Exploring the detectability of short-circuit faults in inverter-fed induction motors

George Georgoulas
Department of Computer Science, Electrical and Space Engineering
Luleâ University of Technology, Lulea, Sweden
geogeo@ltu.se

Lucia Frosini
Department of Electrical, Computer and Biomedical Engineering, University of Pavia
27100 Pavia, Italy
lucia@unipv.it

Petros Karvelis, Chrysostomos Stylios
Laboratory of Knowledge and Intelligent Computing
Department of Computer Engineering,
Technological Educational Institute of Epirus Arta, Greece
{pkarvelis, stylios}@teiep.gr

Ioannis Tsoumas
ABB Corporate Research
Baden - Dättwil
Switzerland
ytsoumas@ieee.org

***Abstract*—This paper explores the possibility of creating an automatic method for assessing the condition of induction motor circuits fed by inverters. The stator current and magnetic flux are processed in the frequency domain and a feature selection stage is employed to pinpoint the most informative components to further be fed to a classifier that performs the assessment of the motor circuit. The results are promising, indicating that short circuit detection as well as quantification is feasible using non-invasive techniques.**

Keywords— ***induction motors; variable speed drives; fault detection; fault diagnosis; current measurement; magnetic flux leakage.***

I. INTRODUCTION

During the last couple of decades maintenance has shifted from preventive to a predictive paradigm [1]. Predictive maintenance heavily relies on condition monitoring techniques, which utilize a continuous or pseudo-continuous monitoring of specific quantities. The latter can capture a fault in an early stage, pinpoint its origin and sometimes even predict its progression. Fault detection, fault diagnosis and failure prognosis allow for a timely intervention. With the advances in sensors, hardware and computational power, condition monitoring methods have started becoming an indispensable means of industrial infrastructures.

One of the fields where condition monitoring techniques have gained popularity is the field of electric machinery. Among the electric machines, the induction motor has received the most attention due to its widespread use, with numerous methods proposed which include more elaborate techniques and consider more realistic scenarios.

A common fault encountered in induction machine relates to stator windings. Short circuits of the stator winding account for 21% - 40% of the total faults, depending on the type and size of the machine. This percentages makes them the second most frequent fault after the bearing [2]. The insulation system is even more susceptible to failure due to stresses caused by the pulsed inverter voltage. The voltage step at the inverter output can be amplified up to a factor of two at the motor terminal due to the reflection of the travelling wave [3]. The latter is caused by the much higher motor impedance compared to the cable impedance.

Lately for assessment of rotating equipment, the traditional vibration-based monitoring techniques are supplemented with techniques focusing on the analysis of the electromagnetic quantities [4]-[8]. The use of these techniques aims to detect various faults as early as possible by detecting the changes caused by the fault to the electromagnetic quantities of the motor. Another boosting factor for the adoption of these type of methods is that the required equipment is often already present for other purposes (motor control) and are thus, no invasive by nature [9].

Among the various electromagnetic quantities that are gaining popularity in the field of induction motor condition monitoring, the currents and the magnetic flux are very popular; the first because it is by far the most non-invasive technique and the latter due to its sensitivity in capturing faults in an incipient phase. For the case of current signature analysis (a common term describing these methods is Motor Current Signature Analysis MCSA), it has been reported that non-fault related phenomena (voltage unbalances, variable-speed operations etc.) can mislead the subsequent analysis creating false positive detections.

The use of inverters has created the need of an extra processing step to remove the high frequency noise that

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contaminates the recordings [10]. In [10] a wavelet-based technique for "cleaning" the measured signals was employed. However, the method did not offer an automatic diagnosis stage. In [11] an automatic classification method was employed based on linear discriminating analysis, but only two levels of short circuit fault were considered. In this work it is investigated whether an automatic method can categorize different levels of short circuit faults.

Therefore, the aim of this paper is to compare different measurement settings and two different classification schemes for the problem of fault severity in the case of short circuits for inverter fed induction motors. This work also aims to investigate whether it is possible for the methods to "extrapolate" to situations where the levels of fault severity were not encountered during the training phase and assess possible limitations and requirements for a more general deployment.

The rest of the paper is structured as follows: Section II summarizes all the necessary background of the involved methods and the experimental set-up. Section III summarizes the results, and finally Section V concludes the paper presenting the major findings, possible limitations and directions for future research.

II. Methods

In this work stator current and magnetic flux measurements were involved with the latter being measured by two different sensors configurations. A description of the set up used is given in the following subsection II.A while the rest of the subsections (II.B-II.F) describe in short, the methods used. The whole severity detection procedure was treated as a standard classification problem, including feature extraction from the raw signals, feature selection and categorization using a classifier.

A. Experimental setup – Data collection

The test bench for all the experiments (Fig.1) is located in the laboratory of the University of Pavia [10] The motor is a three-phase squirrel cage induction motor, rated power 1.5 kW, wye connected, with 4 poles, 36 stator slots, 46 rotor slots, and supplied by a PWM two-level IGBT voltage source inverter. It is modulated with space vector modulation (SVM) with a switching frequency of $f_{switch} = 6$ kHz.

The short circuit faults were simulated using three external connectors at the stator winding for shunting the 5%, the 10% or the 15% of the total number of turns per phase. By providing the supply directly on the first, on the second or on the third connector, shunting the first 15, 30 or 45 turns, we reduce 5%, 10% or 15% the overall impedance of this phase respectively. A detailed description is given in [12].

All experiments were carried out atno-load with the magnetic powder brake coupled to the motor de-energized. The coupling to the brake was necessary for collecting also the speed, beside other quantities. The four measurements collected were the following:

i) the current of one phase (different from the one which the short circuit is applied);

ii) the axial leakage flux, using Emerson M-343F-1204 commercial flux meter, in frontal position, on the fan side of the motor;

iii) the radial leakage flux, by means of a custom probe, positioned on the body of the motor.

iv) the speed, by means of the brake coupled to the motor.

Note: leakage flux signals were adequately hardware filtered (to avoid aliasing). More details about the hardware involved can be found in [12].

The fundamental frequency for all experiments was set at 50Hz. For each condition (no fault/healthy, simulated 5%, 10% and 15% short circuit fault) 40 measurements were collected as a sampling frequency of 120 kHz for a period of 8.7 seconds (leading to signals of 1048576 samples long).

The currents and the flux measurements were subsequently analyzed for the categorization of motor condition.

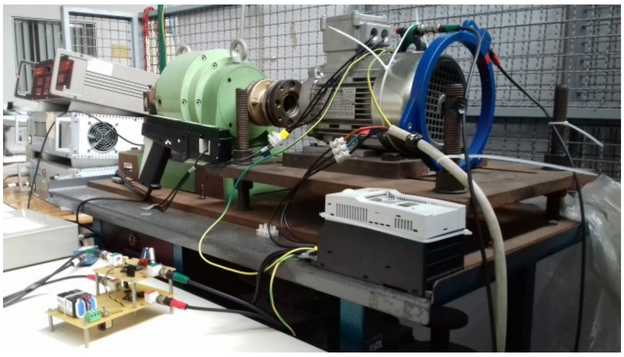

Fig. 1: Experimental test bench

B. Feature extraction

It has been widely documented in the literature that short circuit faults leave their footprints in the frequency domain. While many advanced frequency analysis methods have been developed over the past decades, in this work we focused on the simplest frequency analysis method, which involves the use of the periodogram [13]. After the transformation of the raw measurements to normalized power spectrum values, multiples of the fundamental frequency, as in [11], were extracted. As it can be seen in Fig. 2, which depicts the normalized power spectrum at those frequencies, for four randomly selected measurements (for all three involved quantities), the short circuit fault modulates the frequency content but not in a uniform manner.

Due to the very large number of extracted frequencies, the feature vector has very high dimension. To alleviate the corresponding problem of the "curse of dimensionality" a feature selection stage was involved before passing the feature vector to the classifier.

C. Feature selction / ranking

Feature selection is the process that tries to remove irrelevant and/or redundant features. Moreover, feature selection usually improves the generalization performance of a classifier when the number of training samples is not large compared to the dimensionality of the original feature vectors. Feature selection algorithms are usually categorized as [14]:

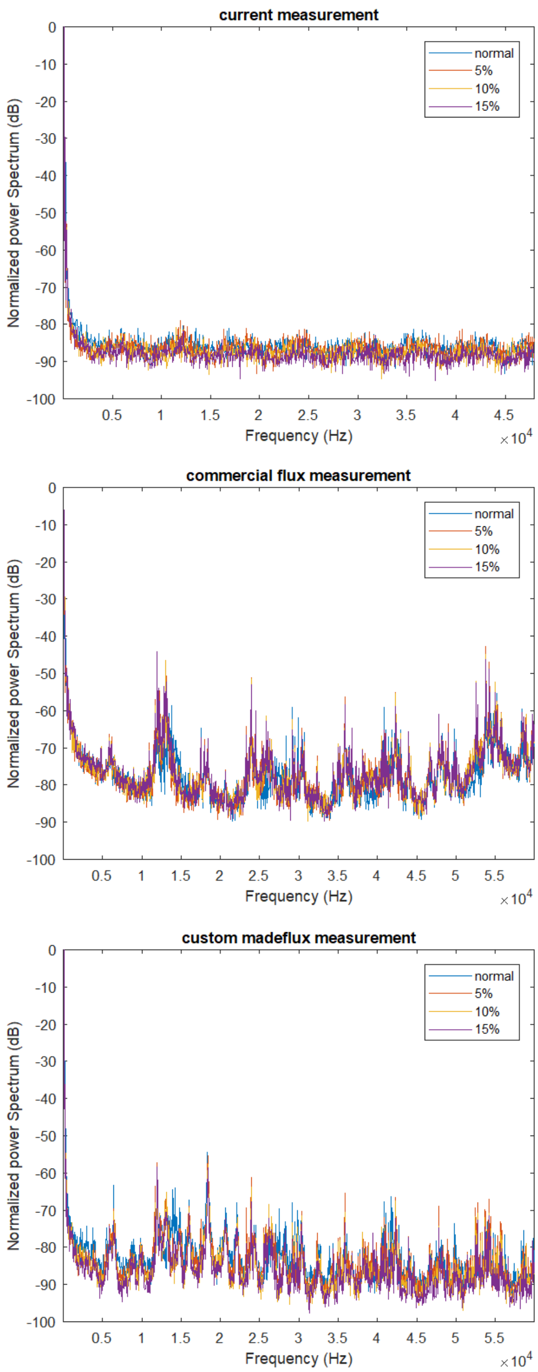

Fig. 2: Aggregated plots of the extracted normalized power spectrum values for the three measurements for all four investigated conditions.

Filters: assess and rank features using a criterion that does not rely on the classifier involved.

Wrappers: use a predictive algorithm to assess subsets of the original feature set.

Embedded methods: perform features selection as part of the classifier building (e.g. Decision Trees (DT)).

In this work a filter approach was selected using as criterion the Area Under the Receiver Operating Characteristic (ROC) curve (AUC) [15]. The AUC, for the case of binary classification problems, can be calculated using the equation below [16]:

$$AUC = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n} I\left(r_i^-, r_j^+\right) \tag{1}$$

with

$$I\left(r_i^-, r_j^+\right) = \begin{cases} 1 & \text{if} \quad r_i^- > r_j^+ \\ 1/2 & \text{if} \quad r_i^- = r_j^+ \\ 0 & \text{if} \quad r_i^- < r_j^+ \end{cases} \tag{2}$$

where r^- (r^+) indicates negative (positive) cases (r_i^-, (r_j^+) is the value of the feature of the i-th (j-th) negative (positive) case), with m (n) being the number of negative (positive) cases.

In case of more than two classes, the AUC is averaged across all class pairs [17]. Using this criterion (average AUC) the extracted features (normalized power of different frequency components) were ranked and fed to the Minimum Mahalanobis Distance (MMD) described below [18]. This ranking was also part of a preprocessing process before feeding the Random Forest (RF) classifier [19] as a means to reduce the computation time and also "bias" the learning towards more promising features.

D. Linear Classifier

The MMD classifier is a very simple (it has not tuning parameters), which can perform "embarrassingly" well when dealing with real life data [18].

The classifier select class i according to:

$$i = \underset{l=1\dots L}{\arg\max}\left\{2\ln\left(P(\omega_l)\right) - \left(\mathbf{x}-\boldsymbol{\mu}_l\right)^T \mathbf{C}^{-1}\left(\mathbf{x}-\boldsymbol{\mu}_l\right)\right\} \tag{3}$$

with $P(\omega_l)$ being the a priori probability of occurrence of class ω_l, (L being the total number of distinct classes) whose average vector is $\mathbf{x}$, while $\mathbf{C}$ is the covariance matrix of all the training data (data from all classes pooled together).

E. Random Forests (RFs)

RFs introduced by Breiman [20] can be used both for regression and classification. RFs can be trained fast and, at the same time, can provide competitive results compared to other state of the art methods [19].

RFs paradigm for classification performs class prediction by taking the majority vote of B DTs. In other words, if $\hat{C}_b(x)$ is the class prediction of the b-th DT for an input x, the prediction of the RF is given by [19]:

$$\hat{C}_{RF}(x) = majority\_vote\left\{\hat{C}_b(x)\right\}_1^B \quad (3)$$

Each DT is trained on a bootstrap sample of the available data. The DT is grown till it reaches the minimum node size $n_{\min}$ (if $n_{\min}=1$ we are talking about decision stamps) and at each step m out of p features are randomly selected (the default value suggest in [20] is $\lfloor\sqrt{p}\rfloor$, where $\lfloor x\rfloor$ returns the greatest integer that is less or equal to x).

F. *Evaluated scenarios*

Multiple experiments were carried in this study. For the first one (multiclass problems see below) three different settings were considered: a) all the extracted features involved, b) features up to frequency 2kHz and c) features up to frequency up to 1kHz. The reason for this setting is to investigate whether viable results can be achieved even with simpler acquisition hardware, which is more likely to be found in an industrial facility.

For the case of the MMD classifier three different input ranges were considered: a) the top five ranked features, b) the top ten ranked features and c) the top 20 ranked features. For the case of the RFs only when the whole feature set was involved the ranking mechanism was invoked to select the top 100 features, so as to increase computational speed and eliminate uninformative frequencies.

Four different evaluation scenarios were considered:

a) All conditions available / multiclass

Data from all four different conditions (healthy, 5%, 10%, 15) were available during training and testing. The classifier would not have to deal with completely "unseen settings" and needed to classify each sample from the testing set into one out of four classes (healthy, 5%, 10%, 15). A 10x10 fold Cross Validation (CV) procedure was involved [21], meaning that the standard 10-fold CV procedure was repeated ten times after reshuffling all the available data.

After this first set of experiments the most promising (and simpler) configuration from the lower frequency range were selected for carrying a second round of experiments.

b) Healthy – "incipient fautl" data available

All data from the healthy class and from the 5% short circuit class were used for training forming a binary classification problem (healthy / short circuit) while for testing all 10% and 15% cases were passed to the classifier for assessment.

c) Healthy – "intermediate fault" data available

All data from the healthy class and from the 10% short circuit class were used for training forming a binary classification problem (healthy / short circuit) while for testing all 5% and 15% cases were passed to the classifier for assessment.

d) Healthy – high level degradation data available

All, data from the healthy class and from the 15% short circuit class were used for training forming a binary classification problem (healthy / short circuit) while for testing all the 5% and 10% cases were passed to the classifier for assessment.

Therefore, for the multiclass problem a resampling procedure was used for the evaluation of the different schemes, while for the other three cases, where "extrapolation" was investigated, the training and testing was carried just once.

III. Results

Due to space limitations, the confusion matrices of the first experiment were not included and only the sensitivities per class (correctly classified instances / total number of instances belonging to that class) are reported in Tables I to III. Some more information is given in the conclusion section regarding the mixing of the classes.

A. *Experiment*

In the following tables "All" stands for the whole frequency range and "xf" means that the x top ranked features were used.

After the first round of experiments, for the current measurements, the 1kHz, 5f, MMD configuration was selected. For this particular measurement the results are suboptimal for this setting but as it was noted the intention was to investigate both simpler classification and hardware related case. For the commercial flux sensor, the 1kHz, 20f, MMD was selected. For the custom-made sensor also the 1kHz, 20f, MMD was selected.

1) *Current measurement data*

TABLE I
All Conditions Available

Case	healthy	5%	10%	15%
All, 5f, MMD	400/400	400/400	391/400	393/400
All, 10f, MMD	397/400	400/400	367/400	351/400
All, 20f, MMD	396/400	400/400	376/400	348/400
All, RF (100f)	389/400	399/400	372/400	374/400
2kHz, 5f, MMD	400/400	400/400	376/400	365/400
2kHz, 10f, MMD	400/400	400/400	380/400	374/400
2kHz, 20f, MMD	400/400	399/400	377/400	359/400
2kHz, RF	400/400	399/400	351/400	370/400
1kHz, 5f, MMD	**400/400**	**400/400**	**380/400**	**384**/400
1kHz, 10f, MMD	400/400	400/400	381/400	369/400
1kHz, 20f, MMD	400/400	400/400	374/400	363/400
1kHz, RF	400/400	400/400	382/400	369/400

2) *Comercial Flux Data*

TABLE II
All Conditions Available

Case	healthy	5%	10%	15%
All, 5f, MMD	400/400	400/400	370/400	390/400
All, 10f, MMD	400/400	391/400	389/400	392/400
All, 20f, MMD	400/400	400/400	393/400	400/400
All, RF (100f)	400/400	400/400	400/400	400/400
2kHz, 5f, MMD	390/400	400/400	364/400	361/400
2kHz, 10f, MMD	390/400	400/400	343/400	354/400
2kHz, 20f, MMD	394/400	400/400	299/400	344/400
2kHz, RF	400/400	400/400	400/400	400/400
1kHz, 5f, MMD	390/400	400/400	363/400	362/400
1kHz, 10f, MMD	390/400	400/400	338/400	358/400
1kHz, 20f, MMD	**400/400**	**400/400**	**400/400**	**400/400**
1kHz, RF	400/400	400/400	400/400	400/400

3) *Flux data from custom made probe*

TABLE III

ALL CONDITIONS AVAILABLE

Case	healthy	5%	10%	15%
All, 5f, MMD	382/400	365/400	400/400	400/400
All, 10f, MMD	398/400	390/400	399/400	400/400
All, 20f, MMD	400/400	400/400	400/400	400/400
All, RF (100f)	400/400	400/400	400/400	400/400
2kHz, 5f, MMD	363/400	359/400	390/400	400/400
2kHz, 10f, MMD	400/400	391/400	393/400	400/400
2kHz, 20f, MMD	400/400	390/400	393/400	400/400
2kHz, RF	400/400	398/400	397/400	400/400
1kHz, 5f, MMD	371/400	372/400	397/400	400/400
1kHz, 10f, MMD	400/400	393/400	397/400	400/400
1kHz, 20f, MMD	**396**/400	**400**/400	**400**/400	**400**/400
1kHz, RF	400/400	400/400	400/400	400/400

B. *Healthy / 5% training – 10%, 15% testing*

1) *Current measurement data*

TABLE IV

CONFUSION MATRIX

Case	healthy	faulty
10%	1	39
15%	0	40

2) *Commercial Flux*

TABLE V

CONFUSION MATRIX

Case	healthy	faulty
10%	0	40
15%	0	40

3) *Custom made probe*

TABLE V1

CONFUSION MATRIX

Case	healthy	faulty
10%	0	40
15%	0	40

C. *Healthy / 10% training – 5%, 15% testing*

1) *Current measurement data*

TABLE VII

ALL CONDITIONS AVAILABLE

Case	healthy	faulty
5%	1	39
15%	0	40

2) *Commercial Flux*

TABLE VIII

CONFUSION MATRIX

Case	healthy	faulty
5%	0	40
15%	0	40

3) *Custom made probe*

TABLE IX

CONFUSION MATRIX

Case	healthy	faulty
5%	6	34
15%	0	40

D. *Healthy / 15% training – 5%, 10% testing*

1) *Current measurement data*

TABLE X

CONFUSION MATRIX

Case	healthy	faulty
5%	15	25
15%	0	40

2) *Commercial Flux*

TABLE XI

CONFUSION MATRIX

Case	healthy	faulty
5%	5	35
15%	0	40

3) *Custom made probe*

TABLE XII

CONFUSION MATRIX

Case	healthy	faulty
5%	39	1
15%	0	40

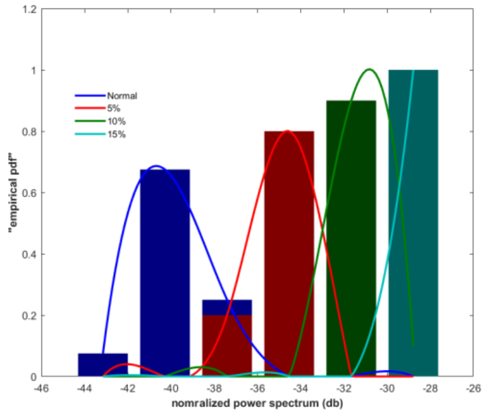

Fig. 3: Histogram (empirical "pdf") of the normalized power spectrum for the four different investigated conditions/.

IV. DISCUSSION - CONCLUSIONS

Tables I to III show that in general the different conditions can be separated. The current measurement schemes perform slightly worse compared to the magnetic flux related ones. The use of more features does not have a uniform effect on all settings, therefore further experimentation is needed. RF perform slightly better than the MMD classifier, but this slight improvement has to be further investigated. Last but not least frequency features that lie bellow 2kHz can be used for the assessment of this particular fault. In all the experiments, the normalized power frequency at 150 Hz for the current measurements and for the magnetic flux measured by the custom made probe and the normalized frequency at 100 Hz for the magnetic flux measured by the commercial sensor were ranked first. However, as it can be seen in Fig. 3, using just one frequency component is not enough for reliable assessment of the windings of an induction motor.

The more interesting findings, however, comes from Tables IV – XII. From these tables it can be deduced that the method can "extrapolate" but the quality of the extrapolation depends on the data used for representing the faulty class: when data with more severe fault are encountered, the classifier can in general correctly assign them to the faulty category (Tables IV -VI). When during training the data for the faulty class correspond to quite severe faults, then the algorithm might or might not detect fault that come from less severe situations (Tables X-XII). This can be further illustrated by looking at the projection of the extracted features in lower dimensional space (Fig. 4) using Principal Component Analysis (PCA) [17]. From these figures it can be seen that with increased severity the data points move towards a specific direction. This in accordance with the intuition and suggests that an ordinal classification approach could also be tested.

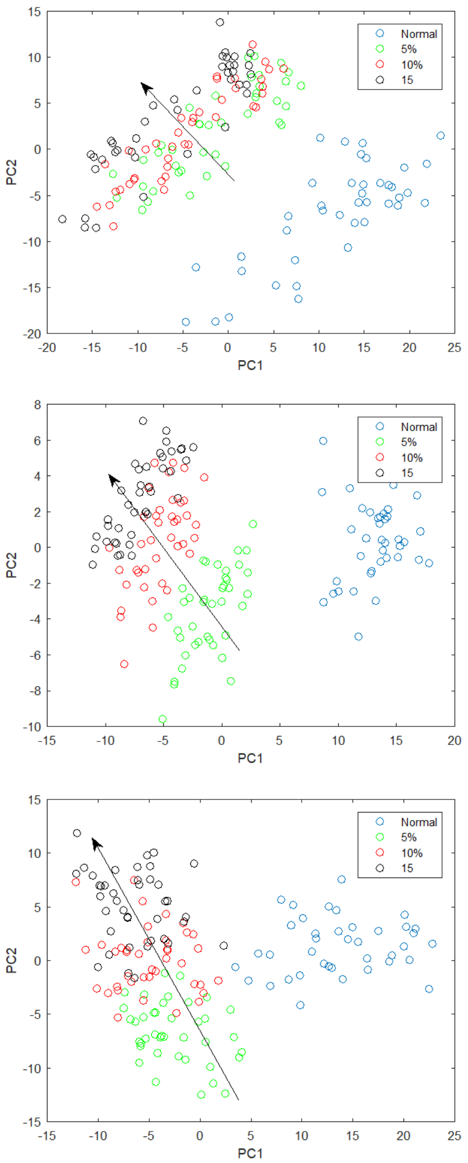

Fig. 4: Projection of the features up to 1 kHz to a 2 dimensional space (from top to bottom: current, commercial flux measurement, custom made probe flux measurement.

In future work, more experiments will be carried out using data coming from other loading conditions as well as from other motors to verify the results of this preliminary study. Furthermore, ordinal classification as well as regression methods will be tested and compared with the conventional classification approach described in this work.

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