TRANSFORMERS FAULT IDENTIFICATION BY FREQUENCY RESPONSE ANALYSIS USING INTELLIGENT CLASSIFIERS

Regelii SA Ferreira[1*], Hassan Ezzaidi[1], Issouf Fofana[1], Patrick Picher[2]

[1]*Research Chair on the Aging of Power Network Infrastructure (ViAHT),*
Université du Québec à Chicoutimi, Saguenay, Canada
[2]*Institut de recherche d'Hydro-Québec (IREQ), Varennes, Canada*
**regelii.suassuna-de-andrade-ferreira1@uqac.ca*

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Abstract

Failures in power transformers generates high financial loss inherent to equipment cost and power interruption. Thus, the industry has been working into developing efficient and reliable monitoring techniques with the objective of detecting incipient faults. Frequency Response Analysis (FRA) is among well-known methods to detect faults in transformers' active parts. FRA is very sensitive to changes in the winding geometry and a comparison between healthy and faulty measurements can present deviations that leads to the fault identification. However, until now, FRA interpretation is performed with the aid of experts. The development of FRA and the spreading of its application in transformers' diagnostics, have led studies to focus on the advancement of objective interpretation techniques. To contribute to this matter, intelligent classifiers are evaluated over its capabilities to classify transformers faults. For this purpose, a database of measurements performed on a laboratory winding model including different faults is used. Numerical indices are used as input for machine learning classifiers. This analysis indicated that the use of one individual index is appropriate for a good classification performance using Radial Basis Function neural network. Meanwhile Support-vector machine and Backpropagation neural network performed better with a combination of indices.

1 Introduction

Condition monitoring in power transformers is of great importance for operational and economic reasons. During its lifetime, a transformer is vulnerable to through-faults raising the mechanical stress in its active parts. Mechanical forces beyond the design limits of the transformer may cause deformations in the windings. Once such deformations occur, the transformer capacity to withstand further mechanical stress is greatly reduced.

Nowadays, there are many monitoring and diagnosis techniques available to detect power transformer incipient failures. Frequency Response Analysis (FRA) is one of those methods, currently well used in the electrical industry.

FRA compares current and reference frequency response measurements of a power transformer. Deviations presented between these measurements can indicate electrical or mechanical damages to the active parts of the transformer [1]. However, the interpretation of the deviations is still subjective and expert's analysis dependent.

The frequency response of a transformer depends extensively on transformer's type, power rating, voltage rating, phase connections, winding design, etc [2]. Therefore, the basic and fundamental principles using simple geometric models need to be understood to guide the quantitative analyses.

Recent studies on FRA quantitative interpretation methods are proposed into three main groups: numerical indices, as presented in [3, 4]; white box physical models, as presented in [5, 6]; and artificial intelligence algorithms, as presented in [7, 8]. Different approaches are used to obtain the FRA traces in these studies: references [1, 9] use real cases transformers; while, reference [10] uses laboratory experiments; and reference [11] uses simulation studies.

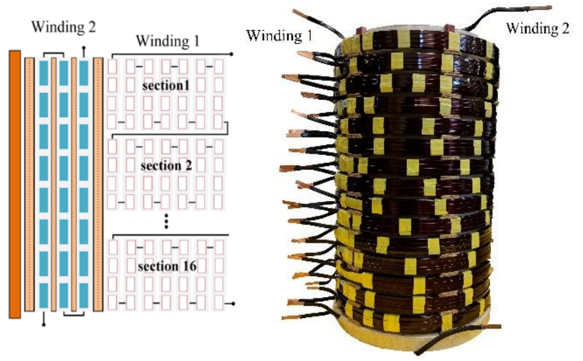
However, up to these days, the most common way of frequency response interpretation remains the visual comparison of reference and faulty traces. In addition, recent interpretation methods rely on numerical indices to obtain a basic quantitative interpretation [4].

To study different interpretation methods, this contribution uses intelligent techniques applied for the classification of deformations in a transformer winding laboratory model. This model allows the administration of several winding deformations and, therefore, the evaluation of their influence in the frequency response. Four different faults are considered: axial displacement (AD), radial deformation (RD), disc-space variation (DV) and shot-circuited turns (SC). The deviations in the frequency response are then quantified using well-known numerical indices such as Comparative Standard Deviation (CSD), Cross-correlation Factor (CCF), Absolute Difference (DABS) and Minimum-Maximum Ratio (MM). And finally, machine learning algorithms are implemented for automatic fault classification using the numerical indices calculated as input. The algorithms are programmed to classify the measurements into five classes: no fault, AD, RD, DV, SC. Then, the performance of the classifiers is evaluated based on the numerical indices used as input. The classifiers performance is tested using CSD, CCF, DABS or MM individually and a combination of the two indices showing highest performance.

2. Methodology

A laboratory winding model is used as a measurement object and the frequency response is recorded under different conditions. This model is of uniform structure with an equal number of turns per winding section. It has solid, non-grated insulation and was designed specifically for FRA testing (there are no power or voltage rating specifications).

The transformer is composed of two windings, the outer coil (winding 1) with 448 turns divided into 16 sections and the inner coil (winding 2) divided into three concentric and fixed layers with a total of 228 turns. Fig 1 shows a schematic connection and a picture for the model.



a *b*

Figure 1 Winding model used for FRA measurements.
(a) connections schematic
(b) model's picture

For the studies presented in this paper, four different fault modes were introduced in winding 1: three mechanical deformations and one electrical fault. Six levels of each fault were tested to verify the evolution of the fault in the frequency responses. The database of FRA measurements is gathered at reference state, axial displacement deformation (AD), radial deformation (RD), disc space variation (DV) and short-circuited turns (SC).

AD faults were created by the displacement of winding 1 in relation to winding 2. Spacers were added in the bottom of the winding increasing winding 1 axial position in steps of approximately 5.4 mm starting from 6 mm (AD 1) up to 34 mm (AD 6).

The RD faults were introduced by interchanging healthy sections of winding 1 with deformed ones. Since this model has 16 identical sections in winding 1, this fault mode replaced a new healthy section by a deformed one at each step of the fault extension from 1 deformed section (RD 1) up to six deformed sections (RD 6) at different locations along the winding. Examples of deformed sections are shown in Fig 2.

Figure 2 Deformed sections used to replace healthy ones to create radial deformation fault.

The DV fault was introduced similarly to AD faults, although, the spacers were added in between sections at different positions of the winding 1. The DV 1 has 6 mm spacer between sections 2 and 3. The DV 2 has 12 mm spacer between the same sections. DV 3 and DV 4 added another 6 mm and then 12 mm, respectively, between sections 8 and 9. And DV 5 and DV 6 added 6 mm and 12 mm spacers between sections 14 and 15.

The SC fault is an electrical fault generated by the short-circuit between turns of winding 1. This fault consists in short-circuiting the turns of individual sections along the winding, starting with 28 turns short-circuited (SC 1) up to 168 turns (SC 6).

All fault modes and extents are replicated several times in order to achieve a large database. The complete database comprises 340 measurements.

Subsequently, the FRA traces deviations are quantified using numerical indices based on a reference state measurement. The numerical indices for this research were chosen based on previous studies on the characteristics of the indices [1, 12, 13]. A summary of these indices is presented in Table 1.

Table 1 Summary of numerical indices used for the quantitative interpretation of FRA traces.

Index	Description	Equation
CSD	Comparative standard deviation is zero in case of a complete match of traces, and there is no upper limit value. For amplitude deviations, this index has lower sensitivity [1, 14].	(1)
CCF	The cross-correlation factor quantifies the linear dependence between two data sets. Its value is closer to 1 if there is large positive correlation between the data sets and closer to zero in case of a weak correlation [3].	(2)
DABS	The absolute variations between two data sets are calculated. DABS is sensitive to new resonances and shifted resonance frequencies [13].	(3)
MM	Minimum-maximum ratio considers only the maximum and minimum values for each pair of data points. MM is sensitive magnitude of resonances changes, and its ideal value is 1 [15].	(4)

The numerical indices described in Table 1 are calculated from equations (1) to (4), where X(i) and Y(i) are the i^{th} element of the magnitude vectors of reference and investigated frequency responses respectively and N is the number of data points.

$$\mathrm{CSD}=\sqrt{\frac{\sum_{i=1}^{N}[(X(i)-\bar{X})-(Y(i)-\bar{Y})]^2}{N-1}} \tag{1}$$

$$\mathrm{CCF}=\frac{\sum_{i=1}^{N}(X(i)-\bar{X})(Y(i)-\bar{Y})}{\sqrt{\sum_{i=1}^{N}(X(i)-\bar{X})^2\ \sum_{i=1}^{N}(Y(i)-\bar{Y})^2}} \tag{2}$$

$$\mathrm{DABS}=\frac{\sum_{i=1}^{N}|Y(i)-X(i)|}{N} \tag{3}$$

$$\mathrm{MM}=\frac{\sum_{i=1}^{N} min(Y(i),X(i))}{\sum_{i=1}^{N} max(Y(i),X(i))} \tag{4}$$

where, $\bar{X}=1/N\sum_{i=1}^{N} X(i)$ and $\bar{Y}=1/N\sum_{i=1}^{N} Y(i)$.

The indices are calculated in particular frequency regions where the deviations are characterized. For example, the mechanical faults affect specifically the region from 400 kHz up to 700 kHz. While the electrical fault affects notably the first resonances (around 25 kHz). Based on this, three frequency bands are used for the index calculation: from 20 kHz to 50 kHz, from 50 kHz to 100 kHz and from 400 kHz to 700 kHz.

Finally, intelligent classifier algorithms such as radial basis function (RBF) neural network, support vector machine (SVM) and backpropagation neural network (BP), are used to classify the faults from the numerical indices calculated as input for training and testing the algorithms. To prevent overfitting in the data used for each model validation, a 10-fold cross-validation method is used. In this method, the data is divided into 10 parts and one part is left out of the training to be used as in the testing set. The classification is repeated 10 times for each of the 10-parts to be used as testing data at a time. Then the average deviation for the repeated classification is returned as the classification error.

RBF is a feedforward multilayer neural network. The output of this network is a decision based on a linear combination of the RBF outputs computed by the hidden layer neurons [16]. Each neuron stores an information vector and then compares the input vector to this information. The output of each neuron is a value between zero and 1, which is calculated based on the similarity between input and stored information. When the input is the same as the stored information at that neuron, the output will be 1. The output tends to zero as this difference increases.

The SVM is a supervised machine learning model with associated learning algorithms. It is one of the most powerful classifiers that can perform with both linear and nonlinear data separation operations [17]. SVM constructs a hyperplane or set of hyperplanes in a high-dimensional space, which are used for classification or regression. The appropriate hyperplane is used as a decision boundary and is defined by the kernel function used in the SVM algorithm. A commonly used kernel function for SVM classification is the polynomial function. In machine learning, the polynomial kernel is a function that represents the similarity of vectors (training samples) in a feature space over polynomials of the original variables, allowing learning of non-linear models. This is the case of this study and the polynomial kernel is used for the SVM classification proposed.

BP is a feedforward neural network trained using an efficient and widely used backpropagation algorithm. The algorithm uses the chain rule of calculus to compute the gradient one layer at a time and backward. The specific order of calculation for the chain rule is highly efficient [18]. The network input provides the initial information that then propagates to the hidden layers and produces the output. During training, forward propagation continues until a minimum cost function is reached. When used for classification, the BP output is a vector of class probabilities.

A summary of methodology used in this paper is presented in Fig 3.

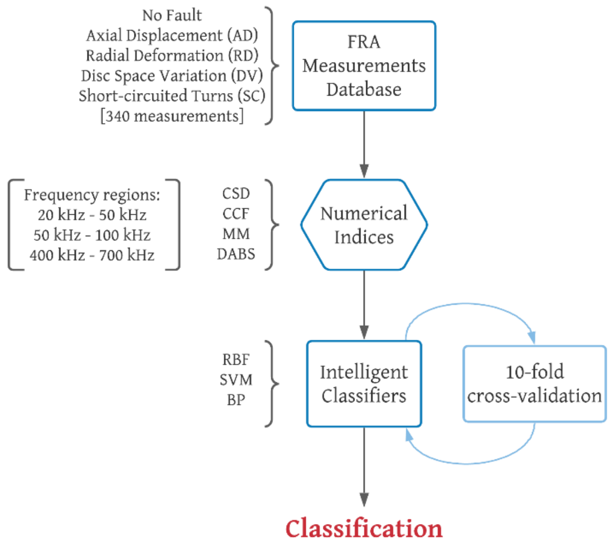


Figure 3 Methodology summary.

3 Results

The results obtained are presented in three parts, first the FRA measurements for the fault modes is obtained. These results are available and well discussed in [10]. However, an example for the radial deformation (RD) fault mode is presented in Fig 4.

As it can be observed in Fig 4, the deviations on the FRA traces in fault conditions are mostly concentrated in the region varying from 400 kHz to 700 kHz, as detailed in Fig 4.b. This region is used for numerical indices presentation.

The second part of the results is related to the calculation of numerical indices for each fault mode. The indices are presented for each failure in Fig 5. To obtain a better visual comparison of the different indices a standardization followed by a normalization are done. The indices CCF and MM are presented as CCF^*=1-CCF and $MM^*=MM-1$ This is done to standardize the indices presentation. With this modifications, the indices value is 0 when there is no deviation between the curves. The normalization divides each index value by the maximum value of its group to obtain a rescale between zero and 1.

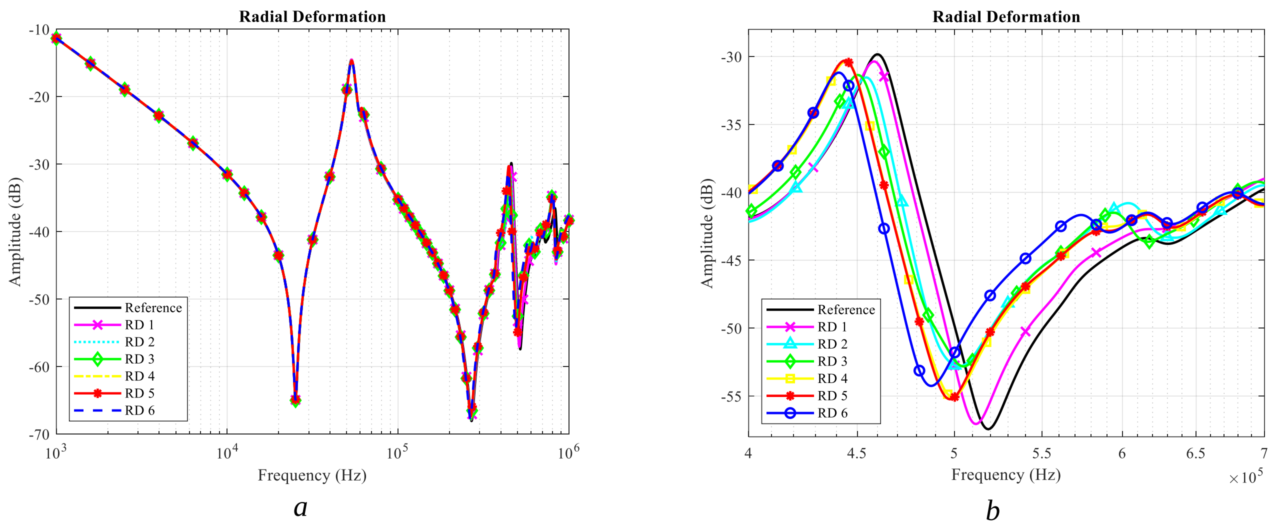


Figure 4 FRA measurements at reference and radial deformation fault conditions [10].
(a) Radial deformation measurement
(b) Zoomed portion from 400 kHz to 700 kHz.

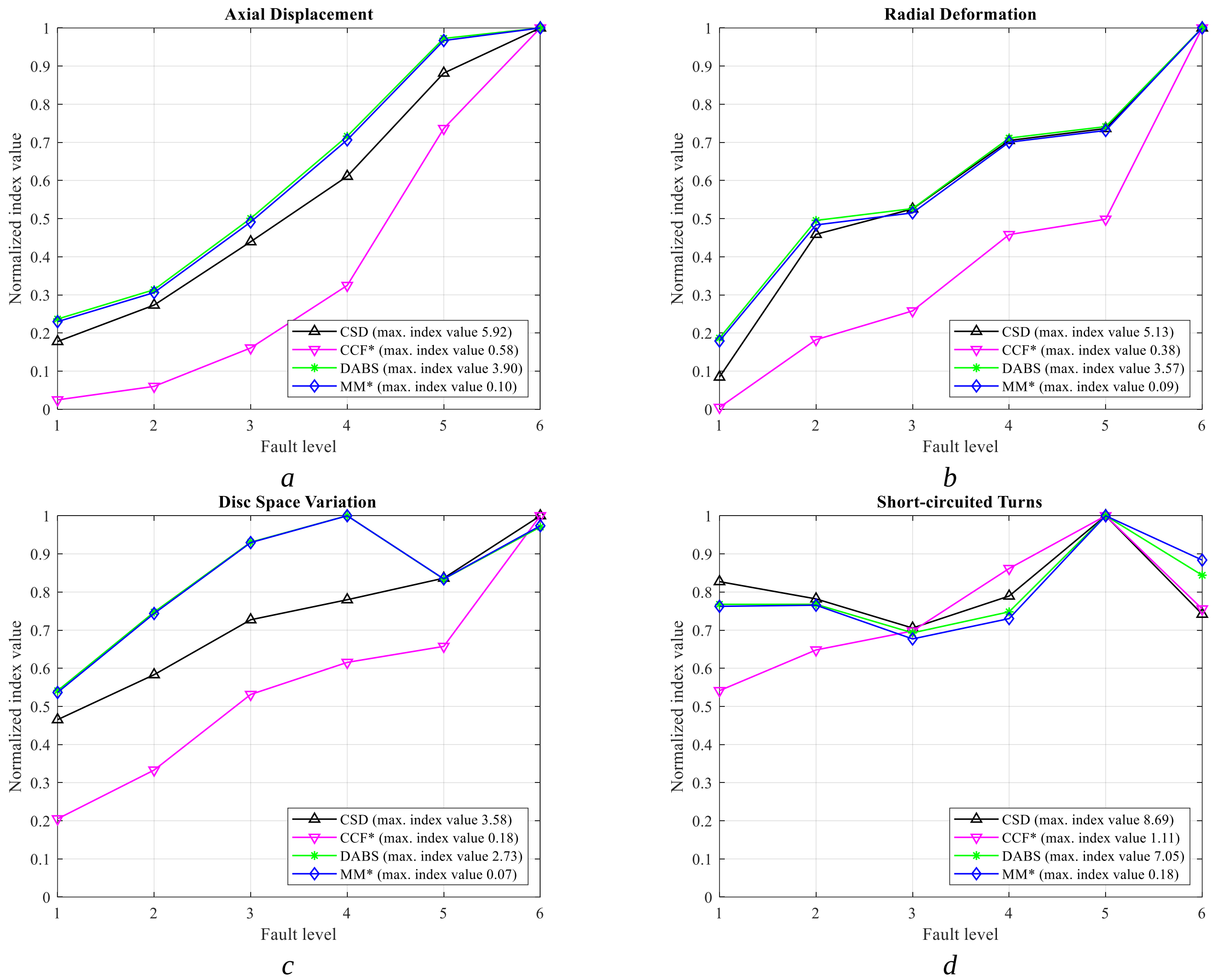


Figure 5 Numerical indices results for fault conditions in frequency range from 400 kHz to 700 kHz
(a) Axial displacement measurement
(b) Radial deformation
(c) Disc space variation
(d) Short-circuited turns measurement.
Please note that “max. index value” present in the graphic’s legends is the maximum value used for the index normalization.

For AD and RD faults, all indices presented monotonic behaviour; the highest fault level also presented the highest index value. Both cases also presented a linear increase of index value along with fault extent. For DV, only CSD and CCF presented monotonic and linear behaviour. And for SC, none of the indices were monotonous or linear. Once the sensitivity of the indices is observed, only CCF presented low sensitivity values (< 0.1) for the first extension of AD and RD.

Finally, the last step presents the machine learning algorithms performance using the index calculations as input for fault classification. The indices are calculated for three frequency regions: 20 kHz to 50 kHz, 50 kHz to 100 kHz and 400 kHz to 700 kHz. The algorithms are asked to classify the faults into five groups: no fault, AD, RD, DV and SC. Only one index is used as input value for the algorithm. These results are presented in Fig 6.

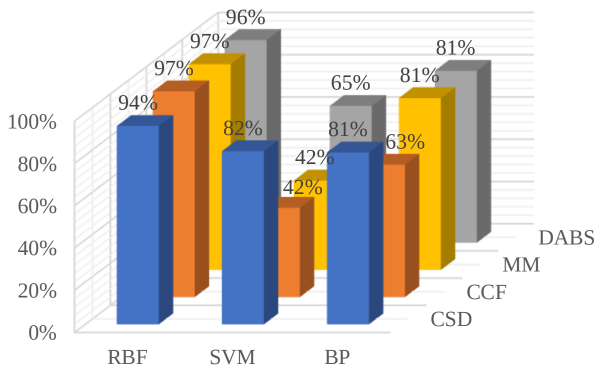


Figure 6 Intelligent classifiers performance based on numerical indices used as input information.

The RBF neural network implements a normalized Gaussian activation function, and the center of hidden neurons are determined using K-Means clustering with two clusters per class. This network presented the best performance being able to well classify the faults (above 90% accuracy) using any of the indices proposed.

Meanwhile, SVM using polynomial kernel function presented inferior performance and only performed above 80% accuracy when CSD is used. When using only CCF, DABS or MM, this machine learning algorithm presented lower performance (42%, 65% and 42% respectively).

The BP neural network is built using simple heuristic method. The nodes in this network are all sigmoid and the number of hidden layers is 4. This BP algorithm presented modest performance when using CSD, MM or DABS with 81% accuracy for any of these indices.

Considering these performances, it is possible to conclude that CSD and DABS have, on average, the best individual performances. Thus, a combination of these two indices is used to re-evaluate the classifiers. Fig 7 presents the confusion matrix for each classifier considering that a combination of CSD and DABS indices is used as input for the algorithms.

Observing the results shown in Fig 7, it is possible to conclude that combining CSD and DABS indices had shown similar impacts on the RBF neural network and SVM algorithms. The RBF general performance (96%) is equal to the maximum performance of the two indices which was obtained with DABS (96%). SVM improved only slightly from its best previous performance, from 82% using CSD to 83% using both indices. However, the BP method improved considerably its performance from 81% with one index to 94% using the two indices combined.

The indices combination has also an impact on the classification processing time, especially when using large databases. The database dimension can rapidly increase with two or more indices. Meanwhile, the use of two indices does not show substantial improvement in the algorithms proposed for this research.

Radial Basis Function Neural Network

General performance: **96%**

a	b	c	d	e	<-- classified as
100%	0%	0%	0%	0%	a = No Fault
0%	91%	9%	0%	0%	b = AD
3%	0%	97%	0%	0%	c = RD
0%	0%	0%	100%	0%	d = DV
0%	0%	0%	0%	100%	e = SC

a

Support Vector Machine

General performance: **83%**

a	b	c	d	e	<-- classified as
100%	0%	0%	0%	0%	a = No Fault
24%	74%	2%	0%	0%	b = AD
16%	4%	80%	0%	0%	c = RD
17%	0%	0%	83%	0%	d = DV
0%	0%	0%	0%	100%	e = SC

b

Backpropagation Neural Network

General performance: **94%**

a	b	c	d	e	<-- classified as
100%	0%	0%	0%	0%	a = No Fault
0%	100%	0%	0%	0%	b = AD
14%	1%	84%	0%	0%	c = RD
11%	0%	0%	89%	0%	d = DV
0%	0%	0%	0%	100%	e = SC

c

Figure 7 Intelligent classifiers confusion matrix based on the use CSD and DABS indices.
(a) Radial basis function
(b) Support-vector machine
(c) Backpropagation

4 Conclusion

This paper used numerical indices and machine learning applications to automatically classify different faults on a laboratory winding model. The model has removable sections and is designed to enable mechanical deformations and short-circuits without compromising its structure due to its removable and spare deformed sections.

The results have shown that the use of different numerical indices have an impact on the intelligent classifier's performance. The combination of indices did not affect the general performance of RBF neural network and SVM. However, the BP has shown an improvement of 13% in its accuracy once two indices are used for classification.

The outcomes of this research indicate that the use of indices combination in automatic classification not always improve its performance. In the case of large databases, the algorithms rather need more processing time without affecting the accuracy gain.

The present research investigates automatic fault classification in a laboratory winding model. The main advantage of this model is the possibility to introduce faults and replicate measurements in order to generate a large database. However, the concept proven in the current study still needs to be tested and optimized to be considered for real case transformers applications. This remains one of the future targets of our research activities.

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