Symbolic time series analysis of the soft starting transient in induction machines

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***Abstract*—Induction motors are in the heart of almost every production line especially due to their robustness under harsh environments. Nevertheless, even induction machines are prone to faults. Among them, the faults related to the breakage of rotor bars have received special attention by the research community with a number of methods proposed both for the case of steady state as well as for transient operation. For the latter, methods relying on the analysis of the start-up transient have proven to be able to effectively isolate the faulty component that is created by the asymmetry caused by the bar breakage. However, very little work has been done concerning the soft starting of induction machines. In this work, preliminary results of the application of a symbolic time series technique for the analysis of the transient, when the motor is controlled by a soft starter, will be presented and experimentally evaluated.**

Keywords—Broken bar fault, Symbolic time series analysis, empirical mode decomposition.

I. Introduction

Induction motors are employed in a countless number of industrial applications and processes [1]. They are probably the most robust within the rotating electrical machines but, due to their widespread use, their eventual failures may imply significant losses for companies and industries. Due to this fact, the research in the induction motors condition monitoring area has drawn a significant interest over these recent years [1]-[3].

Within the different possible faults in induction motors, rotor-related failures have been extensively analyzed in the technical literature, despite they are not among the most common faults in such machines [4]. The eventual effects of a rotor bar fault can be especially dangerous since the fault can propagate toward the adjacent bars without significant effects over the external machine quantities. Only when the fault severity is high enough, the external indications may be evident but at that stage it could be too late to proceed with proper maintenance actions.

The probability of rotor damages is higher for the case of large, line-fed motors that are started under high inertias and/or that operate under heavy-duty cycles. The use of solutions, as the operation under soft-starters, has helped to mitigate some of the effects of such hard conditions, decreasing the probability of bar breakages [5]. However, the use of soft-starters does not influence the high currents during heavy duty cycles and does not necessarily prevent from the appearance of relatively high starting currents; hence it does not avoid the eventual damage in the rotor cage. Indeed, some recent cases have been reported in industry related to soft-starting motors with rotor bar damages.

The breakage of a bar gives rise to a “faulty” component with characteristic frequencies given by the following equation

$$f_b = \left(1 \pm 2 \cdot k \cdot s\right) f_s, \qquad k = 1,2,... \tag{1}$$

where f_s is the fundamental frequency component. Among these components, those corresponding to $k = 1$ are the most widely used for the detection of the presence of a broken bar. These two components are respectively called the lower sideband harmonic $\left(\left(1-2\cdot s\right)f_s\right)$ and the upper sideband harmonic $\left(\left(1+2\cdot s\right)f_s\right)$.

The most widely used method for their detection is the Motor Current Signature Analysis (MCSA) method, which as its name implies relies on the analysis of the line current of the motor. Its non-invasive nature makes it the most appealing method for industrial applications [1], [6]. However, MCSA has some drawbacks, due to the possibility of other phenomena (such as load torque oscillations) causing the appearance of frequency components at frequencies that can be eventually coincident with those caused by broken rotor bars and thus leading to incorrect diagnostic results [7], [8].

These problems led to the development of another family of methods called Transient-MCSA, which focuses on the analysis of the start-up current [7], [9]. These methods usually rely on advanced signal processing methods being able to reveal fault-associated patterns that are very unlikely to be caused by a different phenomenon or reason. Since their introduction, a number of approaches have been proposed with quite a success [7], [9], [10].

Nevertheless, most of these methods have been tested using Direct-On-Line (DOL) starters, where the sinusoidal line voltage is directly (or via a transformer) applied to the motor terminals. The case of a soft starting, utilizing a power electronic converter, more specifically reverse-parallel silicon controlled rectifiers (thyristors) has not been sufficiently investigated. To the best of our knowledge only the work in [11] addressed the issue of the presence of broken bars providing a semi-automated method for assessing the condition of the rotor cage based on wavelet decomposition, while in [12] a method based on frequency domain analysis (focusing on negative sequence harmonics) for detecting stator winding faults in motors during soft starting has been presented.

In this work we employ solely time domain analysis methods for the development of an automatic method for the diagnosis of broken rotor bars. The proposed method relies on the application of Empirical Mode Decomposition (EMD) for the isolation of a component –Intrinsic Mode Function (IMF)- that can be used for the extraction of information regarding the health condition of the motor. The information is extracted using Symbolic Aggregate approXimation (SAX) and ideas from the field of information retrieval. The approach is presented in detail in the following section.

The rest of this paper is structured as follows: in Section II all the involved techniques are presented. In Section III the experimental set-up is described along with the achieved results. Finally Section IV concludes the paper while providing hints for future research directions.

II. PROCEDURE

The overall procedure is depicted in Figure 1 and the main steps are explained in the following sub-sections.

A. Acquisition-Downsampling

Since in our previous works we focused on the lower side band harmonic the signals that were acquired at a sampling frequency of 5 KHz were down-sampled by a factor of 10 taking also care to avoid aliasing effects [13]. This way the rest of the steps were speeded up, without any apparent degradation of the performance as will be shown in the next Section. As it can be observed in Figure 2, the acquired signals have a different behavior than the conventional waveform of the line current during direct start-up.

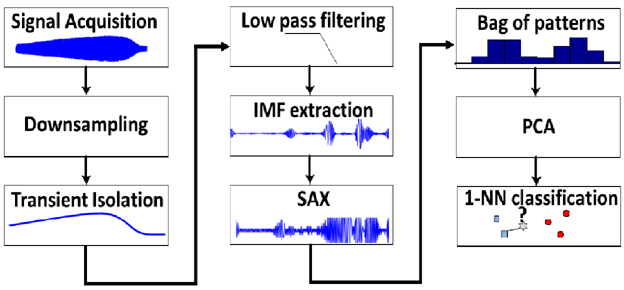

Fig. 1. The overal procedure

B. Transient isolation

The proposed method is meant to be used during the transient of a start-up operation. Therefore, a detector was developed based on the RMS value of the acquired line current, which is being calculated over a sliding window and that has been employed to exclude the steady state regime [14]:

- The RMS value was calculated over using a sliding window, and thus creating a new time series of consecutive RMS values.
- The standard deviation of the RMS sequence was then estimated using another sliding window. Once its value fell below a threshold, steady-state operation was assumed.

C. Low pass filtering

As it was already mentioned our previous work focused on the lower sideband harmonic. In this work we assumed that this harmonic is adequate to characterize the different severity levels of the fault also for a soft-starter-controlled ramp up (with and without a current limiter). Therefore, a linear filter with a cutoff frequency at 55 Hz was applied before the EMD stage. Based on the proposed approach, the extraction of IMFs corresponding to higher frequency components has been avoided and forced in a way the first IMF to capture the main frequency component, while leaving the faulty component footprint mainly in the second IMF. After low pass filtering, the waveforms are also normalized to have a maximum absolute value equal to 1 and thus making the whole approach independent from the peak current.

D. IMF extraction

The second IMF is extracted using the EMD algorithm. In direct connected motors this component, the second IMF, has been shown to contain the fault component associated with the symmetry caused by the broken bar.

EMD is a data driven-non linear-adaptive method, which decomposes a signal into a set of IMFs [15], where an IMF is a simple oscillatory function forced to satisfy the following conditions: a) The number of zero crossings and the number of local extrema are equal or they differ by one, and b) the local average is equal to zero. Therefore, the original signal is eventually decomposed into a sum of IMFs plus a residual term.

Both univariate EMD [16], [17] as well as its bivariate extension [18] have been utilized as preprocessing steps for the diagnosis of broken rotor bars in direct connected machine. Figure 3 depicts the second IMF for the case of: a) healthy machine, b) a machine with one broken bar, and c) a machine with 2 broken bars, all started with voltage ramp. Furthermore, Figure 4 shows the corresponding cases for a machine started using a voltage ramp with current limiter.

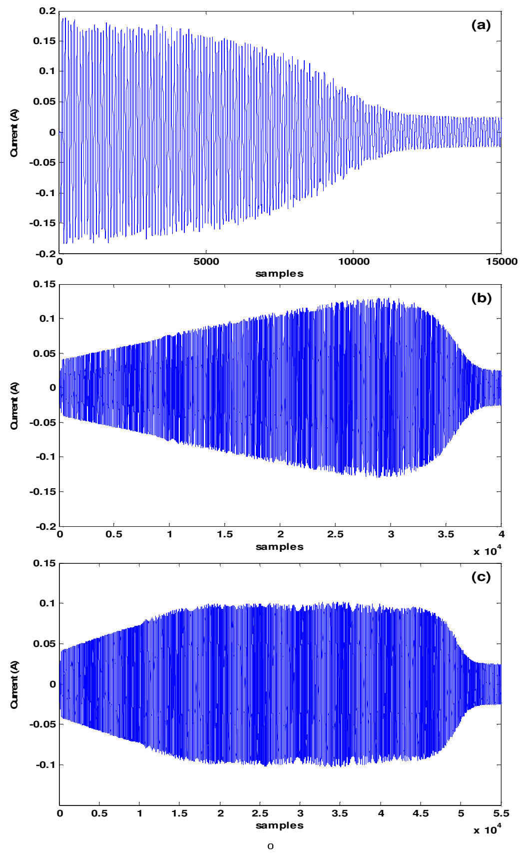

Fig. 2. Three different waveforms during start up (without any further processing) of a healthy machine: a) direct connection b) soft starter – voltage ramp and c) soft starter – voltage ramp with current limmiter

E. SAX

SAX is one of the most popular algorithms for the transformation of a real valued times series $x = \{x[1], x[2], \ldots, x[N]\}$ of an arbitrary length N to a string of symbols of arbitrary length w, where $w < N$ [19], [20]. The whole process consists of a number of steps:

- *Normalization*: each time series is normalized to have a mean value equal to zero and standard deviation equal to one.
- *Application of Piecewise Aggregate Approximation (PAA)* [22], [23]: given a time series x of length N, a new reduced representation is produced $x_{PAA} = \left[\bar{x}[1], \bar{x}[2], \ldots, \bar{x}[w]\right]$ of length w, with:

$$\bar{x}[i] = \frac{w}{N} \sum_{j=\frac{N}{w}(i-1)+1}^{\frac{N}{w}i} x[j] \text{, for } i = 1, 2, \ldots, w \qquad (2)$$

- Discretization/symbolization: using a partitioning of the original continuous space (assuming Gaussian distribution) determine the “breakpoints” that will produce equal-sized areas under a Gaussian curve, creating approximately equiprobable symbols.

The aforementioned steps are illustrated in Figure 5 for the case of the second IMF of a line current corresponding to a machine with 2 broken bars, starting with a voltage ramp soft starter.

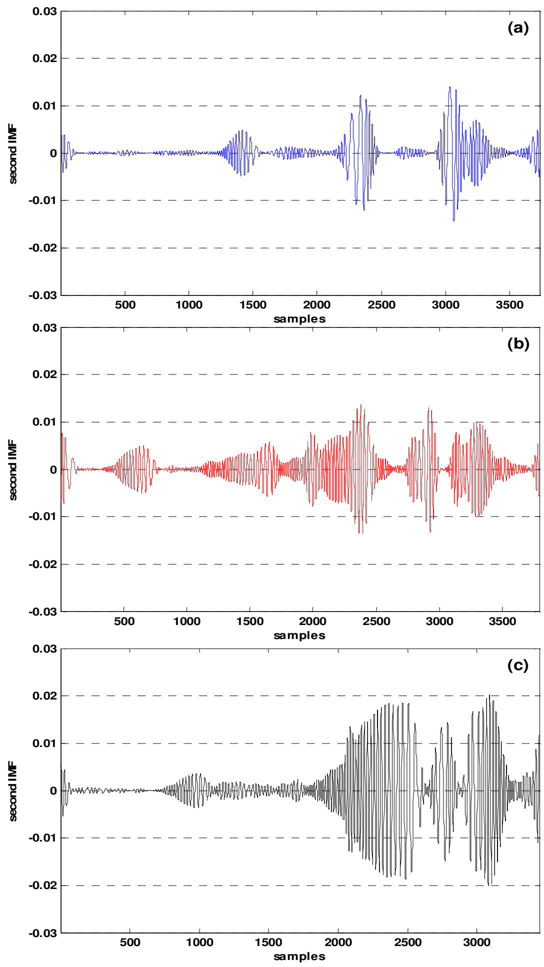

Fig. 3. The second IMF for different conditions using a voltage ramp soft starter: a) normal, b) 1 broken bar and c) 2 broken bars

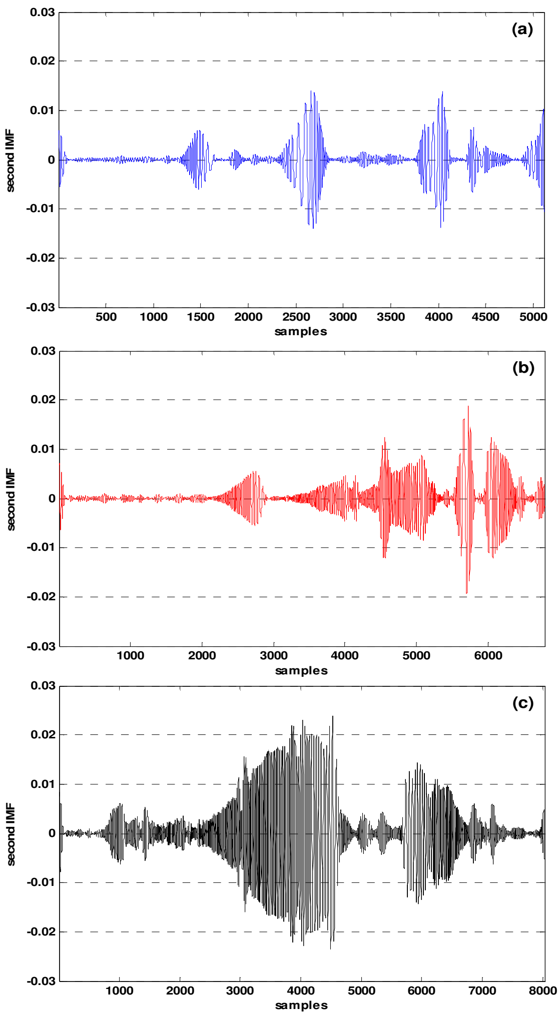

Fig. 4. The second IMF for different conditions using a voltage ramp with current limmiter soft starter: a) normal, b) 1 broken bar and c) 2 broken bars

F. *Bag of patterns*

SAX representation is not the more suitable representation for classification. Therefore, further processing is usually required to transform a SAX string into a representation that can be handled by the most conventional classification algorithms. This is achieved by the “bag of patterns” representation.

The “bag of patterns” representation proposed in [24] builds upon the earlier work of time series bitmaps [25] and intelligent icons [26], without however the restriction of specific combinations for the length of the word and the number of symbols. Treating the created string as a sequence of words it adopts the “bag of words” representation encountered in the field of information retrieval [27].

To put it in simple words, the method counts the appearance of individual “words” in a string and creates a histogram of appearances for each time series, which in turn constitutes a feature vector to be used by a classification algorithm.

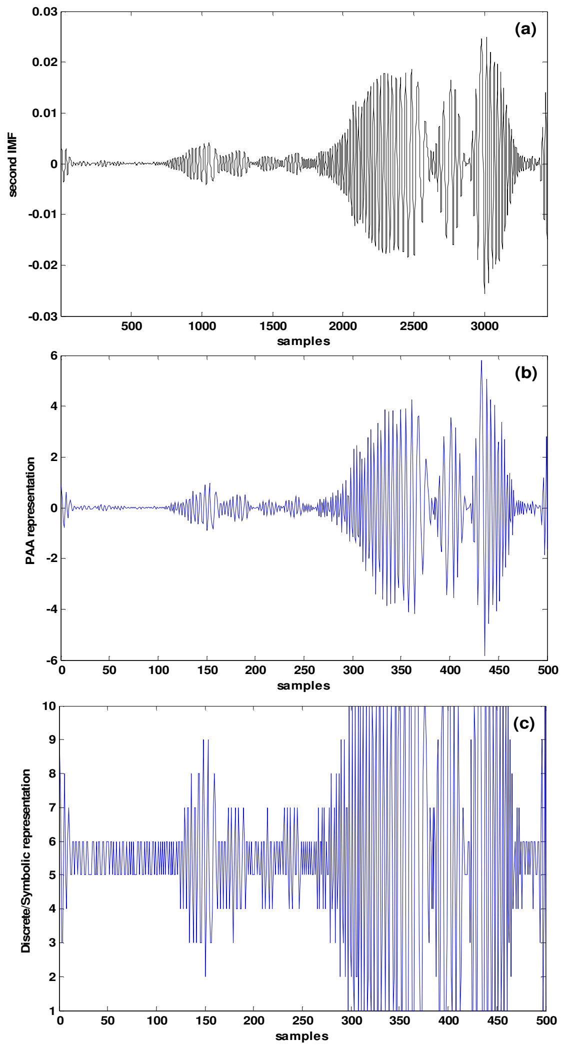

Fig. 5. The SAX algorithm applied to the second IMF of a current corresponding to a machine with 2 broken bars (voltage ramp): a) orignal waveform b) PAA representation (after normalization has take place) ($w = 500$) and c) discrete/symbolic representation using 10 symbols (1,2,…,10)

G. *Principal Component Analysis*

The “bag of patterns” representation creates quite large feature vectors (for example with an alphabet of size 10 and a word length equal to 3, the feature vector has a length of 10^3=1000). In order to avoid problems with this kind of high dimensional representation, Principal Component Analysis (PCA), probably the most widely used dimensionality reduction technique [28], was applied before the final classification stage. PCA projects the high dimensional input space into one with lower dimension maximizing the variance accounted for by the reduced representation [29]. PCA is quite competitive even when compared with much more sophisticated methods when it comes to real life data sets [28].

H. *Nearest Neighbor classifier*

The final part of the proposed scheme constitutes the diagnosis of the condition of the machine. This is done using a nearest neighbor classifier that assigns the respective vector into one of the three predefined categories/conditions (normal – one broken bar – two broken bars). The assignment is performed by finding the most similar case stored to the one at hand and categorizing it using the label of the stored case [30].

III. EXPERIMENTAL RESULTS

A. *Experimental Set up*

For the validation of the proposed method a 1,1 kW induction motor coupled to a DC machine acting as a load was used [11]. The experimental set up is show in Figure 6.

Fig. 6. The experimental set-up

Three different operating conditions (healthy, one broken bar and two broken bars – with the breakages artificially forced in the laboratory by drilling a hole in the junction point between the corresponding bar and the short-circuit end-ring) under two different soft starter (Figure 7) approaches: a) voltage ramp and b) voltage ramp with current limiter. The total number of acquired signals is summarized in Table I.

B. *Results*

In order to test the proposed method a leave one out (loo) procedure was applied: each time one signal was left out for testing and the rest were used for training [30]. No special action was taken for the selection of an optimal set of parameters, which were set based on our experience to similar situations. Therefore for the feature extraction, the following parameters were selected: $w = 500$, 10 symbols and words of length equal to 2. For the PCA a low number of retained components were selected and set equal to 2. The results are summarized in the following Tables II and III indicating that the method seems capable of discriminating between the different operating conditions.

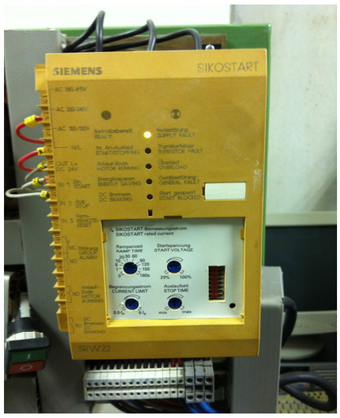

Fig. 7. The soft-starter used during the experimental evaluation

TABLE I. GATHERED DATA

Soft starter type	**Operating Condition**		
	Normal	***1 Broken Bar***	***2 Broken Bars***
Voltage ramp	4	4	4
Current limiter	6	2	4

Furthermore, it should be noted that in the presented case where the absolute value of the second IMF seems to matter, the normalization during the SAX stage was performed pooling together all the training waveforms and not individually to each one of them. The same transformation was applied to the testing case.

TABLE II. CONFUSION MATRIX FOR THE VOLTAGE RAMP

		Estimated class		
		Healthy	***1 BB***	***2 BB***
True class	***Healthy***	4	0	0
	1BB	0	4	0
	2BB	0	0	4

TABLE III. CONFUSION MATRIX FOR THE CURRENT LIMITER

		Estimated class		
		Healthy	***1 BB***	***2 BB***
True class	***Healthy***	6	0	0
	1BB	0	2	0
	2BB	0	0	4

IV. CONCLUSIONS

In this work an integrated approach to fault diagnosis of broken rotor bars relying on the start up current driven by soft-starters. The method relies exclusively on time domain processing and seems quite promising.

However there are some open issues that need further investigation. First of all the resulting second IMF has a quite different pattern than the one occurring during direct start up. This is due to the applied voltage at the motor terminals. A soft starter applies on the motor only portions of the sinusoidal grid voltages; these portions of sinusoidal waveforms can be decomposed into harmonics with frequencies equal to $\left(1\pm 6k\right) f_s$ with $k = 1, 2, \ldots$. The presence of these harmonics as well as asymmetries in the three phase voltages due to the converter and their interaction with saliencies caused for example by the rotor slots at a frequency of $\pm R\frac{\left(1-s\right)}{p} f_s$ (where R is the number of rotor slots and p the number of pole pairs) will create additional harmonic components in the frequency range 0-50 Hz during soft starting. Further analysis, including time-frequency tools could provide a deeper understanding of the underlying phenomenon.

Moreover this method is a data driven one, meaning that historical data is needed in order to train the classifier. Simulation results might provide an answer to that and further effort should be devoted towards that direction. Last but not least, the proposed method was only tested using data coming from one experimental setting. More testing is required before reaching safe conclusions about its robustness.

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