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Determination of interfacial tension of insulating oils by using image analysis and multi-way calibration

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ABSTRACT

Power transformers are of great importance in the distribution of electrical energy. One of their most important parts is the insulating system, consisting of Kraft paper immersed in insulating oil. One of the most important parameters used for evaluating the degradation of this system is the oil interfacial tension. The aim of this study was to determine the interfacial tension in samples of insulating oils by using image analysis combined with a multi-way calibration method, N-PLS (multilinear PLS). Forty eight oil samples were obtained, whose values of interfacial tension were determined by a tensiometer, and divided into calibration (38) and validation (10) sets. Scanner images were obtained, converted to grey-scale, domain transformed and stacked in a three-way data array, before modelling. The best N-PLS model was obtained with mean centering and three latent variables and provided a RMSEP of 3 dyn cm^{-1}. This model provided individual prevision errors between −14 and 16%, which were acceptable for electric energy companies. The proposed method was rapid and non-destructive, showing great advantages over the traditional ones, which are slow and produce chemical waste.

1. Introduction

Power transformers are of great importance in the transmission and distribution of electrical energy and its most important part is the insulating system, which consists of Kraft paper immersed in insulating mineral oil. Kraft paper is obtained by Kraft process, in which bonds that link lignin to cellulose are broken. Insulating oil consists mainly of naphthenic and parafinic hydrocarbons with a minor amount of aromatic hydrocarbons. The extent of a transformer's life is largely determined by the maintenance of this system and insulation degradation is a major concern about its ageing. The main causes of degradation of insulating materials are the high operating temperatures and the presence of oxygen and moisture [1]. Generally, thermal ageing of paper is considered the predominant life limiting process. The major degradation products of paper's cellulose are furfurals, water and gases, such as H_2, CH_4, CO and CO_2, which can be found in the insulating oil [2,3]. Oil hydrocarbons are degraded by peroxidation yielding, as final products, carboxylic acids and derivatives.

The electrical power industry requires reliable methods to assess the conditions of transformers and the current ones are limited. Dielectric measurement techniques, such as recovery voltage measurement (RVM) and polarization and depolarization current technique (PDC), do not provide good measurement of the ageing of system insulation [4]. Some authors have evaluated the ageing of Kraft paper determining its degree of polymerization (DP) or average molecular weight by using chromatographic techniques, such as GPC [5,6] and SEC [3,7], or X-ray photoelectron spectroscopy (XPS) [6]. Nevertheless, these techniques are destructive and need violating the transformer. In practice, they only can be applied during refurbishment or following failure of the transformer. Analysis of insulating oil is an alternative, but most of the available methods are also destructive, such as moisture determination by Karl Fischer titration [8], dissolved gas analysis (DGA) [1,9] or furan analysis by HPLC [1,10]. There is a need to develop non-destructive methods to assess the condition of transformers. In this way, Baird et al. have developed a portable system using fiber optics and NIR spectroscopy that was used to predict DP [11] and water content [12] in transformer insulating paper.

In Brazil, the assessment of transformers' conditions in electrical power industry is carried out by dielectric and physico-chemical assays, such as dielectric rigidity, power factor, moisture, neutralization index and interfacial tension [13]. Among these properties, interfacial tension is the most sensitive to the effects of oil and paper degradation/oxidation, particularly to the presence of polar substances. Since these substances are derived from both, oil and paper, this assay is a way to monitor the whole insulating system. The official method used in Brazilian industry for this assay is slow, destructive and has low precision [14]. Thus, the aim of this work is to propose a

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new simple, rapid and non-destructive method to determine interfacial tension of transformers' insulating oils by using image analysis and second order calibration. Images of oil samples in Petri plates were obtained by using a simple scanner and correlated with interfacial tension values by using multi-way chemometric methods.

2. Image analysis and multi-way methods

2.1. N-way image analysis

Digital images have a finite number of elements with particular coordinates and values, called pixels. Univariate or grey-scale images are two-dimensional functions, where each spatial pair of coordinates (x,y) has an intensity (grey) value. Multivariate or colour images have different channels for each pixel [15]. The most common system for colour images is RGB, which can be described by a histogram of frequency distributions of red, green and blue values, and is used in monitors, scanners and video cameras. An alternative is HSV (hue, saturation, value) system, which is closer to the way that humans discern colour sensations. The use of simpler RGB or grey-scale images can be advantageous over spectroscopic images in some situations, due to their smaller files size, rapidity of acquisition, and simplicity of apparatus required (digital cameras or scanners) [16].

N-way image analysis is used when multiple images are handled simultaneously, and is applied to a stack of images with similar properties (chemical, physical, biological, etc.) [17]. Multivariate image analysis (MIA) is a particular approach to N-way image analysis, which has been applied to chemical data since the last decade [18–20]. MIA employs not true multi-way chemometric methods, such as unfold-PCA/PLS. These methods are not considered truly multi-way, because they firstly unfold three-way data array into two-way, followed by ordinary two-way decomposition, instead of utilizing the intact multi-way structure during the modelling. In general, true multi-way methods, such as PARAFAC [21] and N-PLS [22], have many advantages over unfold methods. They are more parsimonious, restrict (less degrees of freedom) and robust, fitting less noise. Huang et al. have performed a comparative study about the use of multi-way methods in image analysis and demonstrated that true multi-way methods are more suitable for certain kind of applications, in particular, for predicting a physico-chemical property from non-spectroscopic images [17], an application similar to the one of the present work.

Another important aspect highlighted by Huang et al. is the use of domain transformations in image analysis [17], discussed in the following. In the used codification, **O** denotes an object mode, while **V** denotes a variable mode. RGB images obtained for oil samples in the present work are **OOV** (pixel × pixel × colour channel) arrays. If images for several samples are stacked, a four-way array is obtained (**OOOV**). In order to simplify the manipulation of these images, they were firstly converted to grey-scale images (**OO**) and then stacked, yielding a three-way array **OOO** (sample × pixel × pixel). This step involves reducing one data dimension through a simple conversion of multivariate RGB colour channel values to univariate grey-scale intensity image. An **OOO** data array is non-congruent and obviously not trilinear. Thus, it cannot be used directly for N-way analysis, demanding the use of domain transformations techniques, such as fast Fourier (FFT) and wavelet transforms, to convert **OOO** to **OVV** (sample × frequency component × frequency component) data arrays. It has also been pointed out that true multi-way methods are more suitable for **OVV** arrays, while unfold methods (MIA) are better suited for **OOV** image data arrays.

2.2. Multi-way chemometric methods

Instruments that generate a data matrix per sample provide second order data. When data matrices collected for several samples are stacked, a three-way data array is obtained. Methods to deal with this kind of data are called multi-way (or N-way or second order) methods. The most popular multi-way calibration methods are PARAFAC and N-PLS, which have been applied to data generated mainly by spectrofluorimetry, image analysis and hyphenated techniques to obtain quantitative models in several areas, such as environmental [23], food [24], pharmaceutical [25] and clinical [26] analyses.

PARAFAC [21] is a generalization of PCA to higher order data, which presents unique solution independent of rotation. The PARAFAC model is found to minimize the sum of squares of the residues and it is not robust to trilinear deviations, which limits its application on multivariate image regression. N-PLS (multilinear PLS) [22] is an extension of PLS regression to multi-way data. N-PLS algorithm decomposes the three-way array $\underline{\mathbf{X}}$ into a set of triads. Each triad (latent variable) consists of a score vector, **t**, related to the first way, and two weight vectors, $\mathbf{w}^J$ and $\mathbf{w}^K$, related to the other two ways. The model is given as follows:

$$x_{ijk} = \sum_{f=1}^{F} t_{if} w_{jf}^{J} w_{kf}^{K} + e_{ijk} \quad (1)$$

where e_{ijk} are the model residues, t_{if}, w_{jf}^{J} and w_{kf}^{K} are the elements of f vectors **t**, $\mathbf{w}^J$ and $\mathbf{w}^K$, respectively, and F is the total number of triads. N-PLS incorporates information from dependent variables in the data decomposition step, which turn it more prone to deal with trilinearity deviations than PARAFAC.

3. Materials and methods

3.1. Insulating oil samples and reference method

Forty-eight insulating oil samples were obtained from CELG (Centrais Elétricas de Goiás S. A.), a state electrical power company. They were collected from March to September 2008, during the local dry season, from transformers through the whole state of Goiás, which is located in the center-west region of Brazil. These transformers presented a wide variety of conditions, with their lifetimes varying from one to about thirty years. Interfacial tension water/oil of these samples was measured by using a torsion Krüss K8 tensiometer, according to Brazilian norm NBR 6234 [14].

3.2. Acquisition of images

Images were acquired using a simple table scanner Genius. Petri plates were filled with 15 ml of each oil sample and positioned under the scanner central region. A white screen was used to block the light from external sources. Images were digitalized in RGB system and bitmap format, with resolution of 300 dpi. Fig. 1 shows obtained images for twelve different oil samples. Each oil was sampled three times and each triplicate was scanned three times, totalizing nine images per oil.

3.3. Data treatment

Data were treated in MATLAB version 6.5 (The Math Works, Natick, USA) and images were processed using Image Processing Toolbox, version 3.2. PARAFAC and N-PLS models were obtained with the N-way toolbox for Matlab, version 2.10 [27]. From the center of each original image, a fixed positioned square of 200 × 200 pixels was selected. RGB images were converted to grey-scale and processed. This processing consisted in applying a special unsharp filter, followed by a two-dimensional fast Fourier transform (2D-FFT) and a logarithmic transform. Unsharp filter is a contrast enhancement filter used in image analysis which enhances image edges (and other high frequency components in an image), via a procedure which subtracts a smoothed, or unsharp, version of an image from the original one [28,29]. Finally, for each oil sample, the nine obtained replicate matrices were averaged.

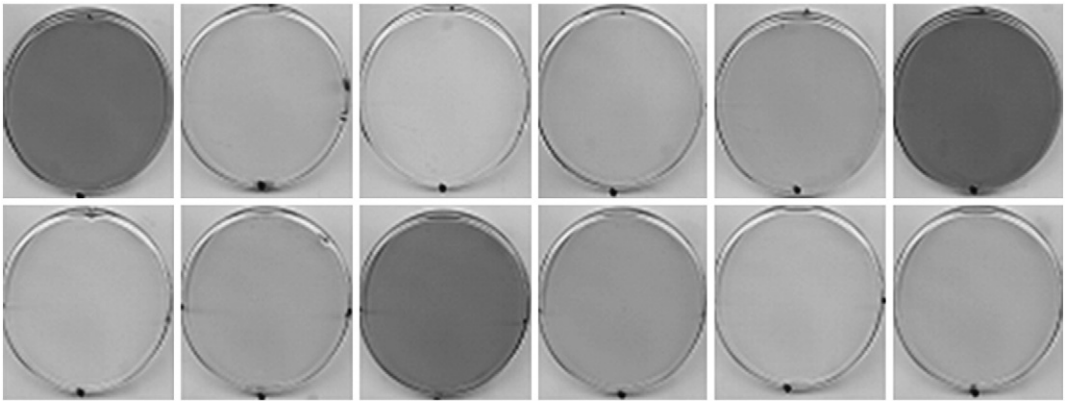

Fig. 1. Obtained images for twelve different insulating oil samples.

4. Results and discussion

The lowest limit for the interfacial tension measurement is 10 dyn cm^{-1}. Experimental values obtained for oil samples ranged from 15 to 44 dyn cm^{-1}. Lower values indicate the presence of polar substances, as a consequence of the insulating system degradation, while higher values are associated to new oils. Although oxidized oils in general tend to darken, degradation is not visually discernible at a first glance. For example, the first upper image in Fig. 1 shows an oil darker than the one shown in the second upper image, but it has a higher value of interfacial tension. This darkening is also dependent of other factors, such as the ratio of naphthenic/parafinic hydrocarbons in the oil composition.

In order to simplify the whole data treatment, RGB images were firstly converted to grey-scale, reducing one data dimension, and then, processed by using a special unsharp filter. Before averaging per oil sample, images were domain transformed by using a 2D-FFT/log transform, in order to obtain a trilinear **OVV** data array, to which true multi-way methods can be applied. Unfold PCA and Kennard–Stone algorithms [30] were used to split the image data set into calibration and validation sets. Thirty-eight oil samples were selected for the calibration set, while the remaining ten samples were used to build an external validation set.

The reference method [14] has low precision and the interfacial tension values were obtained with only two significant digits. For building N-PLS models, a three-way image array $38\times200\times200$ (X block) and a 38×1 **y** vector containing experimental interfacial tension values were used. The best model was selected by leave-one-out cross validation, with mean centering data, three latent variables and accounting for 46.01 and 87.67% of data variance in X and Y blocks, respectively. Table 1 shows predicted values and their respective errors for ten external validation samples. As can be seen, these samples provided relative prediction errors between −14 and 16%, of which seven were smaller than 6% in modulus, what is considered acceptable by electric energy companies. Reference versus predicted values plot presented a correlation coefficient (r) equal to 0.950 and the root mean square error of prediction (RMSEP) was 3 dyn cm^{-1}.

Other chemometric calibration models were tested. Not true multi-way methods, unfold PCA and PLS, provided models clearly worse, with some prediction errors (not shown) above 40%, and in all cases greater than the ones from N-PLS (about twice on average). As previously discussed, these models tend to use an excess of degrees of freedom to fit noise [17,21,22]. A non-preprocessed PARAFAC model with six factors (chosen through the smallest obtained RMSEP value and accounting for 99.86% of total data variance) provided two samples with prediction errors higher than 20% (also not shown), $r=0.898$ and a RMSEP equal to 4 dyn cm^{-1}. PARAFAC results were worse than N-PLS ones, and are explained by the lack of data trilinearity. Another tested alternative was the use of frequency distribution histograms of RGB colour values combined with PLS first order calibration [31]. This model provided results similar to PARAFAC and worse than N-PLS, with $r=0.926$ and a RMSEP of 4 dyn cm^{-1}.

Table 1
Experimental and predicted interfacial tension values for validation oil samples.

Experimental values (dyn cm^{-1})	Predicted (dyn cm^{-1})	Error (%)
40	38	−5
24	25	4
29	29	0
20	19	−5
18	18	0
31	36	16
33	32	−3
33	31	−6
43	38	−12
42	36	−14

5. Conclusions

The assessment of conditions of power electric transformers used to be carried out by laborious and destructive methods based on chemical measurements of insulating oil or Kraft paper. The need of violating the insulating system is another drawback. This work developed a new method for estimating interfacial tension of insulating oils by using image analysis and a multi-way calibration model, N-PLS. The most of the prediction errors were smaller than 10%, which was considered acceptable for the quality control laboratory of CELG company, especially taking into account the relative small number of available samples for this study and the wide variety of these samples' conditions. The proposed method utilizes a practicable instrument of low cost, a table scanner. It is also simple, rapid, non-destructive and does not generate chemical waste. This work opens perspectives for implementing a non-invasive on-line assessment of conditions of insulating systems of transformers.

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