

Condition Based Maintenance on Board (CBM OB)

Alexandre Trilla*, Pau Gratacòs

ALSTOM Transport, Train Life Services (TLS) Spain & Portugal, R+D. C/Pallars, 193 – Inbisa 22@ 08005 Barcelona (Spain)
alexandre.trilla@alstom.com

Rotating mechanical components are critical elements in the rail industry. A healthy condition of these mechanisms is vital to provide a reliable long-term service. In this regard, optimising the corresponding maintenance operations with predictive technology offers many attractive advantages to operating and maintenance companies, being the security and the LLC (life cycle cost) improvement (economic savings) some of the most important criteria. To this end, this paper describes the ongoing research and development works for Prognosis and Health Management at ALSTOM Transport, named Condition Based Maintenance On Board (CBM OB). The system is coined CBM OB after its purpose to be of flexible and easy use and installation on moving train units. It describes a general-purpose framework, with an emphasis on data processing power. It is based on a Wireless Sensor Network that is able to monitor, diagnose and prognosticate the health condition of different mechanical elements. The architecture of this framework is modular by design in order to accommodate data processing modules fitting specific needs, adapted to the peculiarities of the problem under analysis and to the environmental conditions of the data acquisition. Empirical experimentation shows that CBM OB provides a detailed analysis that is equivalent to other commercial solutions even with stronger hardware equipment.

1. Introduction

Rotating mechanical elements are some of most critical parts in trains. They are present in the whole transmission system, from the motors to the wheels, and they are particularly affected by the operational service of rail transport. In case a failure was present in any of these vital elements of such complex kinematic chains, the train could develop severe problems, entailing disreputable consequences for operators. Therefore, it is of utmost importance to develop predictive maintenance tools (both devices and strategies) to monitor the health condition of these components in order to improve the quality of the service, to guarantee its safety, to optimise the expected maintenance costs and to especially minimise the costs associated with the loss of availability and with the unexpected corrective actions (e.g., in case an accident occurs). In this sense, ALSTOM has developed the Condition Based Maintenance On Board (CBM OB), which is a predictive maintenance platform based on an embedded autonomous wireless system. The CBM OB monitors several key parameters in real time in order to keep track of component degradations and to analyse this data flow so as to identify potentially failing components ahead of time.

To conduct the analysis for evaluating the health condition of the components, some basic vibration principles are of convenient use. Vibration is a reliable proxy to identify mechanical problems because it is caused by some form of excitation, e.g., the free movement of an axis will produce some vibration when applied some force function (Lacey, 2008). Vibration analysis can be safely applied to many rotating elements (e.g., bearings, traction fans, gears, etc) because it is a non-intrusive technique that is able to capture data via the attachment of accelerometers with magnets, for example. Other specific elements such as grease are definitely present with the rotating elements (Sanchez et al., 2011), but without loss of generality this work does assume correct lubrication.

This article is focused on analysing the health condition of traction fans. These devices present two main problems that need to be monitored for its proper maintenance: the surface degradation condition of the

output bearing and the build-up of dirt causing imbalance problems. These two situations (worn, faulty or degraded bearings and/or dirty blades) cause specific vibration signatures that the CBM OB analyses a) to diagnose the health status of the traction fans, and b) to prognosticate its Remaining Useful Life (RUL), i.e., to determine how much time is left before the bearings need to be replaced or before the fan needs to be dismantled and cleaned.

The paper is organised as follows: Section 2 shows the wireless architecture of CBM OB. Section 3 explains the problem details associated with the traction fans. Section 4 proposes some problem-centred strategies to deal with diagnostics and prognostics. Section 5 conducts the experimentation and Section 6 discusses the obtained results and draws the conclusions of this work.

2. Wireless Sensor Network

To monitor the health condition of the various traction fans in a train unit, CBM OB has adopted an architecture based on a Wireless Sensor Network (WSN). The WSN is a lightweight and flexible system that avoids cabling the train and that can be rapidly (and almost costlessly) adapted to its variable length geometry. The network is defined by a group of nodes, which first acquire data through several sensors, and then transmit it to neighbouring nodes in order to route all the information to a server, see Figure 1. Thereafter, the data is processed in order to assess the health condition of the component and its RUL.

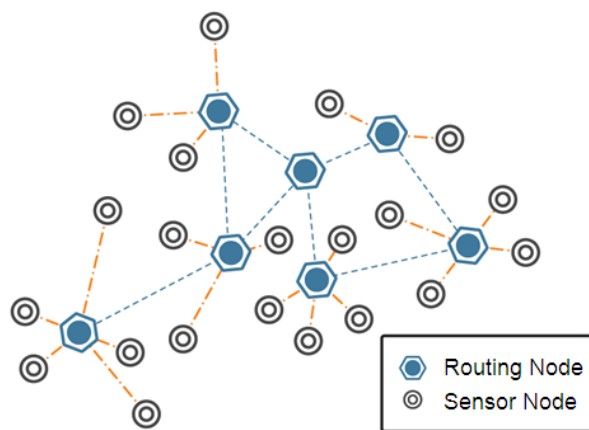


Figure 1: Topology of the Wireless Sensor Network implemented in the CBM OB system.

The main characteristics of the WSN are shown as follows:

- Communication protocol: IEEE 802.15.4/ZigBee
- Transmission frequency: 2,4 to 2,4835 GHz
- Transmission capacity: 250 kbps
- Low power consumption
- Based on an open source embedded operating system (TinyOS)
- Open platform to integrate different types of sensors (accelerometers, temperature, luminosity, humidity, pressure, etc)

2.1 Hardware

Mote

The motes are the units that acquire and transmit the data. They integrate different sensors that allow monitoring the condition of the mechanical elements. For vibration monitoring, an accelerometer with a dynamic range of 12 g and a bandwidth of 2 kHz is used. They also integrate the aerial, the microprocessor, the memory and the battery.

Bridge

Bridges are a special kind of motes (they don't integrate the sensors). Their function is to route the data from neighbouring motes to a common gateway, therefore they are set along the whole train (normally one per coach, depending on its size).

Gateway

The gateway (GW) collects all the data from the bridges (there is one single GW per train). It is based on a Linux platform, powered by the train batteries. It integrates a processing unit, a flash memory and a HSPA modem. The GW contains the management intelligence of the WSN, including the train-ground connection to the server.

The aforementioned devices as shown in Figure 2.



Figure 2: Gateway and mote (attached to a bogie) of use with the CBM OB.

2.2 Software

The server database is managed by a custom data processing framework, which analyses the data, generates pertinent alarms and provides an informative visual interface of the health condition of the elements being monitored: historical data, statistical trends, diagnostics and prognostics. One of the main goals of the developed software is to integrate the monitoring tools of the elements and the operational tasks of the trains. Thus, the application is adapted to display a real-time performance of the train in a maintenance centre.

The core data processing capabilities of the platform have been developed in Matlab/Octave (the compatibility between these two numerical computing platforms was especially taken into account for future platform flexibility). The code has been designed with contracts for module organisation and flexibility, providing three functional groups:

- Data Interface: structures the raw data from the WSN, checking both transmission and sampling errors in order to provide clean and long acceleration signals.
- Processing Tools: provides different modules to handle the signals of the data structure, such as frequency transforms (e.g., Discrete-Fourier Transform, Envelope, etc), noise reduction techniques (e.g., variable sample average) or numerical integration methods to obtain velocity signals from acceleration signals.
- Fault Detectors: given a particular problem, they integrate the necessary aforementioned modules to directly obtain the pertinent diagnostics and prognostics.

3. Traction fan problems

3.1 Bearing surface degradation

Traction fans have a critical bearing supporting the shaft where the blades are attached. Therefore, monitoring the state condition of this bearing is mandatory to avoid breaking the whole device. When bearings wear, they transit a series of degradation stages (Estupiñan et al., 2001). To identify the health condition of worn bearings, it is useful to monitor the vibration levels of its fundamental frequencies, i.e., the particular spectral vibration signature of the bearing (Lacey, 2008). These frequencies are described as follows:

- Band-Pass Frequency of the Outer race (BPFO): defect on the outer race.
- Band-Pass Frequency of the Inner race (BPFI): defect on the inner race.
- Ball Spin Frequency (BSF): defect on the rolling ball.
- Fundamental Train Frequency (FTF): defect on the cage that fixes the balls.

By following this spectral analysis approach, the advantage is two-fold: one the one hand, the magnitude of the defect can be monitored by checking the level of the vibration signal at some particular frequency.

On the other hand, the source of the problem can be determined by matching the spectrum peaks to the bearing fundamental frequencies. In addition, the vibration waveform displays a periodic impulse denoting the presence of some defect in any of the former elements of the bearing (inner and outer races, balls and cage).

3.2 Imbalance

Due to the hard operational conditions of traction fans (underground service, workshops, etc), they are particularly prone to accumulate dirt. After some time (a few months), the build-up of dirt is so considerable that it affects the normal operation of this rotating device, causing an imbalance problem. The vibration produced by the imbalance is shown both in the time domain, which displays a periodic simple non-impacting waveform, and in the frequency domain, which displays a large magnitude peak at the operational frequency of the fan, also known as the first Order.

4. Approaches to Prognosis and Health Assessment

The core data processing functionalities of CBM OB are focused on machine learning and artificial intelligence techniques (Duda et al. 2000). These design criteria aim at automatically grasping the whole scope of the problem, incrementally building a flexible platform with reusable tools considering its future maintainability.

4.1 Health Assessment

The Health Assessment process is aimed at diagnosing the health condition of the monitored component, i.e., determining if the component is OK or not OK. Thus, it is essentially a classification problem. In order to complete this objective, it is proposed to operate on a feature space defined by the relevant characteristics of the problem that is to be identified, e.g., the bearing fundamental frequencies. Then, a regularised linear discriminant function is to be fitted (with least-squares) in this feature space (Duda et al., 2000), separating the instances belonging to the OK category from the instances belonging to the not OK category, thus obtaining a function to automatically evaluate the health condition of the monitored component.

4.2 Prognosis

The Prognosis process is aimed at modelling the evolution of the degradation of the component (formulated as a generally increasing function) in order to estimate when it is going to reach a given threshold. Then, based on the difference between this limit value and the present value provided by the monitoring process, the RUL of the component can be estimated (Lacey, 2008).

There are many different approaches to complete this goal. In this paper, it is proposed to use some models considering a linear regression, two exponential regressions (with different basis) and a stochastic model based on a Gamma process (modelling the degradation increments in time with a Gamma probability distribution) (Duda et al., 2001). Then, by taking the intersection between all these strategies and the given threshold (the three regression methods and a simulation run with a Monte Carlo method), a normal distribution for the life of the component is estimated (and the RUL is directly given by subtracting the time of the last measurement to the inferred distribution).

5. Experiments and Results

5.1 Working environment

The traction fans reported in this article operate at a fixed rotating speed of 2835 rpm (first Order at 47.25 Hz). Therefore, the corresponding fundamental frequencies are shown in Table 1.

Table 1: Fundamental frequencies of the main bearing in traction fans for an operating angular velocity of 47.25 Hz.

Fundamental frequency	Value (Hz)
BPFO	144.22
BPMF	233.78
BSF	94.10
FTF	18.03

As an example, Figure 3 shows the vibration waveform and the spectrum of one of the traction fans used for this study. The data plots display a dominant problem of bearing degradation: note the high peak

corresponding to the spinning balls (the BSF, 94.10 Hz), in contrast to the other fundamental frequencies or the first Order (47.25 Hz, corresponding to imbalance).

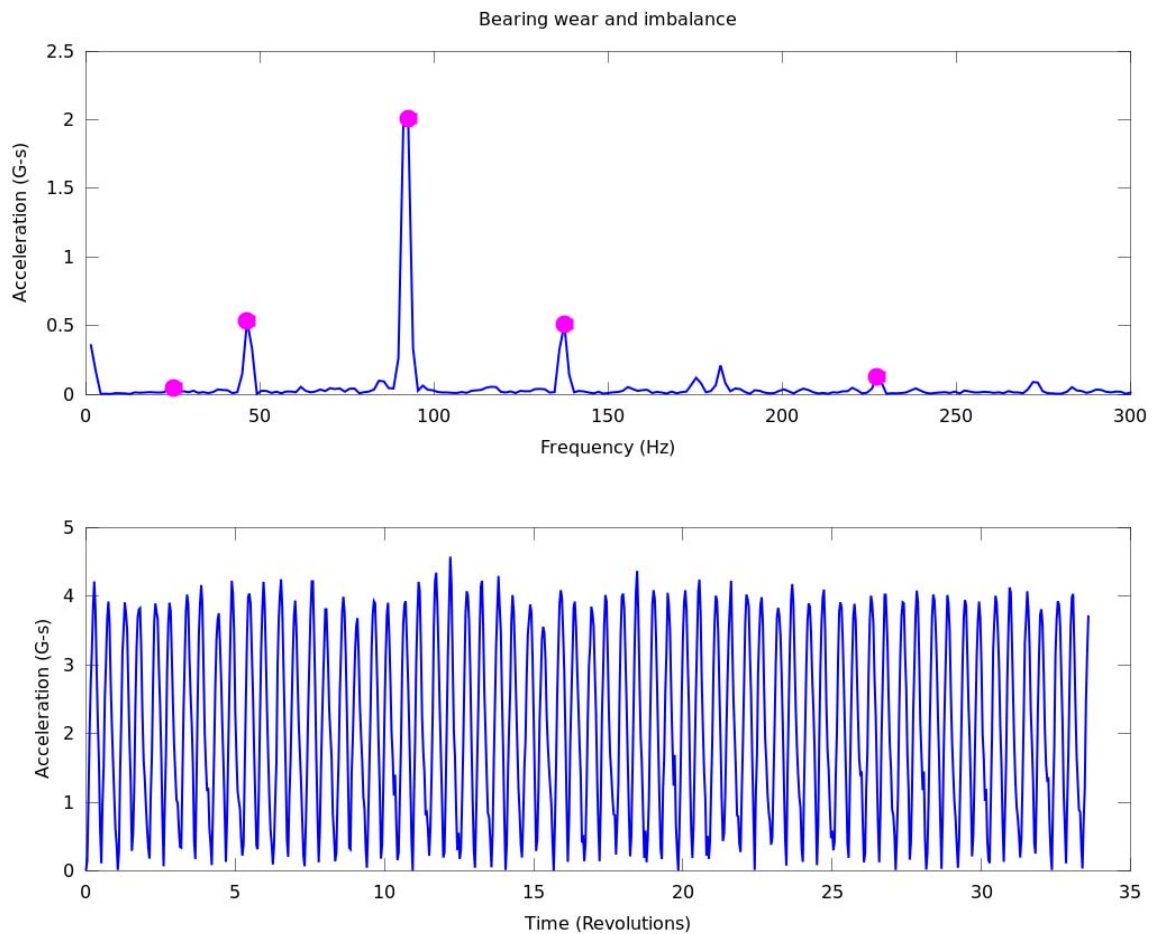


Figure 3: Vibration waveform and spectrum of one of the traction fans showing signs of bearing degradation. The magenta dots correspond to the four bearing fundamental frequencies and the first Order.

5.2 Health Assessment and Prognosis experimentation

The Health Assessment and Prognosis analyses can be applied to a wide variety of parameters for one single element. For the sake of simplicity and without loss of generality, this work conducts the diagnosis of dirt accumulation in the traction fans (which produces imbalance problems) and prognosticates the RUL of the device based on one of its fundamental frequencies.

Figure 4a shows the learnt linear classification function based on two known characteristics of imbalance: the magnitude of the first Order component and the overall energy of the vibration (considering signals with equal length). It can be observed how the linear discriminant function effectively separates the data related to dirty fans from the data related to clean fans. Then, every time a new traction fan needs to be diagnosed, the classifier can automatically determine the condition of the fan.

Similarly, Figure 4b shows the prognosis function of the BSF of a bearing. The results provided by different strategies (linear and exponential regressions and a stochastic Gamma model simulated with a Monte Carlo method) yield a certain distribution of life expectancy points that is modelled with a normal distribution. In fact, this process would be required for all the relevant parameters (i.e., all the fundamental

frequencies), and the minimum prognostic would determine the RUL of the element. However, the example clearly shows the convergence of the prognostic functions to a particular life expectancy.

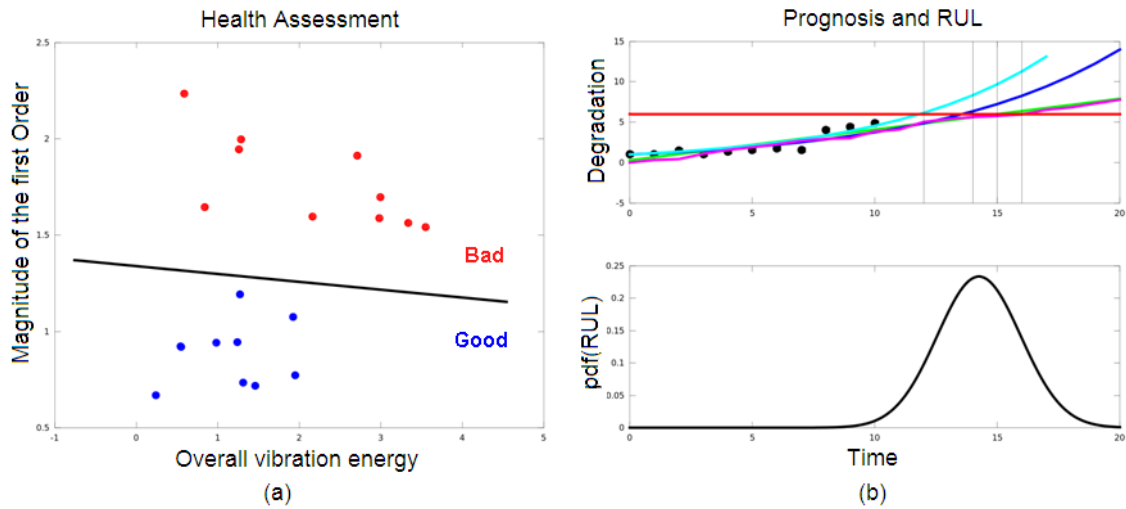


Figure 4: (a) Automatic Health Assessment of the imbalance problem in traction fans. (b) Automatic Prognosis of the bearing degradation problem in traction fans based on the BSF.

6. Discussion and Conclusions

This article has presented our ongoing work at ALSTOM Transport with respect to the CBM OB predictive maintenance system, a lightweight and flexible platform to monitor the health condition of mechanical elements in the rail industry. As an example, traction fans have been used to validate this technology, showing how the relevant features of the tackled problems can be effectively acquired, and how the following processing stages can successfully handle the data and produce reliable results.

Based on the encouraging results obtained with CBM OB, which are comparable to other commercial solutions operating with stronger cabled hardware equipment, the vibration signatures of many different components can be solidly integrated. The automatic learning procedures that constitute the operational basis of the system enable the CBM OB to fully capture the idiosyncrasies of the problems, the solutions of which remain as the focus of the system. In this sense, our efforts are concentrated on enhancing the Health Assessment and Prognosis methods, incorporating the latest advances in these fields while keeping our platform as adaptable as possible to the present and future needs of the rail industry.

References

- Duda R.O., Hart P.E., Stork D.G., 2000, Pattern Classification, Wiley-Interscience, New York, USA, ISBN: 0471056693.
- Estupiñan E.A., Saavedra P.N., 2001, Diagnosis techniques for bearing vibration analysis, 1-6 (in Spanish).
- Lacey S.J., 2008, An Overview of Bearing Vibration Analysis, Maintenance and Asset Management Journal, vol. 23, no. 6, 32-42.
- Sanchez R., Franco J.M., Delgado M.Á., Valencia C., Gallegos C., 2011, Gel-like Dispersions Based on Cellulosic Derivatives and Castor Oil Applicable as Biodegradable Lubricating Greases, Chemical Engineering Transactions, vol. 24, 499-504