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Condition Monitoring of Wind Turbines Based on Amplitude Demodulation

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Abstract—Wind energy conversion systems (WECS) have become a focal point in the research of renewable energy sources. In order to make wind turbine reliable and competitive, it is important to reduce the operational and maintenance costs. The most efficient way to reduce it relies on condition monitoring and fault diagnostics. This paper proposes a new fault detector based on the amplitude demodulation of the three-phase stator current. Simulations show that this low-complexity method is well suited for stationary or non-stationary behavior.

Index Terms—Wind turbine, Fault Detection, Bearings, Signal Processing, Amplitude Modulation

I. INTRODUCTION

Wind energy conversion system is the fastest-growing source of new electric generation technologies in the world and it is expected to remain so for some time. In order to be more reliable and competitive than classical power generation systems and due to geographical location of WECS, it is important to prevent failure and to reduce maintenance cost. To fulfill this task, condition monitoring systems with integrated fault detection algorithms must be implemented. In this paper, the detection algorithm is based on the stator current signal. Many tools have been proposed in the literature to monitor the condition of an electrical machine from the stator current [1]–[3]. To detect a failure, stationary signal processing tools, like the Fast Fourier Transform (FFT) or Multiple Signal Classification (MUSIC) [4], are commonly used. However, these tools are inappropriate for wind turbines since these systems have predominantly transient behavior. Under non-stationary behavior, recent papers describe algorithms based on time-frequency representations [5]–[7], or time-scale analysis [8]–[10]. Nevertheless, these techniques have drawbacks such as high complexity, poor resolution and/or may suffer from artifacts (cross term, aliasing...). Recently, it has been demonstrated that many failures lead to stator current modulation [5], [6], [11]–[13]. Therefore, a natural low-complexity approach to detect a failure relies on the stator current demodulation. In this study, we focus on mechanical failures that lead to stator current amplitude modulation (AM). These include air gap eccentricity and rotor asymmetry faults [6], [12]. To detect a failure, we propose a new detector based on the variance of the demodulated current. This paper is organized

as follows. Section II presents the stator current signal model for healthy and faulty wind turbines. Section III presents two amplitude demodulation techniques and section IV describes a new fault detector based on amplitude demodulation. Finally, the performances of the proposed methods are reported and compared in section V.

II. SIGNAL MODEL

This work focuses on mechanical failures that lead to stator current amplitude modulation (AM). For three-phase generator, the stator currents $i_k(n)$ ($k = 0, 1, 2$) can be described into a discrete form as:

$$i_k(n) = a_k(n) \cdot \cos(\omega n - \phi_k) \quad (1)$$

where $n = 0, \dots, N - 1$ is the sample index, N is the number of received samples and $\phi_k = 2k\pi/3$ ($k = 0, 1, 2$) is the phase parameter. In equation (1), frequency ω is equal to $2\pi f/F_e$, where f and F_e are the supply and sampling frequency, respectively. Amplitude $a_k(n)$ is related to the fault as follows

- for healthy machine, $a_k(n)$ is constant (No AM).
- for faulty machine, $a_k(n)$ varies with time (AM).

In most study, a balanced system is assumed. Balanced system satisfies $\sum_{k=0}^2 i_k(n) = 0$ which also implies that the $a_k(n)$ are equal i.e $a_k(n) = a(n) \forall k = 0, 1, 2$. However, one should note that practical systems rarely have perfectly balanced load in all three phases. Furthermore, failure usually does not affect each of the three phase equally. In this study, the condition $a_k(n) = a(n)$ is relaxed and unbalanced system are also considered.

III. AMPLITUDE DEMODULATION TECHNIQUES

A. Concordia Transform (CT)

The Concordia Transform (CT) converts the 3 phase current to Park's space vector components $i_\alpha(n)$ and $i_\beta(n)$. The Park components are given by:

$$\begin{bmatrix} i_\alpha(n) \\ i_\beta(n) \end{bmatrix} = \begin{bmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ 0 & \frac{1}{\sqrt{3}} & -\frac{1}{\sqrt{3}} \end{bmatrix} \begin{bmatrix} i_0(n) \\ i_1(n) \\ i_2(n) \end{bmatrix} \quad (2)$$

Several fault detectors based on CT have been proposed in literature [14]–[19]. Recently, it has been shown that CT can be viewed as a demodulation technique for balanced system [19]. Indeed, under the assumption that the system is balanced, the Park components can be expressed as:

$$\begin{aligned} i_\alpha(n) &= a(n) \cdot \cos(\omega n) \\ i_\beta(n) &= a(n) \cdot \sin(\omega n) \end{aligned}$$

Then, the amplitude can be estimated by:

$$|a(n)| = \sqrt{i_\alpha^2(n) + i_\beta^2(n)} \quad (3)$$

Therefore, if the system is balanced, CT can be considered as a low-complexity demodulating technique. However, if the system is unbalanced, equation (3) is no longer valid and $|a(n)|$ depends on the three modulating signals $a_0(n)$, $a_1(n)$ and $a_2(n)$.

B. Hilbert Transform (HT)

A standard approach to extract the envelope $a_k(n)$ from $i_k(n)$ is based on the Hilbert transform. Let us consider a discrete sequence $i_k(n)$. The Discrete Hilbert Transform (DHT) of $i_k(n)$ is given by [20]:

$$\mathcal{H}[i_k(n)] = \mathcal{F}^{-1} \{ \mathcal{F}\{i_k(n)\} \cdot u(n) \} \quad (4)$$

where $\mathcal{F}\{\cdot\}$ and $\mathcal{F}^{-1}\{\cdot\}$ correspond to the Fast Fourier Transform (FFT) and Inverse FFT (IFFT), respectively, and where $u(n)$ is defined as:

$$u(n) = \begin{cases} 1, & n = 0, \frac{N}{2} \\ 2, & n = 1, 2, \dots, \frac{N}{2} - 1 \\ 0, & n = \frac{N}{2} - 1, \dots, N - 1 \end{cases} \quad (5)$$

Let us define the analytic signal of $i_k(t)$, denoted $z_k(n)$, as:

$$z_k(n) = i_k(n) + j\mathcal{H}[i_k(n)] \quad (6)$$

Using signal model (1), the amplitude envelope can be estimated by [20]:

$$|a_k(n)| \approx |z_k(n)| \quad (7)$$

In comparison to CT, HT can be used for amplitude demodulation even if the system is unbalanced since it is computed from one-phase only. However, the major drawback of HT lies on the associated computation cost since this method is more complex than CT. Moreover, HT can lead to edge effects problem at the beginning and end of $|a_k(n)|$ whereas CT is free from this artifact.

IV. FAULT DETECTOR

Several fault detectors based on amplitude demodulation have been proposed in literature. These includes Hidden Markov Model (HMM) [21], Neural Networks (ANN) [14], Fuzzy Logic [18]. However, most of these approaches employs unnecessary complicated classifier. Furthermore these methods assume that a training database is available, which can be difficult to obtain in some scenario. In this section, we propose a low complexity detector which does not require any training set. The detector is based on the variance of $|a(n)|$ or $|a_k(n)|$.

A. Fault Detector After CT Demodulation

After applying CT, envelope $|a(n)|$ is extracted with (3). Then, we propose to compute the variance of $|a(n)|$ to detect a fault. This statistic criterion, denoted σ_C^2 , is given by:

$$\sigma_C^2 = \frac{1}{N} \sum_{n=0}^{N-1} (|a(n)| - \mu)^2 \quad (8)$$

where μ is the average of $|a(n)|$ i.e.

$$\mu = \frac{1}{N} \sum_{n=0}^{N-1} |a(n)| \quad (9)$$

The variance σ_C^2 measures the deviation of the amplitude around its mean μ . This criterion can be used to detect amplitude modulation for balanced system. Indeed, if no fault is present, $|a(n)|$ is constant and so $|a(n)| = \mu$. Using (8), it follows that $\sigma_C^2 = 0$. On the contrary, for healthy machine $|a(n)|$ is not constant, which also implies $\sigma_C^2 > 0$. Therefore, we can propose a simple hypothesis test for failure detection under balanced assumption:

- If $\sigma_C^2 < \gamma_C$, the generator is healthy.
- If $\sigma_C^2 > \gamma_C$, the generator is faulty.

where γ_C is a threshold which can be set subjectively. For unbalanced system, one should note that this simple hypothesis test is no longer valid since σ_C^2 is not necessary equal to 0 for healthy machine.

B. Fault Detector Based on HT Demodulation

After applying HT independently on the three currents, we propose to exploit the information given by the three extracted envelopes. To avoid the edge effect problem of HT, each envelope is truncated by removing α samples at the beginning and at the end of $|a_k(n)|$. The proposed criterion, σ_H^2 , is then equal to:

$$\sigma_H^2 = \frac{1}{3(N-2\alpha)} \left(\sum_{k=0}^2 \sum_{n=\alpha}^{N-\alpha-1} (|a_k(n)| - \mu_k)^2 \right) \quad (10)$$

where μ_k is the average of $|a_k(n)|$, i.e.

$$\mu_k = \frac{1}{(N-2\alpha)} \sum_{n=\alpha}^{N-\alpha-1} |a_k(n)| \quad (11)$$

In (10), the average is used to make the criteria σ_H^2 and σ_C^2 equivalent for balanced system. Indeed if $a_k(n) = a(n)$ for all $k = \{0, 1, 3\}$ and if the edge effects problems are neglected, then it can be shown that $\sigma_H^2 = \sigma_C^2$ with $\alpha = 0$. This property no longer holds for unbalanced system. For healthy unbalanced system, envelopes $a_k(n)$ are different but they are all constant. It follows that $|a_0(n)| = \mu_0$, $|a_1(n)| = \mu_1$ and $|a_2(n)| = \mu_2$ and so $\sigma_H^2 = 0$. Therefore, we propose a simple hypothesis test to detect a fault under unbalanced condition:

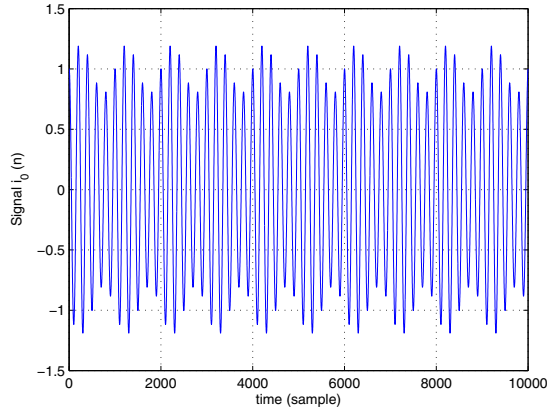


Fig. 1. Time representation of the stator current $i_0(n)$ for a faulty machine ($\beta = 0.2$).

- If $\sigma_H^2 < \gamma_H$, the generator is healthy.
- If $\sigma_H^2 > \gamma_H$, the generator is faulty.

where γ_H is a threshold which can be set subjectively. One should remark that this second hypothesis test is more powerful since it can be employed for balanced and unbalanced systems.

V. EXPERIMENTAL RESULTS

In this section, the result of several simulations is presented to compare the performance of the proposed fault detectors. For each simulation, the amplitude envelope is estimated through CT or HT. Then, depending of the demodulation technique, criteria σ_C^2 or σ_H^2 are computed to detect a failure. The simulation have been performed for healthy and faulty machines.

A. Synthetic Signals

In this subsection, several simulations have been performed with AM synthetic signals, which are given by [6]:

$$i_k(n) = \underbrace{(1 + \beta \sin(\omega_2 n + \psi_k))}_{a_k(n)} \cdot \cos(\omega n + \phi_k) \quad (12)$$

where β is a fault index which is equal to 0 for healthy machines and > 0 for faulty ones. The parameters ψ_k and γ_k are calibrated according to the balanced assumption. If the system is balanced, $\psi_k = \psi$ ($k = 0, 1, 2$) whereas ψ_k depends on k for unbalanced system. Simulations have been run with a sampling frequency $F_s = 10\text{kHz}$ during 1 second with $\omega = 0.1534\text{rad/s}$ (supply frequency $f = 50\text{Hz}$) and $\omega_2 = 0.0307\text{rad/s}$ ($f_2 = 10\text{Hz}$). The fault index has been set to $\beta = 0.2$ to simulate faulty machine (see figure 1 for time representation of $i_0(n)$). After HT demodulation, $\alpha = 10$ samples have been removed at the beginning and at the end of $|a_k(n)|$ to avoid edge effect problems. One should note that a larger α can make the criterion σ_H more sensible to noise or other sources of disturbance.

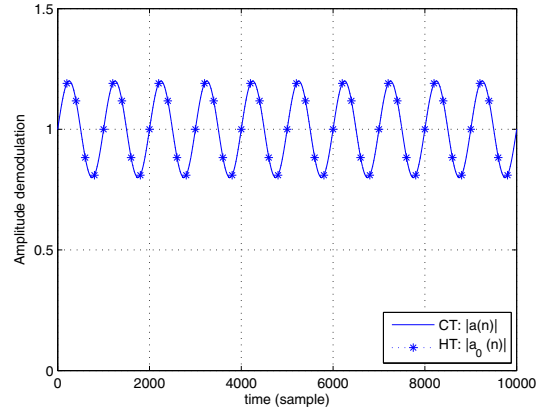


Fig. 2. Balanced system- Faulty machine. Time representation of the envelopes after CT and HT demodulation ($\beta = 0.2$).

1) *Balanced system* ($\psi = 0$): For balanced system, the amplitude envelopes are the same for the three currents. Figure 2 displays $|a(n)|$ and $|a_0(n)|$ extracted with HT and CT, respectively, for a faulty machine. One can notice that the two demodulation techniques lead to the same envelope. Table I shows the values of the fault detector criteria σ_C^2 and σ_H^2 for faulty and healthy machine. The two criteria lead to similar results, indeed $\sigma_C^2 = \sigma_H^2 = 0$ for healthy machine and $\sigma_C^2 = \sigma_H^2 = 0.020$ for faulty ones. Therefore, a fault can be easily detected in this context by setting the threshold of the fault detector to $\gamma_C = \gamma_H = 0.010$. From a practical point of view, one should note that CT demodulation must be preferred for balanced system since it has a lower complexity than HT and does not suffer from edge effects problems.

TABLE I
FAULT DETECTOR FOR HEALTHY AND FAULTY GENERATORS.

System	Demodulation	Fault detector	
		Healthy case	Faulty case
Balanced & Stationary	CT	$\sigma_C^2 = 0.000$	$\sigma_C^2 = 0.020$
	HT	$\sigma_H^2 = 0.000$	$\sigma_H^2 = 0.020$
Unbalanced & Stationary	CT	$\sigma_C^2 = 0.000$	$\sigma_C^2 = 0.005$
	HT	$\sigma_H^2 = 0.000$	$\sigma_H^2 = 0.020$
Unbalanced & Non-stationary	CT	$\sigma_C^2 = 0.000$	$\sigma_C^2 = 0.005$
	HT	$\sigma_H^2 = 0.000$	$\sigma_H^2 = 0.020$

2) *Unbalanced system* ($\psi_0 = 0, \psi_1 = 2\pi/3, \psi_2 = -2\pi/3$): Let us simulate a system which is balanced under healthy condition and unbalanced under faulty condition. Figure 3 displays $|a(n)|$ and the envelope $|a_0(n)|$ extracted with CT and HT, respectively, for a faulty generator. As expected, CT is not able to demodulate the signals. Table I presents the values of the fault detector criterion σ_C^2 and σ_H^2 under healthy and faulty conditions. In our simulations, criterion σ_H^2 leads to the same values for balanced and unbalanced system whereas the value of σ_H^2 decreases under unbalanced condition. One can notice that the difference between healthy and faulty case is larger for σ_H^2 . For fault detection, an hypothesis-test threshold equal to $\gamma_C = 0.0025$ for σ_C^2 and

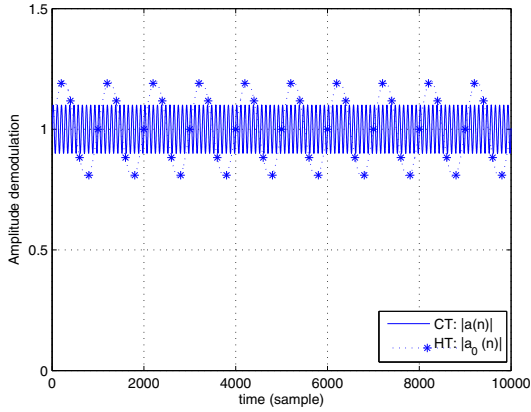


Fig. 3. Non-balanced system - Faulty machine. Time representation of the envelopes after CT and HT demodulation ($\beta = 0.2$).

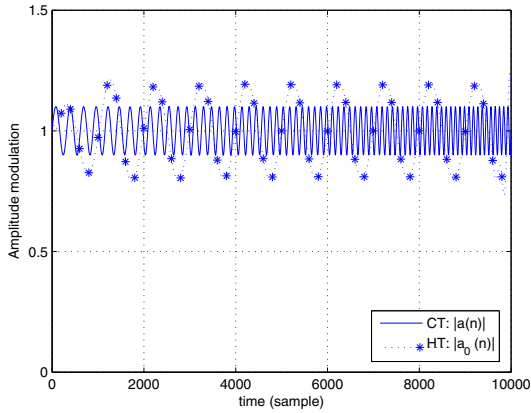


Fig. 4. Non-balanced system under non-stationary condition- Faulty machine. Time representation of the envelopes after CT and HT demodulation ($\beta = 0.2$).

$\gamma_H = 0.010$ for σ_H^2 lead to correct results in this context.

3) *Unbalanced system* ($\psi_0 = 0, \psi_1 = 2\pi/3, \psi_2 = -2\pi/3$) *under nonstationary supply frequency*: To simulate non-stationary environment, supply frequency f is assumed to vary linearly between 10Hz and 50Hz i.e.

$$\omega(n) = \frac{2\pi}{Fe} \left(\frac{40}{2N}n + 10 \right) \quad (13)$$

Figure 4 displays $|a(n)|$ and the envelope $|a_0(n)|$ extracted with CT and HT, respectively, for a faulty machine under non-stationary supply frequency. As edge effect problem occurs for HT (see Fig.4), $\alpha = 500$ samples have been removed at the beginning and at the end of $|a_k(n)|$. Table I presents the values of the fault detector criterion σ_C^2 and σ_H^2 . One should note that the values σ_C^2 and σ_H^2 do not depend on the stationary assumption in our context. Therefore, fault detectors based on amplitude demodulation seem to be well-suited for non-stationary scenario. In particular,

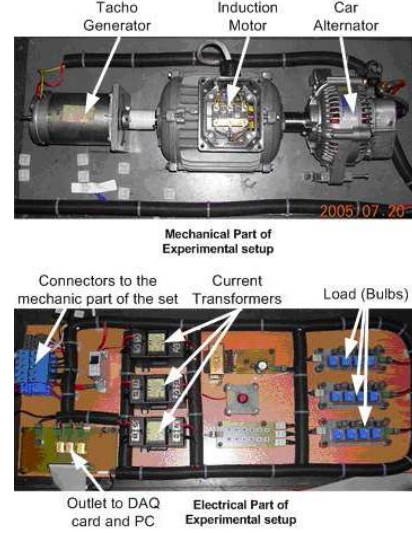


Fig. 5. Experimental setup.

these detectors do not need to employ complicated time-frequency representations, such as spectrogram, Wigner-Ville representation, that suffer from artifact or poor resolution.

B. Experimental signals

In this section, the result of our approach is presented with experimental signals. Fig.5 describes the experimental setup which is composed of a tacho-generator, a three-phase induction motor and an alternator. The experimental setup is operated in the motor configuration for experimental easiness. The alternator is a three-phase synchronous machine with a regulator and a rectifier circuit that stabilize the output voltage at 12VDC. The advantage of using a car alternator instead of DC generator is obtaining constant output voltage at various speeds. The induction motor could be identically loaded at different speeds. Moreover, if the induction motor is supplied from the network, motor current will have time harmonic components as well as bearing fault harmonics. This makes it harder to determine the bearing failure effect on the stator current and therefore complicates the fault detection process. For these reasons, the induction motor is fed by an alternator. By this way, supply harmonics effects are eliminated and only bearing failure effects could be observed on the stator current. The tested induction motor has the following rated parameters: 0.75 kW, 220/380V, 1.95/3.4A, 2780rpm, 50Hz, 2 poles, Y-connected. It has two 6204.2ZR type bearings. From the bearing data sheet the following parameters are obtained: The outside diameter is 47 mm and inside one is 20 mm. Assuming that the inner and the outer races have the same thickness gives the pitch diameter $D_P = 31.85\text{mm}$. The bearing has eight balls ($N=8$) with an approximate diameter of $D_B = 12$ mm and a contact angle $\theta = 0^\circ$. The faulty system is corrupted by a ball deterioration. Statistics of $i_k(n)$ reveal that the currents

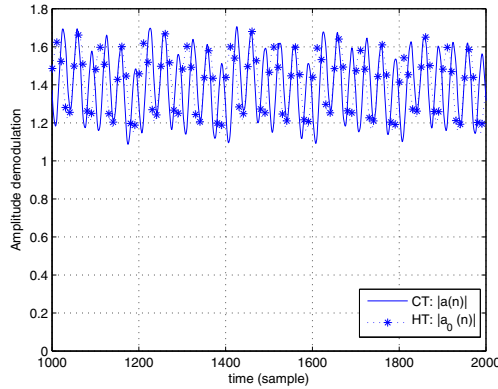


Fig. 6. Faulty machine generator: Time representation of the envelopes after CT and HT demodulation.

TABLE II
NON-BALANCED SYSTEM: FAULT DETECTOR FOR HEALTHY AND FAULTY GENERATORS.

Demodulation	Fault detector	
	Healthy case	Faulty case
CT	$\sigma_C^2 = 0.059$	$\sigma_C^2 = 0.095$
HT	$\sigma_H^2 = 0.039$	$\sigma_H^2 = 0.093$

are not perfectly balanced even for the healthy system. Indeed, the HT-based criterion is expected to give better results than the CT-based one. Figure 6 displays the envelopes $|a(n)|$ and $|a_0(n)|$ for a faulty machine after CT and HT demodulation, respectively. Table II shows the values of σ_C^2 and σ_H^2 for the faulty and healthy machine. As the system is not perfectly balanced, σ_C^2 and σ_H^2 are not equal to 0 for healthy machine. However, it can be notice that σ_C^2 is bigger than σ_H^2 under healthy condition. Under faulty condition, σ_C^2 is multiplied by 1.61 as compared to the healthy case, whereas σ_H^2 is multiplied by 2.38. Therefore, our experimental simulation corroborates the fact that it is easier to detect a fault with σ_H^2 than with σ_C^2 under unbalanced condition.

VI. CONCLUSION

An amplitude demodulation approach has been proposed for fault detection. First, the received currents are demodulated using Concordia Transform (CT) or Hilbert Transform (HT). Then, an hypothesis test based on the statistical variance of the demodulated envelope is performed to discriminate between healthy and faulty generators. The result of several simulations have shown that the proposed method performs well in stationary and non-stationary scenario. Furthermore results have shown that, even if CT is computationally attractive compared to HT, this low complexity demodulation technique can be inappropriate for the diagnosis of unbalanced systems.

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