

Challenges And Opportunities in Applying Vibration Based Condition Monitoring in Railways

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ABSTRACT

Electrical rotating machines are among the most common assets used in industry. In railways applications these devices are present in fixed and rolling stock systems, such as turnouts and traction components. Condition based maintenance (CBM) of rotating machines may significantly improve the availability of critical railway assets. Moreover, by efficiently assessing the state of health of targeted components, it becomes possible to introduce advanced asset management strategies for life cycle cost optimization. In comparison with traditional maintenance approaches, health monitoring enables better maintenance scheduling, fleet size optimization and maintenance costs reduction. CBM applied to rotating machines has been actively studied by many researchers in a wide variety of fields such as: signal processing, anomaly detection, failure diagnostic and failure prognostics. However, there is still a considerable gap between the methods studied in research and the ones successfully applied in industry, and especially in the railway field. This paper discusses the challenges and opportunities for application of CBM methods to electrical rotating machines in railway applications. For the purpose of illustration, a case study focusing on traction motor bearings is considered. Time domain and frequency domain signal processing techniques are employed to extract features from bearing degradation data. The data analyzed in the present study have been obtained in a bearing test bench and during a test conducted on a real traction motor used in trains. The results of the considered methods are discussed and future research directions are suggested.

1. INTRODUCTION

Maintaining railway equipment in operational condition is an industrial, economical and societal need. Fulfilling this requirement represents a challenge because railway systems are

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complex and subject to stress factors affecting their behavior and aging process (e.g. temperature, humidity, varying load, imperfect maintenance, etc.). The operation of railways requires several fundamental assets (Bonnett, 2005):

- The rolling stock: this stands for the vehicles (metros, tramways, locomotives, etc.) that convey passengers and goods.
- The infrastructure: refers to the fixed installations necessary to operate the railway, such as:
 - The tracks: which support and guide the rolling stock without active steering
 - The signaling: that is used for traffic control and to avoid collisions
 - The power supply: responsible of transforming and carrying the current to the rolling stock by using overhead cables or a third rail
 - The facilities: which serve as areas where the passengers may board or step off from trains (stations) or where the trains are maintained and overhauled (depots)

Railway assets are made from engineered systems. For example, rolling stock are formed by means of train systems and comfort systems. Without being exhaustive, the formers provide main functions such as: current collection, traction, air supply and communications. The latter perform auxiliary functions like: heat ventilation and air conditioning (HVAC), toilets and doors operation. Some of the previous systems embed electrical rotating machines in order to provide the key energy or movement required to perform their main function. HVAC units use electrical motor-fans to create the heating/cooling air flow. Doors and pantograph operation rely on a kinematic chain controlled by brushless motors. Vacuum for toilet flushing and pressurized air for braking system is provided by an electrical compressor driven by a motor. Finally, trains are moved using powerful electric motors.

Bearings are one of the most critical components in electrical rotating machines. The survey performed by the the Institute of Electrical and Electronics Engineers (IEEE) Motor reliability working group (O'Donnell, 1985) showed that bearings accounts for 41% of failures in powerful motors as presented in figure 1.

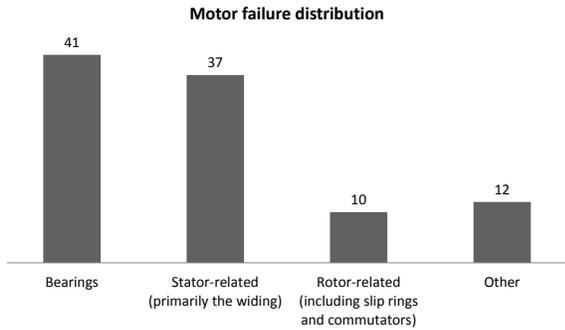


Figure 1. Failure distribution of motors of power greater than 200 HP.

Therefore, the system's availability is conditioned by the health of the motor's bearings and their capacity to accomplish the expected mission. The maintenance of electrical rotating machines is a critical operation for the railways operators. Traditionally, the maintenance strategies performed in the workshops are corrective or preventive. In the first case, the maintenance interventions are performed after the failure. However, this may lead to undesired or dangerous situations. Preventive maintenance seeks to perform the maintenance intervention before the failure's appearance. This approach aims at preserving equipment reliability by replacing worn components before their failure. However, preventive maintenance may be costly and decrease system availability due to the regular maintenance operations. To improve previous approaches, Condition Based Maintenance (CBM) can be applied and consequently achieve significant benefits (Lebold & Thurston, 2001). CBM focuses its efforts in determining the equipment's health condition, estimated or measured through sensors present on the equipment. Through this information it becomes possible to track the evolution of the system's health state, detect its abnormal behaviors, diagnose the type of anomaly and predict its Remaining Useful Life (RUL). The comprehensive literature reviews performed by (Sikorska, Hodkiewicz, & Ma, 2011) and (Javed, Gouriveau, & Zerhouni, 2017) show that CBM has been an active research field for academics and industrials. In the research community, the published literature for bearings covers fields such as: signal processing, feature extraction, anomaly detection, diagnostic and prognostic assessment by mainly using vibration data (Randall & Antoni, 2011; Kan, Tan, & Mathew, 2015; Tobon-Mejia, Medjaher, Zerhouni, & Tripot, 2012). Railway companies have been

actively working in CBM. In 2015, Alstom launched the HealthHub¹ program in order to develop dedicated technology for condition based maintenance and prognostics and health management (PHM). Successful applications have been reported in the field of health monitoring of traction blowers (Trilla, Gratacòs, Guinart, Alessi, & Lamoureux, 2016) and turnouts (Alessi, La-Cascia, Lamoureux, Pugnaloni, & Dersin, 2016), among others.

This paper will focus in the signal processing, feature extraction and anomaly detection applied to electrical rotating machines. The main aim is to extract useful bearing's health information from the raw signals obtained by sensors. The following sections present the results obtained by using time domain and frequency domain feature extraction methods, in vibration signals generated by means of a research test bench and by a real train system. Time domain analysis and frequency domain analysis are chosen and investigated because they are the most discussed approaches in the literature. The paper is structured as follows: Section 2 gives the necessary background about the feature extraction methods; Section 3 describes the different test platforms; Section 4 presents, discusses and compares the results obtained. Finally, conclusion remarks and future research directions are given.

2. SIGNAL PROCESSING AND FEATURE EXTRACTION

As presented in the previous section, bearing failure is one of the most common cause of problems in rotating machines. Bearing fault usually starts as small indentations or material breaks (spalls). In order to track the level of degradation several physical variables have been investigated in the literature, such as: temperature, wear measurement (debris), magnetic field and vibrations (Kurfess, Billington, & Liang, 2006). At each passage of the rolling elements over the defect, a sharp high energy impulse is generated. Thus, local defects in a bearing produce repeated impulses (measurable trough an acceleration signal) as the bearing elements repeatedly strike the fault. The figure 2 illustrates how the vibration is excited by local faults in the different bearing elements. In order to extract useful information from the acceleration signals, a large variety of methods have been published in the literature. The existing literature on the subject may be classified in three classes:

- Time domain: these methods focus on extracting the statistical information of the vibration signal.
- Frequency domain: also known as spectral analysis which rely on the frequency characteristics of the vibration signal.
- Time-Frequency domain: here the methods consider the vibration signal as a non-stationary process.

¹<http://www.alstom.com/press-centre/2014/646105/innotrans2014-alstom-launches-healthhub-an-innovative-tool-for-predictive-maintenance/>

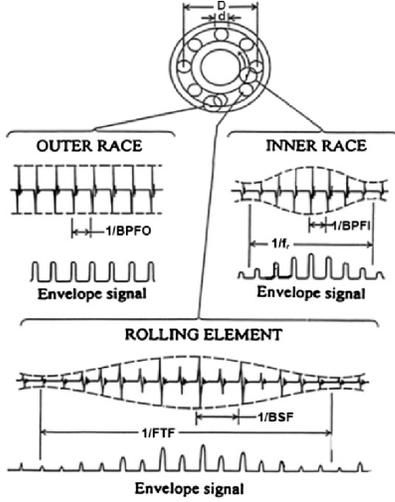


Figure 2. Typical signals and envelope signals from local faults in rolling element bearings.

This paper focuses on the most spread techniques in the literature, namely time domain and frequency domain because they have been successfully applied in “real world” applications (Randall & Antoni, 2011). The following subsections give the background of the studied approaches.

2.1. Time Domain

The vibration signals produced by rotating machines are considered as cyclostationary signals. This implies that the measured signal is produced by a hidden periodic mechanism. Time domain approaches aim to compute signal statistics and signal shape factors characterizing such periodic behavior. As reviewed by (Kurfess et al., 2006), the most used time domain features are: root mean square or RMS Eq. (1), mean Eq. (2), peak value Eq. (3), crest factor Eq. (4), skewness Eq. (5) and kurtosis Eq. (6).

$$x_{rms} = \sqrt{\frac{\sum_{i=1}^N x_i^2}{N}} \quad (1)$$

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N |x_i| \quad (2)$$

$$x_{pv} = \max(x_i) \quad (3)$$

$$x_{cf} = \frac{x_{pv}}{x_{rms}} \quad (4)$$

$$x_{sk} = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^3 \quad (5)$$

$$x_{ks} = \frac{(N-1) \sum_{i=1}^N (x_i - \bar{x})^4}{\sum_{i=1}^N (x_i - \bar{x})^2} \quad (6)$$

Where x is the discrete sampled vibration signal of length N where each measured point is denoted as x_i and $i \in \{i \in \mathbb{N} \mid i \leq N\}$. The RMS is used to compute the average power of the system’s vibrations. The mean is estimated in the rectified vibration signal because in raw signals the mean remains close to zero. The previous features are expected to increase when the bearing deteriorates. Peak value and crest factor catches instantaneous accelerations or burst closely related with cracks and indentations. Skewness and kurtosis are respectively the third order and the fourth order signal’s statistical moment, they characterize the bearing’s surface quality. Machined bearings are supposed to have random asperities which are commonly approximated to a normal distribution. Thus, for normally distributed data $x_{sk} = 0$ and $x_{ks} = 3$; these reference values allow to track shifts in the bearing’s condition.

2.2. Frequency domain

Vibration signals also contain frequency information that may be extracted by transforming the temporal sampled signal in to the frequency domain. Faults in rolling element bearings produce a series of broadband vibrations as the bearing elements repeatedly strike faults. As presented in figure 2, the location of the fault determines the origin of the vibration response. This means that each bearing element has its own characteristic rotational frequency. If a defect appears on a particular bearing element, an increase in the vibrations level at the element’s rotational frequency may be observed. The characteristic fault frequencies can be calculated from kinematic considerations; mainly the geometry of the bearing and its rotational speed (Smith & Randall, 2015). For a bearing with a fixed outer race, the bearing fault frequencies are: ball pass frequency over the outer race (BPFO) Eq. (7), ball pass frequency over the inner race (BPFI) Eq. (8), fundamental train frequency or cage speed (FTF) Eq. (9) and ball (roller) spin frequency (BSF) Eq. (10).

$$\text{BPFO} = \frac{nf_r}{2} \left(1 - \frac{d}{D} \cos(\phi)\right) \quad (7)$$

$$\text{BPFI} = \frac{nf_r}{2} \left(1 + \frac{d}{D} \cos(\phi)\right) \quad (8)$$

$$\text{FTF} = \frac{f_r}{2} \left(1 - \frac{d}{D} \cos(\phi)\right) \quad (9)$$

$$\text{BSF} = \frac{Df_r}{2d} \left(1 - \left[\frac{d}{D} \cos(\phi)\right]^2\right) \quad (10)$$

In the previous equations f_r is the shaft speed, n is the number of rolling elements, and ϕ is the angle of the load from the radial plane. D , d , BPFO, BPFI, FTF and BSF are shown in figure 2. As explained by (Smith & Randall, 2015), it is worth to noticing that the previous fault frequencies are based

on kinematic relationships assuming no slip, but in practice there is always some slip, so a variation up to 1-2% of the calculated frequency is common.

Bearing's fault frequencies are in general "low" and fall in the interval [1 - 1000] Hz. One may reasonably consider to transform the raw signal in to the frequency domain (e.g. by means of the Fourier transform) and directly search the fault frequencies. However, this method is limited and gives poor results. This is because the bearing fault signals have low magnitude and are masked by other components in the spectrum (e.g. gears, axles, belts, noise, etc.). Bearing's vibration signals are generally acquired using a sampling rate comprised in the range 1 Hz - 25 kHz. The sensed accelerations contains rich information. This, enables the possibility of finding an uncontaminated frequency band dominated by the fundamental bearing's frequencies in higher frequency range. The most powerful bearing fault detection techniques depend on enhancing the impulsiveness of vibration signals. As explained by (Tandon & Choudhury, 1999), each time a defect strikes its mating element, a pulse of short duration is generated that excites system's resonances periodically (e.g. electrical motor) at the element frequency. The resonances are thus amplitude modulated at the characteristic defect frequency. By demodulating one of these resonances, a signal indicative of the bearing condition can be recovered. In practice, the signal is bandpass-filtered around one of the resonant frequencies, thus eliminating most of the unwanted vibration signals from other sources. This bandpass-filtered signal is then demodulated by an envelope detector in which the signal is rectified and smoothed by low-pass filtering to eliminate the carrier or bandpass-filtered resonant frequency. The spectrum of the envelope signal in the low-frequency range is then obtained to get the characteristic defect frequency of the bearing. The envelope detector is given in the Eq. (11), where $B(t)$ is the envelope signal, $x_f(t)$ is the raw signal filtered around the resonant frequency and $\hat{x}(t)$ is the Hilbert transform of $x_f(t)$. The Hilbert transform is available in commercial software such as Matlab^{®2} and its theoretical background is well described in (Benitez, Gaydecki, Zaidi, & Fitzpatrick, 2001).

$$B(t) = \sqrt{x_f^2(t) + \hat{x}^2(t)} \quad (11)$$

3. EXPERIMENTAL SETUP

In order to assess the suitability, performance and robustness of the previous signal processing methods the data obtained in two different bearing test benches were studied. The experimental test benches were used to run bearings from the brand new state up to the failure state. The first data set comes from a research test bed called Pronostia developed by the FEMTO-ST Institute. The measurements performed during

the experiments were provided to the IEEE PHM 2012 Prognostic Challenge and are available on line³. The second data set was obtained using an industrial test bench of a train traction motor manufactured by Alstom.

3.1. Research test bench

The figure 3 displays the Pronostia platform where accelerated run-to-failure bearing experiments under constant operating conditions were performed (Nectoux et al., 2012). Thus, a radial load was applied to the bearing in order to boost its degradation. The acquired experimental data is suitable for fault detection, diagnostic and prognostic studies because it covers the entire bearing's life. The test bench is composed of three main elements:

- The rotating parts: mainly the asynchronous motor, a speed reducer (belt) and the shafts. The electric motor drives the whole system and introduces the rotating movement which is reduced and transmitted to the shaft where the tested bearing is placed;
- The degradation devices: a lever arm and a pneumatic jack with its control devices is used to create the radial load. This force is indirectly applied on the outer bearing race using a clamping ring;
- The measurement chain: several sensors are disposed in the test bed in order to measure the bearing's operating condition and its behavior. The bearing's environment is characterized by: the radial force, the rotation speed and the torque. While the bearing's condition is assessed through accelerations (horizontal and vertical) and temperature.

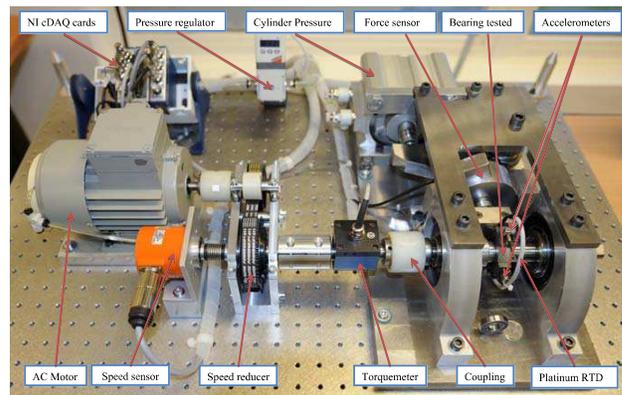


Figure 3. Overview of the Pronostia platform.

²<https://www.mathworks.com/help/signal/ref/hilbert.html>

³<http://www.femto-st.fr/en/Research-departments/AS2M/Research-groups/PHM/IEEE-PHM-2012-Data-challenge.php>

3.2. Railway test bench

A traction motor test bench was developed at the Alstom's motor engineering center⁴. The setup was used to generate data, in order to study the previously mentioned signals processing methods in heavy railway material as shown in the figure 4. Similarly to the Pronostia platform an accelerated run-to-failure bearing experiment was conducted. Thus, an electrical asynchronous motor of 140 kW and 2130 N.m @ 4200 RPM was instrumented with sensors and coupled to an old DC locomotive motor of 800 kW used as load generator. The Alstom's test bench is composed of the following elements:

- The rotating parts: these elements are visible in the figure 4, the asynchronous motor is on the left side and painted in red, the speed reducer is in the middle and painted in light blue and the load generator is in the right side and painted in blue;
- The electrical devices: in order to feed the asynchronous motor an electrical AC/AC converter was used allowing to control the speed. A DC/AC power inverter was disposed to create the traction load and to recover the load energy which was returned to the grid;
- The degradation devices: the bearing was stressed mainly by temperature variations. A hot air blower was used to heat the bearing up to 250°C;
- The measurement chain: sensors were used to measure the motor operating condition and its behavior. The motor environment is characterized by: the phase voltage, the phase current and the rotation speed. The motor behavior is assessed through horizontal and vertical accelerations measured on the motor's body shell in each bearing plan and the internal temperature (stator).



Figure 4. Traction motor test bench.

4. RESULTS AND DISCUSSION

The obtained data sets are used in this section to assess the performance and suitability of the methods introduced in the

⁴<http://www.alstom.com/products-services/product-catalogue/rail-systems/components/motors/>

section 2. First, the data obtained in the Pronostia test bench is used to identify the most sensible features for fault detection. Then, the retained features are computed in the Alstom's data set.

4.1. Research test bench

The presented time domain and frequency domain approaches were applied using the data set named Bearing 1_5. This choice is based in the fact that this is one of the longest data sets in the repository and it was performed several months after the first test. Thus, this data set has abundant measurement points. Additionally, one can expect that after 5 months of testing the bench elements were less tight making the spectrum richer and the detection more difficult due to the vibrations coming from other elements similarly to the industrial applications. The figure 5 presents the results after the calculation of the temporal features given in Eq. (1) - Eq. (6) using the horizontal accelerometer. The horizontal axis was chosen because it is aligned with the radial load direction.

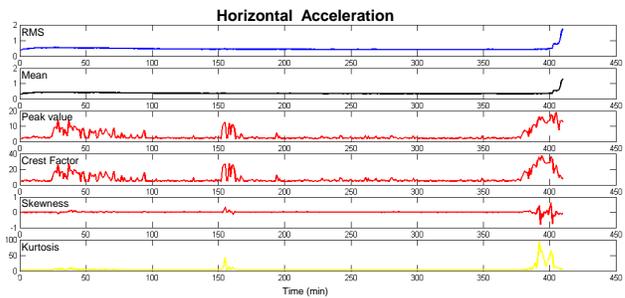


Figure 5. Extracted temporal features using the Pronostia test bench data.

The results presented in the figure 5 show that crest factor and the peak value features are extremely sensitive to the bearing evolution. They capture better than the other features the vibration change. These two features clearly show the vibration increase around 50 min (defect apparition), 160 min (defect evolution) and 390 min (close to failure). However, the drawback of these features is the measurement range. For instance, the crest factor and the peak value generates the same feature magnitudes for the different vibration increase instants. In contrast to this, the RMS and the mean shown a more regular behavior, but their trend modification occurs at the very end of the run-to-failure test. Skewness and kurtosis behave as described in the theory. Skewness remains equal to zero and shows changes at the three vibration increase moments. However, its behavior is not monotonic, this is clearly visible at the end of the test where its values goes above and below zero. Finally, kurtosis is more constant in its behavior, as expected its value is generally equal to 3. The kurtosis value changes in the three vibrations increase moments. Moreover, the kurtosis has a tendency to increase with the fault progres-

sion $x_{ks}(t = 50) < x_{ks}(t = 160) < x_{ks}(t = 390)$ with t in minutes, but at each vibration increase moment after the fault progression the kurtosis goes down to constant value. This phenomenon may be explained by the fact that bearings defects generally initiates as small pits or spalls producing energetic impulses. Then, due to the rolling element passage there is a tendency for the spalled area to become worn, in which case the impacts might be smaller (less energetic). As described in the section 2.2 the envelope analysis could be used to search for the bearing fault frequencies. The NSK 6804DD bearing was used to conduct the tests in the pronostia platform, using its dimensions and the shaft speed during the test (1800 RPM or $f_r = 30$ Hz) the following fault frequencies were calculated: BPFO = 168.34 Hz, BPF1 = 221.66 Hz, FTF = 12.95 Hz and BSF = 215.33 Hz. The 25 kHz sampled accelerations were used to compute the envelope spectrum. One of the difficulties of performing the envelope analysis lies in the choice of the most suitable band for demodulation, some experts recommends the use of hammer tap testing to find bearing housing resonances. However, the pronostia data set didn't contain such information. In this paper the demodulation band was chosen using a set of data considered as healthy. Thus, the spectrum after 10 minutes was computed and used to define the healthy baseline. The figure 6 presents the complete frequency spectrum where three resonant frequencies are visible, they are approximately centered at: 1800 Hz, 3600 Hz and 5400 Hz. The chosen demodulation frequency is the third burst because it is the highest frequency peak in the response spectrum.

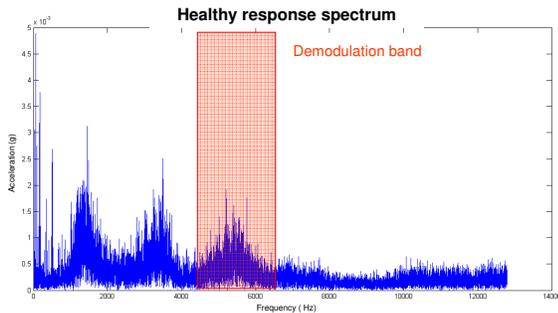


Figure 6. Baseline spectrum obtained after 10 minutes of test.

The envelope signal was estimated using the chosen demodulation frequency. The envelopes for the healthy state and faulty state are displayed in the figure 7. The baseline spectrum is given in the figure 7(a) where no bearing frequency components are present. In contrast to the baseline, the spectrum in the figure 7(b) obtained 10 minutes before the failure clearly shows a sharp component at the BPF1 and its harmonics. A non dominant (low) component at the BPFO is also present. Thus, the envelope analysis successfully localize the defects in this data set prior to the failure.

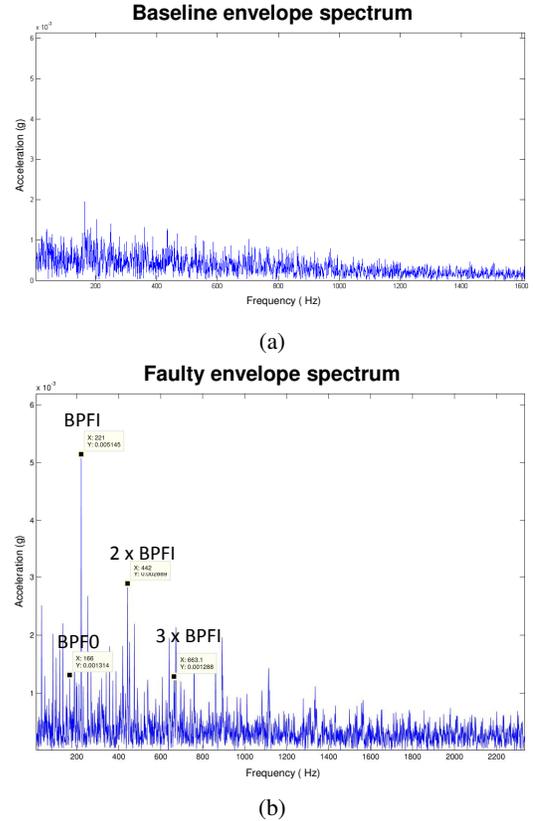


Figure 7. Envelope spectrum: (a) baseline and (b) 10 minutes before the failure.

4.2. Railway test bench

The previous feature extraction methods were assessed using the data obtained in the traction motor test bench. The studied data set is related to a run-to-failure test under a constant speed of 1500 RPM and an air blowing temperature of 200°C. After 11 hours and 29 minutes one of the bearings failed blocking the motor axle. The faulty rolling element bearing was removed and the cage was found totally destroyed as presented in the figure 8.



Figure 8. Faulty traction motor bearing.

The time features displayed on the figure 9 were computed using the data set. The figure 9(a) present the evolution of the

vertical acceleration RMS from $t = 0$ min til the failure at $t = 629$ min. After the beginning of the test, the RMS shows an increasing trend displaying a first sharp peak at $t = 147$ min, this instant is designed as A. Then, the RMS level goes down to a constant level around 50 m/s^2 , then a second peak appears at $t = 415$ min, this event is denoted B. After the peak, the RMS level goes down and increase again up to another peak at $t = 516$ min (instant C). Finally, the feature decreases and increases again and a peak appear at $t = 594$ min (instant D), then the RMS continues the increasing trend stooping at the failure. The kurtosis is presented in figure 9(b), its behavior is coherent with the theory and the instants A, B and C are clearly visible. However, it fails to detect the instant D prior to the failure. It shall be noticed that during the test at the instants previously designated as: A, B, C and D a high frequency noise was heard by the testing staff. The authors suspects that the noise was closely related with destruction of the cage's elements.

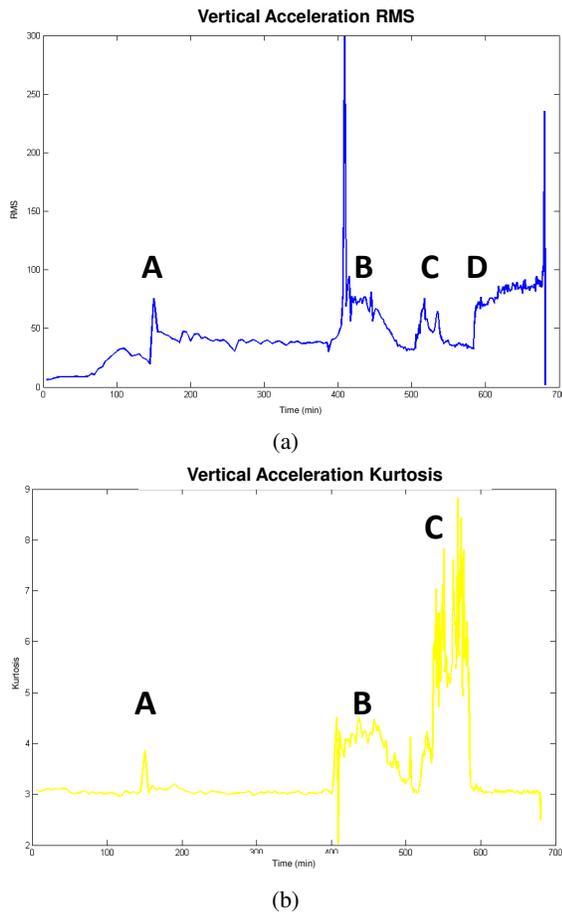


Figure 9. Traction motor time domain features: (a) RMS and (b) kurtosis.

The frequency domain analysis was performed using the data set in order to search for the fault frequencies. The accelerations were sampled at 20 kHz and hammer tap test was

performed in order to identify the resonant frequencies. The figure 10 shows the acceleration spectrum obtained during the resonance test. One frequency response is noticed and is centered around 1100 Hz. The vertical response is slightly higher than the horizontal response. Hence, the envelope analysis was performed on the vertical acceleration signal.

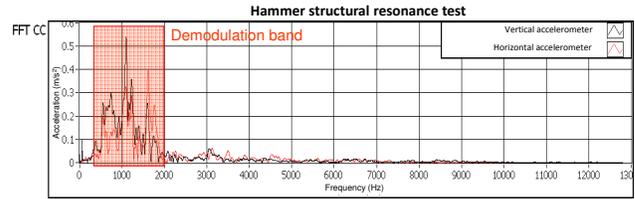


Figure 10. Traction motor resonance spectrum.

The bearing deterministic fault frequencies were calculated using the bearing geometry and the test speed of 1500 RPM or $f_r = 25$ Hz. Using the equations presented in the section 2.2 the following frequencies were estimated: BPFO = 192 Hz, BPFI = 258 Hz, FTF = 10.7 Hz and BSF = 169 Hz. The figure 11 present the results of the different spectra estimated at different time stamps during the run to failure test, where a cage failure was reported. A baseline was taken 20 minutes after the beginning of the test and is presented in the figure 11(a), this graph points out a component related to the shaft frequency f_r , the amplitude at the cage frequency (FTF) and its harmonics are low. As a reminder, at the time instants previously designed as: A, B, C and D the test engineers noticed an audible noise accompanied by an increase of the RMS and kurtosis values. Figures 11(b)-(e) present the envelope spectrum at these instants. In these spectra the components related with the FTF fault and its harmonics are clearly visible. Moreover, their magnitude is greater compared to the baseline envelope spectrum. The spectrum presented in the figure 11(e) contains also frequencies responses matching with the: BPFO, BPFI, BSF with high amplitudes compared to the other envelopes spectrum. This may be explained by the cage's level of degradation. During the bearing removal procedure the technicians found brass powder (cage's material) in the bearing housing and some rolling separators were missing. The test engineers suspect that at the instant D the cage started to disintegrate. We believe that the cage elements were grinded by the rolling elements. Thus, at each passage of the rolling element over the cage's chunks the whole bearing's frequencies were excited.

4.3. Challenges and opportunities

In the previous section two kinds of data sets were studied. The first data set was obtained in a research laboratory test bench where the sensors were placed close to the bearing. The second data set was generated in an industrial test bench where the sensors were disposed in the best accessible lo-

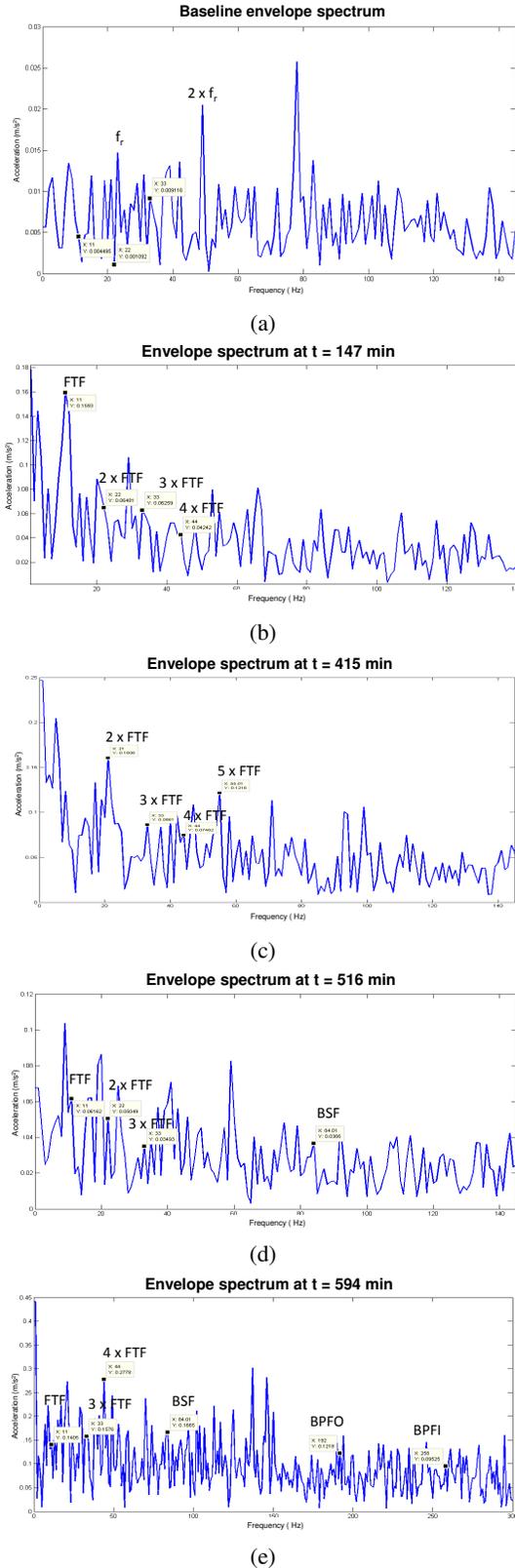


Figure 11. Envelope spectra at different time stamps: (a) baseline, (b) instant A, (c) instant B, (d) instant C and (e) instant D.

ation, in this case the traction motor body shell for the accelerometers. The signal processing methods were applied and the following comments may be done:

- The temporal features behave similarly in both cases;
- The kurtosis detect almost all the different degradation instants, while the RMS catch the energy increase prior to the failure;
- The bearing's fault frequencies are more visible in the research data set as presented in the figure 7(b), than in the traction motor spectrum as shown in the figure 11(e).

An effective method for bearing health assessment which could allow to perform condition based maintenance in railway assets may be developed by combing the strengths of the time and frequency domain methods. In the forthcoming works a special focus will be done in:

- Choosing the demodulation band by tracking the most energetic bandwidth for the envelope analysis and overcome the signal damping issues;
- Combining the features in order to increase the sensitivity of the the features regarding the fault evolution;
- Assessing the impact of the operational conditions into the measures and identifying the optimal measurement condition in order to avoid misdetections;
- Studying the signals under distributed bearing defects;
- Developing a monotonous increasing or decreasing health feature to enable the use of bearing prognostics methods.

5. CONCLUSION

Maintaining railway systems in operating conditions is a major societal and an operator requirement. For this, Condition Based Maintenance provides useful tools, enabling the necessary maintenance activity optimization in order to meet market demand. Electrical rotating machines are key elements in railway's systems and bearings are their Achilles' heel. In this paper, two of the most popular bearing's signal processing approaches have been successfully applied. The results obtained using different data sets brought out the strengths and the weaknesses of the approaches. Thus, in order to provide an adapted algorithm for bearing's health assessment in railway systems the authors recommend to focus the efforts in enhancing the acceleration signal and fusing the features. In the forthcoming works high-frequencies resonance techniques will be used to prepare the signals, then state of the art features will be computed and fused in order to compute a monotonous increasing or decreasing health index.

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BIOGRAPHIES



Diego Alejandro Tobon Mejia was born in Medellin, Colombia, on February 16, 1985. In December 2011, he completed his Ph.D in the field of fault prognostics in rotating machines and graduate with honors of the University of Franche-Comte in France. In his background, He received his Master's degree in Mechanical Engineering in 2008 from the National Engineering School in Metz (France) and the EAFIT University (Colombia). He made a specialization in his last school year in research and development in "Design, industrialization and innovation" supported by the Paul Verlaine University, the ENSAM and the ENIM, all in Metz (France). Actually he is working as a research engineer in Alstom in the field of prognostics and health management in railway's systems. He was honored in 2002 with the "Excellence scholarship" by the "EEPP de Medellin" (Medellin's Public Services Authority) to perform his studies in Colombia. In 2006 he was honored by the The French Ministry of Foreign affairs with the "Eiffel Excellence scholarship" to continue his studies in France.



Pierre Dersin (Ph.D. in Electrical Engineering, Massachusetts Institute of Technology). RAM Director of ALSTOMs Digital Mobility product line. Leader of ALSTOMs Reliability & Availability Core Competence Network. Co-Director of the joint ALSTOM-INRIA Research Laboratory for digital technologies applied to mobility and energy. Manager of the Prognostics branch of the Alstom Predictive Maintenance Center of Excellence, he launched the R&D program on predictive maintenance of point machines and turnouts at Alstom in 2011. He is a member of the IEEE Reliability Society AdCom and the IEEE Future Directions Committee, and is the author of numerous publications in the fields of reliability engineering, PHM, maintenance, control theory and electric power networks; in particular, of a tutorial given regularly at the Annual Symposium on Reliability & Maintainability, on the Availability of Complex Engineering Systems. He was a keynote speaker at the 2nd European PHM Conference in Nantes (2014).



Gerard Tripot received his engineer degree from the "Ecole Catholique des Arts et Mtiers" of Lyon in 1980. After various position in the field of mechanical engineering, reliability and maintainability studies, materials and technologies validation, he is actually in charge of several R&D projects within ALSTOM Transport. He launched the project "FAME" (Reliability Improvement of Embedded Machines) where he developed an embedded platform for predictive machine degradation assessment, remote monitoring and failure prognostics of traction motors. He serves as senior expert for various other projects, providing expertise in development and validation of new technologies.