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RESEARCH PAPER

Analysis of Vibration Signals of Drivetrain Failures in Wind Turbines for Condition Monitoring

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Abstract

In the last years, the wind industry has increased in a large scale. A wind turbine out of service leeds to high costs due to both maintenance and repair costs and the incapability of producing electricity. A substantial part of the wind turbine failures are in the drivetrain, mainly in generator and gearbox. Several recent works focuses in the study of benefits of the integration of condition monitoring with current maintenance techniques, that would drive to the reduction of costs. For condition monitoring, vibration analysis has been widely accepted as the technique that gives most information about faults in a rotating machine, thus vibration sensors are often used in wind turbine applications. In this work, data from several vibration sensors installed in 18 wind turbines in cold climate were analysed using the Wavelet Packets Transform energy. Signals were acquired for more than four years (from 2011 to 2015), registering failures in gearboxes and generators of the wind turbines. Data were obtained under varying conditions of load and speed as well as varying weather conditions. Signals were analysed with the aim of finding parameters that indicate the presence of a fault. This would be useful to predict a failure with enough time to plan a stop of the wind turbine in the proper moment for similar faults in the future.

Keywords Vibration signals · Wind turbines · Faults detection · Condition monitoring

Introduction

The wind energy industry is expanding worldwide in a rapid way. Nowadays, the trend is to locate larger turbines in remote areas and exposed to severe environmental conditions. Consequently, most effective solutions of maintenance are required to solve the new challenges that appear. Gearboxes and related mechanical components are designed with the aim of saving weight, therefore the probability of failure increases. According to [1], the number of unscheduled stops due to failures in a wind turbine is of up to 10 times per year, hence there are inefficient time and cost of maintenance. Condition monitoring (CM) systems are highly demanded in this industry and the research in this area has focused much attention in the last years. The aim of CM is to use measured data to reach a higher understanding of the operation of wind turbine generators (WTG) and to predict deterioration and failure of bearings and other machine components. The elements that generate more costs due to unplanned corrective maintenance and downtime are related to the gearbox, thus the study of condition monitoring of the gearbox has concentrated more attention, as in works as [2, 3]. Besides, generator elements are also a non-negligible source of failures [4].

A review of the different techniques used in CM of WTG can be consulted in [5], that includes techniques such as vibration signals, acoustic emission, or ultrasonic testing. However, it is widely accepted that vibration analysis is the technique that gives more information about faults in a rotating machine, so vibration sensors are often used in wind turbine applications. Despite the majority of the works that use vibration analysis are focused in the diagnosis of the bearings and the gearbox, it is highlighted in [5] that vibration signals have been also used to diagnose blades, rotors, and the tower, but not for the case of the generator.

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However, the advances in this area are not going fast due to the lack of real data available. In the last years, data are being kept for private development. It is highlighted in [6] that there is a lack of public reliability data.

Condition monitoring of WTGs is a special case where the operating conditions of speed and load are variable. That fact makes this application more difficult to analyse. Several works have analysed the problem of condition monitoring in non-stationary conditions. A high number of works have analysed the influence of the operating conditions on the amplitude components in the spectrum of a vibration signal. The possibility of rescaling the observed data to a standard condition is highlighted in [7], in order to make more reliable the diagnosis condition system. A linear model of the relation between the amplitude components and the operating conditions is proposed in [1], according to Eq. 1.

$$Y = b_0 + b_1 \cdot S + b_2 \cdot L + b_3 \cdot F \tag{1}$$

Where Y represents the vibration amplitude, as a function of the speed S, load L and fault level F. The terms b_1, b_2 and b_3 represent slopes of speed, load and fault, respectively. The term b_0 is independent. Under known conditions of speed, load and fault, the three slopes can be easily calculated.

The work [8] proposes a technique that combines vibration, acoustic, and lubrication oil analysis to address the problem of non-stationary conditions in a laboratory scale wind turbine gearbox. A review of the methods to avoid the effects of the non-stationary conditions is done in [9].

Vibration signals comprise a lot of information, so processing techniques are required in order to find the features that indicate the presence of a fault. According to [10], the 80% of the failures in the gearbox are due to bearings. A review of the vibration based methods used in CM for the planetary gearbox is also done in [9]. Some techniques used for gearbox analysis in WTGs using vibration signals are based on statistical methods, cepstrum analysis, FFT or Wavelet transforms [5]. Nowadays, other techniques based in the frequency domain, as the Envelope Analysis [11], are replacing the classical ones. Nevertheless, the Envelope Analysis is hardly affected by the noise. Other popular tool to diagnose bearings in frequency domain is the Empirical Mode Decomposition (EMD), that is performed to calculate the Intrinsic Mode Functions [12, 13]. However, the use of frequency domain techniques has serious limitations since they do not provide information about the time domain. By this reason, their use is not recommended to work with non-stationary signals, which are obtained in this application. Time-frequency analysis techniques are more suitable for this kind of purpose. The Hilbert-Huang Transform (HHT) is a time-frequency analysis technique based on the EMD. The HHT has shown high reliability, as in the case of [14]. The same way as HHT, the Wavelet Transform (WT) also provides information both in time and frequency domain, offering the proper treatment both for stationary and for non-stationary signals. WT has been widely applied for fault diagnosis of rotaty machines, and a review can be consulted in [15]. WT has been applied to detect bearing faults in WTGs, as in [16]. The work [17] proposes an adaptive fault detection method that combines the extraction of the empirical modes with the Wavelet Transform. Specifically, the energy of the Wavelet Packets Transform (WPT), that is a variant of the WT, has shown its effectiveness in previous related works applied to other mechanical rotating systems [18–21].

In the present work, a methodology to find features for condition monitoring in WTGs using vibration signals is proposed. Signals obtained under the same conditions of load and speed are studied to avoid the problem of working with non-stationary conditions. Real time vibration signals obtained from 18 WTGs in operation during more than four years are analysed. The signals acquired registered failures both in the gearbox and in the generator, that are the failures that generate more costs. Thus, this information is really valuable to find features indicators of fault that can be useful to predict the failure before it occurs. This would allow to plan the maintenance tasks for the most convenient moment avoiding costs. Specifically, the trend of the energy of the Wavelet Packet Transform (WPT) is studied before and during the failures studied. Some features found seem to contain information about the fault occurring, since they show strong changes when the failure approaches. These features found can be used for the inverse process of fault detection and failure prediction.

Data Available

A database of 40 Gb information is obtained from 18 WTGs, corresponding to 4 years of acquisition (2011-2015). Database registered several faults in drivetrains during operation. The primary drivetrain components (high speed shaft (HSS), main bearing (MB), gearbox (1st Pl. stage) and generator (GENO)) are sensed, registering time vibration signal information.

The HSS and MB are sensed in the axial direction. The GENO is sensed in the non-drive side (NDS), and the gearbox in the first planetary stage. Accelerometers GENO NDS, HSS, and MB have been mounted on the structural housing components as close to the bearings as possible. The sensor located at 1st Pl. Stage was located in the planetary ring gear.

Each sensor, depending on the mechanical element where it is installed, is configured with the optimal sampling rate and length of the signals to obtain. Thus, the sensors connected to the MB and the Pl. stage have a sampling rate of 2560 Hz. They are elements connected to the slow

Table 1 HSS sensor signal parameters

Data Parameters HSS axial ACC	
Dates	19/03/2011-15/09/2015
Generator speed range (cpm)	700-1200
Sample rate F_s (kHz)	12.8
Number of lines	8192-16384
Time (s)	0.64-1.28

speed shaft, before the gearbox increases the velocity, so the sensors monitoring the high speed shaft and the generator need a higher sampling frequency, that is configured to 12800 Hz. The sensors and signal parameters obtained can be observed in Tables 1, 2, 3, and 4.

Data are stored in a database in SQL server with a specific structure. To extract and process data in Matlab, a specific software is developed. This software connects to a SQL server that contains the database, and using an interface it allows the extraction of the signals in Matlab, selecting them by the sensor and dates. Each signal is converted to a Matlab structure, where besides the vector with the time-signal information, each signal contains the following information:

– Generator speed
– Generator minimum speed
– Generator maximum speed
– Load
– Time signal lines
– Sampling frequency

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The failures registered in the database can be consulted in Table 5.

Data from 6 months before the maintenance task for each failure have been extracted and analysed. This period of time has been considered enough to see the changes on the energy of the WPT that the appearing of a fault causes on the vibration signals, since before this time no changes are observed in any case. The remaining acquired data show similar values of energy in all cases and no trend is observed, so they are discarded for the purpose of diagnosis of the faults analysed in this work.

Table 2 Generator NDS sensor signal parameters

Data parameters Geno NDS	
Dates	19/03/2011-15/09/2015
Generator speed range (cpm)	700-1200
Sample rate F_s (kHz)	12.8
Number of lines	16384
Time (s)	1.28

Table 3 MB sensor signal parameters

Data parameters MB axial	
Dates	19/03/2011-15/09/2015
Generator speed range (cpm)	500-1200
Sample rate F_s (kHz)	2.56
Number of lines	16384
Time (s)	6.4

Data are only acquired while the wind turbine is working, and the acquisition system is programmed to get one signal each day. Besides, some data are discarded to warrantee that all data are measured at stationary conditions of load and speed, as explained further below. Thus, to represent the trend of energies with respect to time, since the time between signals is variable, in the X axis the number of measurement ordered in ascendant order of time before the maintenance task is represented.

Data Processing

Data were obtained under varying conditions of load and speed, as well as varying weather conditions. In order to have a reliable analysis for condition monitoring, since the signal amplitudes depend on the operating conditions, two options are considered; the first one is to rescale data according to [1], and the second one to filter data by equal conditions of load and speed.

Filtering signals by conditions to perform the analysis seems to work better due to different causes; first, data rescaling is based on a linear model that can no be accurate, and the slopes calculated would depend on the data selected, introducing large errors. On the other hand, bearing fault frequencies depend on the speed, however structural frequencies (that are unknown in most cases) are independent from the speed. Thus, the certain knowledge about all frequencies would be required to rescale the frequency axis. All these processes can introduce errors and difficulties to find interesting information.

Figure 1 shows typical registers of load in kilowatts and speed in cycles per minute, versus the number

Table 4 1st planetary stage sensor signal parameters

Data parameters 1st planetary stage	
Dates	19/03/2011-15/09/2015
Generator speed range (cpm)	500-1200
Sample rate F_s (kHz)	2.56
Number of lines	16384
Time (s)	6.4

Table 5 Failures registered during the four years acquisition

Failure	Maintenance task
1	Generator bearing replaced DS
2	Generator bearing replaced DS
3	Generator bearing replaced DS and NDS
4	HSS bearing replaced
5	Gearbox replaced (BPFI in bearing 1st planetary stage)

of measurement in ascendant order by date before the maintenance task.

As can be observed in Fig. 1, the majority of the values of load are close to 1485 kW in this case. However, they tend to group to other values depending on the failure. On the other hand, the speed values always tend to achieve two different values of around 800 and 1150 cpm.

After a preliminary analysis of the trend of energies of the WPT using signals at 800 and 1150 cpm separated, it is concluded that a clearer trend is observed for 800cpm, so it is considered that signals with speed values of around 800 cpm seem to contain better information about failures. Therefore, results will show the trend of energies for signals measured at speeds that falls within the range 785 and 815 cpm for all the cases. For the specific case of the figure, the signals that were measured with load values between 1470 and 1500 kW were analysed. These values have been selected to get a compromise between assuring stationary conditions as much as possible, and including enough signals to analyse the trends. A ramp control for the speed is also set; if the speed variation during the signal is higher than 4 cpm, the signal is also discarded in order to warrantee the stationary conditions during each measurement.

Once data are selected and extracted, the WPT energies are calculated. This parameter can be calculated with low computational cost and constitutes a simple parameter easy to handle and to be automatically classified.

The WPT energy parameter has shown effectiveness diagnosing rotating machinery in works as [18, 19, 21, 22]. A review of the application of the WPT energy to diagnose rotating machinery can be consulted in [23].

Wavelet Packet Transform (WPT)

The WPT is selected, among other reasons, due to its capability to calculate energy using both time and frequency domain information. Thus, the Wavelet Transform is specially efficient to carry out local analysis of non stationary and transient effects that occur when a fault appears in signals [24].

The same way as the Fourier Transform obtains correlation coefficients of the signal with a sinusoidal function, WT obtains correlation between the signal and the mother wavelet. Coefficients obtained depend on the scale (a) and on the shift (b) of the mother wavelet. The WT can be applied in a continuous way (Continuous Wavelet Transform (CWT)) or in a discrete way (Discrete Wavelet Transform (DWT)).

The Continuous Wavelet Transform (CWT) allows the analysis of structures of signals through correlation

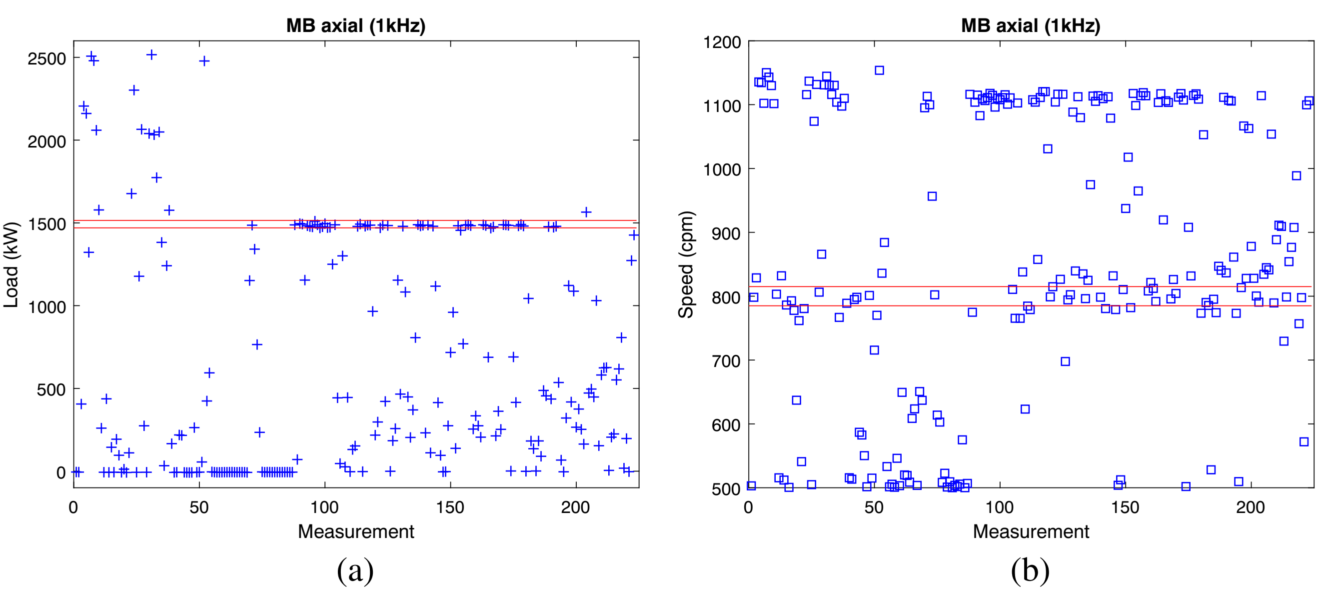


Fig. 1 Evolution of load (**a**) and speed (**b**) registered by the sensor in the main bearing, in the six months prior to the failure 1, and ranks of data selected

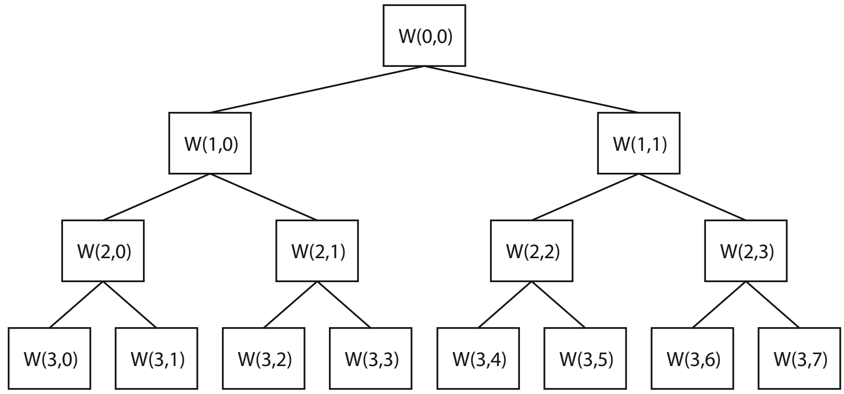


Fig. 2 WPT analysis, procedure of decomposition through low pass filters and high pass filters [19]

coefficients, instead of using the whole signal. The mathematic formulation of the CWT is shown in Eq. 2:

$$T(a,b,\psi) = w(a)\int_{-\infty}^{\infty} S(t)\psi^{*}(\frac{t-b}{a})dt \tag{2}$$

Where $S(t)$ is a time signal and ψ is the mother wavelet. The weight function is represented by $w(a)$ and $T(a,b,\psi)$ are the coefficients of the wavelets as functions of a, b, and ψ. The product of the conjugate mother wavelet with the signal is integrated in the whole range of the signal. This operation is known mathematically as convolution [25].

From the definition of the CWT, it is a usual practise working with Discrete Wavelet transform (DWT). Latest developments of the DWT allow the decomposition of signals by means of recursive filters related to the mother wavelet [26]. A signal is decomposed dividing the spectrum into separate halves with a low pass filter and a high pass filter. The Wavelet Packet Transform (WPT) is an extension of the DWT. The WPT consists on the application of the DWT in a recursive way [24]. The scheme of decomposition in the WPT is shown in Fig. 2.

Where $W(k,j)$ represents the coefficients of the signal in each packet. The decomposition level is represented by k and j is the position of the packet within the decomposition level. Then, each correlation vector $W(k,j)$ has the structure of Eq. 3:

$$W(k,j) = \{w_1(k,j), ..., w_N(k,j)\} = \{w_i(k,j)\} \tag{3}$$

Where i is the position of the coefficient within its packet.

WPT Energy Extraction

When working with WPT, the same resolution is obtained for each packet within the same decomposition level. The decomposition level selection is a critical decision since it determines frequency resolution of each packet. Using a decomposition level k, the signal is divided into a number of packets 2^k that are able to reconstruct the signal until the signal frequency resolution F_r (half of the sampling frequency, F_s, according to the Nyquist theorem). The frequency resolution f_r of each packet is given by Eq. 4 [18].

$$f_r = \frac{F_r}{2^k} = \frac{F_s}{2 \cdot 2^k} \tag{4}$$

Since two different sampling frequencies are used depending on the location of the sensor, two different values of decomposition level are selected. The decomposition levels are selected in order to have a similar frequency resolution for the packets for all the sensors considered. In this case, the decomposition levels selected are $k = 3$ (8 packets) for the case of the sensors in the MB and 1. Pl. stage with a sampling frequency of 2.56 kHz, and $k = 5$ (32 packets) for the sensors in the HSS and Generator, that use a sampling frequency of 12.8 kHz. With these values, the frequency resolution obtained for each packet in all cases is around 200 Hz, that is an optimal value to minimize the computational cost and the number of packets to analyse. Table 6 shows the frequency parameters for each sensor depending on the sampling frequency F_s and the decomposition level selected k.

Table 6 Decomposition level and frequency parameters

Decomposition level k	5	3
Number of packets 2^k	32	8
Measurement points	HSS and Geno NDS	MB and 1.Pl. stage
Sampling frequency F_s (kHz)	12.8	2.56
Signal frequency resolution F_r (kHz)	6.4	1.28
Frequency resolution of each packet f_r (Hz)	200	160

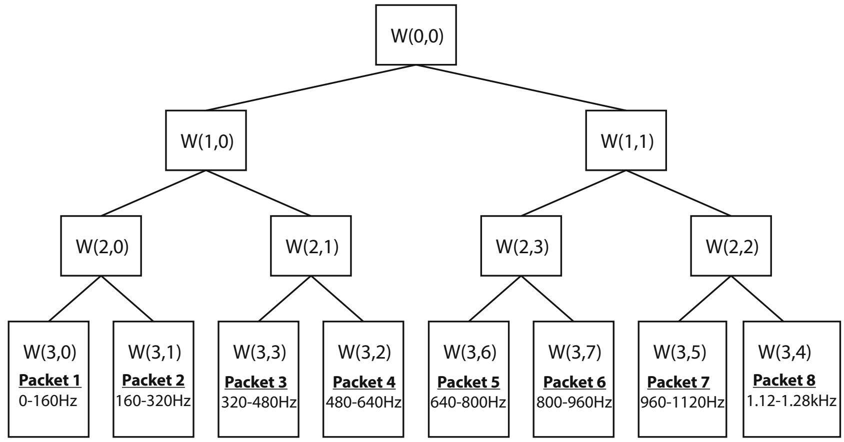


Fig. 3 WPT analysis, node names and frequency bands after reordering for a sampling frequency of 2.56 kHz

The energy of the WPT packets can be obtained as the sum of all the squares of the coefficients of each packet, according to Eq. 5 [24].

$$E_{k,j} = \sum_i \{w_i(k, j)\}^2 \tag{5}$$

The WPT processing as shown in Fig. 2 Results in a order of packets that does not correspond to the natural order of frequencies. In this work, only the last level packets are considered. For showing the results, the packets have been ordered according to natural order of frequencies, so each packet corresponds to the position of the packet within the decomposition level after reordering according to the natural frequency order. Then, after reordering, the nomenclature of nodes and the frequency bands related for the decomposition level $k = 3$ and a sampling frequency of 2.56 kHz are shown in Fig. 3. The energies are represented until the signal frequency resolution F_r for each case.

Thus, the part of the signal energy contained in each frequency band is obtained when calculating the energy of the WPT. Figure 4 shows an example of the energy of the packets obtained using WPT at decomposition level 3 (2^3 packets) for a signal coming from a sensor located in MB.

Results

The WPT energy is calculated for the available signals 6 months prior to the maintenance task for all the failures. The aim is to detect trends in energy when the fault appears, useful to detect it and predict the failure. The evolution with time of the energy of the WPT that seem to have relevant information about the faults are shown. Since the time between signals is not constant, the number of measurement is represented in the X axis in all cases.

Results are shown for signals measured under approximately the same conditions of load and speed. Data are filtered to assure stationary conditions, and only results at 800 cpm are shown, since they seem to contain better information about the faults analysed.

Theoretical fault frequencies depend on the specific location of the fault, that can be the inner race, the outer race, the rolling element or the cage, finding the ball pass frequency inner (BPFI), the ball pass frequency outer (BPFO), the ball spin frequency (BSP) and the fundamental train frequency (FTF), respectively. Theoretical fault frequencies also depend on the bearing geometry, and on the rotation speed [27, 28]. Since the specific location of the faults are unknown, all the theoretical fault frequencies are computed for the speed value of 800 cpm. The purpose is to see if the packets that contain information about the failures match these frequencies.

The results are separated in generator failures (failures 1, 2 and 3) and gearbox failures (failures 4 and 5).

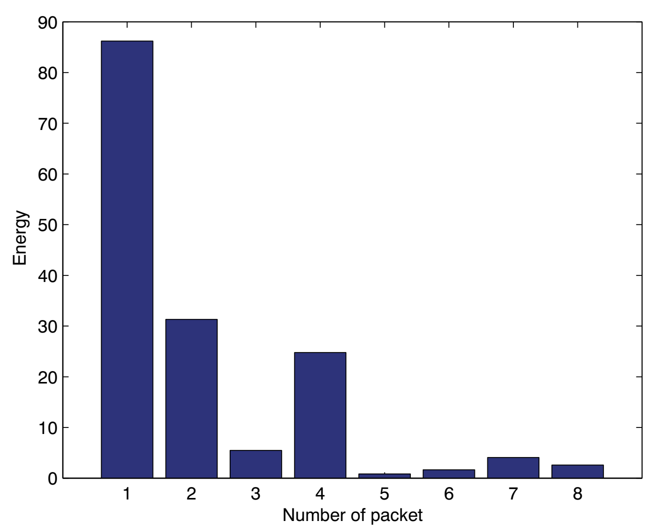


Fig. 4 Energy V^2 calculated using WPT at decomposition level 3 for a signal coming from a the main bearing

Table 7 Theoretical fault frequencies for bearings in DS and NDS of the generator at 800 cpm

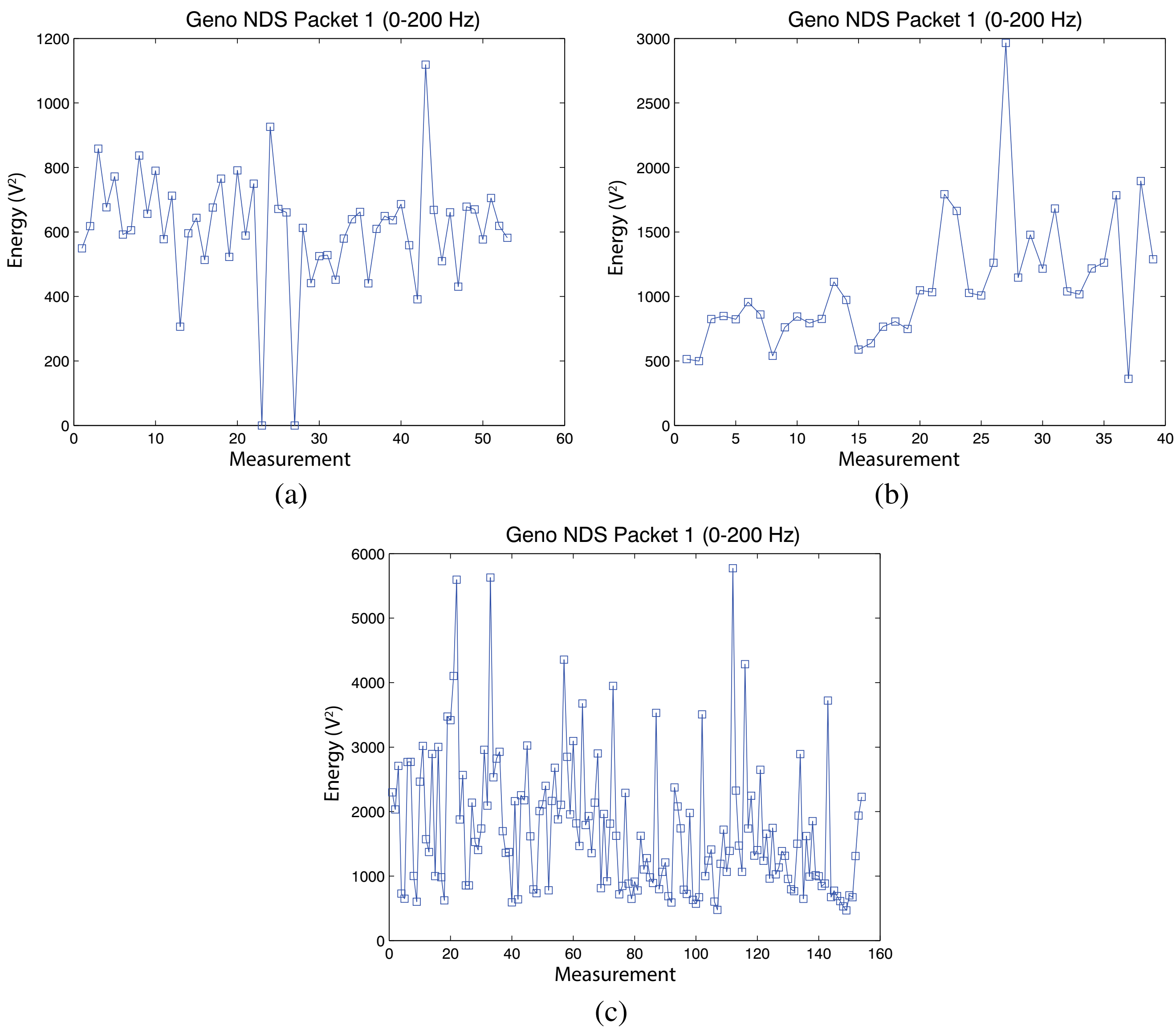
Generator NDS/DS1 (Hz)	
BPFI	167.2
BPFO	136.1
BSF	63.75
FTF	5.78
Generator DS2 (Hz)	
BPFI	71.4
BPFO	47.25
BSF	30.94
FTF	5.15

Generator Failures

According to Table 5, there are three generator failures, numbers 1, 2 and 3. The failures 1 and 2 ended by replacing the bearing in the generator DS. On the other hand, the failure number 3 was solved replacing two bearings, both in DS and NDS. Theoretical fault frequencies both for NDS and DS bearings at 800 cpm, are shown in Table 7.

As the frequency band covered by each packet for the sensor located in the generator NDS is of 200 Hz, all the theoretical fault frequencies are contained in the first packet. Figure 5 shows the evolution in time of the energy of the first packet, containing all the fault frequencies. As can be observed, attending to the packet number 1, only in the case of failure number 2 a change of energy could be detected before the failure, indicating the presence of a fault.

Analysing the WPT energy trends of the rest of the 31 packets obtained for the signals obtained with the sensor Geno NDS for failures 1, 2 and 3, stationary evolutions



(a) (b) (c)

Fig. 5 Evolution of energy V^2 of the first packet with time for the signals obtained using the sensor located in the Geno NDS prior to **a** failure 1 **b** failure 2 and **c** failure 3 are observed in terms of mean and standard deviation in almost all the packets, finding no evidences of the fault. However, in packet number 5 (800-1000 Hz) an upward energy trend is observed for failures 2 and 3. Figure 6 shows the evolution in time of the energy of the packet number 5 for all the generator failures. The energy prior to failures 2 and 3 shows strong increments, specially in the failure number 3 where both bearings were replaced. Thus, this packet contains valuable information about the fault in the bearing. In this case, failures number 2 and 3 could have been predicted using the changes in energy in packet number 5. Packet number 5 is related to a frequency band that contains a structural frequency, where the bearing defects are modulated. However, for the case of failure 1, a stationary evolution of the energy is observed without any changes of energy indicating the presence of a fault, probably due to the lack of a sensor in the DS of the generator (where the faulty bearing was located).

Gearbox Failures

Two gearbox failures are analysed, numbers 4 and 5.

In the case of failure number 4, one of the HSS bearings was replaced. The theoretical fault frequencies at 800 cpm of the two bearings in the HSS can be consulted in Table 8.

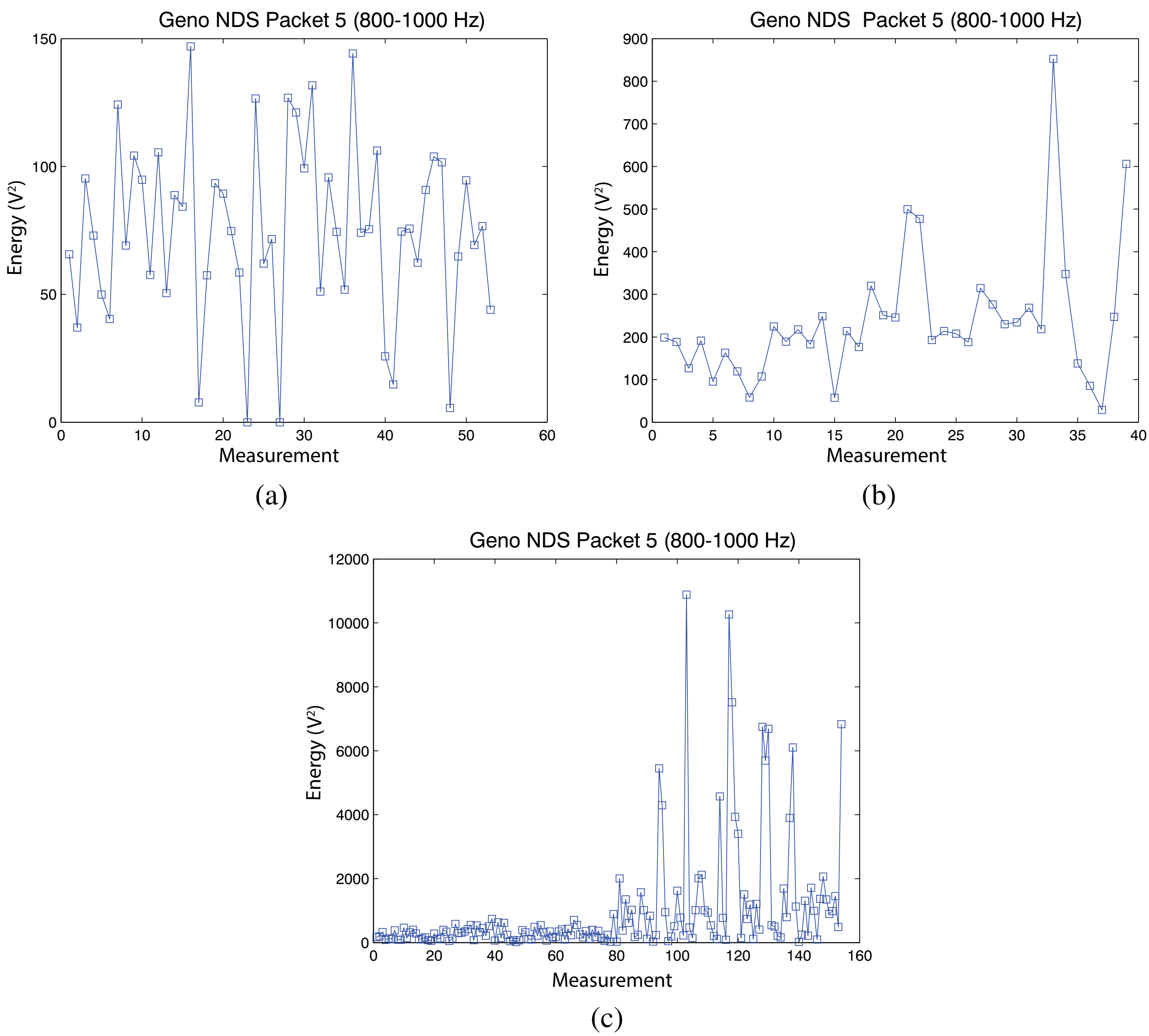
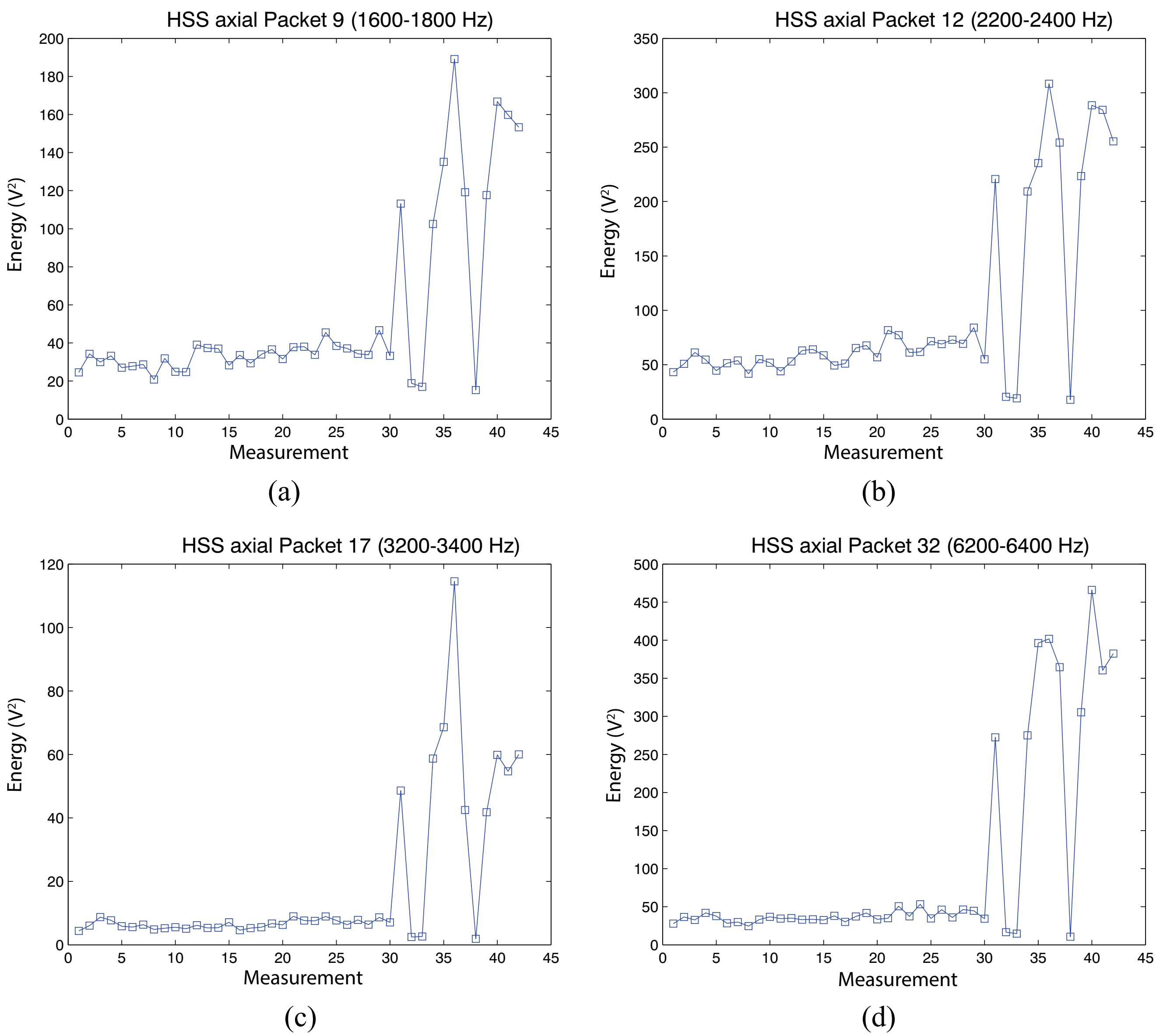


Fig. 6 Evolution of energy V^2 of the fifth packet with time for the signals obtained using the sensor located in the Geno NDS prior to **a** failure 1 **b** failure 2 and **c** failure 3

Table 8 Fault frequencies for bearings located in the HSS at 800 cpm

HSS GS1 (Hz)	
BPFI	127
BPFO	96.7
BSF	40.8
FTF	5.625
HSS GS2 (Hz)	
BPFI	143
BPFO	107.6
BSF	45.8
FTF	5.625

Again, all the theoretical fault frequencies are contained in packet 1, but the energies at this packet show a stationary behavior in terms of mean and standard deviation. Thus, the energies at this packet can not be used to predict the failure. Figure 7 shows the evolution in time of the energy of some packets that seem to have relevant information about the fault, since they show a significant energy increasing when the failure approaches. In the rest of the cases, stationary energy trends are observed. The changes in energy observed in the packets selected may be used to predict the failure. The fault in this case causes an increasing in the vibration amplitude at the high frequencies, probably due to the oscillations that appear in structural frequencies when the impacts due to bearing faults take place. All the packets above the number 9 (1600-1800 Hz) show this behavior.



(a) (b) (c) (d)

Fig. 7 Evolution of energies V^2 with time for signals obtained from the sensor located in HSS prior to failure 4 for **a** packet 9, **b** packet 12, **c** packet 17 and **d** packet 32

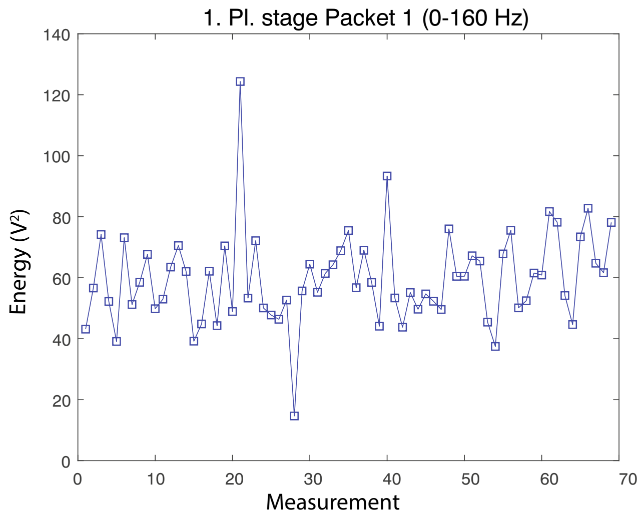


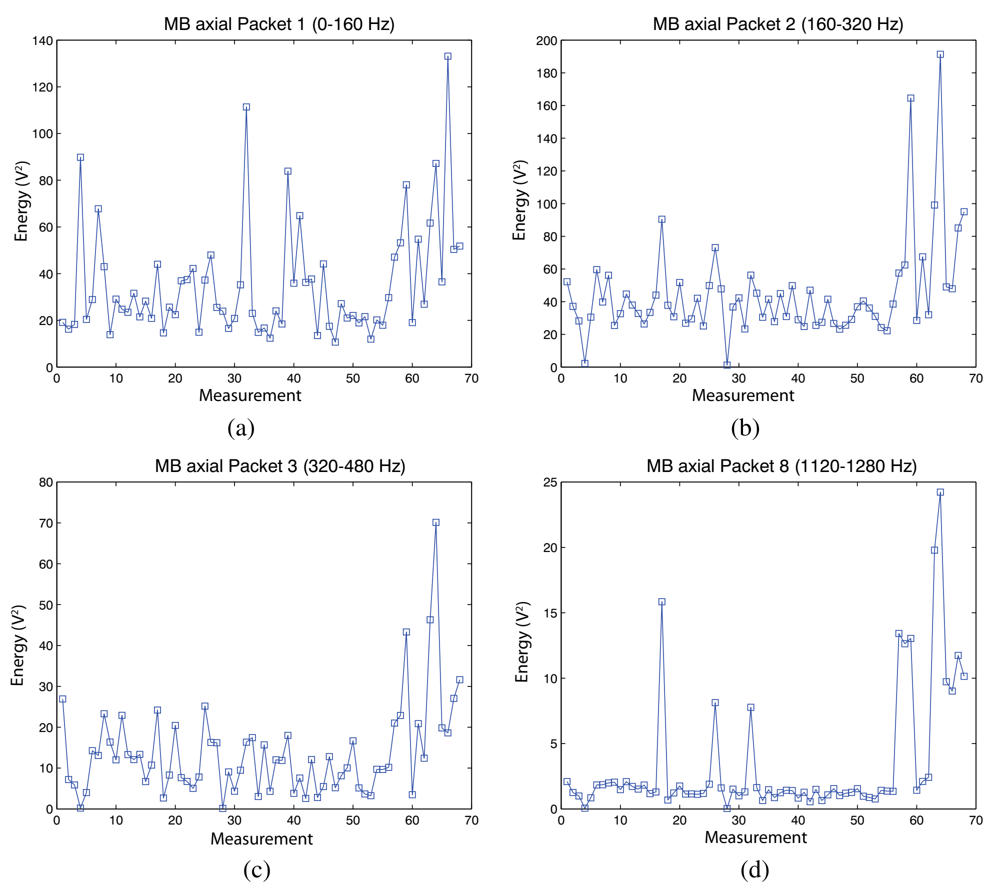
Fig. 8 Evolution with time of energy of packet 1 for signals obtained from the sensor located in the first planetary stage prior to failure 4

In the case of failure number 5, the bearing located in the first planetary stage bearing was replaced. In this case, it is known that the damage was in the inner race. Then, the fault frequency 5 Hz (contained in packet 1).

Figure 8 shows the evolution in time of the energy of the first packet using the signals obtained with the sensor located in the first planetary stage. A slight positive trend is observed, however it does not appear to be enough to predict the failure with reliability.

However, sometimes a fault in a certain element can be observed from other parts of the machine. The malfunction can cause an increasing in the vibration level in certain frequency bands. Using signals obtained from the accelerometers located in the MB and in the GENO NDS, important changes in energy are observed for the case of failure 5. Figures 9 and 10 show the evolution in time of the energy of some packets that seem to have relevant information about the fault occurring in the first planetary stage bearing, using signals from the sensors in MB and in GENO NDS respectively. The packets that seem to have relevant information are related to low frequencies (mainly between 0-480 Hz) in the case of the MB sensor. In the case of the GENO NDS signals, the information about the fault is contained in high frequencies related to a structural frequency around 4300 Hz in the case of the generator sensor. In the rest of the cases, no relevant information about the fault is observed in the energy trends.

Fig. 9 Evolution of energies V^2 with time for signals obtained from the sensor located in the main bearing prior to failure 5 for **a** packet 1, **b** packet 2, **c** packet 3 and **d** packet 8



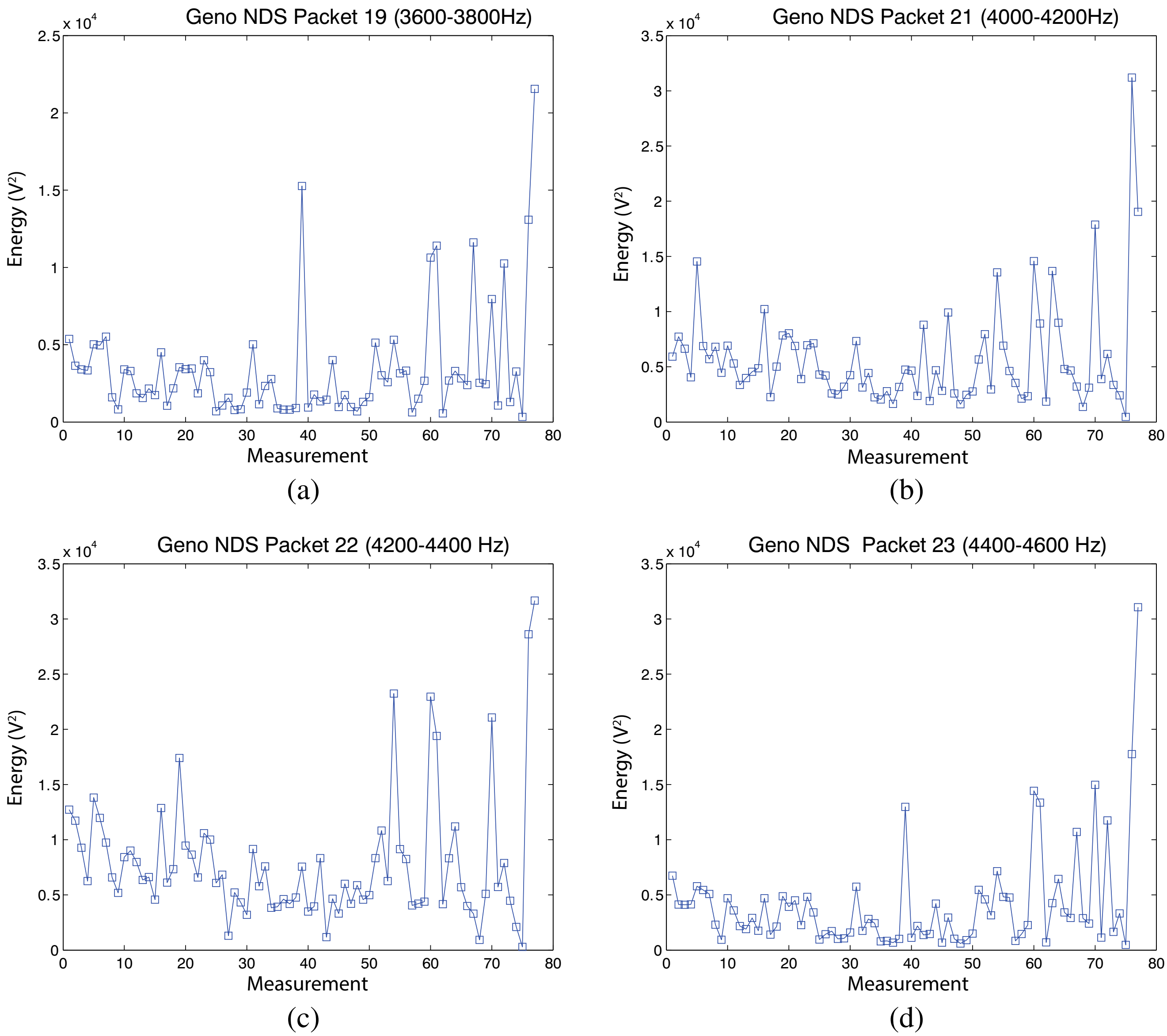


Fig. 10 Evolution of energies V^2 with time for signals obtained from the sensor located in generator prior to failure 5 for **a** packet 19, **b** packet 21, **c** packet 22 and **d** packet 23

Conclusions

A methodology to find features for condition monitoring in WTGs has been proposed. The methodology has been applied to analyse real data coming from a wind farm. Data available are vibration signals corresponding to 4 years of acquisition that registered 5 faults in main components of the drivetrain; the generator and the gearbox. Data corresponding to 6 months before of all maintenance tasks are analysed.

Data have been analysed using the WPT energy looking for parameters that experiment changes with time when a fault appears. In two of the three failures registered in the generator, this behavior is found in certain packets. This behavior is not observed in failure 1, surely due to the lack of a sensor in the DS of the generator (where the faulty bearing was located). The acquisition of time-domain signals in a sensor located in the DS of the generator would improve the reliability detecting generator faults. Regarding the gearbox faults, some of them can cause impacts that can be seen at specific frequencies, and some of them malfunction in the machine that can be observed in the increasing of vibration level in wide frequency bands. Specifically, the faults in the HSS are detected in a wide frequency band of the spectrum, where the vibration level increases in a strong way. The failure occurred in the first planetary stage bearing can also be detected using the changes in trend that can be observed from the sensors located in the MB and in the NDS of the generator, in low and high frequency bands respectively.

The results of this preliminary study are promising, however the reliability of the results need to be statistically verified with the register of more failures of the same type, that are not easily obtained. A further analysis of the frequencies should also be performed to try to predict the frequencies where the fault is going to appear, but this study could not be done due to confidentiality reasons. Besides, Intelligent Classification Systems can be implemented, such as Artificial Neural Networks, that have been successfully applied in the bibliography after acquiring the indicators of fault from the vibration signals [18, 22, 29].

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Compliance with Ethical Standards

Conflict of interests The authors declare that they have no conflict of interest.

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