Journal of Control, Automation and Electrical Systems (2019) 30:832–839
https://doi.org/10.1007/s40313-019-00487-6

A General Methodology for Evaluation and Classification of Oil-Immersed Power Transformers: Application to Electrical and Physicochemical Parameters

Leonardo da Cunha Brito[1] · André Pereira Marques[2,3] · Cacilda de Jesus Ribeiro[1] · Nicolas Kemerich de Moura[1] · Yuri Andrade Dias[1] · Cláudio Henrique Bezerra Azevedo[2] · José Augusto Lopes dos Santos[2] · Pedro Henrique da Silva Palhares[1]

Received: 16 April 2018 / Revised: 6 April 2019 / Accepted: 8 June 2019 / Published online: 8 July 2019

Abstract
Condition monitoring of power transformers is of vital importance to prevent electricity supply stoppages and reduce power plant maintenance costs. To that end, the use of techniques to evaluate and classify the condition of these devices is highly recommended in order to obtain good quality information for their proper maintenance planning. This article presents and details a general methodology for the creation of methods to evaluate and classify these devices, by means of computational modeling and optimization. The results indicate a higher than 93% accuracy rate compared to that of numerical evaluations and symbolic classifications expected by experts, thus demonstrating the applicability of the proposed methodology, which is found to be superior in comparisons against Computational Intelligence and Statistical Learning methods.

Keywords Classification · Evaluation · Methodology · Diagnostic · Power transformers

✉ Nicolas Kemerich de Moura
nicolas.nk@gmail.com

Leonardo da Cunha Brito
leonardo_brito@ufg.br

André Pereira Marques
andre.marques@enel.com.br

Cacilda de Jesus Ribeiro
cacildaribeiro@gmail.com

Yuri Andrade Dias
yuriadias@gmail.com

Cláudio Henrique Bezerra Azevedo
claudio.hb@celg.com.br

José Augusto Lopes dos Santos
jose.augusto@celg.com.br

Pedro Henrique da Silva Palhares
phpalhares@gmail.com

1 School of Electrical, Mechanical and Computer Engineering, Federal University of Goiás, Goiânia, GO, Brazil

2 Enel Distribuição Goiás, Goiânia, GO, Brazil

3 Federal Institute of Education, Science and Technology of Goiás, Goiânia, GO, Brazil

1 Introduction

The development and use of predictive techniques aimed at increasing the efficiency of preventive maintenance processes are essential to preserve the service life of power transformers, which are vital and high-cost devices in the power transmission and distribution system (Marques et al. 2014; Jahromi et al. 2009). Obviously, the same concept applies to the other elements that make up electric power supply systems.

Typically, a wide range of methods can be applied to evaluate the condition of power transformers. These methods usually include, among others:

- Dissolved gas analysis of transformer insulating oil, which reveals the existence of incipient thermal or electrical faults in the transformer (Duval and Lamarre 2014; IEC 2007; Singh and Bandyopadhyay 2010);
- Physicochemical analysis, which allows one to identify the degradation level of transformer insulating oil and infers that of electrical insulation paper (Barbosa et al. 2012; Moulai et al. 2010);
- Detection of partial discharges in power transformers by means of acoustic emission, which can indicate the

existence of partial discharge inside the transformer (IEEE 2000, 2010; Chen et al. 2007); and
- Electrical tests in general, which allow one to diagnose the transformer with regard to the presence of mechanical deformations and movements of its active components and of anomalies in its insulation system, electrical circuit or magnetic core (IEEE 2013).

The literature describes numerous diagnostic techniques to pinpoint problems in the transformer (Duval and Lamarre 2014; IEC 2007; Singh and Bandyopadhyay 2010; Chen et al. 2007; IEEE 2013; Hooshmand et al. 2012; Li et al. 2016; Marques et al. 2015; Contin 2015), and to assess and classify its condition by assigning condition indices (Jahromi et al. 2009; Abu-Elanien et al. 2012; Ashkezari et al. 2013). The diagnostic methods to determine transformer conditions are well established, especially the aforementioned ones. However, the process for evaluating and classifying the condition of power transformers still lacks a general methodology that can be employed to create analytical methods based on the use of an existing historical database. Jahromi et al. (2009) and Abu-Elanien et al. (2012), for example, propose analytical methods involving linearly dependent parameters, which can lead to inaccurate results, given the natural nonlinearity of evaluation and classification processes. Ashkezari et al. (2013) report good results in terms of overall accuracy rates achieved by the proposed method, but one sees a high accuracy rate for good ratings (1 and 2, which can be seen as ratings “A” and “B”) and a significant decrease in accuracy for the worst ratings (3–4, or “C” to “E”), which can be worrisome because poorer ratings have a stronger impact on decision making.

Expert power transformer analysts usually classify the condition of transformers based on guidelines, recommendations or standards, as well as on field experience, examining each criterion or parameter separately, or a subset of parameters, and then analyzing the overall results, in order to generate final global classifications to underpin decision making about the set of transformers that make up the installed power plant. The results of these analyses can be used to create evaluation and classification methods, so that the results of the application of the knowledge of specialists can be mapped computationally, thereby greatly assisting decision making about the operational planning for these devices.

Therefore, aiming to contribute to this area, this article presents in detail a general methodology for the evaluation and classification of oil-immersed power transformers, although it can be applied to any elements with characteristics similar to those described below.

To use the proposed methodology, the following information is required:

- A database of historical records about the analytical method in question, in which each record must contain the values of the parameters considered in the analysis, as well as the global symbolic classification prepared by the specialist, in order to consider the values of all the parameters involved; and
- For each parameter of the analytical method, classification ranges whose values are mapped into symbolic classifications that are suitable for the separate observation of the respective parameter, which are typically obtained from preexisting guidelines or standards (Jahromi et al. 2009; IEC 2007; IEEE 2013), as well as from the experience of maintenance specialists.

The methodology itself comprises the following elements:

- The evaluation and classification method that can provide a numerical score of 0 (terrible condition) to 1 (perfect condition) and a symbolic rating of “A” (best rating) to “E” (worst rating), for example; and
- The optimization method adapted to find optimal or near-optimal values for the variables of the evaluation and classification method, in order to maximize the assertiveness of the results when comparing the ratings provided by expert analysts.

Section 2 presents the evaluation and classification method, while Sect. 3 describes the optimization method. Lastly, Sects. 4 and 5, respectively, present two case studies and our final conclusions.

Although the evaluation and classification model has been applied in Marques (2017a), its detailed exposition and generalization is originally presented in this paper (Sect. 2), as well as the first description of the optimization strategy (Sect. 3) to (quasi) optimally tune its parameters, aiming the maximization of the classification accuracy. Also, the aforementioned work did not compare the proposed method against other classification methods.

2 Evaluation and Classification Model

The input data for the evaluation and classification method are the ranges that map the parameters that are considered in their respective individual classifications, which are defined when each parameter is analyzed separately. Table 1 describes the general form of these input data. In this table, note that:

- v_p is the value assigned to the p-th parameter, with $p \in \{1, 2, \ldots, P\}$;

Table 1 General form of mapping between ranges of values and individual classifications for the parameters

Range	Classification
$v_p^{q,(V-1)} \le v_p \le v_p^{q,(V)}$	$c_p^{(V)}$
$v_p^{q,(V-2)} \le v_p < v_p^{q,(V-1)}$	$c_p^{(V-1)}$
$\vdots$	$\vdots$
$v_p^{q,(2)} \le v_p < v_p^{q,(3)}$	$c_p^{(3)}$
$v_p^{q,(1)} \le v_p < v_p^{q,(2)}$	$c_p^{(2)}$
$v_p^{q,(0)} \le v_p < v_p^{q,(1)}$	$c_p^{(1)}$

- $v_p^{q,(i)}$ is the i-th limit, with $i \in \{1, 2, \dots, V-1\}$, corresponding to the q-th magnitude, with $q \in \{1, 2, \dots, Q\}$, of the p-th parameter of the method of analysis; and
- $c_p^{(i)}$ is the classification attributed to the corresponding range.

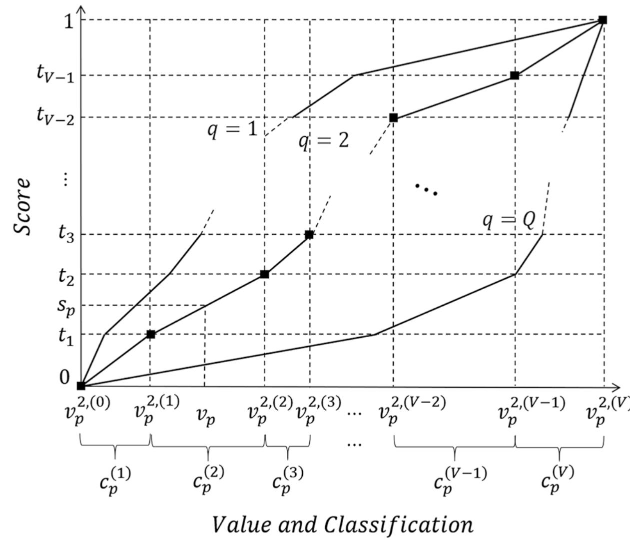

Fig. 1 Injective functions for mapping the values of scores

In the proposed method, for classifications that are more consistent with what is considered in real cases, it is possible to use parameters that depend on other magnitudes. For example, in a physicochemical analysis, it is known that the definition of classification ranges of the dielectric strength of insulating oil depends on the highest nominal voltage of the power transformer, since higher voltages require more rigorous evaluations in this regard. If one considers three voltage ranges, for instance, one will have up to three classification tables, one for each value of $q \in \{1, 2, 3\}$. Thus, for the analysis of a specific case, the table that corresponds to the highest nominal voltage of the device in question should be used.

The value of each parameter of analysis is mapped into scores, applying continuous injective functions, which are expressed by piecewise linear functions. Figure 1 illustrates the correspondence between the value v_p of the parameter and its respective score, s_p, which is obtained, here, by means of simple linear interpolation. It should be noted that for real mapping, it is necessary to adopt suitable values for the limits of scores, $\{t_1, t_2, \dots, t_{V-1}\}$, which are also applied to all the parameters of this proposed method.

After determining the scores of all the analysis parameters, Eq. (1) is applied to obtain a global score, s^g, for a given set of values of the parameters.

$$s^g = \frac{\sum_{p=1}^{P} \alpha_p \cdot \beta(s_p) \cdot s_p}{\sum_{p=1}^{P} \alpha_p \cdot \beta(s_p)} \tag{1}$$

In Eq. (1):

- The value α_p is the weight that represents the importance of the p-th parameter in the composition of the global score; and
- The second weighting $\beta(s_p)$ follows Eq. (2), which should indicate that poorer scores are more penalized when determining the composition of the global score.

$$\beta(s_p) = a \cdot e^{b \cdot s_p} + c \tag{2}$$

Equation (2), which is exponential, decreases as the s_p score increases when $b < 0$, resulting in the application of an increase in poor scores. Note that the values of parameters a, b and c must be properly dimensioned to result in suitable global s^g scores.

Lastly, the global score is mapped for the global classification, as illustrated in Fig. 2, by using appropriate values for the limits $\{l_1, l_2, \dots, l_{V-1}\}$ that demarcate the global classifications with respect to the scores.

3 Optimization Strategy

To use the evaluation and classification method presented in Sect. 2, suitable values must be adopted for the following parameters of model, which are indicated in vector form for convenience:

- $\boldsymbol{T} = (t_1, t_2, \dots, t_{V-1})$, which provides the limits used in mapping the values and the individual scores of the parameters;

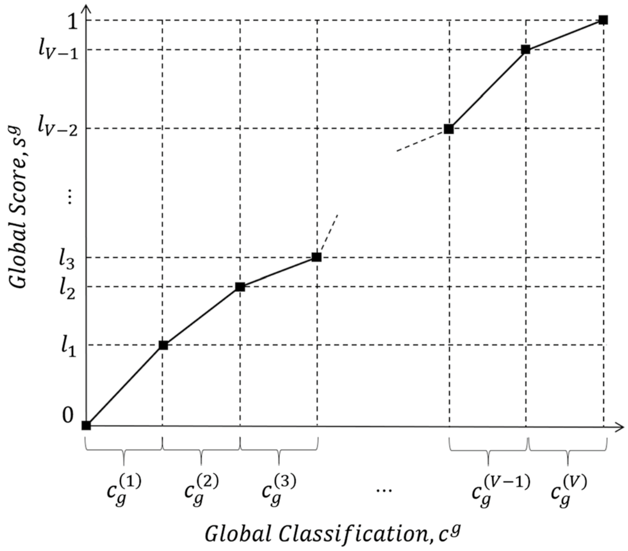

Fig. 2 Injective function for mapping the global score for the global classification

- $\boldsymbol{W} = (\alpha_1, \alpha_2, \ldots, \alpha_P)$, which are the weights that express the importance of each parameter of analysis;
- $\boldsymbol{E} = (a, b, c)$, which shapes the exponential function that emphasizes poor scores assigned to values of the parameters under analysis;
- $\boldsymbol{L} = (l_1, l_2, \ldots, l_{V-1})$, which defines the limits applied in mapping the global score and the global classification.

Thus, the vector $\boldsymbol{X} = (\boldsymbol{T}, \boldsymbol{W}, \boldsymbol{E}, \boldsymbol{L})$, which determines the quality of the evaluation and classification method, can be obtained by trial and error, or, more conveniently, because it is a nontrivial problem with several variables, by using an optimization algorithm. In this work, we used the hill climbing algorithm (Engelbrecht 2007; Michalewicz and Fogel 2004), which is associated with the "1/5 rule" (Michalewicz and Fogel 2004). This combination provides a balance between global exploration and local exploitation in the process of searching for optimal or quasi-optimal solutions. The pseudocode of the algorithm is presented below in Procedures 1–4. In these procedures, we use the various data records from the application of the parameter measurement technique that composes it to measure the quality of the evaluation model and the resulting classification.

Procedure 1 – optimizeModel

Inputs:
Data (*data for creation of the evaluation and classification model*),
Ranges (*ranges of correspondence between the values of the parameters and their symbolic classifications, as exemplified in Table 1*),
V (*number of classification ranges of the model*).
n_{max} (*maximum number of iterations*),
Err_{min} (*maximum tolerable error*),
k_{max} (*maximum number of iterations for evaluation by the 1/5 rule*).

Outputs:
$\boldsymbol{X}$ (*optimal or quasi-optimal parameters of the evaluation and classification model*),
Err (*modeling error achieved*).

start
  $\boldsymbol{X} \leftarrow$ generateInitialSolution(n_{class});
  $Err \leftarrow$ evaluateSolution($\boldsymbol{X}$, ***Data***, ***Ranges***);
  $k \leftarrow 0$; (*attempts counter of the 1/5 rule*)
  $k_s \leftarrow 0$; (*successful attempts count of the 1/5 rule*)
  $\sigma \leftarrow 0.1$; (*deviation applied to generate the neighboring solution*)
  for i = 1 **up to** n_{max} **do**
    $k \leftarrow k + 1$;
    $\boldsymbol{X}^n \leftarrow$ generateNeighboringSolution($\boldsymbol{X}, \sigma$);
    $Err^n \leftarrow$ evaluateSolution($\boldsymbol{X}^n$, ***Data***, ***Ranges***);
    if $Err^n < Err$ **then**
      $k_s \leftarrow k_s + 1$;
      $\boldsymbol{X} \leftarrow \boldsymbol{X}^n$; $Err \leftarrow Err^n$;
      if $Err \leq Err_{max}$ **then**
        return $\boldsymbol{X}$ and Err;
      end
    end
    if $k = k_{max}$ **then**
      if $k_s/k_{max} \geq \frac{1}{5}$ **then**
        $\sigma \leftarrow 2\sigma$;
      otherwise
        $\sigma \leftarrow \sigma/2$;
      end
      $k \leftarrow 0$; $k_s \leftarrow 0$;
    end
  end
end

The use of the "1/5 *rule*," which renders the search process adaptable, enables the deviation applied to the generation of a proposed neighboring solution to be increased when the number of hits is relatively large, expanding the search to larger regions, whereas, when the number of hits is small, it is preferable to concentrate the search in a smaller search space.

Procedure 2 – generateInitialSolution

Inputs:
V (*number of classification ranges of the model*).

Outputs:
$\boldsymbol{X}$ (*initial solution for the model*).

start
$\boldsymbol{T} \leftarrow (1/V, 2/V, \ldots, (V-1)/V)$(*values distributed uniformly between 0 and 1, after exclusion of the values 0 and 1 of the set*);
$\boldsymbol{L} \leftarrow (1/V, 2/V, \ldots, (V-1)/V)$;
$\boldsymbol{W} \leftarrow (1{,}1, \ldots, 1)$, com $|\boldsymbol{W}| = P$(*unitary values corresponding to the unitary weights for all the parameters*);
$\boldsymbol{E} \leftarrow$ numerical values for the parameters (a, b, c) of equation (2), originating from an exponential approximation of the Fibonacci sequence with $V+1$ terms, for which the highest and lowest value correspond, respectively, to the highest and lowest score;
$\boldsymbol{X} \leftarrow (\boldsymbol{T}, \boldsymbol{W}, \boldsymbol{E}, \boldsymbol{L})$;
end

Empirically, the Fibonacci sequence proved to be adequate to generate weights for the individual scores assigned to the analysis parameters, since the corresponding weight grows rapidly in response to the reduction in the score and respective assigned classification. For continuous mapping of the scores and their amounts in the application of Eq. (1), an exponential approximation of the aforementioned sequence is proposed, in the form of Eq. (2). To this end, the linear system (3) is solved by the least squares method (Press et al. 2007), using the pairs $\{x_i, y_i\}$, $i = 0, 1, \ldots, V$, where $x_i = i/V$ and $y_i = F_{V-i+1}$ (the numerical term of the Fibonacci sequence, $V - i + 1$, in which $F_1 = F_2 = 1$ and $F_n = F_{n-1} + F_{n-2}$), in addition to $a = e^A$ and the initial value of $c = 0$.

$$\begin{bmatrix} \sum_{i=0}^{V} y_i & \sum_{i=0}^{V} x_i \cdot y_i \\ \sum_{i=0}^{V} x_i \cdot y_i & \sum_{i=0}^{V} x_i^2 \cdot y_i \end{bmatrix} \begin{bmatrix} A \\ b \end{bmatrix} = \begin{bmatrix} \sum_{i=0}^{V} y_i \cdot \ln(y_i) \\ \sum_{i=0}^{V} x_i \cdot y_i \cdot \ln(y_i) \end{bmatrix} \tag{3}$$

Procedure 3 – evaluateSolution

Inputs:
Data (*data for creation of the evaluation and classification model*),
Ranges (*ranges of correspondence between the values of the parameters and their symbolic classifications*),
$\boldsymbol{X}$ (*proposed solution for the model*).

Output:
Err (*total absolute error calculated for the proposed solution*).

start
$Err \leftarrow 0$;
for each record in ***Data*** **do**
for each parameter of the model **do**
$s_p \leftarrow$ individual score obtained by means of the graph shown in Fig. 1, based on the ***Ranges***;
end
$s^g \leftarrow$ global score obtained by applying equation (1);
$c^g \leftarrow$ global classification obtained by means of the application shown in Fig. 2;
$Err \leftarrow Err +$ absolute distance between c^g and the classification attributed by the specialist in this record;
end
end

The absolute distance is the difference between the response obtained by taking the proposed solution to the model and the answer previously provided by the specialist. For example, if the classification estimated by the model is "B," but the predefined classification is "D," is the absolute error is 2.

Procedure 4 – generateNeighboringSolution

Inputs:
$\boldsymbol{X} = (\boldsymbol{T}, \boldsymbol{W}, \boldsymbol{E}, \boldsymbol{L})$ (*proposed solution for the model*),
σ (*deviation applied in the generation of the neighboring solution*).

Outputs:
$\boldsymbol{X}^n = (\boldsymbol{T}^n, \boldsymbol{W}^n, \boldsymbol{E}^n, \boldsymbol{L}^n)$ (*neighboring solution*).

start
$\boldsymbol{R} \leftarrow \boldsymbol{N}(0{,}1)$; (*vector composed of numbers obtained randomly by means of the canonical Gaussian probability density function, of size* $|\boldsymbol{X}|$)
$\boldsymbol{X}^n \leftarrow \boldsymbol{X} + \sigma\boldsymbol{R}$;
$\boldsymbol{X}^n \leftarrow truncate(\boldsymbol{X}^n)$; (*the components of* $\boldsymbol{X}^n$ *corresponding to the limits of* $\boldsymbol{T}^n$ *and* $\boldsymbol{L}^n$ *scores are truncated between 0 and 1*)
$\boldsymbol{X}^n \leftarrow sort(\boldsymbol{X}^n)$; (*components* $\boldsymbol{T}^n$ *and* $\boldsymbol{L}^n$ *are reorganized in ascending order*)
end

4 Case Studies and Results

The proposed methodology was applied to two datasets, one pertaining to physicochemical parameters and the other to electrical tests on power transformers. The records used here pertain to transformers with power ratings ranging from 1 to 50 MVA, with nominal voltages in the range of 34.5–138 kV, with ages varying from 1 to 58 years, whose data were obtained over a period of 36 years (1979–2015). The most representative subsets were extracted from the entire available databases (approximately 5000 records), balancing classifications from “A” (excellent) to “E” (very poor). The variety and number of records used in this study was considered suitable by the maintenance engineers, since the great majority of cases were “A” (excellent) or “B” (very good) conditions, which could unsuitably bias the results, inadvertently increasing the correct predictions.

The following configuration was considered in both cases: $V = 5$, corresponding to classifications of “A”–“E”); $n_{\max} = 10{,}000$ iterations; $k_{\max} = 100$ iterations as an interval to proceed with the application of the “1/5 rule”; and $Err_{\min} = 0$ (utopian error).

All the presented results are given by the average correctness ratios considering 100 runs of each method and considering, at each run, a training dataset randomly composed by 90% of the cases and a validation dataset with the remaining 10% of the cases. Thus, this leave-10%-out cross-validation procedure was used to accurately estimate the prediction performance of the classification methods.

4.1 Case 1: Physicochemical Results

The parameters considered in the physicochemical analysis of the transformer insulating oil were: interfacial tension (IT), neutralization index (NI), color index (CI), dielectric strength (DS), moisture content (MC) and power factor (PF). To optimize the evaluation and classification model, we used 218 diversified representative records, each with a symbolic quality classification predefined by maintenance engineering specialists.

An average accuracy rate of 93.6% was obtained for the datasets used to create the models, whose one of the results is shown in “Appendix A,” and all the observed errors showed an absolute difference of only one unit. To validate the methodology, 21 (10%) cases not used to create the model were also applied, resulting in an average accuracy rate of 85.0%, which confirms the quality of the classification model.

The following methods were also applied (Engelbrecht 2007) for comparison purpose, and the corresponding results were obtained.

- *Naive Bayesian Network (NBN)* resulted in an 85.7% average accuracy rate for the training datasets and 82.0% for the validation datasets. The advantages of this approach stem from its ability to provide a degree of belief (probability) for each classification, and because it is unnecessary to provide the individual classification ranges for each parameter, while its disadvantages are the need to use a larger number of training cases to ensure a lower classification error, and the impossibility of directly generating a numerical value pertaining to the global evaluation (condition index).
- *Decision Tree (DT)* resulted in an 85.46% average accuracy rate for the training datasets and 72.59% for the validation datasets. These results were achieved with very deep trees and showed undesirable overfitting. The errors increased considerably with smaller depths. The advantage of this approach stems from the simplicity of its implementation. However, it is not able to provide a global evaluation, but only a global classification.
- *Linear Discriminant Analysis (LDA)* this approach provided an average accuracy rate of 87.6% for the training datasets and 81.0% for the validation datasets, and presented the same advantages and disadvantages as those of a Naive Bayesian Network.

These results demonstrate that the proposed methodology can provide better results than the three methods applied. Moreover, it should be noted that the three aforementioned approaches presented errors with an absolute distance greater than 1, which may result in a highly undesirable gross classification error for new cases.

4.2 Case 2: Electrical Results

The methodology developed on this work was applied to insulation resistance and power factor tests. The following analysis parameters were considered in the Insulation Resistance (IR) case study:

(a) R_{H}: IR from HV (high voltage) winding to ground;
(b) PI_{H}: Polarization Index (PI) of R_{H};
(c) R_{HL}: IR between HV and LV (low voltage) windings;
(d) $\mathrm{PI}_{\mathrm{HL}}$: PI of R_{HL};

(e) R_L: IR from LV winding to ground; and
(f) $\mathrm{PI_L}$: PI of R_L.

To optimize the model applied to insulation resistance tests, we used 150 diversified representative records, each with a symbolic quality classification predefined by maintenance engineering specialists.

Average accuracy rates of 86.7% and 88.9% of the cases were obtained in training and validation datasets, respectively, which also confirms the quality of the classification model. The results achieved applying the other methods, considering training and validation, respectively, were: NBN with average accuracies of 68.75% and 46.6%; DT with average accuracies of 59.4% and 34.4%; and LDA with average accuracies of 68.1% and 42.0%.

Applying the general methodology to power factor tests (PF), the following parameters were considered:

(a) $\mathrm{PF_{HV/(LV+G)}}$: PF of the insulation of HV winding in relation to LV winding and ground, together;
(b) $\mathrm{PF_{HV/G}}$: PF of the insulation of HV winding in relation to ground;
(c) $\mathrm{PF_{LV/(HV+G)}}$: PF of the insulation of LV winding in relation to HV winding and ground together; and
(d) $\mathrm{PF_{LV/G}}$: PF of the insulation of LV winding in relation to ground.

In this case, we also analyzed 150 results of power factor tests, obtaining average accuracy rates of 92.4% in training sets and 93.3% in validation sets, which shows its efficiency for the characterization of the insulation system of power transformers. The results achieved by applying the other methods, considering training and validation, respectively, were: NBN with average accuracies of 75.92% and 71.9%; DT with average accuracies of 79.2% and 64.4%; and LDA with average accuracies of 81.57% and 69.1%.

"Appendix B" illustrates results obtained for the parameters of the electrical classification/evaluation methods.

5 Conclusion

This work proposed a methodology for developing evaluation and classification models for power transformer preventive maintenance, although it can be used for any type of component or device for which there are previous records of measurements of their parameters and classifications prepared by specialists. The fundamental purpose of the proposed methodology is to map the function performed by specialists, i.e., evaluation and classification of the equipment for decision-making purposes, including the prioritization of actions to be taken in urgent and emergency cases. This tool can be used jointly with well-established diagnostic techniques, to provide not only the diagnosis itself but also the condition index and the respective classification.

Compared with decision trees, Naive Bayesian networks and linear discriminant analysis, the proposed method showed superior results, i.e., accuracy rates exceeding 93% in the case of physicochemical analysis classification, with a maximum absolute error of one unit in terms of classification, which is highly desirable.

Acknowledgements The authors thank the Federal University of Goiás and the Federal Institute of Education, Science, and Technology of Goiás for their practical support, as well as the Goiás State Research Foundation (FAPEG) and the Brazilian Electricity Regulatory Agency (ANEEL) for their financial support of this work.

Appendix A: Physicochemical Evaluation and Classification Method

The results of the optimization of evaluation and classification model with respect to physicochemical parameters (Marques et al. 2017a) are presented in Table 2.

Table 2 Results of optimization of the model applied to physicochemical tests

Parameter	Value
T	(0.250, 0.541, 0.628, 0.925)
W	(0.1488, 0.2746, 0.0316, 0.2771, 0.1690, 0.0990)
E	(7.6409, −2.2542, 0.0242)
L	(0.468, 0.641, 0.758, 0.877)

Appendix B: Electrical Evaluation and Classification Method

The results of the optimization of evaluation and classification model with respect to insulation resistance parameters (Marques 2017b) are presented in Table 3.

The results of the optimization of evaluation and classification model with respect to power factor parameters (Marques et al. 2018) are presented in Table 4.

Table 3 Results of optimization of the model applied to insulation resistance tests

Parameter	Value
T	(0.3070, 0.5155, 0.6416, 0.7896)
W	(0.2790, 0.0417, 0.2790, 0.0641, 0.2721, 0.0641)
E	(7.0876, – 1.8332, 0)
L	(0.3070, 0.5659, 0.6618, 0.8536)

Table 4 Results of optimization of the model applied to power factor tests

Parameter	Value
T	(0.0974, 0.3224, 0.7519, 0.9201)
W	(0.3191, 0.1617, 0.3252, 0.1939)
E	(8.5968, – 2.7736, 0)
L	(0.0974, 0.3224, 0.7519, 0.9201)

References

Abu-Elanien, A. E., Salama, M. M., & Ibrahim, M. (2012). Calculation of a health index for oil-immersed transformers rated under 69 kV using fuzzy logic. *IEEE Transactions on Power Delivery, 27*(4), 2029–2036.

Ashkezari, A. D., Ma, H., Saha, T. K., & Ekanayake, C. (2013). Application of fuzzy support vector machine for determining the health index of the insulation system of in-service power transformers. *IEEE Transactions on Dielectrics and Electrical Insulation, 20*(3), 965–973.

Barbosa, F. R., Almeida, O. M., Braga, A. P., Amora, M. A., & Cartaxo, S. J. (2012). Application of an artificial neural network in the use of physicochemical properties as a low cost proxy of power transformers DGA data. *IEEE Transactions on Dielectrics and Electrical Insulation, 19*(1), 239–246.

Chen, L. J., Lin, W. M., Tsao, T. P., & Lin, Y. H. (2007). Study of partial discharge measurement in power equipment using acoustic technique and wavelet transform. *IEEE Transactions on Power Delivery, 22*(3), 1575–1580.

Contin, A. (2015). Diagnostics of insulation systems by means of partial discharge. In *10th international symposium on diagnostics for electrical machines, power electronics and drives (SDEMPED), 2015, IEEE, Guarda* (pp. 191–197).

Duval, M., & Lamarre, L. (2014). The Duval Pentagon – a new complementary tool for the interpretation of dissolved gas analysis in transformers. *IEEE Electrical Insulation Magazine, 30*(6), 9–12.

Engelbrecht, A. P. (2007). *Computational intelligence—An introduction* (2nd ed.). Hoboken: Wiley.

Hooshmand, R. A., Parastegari, M., & Forghani, Z. (2012). Adaptive neuro-fuzzy inference system approach for simultaneous diagnosis of the type and location of faults in power transformers. *IEEE Electrical Insulation Magazine, 28*(5), 32–42.

IEEE Guide for the Detection of Acoustic Emissions from Partial Discharges in Oil-Immersed Power Transformers. (2000) In *IEEE Std C57.127-2000* (pp. 1–24).

IEEE Guide for Diagnostic Field Testing of Fluid-Filled Power Transformers, Regulators, and Reactors. (2013) In *IEEE Std C57.152-2013* (pp. 1–121).

IEEE Recommended Practice for Partial Discharge Measurement in Liquid-Filled Power Transformers and Shunt Reactors. (2010) In *IEEE Std C57.113-2010 (Revision of IEEE Std C57.113-1991)* (pp. 1–47).

International Electrotechnical Commission - IEC. (2007) *Mineral Oil-Impregnated Electrical Equipment in Service-Guide to the Interpretation of Dissolved and Free Gases Analysis, IEC Publication 60599*.

Jahromi, A., Piercy, R., Cress, S., Service, J., & Fan, W. (2009). An approach to power transformer asset management using health index. *IEEE Electrical Insulation Magazine, 25*(2), 20–34.

Li, J., Zhang, Q., Wang, K., Wang, J., Zhou, T., & Zhang, Y. (2016). Optimal dissolved gas ratios selected by genetic algorithm for power transformer fault diagnosis based on support vector machine. *IEEE Transactions on Dielectrics and Electrical Insulation, 23*(2), 1198–1206.

Marques, A. P., Dias, Y. A., Moura, N. K., Ribeiro, C. J., Rocha, A. S., Azevedo, C. H., et al. (2018). Method for optimized analysis of electrical tests of insulation power factor in power transformers. *IEEE Latin America Transactions, 16*(3), 823–828.

Marques, A. P., Moura, N. K., Dias, Y. A., Ribeiro, C. J., Rocha, A. S., Brito, L. C., et al. (2017a). Method for the evaluation and classification of power transformer insulating oil based on physicochemical analyses. *IEEE Electrical Insulation Magazine, 33,* 39–49.

Marques, A. P., Moura, N. K., Ribeiro, C. J., Dias, Y. A., Rodrigues, A., Rocha, A. S., Azevedo, C. H., Santos, J. A., Sousa, F. C., & Brito, L. C. (2017). Insulation resistance of power transformers—Method for optimized analysis. In *19th IEEE international conference on dielectric liquids – ICDL*. Manchester, United Kingdom.

Marques, A. P., Ribeiro, C. J., Azevedo, C. H., Santos, J. A., Sousa, F. R., & Brito, L. C. (2014). Power transformer disruptions- a case study. *IEEE Electrical Insulation Magazine, 30*(2), 17–21.

Marques, A. P., Sousa, F. R., Brito, L. C., Ribeiro, C. J., Azevedo, C. H., Santos, J. A. (2015) A mathematical contribution to the analysis of moisture migration in power transformer oil-paper insulation systems. In *IEEE 10th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED), 2015, Guarda* (pp. 1–6).

Michalewicz, Z., & Fogel, D. B. (2004). *How to solve it: Modern heuristics* (2nd ed.). Berlin: Springer.

Moulai, H., et al. (2010). Physico-chemical properties of power transformer oil mixtures. In *15th IEEE mediterranean electrotechnical conference Melecon 2010, Valletta, 2010* (pp. 1105–1110).

Press, W. H., Teukolsky, S. A., Vetterling, W. T., & Flannery, B. P. (2007). *Numerical recipes: The art of scientific computing* (3rd ed.). New York: Cambridge University Press.

Singh, S., & Bandyopadhyay, M. N. (2010). Dissolved gas analysis technique for incipient fault diagnosis in power transformers: A bibliographic survey. *IEEE Electrical Insulation Magazine, 26*(6), 41–46.