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Research Article

Enhancing Wind Turbine Generator Diagnostics via Wavelet Transform: A Multi-Algorithm Approach for Fault Detection

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ABSTRACT

This study presents an advanced diagnostic method for wind turbine generators based on the Wavelet Transform (WT), aimed at enhancing the accuracy of fault detection and localization.

By analyzing the stator and rotor currents, the method leverages WT's capacity to process nonstationary and transient signals, which is particularly effective for capturing dynamic anomalies in wind energy systems. Three distinct algorithms—Morlet, Gabor, and Wigner-Ville—were implemented to classify faults in both stator and rotor circuits. These approaches collectively form a robust framework suitable for real-time condition monitoring. The diagnostic method significantly improves early fault identification, minimizes operational downtime through precise localization, and enhances the reliability of wind energy generation systems. Moreover, it enables the optimization of maintenance strategies by facilitating the targeting of specific fault types. Experimental results confirm the effectiveness of WT in converting raw current data into diagnostically relevant insights, thereby contributing to the development of more efficient and resilient wind energy infrastructures.

Keywords: Wavelet Transform, Wind Turbine Diagnostics, Fault detection, Stator-Rotor Currents, Morlet Algorithm, Predictive Maintenance.

INTRODUCTION

OVER the past two decades, the demand for robust and intelligent diagnostic methodologies has surged, propelled by the growing complexity of modern systems and the imperative to improve their reliability, efficiency, and operational continuity—especially in the field of renewable energy generation [1-5]. Among these systems, wind turbines have emerged as pivotal components of sustainable energy infrastructure. Their continuous and optimal operation hinges on timely maintenance interventions and accurate, real-time fault detection mechanisms. Without such capabilities, unexpected failures can lead to costly downtimes, reduced energy output, and premature equipment degradation. Consequently, advanced monitoring strategies are essential to prevent generator faults, extend system lifespan, and optimize maintenance planning, all while minimizing operational costs [6-9].

In parallel with these technological needs, wavelet analysis has gained prominence as a powerful and versatile signal processing tool, offering significant advantages over traditional approaches such as Fourier analysis. While conventional methods primarily provide insights in the frequency domain, wavelet transforms deliver joint time-frequency representations, enabling the precise localization of transient, non-stationary phenomena within signals [6], [10-14]. This attribute is particularly beneficial for diagnosing electrical and mechanical faults in highly dynamic systems like wind turbine generators, where signal patterns often exhibit abrupt, unpredictable variations due to fluctuating environmental and operational conditions [15-19].

The global transition toward cleaner energy sources has further accelerated the development of innovative diagnostic and control technologies. In 2009 alone, renewable energy technologies—led by wind, solar, and hydroelectric power—added over 157,531 MW to global energy capacity, marking a 30% increase from the previous year [20-25]. As wind energy continues to account for a growing share of the global power mix, ensuring the stability and sustainability of this energy source depends heavily on the deployment of smart diagnostic tools capable of maintaining system integrity and supporting grid resilience.

DIAGNOSIS METHODOLOGIES

Monitoring wind turbines involves comprehensive, real-time analysis of their operational processes to ensure both performance optimization and system reliability. This is particularly crucial given the susceptibility of wind turbines to a wide array of mechanical and electrical faults. Figure 1 highlights the core components of a typical wind turbine that are subject to failure analysis, along with a statistical distribution of failures observed in Swedish wind power plants between 2000 and 2004 [13], [18]. The data clearly show that the majority of reported failures were linked to the electrical system, followed by sensor malfunctions and issues with the blades or pitch control mechanisms. These findings underscore the importance of deploying effective and targeted diagnostic techniques to monitor critical subsystems, thereby reducing unplanned downtime, maintenance costs, and the risk of catastrophic failure.

A broad spectrum of diagnostic techniques has been developed over the years, drawing on disciplines such as electrical engineering, signal processing, artificial intelligence, and mechanical diagnostics. Many of these methods, initially designed for induction motors—which share operational similarities with wind turbine generators—have been adapted and applied in the wind energy sector. Commonly used diagnostic approaches include:

- Electromagnetic field monitoring: Detects anomalies by analyzing electromagnetic emissions indicative of faults.
- Temperature measurement: Monitors thermal behavior to detect overheating or thermal stress in components.
- Infrared thermography: Uses infrared imaging to identify thermal irregularities and potential hotspots.
- Radio frequency (RF) emissions monitoring: Captures high-frequency signals related to partial discharges or insulation degradation.
- Noise and vibration analysis: Analyzes acoustic and vibrational patterns to diagnose mechanical imbalances or structural failures.
- Motor Current Signature Analysis (MCSA): Interprets electrical current waveforms to detect electrical and electromechanical defects.
- Model-based and AI-driven methods (e.g., neural networks): Utilize computational models and machine learning techniques for automated fault classification and predictive diagnostics.

Each of these techniques offers specific advantages and is typically optimized for detecting certain categories of faults. However, the increasing complexity of modern wind turbines, combined with the demand for high reliability and predictive maintenance, necessitates the development of more sophisticated and versatile diagnostic frameworks capable of identifying a range of fault types with high precision and adaptability.

In this study, we propose a diagnostic approach centered on the spectral analysis of electrical current signals and their time-frequency representation. By employing the wavelet transform, which excels at capturing transient and non-stationary signal features, the methodology aims to detect and classify faults in the electrical components of wind turbine generators. This advanced signal processing technique enhances diagnostic accuracy, enabling early fault detection and supporting condition-based maintenance strategies. Ultimately, the proposed framework contributes to increased system uptime, operational efficiency, and the long-term sustainability of wind energy infrastructure.

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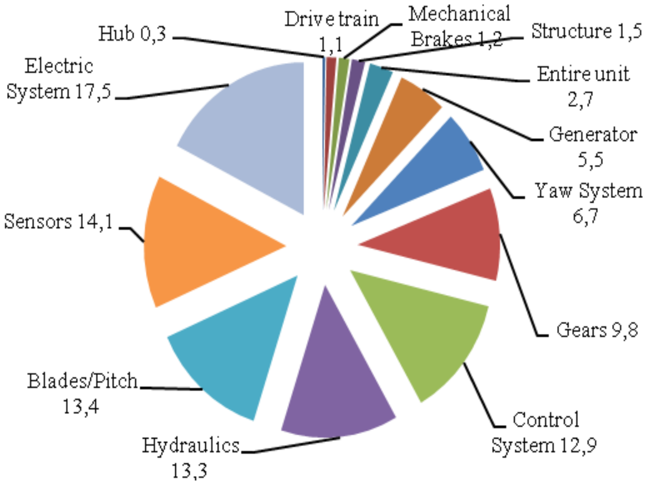

Fig.1. Failures number distribution [%] for Swedish wind power plants

DOUBLY FED INDUCTION MACHINE MODELLING

The doubly-fed induction generator (DFIG) shares operational similarities with conventional wound-rotor induction machines, but differs fundamentally in its treatment of rotor voltages. While following the same basic modeling principles as standard induction machines, the DFIG model incorporates non-zero rotor voltages - a critical feature that accounts for the active power control applied to the rotor circuit [1], [16], [18], [26-32]. This distinctive characteristic enables advanced control capabilities in wind energy applications. The machine's dynamic behavior is most effectively represented in the synchronous rotating d-q reference frame, yielding the following mathematical formulation:

$$\begin{aligned} V_{ds} &= R_s I_{ds} + \frac{dj_{ds}}{dt} - \dot{\theta}_s \phi_{qs} \\ V_{qs} &= R_s I_{qs} + \frac{dj_{qs}}{dt} + \dot{\theta}_s \phi_{ds} \\ V_{dr} &= R_r I_{dr} + \frac{dj_{dr}}{dt} - \dot{\theta}_r \phi_{qr} \end{aligned} \tag{1}$$

$$V_{qr} = R_r I_{qr} + \frac{d\phi_{qr}}{dt} + \dot{\theta}_r \phi_{dr} \tag{2}$$

$$\begin{aligned} \phi_{ds} &= L_s I_{ds} + M I_{dr} \\ \phi_{qs} &= L_s I_{qs} + M I_{qr} \\ \phi_{dr} &= L_r I_{dr} + M I_{ds} \end{aligned} \tag{3}$$

$$\phi_{qr} = L_r I_{qr} + M I_{qs} \tag{4}$$

$$g = \frac{\dot{\vartheta}_s - \dot{\vartheta}_r}{\dot{\vartheta}_s} \tag{5}$$

The expression of the torque is:

$$\Gamma_{elm} = p\, M/L_s \; (I_{qr}\, \phi_{ds} - I_{dr}\, \phi_{qs}) \tag{6}$$

Where:

V_{ds} , V_{qs} : d and q axes stator voltages.
ϕ_{ds} , ϕ_{qs} d and q axes stator fluxes.
I_ds, I_qs: d and q axes stator currents.
R_s, R_r: stator and rotor resistances.
L_s, M: : stator, rotor and mutual inductances.
$\dot{\vartheta}_r, \dot{\vartheta}_s$: stator and rotor speed.

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P: pole pairs.
L_s: electromagnetic torque.
g : slip speed.
By substituting the expressions for the fluxes, the system of equations (2) can be reformulated as follows

$$\begin{aligned} V_{ds} &= R_s I_{ds} + s(L_s I_{ds} + M I_{dr}) - \dot{\theta}_s (L_s I_{qs} + M I_{qr}) \\ V_{qs} &= R_s I_{qs} + s(L_s I_{qs} + M I_{qr}) + \dot{\theta}_s (L_s I_{ds} + M I_{dr}) \\ V_{dr} &= R_r I_{dr} + s(L_r I_{dr} + M I_{ds}) - \dot{\theta}_r (L_r I_{qr} + M I_{qs}) \\ V_{qr} &= R_r I_{qr} + s(L_r I_{qr} + M I_{qs}) + \dot{\theta}_r (L_r I_{dr} + M I_{ds}) \end{aligned} \tag{7}$$

By choosing state variables vector:

$$X = [I_{ds} \quad I_{qs} \quad I_{dr} \quad I_{qr}]^T \tag{8}$$

$$\dot{X} = AX + BU \tag{9}$$

Where state matrices A and B are:

$$[A] = \frac{1}{M^2 - L_r.L_s} \begin{bmatrix} -L_r.L_s & L_r.L_s\omega_s - \omega_r.M^2 & MR_r & ML_r g\dot{\theta}_s \\ \omega_r.M^2 - L_r.L_s\omega_s & -L_r.R_s & M(L_r\omega_r - \omega_s.L_r) & MR_r \\ R_s.M & -g\omega_s L_s.M & -L_s.R_r & L_s.\omega_r.L_r - \omega_s.M^2 \\ g\omega_s L_s.M & MR_s & \omega_s.M^2 - L_s.L_r.\omega_r & -L_s.R_r \end{bmatrix} \tag{10}$$

$$[B] = \frac{1}{M^2 - L_r.L_s} \begin{bmatrix} -L_r & 0 & M & 0 \\ 0 & -L_r & 0 & M \\ M & 0 & -L_s & 0 \\ 0 & M & 0 & -L_s \end{bmatrix} \tag{11}$$

As the matrix A varies with time or operating conditions, system (7) becomes inherently nonlinear. Consequently, traditional Fault Detection and Isolation (FDI) techniques must be adapted to account for this nonlinear behavior. To address this challenge, we propose an alternative approach based on wavelet transform analysis, which offers enhanced capabilities for detecting and isolating faults in nonlinear dynamic systems.

EXPERIMENTAL RESULTS

The experimental data used in this study were collected at the Automation Laboratory of the National Polytechnic School of Oran, Algeria. The experimental setup is carefully designed to emulate real-world operating conditions, providing a platform for the testing and validation of advanced diagnostic methods for electrical machines. At the heart of the test bench is a three-phase induction motor (Leroy Somer LS 132S), mechanically coupled to a powder brake. This configuration enables the simulation of various load profiles and mechanical stress conditions, thus offering a controlled environment for fault generation and analysis.

As shown in Fig. 2, the experimental system includes a data acquisition unit that continuously monitors and records essential electrical parameters. Specifically, the three-phase supply currents of the induction machine are captured in real time, serving as the primary input signals for diagnostic analysis using wavelet transforms and other signal processing techniques. The use of the Leroy Somer LS 132S—a robust, industry-standard motor known for its reliability—ensures that the experimental results are both meaningful and applicable to a wide range of practical scenarios.

The inclusion of a powder brake allows for precise manipulation of the mechanical load applied to the motor, making it possible to recreate typical fault conditions under controlled circumstances. By systematically varying the operational load and other parameters, the test bench generates a comprehensive dataset suitable for assessing the performance of fault detection, isolation, and classification techniques. This well-structured experimental framework highlights the importance of laboratory-based validation in the development of reliable, real-world-ready diagnostic systems aimed at improving the operational safety and efficiency of electrical machines.

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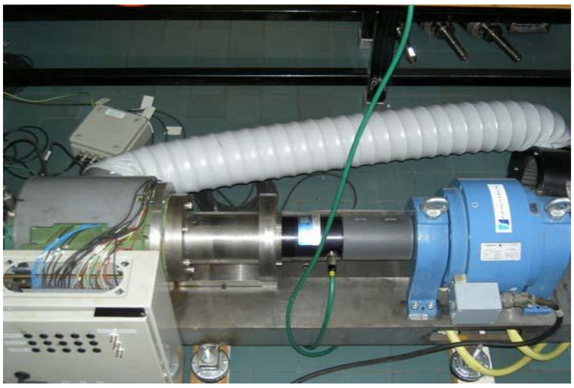

Fig. 1 Experimental benchmark

The acquisition duration is one second with a sampling rate of 10 KHz. In Fig. 3 and 4, we show the current stator without default and with default.

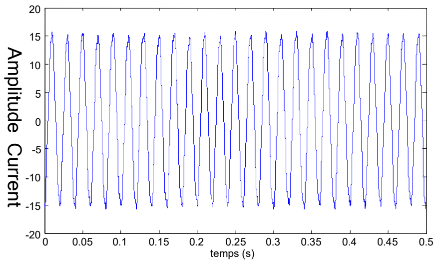

Fig. 3A. Asynchronous generator current without default

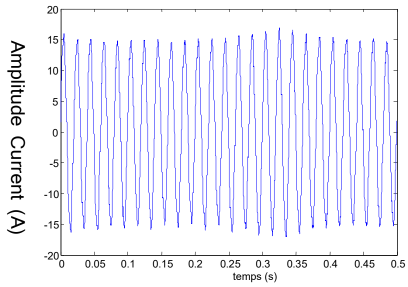

Fig. 3B. Asynchronous generator current without default

The most notable observation is that a time-domain representation alone is insufficient to distinguish between healthy and faulty generator conditions. This limitation necessitates a shift toward a time-frequency representation for more effective fault detection.

WAVELET TRANSFORM OF A CURRENT SIGNAL

All wavelet families are derived from a fundamental function known as the mother wavelet ψ. This function is characterized by having a zero mean, which is a key property for effective signal analysis

$$\int_{-\infty}^{-\infty} \psi(t)dt = 0 \tag{12}$$

This mother wavelet generates all other wavelets in the family through two key operations:

- Dilation: Controlled by scale parameter *a* (where a > 0)
- Translation: Determined by shift parameter *b*

The scaled and shifted wavelet is expressed as:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{13}$$

The wavelet transform analyzes a current signal $i(t)$ by decomposing it into different scales and translations. This is achieved by correlating the signal with a mother wavelet ψ, which is dilated by a scale parameter a and translated by a shift parameter b.

Mathematical Formulation

The continuous wavelet transforms (CWT) of a signal $i(t)$ such as a current signal, at a given scale a and position b, is obtained by correlating the signal with the scaled and translated version of the mother wavelet. This is expressed as:

$$TO[i(a,b)] = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} i(t)\psi^*\left(\frac{t-b}{a}\right)dt \tag{14}$$

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Where:

$i(t)$:	Current
$\psi(t)$	Mother wavelet A
a	called scale factor.
b	translation factors
$*$	operation of complex conjugate

1. **Haar Wavelet** (Discrete, orthogonal):

$$\Psi(t)=\begin{cases} 1 & if\ 0\leq t\leq \frac{1}{2} \\ -1 & if\ \ -\frac{1}{2}\leq t\leq 1 \\ 0 & else \end{cases} \tag{15}$$

2. **Morlet Wavelet** (Continuous, complex):

$$\psi(t)=e^{-\pi t^2}e^{\ 10i\pi t} \tag{16}$$

$$\int_{-\infty}^{-\infty}\psi(t)dt=0 \tag{17}$$

For practical implementations (with ωo ≥ 5), the simplified version is:

$$\psi_{a,b}(t)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{18}$$

I is a complex number: $I^2=-1$

These wavelet functions allow for detailed time-frequency analysis, capturing both high- and low-frequency components of the signal with varying resolutions, making them particularly effective for non-stationary signal processing such as fault detection in electrical machines.

4.1. Application of short Fourier transforms

In light of the well-documented limitations of the traditional Fourier transform in accurately detecting signal anomalies and failures—particularly in the context of non-stationary signals—we sought to investigate alternative signal processing techniques better suited for this task. As an initial step, we employed the Short-Time Fourier Transform (STFT), which offers a time-frequency domain representation of signals. This method was selected for its ability to analyze non-stationary signals by segmenting them into smaller time windows, thereby enabling the capture of localized spectral characteristics. By leveraging the STFT, our objective was to overcome the inherent drawbacks of the classical Fourier approach and to enhance the precision, relevance, and interpretability of failure detection in dynamic signal environments.

$$SFT(v,b)=\int_{-\infty}^{+\infty}I(t)\cdot g_{v,b}(t)dt \tag{19}$$

Where:

$SFT(v,b)$: à Short Fourier Transform

$g_{v,b}(t)$: is a time-frequency atoms

The application of the Short-Time Fourier Transform (STFT) enables the detection of the transition from a healthy condition to a faulty one, as evidenced in Figures 3A and 3B.

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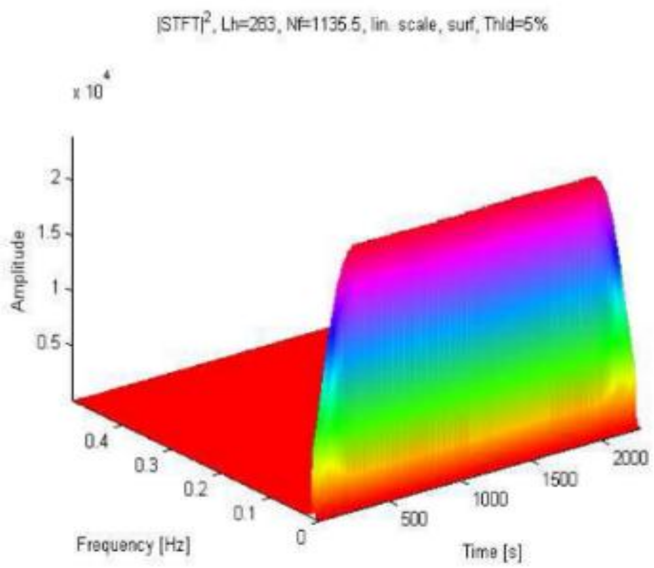

Fig. 4A. Short time Fourier transform of healthy machine current

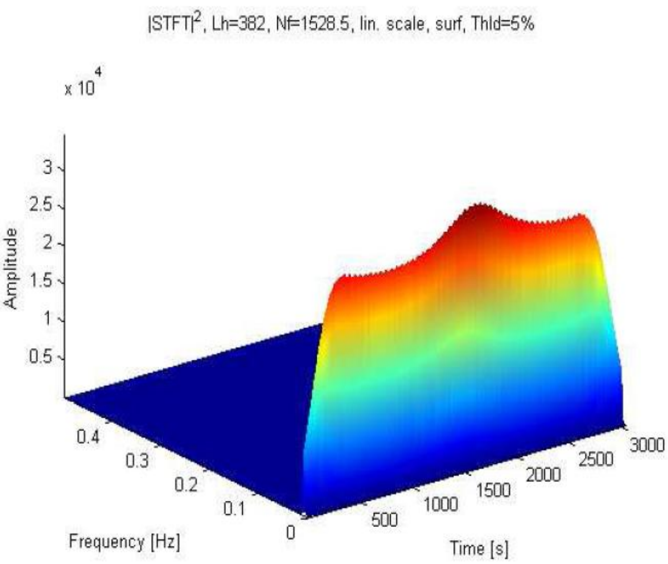

Fig. 4B. Short time Fourier transform of faulty machine current

By examining Figures 3A and 3B, it becomes clear that the presence of the defect is markedly more pronounced in Figure 3B. This enhanced amplification significantly improves the defect's visibility, making it easier to detect and interpret. The increased clarity not only facilitates more accurate diagnosis but also demonstrates the effectiveness of the applied method in isolating and emphasizing fault characteristics. This improvement underscores the method's value in enhancing diagnostic precision and supporting early failure detection.

APPLICATION OF GABOR AND MORLET TRANSFORMS

Wavelet analysis has emerged as a highly effective tool for the examination and reconstruction of complex signals, particularly those exhibiting non-stationary behavior. In our investigation, we initially applied the Gabor transform due to its well-established strength in analyzing highly non-stationary signals. Its ability to focus on localized frequency bands makes it especially suitable for identifying transient phenomena, as noted in studies [2], [4], and [6].

Both the Gabor and Morlet transforms demonstrated robust performance in detecting the characteristic frequency components associated with the defect, while also enabling a precise quantification of their amplitudes. This dual function—simultaneous detection and quantification—positions these transforms as powerful tools for fault diagnosis. Their application provides a detailed time-frequency representation that captures the subtle spectral variations introduced by the presence of defects, thereby improving signal interpretability and reliability of the analysis [7].

WIGNER-VILE DISTRIBUTION

The Wigner-Ville Distribution (WVD) is a high-resolution time-frequency representation particularly suited for the analysis of non-stationary signals encountered in diagnostic applications. By providing joint time and frequency information, the WVD enables precise localization of transient events and frequency shifts, which are critical for identifying system faults and degradations. Its application in fault diagnosis enhances the detection of subtle signal variations that may not be visible with conventional spectral methods, making it a valuable tool in predictive maintenance and condition monitoring.

$$Wi(t,i) = \int_{-\infty}^{+\infty} i(t+\frac{\tau}{2})i^{*}t-\frac{\tau}{2}) \cdot e^{(-jw\tau)}\,d\tau \tag{18}$$

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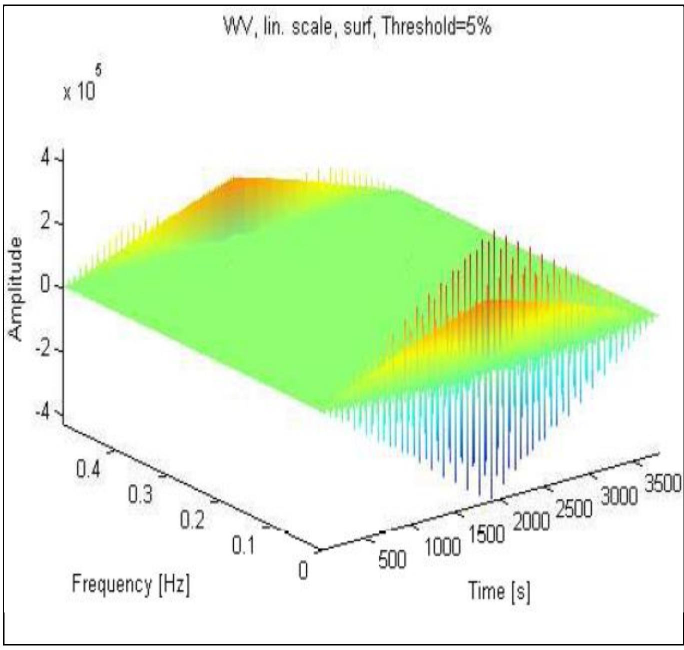


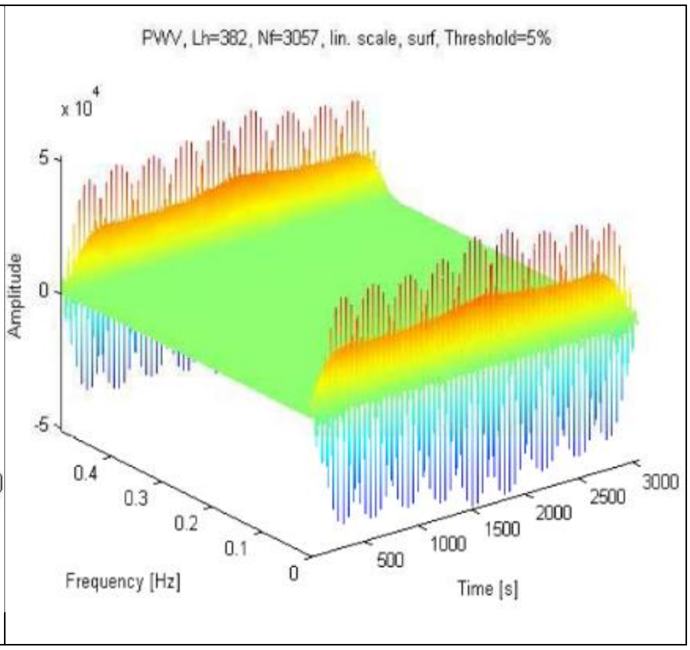
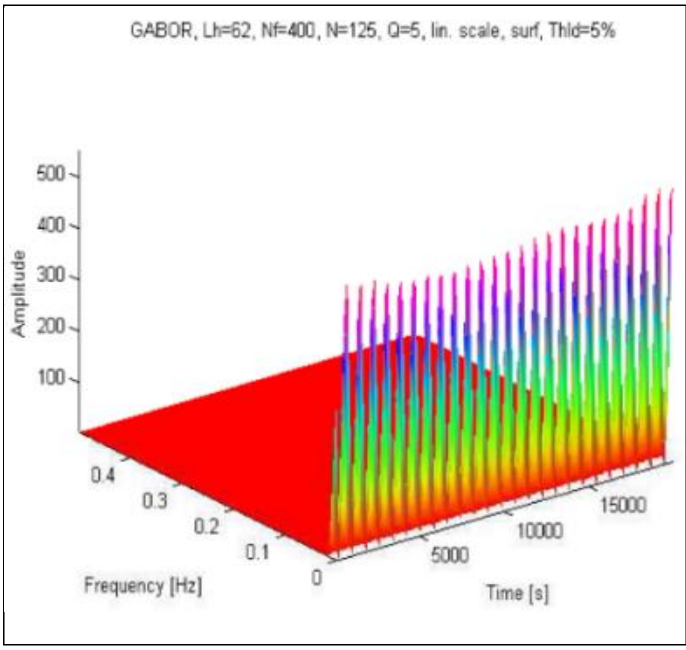


Fig. 5A. Wigner-Ville distribution of healthy machine current

Fig. 5B. Wigner-Ville distribution of faulty machine current



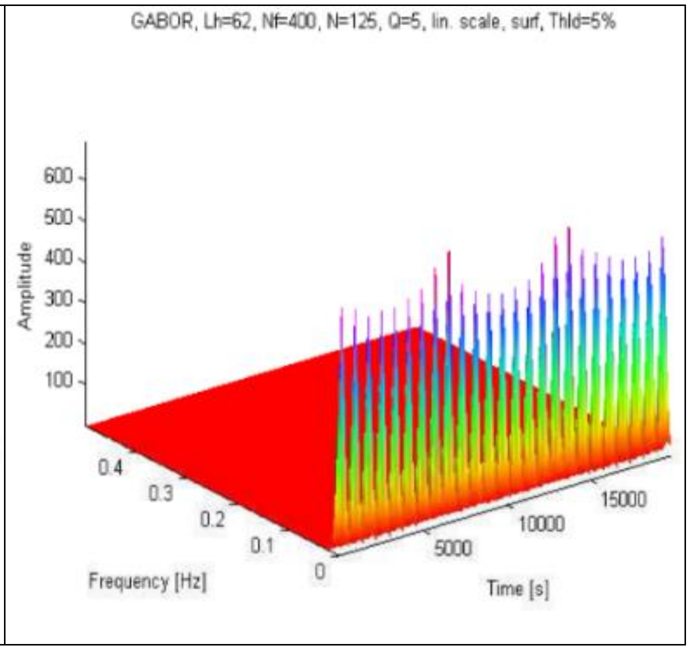


Fig. 6A. Gabor distribution of healthy machine current

Fig. 6B. Gabor distribution of healthy machine current

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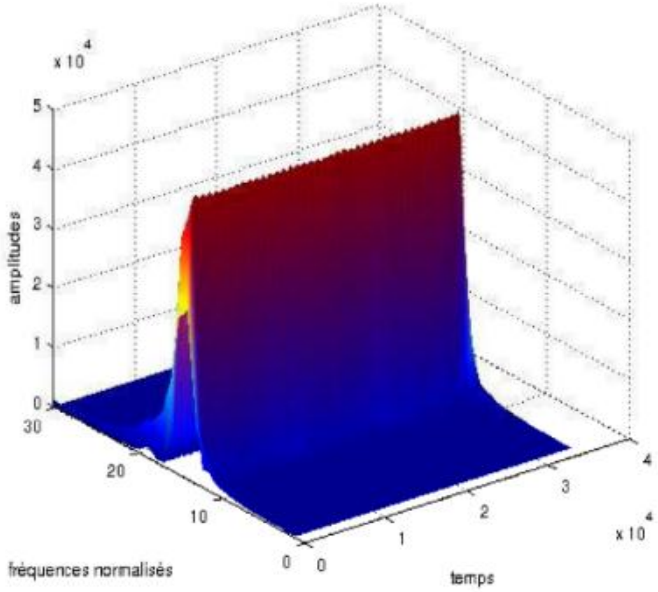

Fig. 6A. Morlet distribution of healthy machine current

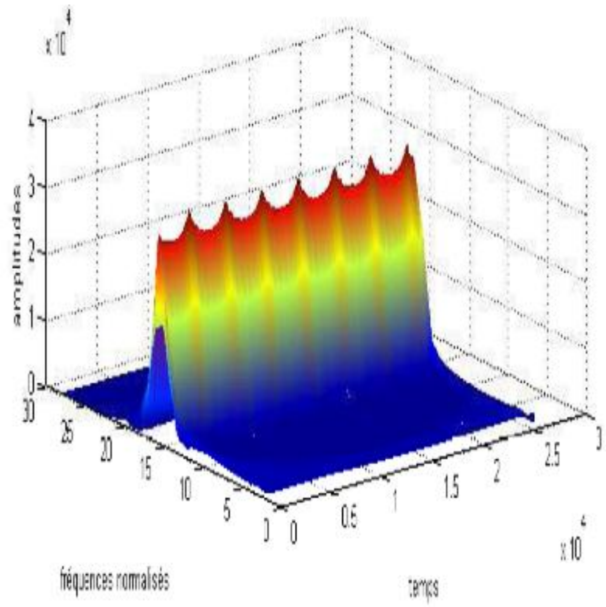

Fig. 6A. Morlet distribution of healthy machine current

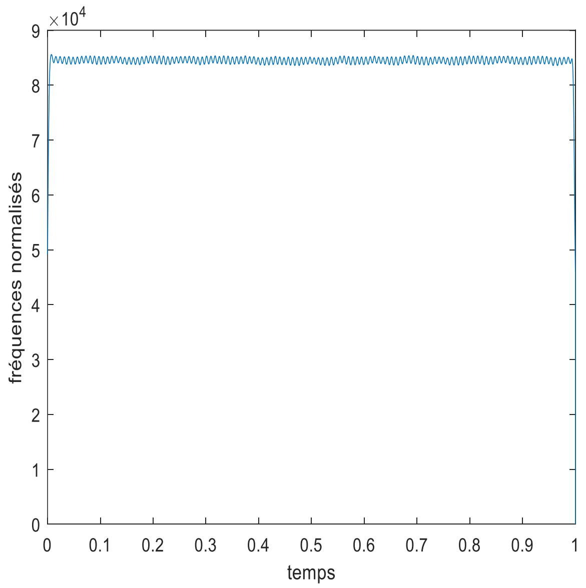

Fig. 7A. Morlet distribution healthy machine current

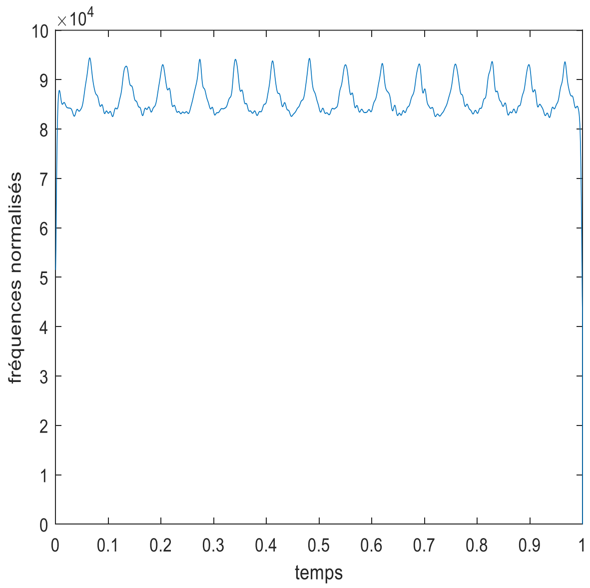

Fig. 7B. Morlet distribution faulty machine current

CONCLUSION

This paper has presented a comprehensive methodology for fault detection in wind turbine generator currents, supported by both theoretical modeling and simulation-based validation. The analysis demonstrated that faults introduce distinct, localized patterns in the time-frequency representation of the signal, underscoring the importance of selecting appropriate time-frequency analysis tools for accurate interpretation.

By employing advanced wavelet-based methods, particularly the Gabor and Morlet transforms, the proposed approach effectively captures transient frequency components associated with electrical faults. This enables enhanced real-time condition monitoring capabilities for wind turbine systems. The time-frequency features extracted using this framework offer both high resolution and robustness to non-stationary operating conditions.

A hybrid fault diagnosis scheme was developed, combining wavelet-based feature extraction with a polynomial-based representation tailored to dynamic linear systems. Applied to a Doubly Fed Induction Generator (DFIG) under

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varying operational scenarios, the method achieved high diagnostic accuracy. Furthermore, the proposed approach demonstrates scalability to a wide range of fault types, suggesting strong generalization potential.

The performance of the methodology under nonlinear and variable-speed regimes—typical of real-world wind turbine operation—confirms its applicability in practical deployment environments. These findings contribute to the development of more resilient and intelligent fault diagnosis systems for wind energy applications.

FUTURE WORK

Future research will focus on the following directions to further extend the applicability and impact of the proposed approach:

Fault Diagnosis under Partial Observability:

- Development of estimation techniques to enable accurate diagnosis with incomplete or noisy sensor data.
- Multi-Fault and Hybrid System Integration: Extension of the framework to detect simultaneous faults and to operate within hybrid renewable energy systems (e.g., wind–solar systems).

Edge Computing and IoT Implementation: Design and deployment of lightweight versions of the diagnostic algorithm suitable for embedded platforms and edge devices in industrial monitoring architectures.

IMPACT AND RELEVANCE

The proposed framework contributes toward the realization of reliable, scalable, and intelligent diagnostic systems for renewable energy technologies, By improving the accuracy, adaptability, and implementation readiness of wind turbine fault detection.

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