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PREDICTIVE APPROACH OF ROTATING EQUIPMENT, GEARS AND BEARING FAULTS

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Abstract

The operational maintenance of civil and military aircraft fleets is a major economic and safety issue for the aeronautical sector. In this context, the control of the non-failure of rotor components, such as bearings and gears, is a major concern. Early prediction of the occurrence of these failures according to usage is a solution to reduce the risk of long term aircraft downtime, to anticipate supplies, and to improve safety.
Monitoring the rotor components requires invasive and heavy instrumentation, sometimes impossible to implement, due to the lack of available space and ambient temperatures. Moreover, the acquisition of dynamic signals from the sensors generates large volumes of data that must be stored and post-processed.
The method proposed here can be deployed from a single sensor placed on a shaft line. In the ideal case, following requirements shall be fulfilled: the sensor shall be without contact with the rotating part and shall be able to measure relevant data to monitor the whole shaft line. A particular attention was made on the instrumentation side and on the signal processing to be undertaken to get relevant information.
The health of the organs can be evaluated from global indicators, resulting from a learning phase (Machine Learning), via the implementation of a semi-supervised algorithm.
The early fault detection algorithm was tested using test data collected on a dedicated endurance test bench. Endurance tests were split in two sets of experiment:

- Endurance on bearing with ball indention,
- Endurance with crack initiation on one pinion tooth.

A digital twin of the bench was used to anticipate the life of a healthy pinion, by recalibrating the numerical model from the first readings taken on the bench, in terms of loading and dynamic response. The first results obtained on a partial bench demonstrate the ability to identify early changes of state based on global indicators on a use case. These conclusions were confirmed by test performed on a part of a helicopter kinematic chain to detect bearing faults.
These generic methods also open new perspectives in land and maritime transport or in the energy sector.

Keywords: Machine learning, early fault detection, digital twins, instantaneous speed measurement

1. Introduction

The economical and the environmental aspects push industrial companies to a better monitoring of their equipment and it is in particular the case in aeronautic sector. For rotating machines, main risks of failure are due to gears and bearings. The literature abounds in this direction by more than 60.000 publications. The monitoring is performed, historically, using vibration signals (from accelerometers), and more recently using the instantaneous angular speed (IAS), most of the time using encoder sensors. These encoders are very accurate thanks to a high angle resolution. The main constraints in these methods are the need of angular sampling, which requires an expensive equipment. Low resolution encoder sensors may also be implemented but they will present poor signals inducing a stronger effort in signal processing.

The innovative method discussed in this paper proposes a new approach to detect fault on gear or bearing. This method based either on accelerometers or encoder signals and involved specific advanced signal processing coupled with Machine Learning technics.

2. General method presentation

Structural health monitoring (SHM) means to detect any sign which can predict an incoming failure of the system to prevent it before it occurs in order to limit the danger or the financial cost (e.g. number of hours of shutdown of a production line).

In this context, the development of signal processing tools and Machine Learning (ML) techniques can be a great help for that kind of task, a concept widely discussed in the literature [1][2][3]. The approach consists in studying the processing chain which links the perception of a given data to the potential resulting anticipation as presented Figure 1.

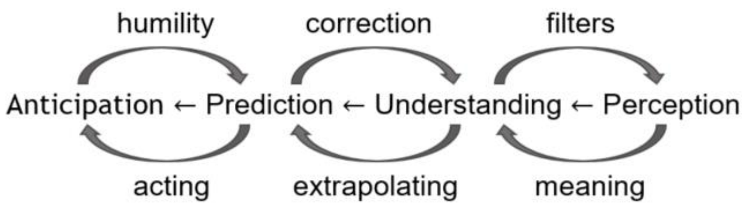

Figure 1 - A data processing chain

Thereby some data is first perceived. Data can be converted to information according to the meaning that can be draw from it. The data understanding can be associated to (cognitive) filters directly linked to the perception. If our understanding is correct we can extrapolate from those data in order to make some predictions which can feed our understanding back by correcting it in order to improve our predictions. The last step, but not the least, will concern the anticipation strictly speaking in the sense that we take actions and make decisions based on the confidence on the information drawn from the data. The confrontation of the outcome of our actions with the reality may lead to some humility in matter of predicting the future. Those previous steps can be somehow related to the ML classical steps of training, validating and testing.

The method used here is from one side a similar approach as presented by [4] consisting in extracting information form accelerometers or encoder sensors, splitting them into a given number of chunks of time signal on which common indicators (CI) are computed: root mean square (RMS), skewness, kurtosis, peak value and crest factor (peak/RMS).

The health condition in this case is considered to be the resulting set of CI averaged on the first few acquisitions, i.e. the initial condition of the system. The distance of Mahalanobis [5] d_{MH} is computed on the basis of those CI to determine the health condition of the system.

$$d_{MH} = \sqrt{(x-\mu)^T \Sigma^{-1} (x-\mu)} \quad (1)$$

x is the vector of the CI, μ is the vector of their mean values and Σ the associated covariance matrix. The strength of the method is to detect an anomaly as a deviation compared to the initial state of the system without specific prior knowledge of the system failure expected.

3. Gears fault detection on partial test bench

3.1 Gear endurance partial test bench and digital twin concepts

In [6], Bertoni and al. present in detail the partial test bench (see Figure 2) used to perform an endurance test on spur gears.

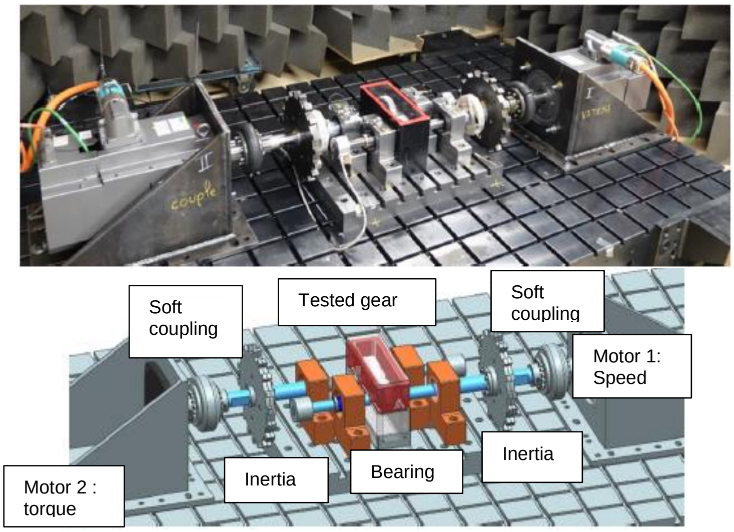

Figure 2 - Presentation of the test bench

The studied part is the spur gear stage. There mounted on two parallel shafts, supported by four bearings. Two inertia are also added to be representative to an industrial case. Then soft coupling components connect the two shafts on the two motors (driver and brake). This gear endurance test bench was set up to generate cracks on a spur gear composed of two pinions (speed shaft: 42 teeth; torque shaft: 55 teeth).

As this test bench was explorative, several types of sensors have been experienced on this bench: incremental encoders, accelerometers, strain gauges, proximity probes and reluctance sensors aiming at a cogging wheel. Indeed, industrial systems do not necessary permit intrusive instrumentation, either due to balancing, space, temperature, or other restrictions.

A corresponding Finite Element (FE) model is developed to predict the calculation of the stress undergone by the pinion’s teeth. An Experimental Modal Analysis (EMA) is first performed to evaluate the frequency of the torsion mode of the shaft line inertia on the gear contact stiffness. The EMA is also used to fine tune the numerical model used as a virtual prototype.

A fatigue analysis is then conducted leading to a 19 hours lifetime prediction. Such relative low number of hours demonstrates the ability of the test bench to study the emergence of a failure.

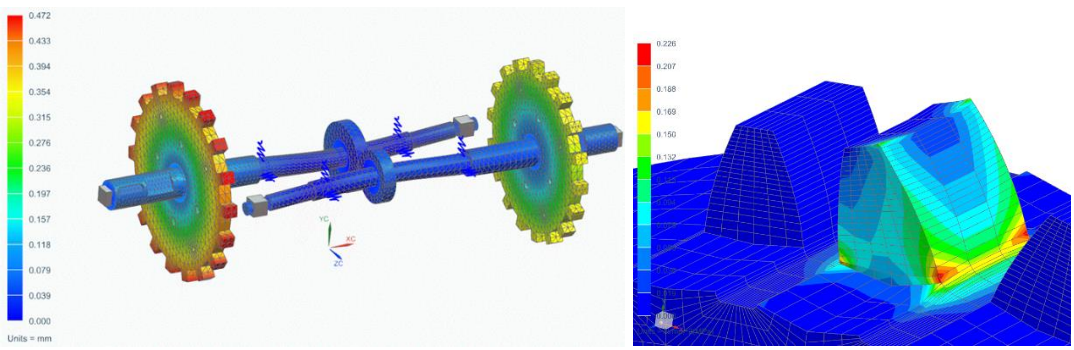

Figure 3 - Test bench numerical model

Based on this fatigue analysis, the endurance test was performed at a rotation speed exciting the torsion mode. Thanks to the modal amplification, the dynamic torque undergone by the teeth was much higher than the simple static torque, and the pinion broke after 20 hours. Rather than the excellent correlation between the measurements and the simulation, it is the order of magnitude that is to consider: the dual methodology simulation/measurement is validated.

This study allowed validating the digital twin approach, using experimental data to correlate models, and numerical simulations to predict the test results.

3.2 Endurance tests results analysis

3.2.1 Results on accelerometer signals

From raw signals, based on previous work (see [7]) on bearings and gearboxes monitoring, some condition indicators (CI) are extracted such as RMS, kurtosis, crest factor (as depicted in previous figure).
Example of condition indicators calculated on accelerometer signals are given in the following figure:

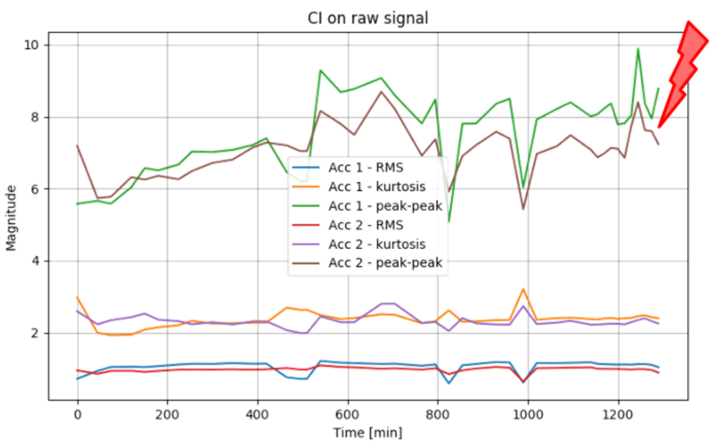

Figure 4 - Sample of calculated condition indicators – Red flash indicates the failure time

With a simple analysis based on these indicators it is not clear to see a prior change of state announcing the failure coming. The second step is to reduce the number of indicators to ease and to ensure the monitoring of the system. This step is performed using the Mahalanobis distance and a principal component analysis (PCA).

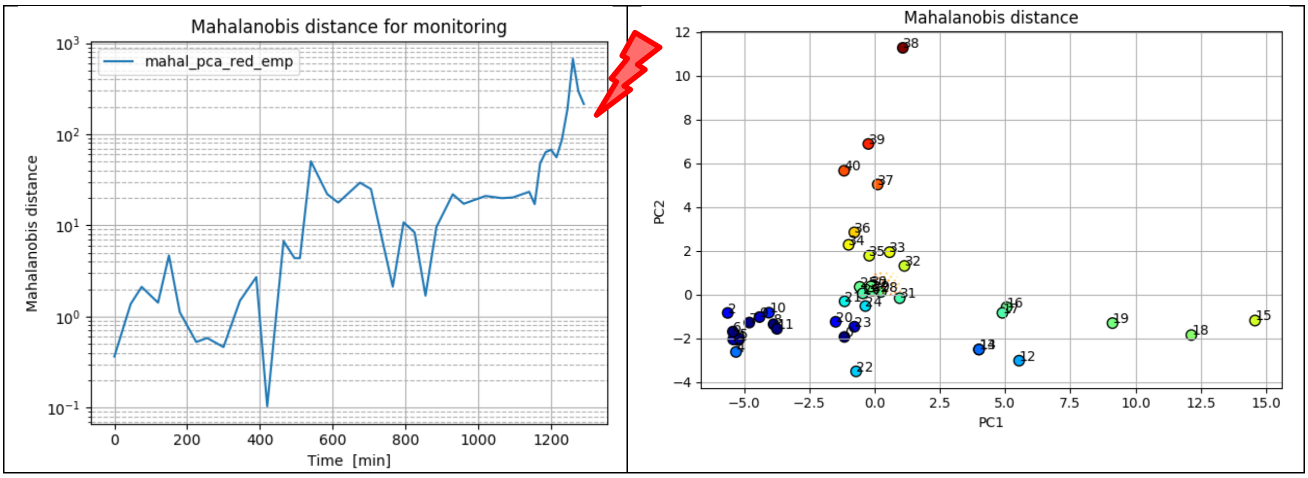

Figure 5 - Mahalanobis distance on the left and PCA results on the right – on accelerometer signal

3.2.2 Application of the method on angular speed information

The method presented for the accelerometers signal is then used on IAS signals coming from an angular encoder.

Two measures are compared: at the beginning and at the end of the fatigue test. The IAS signal shows a periodic signal with 3 periods on the 2 left figures and a zoom into one period on the right. At the end of the test, both of the teeth are clearly softer, with a lower IAS amplitude. It highlights clearly the incoming of a crack on the teeth.

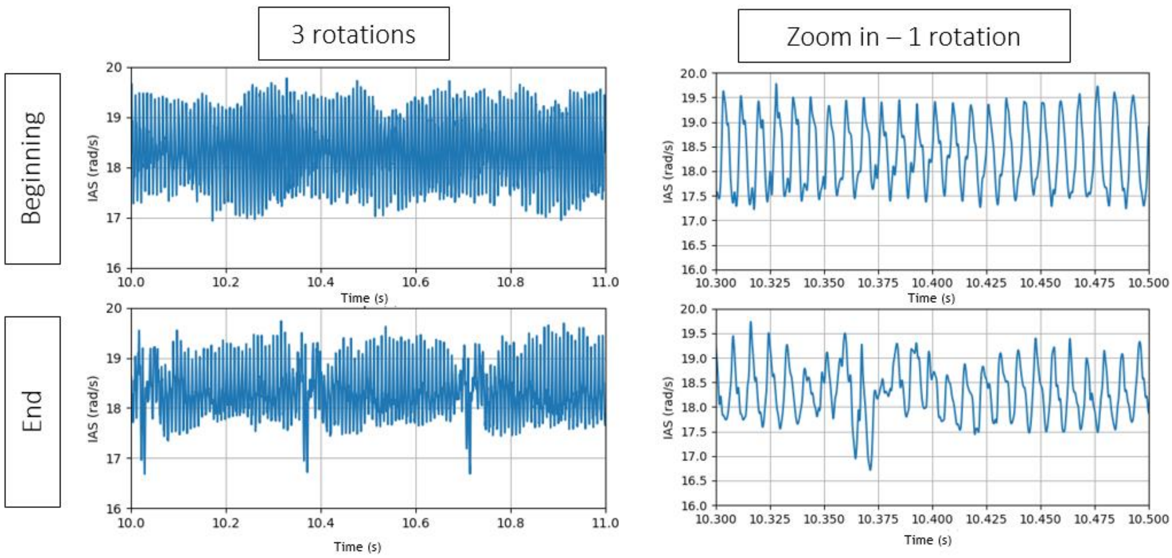

Figure 6 - Raw encoder signal – beginning and end of the endurance test

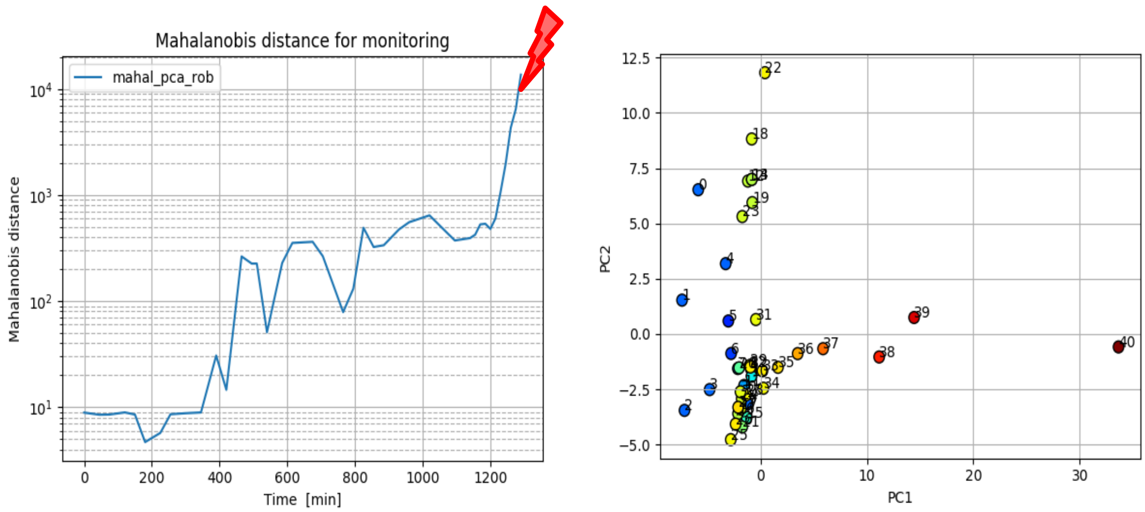

Figure 7 - Mahalanobis distance on the left and PCA results on the right – on IAS signal

After a stable phase around an amplitude of 10 for 400 min, the Mahalanobis distance indicator increases quite regularly by a 10 to 50 ratio until, reaching around 500 at 1200 minutes. At the end of this fatigue test, the 90 final minutes (from 1200 to 1290), the indicator grows up over 10 000.

Greatest interests of this indicator are its robustness, with the thousand ratio between the beginning and the end, the early detection with a significant change of behavior at min 450, giving a first and very early alert.

4. Bearing fault detection on helicopter kinematic chain – MACCHELI test bench

4.1 Context

The MACCHELI project (MAintenance de Chaîne Cinématique d'HELIcoptère, DGA RAPID project n° 182906031) aims to instrument a section of a helicopter's kinematic chain to early detect the appearance of bearing or gearing faults. For this project, a specific test bench was designed, and endurance tests were conducted on bearings - previously indented - and gears (pinions cracked by electro erosion). The test bench allows the integration of a large number of sensors, and its control by electric motors ensures a good monitoring of the applied load.
The main idea is to apply a predefined load on the tested kinematic chain, while recording the signals coming from adequate sensors, in order to detect the defects as soon as possible. The complete methodology is detailed in the following sections. In this section, results are presented for bearings. Endurance tests are ongoing for the gear fault detection analysis.

4.2 Endurance test bench setup

In order to overcome the constraints inherent to an engine test bench (background noise linked to combustion, poor accessibility, availability of test cells), a dedicated test bench has been designed. The latter, illustrated Figure 8, allows the integration of a section of a representative TRL5 helicopter kinematic chain composed of 4 shafts and 3 pairs of pinions. The total reduction ratio is 4.6.

Although this bench differs significantly from the engine in terms of bearing stiffness and absorbed mechanical power, the production line constraints of assembly and adjustment have been respected. The alignments, inter-tooth clearances and teeth contact areas have been subject to a metrological control, and are accurate to those observed on the serial engine.

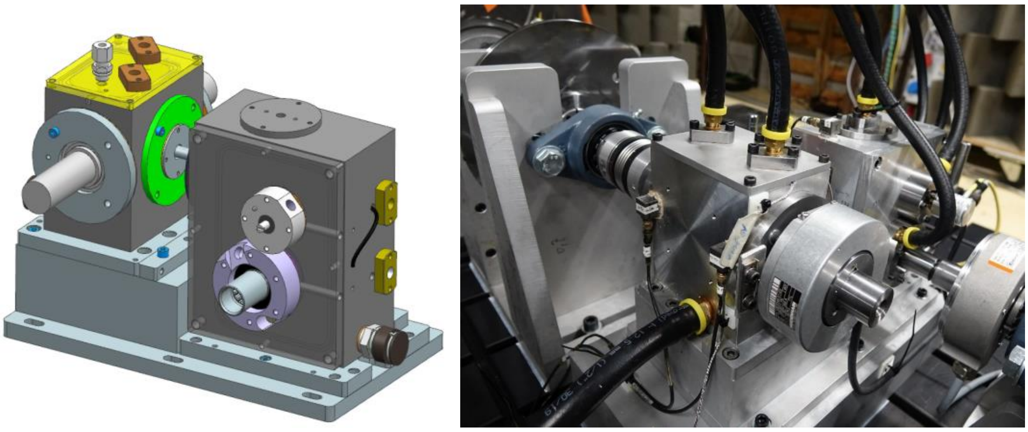

Figure 8 - Left: Numerical model; right: Test bench.

The test bench instrumentation is composed of four tri-axial accelerometers distributed on the input and output bearing housings, but also of incremental encoders positioned on each shaft.

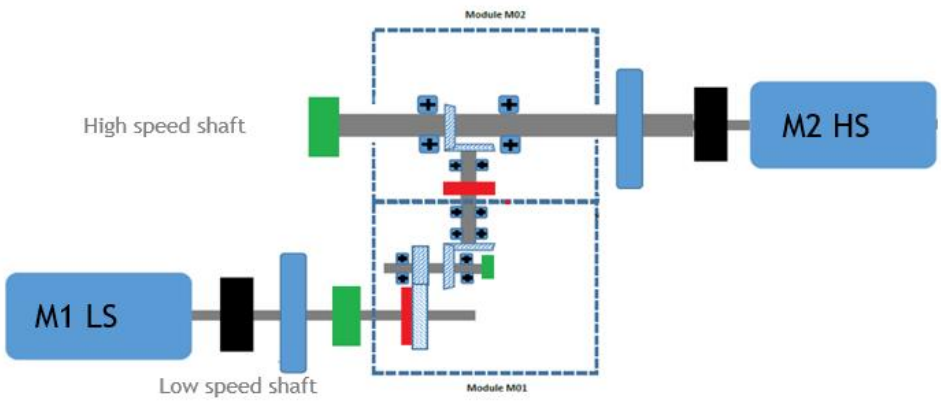

Figure 9 - Incremental encoder locations (high resolution encoder, low resolution encoder)

The latter gives access to the instantaneous angular speed of each shaft, and especially to its variations. These variations reveal the presence of kinematic defects, such as unbalance, bearing spalling, or pinion tooth cracks.

In addition, speed information provides the ability to resample accelerometer signals directly into the angular domain for synchronous analysis or order processing. Spectral analysis in this angular domain provides a very accurate measurement of kinematic frequencies, or of bearing characteristic frequencies. Depending on the selected projection shaft - and thus the resampling encoder signal - it is also possible to subtract the synchronous kinematic components from it, and therefore to clean the signals.

4.3 Endurance test

The torque applied on the pinions is equivalent to that seen by the turbine in operational conditions. The speed of rotation is almost ten times lower (around 4000 rpm).

The bearing endurance test was performed with the objective of degrading a bearing located on the high-speed shaft. A measurement of 60s every 10 minutes was carried out. After 83 hours of endurance, the vibration levels measured on the high speed shaft bearing housing increased significantly (> 8 mm/s RMS 10-1000 Hz), and exceeded the normative criteria usually applied to rotating machines. The test was then stopped, and the expertise of the bearing revealed an inner ring defect (Figure 10).

Figure 10 - Faulty bearing inner ring

The analysis of the signals corresponding to this endurance test is presented in the following chapters.

4.4 Signals pre-processing technics

The raw signals, whether they come from accelerometers or encoders, have a very rich harmonic content. They contain both the harmonics of the rotation frequency of each shaft, those related to the gear meshes, but also those due to the possible presence of defects.

In the case of accelerometric signals, sampled in the time domain, a smearing phenomenon is also present, due to the instability - albeit minimal - of the rotation speed. The encoders are directly sampled in the angular domain, and are therefore insensitive to this phenomenon, just as they are blind to the structural response of the casings due to their positioning.

Finally, the background noise on the bench is moderate: no combustion, air flow or other broadband excitation that could mask components. This is an undeniable advantage in the analysis of the signals.

When a bearing defect is present, it generates cyclic pulses that excite the structural resonances. The resulting low-energy pulse response is covered by the background noise and the kinematic components. In order to highlight the defect, the envelope of the filtered signal around a structural resonance is extracted, via Hilbert transform. Its modulus carries the fault. This envelope is then re-sampled in the angular domain in order to take into account the cyclic periodicity, and to avoid smearing effects. In the first approach, the kinematic components are not filtered. If they are too energetic, they must be removed before filtering the signal.

Note as for gear fault detection, the direct exploitation of the encoder signals is also possible with some processing, and leads to very conclusive results. This type of post-processing has been applied in these tests but is not presented here. It will be the subject of a future publication.

4.5 Machine Learning on the accelerometers signals

The different accelerometer signals have been processed and different visualizations are proposed: the distance of Mahalanobis, the principal component analysis in comparison with the use of a classical indicator such as the RMS value presented in Figure 11 for instance.

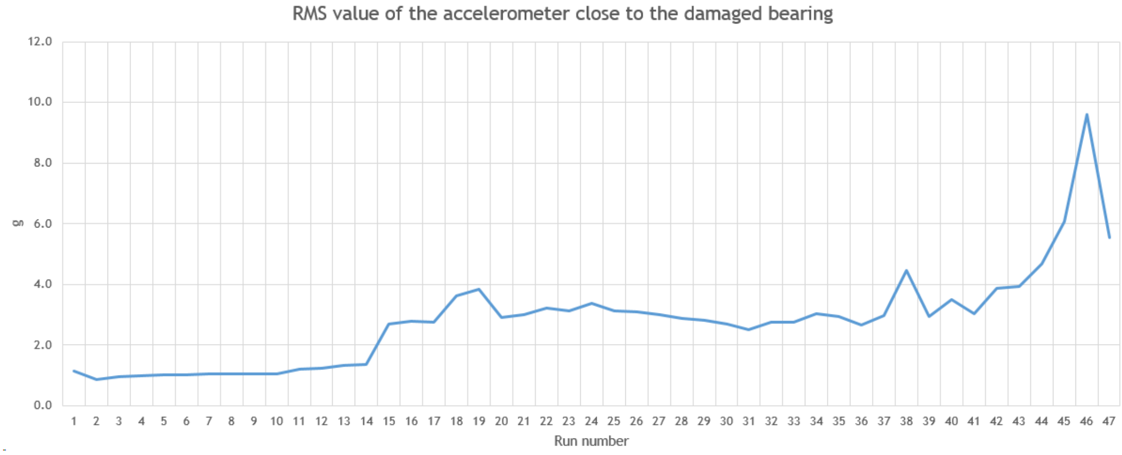

Figure 11 - RMS overall level of the accelerometer close to the damaged bearing

It is not obvious to tell that there is something wrong before the run 45. The first increase of the signal at run 15 could be interpreted as an initiation of something but as the signal stabilizes after, an intervention could have been useless.

If we now consider the distance of Mahalanobis based on the Cis specified earlier in Figure *3*, we observe a regular increase starting at run 25. The criterion of the level at which one should take action is still not obvious. Here, to accumulate data from many systems to feed machine learning database could facilitate the task. Anyway, one could consider that at run 31, we never stably reach that level. The peak at run 14 is related to a stop and a restart of the system.

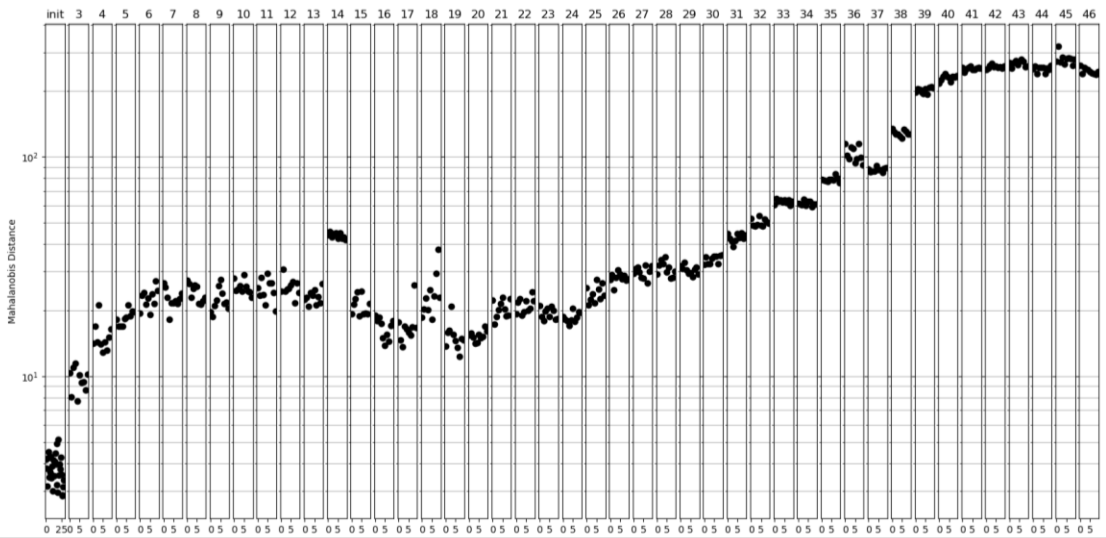

Figure 12 - Mahalanobis distance computed for the accelerometer close to the damaged bearing

Another way to observe the data is to plot the principal components obtained from a principal component analysis as presented in Figure 13. The ellipses represents the covariance for each run.

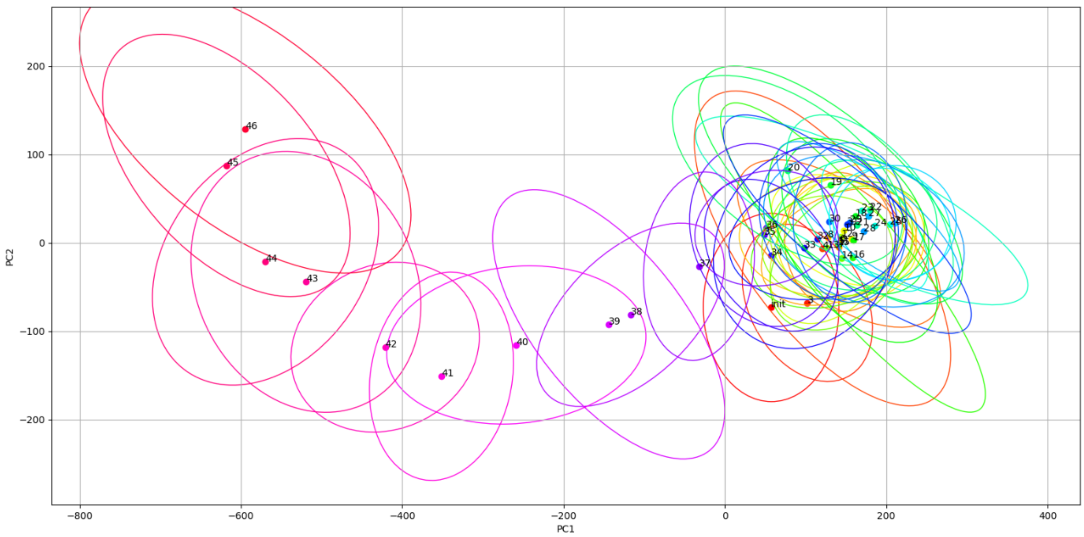

Figure 13 - Principal components analysis

By looking at Figure 13, it possible to detect the damage starting at run 37.

As we can see, this simple utilization of classical condition indicator coupled with machine learning techniques allows an early detection of the damage propagation.

5. Synthesis and prospectives

A complete approach has been set up to detect gears and bearings faults. Two test benches were designed in order to experimentally generate bearing and gear fault. Numerous sensors have been implemented on the test bench (accelerometers and without contact encoders), and their processing leads to early fault detection for both cases.
Gear fault was not detected considering standard condition indicator but was detected considering several indicators coupled with the distance of Mahalanobis and PCA analysis. Same methods were applied with similar results for bearing fault detection.
Gear endurance tests are currently on-going on the MACCHELI test bench with the aim to confirm the conclusion from partial test bench and in particular the feasibility of detecting defect using without contact sensors with low resolution on a more complex kinematic chain.

6. Acknowledgement

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8. Copyright Statement

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