T. A. Garcia-Calva, D. Morinigo-Sotelo and R. de Jesus Romero Troncoso, "Fundamental Frequency Normalization for Reliable Detection of Rotor and Load Defects in VSD-Fed Induction Motors," in IEEE Transactions on Energy Conversion, vol. 37, no. 2, pp. 1467-1474, June 2022, doi: 10.1109/TEC.2021.3124803.

Fundamental Frequency Normalization for Reliable Detection of Rotor and Load Defects in ASD-fed Induction Motors

T. A. Garcia-Calva, *Student Member, IEEE*, D. Morinigo-Sotelo, *Member, IEEE*, and R. de J. Romero-Troncoso, *Senior Member, IEEE*

***Abstract*-- Rotor fault is a condition that may occur in induction motors due to high forces and stress on rotor bars or end rings. When this occurs, the machine may lead to a forced outage in production lines. Several methods have been proposed in the literature for the detection of rotor faults, however, they cannot work under variable frequency conditions, and are very sensitive to mechanical load oscillation. This paper presents a novel frequency normalization methodology for reliable rotor fault diagnosis in variable frequency drives fed systems. The normalization is implemented by demodulating with a time-variant factor the stator current signal. As a result, the fundamental component of the stator current is normalized in a constant frequency value, while avoiding spectral leakage and frequency smearing. This enables the transient stator current signature analysis to accurately locate targeted fault signatures. The effectiveness of the proposed adaptive modulation approach was demonstrated by analyzing the stator current of motors under non-stationary conditions. Experimental results showed that the proposed methodology can detect and distinguish between load oscillation and rotor fault signatures for avoiding false rotor fault alarms.**

***Index Terms*-- condition monitoring, fault diagnosis, frequency modulation, induction motors, inverters, time-frequency, transient analysis, load unbalance, spectral analysis.**

NOMENCLATURE

Δf	Frequency resolution.
ASD	Adjustable speed drive
f_b	Rated frequency.
f_e	Supply frequency.
f_{ecc}	Eccentricity frequency.
FrFT	Fractional Fourier transform
f_{rf}	Rotor fault frequency.
f_s	Sampling frequency.
k	Order of the time harmonic.
p	Number of pole pairs.
s	Slip.
STMN	Short-time minimum norm.
sf_e	Rotor frequency.
(t,f)	Time-frequency.

I. INTRODUCTION

INDUCTION motors (IM) are so common in industry that in many manufacturing facilities no other type of rotatory machines can be found. This is due to the simple structure, high efficiency, and easy maintenance of IM. Despite their robust nature, induction motors fail due to electric and mechanical failures. The presence of anomalies, defects, or faults increases the losses and reduces the efficiency of the machine. Rotor faults degrade the machine's performance and can cause additional damage in its structure that can lead to a forced outage of the motor and production lines [1]-[2].

There are a huge number of papers on condition monitoring and fault detection based on the study of IM in steady-state operation. Most of them extract time-domain [3]-[4] or frequency-domain features [5]-[7] for the fault diagnosis. Recently, transient motor current signature analysis (TMCSA) has become popular because the classical and established approaches, which analyze the steady-state, are no longer deemed reliable to detect rotor faults [8]-[9]. The mean reason behind the TMCSA trend is that time-frequency (t,f) analysis can identify the frequency signal trajectories, reveal their origin, and monitor their behavior along the time, which has been an effective tool for avoiding false diagnostics due to the existence of rotor cooling axial ducts, blade pass vibrational frequencies or torque oscillations due to load defects [10]-[13].

Various TMCSA methods have been proposed and applied to IM for fault detection, considering a direct online starting [14]-[15]. However, in recent years, adjustable-speed drives (ASD) with IM have increasing popularity in industrial practices because their installation allows significant energy savings in the motor and actually reduces the total current in the system. Although the usage of ADS improves machine efficiency, condition monitoring and fault detection in ASD-fed IM systems entail challenges due to the facts that current harmonics caused by the ASD introduce interference in the stator current signal, fundamental component of the supply and fault frequency patterns are closely space in the (t,f) plane. Furthermore, the fundamental component and all its harmonics

---

This work was supported in part by the Mexican Council of Science and Technology (CONACYT) by the scholarship 487058, México City, México.

T. A. Garcia-Calva is with the Electronic Engineering Department, University of Guanajuato, GTO 36700 MX (e-mail: ta.garciacalva@ugto.mx).

D. Morinigo-Sotelo is with the Electrical Engineering Department, University of Valladolid, Valladolid VLL 47002 ES (e-mail: daniel.morinigo@eii.uva.es).

R. de J. Romero-Troncoso is with the Mechatronics Engineering Department, Autonomous University of Querétaro, San Juan del Río, QRO 76806 MX (e-mail: troncoso@hspdigital.org).

have a time-varying frequency, which adds further complications to the fault detection techniques due to the uncertainty principle in the time-frequency analysis [16], which leads to a trade-off between time resolution and frequency resolution.

Tracking fault signatures in variable frequency systems can be considered an important technical problem because the time-variable components introduce several fundamental drawbacks in the stator current analysis. To address this issue, some methods have been proposed for the analysis of time-varying signals, these methods include the use of advanced time-frequency transforms [17]-[18], harmonic multi-resolution transforms [19], Hilbert-Huang analysis [20], empirical mode decompositions, and combinations of these methods [21]-[22]. Recent developments have paid attention to improve the time-frequency localization information. In [23] the fractional Fourier transform (FrFT) is proposed to generate a spectrum where the fault signatures appear as a single spectral line. The action of the FrFT on the time-frequency coordinates results in a rotation by an arbitrary angle. The methodology has the ability to represent a non-stationary component as a Dirac's delta in the frequency domain, but this transform is limited to linear chirp signals. In [24]-[25] a re-scaling method based on speed information is applied to maps the 3D information of time-frequency representations into simple 2D graphs, similar to a Fourier spectrum. In [26]-[29] resampling algorithms are used to expand and compress the time-domain signal, which converts non-stationary (*t,f*) components to constant values when IM operates in transient regime, however, they suffer from signal length reduction and interpolation errors.

This paper presents a novel adaptive demodulation of the stator current for rotor and load defects detection in VSI-fed induction motors. The time-varying demodulation performs a frequency normalization of the non-stationary fundamental component, which is mapped into a constant frequency value. The proposed methodology enables a clear detection of rotor fault signatures at startup transients by reducing the spectral leakage and maximizing the stationarity of the fundamental component. The results show that the time-frequency analysis of the demodulated stator current provides reliable information not only for rotor fault detection but also for load defects detection. Experimental testing on an ASD-fed IM under different starting scenarios is given to validate the proposed methodology.

II. THEORETICAL BACKGROUND

A. VSI-fed Induction Motor Current Spectral Content

The stator current of an ASD-fed IM can be expressed as:

$$i_a = i_e + i_v + i_{ecc}\,, \tag{1}$$

where i_e is the current produced by the fundamental supply component and its harmonics, i_v is the harmonic content produced by the ASD, and i_{ecc} is current induced by spectral harmonics due to eccentricity of the rotor. According to modulation theory, the time-varying fundamental supply frequency and its harmonics can be modeled as:

$$i_e = \sum_{k=1}^{\infty} I_k \cos\left(\theta(t)\right), \tag{2}$$

where k is an integer, the argument of the cosine function is the phase angle and can be expressed as:

$$\theta(t) = \omega_b t + 2\pi k_f \int_0^t m_x(\tau)d\tau\,, \tag{3}$$

where ω_b is the rated angular frequency of the IM, k_f is a frequency deviation constant, and m_x the modulating function [30]. The harmonic content injected by the ASD can be written as [31]-[32]:

$$i_v = \sum_{n=6v\pm1}^{\infty} I_n(t)\cos\left(n\theta(t)\right), \tag{4}$$

where v is the VSI harmonic order. In any electric motor exist a certain level of mixed eccentricity, under this condition current is induced as frequency sidebands [33]-[34], which can be seen around the supply frequency given as:

$$i_{ecc} = \sum_{q=1}^{\infty} I_q(t)\cos\left(2\pi f_e\left(1 \pm q\left(\frac{1-s}{p}\right)\right)t\right), \tag{5}$$

where f_e is the supply fundamental frequency, q=1,2,3,… is the order of eccentricity harmonics, p is the number of IM pole pairs, and s is the motor slip.

The detection of rotor cage faults can be done by monitoring the presence of the $2sf_e$ sidebands of f_e given by:

$$f_{rf} = f_e(1 \pm k_1 2s)\,, \tag{6}$$

where k_1 is an integer [35]. A typical variable frequency drive composed of switches $S_{1\ldots6}$, and a 6-pulse diode rectifier feeding an induction motor is shown in Fig. 1.

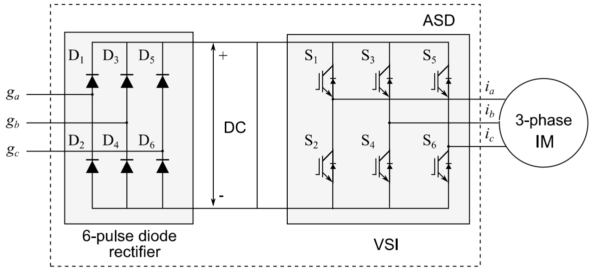


Fig. 1. PWM inverter-fed induction motor system schematic.

Fig. 2 presents the theoretical time-varying spectral content of the stator current given by (1), as well as the trajectories of the fault-related signatures given by (6). The theoretical *t-f* representations show the spectral content for 2 different starting profiles of f_e, linear FM (Fig. 2.a) and nonlinear FM (Fig. 2.b). The representations depict the frequency evolution of the signatures produced by an ASD at $|f_e(6v\pm1)|$, eccentricity harmonics at $|f_{ecc}{}^q|$, and the harmonics induced by a rotor fault at $|\,f_{rf}^{k_1}\,|$.

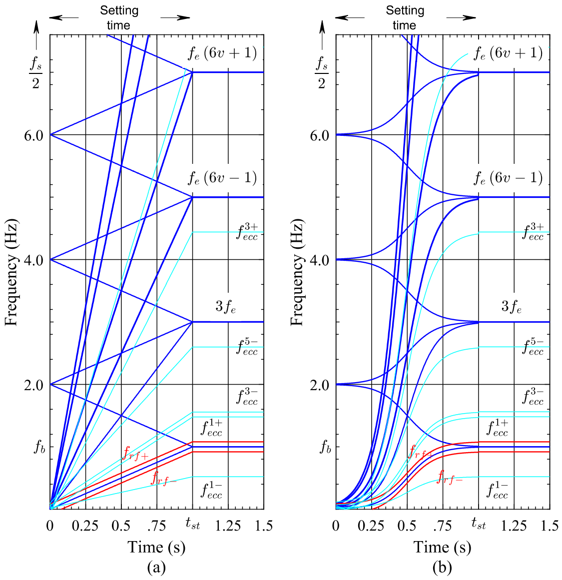


Fig. 2. Theoretical spectral content of the stator current in an inverter-fed induction motor. (a) Linear startup transient, and (b) Non-linear startup transient.

B. Minimum Norm Spectral Estimation

The minimum Norm (Min-Norm) is a high-resolution spectral estimation technique based on subspace decomposition. The multi-component stator current signal of an ASD-fed IM can be modeled as:

$$s(l) = \sum_{k=1}^{K} v(\psi_k) z_k(l) + \eta(l)\ , \tag{7}$$

where the signal is a superposition of K components, $k \in \Re$, $v(\psi_k)$ is the discrete complex frequencies vector, and η is white Gaussian noise with zero mean and variance σ^2. The power spectral density of $s(t)$ is given by:

$$PSD_{MN}(\psi) = \frac{1}{\left| v^H(\psi)\psi^2 \right|}\ , \tag{8}$$

where ψ_k belongs to the sample noise subspace, its first element is equal to 1 and it has minimum norm. The Min-norm espectral estimation technique reduces spurious frequencies and anomalies compared with other subspace methods [36].

III. FUNDAMENTAL FREQUENCY NORMALIZATION

The proposed fundamental frequency normalization is composed essentially of 5 signal processing stages as shown in Fig. 3.

First, the sampling frequency of the measured stator current signal is changed to an f_s such that $f_s/f_b = 2^n$ using a sample rate converter, by changing the original sampling frequency with an adequate rate L/M [37], it is possible to place f_b at an exact multiple of the digital frequency resolution and therefore minimize the undesired effects of spectral leakage.

Second, the resampled current signal is passed through a half-band pass filter to yield an output $i_r(t)$ with spectrum **Re**$[i_a(e^{j\omega})]$, imaginary part of the original spectrum is rejected by the filter to avoid introduce imaginary spectral components during the subsequent time-frequency analysis.

At the phase calculation stage, the Hilbert transform is used to create an analytical function from the stator current signal:

$$z_i(t) = i_a(t) + j(\mathbf{H}i_a)(t)\ , \tag{9}$$

from $z_i(t)$ it is possible to compute an instantaneous phase $\varphi_i(t)$ of $i_a(t)$ by $arg|z_i(\mathrm{t})|$ and an instantaneous (angular) frequency $\omega(t)$ can be obtained by

$$\omega_i(t) = \frac{d}{dt}\arg\left|z_i(t)\right|. \tag{10}$$

Once the instantaneous phase is computed, in the demodulation stage, the stator current i_r is multiplied by a complex signal $m(t) = e^{j\omega_m t}$, the result is a frequency shifting in the spectrum according to the Fourier property:

$$\int_{-\infty}^{\infty} e^{j\omega_m t} x(t) e^{-j\omega t} = \int_{-\infty}^{\infty} x(t) e^{-j(\omega-\omega_m)t}\ , \tag{11}$$

for the spectrum $X(e^{-j(\omega-\omega_m)t})$ to remain within the analysis frequency bandwidth analysis we should have $\omega+\omega_m <= 2\pi$ or $\omega_m \leq 2\pi-\omega$.

Finally, a time-frequency decomposition is performed by means of the Min-Norm algorithm, the short-time analysis utilizes a sliding window to segment the signal and extracts the frequency components of the demodulated signal $i_a{}^m$.

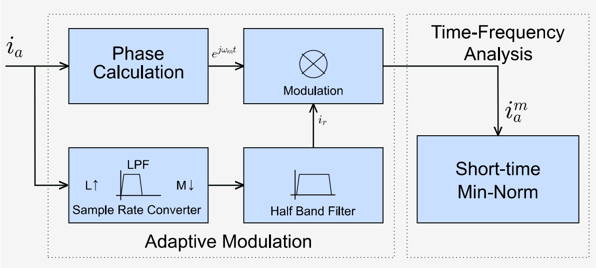


Fig. 3. Simplified block diagram of the proposed methodology.

From a perspective of a time-frequency representation, the proposed methodology corresponds to a time-varying frequency shifting of the spectrum $i_a(e^{j\omega})$ by an $f_m(t)$ function (as shown in Fig. 4).

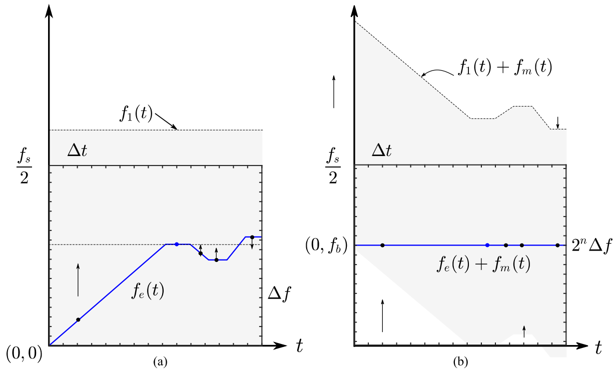
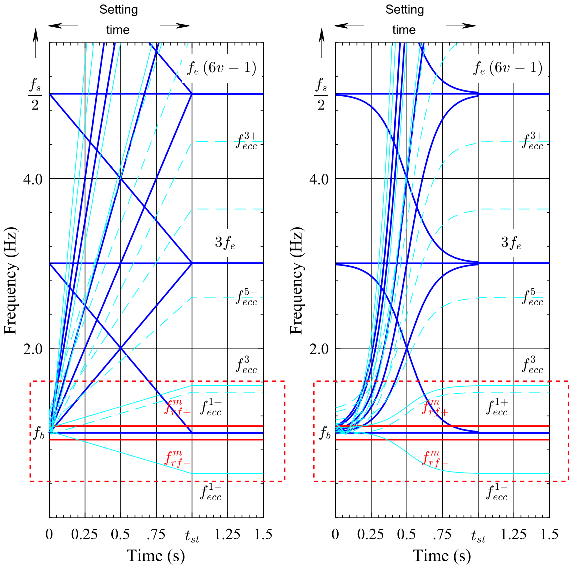


Fig. 4. Proposed frequency normalization by adaptive modulation.

The algorithm presented here maps the fundamental component f_e to a constant frequency value f_b by selecting the angular frequency of the demodulation function $\omega_m = \omega_b - \omega_i$. Fig. 5 shows the theoretical time-varying spectral content of the demodulated stator current. As a result of the frequency shifting, each point of the original spectra (t_x, f_x) in Fig. 2 is mapped to the point (t_x, $f_x + f_m$) in Fig. 5.



(a) (b)

Fig. 5. Theoretical spectral content of the demodulated stator current in an inverter-fed induction motor. (a) Linear startup transient, and (b) Non-linear startup transient.

IV. TEST BENCH

The experimental system consists of a commercial digital waveform generator, a powder brake, a PWM motor drive, a 1-Hp induction motor, a NI data acquisition board, and a personal computer. Two induction motors are evaluated, one with a normal rotor and one with a damaged rotor bar. The rotor bar damage is created by drilling a hole in a rotor bar. A picture of the experimental testbench is illustrated in Fig. 6.

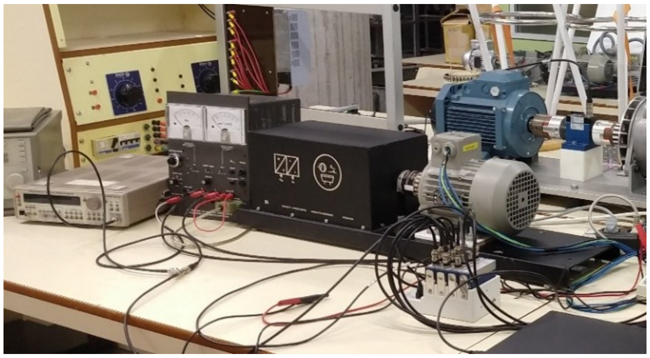


Fig. 6. Experimental set up.

The parameters of the motor are presented in Table I.

TABLE I
Induction Motor Parameters

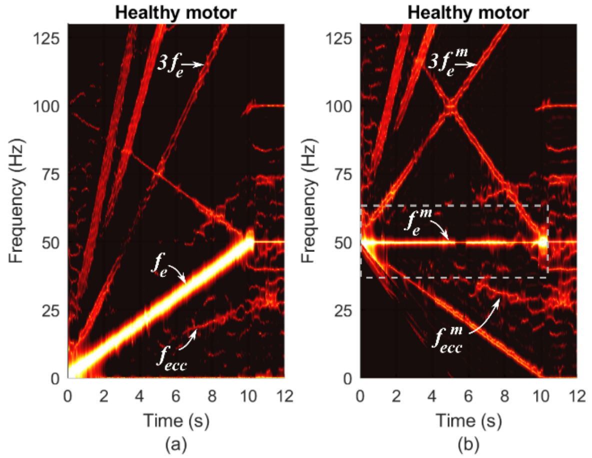
Rated power	hp	1
Rated voltage	V	230/460
Rated current	A	2.9/1.4
Rated frequency	Hz	60
Rated speed	r.p.m.	3355
Efficiency	%	75.5
Power factor	p.u.	0.87
Rated torque	Nm	2.1

V. EXPERIMENTAL RESULTS

To verify the practical feasibility and performance of the proposed methodology, three cases of study are considered: linear FM startups, nonlinear FM startups, and transients under periodic load oscillations. Startup transient analysis of the original stator current signal and the demodulated signal are presented for comparison purposes. In all cases, *t-f* analyses have been performed by the STMN algorithm with a window of 256 samples, time step of 8 samples, and a low-frequency band analysis [0 Hz, 125 Hz].

A. Linear Startup Transient

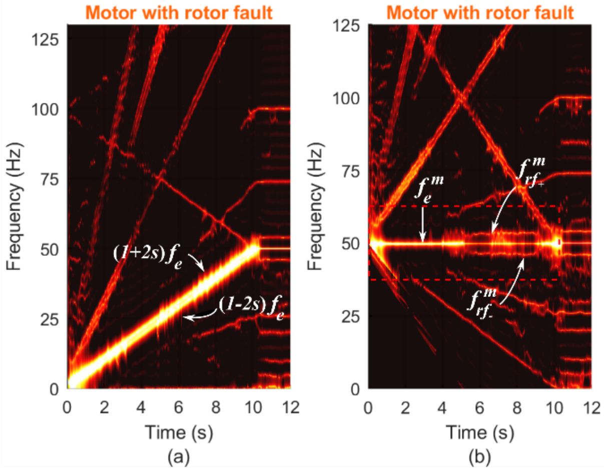
Linear FM profile is the most common scheme of startup transient for inverter-driven induction motors. This is the simplest scheme of an ASD where the fundamental frequency of the stator current is varied proportionally with the time. Fig. 7 displays stator current analyses in the *t-f* domain for the healthy induction motor. The *t-f* decomposition of the original stator current is presented in Fig. 7.a. It can be observed that the fundamental component f_e is the strongest mode of the current signal, and follows the instantaneous frequency law $f_e(t)=5t$. The stator current also includes significant energy contribution from time harmonics of f_e and space harmonics generated by the stator winding, as predicted by (5). Although there is not damage in the rotor, after the startup transient a side-harmonic is present below f_e. This spectral component migh leads to a false positive diagnostic in a classical TMCSA becouse the signature is located at the same zone that the fault-related component $|(1-2s)f_e|$. The result of the proposed method (for the same test that Fig. 7a.) is shown in Fig. 7.b, it is easy to see that all the *t-f* trajectories are shifted in frequency (with a displaced function f_m) by the adaptive demodulation. As a result, the frequency of the fundamental mode is normalized and the linear FM is mapped to a constant frequency value f_b=50 Hz, thus avoiding spectral leakage and smearing in frequency. The PM permits to examine the vecinity of f_e when motor is under startup transient, the analysis reveals the absence of fault-related trajectories $|(1\pm 2s)f_e|$ close to f_e in the stator current.



(a) (b)

Fig. 7. STMN analyses of the stator current signal during a linear startup transient: (a) original signal-healthy motor, (b) proposed technique-healthy motor.

Time-frequency decompositions of the starting current when motor is under fault condition are shown in Fig. 8. As it can be seen from Fig. 8.a, even though the high-resolution technique is performed for the short-time analysis instead of the classic STFT, fault-related trajectories cannot be tracked in the startup transient because they evolve very close to f_e and the uncertainty relation between time and frequency puts a limit on the trajectory's localization. The application of the proposed fundamental frequency normalization is shown in Fig 8.b. As it can be observed, the time-frequency decomposition of the demodulated current clearly shows the existence of the fault-related signatures and its behavior in the vicinity of the fundamental component. This result correctly reflects the existence of a damage in the rotor.

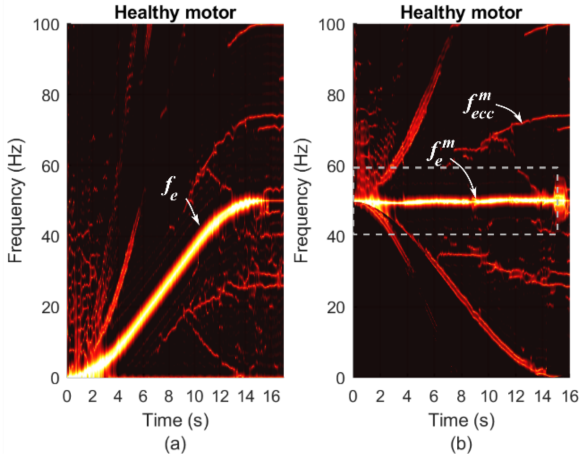


(a) (b)

Fig. 8. STMN analyses of the stator current signal during a linear startup: (a) original signal-motor with rotor fault, and (b) proposed technique- motor with rotor fault.

B. Non-linear Startup Transient

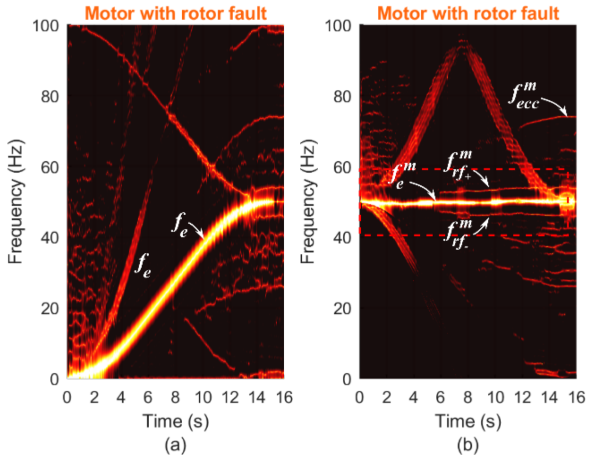
Experimental results of startup transients with S-curve FM profile are given in Fig. 9 and Fig. 10 for healthy and motor with rotor fault, respectively. This FM profile is commonly used inverter-fed IM systems to reduce abrupt acceleration changes and thereby smooth out the motion. Fig. 9.a presents the *t-f* analysis of the original current. It can be observed that f_e follows a nonlinear law when the motor is started. On the other hand, the result of applying the STMN to the demodulated current is presented in Fig. 9.b. The spectral content of i_a^m is now similar to the result presented in Fig. 7.b, where f_e^m.is a signature with constant frequency.



(a) (b)

Fig. 9. STMN analyses of the stator current signal during a nonlinear startup: (a) original signal-healthy motor, (b) proposed technique-healthy motor.

The *t-f* decomposition of the original current (i_a) for the IM under fault condition is exposed in Fig. 10.a. Important to note that both the healthy and the faulty cases (Fig.9.a and Fig. 10.a, respectively) have a quite similar spectral trajectories. It is therefore difficult, to correctly diagnose the condition of the machine from a normal t-f analysis of the starting current. In contrast, the time-frequency content of the demodulated current reveals the fault-related trajectories, which are induced by the asymmetry in the rotor because of the fault (see Fig. 10.b). This result together with the model prediction given by (1) and the fault-related trajectories (10).



(a) (b)

Fig. 10. STMN analyses of the demodulated stator current signal during a nonlinear startup: (a) original signal-healthy motor, (b) proposed technique-healthy motor.

C. Transients Under Load oscillations

Induction motor under mechanical load oscillations is a challenging condition for diagnostic techniques. This condition often leads to false positives or false negatives of rotor fault due to the inter-harmonics produced by the load fluctuations.

Experimental result of the PM for a healthy motor under a periodic load oscillation of f_o=4 Hz is given in Fig. 11. This time, the startup transient has a duration of 5 seconds to validate the PM effectiveness under short startup transients. The *t-f* decomposition of the demodulated stator current contains the normalized fundamental mode f_e^m, which can be see along the 50 Hz line. Unlike the rotor fault cases, the spectral signatures generated by the load oscillation ($f_{lo-}$and f_{lo+}) hold in every time a constant distance to f_e^m because this separation is independent of the f_e. Fig. 11.a and Fig.12.a show the instantaneous speed of the motor.

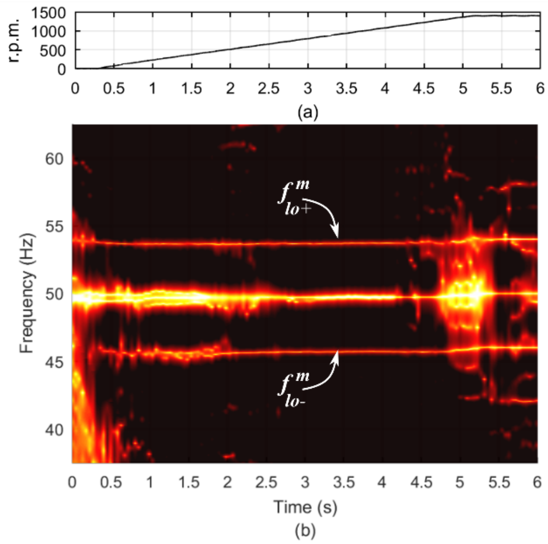


Fig. 11. Healthy induction motor with load oscillation (a) speed, and (b) STMN analysis of the demodulated stator current.

In Fig. 12, the PM allows to detect not only the load oscillation signatures and the normalized mode f_e^m, but also the fault-signatures (f_{rf-} and f_{rf-}) produced by the rotor damage. The fault-related trajectories evolve away from f_e^m as time increase, and its maximum separation is reached at the end of the transient, when the supply frequency f_e has maximum value.

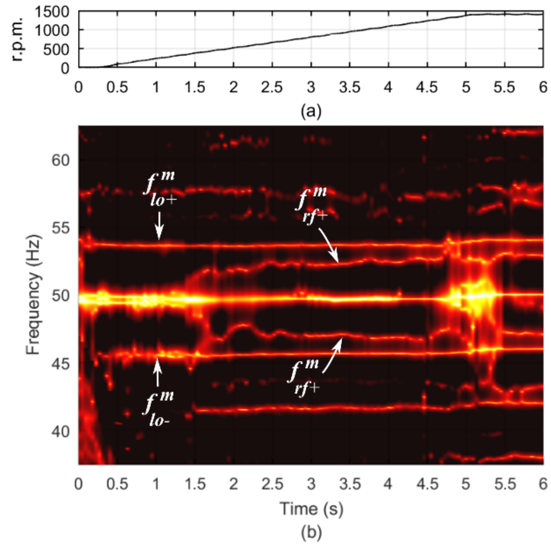


Fig. 12. Faulty induction motor with load oscillation (a) speed, and (b) STMN analysis of the demodulated stator current.

All the experimental results demonstrate the capability of the proposed strategy not only to detect rotor faults and load oscilations but also to avoid false positives or false negatives of rotor fault.

VI. CONCLUSION

An adaptive demodulation technique has been presented in this paper for the fundamental frequency normalization of the stator current in inverter-driven induction motors. The technique improves the detectability of fault-related harmonics and increases the reliability of the startup transient analysis. The proposed methodology is able to distinguish between a rotor fault-related signature and harmonics generated by load oscillations. Experimental results demonstrated the suitability of the proposed methodology. Although the algorithm presented here focus on maps the fundamental component into a constant frequency value. The proposed methodology could be implemented with any other arbitrary time-varying demodulation function to maps the time-frequency plane in a convenient way for a different application.

VII. REFERENCES

[1] M. Garcia, P. A. Panagiotou, J. A. Antonino-Daviu and K. N. Gyftakis, "Efficiency Assessment of Induction Motors Operating Under Different Faulty Conditions," *IEEE Trans. Ind. Electron.*, vol. 66, no. 10, pp. 8072-8081, Oct. 2019.

[2] J. Shin, Y. Park and S. B. Lee, "Flux-Based Detection and Classification of Induction Motor Eccentricity, Rotor Cage, and Load Defects," *IEEE Trans. Ind. Appl.*, vol. 57, no. 3, pp. 2471-2480, May./Jun. 2021.

[3] L. Frosini, C. Harlişca and L. Szabó, "Induction Machine Bearing Fault Detection by Means of Statistical Processing of the Stray Flux Measurement," *IEEE Trans. Ind. Electron.*, vol. 62, no. 3, pp. 1846-1854, Mar. 2015.

[4] G. H. Bazan, P. R. Scalassara, W. Endo, A. Goedtel, R. H. C. Palácios and W. F. Godoy, "Stator Short-Circuit Diagnosis in Induction Motors Using Mutual Information and Intelligent Systems," *IEEE Trans. Ind. Electron.*, vol. 66, no. 4, pp. 3237-3246, Apr. 2019.

[5] J. E. Garcia-Bracamonte, J. M. Ramirez-Cortes, J. de Jesus Rangel-Magdaleno, P. Gomez-Gil, H. Peregrina-Barreto and V. Alarcon-Aquino, "An Approach on MCSA-Based Fault Detection Using Independent Component Analysis and Neural Networks," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 5, pp. 1353-1361, May. 2019.

[6] R. Razavi-Far et al., "Information Fusion and Semi-Supervised Deep Learning Scheme for Diagnosing Gear Faults in Induction Machine Systems," *IEEE Trans. Ind. Electron.*, vol. 66, no. 8, pp. 6331-6342, Aug. 2019.

[7] A. Naha, A. K. Samanta, A. Routray and A. K. Deb, "Low Complexity Motor Current Signature Analysis Using Sub-Nyquist Strategy With Reduced Data Length," *IEEE Trans. Instrum. Meas.*, vol. 66, no. 12, pp. 3249-3259, Dec. 2017.

[8] H. Henao et al., "Trends in Fault Diagnosis for Electrical Machines: A Review of Diagnostic Techniques," *IEEE Ind. Electon. Mag.*, vol. 8, no. 2, pp. 31-42, Jun. 2014.

[9] K. N. Gyftakis, D. V. Spyropoulos and E. Mitronikas, "Advanced Detection of Rotor Electrical Faults in Induction Motors at Start-up," *IEEE Trans. Energy Convers.*, doi: 10.1109/TEC.2020.3025786.

[10] Z. Gao, C. Cecati and S. X. Ding, "A Survey of Fault Diagnosis and Fault-Tolerant Techniques—Part I: Fault Diagnosis With Model-Based and Signal-Based Approaches," *IEEE Trans. Ind. Electron*, vol. 62, no. 6, pp. 3757-3767, Jun. 2015.

[11] B. Trajin, J. Regnier and J. Faucher, "Comparison Between Stator Current and Estimated Mechanical Speed for the Detection of Bearing Wear in Asynchronous Drives," *IEEE Trans. Ind. Electron.*, vol. 56, no. 11, pp. 4700-4709, Nov. 2009.

[12] Y. Park, M. Jeong, S. B. Lee, J. A. Antonino-Daviu and M. Teska, "Influence of Blade Pass Frequency Vibrations on MCSA-Based Rotor

Fault Detection of Induction Motors," *IEEE Trans. Ind. Appl.*, vol. 53, no. 3, pp. 2049-2058, May./Jun. 2017.

[13] Y. Park et al., "Stray Flux Monitoring for Reliable Detection of Rotor Faults Under the Influence of Rotor Axial Air Ducts," *IEEE Trans. Ind. Electron.*, vol. 66, no. 10, pp. 7561-7570, Oct. 2019.

[14] J. Antonino-Daviu, "Electrical Monitoring under Transient Conditions: A New Paradigm in Electric Motors Predictive Maintenance, " *Appl. Sci.*, vol. 10, pp. 6137. Sept. 2020

[15] S. B. Lee et al., "Condition Monitoring of Industrial Electric Machines: State of the Art and Future Challenges," *IEEE Ind. Electon. Mag.*, vol. 14, no. 4, pp. 158-167, Dec. 2020.

[16] J. Pons-Llinares, M. Riera-Guasp, J. A. Antonino-Daviu and T. G. Habetler, "Pursuing optimal electric machines transient diagnosis: The adaptive slope transform", *Mech. Syst. Signal Process.*, vol. 80, pp. 553-569, Dec. 2016.

[17] J. Pons-Llinares, J. A. Antonino-Daviu, M. Riera-Guasp, S. Bin Lee, T. Kang and C. Yang, "Advanced Induction Motor Rotor Fault Diagnosis Via Continuous and Discrete Time–Frequency Tools," *IEEE Trans. Ind. Electron.*, vol. 62, no. 3, pp. 1791-1802, Mar. 2015.

[18] V. Fernandez-Cavero, J. Pons-Llinares, O. Duque-Perez and D. Morinigo-Sotelo, "Detection of broken rotor bars in non-linear startups of inverter-fed induction motors," *IEEE Trans. Ind. Appl.* doi: 10.1109/TIA.2021.3066317.

[19] M. A. Hmida and A. Braham, "Fault Detection of VFD-Fed Induction Motor Under Transient Conditions Using Harmonic Wavelet Transform," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 10, pp. 8207-8215, Oct. 2020.

[20] E. T. Esfahani, S. Wang and V. Sundararajan, "Multisensor Wireless System for Eccentricity and Bearing Fault Detection in Induction Motors," *IEEE/ASME Transactions on Mechatronics*, vol. 19, no. 3, pp. 818-826, Jun. 2014.

[21] T. A. Garcia-Calva, D. Morinigo-Sotelo, A. Garcia-Perez, D. Camarena-Martinez and R. de Jesus Romero-Troncoso, "Demodulation Technique for Broken Rotor Bar Detection in Inverter-Fed Induction Motor Under Non-Stationary Conditions," *IEEE Trans. Energy Convers.*, vol. 34, no. 3, pp. 1496-1503, Sept. 2019.

[22] Frosini, L. "Novel Diagnostic Techniques for Rotating Electrical Machines—A Review". *Energies*, vol 13, pp. 5066, Sept. 2020.

[23] M. Pineda-Sanchez, M. Riera-Guasp, J. A. Antonino-Daviu, J. Roger-Folch, J. Perez-Cruz and R. Puche-Panadero, "Diagnosis of Induction Motor Faults in the Fractional Fourier Domain," *IEEE Trans. Instrum. Meas.*, vol. 59, no. 8, pp. 2065-2075, Aug. 2010.

[24] A. Sapena-Bano, J. Burriel-Valencia, M. Pineda-Sanchez, R. Puche-Panadero and M. Riera-Guasp, "The Harmonic Order Tracking Analysis Method for the Fault Diagnosis in Induction Motors Under Time-Varying Conditions," *IEEE Trans. Energy Convers.*, vol. 32, no. 1, pp. 244-256, Mar. 2017.

[25] A. Sapena-Baño et al., "Harmonic Order Tracking Analysis: A Novel Method for Fault Diagnosis in Induction Machines," *IEEE Trans. Energy Convers.*, vol. 30, no. 3, pp. 833-841, Sept. 2015.

[26] T. A. Garcia-Calva, D. Morinigo-Sotelo and R. de Jesus Romero-Troncoso, "Non-Uniform Time Resampling for Diagnosing Broken Rotor Bars in Inverter-Fed Induction Motors," *IEEE Trans. Ind. Electron.*, vol. 64, no. 3, pp. 2306-2315, Mar. 2017.

[27] S. Lu, Y. Qin, J. Hang, B. Zhang and Q. Wang, "Adaptively Estimating Rotation Speed From DC Motor Current Ripple for Order Tracking and Fault Diagnosis," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 3, pp. 741-753, Mar. 2019.

[28] P. M. De La Barrera, M. Otero, T. Schallschmidt, G. Bossio and R. Leidhold, "Active broken rotor bars diagnosis in induction motor drives," *IEEE Trans. Ind. Electron.*, doi: 10.1109/TIE.2020.3007108.

[29] D. Lu, W. Qiao and X. Gong, "Current-Based Gear Fault Detection for Wind Turbine Gearboxes," *IEEE Trans. Sustainable Energy*, vol. 8, no. 4, pp. 1453-1462, Oct. 2017.

[30] J. G. Proakis and M. Salehi “Fundamentals of Communication Systems,” 2nd ed., New Jersey: Prentice Hall, 2014, pp. 161–164.

[31] G. W. Chang and S. K. Chen, "An analytical approach for characterizing harmonic and interharmonic currents generated by VSI-fed adjustable speed drives," *IEEE Trans. Power Del.*, vol. 20, no. 4, pp. 2585-2593, Oct. 2005.

[32] S. V. Giannoutsos and S. N. Manias “A Systematic Power-Quality Assessment and Harmonic Filter Design Methodology for Variable-Frequency Drive Application in Marine Vessels,” *IEEE Trans. Ind. Appl.,* vol. 51, no. 2, pp. 1909–1919, Abbrev. Mar./Apr. 2015.

[33] X. Song, Z. Wang, S. Li and J. Hu, "Sensorless Speed Estimation of an Inverter-Fed Induction Motor Using the Supply-Side Current," *IEEE Trans. Energy Convers.*, vol. 34, no. 3, pp. 1432-1441, Sept. 2019.

[34] R. S. C. Pal and A. R. Mohanty, "A Simplified Dynamical Model of Mixed Eccentricity Fault in a Three-Phase Induction Motor," *IEEE Trans. Ind. Electron.*, vol. 68, no. 5, pp. 4341-4350, May. 2021.

[35] K. N. Gyftakis, P. A. Panagiotou and S. B. Lee, "Generation of Mechanical Frequency Related Harmonics in the Stray Flux Spectra of Induction Motors Suffering From Rotor Electrical Faults," *IEEE Trans. Ind. Appl.*, vol. 56, no. 5, pp. 4796-4803, Sept./Oct. 2020.

[36] T. A. Garcia-Calva, D. Morinigo-Sotelo, O. Duque-Perez, A. Garcia-Perez, and R. de J. Romero-Troncoso, " Time-Frequency Analysis Based on Minimum Norm Spectral Estimation to Detect Induction Motor Faults," *Energies*, vol. 13, Aug. 2020.

[37] R. de Jesus Romero-Troncoso, "Multirate Signal Processing to Improve FFT-Based Analysis for Detecting Faults in Induction Motors," *IEEE Trans. Ind. Informat.*, vol. 13, no. 3, pp. 1291-1300, Jun. 2017.

VIII. BIOGRAPHIES

T. A. Garcia-Calva received the B.S. degree in 2014 and the M.E. (cum laude) degree in 2016 from the University of Guanajuato, México, where he is currently working toward the Ph.D. in electrical engineering. He was an intern with the Universidad de Valladolid (UVA), Spain, and with the Universitat Politècnica de València (UPV), Spain in 2016. His research interests include signal processing, spectral analysis, time-frequency distributions, and condition monitoring of electrical machines.

D. Morinigo-Sotelo (M’04) received the B.S.and Ph.D. degrees in electrical engineering from the University of Valladolid (UVA), Spain, in 1999 and 2006, respectively. He was a Research Collaborator on Electromagnetic Processing of Materials with the Light Alloys Division of CIDAUT Foundation since 2000 until 2015. He is currently with the Research Group on Analysis and Diagnostics of Electrical Grids and Installations (ADIRES), which belongs to the ITAP Institute (UVA), and with the HSPdigital Research Group, México. His current research interests include fault detection and diagnostics of induction machines, power quality, and smart grids.

R. de J. Romero-Troncoso (M’07–SM’12) received the Ph.D. degree in mechatronics from the Autonomous University of Queretaro, Queretaro, Mexico, in 2004. He is a National Researcher level 3 with the Mexican Council of Science and Technology, CONACYT. He is currently a Head Professor with the Autonomous University of Queretaro, Mexico. He has been an advisor for more than 200 theses, an author of two books on digital systems (in Spanish), and a coauthor of more than 130 technical papers published in international journals and conferences. His fields of interest include hardware signal processing and mechatronics. Dr. Romero–Troncoso was a recipient of the 2004 Asociación Mexicana de Directivos de la Investigación Aplicada y el Desarrollo Tecnológico Nacional Award on Innovation for his work in applied mechatronics, and the 2005 IEEE ReConFig Award for his work in digital systems. He is part of the editorial board of Hindawi’s International Journal of Manufacturing Engineering.