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A cognitive system for fault prognosis in power transformers

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ABSTRACT

The power transformer is one of the most critical and expensive equipments in an electric power system. If it is out of service in an unexpected way, the damage for both society and electric utilities is very significant. Over the last decades, many computational tools have been developed to monitor the 'health' of such an important equipment. The classification of incipient faults in power transformers via Dissolved Gas Analysis (DGA) is, for instance, a very well known technique for this purpose. In this paper we present an intelligent system based on cognitive systems for fault prognosis in power transformers. The proposed system combines both evolutionary and connectionist mechanisms into a hybrid model that can be an essential tool in the development of a predictive maintenance technology, to anticipate when any equipment fault might occur and to prevent or reduce unplanned reactive maintenance. The proposed procedure has been applied to real databases derived from chromatographic tests of power transformers found in the literature. The obtained results are fully described showing the feasibility and validity of the new methodology. The proposed system can help Transformer Predictive Maintenance programmes offering a low cost and highly flexible solution for fault prognosis.

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1. Introduction

Power transformers are considered key-elements for the Electric Utilities (EU). When those equipments fail, households, industries, and hospitals, to name a few, are prone to suffer somehow. Besides, an unplanned interruption in the power supply can be translated into heavy fines for the EU. Hence, tools for diagnosis, fault detection and fault prognosis are required. In the context of power transformers, several studies are noteworthy regarding the aspects of protection, monitoring and diagnostics, see for instance [1–5].

For many years, preventive maintenance programmes in power transformers consisted of inspections, tests and actions in periodic time intervals usually suggested by the manufacturers or determined through practical experience. It was also common the application of routine tests and procedures such as: measurement of dielectric losses, insulation resistance and winding resistance; physical–chemical analysis and chromatographic oil analysis; manual or automatic monitoring of temperature [6]. Such analyses allowed the operators to verify if a given transformer was operating normally or if there were evidences of thermal and/or electrical failures, for instance. These kind of failures stem from natural wear, environmental actions and overloads, among other causes. Reference work in this area can be found in [6–8].

Among several fault detection methods, many faults that occur in power transformers can be detected if one measures the gases concentrations in their insulating oil. This procedure is known as fault detection via Dissolved Gas Analysis (DGA) [6]. Usually, DGA can be carried out in two modes: off-line and on-line modes. In the off-line mode, the power transformer has to be disconnected from the power system and an oil sample is collected and taken to a laboratory where it will be analysed via a gas chromatography technique. Yet in the on-line mode, the power transform is kept connected to the power system and the DGA is performed in loco with a determined time interval (e.g. every 2 h) using, e.g., a compact closed-loop gas chromatograph unit, which is mounted on or near the monitored transformer. Techniques such as optical and chromatography [9–11], electrical–chemical systems [12,13] and

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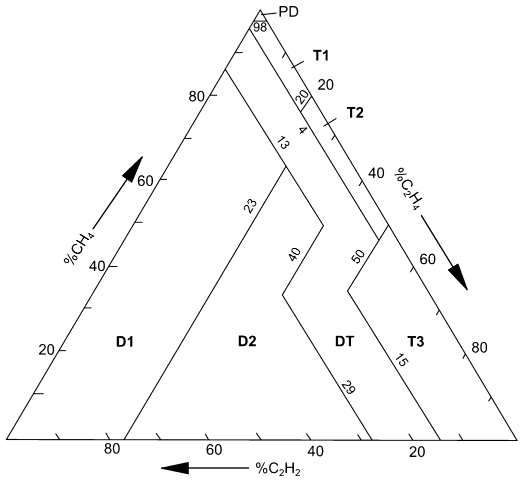

Fig. 1. Duval's Triangle Method.

near-IR absorption spectroscopy [14] can be employed in the DGA as well.

A method for fault classification in power transformers named *Duval's Triangle Method (DTM)* is introduced in [6] and described in IEEE C57.104 [7] and in IEC 60599 [8] (see Fig. 1). DTM is based on the levels of the three dissolved gases found in the power transformer oil: ethylene (C_2H_4), methane (CH_4) and acetylene (C_2H_2). The DGA by DTM involves the percentages of the aforementioned gases ratios, see Eqs. (1)–(3), presented in a graphical form. The three sides of the triangle in cartesian coordinates x, y and z represent the relative proportion of CH_4, C_2H_4 and C_2H_2, from 0 to 100% for each gas. The intersections of all three gases ratios indicate the kind of fault presented by the transformer. All types of faults in the Duval triangle can be found in Table 1.

In Eqs. (1)–(3), x is the concentration of CH_4 in ppm, y is the concentration of C_2H_4 in ppm and z is the concentration of C_2H_2 in ppm.

$$CH_4\,(\%) = 100\frac{x}{(x+y+z)} \tag{1}$$

$$C_2H_4\,(\%) = 100\frac{y}{(x+y+z)} \tag{2}$$

$$C_2H_2\,(\%) = 100\frac{z}{(x+y+z)} \tag{3}$$

Taking into consideration that there are not efficient mathematical models to describe the relationship between the rate of evolution of these concentrations and the failures, and the process of gathering historical data is a common practice nowadays, the development of pattern classifiers based on Support Vector Machines [15–17], Fuzzy Logic approach [18], Neuro-Fuzzy models [19,20], Wavenets [21,22], Neural Networks [23,24], stochastic Petri net based methodology [25], probabilistic classifier based on particle swarm optimizer [26], Decision Trees [27–29], and bootstrap and Genetic Programming [30] has received a great deal of attention. More recently, Duval himself and his colleagues published a new fault detection method based on the application of a gas-ratio combination [31].

The aforementioned works have at least two common points:

- the vast majority of papers in this field deal with off-line DGA.
- the authors focused on fault diagnosis in power transformers. Fault prognosis was not a major concern. Incidentally, this latest strategy is relatively new. Refs. [32–36] are few exceptions in this particular subject.

It is in this context that we present a new computational system capable of carrying out fault prognosis in power transformers. The new approach is based on a hybrid system formed by connectionist and evolutionary mechanisms, which was applied to real databases derived from chromatograph tests of power transformers found in the literature [37]. Instead of informing the current state of the transformer only, e.g. *Normal Condition* (NC), *Electrical Fault* (EF), *Thermal Fault* (TF), the fault prognosis tool will estimate – from a given current transformer state – if the transformer under analysis is likely to present, for instance, a thermal failure in six months and how the failure will evolve through time. Such tool is of interest of the EU because it can become an essential tool for the Transformer Predictive Maintenance (TPM). TPM can be seen as a maintenance strategy that provides transformer failure early detection and is able to recognize conditions that lead to defects. Ideally, TPM should allow the maintenance frequency to be as low as possible preventing unplanned reactive maintenance and reducing unnecessary preventive maintenance. The proposed prognosis system is an intelligent system that was implemented with an architecture for modelling cognitive systems.

The main contributions of this work are: (i) proposition of an online intelligent fault prognosis system for power transformers that is capable of predicting when and which type of fault is expected to occur. The proposed system can help TPM programmes offering a low cost and highly flexible solution for fault prognosis; additionally the prognosis system manipulates the gases concentrations at the same time as multiple inputs to the system. (ii) Proposition of a general architecture for cognitive and knowledge based systems, on which the fault prognosis system is implemented.

2. Fault prognosis system in power transformers

Prognosis (also Prognostics) is an engineering discipline involving the prediction of when a system or component will no longer perform as intended and, if possible, classify which kind of fault will occur [38–41]. The predicted time is termed Remaining Useful Life (RUL), which is an important concept in contingency and in System Health Management (SHM). Prognosis systems can be categorized into data-driven methods and model-based methods [43]. In any case, the method requires some initial knowledge about a model of the system or component; or knowledge in the form of information about previous fault cases and conditions.

Data-driven prognosis systems usually employ pattern recognition and machine learning techniques to detect changes in the states of the system of interest or changes in the monitored variables. They are recommended when there is no appropriate understanding of the physics behind the operation of the system, or the principles relating its operation to fault conditions.

Industrial applications of Prognosis are diverse, ranging from manufacturing, automotive and aerospace industries and also power generation and distribution. In the power generation industry, commercial applications of SHM include rotating machinery [43] and wind turbines [44]. Renewable energy applications, such as wind turbines, can also benefit from SHM technology based on

Table 1
Faults described by the Duval's Triangle Method (DTM).

Nomenclature	Type of fault
PD	Partial discharge
D1	Low energy discharge
D2	High energy discharge
DT	Mix of thermal and electrical faults
T1	Thermal fault with $T < 300\,^{\circ}C$
T2	Thermal fault with $300 < T < 700\,^{\circ}C$
T3	Thermal fault with $T > 700\,^{\circ}C$

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