Identificación mejorada de componentes en baja frecuencia de turbinas eólicas empleando EEMD e integración en el tiempo

Improvement of low frequency identification for wind turbines employing EEMD and time integration

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ABSTRACT

Nowadays wind turbines are wide employed as a clean energy resource. Their use implies a wide number of eolic structures which also requires a demanding monitoring and maintenance. Vibration analysis allows programming the maintenance in a proper time. In addition, the accessibility for installing several sensors into the machine is limited. Therefore, it is useful and needed to perform an analysis using just one sensor. In that sense, accelerometers can extract the velocity and displacement through a double digital integration, signals with additional information about the machine. However, digital integration evolves several difficulties such as biased errors, leakages in the signal, and others. This paper proposes a new methodology based on the ensemble empirical mode decomposition (EEMD) for extracting and improving interpretation of low frequency components from a wind turbine structure using a single-channel vibration measurement and double integration.

KEYWORDS

EEMD; wind turbines; time integration .

RESUMEN

Hoy en día las turbinas eólicas se emplean ampliamente como una fuente de energía limpia. Su uso implica gran número de estructuras eólicas que requieren vigilancia y mantenimiento exigente. El análisis de vibraciones permite programar mantenimientos en tiempos adecuados. Por otro lado, la instalación de varios sensores en la máquina es limitada. Por tanto, se debe realizar un análisis con solo un sensor. En ese sentido, los acelerómetros pueden extraer la velocidad y el desplazamiento, señales con información adicional de la máquina, a través de una doble integración digital. Sin embargo, la integración digital presenta varias dificultades, como errores sesgados, fugas en la señal, y otros. El presente trabajo propone una nueva metodología basada en la descomposición ensamblada de modos empíricos (EEMD) para la extracción e interpretación de componentes de baja frecuencia en estructuras de turbinas de viento empleando un canal de vibraciones y doble integración.

PALABRAS CLAVE

EEMD; turbinas eólicas; integración en el tiempo.

I. INTRODUCTION

In the last decades there have been especial interest in clean energies development including solar panels and wind turbines in issues related with monitoring and maintenance. Specially attention is required for wind turbines due their complex dynamical behavior together to the high cost of corrective maintenance. Those problems make necessary new methodologies to extract and to analyze sensible components of the wind turbines. In consequence, several studies have been carried on this topic in the last decade [1] [2] [3]. However the studies have been developed on signals under several damage levels in just acceleration format and using several channels for measurement. In real world applications, the accessibility for installing several mechanical vibration transducers into the machine is limited either by the physical space or the high cost of sensor networks. Therefore, it is useful and needed to perform an analysis using just one sensor. In order to extract several components of single channel signals, several methodologies have been studied as SSA [4], Wavelet [5] and EMD [6]. However, EMD offers a nonparametric advantage over the other techniques, conserving high decomposition capability. Recently, a new methodology based on EMD and called EEMD have been introduced [7] [8] improving the orthogonality of the decomposition, making more separable the IMFs. Nevertheless, the IMFs extracted from EEMD do not offer a complete interpretation about the components of the wind turbine. In order to solve this issue, a velocity and displacement signal could be added due they offer additional information about the machine operation, and they are specially suitable because the low frequency behavior typical of wind turbines and inherent of velocity and displacement signals.

In that sense, the accelerometers are commonly utilized since these sensors allow extracting the velocity and displacement information through a double digital integration procedure.

Nonetheless, digital integration methods present several issues as DC components drifted into accelerometer recordings [9], lack of initial conditions of velocity and displacement, and numerical integration errors [10]. Those problems remain without a final solution and just a few applications are studied in [11] [12] [13]. The present paper proposes a new methodology for components identification in wind turbines using displacement and velocity signals integrated from acceleration IMFs recordings. The methodology is based on iterative procedure where the signal is first decomposed using EEMD, then integrated in time domain and filtered using a high-pass filtering. The methodology shows visual improvement in the identification of low frequency behaviors of the machine and its results are promising for applications in other fields.

II. METHODS

A. Empirical mode decomposition (EMD)

Empirical mode decomposition is a method to decompose non-linear, multi-component signals into a series of zero-mean AM-FM components that are called intrinsic mode functions. It was developed based on the assumption that any signal consists of different simple intrinsic modes of oscillations.

According to the definition of IMF [14], two conditions should be satisfied: 1) the number of extrema and zero crossings may differ by no more than one; 2) the local mean is zero. As discussed in [14], EMD is defined by the algorithm and does not have an analytical formulation. Given a signal $x_{(t)}$, the algorithm of EMD can be summarized as below [14]

1. Find all the local extrema of $x_{(t)}$.
2. Connect all the local maxima of the signal using a cubic spline line. The connected line is called the upper envelope $e_{max(t)}$. Similarly, find the lower envelope $e_{min(t)}$ with the local minima.
3. Calculate the mean of the upper and lower envelopes $m_{(t)}$, and the detail $h_{i(t)}$ can be obtained as follows

$$m_{(t)} = \frac{(e_{\min(t)} + e_{\max(t)})}{2}$$
$$h_{i(t)} = x_{(t)} - m_{(t)}$$

4. Check whether $h_{i(t)}$ is an IMF. If $h_{i(t)}$ is not an IMF, repear the loop on $h_{i(t)}$. If $h_{i(t)}$ is an IMF, then set $c_{1(t)} = h_{i(t)}$.
5. Separate $c_{i(t)}$ from $x_{(t)}$, and a residual $r_{i(t)}$ can be given as

$$r_{1(t)} = x_{(t)} - c_{1(t)}$$

6. Treat the residual $r_{i(t)}$ as the original signal and iterate steps (1) (5) n 1 times. As a result, n-IMFs can be obtained, as follows:

$$r_{2(t)} = r_{1(t)} - c_{2(t)}$$
$$\bullet$$
$$\bullet$$
$$\bullet$$
$$rn_{(t)} = rn{-}1_{(t)} - cn_{(t)}$$

The decomposition process does not stop until the residual $r_{n(t)}$ becomes a monotonic function or a constant from which no more IMF can be extracted. Then the EMD is completed, and the original signal $x_{(t)}$ is decomposed as:

$$x_{(t)} = \sum_{i=1}^{n} c_{i(t)} + r_{n(t)}$$

B. Ensemble Empirical Mode Decomposition

This adaptive method decomposes time series into a set of so termed intrinsic mode functions (IMF), which follows: *i)* the amount of local extremes and the zero crossing differs at most by one, *ii)* at any point the mean value between the superior envelope defined by the local maxima and the inferior envelope defined by the local minima is zero. Thus, a time series *x(t)* can be represented by EMD as follows:

$$x(t) = \sum_{k \in K} \hat{c}_k(t) + r(t),\ \forall t \in T$$

where $\{\hat{c}_k(t)\}$ is the set of IMF, $r(t)$ is the remainder term, and K is the number of the IMF extracted from original data. The first IMF is related to the highest frequency while the last one to the lowest.

However, EMD faces the mode mixing problem because of reached low orthogonality between neighboring IMFs. This issue is overcame by the use of the ensemble empirical mode decomposition (EEMD) that takes advantage of the additive white gaussian noise (AWGN) cancelation property within dyadic filter bank EMD structures [7]. The EEMD is sequentially carried out as follows:

1) An input time series $x(t)$ is contaminated with AWGN as much as J times, i.e., $xj(t)=x(t)+ \eta j\ (t),\ \forall t \in T, j=1, \dots , J$, being $\eta j\ (t)$, each j-th trajectory of the randomly generated AWGN,
2) Afterwards, obtained xj (t) is decomposed, using the conventional EMD, into the corresponding IMF set, $\{\hat{c}k,j\ (t): k=1,\dots,K\}$. f
3) At last, an averaged version of $c_k(t)$ is obtained as:
$$ck(t)= \mathbb{E}\{\hat{c}_{k,j} : \forall j \in J\},\ \forall t \in T$$
where notation $\mathbb{E}\{\cdot\}$ stands for expectation operator. Generally, J should be large enough to cancel the AWGN since there is a directly proportional relation between the standard deviation of the AWGN and the amount J.

C. Integration

In mechanical systems, the acceleration signal taken directly from the accelerometers has a DC component related with spurious voltage and current at the sensor. Characteristic perturbations in low frequencies are generated in double integration by two main sources: lack of velocity and displacement initial conditions and the natural behaviour of the integration process as a low pass filtering. Therefore, an accelerometer signal, as the decomposition outputs from EEMD, $c_k(t)$ is double integrated as follows:

$$v_{(t)} = v_{(t_0)} + \int_{t_0}^{\psi} c_{k(\tau)} d\tau, x_{(t)} = x_{(t_0)} + \int_{t_0}^{\psi} v_{(\tau)} d\tau, \mathrm{x}_{(\tau)}, v_{(\tau)} \in \Re$$

where $v(t)$, $x(t)$ are the velocity and displacement time series obtained from integration; $\mathrm{v}_{(t0)}$, $\mathrm{x}_{(t0)}$ are the initial conditions of velocity and displacement, respectively; t express the time domain, and $t0$, ψ are the integration limits. Usually in rotating machines, the initial conditions $\mathrm{v}_{(t0)}$, $\mathrm{x}_{(t0)}$ are not provided since only $c_{k(t)}$ is measured, and the lack of those variables introduce a linear increment into displacement signals [15]. Besides, the double integration process can be seen as a natural low-pass filtering where the magnitude of the significant frequency components becomes less than the noise components [10]. In order to solve those issues, a high-pass filter is introduced below. The magnitude squared frequency response $H_{(j\omega)}$ of a Butterworth filter is:

$$\left|H_{(j\omega)}\right|^2 = \frac{1}{1+\left(\frac{\omega}{\omega_c}\right)^{2n}}$$

where, n is the order of filter, ω_c is the cutoff frequency (-3dB frequency) and ω represents frequency in radians. The IIR filters offer the same magnitude response specifications than FIR filters, but with lower order, making the computational calculus faster than FIR filters [16], [?]. Therefore, an alternative approach to represent an IIRfilter is given by:

$$\eta_{[n]} = -\sum_{i=1}^{M} \alpha_i \eta(n-i) + \sum_{j=1}^{L} \beta_i \chi(n-j)$$

where α_i = , 0,1, 2,...,M = and β_i = , 1,2,...,L are the coefficients of the filter. Again, $\eta_{[n]}$ represents the sampled signals $v_{[n]}$ and $x_{[n]}$. The Butterworth filter rolls off more slowly around the cut-off frequency and more linear phase response than others like Chebyshev or elliptic, but without ripple maintaining the same shape for higher orders. That feature is an advantage for low spurious components removal and allows smoother filtering results. These filters properly adjust the cut-off frequency according to frequency behaviour of data, allowing analysis even for monitoring under nonstationary operating condition [17].

III. EXPERIMENTAL SETUP

The present paper proposes an analysis of signal decomposition of a wind turbine acceleration signal. EEMD is employed to decompose the signal and then an iterative algorithm to double integration is used in order to improve the interpretability of the main signal components by using the velocity and displacement signals. Firstly, a preprocessing step is applied to eliminate the DC noise from the acceleration recording. Secondly, EEMD is employed to decompose the original signal in their corresponding IMFs. Thirdly, time domain integration with trapezoidal rule is employed and a Butterworth filter is used after integration to remove the spurious components resulting from the lack of initial conditions and integration numerical errors. Then, the methodology is repeated in order to obtain the velocity and displacement time series. Lastly, displacement and velocity spectrums are inspected visually aiming to retrieve cleaner information about components of the wind turbine signal. The proposed methodology is presented in the Figure 1.

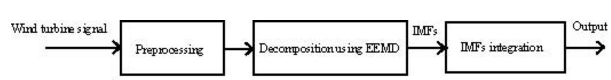

Figure 1: Methodology scheme

The current methodology for temporal integration with high pass filtering correction is described in the Table.

Input: $IMFs_{(t)}$
Initialization 1. $A_{(t)} = Normalize(IMFs_{(t)})$ 2. $V_{(t)} = \text{Timedomainintegration}(A_{(t)})$ 3. $V_{filt} = Butterfilter(V_{(t)})$ 4. $D_{(t)} = \text{Timedomainintegration}(\text{V}_{filt})$ 5. $D_{filt} = Butterfilter(D_{(t)})$ **end**
Outputs: V_{filt}, D_{filt}

Table I: Algorithm 1

A. Database

The vibration acceleration signal used in the study was acquired on the tower of a NegNicon NM52/900 wind turbine located a t the Rhodes Wind Farm, Greece (IWECO M.V. S.A.). The wind generator consists of a tubular steel tower of approximately 49 m tall and blades that are 25 m long. A set of piezoelectric accelerometers are placed within the height of the tower, measuring (via a 4-channel portable data acquisition device) vibration in the x and y directions parallel to the horizontal plane. For this paper, only the data acquired at sensor D (48 m above the ground) along the x direction is used. Following acquisition, the signals are normalized and resampled. Wind speed, average rotor and generator speed are also monitored by means of an in-situ SCADA system [18]. The original signal can be seen in the Figure 2.

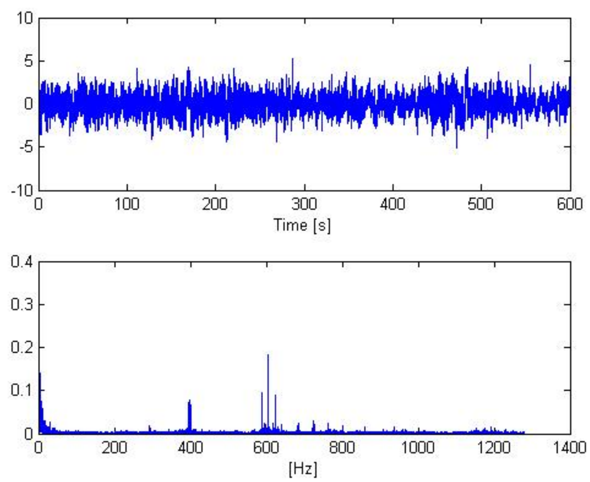

Figure 2: Original vibration acceleration signal from the wind turbine.

B.Experiment 1:syntheticsignals

A synthetic signal similar to vibration acceleration signal is selected from [12] and defined as follows:

$$A_{(t)}=10\sqrt{2}sin(2\pi 50t)+5\sqrt{2}sin(2\pi 120t)+8\sqrt{2}sin(2\pi 315t)$$

The factor of $\sqrt{2}$ has been included explicitly for relating the amplitude and the rms signal value. The sampling frequency is establishedas 1024 Hz and 1 second of duration [19]

In the Figure 3 shows the synthetic signal in time and frequency domain. Only it is shown a relevant part of the signal where is possible to observe the spectral components in low frequency.
The proposed methodology is applied to the synthetic signal and the results can be seen in the Figure 4. Only frequency domain is shown due it contains the relevant interpretable information about the signal. As can be seen in the Figure 4, only two IMFs are shown due they contain the main information of the signal. Also, the low frequency components of the signal are magnified in the integration process and the high frequency levels decreased. In real wind turbine signals, the desire bandwidth is in low spectrum, so the integration process proves to be usefull for further analysis.

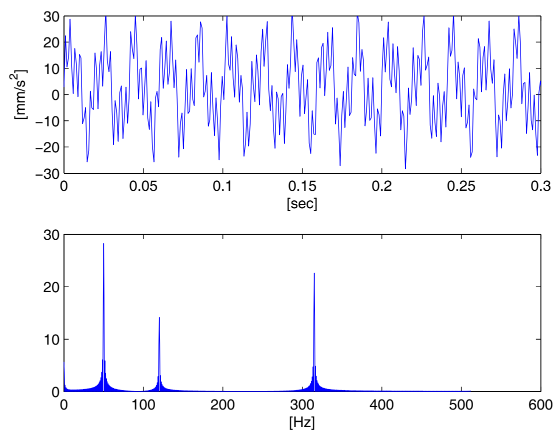

Figure 3: Synthetic signal (up) time and (down) frequency domain.

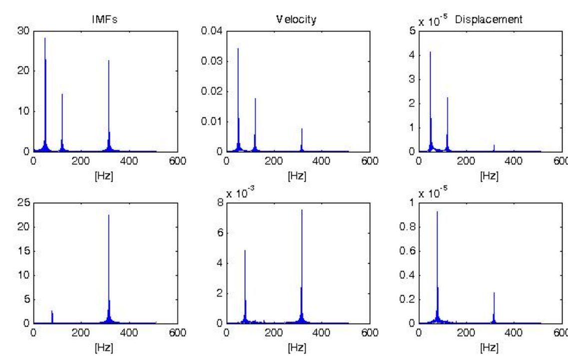

Figure 4: Synthetic signals using the methodology proposed.

C. Experiment 2: Real signals

For this experiment single channel signal from wind turbine is employed. After applying decomposition process with EEMD, the IMFs are obtained. The last IMFs obtained are too monotonic and it can be discarded from the analysis. Also, the first IMFs are too similar to the original signal, and it is difficult to extract components directly from them. For the present study, the IMFs 3 to 5 are showed due they represent better the energy distribution of the signal in several bands.

Once with the pseudo-channels it is feasible to applied integration methodology and then to analyse the velocity and displacement time series.

Time-Frequency representation (TFR) is used in order to visualize the differences between each IMF and it corresponding velocity and displacement representation. Integration results are shown in Figure 5, Figure 6 and Figure 7, where it is possible to observe that according as the acceleration signal is integrated, the amplitude of spectral components in low frequency is compensated. Thereby, in vibration velocity and displacement, the spectral information is considered as machine general vibration because the amplitude preserves the original magnitude of spectral components. The scales in the time series of Figure 5, Figure 6 and Figure 7 are not the same because of the amplitude modification in the integration process. In order to visualize the time series signal, the scales in time representation have been modified.

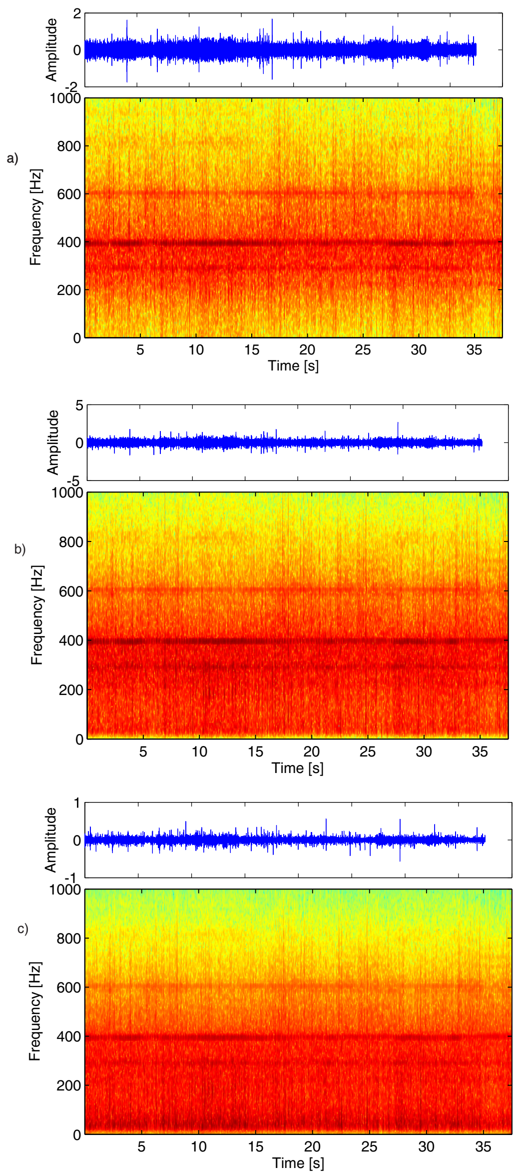

Figure 5: Proposed methodology for IMF 3. a) IMF, b) Velocity and c) Displacement

The velocity and displacement signals are useful for further analysis in model-based damage identification or directly inference of direct failures detection given the rules of correct behavior of the rotating machine according the manufacturer.

IV. CONCLUSION AND DISCUSSION

The present paper proposes a new methodology for improve visual interpretation of low frequency information from wind turbines using a single channel record based on EEMD decomposition and temporal digital integration. The current methodology is tested with synthetic signals and then it is applied to signals from a wind turbine structure. The visual results evidence the feasibility of the methodology to improve the identification of low frequency components in frequency domain. Although EEMD shows several advantages over other techniques like SSA and discrete Wavelet, future work will

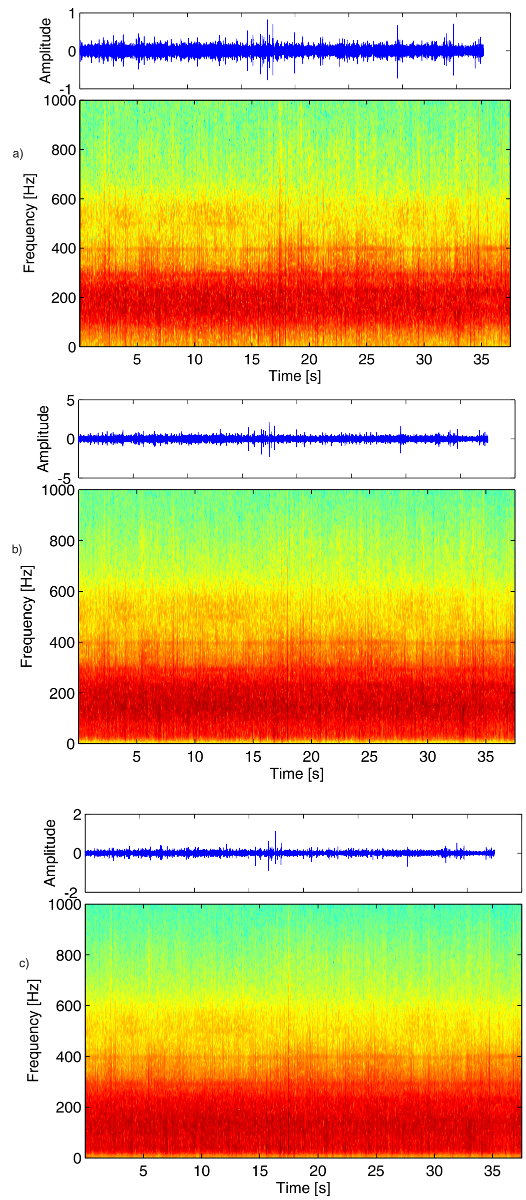

Figure 6: Proposed methodology for IMF 4. a) IMF, b) Velocity and c) Displacement

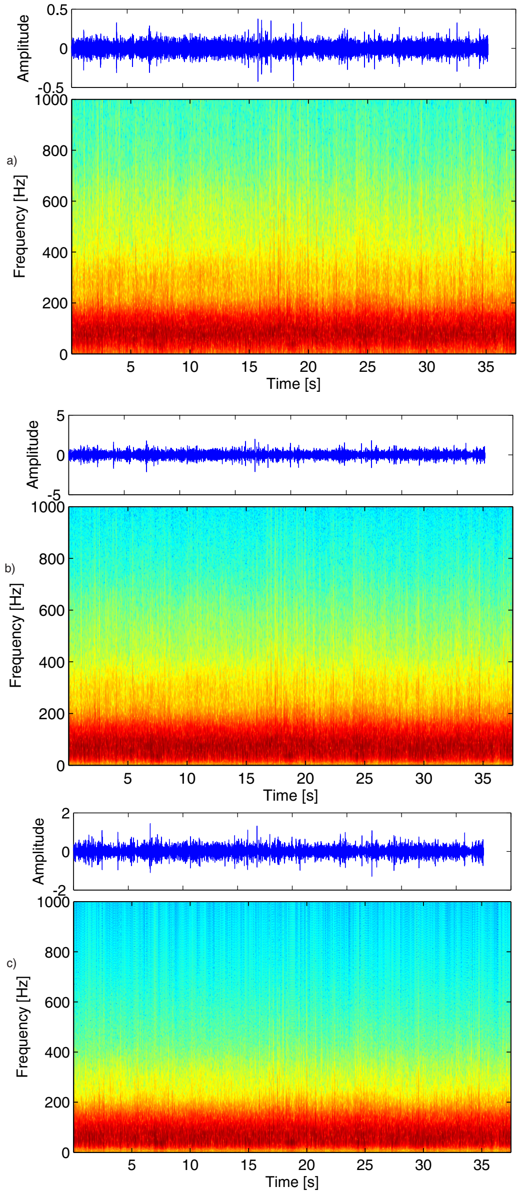

Figure 7: Proposed methodology for IMF 5. a) IMF, b) Velocity and c) DisplacementD

explore the use of those decomposition methods for component identification. Also, a model-based analysis using the acceleration, velocity and displacement signals will give more information about the failures and their spatial localization. The current methodology can be applied to other rotating machines as pumps, vessels engines and others.

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