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DATA CLASSIFICATION APPROACHES APPLIED TO DGA FOR FAULT DIAGNOSIS IN OIL-FILLED POWER TRANSFORMERS

Leandro dos Santos Coelho
Industrial and Systems Engineering Graduate Program (PPGEPS), Pontifical Catholic University of Parana (PUCPR)
Imaculada Conceição, 1155, Curitiba, PR, Brazil and Department of Electrical Engineering (DEE/PPGEE)
Federal University of Parana (UFPR), Rua Cel. Francisco Heraclito dos Santos, 100, Curitiba, PR, Brazil
leandro.coelho@pucpr.br
Viviana Cocco Mariani
Mechanics Engineering Graduate Program (PPGEM), Pontifical Catholic University of Parana (PUCPR)
Imaculada Conceição, 1155, Curitiba, PR, Brazil and
Federal University of Parana (UFPR), Rua Cel. Francisco Heraclito dos Santos, 100, Curitiba, PR, Brazil
viviana.mariani@pucpr.br
Diego Luís de Andrade Bernert
Marcelo Wicthoff Pessôa
Camila da Costa Silveira
Industrial and Systems Engineering Graduate Program (PPGEPS), Pontifical Catholic University of Parana (PUCPR)
Imaculada Conceição, 1155, Curitiba, PR, Brazil
dbernert@gmail.com, celowp@gmail.com, camila.silveira@br.bosch.com
Júlio Xavier Vianna Neto
Federal University of Parana (UFPR), Graduate Program in Electrical Engineering,
Rua Cel. Francisco Heraclito dos Santos, 100, Curitiba, PR, Brazil
jxvneto@gmail.com
Marino Borges Seixas Júnior
Federal University of Parana (UFPR), Undergraduate Program in Electrical Engineering
Rua Cel. Francisco Heraclito dos Santos, 100, Curitiba, PR, Brazil
marinobsjunior@gmail.com
Cleber Onofre Inacio
Centro de Pesquisa e Desenvolvimento Leopoldo A. Miguez de Mello (CENPES) – PETROBRAS
Av. Horácio de Macedo, 950, 21941-915, Rio de Janeiro, RJ, Brazil
cleberoi@petrobras.com.br

Abstract. *Transformers are one of the most important and cost-intensive components of electrical energy supply networks, thus it is of special interest to prolong their life duration while reducing their maintenance expenditures. Dissolved Gas Analysis (DGA) is a popular method to detect and diagnose different types of faults occurring in power transformers. This paper describes the development and the implementation of a tool to diagnose faults in power transformers through the analysis of dissolved gases in oil. The adopted computational system approach is based on a combined use of traditional criteria of the dissolved gas analysis published in standards combined with support vector machine, Naïve Bayes classifier, bagged decision trees and probabilistic neural network approaches. For validation of the implemented methodology, two groups of data of generated gases were used: one from IEC (International Electrotechnical Commission) and another from a set of historical data of six PETROBRAS' thermoelectric plants. The results obtained with this tool are promising in the diagnosis of incipient faults in transformers, reaching success levels above 80%.*

Keywords: *dissolved gas analysis, incipient faults, transformers, thermal units, support vector machine, Naïve Bayes classifier, probabilistic neural network.*

1. INTRODUCTION

Power transformers are considered key components in the power supply chain. Beyond of being a costly component, it must be in perfect working conditions to not interfere in the transmission system. Transformer fault detection and diagnosis is becoming more relevant due to the restructuring of the electric power industry. Power transformers are designed to transmit and distribute electrical power. Depending on the size of a transformer, replacement costs can range from a few hundred dollars to millions of dollars.

A transformer can fail from any combination of electrical, mechanical or thermal factors or may have more than one causal factor. It is of great importance to detect incipient failures in power transformers as early as possible. The failure of transformers can have a direct or indirect impact on the reliable delivery of quality power. Incipient transformer faults lead to electrical and thermal stresses on insulating materials.

The breakdown of electrical insulating materials and related components inside a transformer generates gases within the transformer. The analysis of these gases provides useful information about the fault conditions and the type of

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materials involved. Gases dissolved in transformer oil can be extracted by various methods, and the identity and concentration of each gas can be determined by gas chromatography.

Dissolved gas analysis (DGA) is one of the most recent and well-known techniques (Duval, 2002; Singh and Bandyopadhyay, 2010; Sun et al., 2012) in the industry developed to diagnose the fault condition on oil filled insulation transformers. DGA can be an investigative tool to monitor the transformers health and to detect impending failures by recognizing anomalous patterns of gas concentrations. In this context, many years of empirical and theoretical study have gone into the analysis of transformer fault gases. The identity of the gases being generated can be useful information in any preventive maintenance program. The gases dissolved in the oil can be detected in ppm (parts per million) level by DGA inspections to determine the “health” of a transformer.

The difficulty in making use of DGA results, which arises from its high sensitivity, is that it is not easy to draw the line between normal and abnormal results, i.e. to be sure that a fault really exists. Most, but not all, interpretation schemes include a normal condition as one of the diagnostic outcomes, but have not been particularly effective in reliably identifying a normal condition (Gray, 2010).

DGA can be useful to identify deteriorating insulation and oil, over heating hot spots, partial discharge and arcing. DGA is performed based on the IEC60599-1999 (International Electrotechnical Commission - IEC publication 60599, 1999) and IEEE C57-.104-1991 (Institute of Electrical and Electronics Engineers - IEEE publication 57104, 1991) standards. The mentioned standards provide guidance for the interpretation of DGA results in service. Furthermore, the IEC TC10 databases of DGA results corresponding to faults identified by visual inspection of faulty transformers in service can be useful and have been presented in Duval and dePablo (2001).

Interpretation schemes are generally based on defined principles such as gas concentrations, key gases, key gas ratios, and graphical representations. Common schemes include Key Gas Analysis, Dornenberg ratio method, Rogers ratio method, Nomograph, IEC ratio, Duval triangle, and CIGRE (International Council on Large Electric Systems) method (Sun et al., 2012).

Diagnostic experts are required because the DGA diagnostic procedure is complicated and time-consuming, since the knowledge embedded in previous gas records and their corresponding diagnosis results strengthen the diagnosis of similar fault cases (Huang et al., 2003). On the other hand, some studies have reported the use of DGA samples with artificial neural networks (Guardado et al., 2001; Huang et al., 2003; Chen et al., 2009; Shaban et al., 2009), fuzzy systems (Abu-Siada et al., 2010; Muhamad et al., 2007) and expert systems (Lin et al., 1993) for incipient fault detection in power transformers. In this paper, the data classification approaches including support vector machine (SVM), Naïve Bayes classifier, bagged decision trees and probabilistic neural network are evaluated and compared for transformer fault classification based on DGA.

The classification approaches were validated using a database of chromatography analysis of the oil-filled power transformers with historical data of PETROBRAS’ thermoelectric plants. Furthermore, the data mentioned by Duval and dePablo (2001) were used in the computational classification approaches too.

The remainder of this paper is organized as follows. The fundamentals of the data classification approaches are mentioned in the section 2. A description of the classification methodology and data can be found in section 3. Section 4 is devoted to the analysis of the classification results. Section 5 summarizes this study and the conclusions are presented.

2. FUNDAMENTALS OF THE DATA CLASSIFICATION APPROACHES

In the next subsections, first a brief overview of the SVM is provided; then, the basics of the Naïve Bayes classifier, probabilistic neural network and bagged decision trees are explained.

2.1 Support vector machine

The SVM technique is a machine learning method based on statistical learning theory developed by Vladimir Vapnik (Vapnik, 1993). The SVM is a technique used for the training of classifiers based on the concept of structural risk minimization (Burges, 1998). It is used to train nonlinear relationships based on the structural risk minimization principle that seeks to minimize an upper bound of the generalization error rather than to minimize the empirical error implemented in artificial neural networks.

This induction principle is based on the fact that the generalization error is bounded by the sum of the empirical error and a confidence interval term that depends on the Vapnik-Chervonenkis (VC) dimension. Using this principle, the SVM will achieve an optimal model structure by striking the right balance between the empirical error and the VC-confidence interval (Santos et al., 2012).

Despite the good theoretical fundamentals for the principle of structural risk minimization, it can be difficult to implement because of the difficulty in calculating the VC dimension of a hypothesis, and the difficulty of resolving the optimization problem coupled with it. The success is achieved by training of SVMs, which can simultaneously minimize the error rate of training and the error rate of generalization (Lima, 2009).

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Some of the main advantages of the SVM can be summarized as (Maretto, 2007):

- High generalizing capacity, which avoids overfitting;
- Robustness in case of many dimensions, what allows the SVM application to classification problems with large feature vectors;
- Convexity of the objective function – the application of SVMs involves the optimization of a quadratic function, which has only one minimum;
- Well-established theory within mathematics and statistics.

In this paper, the least squares support vector machines (LS-SVMs) were adopted. LS-SVMs are a class method that uses functions of positive definite nuclei to construct non-linear representation of inputs in a multidimensional space. The LS-SVM is a modification of the original SVM, which applies a system of linear equations, in addition to using also a cost function based on least squares. Furthermore, the LS-SVM uses equality constraints instead of inequality constraints. Due to all of this, this technique reduces the mathematical complexity and computational time when compared to the SVM (which uses the quadratic programming) without compromising the quality of the result. The formulation and details of the LS-SVMs can be found in Suykens et al. (2002).

2.2 Naïve Bayes classifier

The Naïve Bayes algorithm, also known as "Naive Bayesian Classifier", is one of the methods of Bayesian learning. Despite its simplicity, this algorithm is becoming more popular in solving classification problems, compared with other algorithms, such as neural networks and decision trees (Silveira, 2012).

The basis of this classifier is to consider that the different attributes are independent of each other within the same class (Fan, 2009). This assumption is known as conditional independence. This is adopted to ease the computations involved.

The advantage of this classifier is due to the simplicity of its approach, which considers the independence between attributes to achieve the classification that maximizes the multiplicand of its equation (Mitchell, 1997). The equation of the Bayes theorem for Naïve Bayes classifier is

$$h_{NB} = \underset{h_j \in H}{\arg\max}\, P(h_j) * \prod_i P(a_i \mid h_j) \tag{1}$$

where h_{NB} (the Naive Bayes hypothesis) maximizes the product between the occurrence probability of a hypothesis h_j (among the set of possible hypotheses H) and the multiplicand of the valuations probability of the i-th attribute, given the hypothesis h_j. It can be considered that the main features of the Naïve Bayes algorithm are (Tan et al., 2005 Amatrian et al., 2011):

- As the conditional probabilities are obtained from an average, this algorithm is robust to isolated noise points;
- Is robust to irrelevant attributes, since they do not modify the uniform probability distribution;
- In cases of correlated attributes, the independence assumption may not be valid.

2.3 Probabilistic neural network

Artificial neural networks are often employed in tasks related to pattern classification, especially when a data set is available to the algorithm learning. There are different learning rules to neural networks, which basically determine statistical patterns from a set of training samples in order to classify new patterns based on the acquired information (Specht, 1990).

Specht (1990) proposed the Probabilistic Neural Network (PNN) algorithm based on the radial basis neural network and replacing only the sigmoid activation function for a probability distribution function. In this way, the PNN approximates the Bayes optimal decision surface. Another advantage of PNN is that it only requires one step for the training process.

Among the disadvantages of PNN, one can mention the need to store all the samples used in the training process for the classification of new patterns (Machado, 2006).

2.4 Bagged decision trees

Classifiers based on decision trees date back to the 1950s. The decision tree learning is one of the most used methods for inductive inference. It is a method that can make approximations of functions with discrete values, and has the advantage of being robust to manipulate noisy data, being capable of learning disjunctive expressions.

The operating principle of any algorithm based on decision trees is very simple. This model classifies instances by following a path in a tree starting from the root until it reaches a leaf. Each of the nodes tests the value of a single attribute, and for each of its valuations, offers different edges to be followed in the tree from this node on. Its advantage is the strategy adopted known as "divide-to-conquer", which divides a larger problem into smaller problems. Thus, its ability to disaggregate data comes from dividing the space defined by attributes into subspaces (Mitchell, 1997).

Two widely applied algorithms for the supervised learning of decision trees are the ID3 (Iterative Dichotomiser 3), from Quinlan (1986), and its successor, the C4.5 (Quinlan, 19993). These algorithms build the decision trees from the top-down, by determining which attribute must be tested at each node, in order to achieve the highest classification rate on that node.

Bagging stands for "bootstrap aggregation", and is a type of ensemble learning. Bagged decision trees are multiple decision trees built by repeatedly resampling training data with replacement, and plurality vote between them is performed in order to predict a class. Bagging can give substantial gains in accuracy. The disadvantage of bagging decision trees is that a simple and interpretable structure is lost (Breiman, 1996).

3. THE ADOPTED DATABASES AND CLASSICATION PROCEDURE

The research was based on a database containing the track record of insulating oil chromatographic analysis of power transformers from six PETROBRAS power plants. The concentrations of the following dissolved gases in transformer oil were available: hydrogen (H2), methane (CH4), acetylene (C2H2), ethylene (C2H4), ethane (C2H6), carbon monoxide (CO) and carbon dioxide (CO2). Furthermore, in some cases two other gases were also included, nitrogen (N2) and oxygen (O2), as well as the results of physico-chemical analysis of the insulating oil contained in the power transformers. Additionally, the study was also based on the data presented by Duval and dePablo (2001). The PETROBRAS' thermoelectric plant data subjected to normal operation regime conditions were combined with fault data mentioned in Duval and dePablo (2001).

In this study, the researchers made the interpretation of the IEC 60599 standard for the analysis of gases dissolved in oil of electrical equipment and examined the information of IEC 10 database. This database contains information from the inspection of faulty equipment that was removed from service and was examined by experienced engineers and maintenance experts to find the root cause of the equipment failure.

In this work, Duval and dePablo (2001) outlined the faults according to their characteristics:

- Partial discharges (PD);
- Discharges of energy:
  - Discharge of low energy (D1);
  - Discharges of high energy (D2);
- Thermal faults:
  - Thermal faults below 300°C (T1) and between 300 and 700°C (T2);
  - Thermal faults above 700°C (T3).

In addition, the database IEC TC 10 has also the normal gases concentration of in-service equipment (the term used in the standard is "typical value"). In this case, if the concentration of DGA is less than the typical value, it means that the fault probability is low. The tables report the following cases of "typical values":

- Power transformer without communicating OLTC (On-load tap changer);
- Power transformers with communicating OLTC;
- Values for OLTC;
- Instrument transformers;
- Data on the influence of various parameters in power transformers.

Supervised learning was considered in the applied methodology. The main motivation of an attribute selection task is to select user-interested attributes for generating useful data classification. The following classes were adopted in the classification tasks in this work:

0 → Without fault;
1 → Partial discharges (PD);
2 → Discharge of low energy (D1);
3 → Discharges of high energy (D2);
4 → Thermal faults below 300°C (T1) and between 300 and 700°C (T2);
5 → Thermal faults above 700°C (T3).

In this context, the class #0 is related to normal condition regime and the other classes (#1 to #6) are related to fault condition.

For learning process, the available data were divided in two sets: a training set and a model validation set. In this case, two approaches were used for this division:

- Percentage split: 2/3 of the data for the training set and 1/3 for the test set;
- *k*-fold cross validation (or layers estimation): in this approach the samples are divided into *k* subsets and several tests are then carried out. In this case, the model is tested with all subsets except one. This untested subset is used in model validation. This procedure is repeated for a total of *k* trials, each time

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using a different subset for validation. Model performance is evaluated by the average of all errors (Haykin, 2001). In this work, 10 possible settings were considered for the performed analysis (10-fold cross-validation)

- 100% training / 0% test split;
- 90% training / 10% test split;
- 80% training / 20% test split;
- 70% training / 30% test split;
- 60% training / 40% test split;
- 50% training / 50% test split;
- 40% training / 60% test split;
- 30% training / 70% test split;
- 20% training / 80% test split;
- 10% training / 90% test split.

In order to compare the methods, the following criteria were taken into account:

- Success rate or amount of correct classifications;
- Total learning time;
- Average error.

4. CLASSIFICATION RESULTS

The results obtained by four tested classifiers are shown in Table 1. The obtained results of the tested classifiers can be ranked in terms of the correct classification rate in the following sequence (best → worst): Bagged decision trees, LS-SVM, Naïve Bayes, and PNN.

Table 2 presents the average time (in seconds) of learning and classification tasks in the case of the test split equal to 90% using a Intel Core i7 Q720 computer, 1.60 GHz with 6 GB RAM. In terms of execution average time, the Naïve Bayes was the fastest approach of the tested classifiers.

Table 1. Results of the classification in terms of the correct classification rate (%) and the its standard deviation values (%).

Split	Split samples	Test samples	PNN	Naïve Bayes	LS-SVM	Bagged decision trees
90%	266	29	75.17 ± 6.25	63.45 ± 8.93	74.48 ± 8.16	80.34 ± 9.20
80%	236	59	73.39 ± 4.86	67.12 ± 8.31	73.56 ± 6.15	80.68 ± 5.99
70%	207	88	72.16 ± 3.52	67.84 ± 5.65	74.66 ± 4.70	80.00 ± 5.17
60%	177	118	72.54 ± 3.23	69.83 ± 3.62	74.75 ± 4.57	81.36 ± 2.65
50%	148	147	72.04 ± 3.21	69.59 ± 3.33	74.01 ± 3.52	79.73 ± 2.44
40%	118	177	71.30 ± 2.61	68.42 ± 3.28	72.82 ± 3.28	79.55 ± 3.00
30%	88	207	70.00 ± 2.88	67.10 ± 2.66	71.01 ± 2.64	78.89 ± 2.64
20%	59	236	69.87 ± 1.74	66.65 ± 3.31	70.51 ± 3.00	77.16 ± 2.81
10%	29	266	66.69 ± 3.23	63.05 ± 3.34	63.65 ± 3.41	73.87 ± 2.92

Table 2. Average time of the tested classifiers.

Classifier	Average time (in seconds)
PNN	0.6
Naïve Bayes	0.2
LS-SVM	15.7
Bagged decision trees	1.7

5. CONCLUSION

DGA is an efficient tool for monitoring, provide an early diagnosis, and ensure transformers' maximum uptime. Because it detects incipient transformer faults, DGA can help prevent further damage.

This paper presented a comparative study of four classifiers for DGA. As can be observed from the results given by Tables 1 and 2, in this study, the Bagged decision trees presented the best result in terms of classification quality. The results obtained reaching success levels above 80%.

In the future, other classification methods for solving DGA problems will be validated using the PETROBRAS' thermoelectric plants.

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