Vibration Based Blind Identification of Bearing Failures for Autonomous Wireless Sensor Nodes

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ABSTRACT

Despite all the attention received by maintainers, undetected roller bearings failures are still a major source of concern in relation with reliability losses and high maintenance costs. Because of that, bearing condition assessment through vibration monitoring remains an intensive topic of scientific research, focusing on the definition of monitoring strategies that allow early stage damage detection, failure causes identification and remaining life prediction. Next to the developments on signal processing, new opportunities of advanced monitoring platforms are devised as those based on Wireless Sensor Networks (WSNs). The combination of integrated sensing, embedded computing and wireless communication provides interesting elements on the development of a new generation of vibration monitoring systems. The algorithms for bearing assessment remain a crucial point for achieving a balance between efficient monitoring strategies and highly flexible monitoring platforms. Though current trends on signal processing for mechanical vibrations focuses on the development of robust techniques, the constraints of embedded processing in relation to energy and memory consumption hamper their implementation on WSN.

The present paper discusses the problem of bearing condition characterization from the basis of extraction of damage features associated with the specific stage of its deterioration process. This, other than data driven methods, allow to find the best compromise between robustness of the bearing assessment algorithm and the applicability of the algorithm on a WSN. Two cases are presented as validation of this approach: an artificial damage on a lab setup and a train bearing, for which the possibilities for detection, diagnostics and prognostics are discussed. The advantages and constraints of the use of autonomous wireless sensor nodes is discussed as final part of the paper.

1. MONITORING STRATEGIES

On the design and development Vibration Monitoring Systems (VMS), the authors (Sanchez et al, 2013) have proposed a design framework following a systems engineering approach. The framework is based on the hypothesis that the success of a VMS depends on the agreement among the choice of appropriate monitoring strategies that satisfy the maintenance requirements, and the physical components and algorithms that shape the monitoring platforms that carry out the selected strategies. In other words: to make a WSN based VMS a success, it is of crucial importance to revisit the physical characteristics of damage and vibrations in bearings.

According to the framework, a VMS is called to support on the damage detection (existence), diagnostics (origins) and remaining life prognostics (evolution). It is generally accepted that autonomous detection of abnormal vibration response can be achieved by a proper selection of alarm thresholds for vibration levels. Identifying the causes of the abnormal signals requires deeper understanding of the failure modes and failure mechanisms that may be taking place in the system. Lastly, the prediction of remaining useful life builds on top of the failure status diagnostics by the quantification of the actual loading as caused by the actual usage of the system (Tinga, 2013).

These VMS functions as described in the previous paragraph are of incremental nature. However this does not imply that all the VMS must fulfill the functions of detection, diagnostics and prognostics. For the case of bearings, accurate diagnostics becomes relevant when restoring maintenance actions (such as re-lubrication, balancing, etc.) can be taken for extending the bearing life. Prognostics becomes relevant for cases where no on-service restoring actions are possible, and bearing replacement is the only option left. Furthermore, prognostics is not only based on predicting the deterioration of the component, it also involves/requires the definition of safe vibration limits without compromising the operation and integrity of the machine.

1.1. Failure Mechanisms and Bearing Life Prognostics

A physics approach on prognostics is defined by the balance between the load-carrying-capacity of a material and the actual loading experienced the system. Several bearing prognostics models, including the classical fatigue life rating of roller bearings follow similar reasoning, by using the bearing dynamic load for a rated fatigue life *C*, the equivalent load rating P and the life equation exponent *p* into the well-known L_{10} life equation Eq. (1).

$$L_{10} = \left(\frac{C}{P}\right)^{p} \quad (1)$$

Classical fatigue life is based on the traditional spalling due to subsurface fatigue, for which cracks are initiated below the surface and propagate towards the surface. As Lugt (2012) states "*…the L_{10} basic rating life equation constitutes the foundation of all national and international standards for fatigue life rating of roller bearings, subsequent theories and developments." (pp 286)*

Besides the material related failure mechanisms, surface initiated failures are significant contributors to bearing life shortening. Surface distresses generated by loaded asperities cause micro-spalling, while the over-rolled wear particles create dents in the surfaces leading to stress concentrations which again lead to spalls and fatigue. Lubricant rheological flow properties, as in the case of grease lubricated bearings, are also a main decisive factor on the bearing life, for which the lubricant life is expected to be considerable shorter than the material life (Lugt,2012).

1.2. Vibration as Failure Mode

Although the definition of developing failure mechanisms is central to life prognostics, in practice direct quantification of failure mechanisms is difficult, therefore practitioners must rely on indirect measures for its quantification. This poses the main justification of the use of vibration *response* as an "useful indicator" of the developing failure mechanisms. It must be noticed the word response is included for highlighting the fact that measured vibrations are due to the effect of a force on a system. Given the multiple forces acting on bearings and the complexity of the system itself, it is expected that discussion about the vibration response is everything but straightforward.

A functional approach as guideline for decomposing the vibration signal as support of the bearing deterioration assessment is proposed. Tinga (2012) defines failure mode *as the manner in which a system or component functionally fails, that is, describing to what extent a certain function cannot be fulfilled anymore (pp 3).* For the sake of generalization, the case of bearings can be described by two simple functions. Firstly, to enable free relative motion between two components, named hereafter *free rotation*. The second function relates to ensuring the correct distribution of the concurrent forces, named as *structural support*. These two functions are considered as the basis of the vibration signal as descriptor of the bearing failure as presented in Table 1.

Table 1. Bearing Vibration Classification

Vibration Level	*Failure mode*	*Description*
Normal: Structural Support	Varying compliance (normal Vibrations)	Change in bearing stiffness and load asymmetry
Incipient: Free Rotation	Lubrication problems	Film thickness instabilities Mixed lubrication regimes Increase friction forces
Incipient: Structural Support	Short duration pulses due to metal-to-metal contact	Changes on local stresses due to local defect or increased loading
Moderate: Structural Support	Resonance due to Impulsive Response	Localized impacts due to cracks on races-rolling elements excite bearing structural modes
Severe: Structural Support	Surface deterioration becomes distributed due to extended superficial cracks and spalling.	Bearing functioning becomes instable and auto excited. Danger to compromise integrity of related components.

The starting point of the discussion on vibration response characterization is by recognizing that that even under perfect conditions, bearings are an intrinsic source of vibrations. As described by Liew and Lim (2005) the change of the number of rolling elements and their position in the load zone gives rise to periodical variation of the total stiffness of the bearing assembly, which leads to varying-compliance vibrations. In other words, small levels of vibrations are acceptable, and for some cases even positive, as they act as the mechanism for lubricant replenishment on heavily starved contacts (Lugt,2012).

The free rotation function is of particular relevance for the new generation of bearings for low energy consumption and friction, which use thinner oils and grease lubrication. Instabilities on the lubrication film become very critical for the fulfillment of the free rotation function. Although the relation between vibration and shock loads for bearing lubrication is not fully defined, there is a general consensus that such loads may alter the film thickness and affect the contact dynamics of the rolling elements (Wijnant, 1998), and lead to some other failure mechanism such as fretting corrosion. Lubrication thickness disturbances have a direct effect on the rheological flow properties of the lubricant, and therefore the bearing life (Lugt, 2012).

The support function refers to distortions on the bearing load distribution due to defects on the bearing contact surfaces. The presence of surface defects such as superficial cracks or added material due to over-rolled wear particles has significant effects on the vibration response of the bearings. Local superficial defects cause abrupt changes on the contact stresses which generates short duration pulses at very high frequencies. As the severity of the defect progresses, the energy released by the impacts becomes higher, and therefore more sensible to be monitored. The accurate characterization of an impulse response relies on the identification of the natural frequencies and modes excited during the impact. These are valuable indicators of how the system responds to the effect of the loads. For instance, the rolling elements display natural frequencies in the range of hundreds of kilohertz (Swartjes,1995) while for the bearings and machine components modes at lower frequencies are excited (Wensing,1998).

As consequence of the discrete impact loading, wear develops throughout the contact element surfaces, which is typical of advanced bearing damage. Tandon and Choudhury (1999) state that variation in contact force between the rolling elements and raceways due to distributed defects result in an increased vibration level. Also the behavior of the signal changes. By increasing the occurrence of the impact loading, the leading edge of the impact response is buried in the delay of the previous impact. Therefore the superposition of impact responses turns into higher overall vibration levels with higher stochastic behavior. Figure 1 presents a comparison of the time signal between a discrete surface damage and distributed damage.

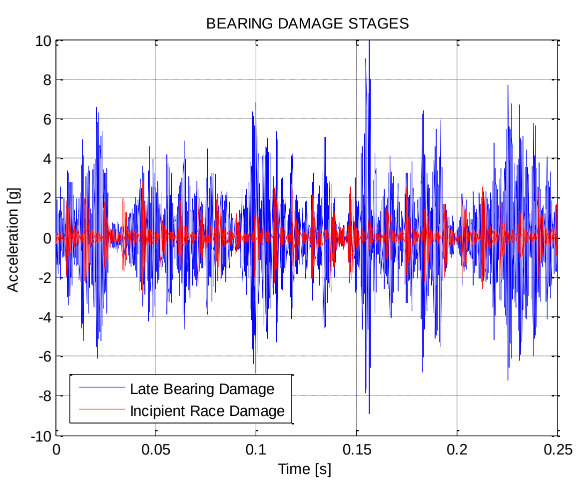


Figure 1. Time signal from bearings at incipient and advanced surface damage.

2. ALGORITHMS FOR BEARING EVALUATION

The complexity of bearing failure and the fact that the vibration signal captured at the bearing location may contain additional information regarding other machine components reflects the complexity of vibration analysis. The definition of appropriate steps for extracting information about the bearing deterioration from the vibration signal is presented in the following sections. The procedure is depicted on the Figure 2 and will be discussed in the next subsections.

2.1. Preliminary considerations

The failure evaluation of a bearing involves multiple factors such as the kinematic and dynamic characteristics of the system itself, the response to environment and the effects of developing failure mechanisms and failure modes. These factors are included in the proposed procedure depicted in Figure 1. All steps in this figure will be elaborated next.

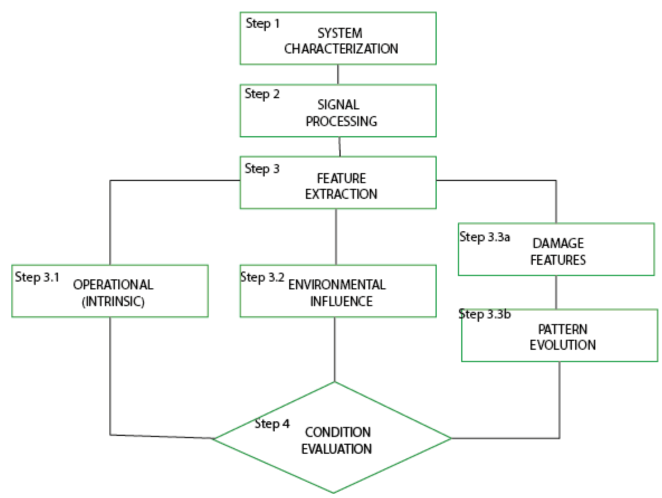


Figure 2. Flowchart for steps on bearing evaluation

2.1.1. (Step 1) System Characterization

There is a wide range of signal processing techniques that can be used to decompose vibration signals from mechanical sources. Nevertheless, the application of such techniques without knowledge of the monitored system and specific criteria on the evaluation may be daunting. Step 1 refers to the specification of the monitored system, both for machines and structures. It includes the definition of operational conditions, kinematic data for participating mechanisms and the influence of environment. Existing knowledge of the particular failure mechanisms and failure modes expected through the operational life is also of valuable aid.

2.1.2. (Step 2) Signal Processing: Conditioning, Domains and Transformation

To support the choice of signal processing for enhancing the damage-related features within the vibration signal, the following criteria are proposed for selecting techniques and domain transformations to apply to the signal:

i) Enhanced signal quality

ii) Display the signal on the domain that represent the best its dominant characteristics

iii) Decompose the signal according to the specifically sought features

Enhancing signal quality is fundamental for accurate characterization of different vibration phenomena, especially those associated to early damage. Although noise is usually highlighted as undesired for the signal, it should be realized that there are different sources of noise, such as: a) random noise, as caused by random excitation forces, b) mechanical noise due to the transmission path from the vibration source to the measurement point, and c) numerical noise due to the processing techniques. The first category can be actively reduced by using appropriate averaging techniques, while the second is inherent to the complexity of mechanical systems. Numerical noise has to be considered for each technique.

The following two criteria are satisfied by mathematical transformations, which are used for maximizing certain features of the vibration signals according to the intrinsic characteristics and the likelihood to identify a damage. There are several domain transformations involved in the monitoring problem, from the transduction of physical quantities (displacement, velocity, acceleration, strain, etc.) to voltages. Once the signal is digitalized, the starting domain is the time domain, for which the initially captured quantity, represented by a voltage, is presented as it occurs on time.

After the time domain, further domain transformation are used to extract particular features of the signal according to its changing nature (Randall, 2011**)**. For instance Fast Fourier Transform (FFT) for constant frequency excitation; Short Time Fourier Transform (STFT) for slow fundamental frequency changes; the wavelet domain and Hilbert domain are employed for signals with high level of nonlinear and non-stationary behavior. The modal domain is an important transformation for the analysis of spatially distributed systems for which the principal coordinates define the prime motions of a body.

Other types of transformation refer to the derivation of new signals within the domain. The derivation of analytic signals for Hilbert transform, Intrinsic Mode Functions (IMF) for Empirical Mode Decomposition (EMD) and residuals for Wavelet transformations are examples of transformations within the domain. Given the large range of algorithms and steps to consider, defining specific target features to base the analysis on results in a practical guide towards the signal decomposition.

2.2. Blind Identification Strategy - Features Extraction

Step 3 deals with the selection of specific features to aid in the problem of –understanding vibration signals and how these relate to the normal and abnormal functioning of a bearing.-Generally, mutliple features have to be taken into account. All features must be monitored (blind identification), potentially leading to excessive resource requirements of a WSN. A smart way of performing this blind identification is therefore considered to be a crucial element in the VMS designTable 2 presents an overview of vibration features according to the machine characteristics, environment and damage influence.

2.2.1. (Step 3.1) Intrinsic features

Prior to the actual processing of the signal, one should ask *what are the most relevant physical mechanisms that originate the signal observed.* A first attempt to answer this lies the definition of the expected frequency components displayed on the signal. Four different types of vibration sources from mechanical machines can be distinguished: a) fundamental frequency, b) power related c) structural resonances d) random sources as presented on Table 2.

Table 2. Bearing Vibration Classification

	Feature	Example
Fundamental Frequency	Amplitude	High Forces
	Harmonic Distortion	Nonlinear Forces
	Frequency Shift	Change operation
Mechanism related	Harmonic Distortion	Unbalance. Nonlinear Forces
	Amplitude Modulation	Critical speed (Compressor) Frequency Multiplication Beat phenomenon
	Frequency/Phase Modulation	Torsional Vibration
Structure Related	Impulse Response – Excited	Related to Resonance
Random Vibrations	Broadband vibration	Related to field interaction

The fundamental frequency refers to the rotational speed of the shaft the bearing is supporting. This may be already difficult to identify for machines with transmissions or changing rotation speeds.

Power related frequencies relate to the power transferences happening at the machine. These can be due to punctual forces as in the case of gear transmission, for which the forces as concentrated on specific points of the mechanism. Other type of power-related frequencies are those due to distributed forces as in the case of rotors.

Structural frequencies are usually not excited under normal machine operation, however these are likely to be displayed during transient responses. Impact damages are the most common source of natural frequencies excitation. Recognition of natural frequencies from an operational vibration spectrum is in general a not a straight forward process.

2.2.2. (Step 3.2) Environmental Influence

The effect of environment on the normal behavior of the bearing response depends on the specific case. Environment can refer to the variation of the main input forces of the machine, both in a deterministic or non-deterministic fashion. Such changes can lead to nonlinear behavior of the features discussed in previous step.

A practical consideration of environment influence relates to the problem of alarm definition. For machines with continuously changing input forces, the signal response is often normalized for detection purposes. The vibration signature with environmental factors can also be updated by learning algorithms on the node or externally.

2.2.3. (Step 3.3a) Damage Features

Deviations on the vibration pattern that do not arise as consequence of environmental factors are presumed to be related to failure or damage on the system. The more knowledge available on the physics involved in the failure mechanism, the better the chances to find a relation with the vibration signal and its evolution. Some of the disturbances due to damage are listed below:

- Amplitude increment
- Fundamental frequency instabilities
- Harmonic distortion
- Amplitude modulation
- Frequency modulation
- Impulse response
- Broad band and narrow band noise

The specifics of how some of these features are related to bearing damage depend on the failure modes, however the specifics are largely influenced by the characteristics of the systems the bearings are contained in. Detailed explanation of the treatment of a particular damage feature is presented in section 3. The main advantage of defining specific features to base the monitoring strategy on is the possibility to reduce the signal complexity in discrete characteristics.

2.2.4. (Step 3.3b) Pattern Evolution

Once the signal is decomposed on specific signal features, such features have to be monitored independently. Tracking the evolution of distinctive features provides valuable information of the remaining life estimation, especially for the cases when it is normalized with the loading conditions.

2.2.5. (Step 4) Evaluation

The following steps provide the ground for gathering information on the bearing condition. The evaluation steps refer to the goals of the monitoring system, once again back to the detection, diagnostics or prognostics. Some of the possible results of the evaluation are:

- System operation is within acceptable levels.
- The system condition is stable, and there are no symptoms of accelerated deterioration.
- The system is underperforming, resetting of the system condition is required.
- System condition is worsening. Maintenance intervention must be planned according to usage expectations.

3. VALIDATION – CASE STUDIES

The proposed steps are applied for two bearing cases. The first one relates to artificial damage of a bearing running on an simple mechanical setup with little operational and environmental disturbances. This simple case highlights the classical failure modes of bearings referring to race damage and rolling elements damage. The second case refers to train bearing monitoring, which displays strong influence of the operation and environment.

3.1. Bearing with Artificial Damage

A simple bearing test setup was used for validation of impulsive behavior due to surface defects (Cisi. et al, 2013). The set of data composed by a pristine signal and three artificial defects on the inner race, outer race and rolling elements. The setup was run under stable conditions of load and speed, therefore the signals are expected to behave on a rather stationary manner. No environment disturbances were relevant during the data acquisition.

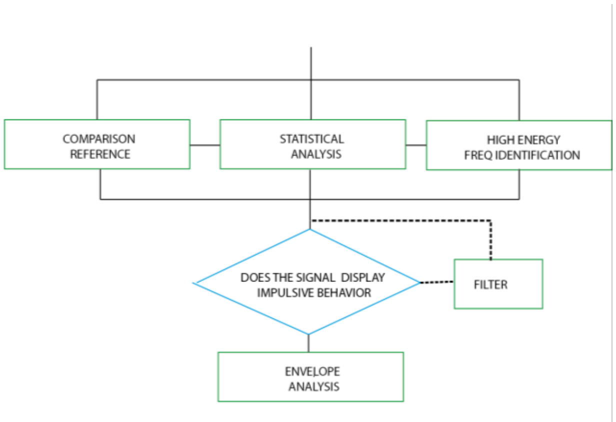


Figure 3. Feature treatment for signals with impulsive behavior.

Based on the discussion of superficial defect (section 1.2), the impulsive feature is used to elaborate the signal processing around it. Figure 3 presents the detailed treatment for the damage feature as presented in step 3.3a.

Figure 4 a, b, c, d presents the time data signal from the four cases. Figure 4.a corresponds with the bearing without defect or pristine condition. A reference line is extracted as an equivalent sinusoidal signal with the same peak to peak amplitude as the pristine condition (red line). Surface damage is introduced by creating a small scratch on the outer race (Figure 4.b) and inner race (Figure 4.c). Advanced damage is achieved by affecting the surface of the rolling elements (Figure 4.d). The time signals are very distinctive of the evolution of bearing damage as discussed in section 1.2.

The pristine condition shows low amplitude levels and no apparent damage feature is depicted on the time signal. Localized superficial defects lead to very distinctive impact response modulated by the bearing kinematic characteristics, namely the inner race and outer race failure frequencies. The amplitude of the vibration signal increases considerably at the moment of the impulse, as compared to the normal value represented by the red line of the pristine condition. For the advanced damage condition, although the impacts become less defined, the overall vibration in comparison with the pristine condition increases significantly.

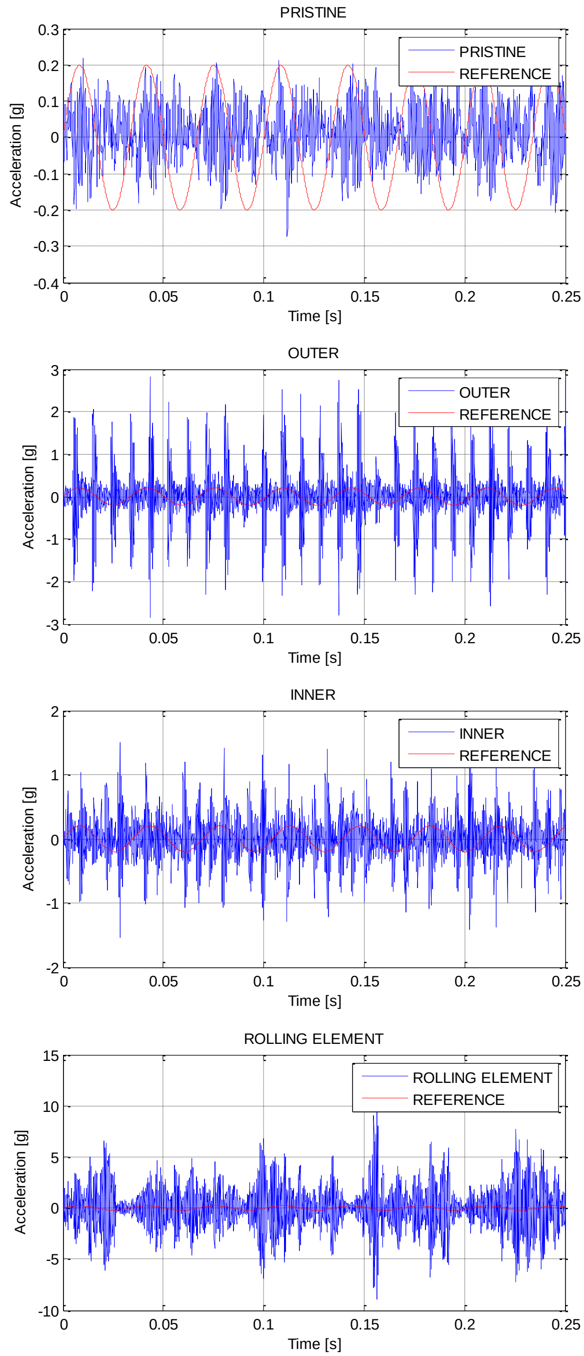


Figure 4. Time domain signal for a) Pristine, b) Outer race damage, c) Inner race damage, d) Rolling element damage.

Table 3 presents some statistical quantities related to the signals. It can be seen that kurtosis, zero-peak and rms value can also be used as a measure for the impulsiveness of the signal. On actual signals, evaluating kurtosis for specific frequency ranges around structural frequencies is suggested (Randall, 2011).

Table 3. Summary Statistical Analysis

Feature	Pristine	Inner Race	Outer Race	Rolling Element
Mean:	0.0595	0.0046	0.3665	0.013
Variance:	0.0056	0.3575	0.3665	4.247
Kurtosis	2.7642	5.2911	7.5950	3.871
Zero-Peak	0.298	3.062	1.605	10.11
rms	0.0738	0.59	0.313	1.027

Subsequently, the frequency content of the signal is analyzed by performing an FFT on the time signal. For this case, the impact oscillating –carrier- frequency is identified as the highest peak of the frequency domain, around which a band pass filter is defined, see Figure 5. The filtered signal is subjected to an rectification and enveloping treatment as presented in Figure 6.a. The frequency displayed in the spectrum of the enveloped signal corresponds to the modulating frequency of the inner race as presented in Figure 6.b. Analysis of the signal displaying the rolling elements damage did not result in clear carrier and modulating frequencies as predicted for an adavanced damage stage.

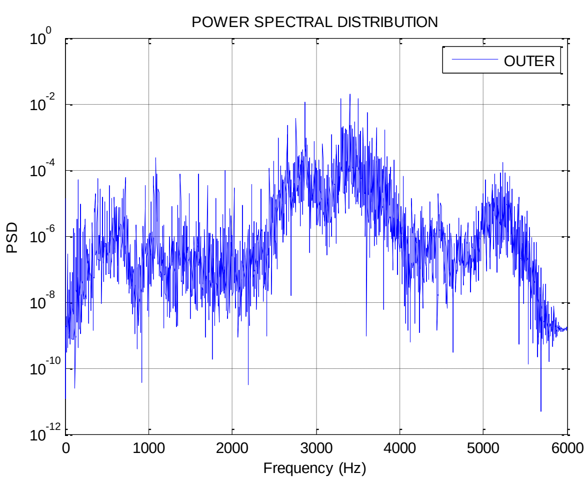


Figure 5. Power Spectral Distribution for bearing signal displaying outer race defect.

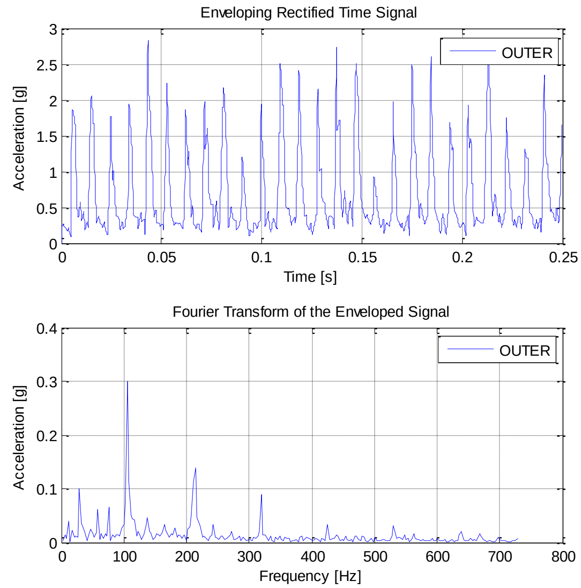
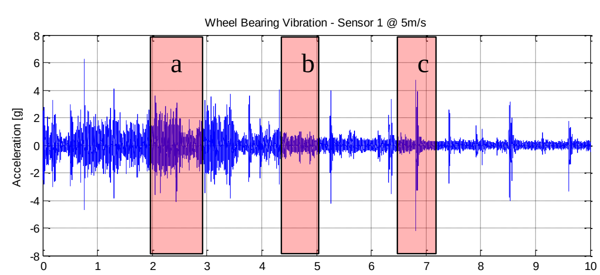


Figure 6. a) Envelope from the rectified time signal for the outer race damage b) Fourier representation of the enveloped signal.

3.2. Train Wheel Bearing

The second validation case of the proposed bearing identification algorithm corresponds to the case of train bearings. Suspension bearings are very sensitive components since these are subjected to heavy loading from the train weight and dynamic loading due to the wheel-rail interactions. For this case, the bearings correspond to a CRB type from SKF which offer low friction characteristics and high clearance to withstand moderate impacts and changes on operational temperature. They also contain good lubrication conditions to protect against fretting corrosion (Railways SKF, 2012). From the monitoring perspective, train bearings display several challenges because of the difficulty in separating the influence of operation (weight of the wagon, speed), environment (wheel-rain interaction) and the bearing condition itself.



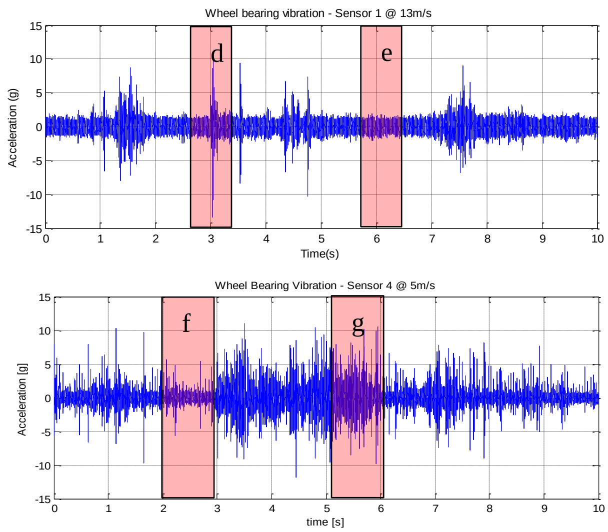


Figure 7. a) Train Bearing 1 at 5.3 m/s, b) Train Bearing 1 at 13m/s c) Train Bearing 4 at 5.3m/s

Figure 7 present three typical vibration signals from two different bearings of the same wagon. Figure 7.a and Figure 7.b correspond to the same bearing but during different train speeds (5.4m/s and 13.2m/s respectively). Figure 7.c corresponds to a suspected bearing during the captured at the same time as the first signal. For this signal it is already possible to see the increment on the overall vibration values and the peak amplitude. For the analysis, small periods from the signal are taken for further study, as indicated by the colored bands in the spectra. Table 4 presents a summary of the events for the analysis of rms and kurtosis values.

3.2.1. Detection

Following the proposed methodology, the signal is subjected to feature extraction, for which the normal operational conditions and the influence of the environment are analyzed.

Table 4. Rms and Kurtosis for different events for the train bearing signals

	Description	Train Speed [m/s]	Rms (g)	Kurtosis
a	Random Excitation	5	0.53	5.72
b	Stable response	5	0.15	3.18
c	Impact	5	0.49	15.81
d	Impact	13	3.15	4.95
e	Stable response	13	0.48	2.92
f	Repetitive Impact	5	0.71	21.82
g	Repetitive Impact Random Excitation	5	1.72	5.71

Step 3.1 - Operational Influence

Events *b* and *e* are used for comparison of the rms and kurtosis values of the bearing 1 under stable operation. Although there is a significant increment on the rms value (0.15g - 0.48g) , the kurtosis levels remains relatively stable (3.18 - 2.9). The comparison of the spectral density at the both events (Figure 8) shows a correlation on the energy distribution but with marked amplitude differences.

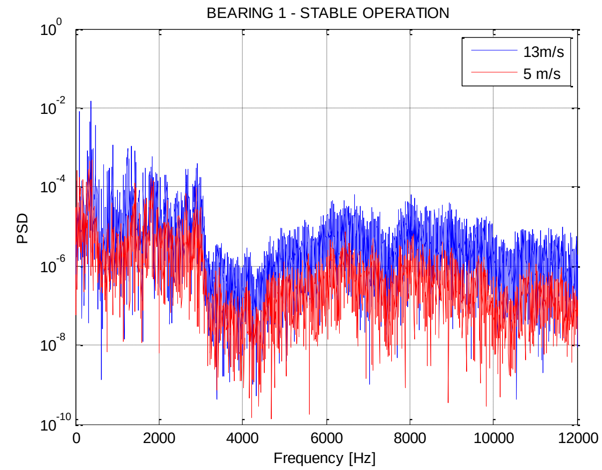


Figure 8. PSD comparison for stable operation of bearing 1 at 5m/s and 13 m/s.

Step 3.2 – Environment Influence

For understanding the environment influence, two different type of events are analyzed. The first influence relates to a random excitation as shown in event (*a*), for which both rms and kurtosis change relatively much in comparison to the stable response (rms 0.53g, K 5.72). The power spectral density shows in Figure 9 the increment of the vibration response at frequencies above 6000Hz.

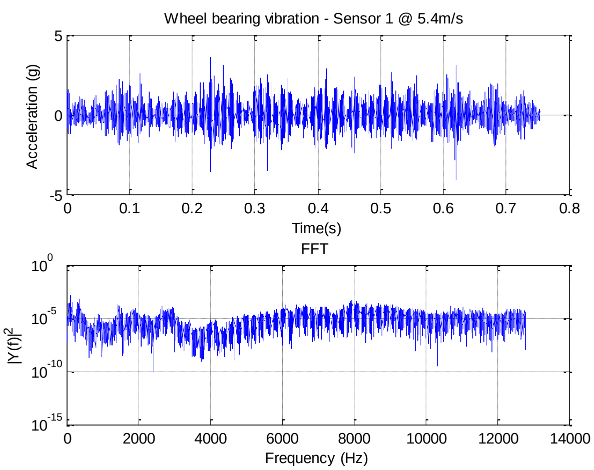


Figure 9. Environmental disturbance of stochastic nature for bearing 1.

The second type of environmental influence refers to the moderate impact loading due to several phenomena in the wheel-rail contact. The characteristics of the impulse response are valuable to understand the impact of such sudden loads for exciting natural frequencies of the system. Figure 10 a, b, c relate to the impact events *c* (rms 0.49g, K 15.81)), *d* (rms 3g, K 4.9) and *f* (rms 0.71g, K 21).

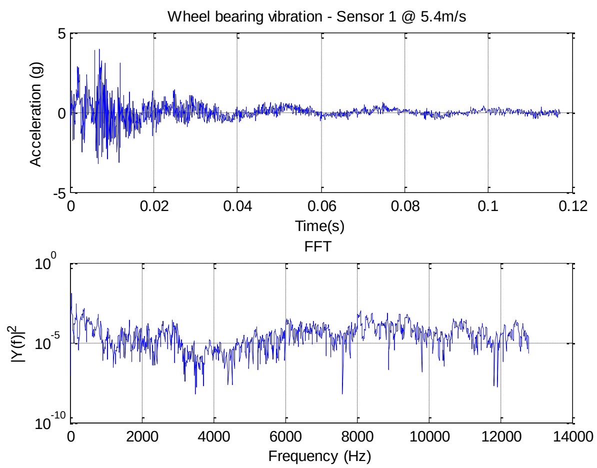
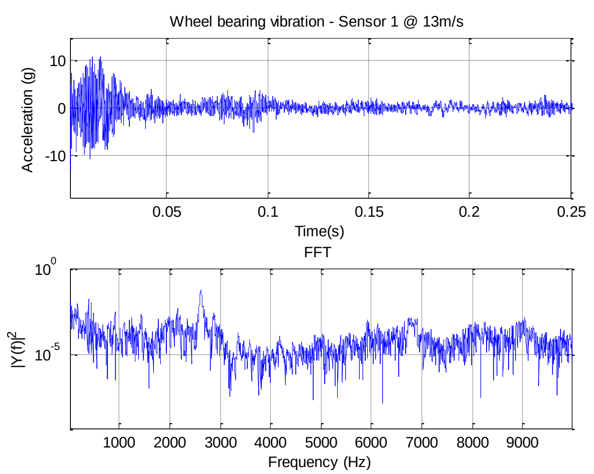


Figure 10. Environmental disturbance of impulsive behavior for a) bearing 1 at 5m/s b) bearing 1 at 13 m/s, c) bearing 4 at 5m/s.

From the comparison of the different events, again the strong influence of environment on the kurtosis level of the signal can be seen. However, the impact occurrence on the third case is an important indicator that the impact behavior is related to an intrinsic damage of the bearing.



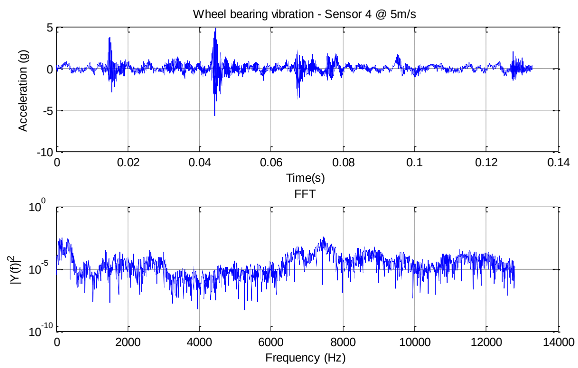


Figure 10 Cont. Environmental disturbance of impulsive behavior for a) bearing 1 at 5m/s b) bearing 1 at 13 m/s, c) bearing 4 at 5m/s.

Step 3.3 –Bearing Damage

After completing the assessment of the occurrence of impacts due to bearing damage, a demodulation procedure is performed (Figure 11). The envelope spectrum reveals a modulation at 19.34Hz with harmonics, which corresponds to the circular frequency of each rolling element as it spins also known as Ball Spin Frequency (BSF). This was calculated for a CRB Bearing with pitch diameter of 136.186mm, rolling element diameter of 18.158mm, number of rolling elements 21 and rotational speed of 320rpm (SKF, 2014).

3.2.2. Step 4. Evaluation

The last step on the strategy aims at the evaluation of the bearing condition in relation to the possible damage. From the analysis of impact response at events c, d and f, it becomes interesting to look at the frequencies excited during the impact response. Those relate to how the system is responding to the sudden loads, both intrinsic and extrinsic.

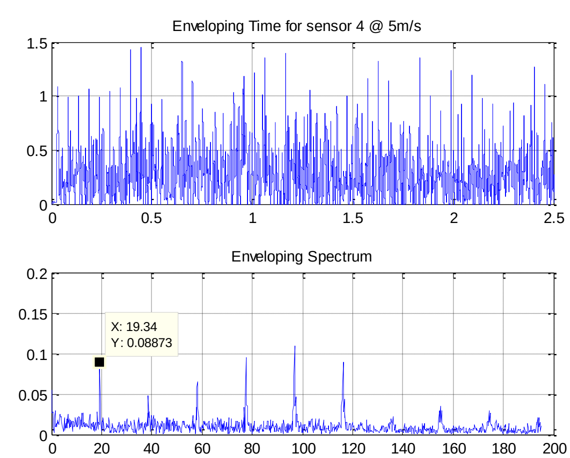


Figure 11. Enveloping analysis for suspect bearing .

Figure 12 present the signal decompositions using a filter of 500Hz, for low band-pass (red) and high band-pass (blue). It is up to the specialist on train dynamics to analyze the incidence of those signals for the quantification of load-carrying-capacity and actual loading.

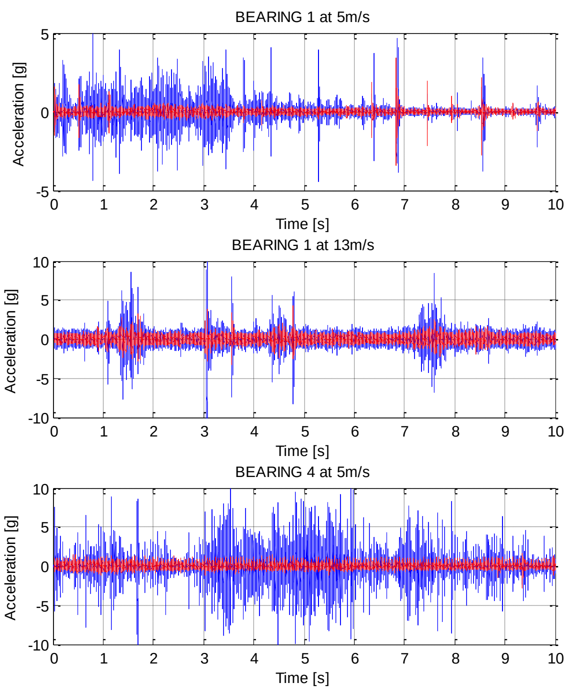


Figure 12. Signals decomposition. Red-below 500Hz, blue above 500Hz. a) bearing 1 at 5m/s b) bearing 1 at 13 m/s, c) bearing 4 at 5m/s.

4. IMPLICATIONS FOR AUTONOMOUS WIRELESS SENSOR NODES

The case of the train bearing highlights the particularities of using Autonomous Wireless Sensors for vibration monitoring. For this application, the possibility to sample at 25.6KHz allows very detailed analysis of local resonances above the structural range. Therefore the possibility of detecting incipient damages in bearings is increased.

Furthermore, the definition of simple features to base the evaluation strategy upon provides a guideline for selecting signal processing algorithms adaptive to the signal current characteristics. Features-based algorithms are suitable for optimization of for efficient usage of the node processing and energy resources.

High sampling and specialized algorithms for bearing evaluation derive into inexorable high energy load and increasing complexity for such autonomous nodes. To enable its execution using embedded platforms, the nodes must incorporate smart operation management systems suitable to tune the power and memory requirements for signal acquisition and processing and communication.

5. CONCLUSION

The term ***blind identification,*** does not imply that physics knowledge of the monitored object is no longer required. On the contrary, a blind identification strategy for bearing assessment on WSN relies on concise understanding of the bearing failure process and associated mechanisms that allows the identification of the current damage state although some specific or historic data may be missing.

From the general understanding of the failure mechanisms taking place during the deterioration process, the more specific failure modes that are likely to be displayed due the intrinsic design features, operation and environment disturbances associated to a specific bearing application can be understood.

The present article discusses the multiple physical phenomena related to bearing degradation. It has been shown that it is unlikely that a unique signal processing technique could capture such complexity. Instead, the authors propose the construction of a monitoring strategy based on fundamental features of the vibration signal, which are modified by the effect of loading, environment or damage. The simplicity of such distinctive features enables the design of flexible, but yet robust monitoring systems, bringing the implementation of VMS based on wireless sensor networks within reach.

The feature used for the case of bearing assessment is impact behavior, both as a response to extrinsic factors such as in the case of environment loading, and due to bearing intrinsic surface damage. Although the phenomenological description exhibits similarities for those cases, the effects on the system are particularly different. Still, the identification of the natural frequencies excited by the impact is a valuable indicator of the impact loading on the general system.

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Andrea Sanchez Ramirez obtained her master degree Cum Laude in Mechanical Engineering, research group of Applied Mechanics (2009) and her master degree of Business Administration (2010), both at the University of Twente in the Netherlands. Previously she obtained the bachelor degree (2004) at the Universidad Nacional de Colombia. From 2005 onwards she has been working on vibration monitoring topics at different industries, including oil industry in Colombia and Trinidad and Tobago, industrial sector as part of the Condition Monitoring division of SKF for Latin America and Wind industry in the Netherlands. Currently she is pursuing her PhD at the University of Twente in the Chair of Dynamics Based Maintenance on the topic of Advance Vibration Monitoring Systems.

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