Automatic diagnosis of electromechanical faults in induction motors based on the transient analysis of the stray flux via MUSIC methods

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***Abstract* — In the induction motor predictive maintenance area there is a continuous search for new techniques and methods that can provide additional information for a more reliable determination of the motor condition. In this context, the analysis of the stray flux has drawn the interest of many researchers. The simplicity, low cost and potential of this technique makes it attractive for complementing the diagnosis provided by other well-established methods. More specifically, the study of this quantity under the starting has been recently proposed as a valuable tool for the diagnosis of certain electromechanical faults. Despite this fact, the research in this approach is still incipient and the employed signal processing tools must be still optimized for a better visualization of the fault components. Moreover, the development of advanced algorithms that enable the automatic identification of the resulting transient patterns is another crucial target within this area. This paper presents an advanced algorithm based on the combined application of MUSIC and neural networks that enables the automatic identification of the time-frequency patterns created by the stray flux fault components under starting as well as the subsequent determination of the fault severity level. Two faults are considered in the work: rotor problems and misalignments. Also, different positions of the external coil sensor are studied. The results prove the potential of the intelligent algorithm for the reliable diagnosis of electromechanical faults.**

***Index Terms* — Induction motors; transient analysis; stray flux; MUSIC; neural networks; fault diagnosis; reliability; rotor; predictive maintenance.**

I. INTRODUCTION

THE ultimate trend in the induction motors condition monitoring area relies on combining the information coming from the analysis of different quantities in order to reach a more accurate and reliable conclusion of the motor condition. It has been concluded that no technique based on the analysis of a single quantity is able to provide a complete knowledge of the motor health, since each particular quantity is valid for the diagnosis of specific failures. In this regard, *analysis of vibrational data* is the most widespread technique in industry and has provided good results for diagnosing faults with mechanical origin, such as misalignments, bearing faults or gear failures, among others [1-2]. On the other hand, the *analysis of motor currents* has been also proven to be effective for the detection of certain faults, such as rotor damages or eccentricities, becoming an interesting complementary option for the diagnosis of bearing damages, coupling system problems or even load anomalies [3-4]. Analysis of motor currents includes both classical methods relying on the analysis of steady-state currents [5], as well as modern techniques based on the analysis of transient current signals; these latter have proven to provide some advantages versus the classical steady-state methods under several situations [6-7]. *Infrared (IR) data analysis* is suitable to detect faults such as cooling system problems, deficient bearing lubrication or transmission system issues [8-10]. However, none of the aforementioned techniques has proven to be effective to detect other types of faults such as insulation damages. For this specific fault, *analysis of partial discharge (PD) data* has given satisfactory results [11]. In addition to these facts, each particular technique has its own constraints that may make its application difficult in specific cases. For instance, installation of vibration, PD or even current sensors is not feasible in some specific applications. In other situations, one technique can provide false indications when diagnosing the faults for which it is theoretically more appropriate.

The insufficiency of a single technique to determine the health condition of the whole motor has led to the emergence of new collaborative systems that try to combine the information obtained from the analysis of different motor quantities. In this regard, the combination of current data analysis and IR thermography was proposed in [12], while [13] proposes to merge the information obtained from wireless current, vibration and acoustic sensors, among other works. However, in spite of these advances, the need of additional techniques and approaches that overcome the problems of the currently existing methods or that can be used in cases in which the available techniques are not reliable still remains.

During these last years, the research on stray-flux-based diagnosis techniques is living a renewed dynamism in the

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electric motors condition monitoring area. The fact that occasional faults in an electric motor lead to effects in the magnetic field in the vicinity of the machine was known for years and, especially since the 2000s, several works have proposed the analysis of stray-flux data for the detection of rotor problems, stator short-circuits, bearing damages or even coupling system problems [14-26]. The great majority of these works has been based on the analysis under steady-state conditions and already reported the main drawbacks of this technique, which mainly rely on the strong influence of the sensor position on the results, as well as on the lack of validated thresholds for determining the fault severity. However, the progressive cost decrement of the necessary equipment to acquire flux data (which has come together with the spectacular development of their features) [27], along with the optimization of sophisticated signal processing tools haven given a strong impulse to the research devoted to this technology, that has proven to be effective to avoid some false positives obtained with other techniques [28]. In this context, very recent papers have proposed, for the first time, the analysis of stray-flux data that are collected under transient operation conditions of the motor (such as the starting) [26, 29-31]. These works showed that the analysis of these data has been proven to provide very useful information for the diagnosis of some electromechanical failures and even enables, together with other quantities, to discriminate among different types of mechanical faults [31]. The characteristic patterns created by the fault components in the maps resulting from the application of time-frequency transforms to the stray flux-related signals can be employed to reliably detect the existence of the fault and even to determine its severity. Nonetheless, a significant research work still needs to be done in this area since, for instance, it is pending the development of reliable algorithms making possible the automatic identification of the fault patterns and computation of the fault severity indicators based on the stray flux analyses. This would avoid the necessity of user intervention and the need of expertness for interpreting the results, which is a crucial feature for the incorporation of this technology in portable condition monitoring devices. In this context, the use of MUSIC-based methods emerges as an excellent option since they have shown advantages versus other alternatives when tracking fault components present in other quantities [32-33] and increase the possibilities of automatization of the method.

The present paper applies an advanced algorithm, based on the combination of MUSIC methods and artificial neural networks (ANN). Its main advantage is to enhance the visualization of the harmonics caused by motor failures in the electromotive force (emf) signals induced by the stray flux in external coil sensors attached to the motor frame. Moreover, the intelligent algorithm enables the automatic computation of fault severity indicators based on the combination of several features of the MUSIC results. These crucial characteristics significantly enhance the algorithm versus the preliminary version presented in [34], converting it in an ideal option to be incorporated in autonomous systems relying on transient stray flux data analysis.

II. TRANSIENT ANALYSIS OF THE EXTERNAL MAGNETIC FIELD

Previous works proved that the presence of faults in an induction motor leads to distortions in the external magnetic field and can induce specific frequency components in the emf force signals induced in external coil sensors attached to the motor frame [14-19]. Depending on the position of these sensors, a higher portion of axial or radial flux is captured and, therefore, components with axial or radial origin are more discernible in the emf signals captured at each considered position. For instance, at position A of Fig. 1, the flux captured by the sensor is mostly axial, while at position B, the sensor captures a portion of axial flux and a portion of radial flux. Position C captures mainly the radial flux [14].

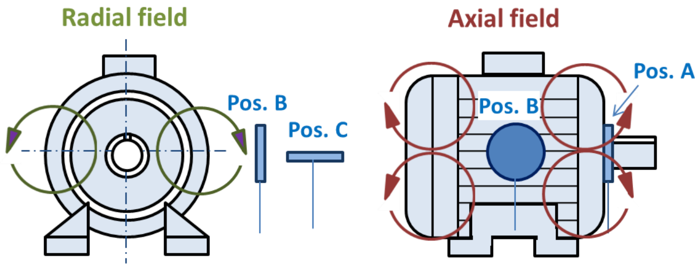

Fig. 1. Nature of the flux captured at each sensor position.

As justified in those works, in the case of *rotor damages*, several components are induced in the FFT spectrum of the induced emf signals at steady-state regime, the most significant ones being:

- Components at $s{\cdot}f$ and $3{\cdot}s{\cdot}f$ (s=slip and f=supply frequency): these have an axial nature and they can be also amplified due to the presence of eccentricities and/or misalignments in the machine [14].
- Sideband harmonics at $f{\cdot}(1\pm2{\cdot}s)$, which have a primarily radial nature and also appear in the spectrum of the steady-state current [17, 30].

On the other hand, in the case of *mixed eccentricities or misalignments*, the following components arise [35]:

- Components at $f_{ecc} = f\cdot(1 \pm m\cdot(1-s)/p)$ (with m=1,2…and p=number of pole pairs) or, equivalently, at $f \pm f_r$ with f_r=rotational frequency.

  These components are justified in several works [31,37]. In [31], for instance, the authors deduce the expression of the airgap flux density in a machine with eccentricities $B_{ag,\,ecc}$, as well as on the corresponding induced voltage in a coil v_c (see (1) and (2), where μ_0 is the permeability of air, g is the nominal airgap length, and φ_s is the angle of minimum airgap position due to static eccentricity. δ_s and δ_d represent the severity of static and dynamic eccentricity normalized to 1, N_c, is the number of coils of the coil and A_c, its cross-sectional area [31]), deducing the appearance of the components at $f \pm f_r$ in v_c.

$$B_{ag,ecc}(t,\theta=0°)=\frac{\mu_0\cdot J}{pg}\cdot\left\{(1+\delta_s\cdot\cos(\varphi_s))\cdot\cos(2\pi f_s\cdot t)+\frac{\delta_d}{2}\cdot\cos(2\pi(f_s+f_r)\cdot t+\cos(2\pi(f_s-f_r)\cdot t)\right\} \quad (1)$$

$$v_c=N_c\cdot A_c\cdot\frac{dB_{ag}}{dt} \quad (2)$$

Note that recent works have stated that these latter components can be also amplified due to the existence of rotor damages [38]. Moreover, other works have proven that eccentricity faults amplify the previous components at f_{ecc} much more significantly than misalignments do [31].

Recent works [30] showed that, under a direct-on-line starting of an induction motor, as the slip s changes, the aforementioned frequency components follow particular trajectories over time. More specifically, the time- frequency evolutions followed by these components under starting are those indicated in Table I. All these evolutions can be identified in the time-frequency maps resulting from the application of suitable transient analysis tools. The identification of these evolutions is only helpful for the detection of the corresponding fault, but also for discriminating among different failures (for instance, if $f\pm f_r$ appear in the time-frequency map of the starting current but not in that of the stray flux under starting, they may be due to a misalignment or load-related problems, while if they appear in both maps, they are probably related to an eccentricity) [31].

The objective of this work is to apply a MUSIC-based algorithm to visualize these evolutions, improving the performances of tools presented in previous works. Moreover, a feedforward neural network (FFNN) is employed to automatically identify the fault components evolutions as well as the corresponding fault severity, taking as inputs different statistical parameters resulting from the MUSIC plots. Note that the developed algorithm is especially robust, since it is not only based on detecting the evolution of a single component amplified by the fault but on various components. For instance, in the case of rotor damages, it relies not only on the detection of the classical evolutions of the sideband harmonics ($f\cdot(1\pm2\cdot s)$) but also on other components amplified by this failure such as $s\cdot f$ or f-f_r.

TABLE I. EVOLUTIONS OF THE COMPONENTS IN THE INDUCED ELECTROMOTIVE FORCE SIGNALS UNDER STARTING.

Component	**Fault**	**Evolution under starting**
$s\cdot f$	Rotor damages (axial)	Its frequency decreases from f to near 0 Hz under starting.
$3\cdot s\cdot f$	Rotor damages (axial)	Its frequency decreases from $3\cdot f$ to near 0 Hz under starting.
$f\cdot(1\text{-}2\cdot s)$	Rotor damages (radial)	Its frequency decreases from f to 0Hz and later increases again to near f.
$f\cdot(1+2\cdot s)$	Rotor damages (radial)	Its frequency decreases from $3\cdot f$ to near f Hz.
f-f_r	Mixed eccentricities / misalignment	Its frequency starts at f and ends at near $f/2$ (for p=2)
$f+f_r$	Mixed eccentricities / misalignment	Its frequency starts at f and ends at near $3\cdot f/2$ (for p=2)

III. MUSIC METHOD

Over recent years, the multiple signal classification (MUSIC) algorithm has been used in several works to detect faults in electric machinery [32-33]. This algorithm belongs to the family of methods based on the decomposition of the observation space into signal and noise subspaces. MUSIC is especially suited for detecting low amplitude components in signals with low signal-to-noise ratio. Furthermore, it offers an excellent resolution with non-stationary signals whereas it requires only a short time window.

MUSIC considers that a signal $x(t)$ is a sum of P complex sinusoids plus an additive noise (see (3)).

$$x(t)=\sum_{k=1}^{P}A_k e^{j(2\pi f_k t+\varphi_k)}+w(t) \quad (3)$$

where A_k is the amplitude, f_k is the frequency, φ_k is the phase of the kth space vector, $w(t)$ is white noise, and P is known as the MUSIC order. The sinusoid amplitude and frequency are not random and unknown. The phases of the sinusoids are uncorrelated random variables, uniformly distributed over the interval [-π, π].

The power spectrum of $x(t)$ consists of a set of P impulses of area $2\pi|A_k|$ at frequencies f_k for k = 1, 2, ..., P, plus the power spectrum of the additive noise $w(t)$. Based on the orthogonality of the signal and noise subspaces, the MUSIC pseudospectrum P_{MUSIC} of the current signal is given by the following frequency estimation function:

$$P_{MUSIC}(f)=\frac{1}{\sum_{i=P+1}^{M}\left|\bar{e}_1^H\bar{v}_1\right|^2} \quad (4)$$

where $\overline{v_i}$ is the noise eigenvector and $\overline{e_i}^H$ is the signal vector defined as $\overline{e_i}^H(f_i)=[1,e^{-j2\pi f_i},\ldots,e^{-j2\pi f_i(M-1)}]$. Expression (4) shows a maximum when, for a certain f_k that is truly present in the signal, the signal and noise subspaces projections are zero.

In conclusion, the MUSIC method is a tool that extracts meaningful frequencies from the signal with an enhanced resolution. Moreover, thanks to the MUSIC results and processing, it is possible to apply simple ANN for fault classification. Due to this, the combination between MUSIC and a FFNN is the option selected as a basis of the proposed automatic algorithm.

The complete scheme of the method proposed in this paper is shown in Fig. 2. As it is shown there, the process starts with the capture of the stray flux signals under starting at each sensor position. Subsequently, the corresponding MUSIC analyses are performed by applying a short-time MUSIC algorithm, in which each of the stray flux signals is subdivided and processed into rectangular sliding windows with a length size of 4096 data points and an overlapping of 75%, thus obtaining a time-frequency representation in high-resolution of the harmonic evolution amplified by the studied faults. This approach allows to retrieve information related to time, which is not provided by the MUSIC pseudo-spectrum itself. Besides, as pointed out in [39], this short-time MUSIC analysis provides more regular surfaces, mitigates the effects of noise, and evidences only larger frequency components making it a useful tool for the analysis of noisy signals with time-shifting frequencies. Then, the proposed automatic algorithm starts with the normalization of the MUSIC maps and their division into different representative frequency regions. Different features (statistical and non-statistical) will be extracted from each region of interest. These features will serve to build an input matrix that will be used to train the ANN which will be in charge of the automatic decision process. This will be a FFNN with three hidden layers. This process will be described with further detail in Section VI.

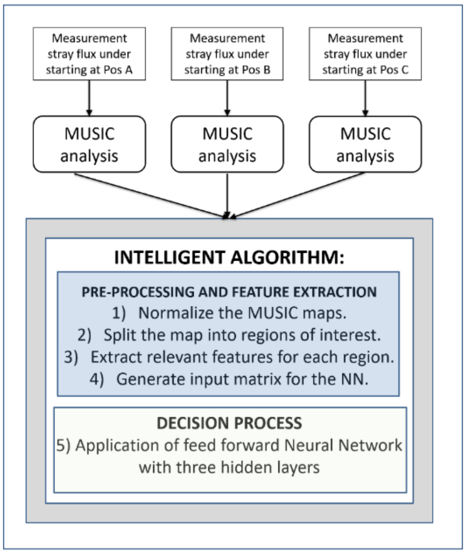

Fig. 2 Scheme of the proposed intelligent algorithm

IV. EXPERIMENTS

Different tests were developed in the laboratory using a 1.1 kW cage motor with 2 pole pairs (motor 1). The motor was driving a D.C. generator that enabled to change the load level (see Fig. 3). A coil sensor with 1000 turns (see geometric characteristics in Fig.4) was attached at different positions of the motor frame. The three considered positions of the sensor were those depicted in Fig.1 (pos. A, pos B and pos C). Motors with different levels of rotor damage were tested (healthy motor, one broken bar and two broken bars). Since the motor was not properly aligned with the driven load, a certain level of misalignment was unavoidable although, as proven in recent works [31], this has a relatively minor effect on the stray flux signals. In each test, the emf signal induced in the external coil sensor was registered both under starting and during 30 seconds of the subsequent steady-state regime using a YOKOGAWA DL-850 oscilloscope. A sampling rate of 5 kHz was used for the acquisition of the signals. The captured signals were later transferred to a computer where they were subsequently analyzed in Matlab.

On the other hand, additional tests were performed in a larger cage induction motor (motor 2), which was analogue to those used in real industrial applications (see Fig. 5). The exact condition of this motor was unknown a priori, so that it was useful to validate if the application of the stray-flux based methodology worked well when diagnosing its health. The main characteristics of this motor were: rated power=7.5 kW, rated voltage=380 V, rated current=15.2 A, rated speed= 1435 rpm, number of pole pairs=2.

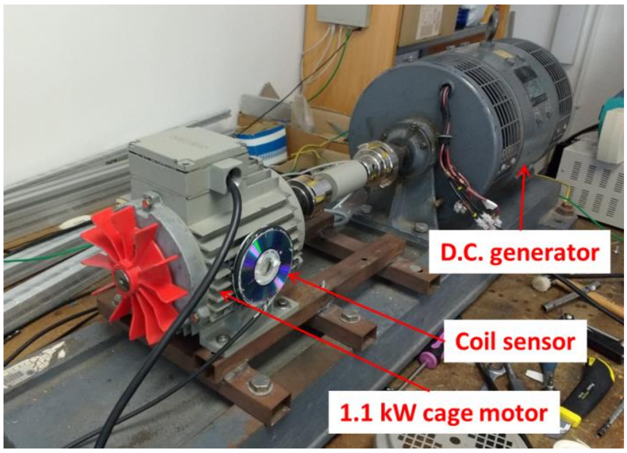

Fig. 3 Laboratory test bench (motor 1)

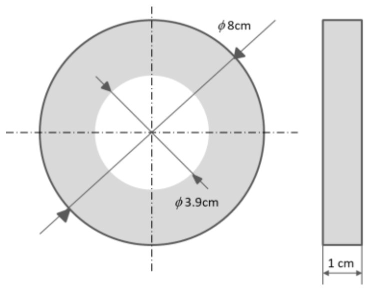

Fig. 4. Dimensions of the coil sensor.

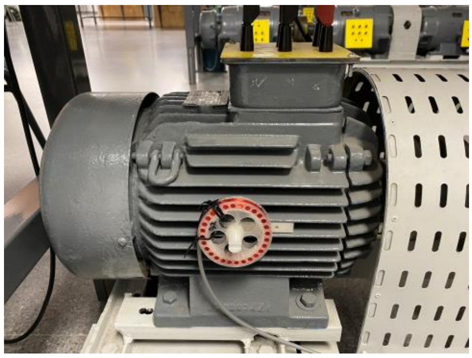
Fig. 5 Second tested motor (motor 2): 7.5 kW, 2 pole pairs

V. MUSIC RESULTS AND DISCUSSION

Figure 6 shows the MUSIC analyses of the emf signal captured under starting at the three sensor positions (Pos. A, Pos B. and Pos. C) and for the three considered conditions of motor 1, namely: healthy motor, motor with one broken bar and motor with two broken bars. At every fault level (even at healthy), the motor had a certain misalignment versus the driven load.

First of all, note that, when the machine is in healthy condition, only slight traces of the evolutions of two components are detected at every sensor position: the component $f\text{-}f_r$ and $s{\cdot}f$. The first of these components is caused by the existence of the misalignment between the motor and driven load that yields certain amplitude of this harmonic. In recent works [31], it was proven that the existence of misalignment has much lower repercussion in the stray flux signals (compared to the effects on the starting current signal) but, even so, certain traces of this component are detectable. On the other hand, the component $s{\cdot}f$ presents a small amplitude; its presence is attributed to the existence of a certain level of inherent rotor asymmetry and eccentricity even in healthy conditions. This component is clearly noticeable at Pos. A, in which the axial flux is predominantly captured.

The effect of rotor damages (broken rotor bars) is clearly detectable through the amplification of different components in the time-frequency maps:

- On the one hand, note that the axial component at $s{\cdot}f$ is amplified at every sensor position when the rotor fault is present. The amplification is especially evident at Pos. A and Pos. B, which are the positions in which a higher portion of axial flux is captured. Note that, as reported by some authors [36], this component, alone, is not sufficient to be used as a rotor fault indicator, since it is also amplified by other failures (e.g. eccentricities) or

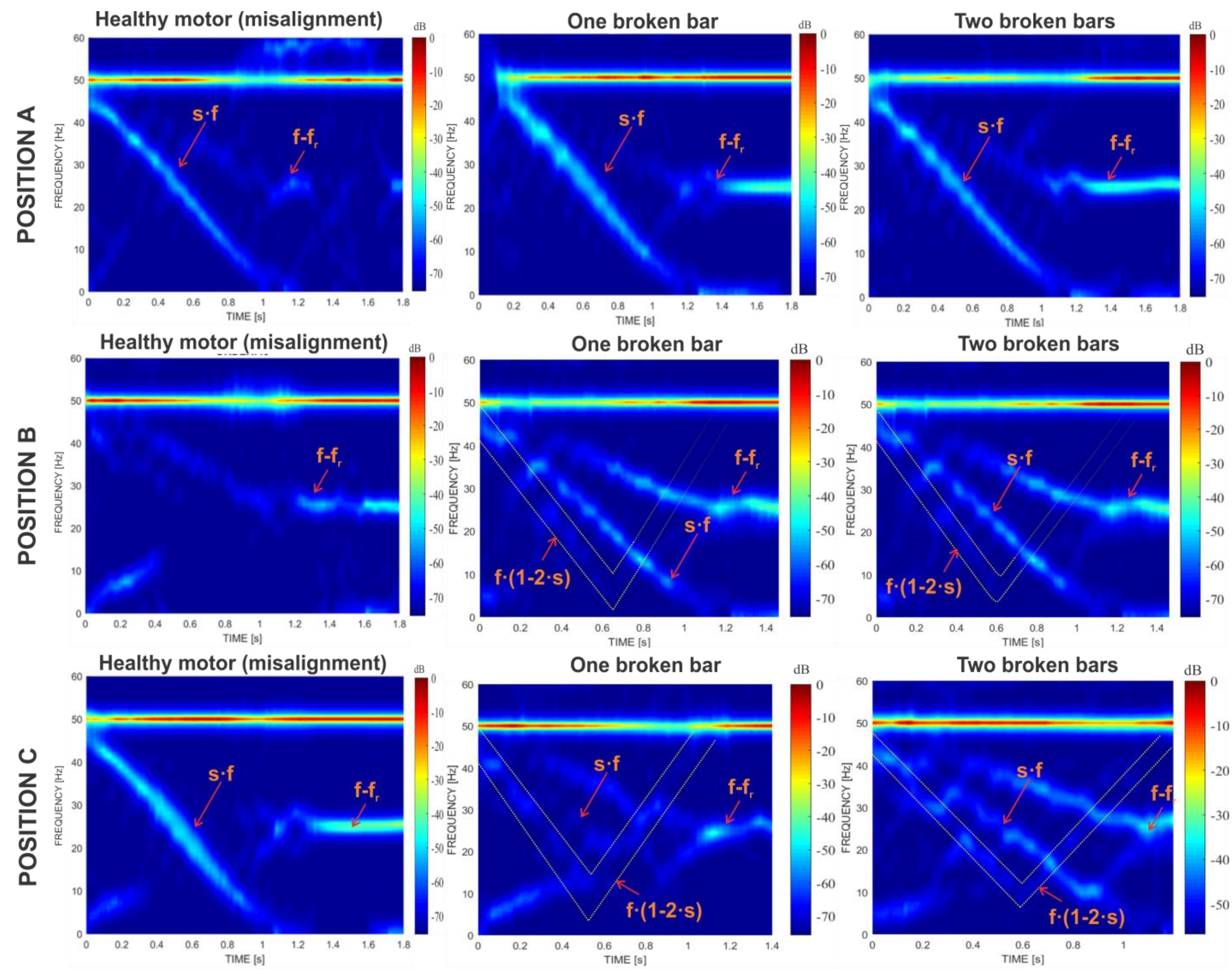

Fig. 6. MUSIC analyses of the emf signals under starting of motor 1 for the sensor at positions A, B and C and for the different fault conditions, namely healthy motor (with inherent misalignment), motor with one broken bar and motor with two broken bars.

effects. However, its amplitude increment is a first evidence of the presence of the failure.

- On the other hand, the component at f-f_r is also clearly amplified when the fault is present. This occurs at all sensor positions. Furthermore, this increment is more evident when the level of failure gets worse (compare one and two broken bars). The increase in the amplitude of this component (and therefore, of its signature in the time-frequency map) is in concordance with the recent conclusions reached by other authors [38]. This increment in its amplitude is a second evidence of the presence of the rotor failure.
- Finally, the evolution component at $f\cdot(1\text{-}2\cdot s)$ is also discernible in the MUSIC results. The characteristic V-pattern caused by the evolution of this component is more evident at those sensor positions capturing a higher portion of radial flux (Pos B. and Pos. C). This pattern has been emphasized in the graph. The detection of such pattern is not so clear at pos B, due to the rich harmonic content of the frequency region below the fundamental in which different harmonics evolve under starting (e.g. f-f_r and $s\cdot f$) – note that at this position the sensor captures not only the radial flux but also the axial, so many components are contained in the captured signal.

In any case, note that the MUSIC analyses of the starting emf signals are very useful for the diagnosis, presenting two very interesting advantages in comparison with other approaches: 1) the diagnosis of the fault relies on the evolutions of multiple fault harmonics (e.g. $s\cdot f$, f-f_r and $f\cdot(1\text{-}2\cdot s)$)and not only on a single one, a fact that confers a high reliability in the diagnosis and 2) the harmonic content in the stray flux data analyses under starting is much richer than that of the analysis of the starting current, in which fewer fault harmonics are visualized. This also confers a higher potential to the technique, compared to other alternatives.

In order to validate the generality of the methodology, it was applied to a different motor (motor 2), which was larger than motor 1 and had different constructive characteristics. Initially, its condition was uncertain so the idea was to apply the methodology and verify if it correctly diagnoses the condition of this motor. The results of the application of the MUSIC method to this motor are shown in Fig.7. Note that, at all sensor positions, the only discernible component was f-f_r. No traces of $f\cdot(1\text{-}2\cdot s)$ and only slight traces of $s\cdot f$ were detected. This was indicative of two facts: 1) there was no evidence of rotor damages in the motor (since the evolutions of $s\cdot f$ and $f\cdot(1\text{-}2\cdot s)$ were not observable) and 2) there were clear symptoms of eccentricities/misalignment in the machine (since f-f_r was present). These diagnostic conclusions provided by the method were proven to be valid later, after inspecting the machine; it was corroborated that the rotor was healthy and that a significant level of misalignment was present (measured through a dial gauge).

VI. AUTOMATIZATION OF THE FAULT DIAGNOSIS PROCESS

The idea behind the proposed method for enabling the automatic diagnostic of the rotor failure is to extract as much information as possible from the MUSIC analyses and, more specifically, from the frequency region below the fundamental since, in that region, most of the harmonics of interest evolve under starting. With this idea in mind, the intelligent algorithm has been built. This is based on the following steps (see Fig. 2):

1) Obtain the time-frequency maps by applying the MUSIC approach to the stray flux signals under starting.
2) Normalize the obtained map by dividing by the maximum value (fundamental component).
3) Split the map into regions of interest. In this work, four regions below the fundamental frequency have been considered: region 1 (~ [0-11] Hz), region 2 (~ [11-22] Hz), region 3 ((~ [22-33] Hz) and region 4 (~ [33-44] Hz). These are depicted in Fig. 8.
4) Obtain statistical and non-statistical parameters to characterize the regions (frequency bands). The following thirteen parameters have been considered:

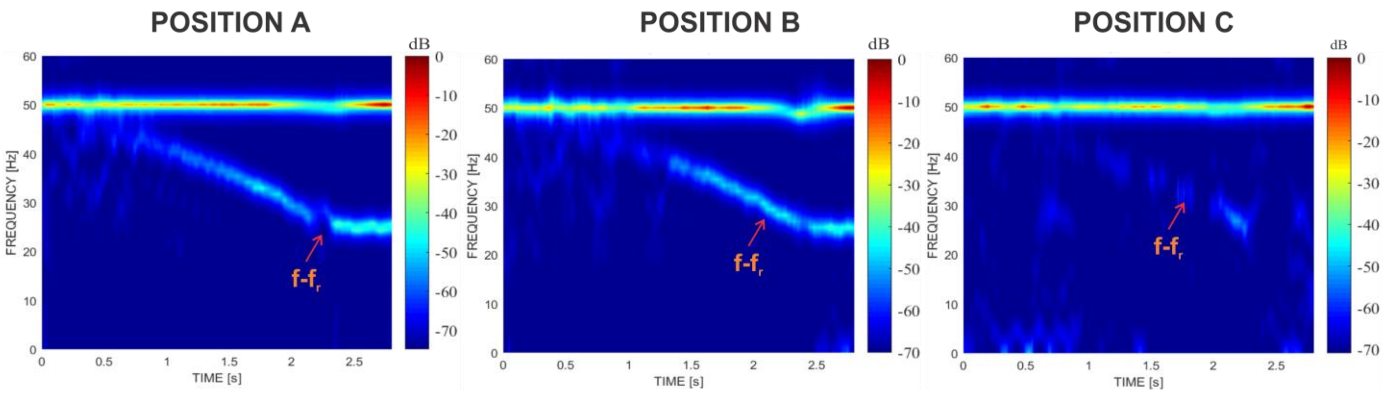

Fig. 7. MUSIC analyses of the emf signals under starting of motor 2 for the sensor at positions A, B and C.

(1) *Non-Normalized Wavelet Entropy*, (2) *Shanon Entropy*, (3) *Signal Energy*, (4) *Standard Deviation*, (5) *Mean*, (6) *Median*, (7) *Kurtosis*, (8) *Skewness*, (9) *RMS*, (10) *RSSQ*, (11) *Peak-to-average ratio*, (12) *Shape Factor* and (13) *Crest Factor*.

5) Generate the input matrix for the training of the NN: the most representative parameters of the analyses are selected for each of the four considered regions (frequency bands). Table II shows an example of four considered parameters for the case of the motor started under two different fault conditions (sensor at Pos. B).

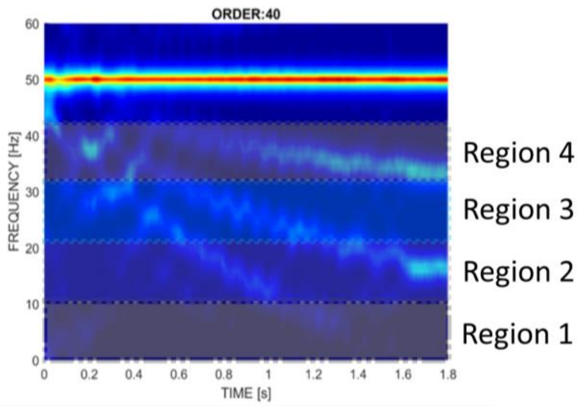

Fig. 8. Regions considered in the MUSIC maps

TABLE II. VALUES OF THE MOST REPRESENTATIVE STATISTICAL PARAMETERS AT EACH FREQUENCY REGION FOR TWO DIFFERENT FAULT CONDITIONS AND FOR THE SENSOR AT POS. B

HEALTHY MOTOR				
Region	**Std deviation**	**Mean**	**Skewness**	**RMS**
1	0.005	0.0022	3.858	0.0024
2	0.0076	0.0024	4.8551	0.0089
3	0.0058	0.0026	3.2846	0.0076
4	0.0036	0.0036	3.2385	0.0058
MOTOR WITH ONE BROKEN BAR				
Region	**Std deviation**	**Mean**	**Skewness**	**RMS**
1	1.320e-05	0.00011	3.846	0.000117
2	0.0024	0.000123	7.7093	0.00248
3	0.0015	0.000135	4.8940	0.00161
4	0.0012	0.000143	6.4825	0.00129

Fig. 9 illustrates the results of applying the described procedure to the stray flux data captured under starting for a specific sensor position (pos. B) and for the different fault conditions. This figure shows the value of the aforementioned statistical and non-statistical indicators (1 to 13), which are the inputs of the FFNN after being computed for the four time-frequency regions under interest. A simple observation of this figure reveals that most of these MUSIC-based indicators show higher values when the fault severity is greater.

These parameters are the inputs of the proposed ANN which is based on a FFNN with three hidden layers (10, 6 and 4 neurons in each hidden layer). In order to train the FFNN, the resilient backpropagation algorithm is used for identifying a healthy condition in the induction motor or the presence of broken rotor bars. For this, 38 real sampled signals are employed under each motor condition, resulting in a total of 114 samples. Out of the 38 tests obtained for each case study, 19 were used to train the FFNN and 19 to validate it. The inputs to the FFNN correspond to the 13 statistical and non-statistical parameters drawn from the MUSIC time-frequency maps and the targets used for training are the three study cases (healthy motor, one broken rotor bar and two broken rotor bars). After training and validation, the final weights and biases of each layer neuron are used for implementation of the proposed automatic diagnosis. The FFNN showed a success rate of 100% for the cases of healthy machine and machine with one broken bar and a percentage of 84.2% for the case of two broken bars. Note that in this latter situation, cases of two non-adjacent broken bars were considered together with cases in which the broken bars were adjacent. The occurrence of the fault at non-adjacent positions has been proven to cause problems in the determination of the level of failure] [40]. In spite of this, the obtained success rate was very satisfactory for that case.

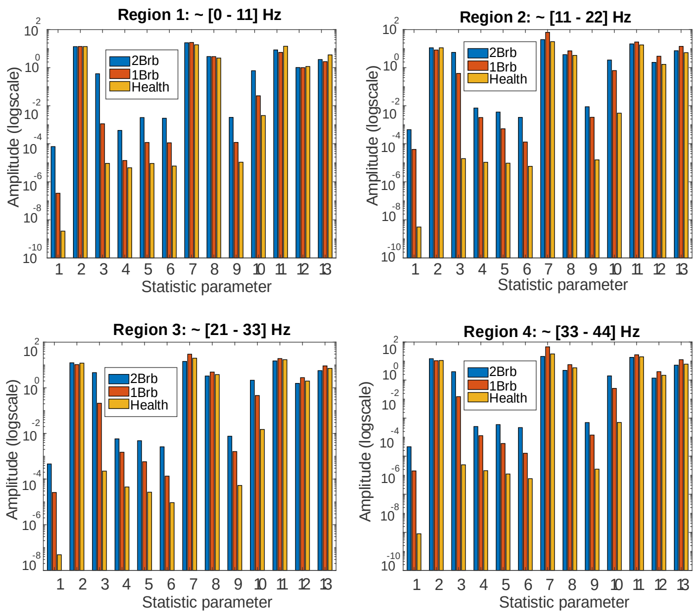

Fig. 9. Computation of statistical and non-statistical parameters (inputs of the artificial neural network) for the different regions of the MUSIC analyses of stray flux data under different fault conditions (sensor position B).

VII. CONCLUSIONS

The present paper has proposed an intelligent algorithm for the automatic detection of electromechanical faults in induction motors, which relies on the analysis of the emf force induced in an external coil sensor under starting. The proposed algorithm is based on the combined application of MUSIC methods, which enable the enhanced visualization of fault components and a FFNN which enables the automatic identification of the patterns caused by the fault components under starting.

The presented method has been applied to detect different levels of rotor failure, but it has also shown potential to detect the presence of misalignments between the motor and driven load (through the amplification of the component at f-f_r).

The results show that, depending on the considered position of the coil sensor, components of different nature (axial or radial) are induced; this depends upon whether in the considered position a larger portion of axial or radial flux is captured. Hence, the corresponding MUSIC analyses of the emf signals contain different information depending on the position. However, since the developed system is based on combining the information obtained at all sensor positions, the diagnosis is more reliable since, for the diagnosis of a single fault (e.g. rotor faults), the evolutions of multiple components are considered.

In conclusion, the method presented in this work has certain differences as well as important advantages versus other works presented in previous literature, namely:

- On the one hand, the proposed method is based on the detection of patterns in the MUSIC analyses of transient stray flux signals. The detection of the 'patterns' or 'signatures' followed by fault components during transient operation proves to be a reliable way to detect many faults, providing important advantages versus classical methods based on the evaluation of fault-related frequencies in the FFT analyses of stationary signals. This is due to the fact that these characteristic patterns are very unlikely caused by other phenomena that are not a fault, whereas a frequency component in the FFT spectrum can be amplified by the fault but also by other effects related to the machine operation (load fluctuations…) or constructive characteristics (rotor cooling ducts). Due to these facts, conventional methods based on stationary analysis can easily lead to false indications (positive or negative) when diagnosing the condition of the machine.
- Second, the short-time MUSIC analysis used in this paper allows to retain the outstanding characteristics of the pseudo-spectrum MUSIC which mitigates the effects of noise and evidences only larger frequency components with the advantage of also recovering information in the time-domain.
- Third, unlike other works, the paper proposes the use of the stray-flux as a basic quantity for the diagnosis. The harmonic content in the stray flux signals is much richer than that of other quantities (such as currents). As a consequence, the diagnosis of the fault is not only based on the identification of the evolution of a single component under starting but of multiple components (e.g. $s \cdot f$, $f \cdot (1\text{-}2 \cdot s)$, f-f_r…), a fact that confers a much higher reliability for the diagnosis.
- Finally, as far as the authors know, it is the first time in the literature that an automatic method based on stray-flux analysis under transient for induction motor condition monitoring is proposed. Unlike other works, the presented method does not require the intervention of an expert user to identify the fault patterns in the stray-flux signals and reach a diagnosis conclusion. The intelligent method developed in the work is able to identify itself the evolutions of multiple fault related components in the MUSIC results and reach a direct conclusion on the health of the machine.

The success rates for the determination of the level of failure, achieved by the developed system, confirm its potential for its future incorporation in autonomous diagnosis systems that enable to determine the health of the motor based on the analysis of stray flux signals.

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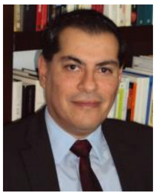

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