do diagnostyki transformatorów. Zwykle rozmieszczenie tych danych (ściśle ilorazów koncentracji wybranych gazów) w przestrzeni jest bardzo nierównomierne, a ponadto jednoznaczny podział tej przestrzeni na obszary decyzyjne o rozsądnej wielkości i liczbie jest bardzo trudny. Celem pracy jest dokonanie przeglądu zastosowań nowych metod, wśród nich tych mających korzenie w obliczeniach inteligentnych i odniesienie się do wyników uzyskiwanych za pomocą standardu IEC (*International Electrotechnical Commission*).