Analysing Current Signature Data to Diagnose an In-Service Wind Turbine Generator

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Abstract. Condition-based maintenance (CBM) is currently seen as the preferred approach to optimise operation and maintenance (O&M) strategies by the early detection and diagnosis of critical failures for wind turbines (WT). WT reliability is highly affected by failures of the mechanical components from the drive train, although doubly-fed induction generators (DFIG) also contribute to high failure rates and downtime. As DFIG is the dominant technology employed for variable speed WTs, dedicated failure detection and diagnosis techniques are required. Current signature analysis (CSA) has emerged as a powerful tool for this purpose, despite some limitations. In this work, the variability of CSA through time by means of spectra waterfall and the wavelet transform are investigated to overcome these limitations. The analysis of a faulty in-service WT DFIG presented in this work raises the usefulness of the suggested approaches to identify patterns related to failure development through time.

1. Introduction
The global installed wind energy capacity continues to grow, reaching nearly 540 GW by the end of 2017 [1]. Of these, around 18 GW were located offshore, market led by the European countries [2]. Onshore availability has been found to be over 97%, achieved through appropriate O&M activities [3]. Different numbers are obtained for offshore sites, of about 85% availability; this significant difference is mainly due to inaccessibility issues and to the current uncertainty surrounding failure characteristics [4].

With larger and more modern wind turbine (WT) generators under continuous development, operation and maintenance (O&M) activities are key to improve reliability and availability of WTs while reducing costs [5], hence becoming the spotlight in the wind energy sector. Three maintenance strategies are commonly implemented for WT O&M: time-based maintenance (TBM), failure-based maintenance (FBM), and condition-based maintenance (CBM) [6]. TBM refers to scheduled actions that take place to ensure a certain performance level of the system; these interventions are regularly programmed disregarding the presence of failures in the system, such as the typical summer maintenance campaigns in offshore wind farms. Conversely, FBM is carried out once a functional failure is confirmed; these interventions are inevitably linked to higher WT downtime and costs. Conventional onshore O&M activities consist of a combination of TBM and FBM, such strategy has room for improvement and is unwise offshore. New trends are moving from these two towards CBM, where condition monitoring (CM) determines
the optimum point between scheduled and corrective actions [7]. Necessary interventions can therefore be planned when needed, with sufficient time, leading to reduced downtime and costs [8].

WT components are unequally affected by failures, both in terms of occurrence and criticality, which is typically linked to the resulting downtime and repair or replacement cost. The mechanical drive train is among the top three contributors to failure rates and downtime of WTs, together with electric generators [9], where doubly-fed induction generator (DFIG) is the dominant technology employed for variable speed WTs [10]. Early detection of gear, bearing and generator faults is therefore crucial if CBM is to be implemented in order to reduce corrective and scheduled actions. Nonetheless, while commercial solutions are readily available and widely used for monitoring the mechanical condition of rotating equipment, mainly based on vibration analysis, there is no such an established approach for electric systems.

Data from real operating WTs over the period preceding a functional failure are rarely academically analysed since they are hardly ever made available. Particularly, there is a lack of electrically-based diagnosis techniques applied specifically to in-service WT equipped with DFIGs. Many efforts have been made through computer simulations and at laboratory test benches, but very few on in-service WT generators. Furthermore, the studied failure modes are commonly known to the authors before the analysis is carried out, and sometimes a baseline of the healthy-stage is also available, so that the deviations due to the developing failure symptoms are more easily identified. Hence, it is clear that further research applied to in-service WTs is required to validate experimental simulations and models, especially for machines under unknown health status.

In the present work, an in-service WT DFIG has been analysed for a period of eight months to assess the development of a failure. Such failure had been previously diagnosed using current signature analysis (CSA), which was confirmed through vibration analysis, see [11]. CSA for wind turbine monitoring is still at an early stage; current spectra are particularly difficult to be tracked over time. Unlike vibration analysis where specific features from the spectra can be traced over time and linked to specific failure modes, CSA is negatively affected by a higher complexity and a lack of maturity currently limiting their detection and diagnosis capabilities. In this work, we explore the variability of CSA over time by means of spectra waterfall and wavelet transform, and address its usefulness to identify patterns related to failure development as a first step towards improving the detection and diagnosis of WTs equipped with DFIGs.

2. Methodology
Condition monitoring approaches for induction machines, such as DFIGs, include temperature, chemical and wear, mechanical vibration, and electrically-based analysis [12]. The latter usually covers current, voltage, instantaneous power and flux analysis. Of all these, stator current analysis is the most widely applied, as it is cheap, non-intrusive, and can monitor both electrical and mechanical failures. DFIGs major failures are most often due to bearing (between 40% and 60%), stator (between 28% and 38%) and rotor failures (around 10%) [13].

2.1. Current Signature Analysis (CSA)
This work explores the possibility of detecting failure related symptoms revealed as variations in CSA over time. Indeed, CSA is based on the principle that each developing failure mode has its own effect on the current spectra [10]. The appearance and development of an incipient failure should be therefore translated into a variation of the current spectra. Several signal processing methods can be applied for the purpose of faulty state identification, typically classified into time-domain, frequency-domain and time-frequency domain [14]. CSA lies within the frequency-domain techniques, whose most obvious disadvantage is the loss of temporal information. To
overcome this limitation, two approaches are explored in the present work, and applied to data from a real operating WT equipped with a DFIG for a period of eight months.

Firstly, frequency-domain analysis is applied to current signals from the stator via Fast Fourier Transform (FFT). This technique transforms the waveform signal from the time domain to the frequency domain. It is widely used for fault diagnosis because the variations of certain harmonic components in the frequency spectrum of a signal can be related to a specific fault type [14, 15, 16]. The following fault frequencies have been identified in the current spectra of the machine under study, and tracked over time. In the presence of rotor mechanical asymmetries, a set of new components at frequencies given by Eq. (1) appear:

\[ f_{RFS} = f_s \pm \kappa f_s \]  

(1)

Rotor electrical unbalance can be identified by the components given by Eq. (2):

\[ f_{FRU} = f_s \left| \frac{\kappa}{p} (1 - s) + l \right| \]  

(2)

However, since a minimal degree of asymmetry always exists in an induction machine, the presence of the first pair of \( f_{RFS} \) and/or \( f_{FRU} \) is not sufficient to diagnose such fault(s). It is the amplitude increment of these faults, and the increment in the number of sub-harmonics (\( \kappa > 1 \)) that will determine the presence of such fault(s).

There are other fault types, such as gearbox-related faults, whose frequency components will only be seen in the presence of a fault. Gearbox faults can originate from a gearbox shaft, bearing, gear, pinion, or a combination of these, generating characteristic rotor eccentricity components. Frequency components related to damaged teeth, scoring and debris can be calculated by Eq. (3):

\[ f_{GBX} = f_s \left| 1 \pm \frac{\kappa}{G_r p} \right| \]  

(3)

Once these fault-related frequencies have been identified, their behaviour is monitored throughout time with the purpose of identifying symptoms related to a developing failure. This work proposes the study of spectra waterfall with the goal of detecting any temporal variability. Spectra waterfall is a 3D representation of the signal spectra (current spectra in this case) at successive intervals of time, thus allowing to track changes in the current spectra over time. The chosen signals must be obtained at the same operating conditions in order to have consistency on the fundamental frequency and other derived frequencies of interest.

2.2. Wavelet Analysis

The second approach used in this work lies within the group of time-frequency techniques, as an alternative to overcome the loss of temporal information related to CSA. Wavelet analysis is the most widely applied time-frequency domain analysis technique. Over the past years, it has emerged as a powerful tool in many areas such as data analysis, image processing and fault detection, especially for electrical machines [17].

Like Fourier analysis, wavelet analysis is based on the principle of function expansion in terms of a set of basis functions. While in Fourier Analysis the basis functions are trigonometric, wavelet analysis decomposes functions in terms of wavelets, generated from translations and dilations of a prototype, called mother wavelet [18]. One of the main differences is the finite nature of this mother wavelet function versus the infinite character of sinus and cosinus. This makes time localisation possible in wavelet analysis. Unlike the FFT that provides a local representation of a signal, the wavelet transform represents changes in frequency throughout time facilitating the analysis of non-stationary signals and transient detection of abnormal
events. This hybrid nature of time-frequency domain analysis techniques poses a challenge in time and frequency resolution, due to the Heisenberg uncertainty principle: higher precision in one quantity implies lower in the other. As a result, appropriate time resolution and poor frequency resolution are obtained at high frequencies and vice versa. The interested reader is referred to [18, 19] for more information about wavelet analysis and theory.

Since the faulty state in the analysed turbine is related to rotor mechanical asymmetries, the Morlet wavelet was selected, as its shape is similar to mechanical shock signals. This wavelet transform has already been used for WT condition monitoring, although applied to vibration signals [20]. In this work, the wavelet transform is computed for the current signals from the stator and then the temporal evolution of wavelet power levels at frequencies close to the frequencies of interest, previously identified (see section 2.1), is further analysed.

3. Case Study

A Spanish company who provide O&M services, specialising in power converters, generators, turbine controllers, CM systems and SCADA systems, has provided the data for the case study. The reported WT is equipped with a DFIG with the following characteristics, Table 1:

| Table 1. Main characteristics of the DFIG under study. |
|-----------------------------------------------------|
| **Rated Power** | 1,500 kW |
| **Pole Pairs, \( p \)** | 3 |
| **Synchronous Speed** | 1,000 rpm |
| **Supply Frequency, \( f_s \)** | 50 Hz |

The WT under study was diagnosed with rotor mechanical asymmetry [11], as previously mentioned. The database provided contained between 300 and 900 acquisitions per month, with each acquisition comprising six generator current measurements (three stator and three rotor currents) under different WT loading conditions. A sub-set of the database is given in Figure 1, showing the distribution of measurements for different values of speed and power.

![Figure 1. Selected WT measurements.](image-url)

Of these, ten signals per month have been selected to illustrate the development of the fault over time, both at sub-synchronous and super-synchronous regimes. Such evolution is
explored by means of spectra waterfall and wavelet analysis, presented as follows in sections 3.1 and 3.2, respectively. Once the appearance of the fault is detected, advanced diagnosis is achieved through CSA (section 3.3).

3.1. Spectra Waterfall Results

Previous studies of vibration spectra waterfall have proven very useful in detecting changes in the spectra over time [11, 21]. The same methodology has been applied to the wind turbine under analysis, using the current spectra instead, as shown in Figure 2, for the eight-month period.

![Figure 2](image_url)

(a) Super-synchronous regime  
(b) Sub-synchronous regime

**Figure 2.** Evolution of the current spectra from January 2016 to August 2016 at super- and sub-synchronous regimes.

Since the faulty state in the turbine under analysis is related to rotor mechanical asymmetries, the objective is to track fault frequency components given by $f_{RFS}$ (Eq. (1)) and $f_{FRU}$ (Eq. (2)). Looking at the current spectra waterfall (Figure 2) the increment in amplitude or appearance of sub-harmonics related to $f_{RFS}$ and/or $f_{FRU}$ over time is not evident.
3.2. Wavelet Analysis Results
The wavelet transform was computed for the signals acquired separately, as well as concatenated. Figure 3 shows the resulting scalogram for one of the signals acquired in January 2016 at nominal power (super-synchronous regime), while Figure 4 illustrates the scalogram for the concatenated signals. As one can see in Figure 3, the scalogram shows the temporal evolution of the wavelet power levels for the covered range of frequencies. Additionally, the low temporal resolution at low frequencies is clearly seen at the top of the graph, and so is the high temporal resolution at high frequencies at the bottom. Apart from the first and second harmonics of the fundamental frequency, no significant wavelet power levels are observed.

Conversely, some peaks are observed in Figure 4, due to the discontinuities between the different samples analysed, and these are not meaningful for any deviation detection purposes. Ideally, a continuous signal should have been analysed for the purpose of tracking changes over time, which is currently not possible as can be seen in Figure 4.

**Figure 3.** Wavelet scalogram of one of the current signals measured in January 2016.
Figure 4. Scalogram of the signals measured over the eight months.

It should be noted that the limited resolution in frequency does not allow to track changes around the faulty frequencies identified with CSA. Also, the frequencies of interest are close to the supply frequency and this also tarnishes any significant deviation over time. To overcome this disadvantage, the wavelet power levels have been further analysed to detect any variability though time related to failure development. The average wavelet power was computed separately for the different monthly signals and for frequencies around 30 Hz (corresponding to the frequency of interest at nominal power). Results are illustrated in Figure 5.

Figure 5. Average wavelet power levels of the monthly signals for frequencies around 30 Hz.

As one can see, as the failure develops the wavelet power level related to the faulty frequency increases. Notwithstanding the limited resolution in frequency, this supports the usefulness of the wavelet transform for tracking changes in electrical signals for monitoring purposes. Additionally, further harmonics were analysed also for signals at sub-synchronous regimes (lower loads), to identify regions where deviations could be more significant. Also, maximum wavelet power levels were retained, as this statistic is more likely to capture peaks than average, where deviations
could be smoothed out. Maximum wavelet power levels over time are illustrated for frequencies around 26.9 Hz, 3.84 Hz and 19.2 Hz in Figure 6 (a), (b) and (c), respectively.

![Figure 6](image)

**Figure 6.** Maximum wavelet power levels of the monthly signals for frequencies around $k = 1$ (26.9 Hz), $k = 2$ (3.84 Hz) and $k = 3$ (19.2 Hz).

Although the increasing trend is doubtful for $k = 2$, it can however be clearly identified for the other cases in Figure 6. Furthermore, the magnitude of the observed increments are much higher than in Figure 5, where the average wavelet power levels were computed. Monitoring the maximum power levels at different frequencies over time opens the door to new faulty state detection possibilities for WT DFIGs. However, the limitation related to frequency resolution impedes a correct diagnosis, that could be overcome by punctual CSA.

Summing up, time-frequency domain analysis techniques, such as wavelets, allow the detection of changing behaviour of stator current signals over time but do not offer enough frequency resolution for an advanced diagnosis of the failure mode developing in the system. Once a deviation is detected through a wavelet analysis, diagnosis can be assessed through specific CSA that offers a very good precision in the frequency domain.

In practice, this solution could be implemented by performing the wavelet analysis for current data recorder at medium resolution (10 ms would be enough to cover frequencies around 30 Hz), that is readily available for modern WTs. CSA of higher frequency signals would only need to be performed in the event of a deviation detected by the first analysis.

### 3.3. Advanced Diagnosis through CSA

Once the deviation has been detected, an in-depth analysis is carried out through CSA. The wavelet analysis showed that fault-related frequency components given by $f_{RFS}$ (Eq. (1)) increase in amplitude from January to August 2016, which was clear for the sub-harmonics $k = 1$, 3 and doubtful for $k = 2$. In order to validate these results, the current spectra of punctual measurements were analysed.

Figure 7 shows CSA for the sub-synchronous regime. As one can see, further peaks appear in August 2016 (Figure 7 (b)) compared to January 2016 (Figure 7 (a)). When analysing Figure 7 (b) one can observe one full pair for $f_{RFS}$ for $k = 1$ and the left side for $k = 3$, plus two full pairs of $f_{FRU}$ (for $k = 1$, 3). Whereas only the left side for $f_{RFS}$, $k = 3$ appears in Figure 7 (a). It must be noted that no pair corresponding to $k = 2$ is present, which explains why the wavelet analysis results were not able to confirm the increment for such component. It is very common that only the odd sub-harmonics appear in the faulty spectra.

The results at super-synchronous regime are shown in Figure 8. In this case, two full pairs of $f_{RFS}$ (for $k = 1$, 3) and one full pair of $f_{FRU}$ ($k = 1$) can be seen in August 2016 (Figure 8 (b)). Whereas in January 2016, Figure 8 (a), only the right-side components of $f_{RFS}$ for $k = 1$, 3 and one full pair of $f_{FRU}$, ($k = 1$), are found. An increment both in amplitude and number of sub-
harmonics is therefore appreciated in August 2016 compared to January 2016, which belongs to the sub-harmonics $k = 1, 3$; again, no sub-harmonics appear for $k = 2$.

4. Conclusions
The current outlook of O&M in the wind energy sector has been briefly presented, introducing the motivation of the present work: to enhance O&M activities through CM in order to increase reliability and availability of WTs while reducing costs.

In this work, the basis of CSA and its application on WT DFIGs diagnosis have been presented. Two different approaches have been applied to an in-service WT equipped with a DFIG, for a period of eight months in order to assess the development of a failure. The variability of CSA through time by means of spectra waterfall and wavelet transform have been explored to address its usefulness to identify patterns related to failure development.

The wavelet transform, that is less computationally expensive for being run routinely, can contribute to the detection of abnormal behaviour and localisation in time. Then, the punctual
CSA can diagnose the failure mode under development. This combination could overcome the limitations of applying both techniques separately.

Further research would be needed to validate the detection capabilities arisen from this work. Namely, the most important failure modes affecting DFIGs should be explored, to be related to specific patterns in both approaches. Also, other wavelet basis functions should be investigated to identify suitable mother wavelets to describe variations in current signals.

5. Learning Objectives
- Doubly-fed induction generators (DFIG).
- Current Signature Analysis.
- Real analysis on operating wind turbine DFIG.
- Application on condition monitoring of wind turbines.

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