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# Maximal margin classifiers applied to DGA-based diagnosis of power transformers

***Abstract.*** *The paper addresses a modern approach to the problem of power transformer diagnosis. The method called support vector machines enables the creation of an expert system for oil transformer technical condition diagnosis. The system, which is based on real results of chromatography of gases dissolved in transformer oil (DGA), performs better than an internationally acknowledged standard – the IEC code.*

**Keywords**: power transformers, DGA, IEC, classification, maximal margin classifiers, SVM

## Introduction

To a large extent, the chromatographic data obtained by measurements on power transformers (analysis of gases dissolved – DGA) reflect the state of a power transformer and allow reasoning about the presence of possible faults. Data used to evaluate a transformer are defined by three variables $(x,y,z)$

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

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 the gas under examination (in ppm units – parts per one million), respectively. The meaning of these variables is the same as in the IEC code; they reflect the DGA results. (IEC – International Electrotechnical Commission; Geneva; 1979). Following the IEC code, it has been assumed that there are nine classes describing the state of the transformer:

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

Consequently, every triple $(x,y,z)$ enables reasoning about the technical condition of the examined transformer. Partitioning of decision space of the ratios calculated for chromatographic data obtained by measurements on power transformers is a difficult task because the data are not distributed uniformly and frequently are not separable. This is the reason why classic methods of clustering are of limited use. Thus, classification performed by systems learning from these data is not entirely accurate. To eliminate these difficulties, researchers have been working on applying soft computing methods. Among those methods there 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.

The paper addresses a modern approach to the problem of power transformer diagnosis. The aim is to present the results of application of an IEC-based classifier and the method called support vector machines – SVM (or alternatively „maximal margin classifier"). The SVM method enables the creation of an expert system for oil transformer technical condition diagnosis. One can notice the difference: while IEC leaves most of the feature space unrecognised, 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.

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