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## **Vibration condition monitoring in a paper industrial plant: Supreme project**

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### **Abstract**

This paper presents a condition monitoring methodology applied to the suction roll and the Press roll of a paper machine. Experimental results obtained for the detection and identification of many defects that may occur to different mechanical components are presented. To this end, many fault indicators are calculated using a set of signal processing methods. We endeavor to propose robust fault indicators with respect to the variations of the operation parameters as the speed variation. Cyclostationary and cepstral approaches are used in order to make vibration source separation and to extract pertinent indicators closely related to the health of the paper machine. AStrion strategy, a stand-alone, data-driven and automatic tracking analyzer, is applied in order to characterize a sensor failure on the suction roll and a fault on the motor that drives the press roll. The trends of these parameters have shown the effectiveness of these methods to detect and identify the failure modes of the equipment thus allowing the reduction of the overall maintenance cost. This work has been done within the SUPREME project, funded by the European Commission, under the FP7 program.

### **1. Introduction**

Non-stationary signals can be defined as signals which satisfy a non-property, i.e. they do not satisfy the property of stationarity. It is not possible to define a general theory which treats non-stationary signals. The non-stationary behavior of each signal has to be individually evaluated. For instance time-frequency analysis can be considered a useful tool to analyze the amplitude and frequency non-stationarities within a signal. In the case that signals present periodic energy variations, which are synchronous with the machine cycle, a particular class of non-stationary signals can be defined as cyclostationary signals [1].

A signal is said cyclostationary if it contains cyclic transfer of energy. The amplitude modulated signal is an intuitive example of these signals. Cyclostationarity may be classified into several orders:

1st-order cyclostationarity: the cyclic energy flow is carried by deterministic components (sum of sinusoids plus stationary noise as for example the gear noise.

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## 2. Signal Processing Techniques: Formulation and Properties

### 2.1 Cyclostationary indicators

The procedure for computing the four cyclostationary indicator is illustrated by Figure 1, [2]. The procedure of calculating of these indicators uses the angular vibration signal sampled with ‘SmpRev’ samples per revolution and two order frequencies in order to extract two sets of the four cyclostationary indicators related to the two last orders. First we can see that the angular vibration signal is averaged with respect to a reference frequency in order to extract the mean signal. By subtracting the mean from the original angular signal we obtain the residual one. The first cyclostationarity indicator is computed from the mean signal and the three other indicators from the residual one. Generally when computing the Cyclostationary Indicators we exclude all the non-synchronous frequencies (with respect to the reference) and we exclude all the meshing ones. This will help to quantify cyclostationarity related to mechanical defects that appear respectively in the mean signal, in the power2, power3 and power4 of the residual signal.

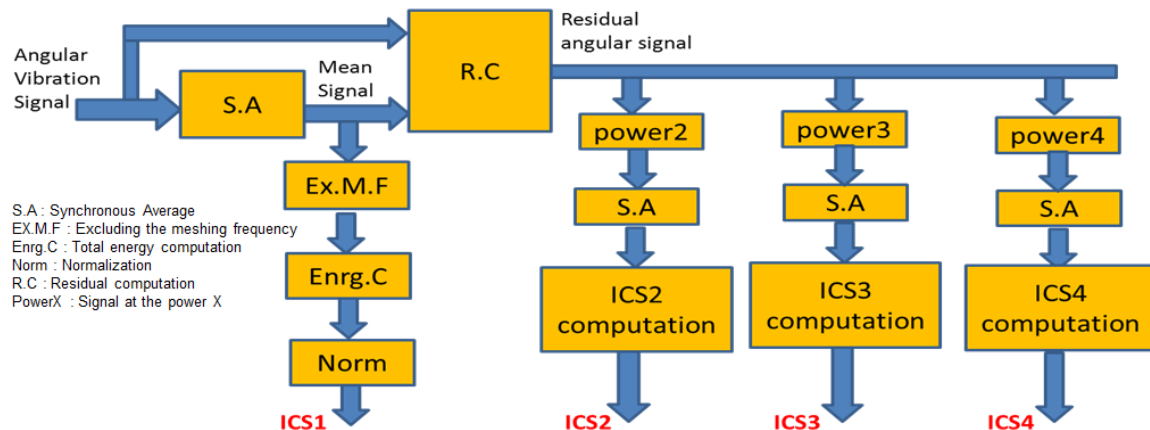
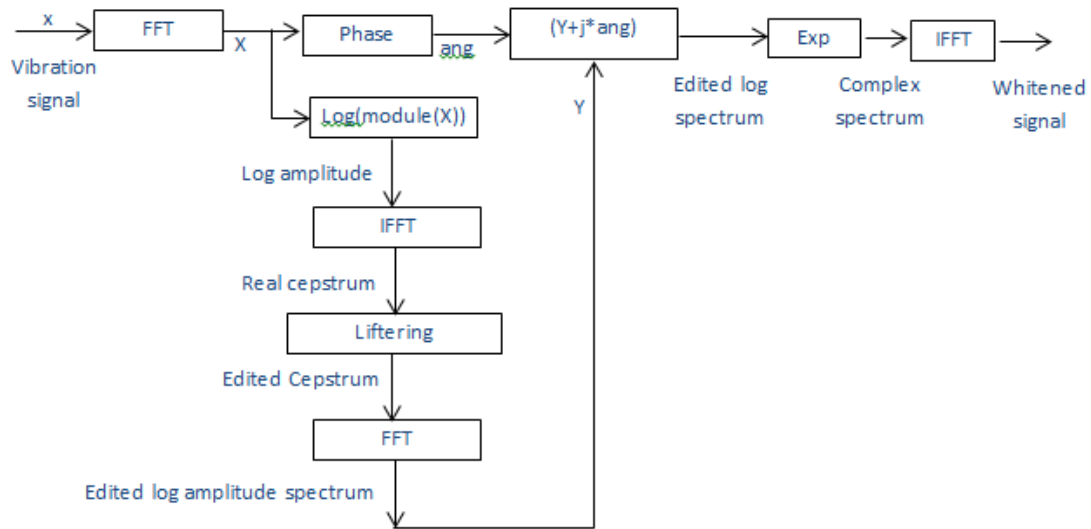


Figure 1. Computation of the four cyclostationary indicators

### 2.2 Cepstral prewhitening

This method has the ability to separate the deterministic/random parts of a vibration signals. It uses the cepstrum computation [3]. It is well adapted to rolling element

bearing fault detection and is crucial in vibration gear and bearing source separation. The method is illustrated by Figure 2.



**Figure 2. Schematic diagram of the Cepstral prewhitening**

### 2.3 Astrion: an automatic spectrum analyzer

Due to the periodic nature of the vibration signals of rotating machines, spectrum-based analysis is a common approach in mechanical fault diagnosis. AStrion is a spectrum analyser which combines 5 different spectrum estimators to optimize the resolution and to reduce the variance. The analysis process is totally automatic and modularized in the following order: AStrion-A (optional): angular resampling, AStrion-D: data validation, AStrion-I: peak identification, AStrion-K (optional): kinematic Association, AStrion-H: harmonic and sideband identification, AStrion-M: sideband demodulation, AStrion-T: feature trajectory tracking, AStrion-S: surveillance. A more detailed description of the architecture can be found in [4][5].

There are many difficulties with the system-driven fault detection approach or by the manual spectral inspection. This type of method often requires a careful configuration to work correctly on each individual machine. The accuracy fault detection and tracking are also heavily depends on the configuration or the user. Therefore a correct conclusion requires the expert knowledge. It consists of another risk in application that the possible frequency band where the fault will appear has to be located before the fault is detectable.

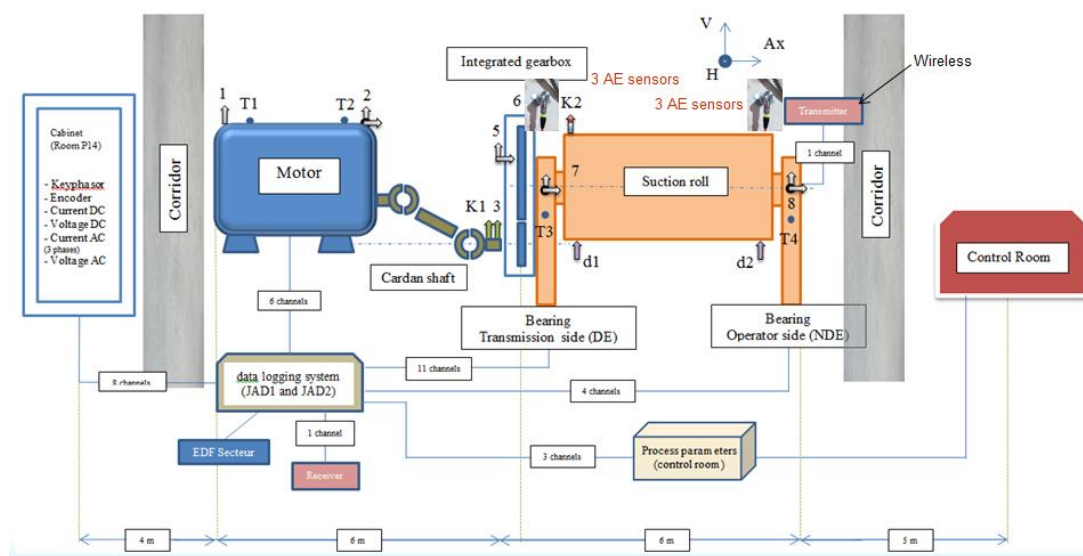
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way. Moreover, some types of faults can be detected simply at the phase of the data validation, without being processed by the following modules.

### 3. Application

#### 3.1 Critical machines in paper industry

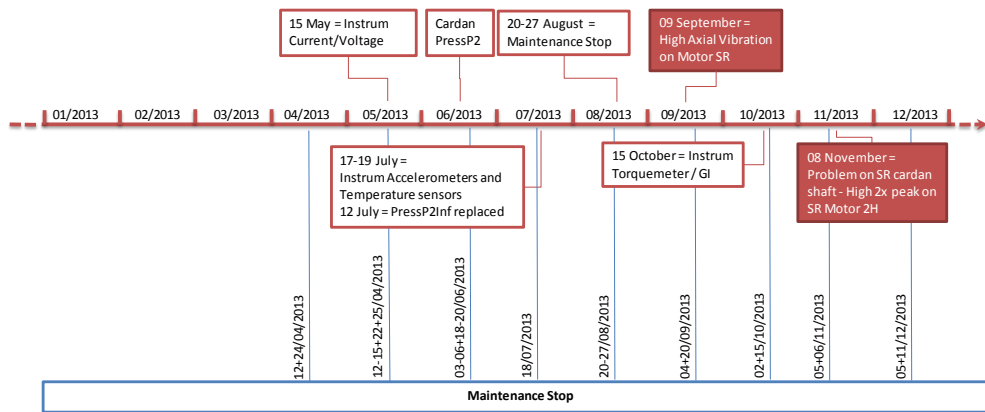
In the beginning of the project supreme, a visit to the paper industry has shown that the main maintenance activities are focused at the suction roll and the press P2 parts. In fact, these parts of the paper machine are equipped by DC motors and gears see Figure 3.



**Figure 3 Critical machine in the paper industry: The suction roll**

##### 3.1.1 The time life maintenance on Condat industry

Hereafter the time life maintenance that occurs on the suction roll over the period of the project (2013-2015), see Figure 4.



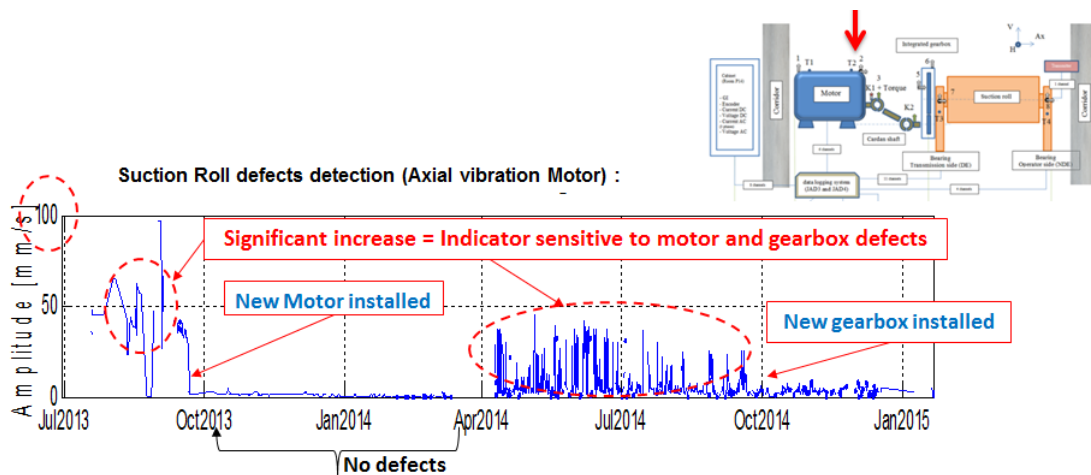
**Figure 4 The time life maintenance over the project for the suction roll**

We can see clearly that:

- The motor of the Suction Roll ‘SR’ is replaced on September 2013 (bearing fault) due to excessive vibrations.
- Cardan looseness fixed on November 2013.
- Integrated Gearbox replaced October 2014 due high axial vibration.

### 3.2 Standard vibration analysis Results

The evolution of simple condition monitoring parameters is extracted from different vibration signals. Figure 5 show the evolution of one of the global velocity RMS value calculated from the axial direction of the vibration signal coming from motor accelerometer.

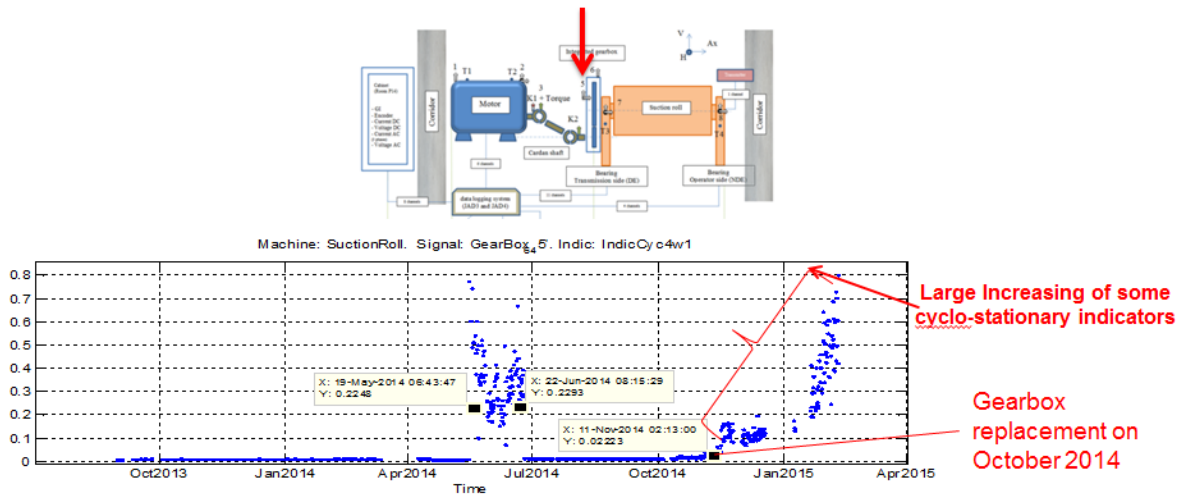


**Figure 5 Evolution of standard condition monitoring indicator  $V_{rms}$  from axial direction vibration signal**

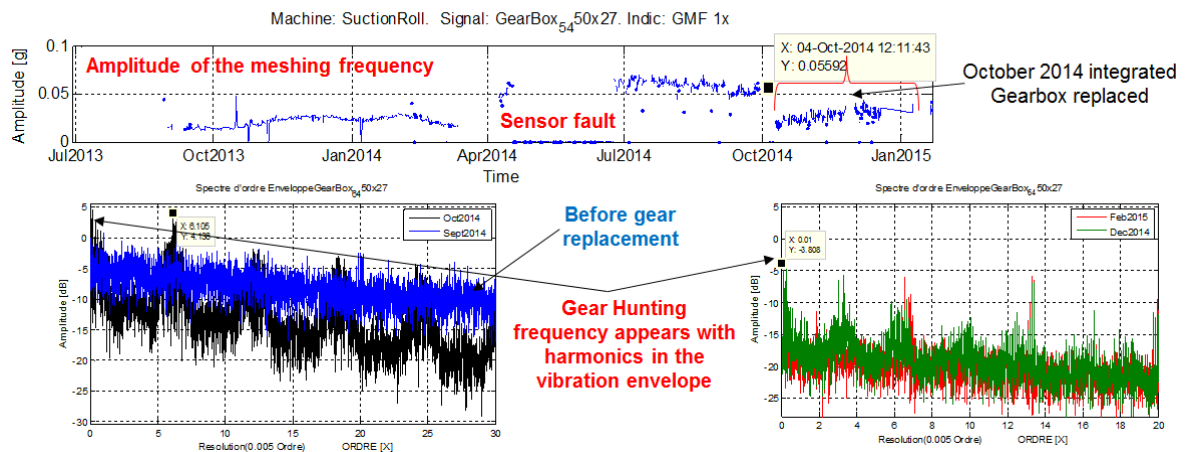
We notice that this indicator has increased in August 2013 which mean that it was very sensitive to motor faults. Inspection confirms a broken elastic ring in a rolling element bearing of the motor.

### 3.3 Cyclostationary analysis Results

Looking to the cyclostationary indicators (Figure 6), their evolution were quiet stable in the beginning of the project and increased drastically between 19 of May and 22 of June 2014 because of a sensor fault and in October 2014 since the gearbox was replaced! In order to isolate the fault that occurs in October 2014 that makes the cyclostationary indicators increases, we make deeper spectral analysis by comparing spectra before and after October 2014. Indeed this analysis reveals that a hunting frequency appears on the new gearbox at very low frequency (0.01Hz) reflecting localized tooth fault due, perhaps, to fault manufacturing, see Figure 7.



**Figure 6 Evolution of one of cyclostationary indicator coming from the gearbox vibration signal**

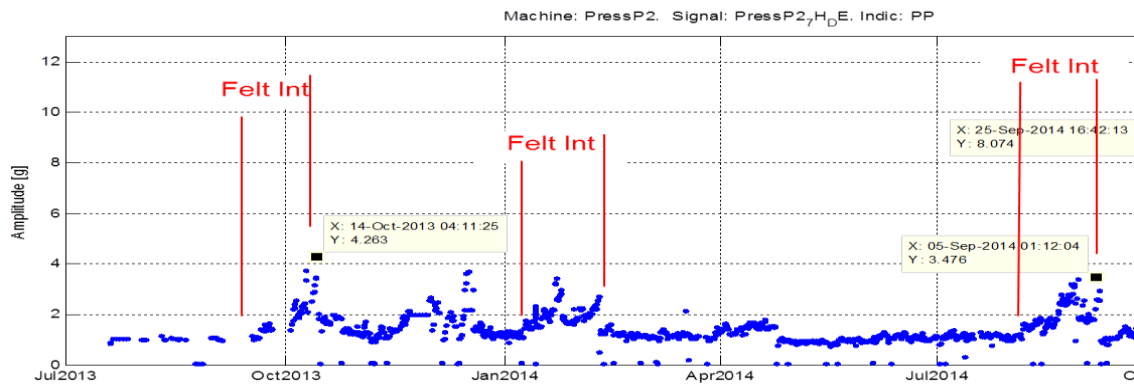




**Figure 7. Spectral analysis from the gearbox vibration signal**

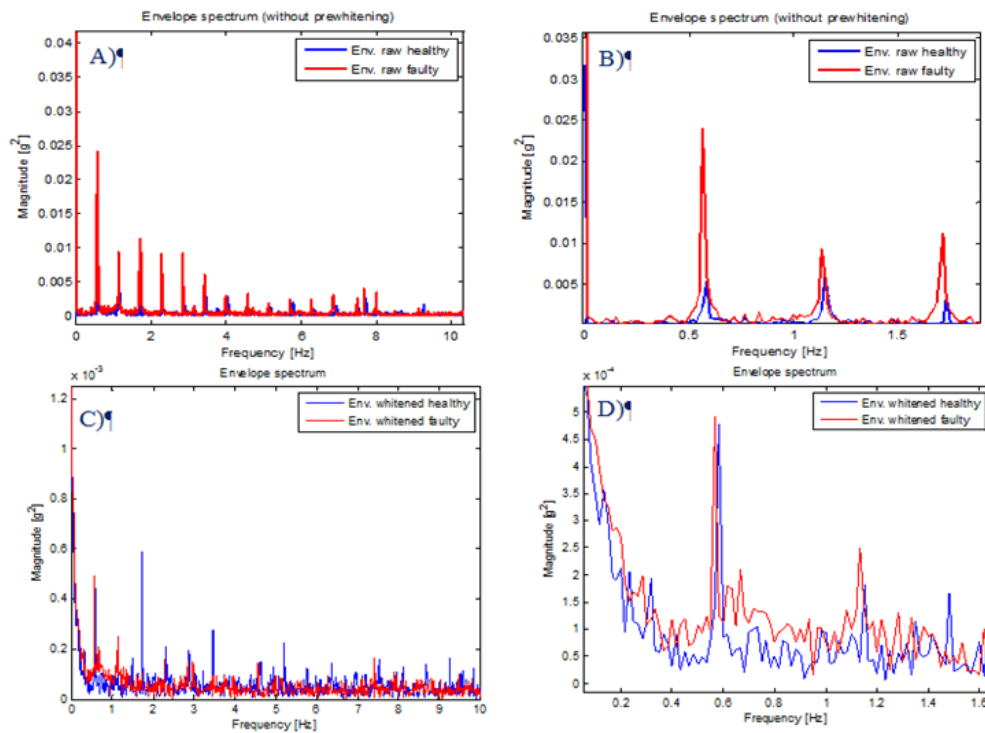
### 3.4 Cepstral Results

On the press P2 we were interested to detect felt wear. Figure 8 show the peak to peak condition monitoring indicator over the project period. In fact we remark that this indicator (Peak-peak indicator) extracted from the horizontal direction of the roll bearing vibration signal was sensitive to the felt wear: level increased before the felt replacement and decreased just after. Seven periods of wear felt were detected from July 2013 till August 2015. It seems that the vibration levels are more sensitive to a particular type of the roll felt.



**Figure 8. Spectral analysis from the gearbox vibration signal**

Spectral analysis show a modulation phenomenon at 0,57Hz around deterministic frequencies ( $38 \times \text{roll speed} = 144\text{Hz}$ ). In order to isolate the source of this fault we used the cepstral prewhitening. Figure 9 shows a comparison between envelopes spectra of vibration signal (raw and whitened) and for a healthy and faulty felt. From Figure 9B we notice that the amplitude of the characteristic frequency increases when felt wear appear. From Figure 9D we notice that fault characteristic frequency disappear from the whitened signal. This reveals clearly that fault source is deterministic and occurs periodically due to felt face fault.



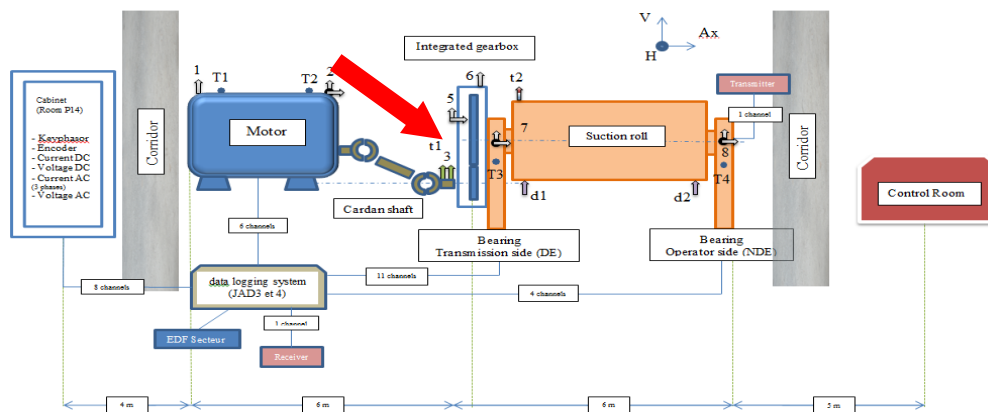
**Figure 9 Cepstral analysis: A) Comparison between envelope spectra of raw vibration signals, B) Zoom of envelope spectra for raw signals. C) Cepstral whitened envelope spectrum comparison, D) zoom of the whitened envelope spectra**

### 3.5 AStrion Results

In this paragraph, two examples on the Condat paper factory, a partner of the SUPREME project, are shown to demonstrate the capability of AStrion in the automatic detection of real-world mechanical faults. The first example is a sensor fault while the second is a mechanical fault of a motor bearing.

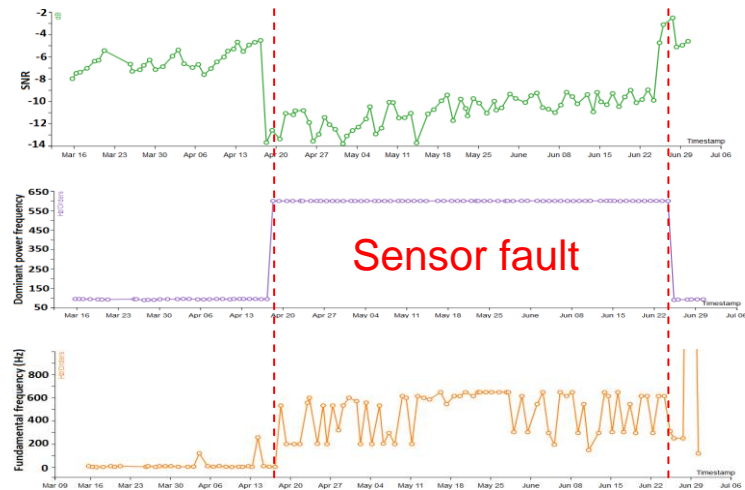
#### 3.5.1 Results on the detection of a cable disconnection of an accelerometer

During April 17<sup>th</sup> and June 25<sup>th</sup> 2014, a cabling problem had been identified at the accelerometer n.5 installed with a 45 degree angle at the gearbox of the suction roll. The sensor location in the overall mechanical configuration is shown as in Figure 10.



**Figure 10. The location of the faulty accelerometer in the suction roll, as marked by the red arrow.**

Without being alerted by a specialist, AStrion is able to autonomously detect the fault. Due to the cabling fault, the accelerometer did not contain the vibration-induced spectrum structure, the dominant spectral content was the instrumentation noise, and some high frequency resonance components, therefore some data validation features provided good indicators of the fault, as presented in Figure 11.

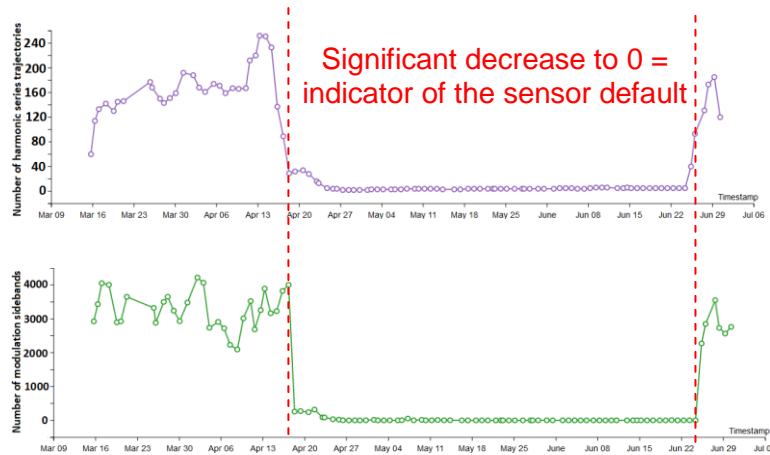


**Figure 11. AStrion-D (data validation) result of the faulty accelerometer of Figure 10 from March 15<sup>th</sup>, 2014 to June 30<sup>th</sup>, 2014. Above: The SNR; Middle: The dominant power periodicity; Bottom: The fundamental frequency.**

In Figure 11, the signals are transformed to order domain using AStrion-A (angular resampling) and the features are computed using AStrion-D (data validation). Since the cable was detached, the accelerometer no longer measured the vibration of the gearbox, therefore the absence of the vibration components significantly suppress the signal power compared to the noise. The Signal-To-Noise (SNR) decreased dramatically compared to the signals under the normal operational condition.

Moreover, the observed signal can be considered as the composition of two types of spectral structure. The first is the vibration components, under normal operational condition they dwell on low frequency range and concentrate high power; the second is the high frequency resonance, which is normally overwhelmed by the vibration components. During the cabling fault, the vibration components were not captured, therefore, the dominant power of the signal will be the high frequency resonance. The significant increase of the dominant power frequency and the fundamental frequency clearly reveal this phenomenon.

Besides the data-validation, the following spectral analysis of the harmonic and sideband structure also provides reliable indicators of the fault, as Figure 12 shows.

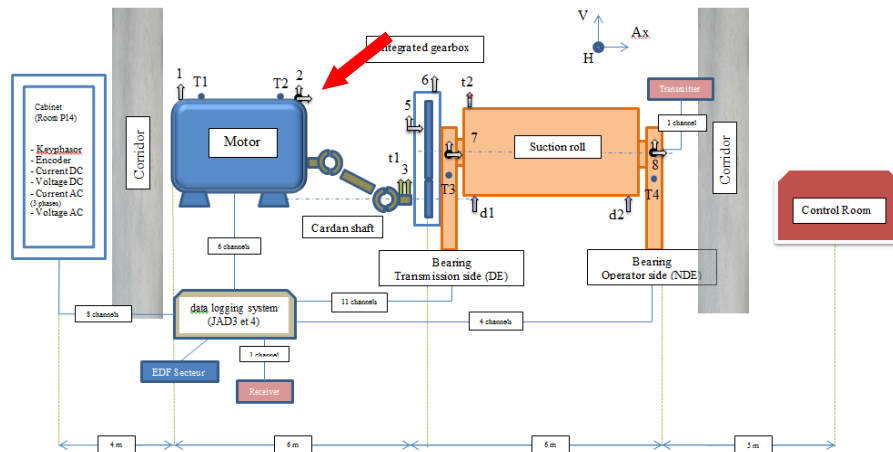


**Figure 12. AStrion-H (harmonic and sideband identification) result of the faulty accelerometer of Figure 10.**

Normally, the harmonics and the sidebands are generated by the vibration of the mechanical parts. When the sensor was disconnected, these spectral structures vanished, the number of the harmonic families and the sidebands also significantly decreased. Moreover, in Figure 12, the number of harmonic series and the sidebands correspond only to those with kinematic associations. Since during the sensor fault, these components were inexistent, both numbers were therefore close to zero.

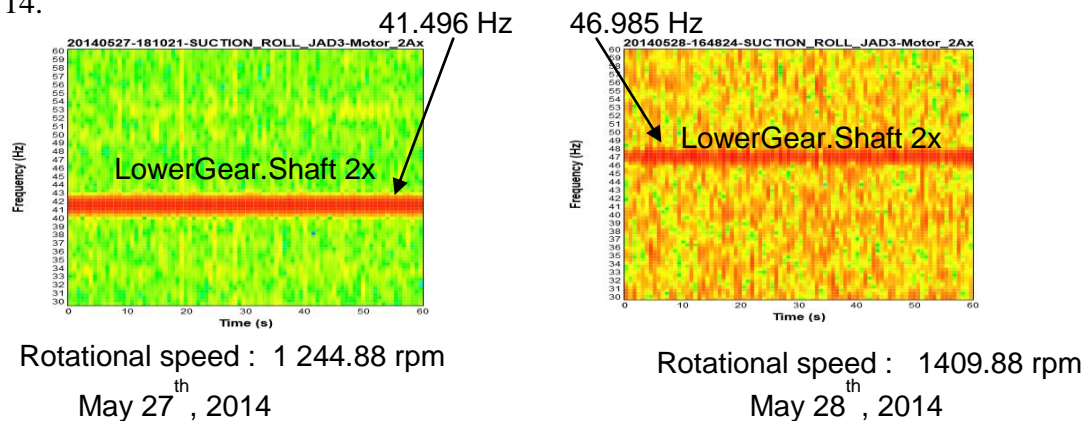
*3.5.2 Results on the detection of a bearing fault in a motor*

It has been reported by a maintenance technician at the end of October 2014 that there had been a failure of the motor in the Suction roll. But the faulty part of the motor had not been identified. However, AStrion carried out continuous surveillance and was capable to automatically detect the fault from the accelerometer signal. The location of the motor and the accelerometer under study are shown in Figure 13.



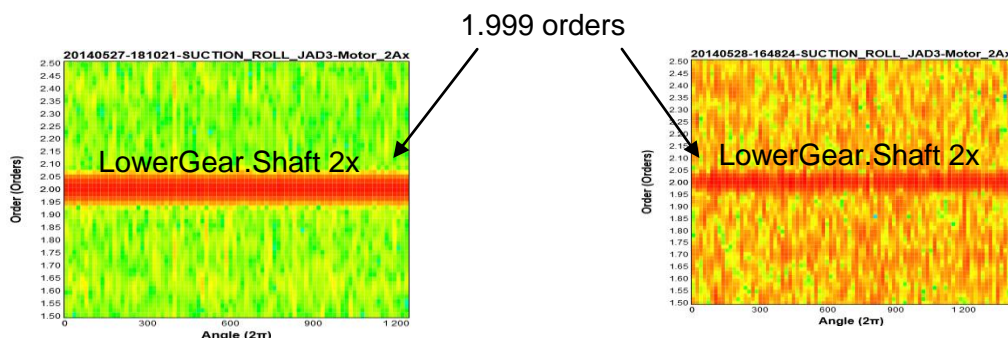
**Figure 13. The location of the faulty motor and the accelerometer (marked by the red arrow) on which AStrion is applied.**

Since the rotational speed of the motor is time-varying, especially over different days, the spectral content of the signal also varied in frequency. It consists of the major difficulty of the tracking of the spectral components by the frequency, as shown in Figure 14.



**Figure 14. The spectrogram of the accelerometer in Figure 13 zoomed around the same kinematic component (2<sup>nd</sup> harmonic of the shaft speed on the low speed gear) at May 27<sup>th</sup> 2014 and May 28<sup>th</sup> 2014.**

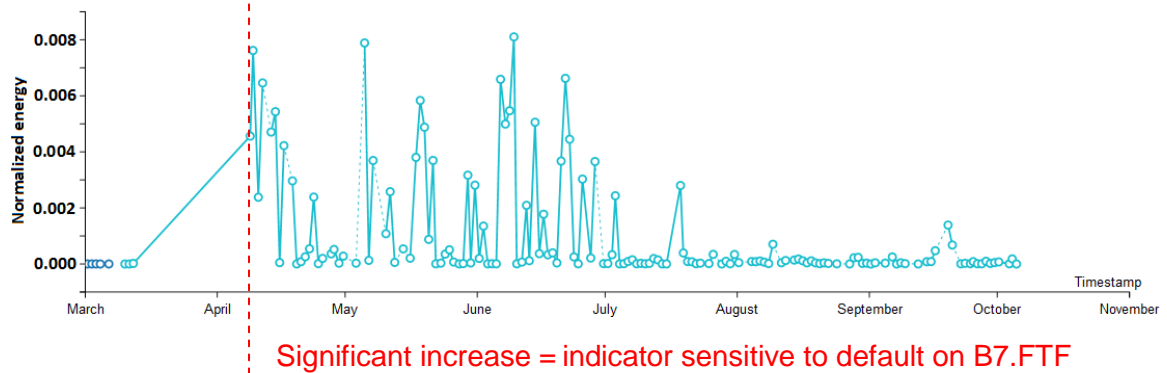
Figure 14 shows the difference in the frequency of the same kinematic component. The frequency shift is proportional to the difference of the rotational speed. After the angular resampling, the signal is synchronized to the angular rotational speed. The frequency spectrum can be transformed to an order spectrum on which the difference of the rotational speed is cancelled, as shown in Figure 15.



**Figure 15. The order spectrogram of the signals under different rotational speed in Figure 13, calculated after being transformed to the order domain by AStrion-A.**

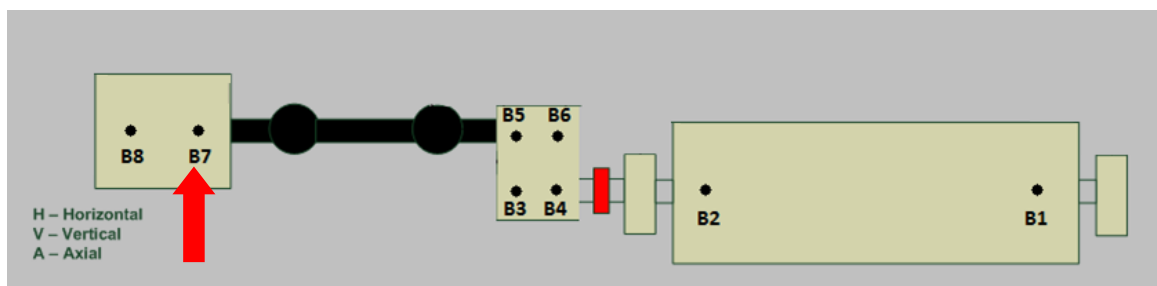
In figure 15, the same kinematic component is aligned at the same order, even if the rotational speed varies. It makes the continuous tracking of the spectral structure easier

and more robust. Over the order spectrum, AStrion-H, the harmonic and sideband identification module, identified a significant increase of the energy of the harmonic family B7.FTF (Fundamental Train Frequency of the bearing 7) of the signal, shown in Figure 16.



**Figure 16. The energy of the harmonic family of B7.FTF of the signals of the accelerometer n.2 of Figure 10.**

The results obtained in Figure 16 are based on the tracking of the harmonic identification of all the signals. The harmonic identification and tracking are carried out in a non-supervised manner: the peaks of the spectrum are detected by AStrion-I, the harmonic families were identified by AStrion-H, the kinematic components were associated by AStrion-K, and the trajectory of the B7.FTF was automatically connected and tracked by AStrion-T. No human intervention was required. The trend of the energy variation clearly indicates the beginning of the fault. After replacing the motor, the trend again stabilized at a low level. The detection results reveal a possible fault at the bearing 7, as shown in Figure 17.



**Figure 17. Location of the bearing 7 in the faulty motor.**

Using Astrion, it is not only possible to detect the fault, but also able to deduce the faulty part before the teardown and the inspection of the motor.

## 4. Conclusions

This work has been done within the SUPREME project, funded by the European Commission, under the FP7 program. In this paper we present condition monitoring methodology applied to the suction roll and the Press roll of a paper machine. Experimental results obtained for the detection and identification of many defects that may occur to different mechanical components are presented. The trends of multiple simple and advanced condition monitoring parameters have shown the effectiveness of indicators to detect and identify the failures that may occur to critical machines.

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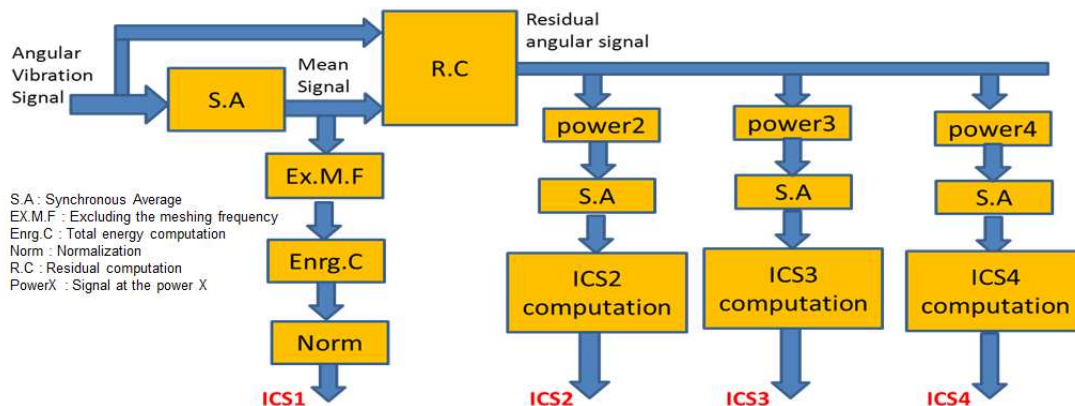
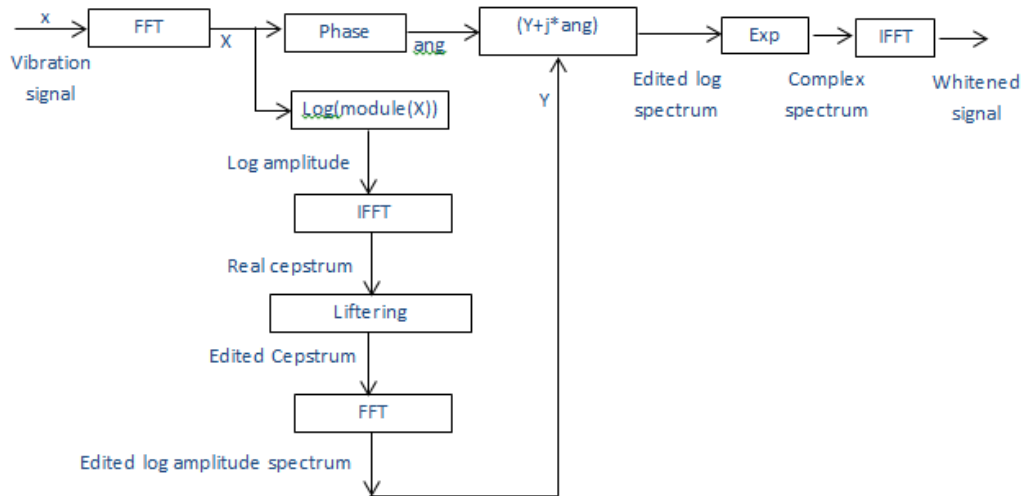


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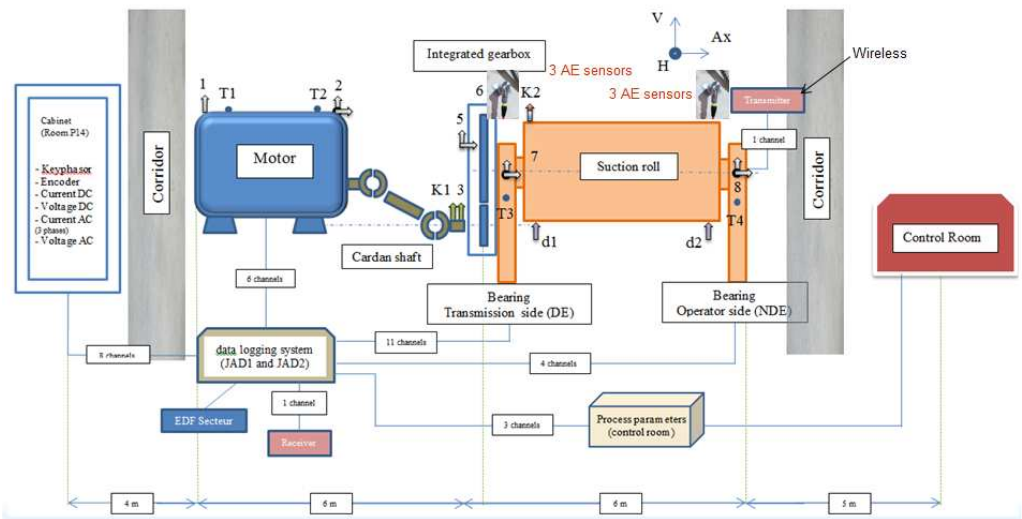
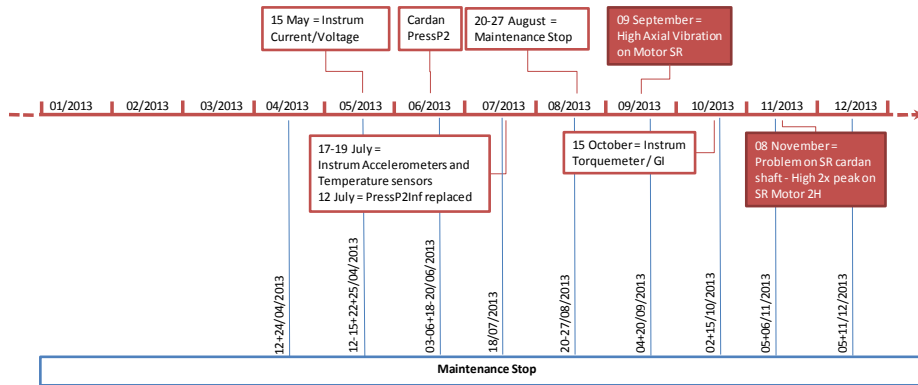


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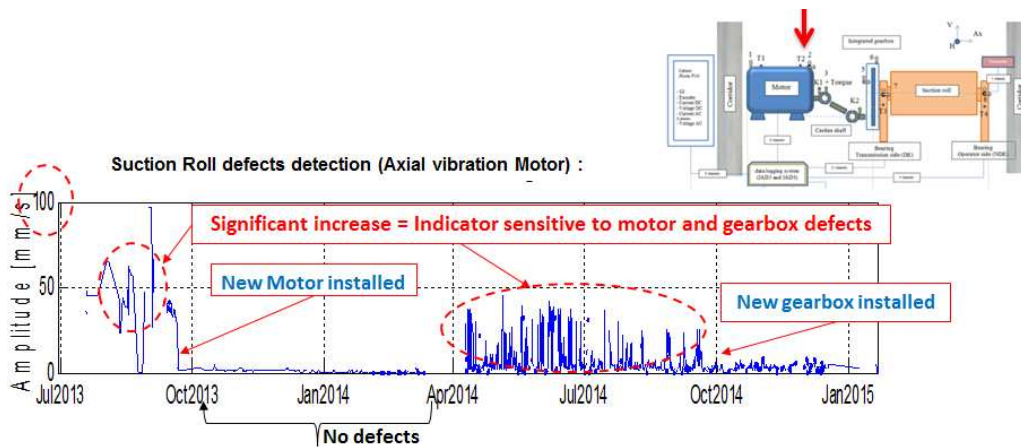
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The evolution of simple condition monitoring parameters is extracted from different vibration signals. Figure 5 show the evolution of one of the global velocity RMS value calculated from the axial direction of the vibration signal coming from motor accelerometer.



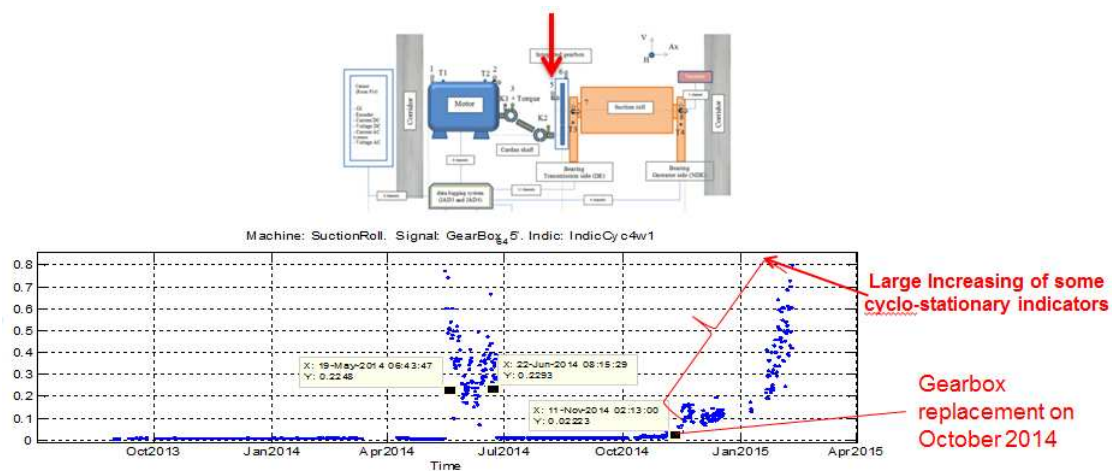
**Figure 5 Evolution of standard condition monitoring indicator  $V_{rms}$  from axial direction vibration signal**

We notice that this indicator has increased in August 2013 which mean that it was very sensitive to motor faults. Inspection confirms a broken elastic ring in a rolling element bearing of the motor.

### 3.3 Cyclostationary analysis Results

Looking to the cyclostationary indicators (Figure 6), their evolution were quiet stable in the beginning of the project and increased drastically between 19 of May and 22 of June 2014 because of a sensor fault and in October 2014 since the gearbox was replaced!

In order to isolate the fault that occurs in October 2014 that makes the cyclostationary indicators increases, we make deeper spectral analysis by comparing spectra before and after October 2014. Indeed this analysis reveals that a hunting frequency appears on the new gearbox at very low frequency (0.01Hz) reflecting localized tooth fault due, perhaps, to fault manufacturing, see Figure 7.



**Figure 6 Evolution of one of cyclostationary indicator coming from the gearbox vibration signal**

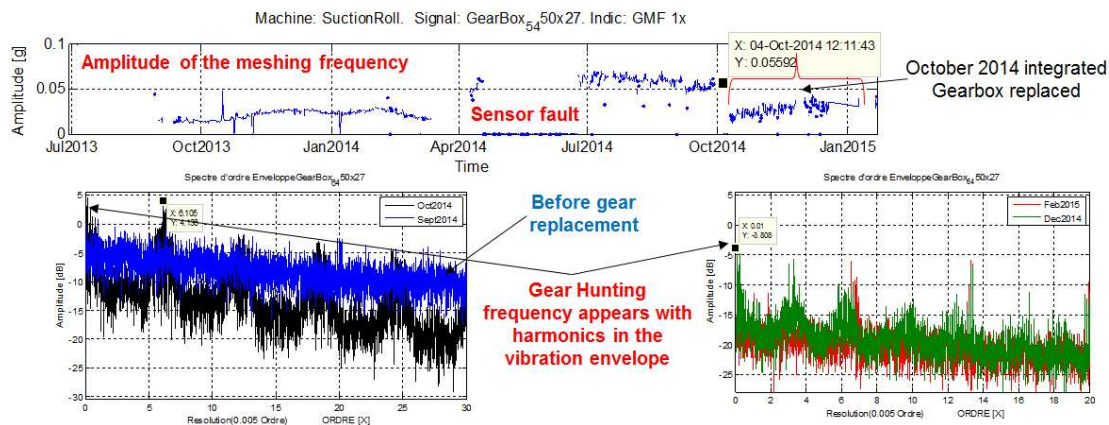


Figure 7. Spectral analysis from the gearbox vibration signal

### 3.4 Cepstral Results

On the press P2 we were interested to detect felt wear. Figure 8 show the peak to peak condition monitoring indicator over the project period. In fact we remark that this indicator (Peak-peak indicator) extracted from the horizontal direction of the roll bearing vibration signal was sensitive to the felt wear: level increased before the felt replacement and decreased just after. Seven periods of wear felt were detected from July 2013 till August 2015. It seems that the vibration levels are more sensitive to a particular type of the roll felt.

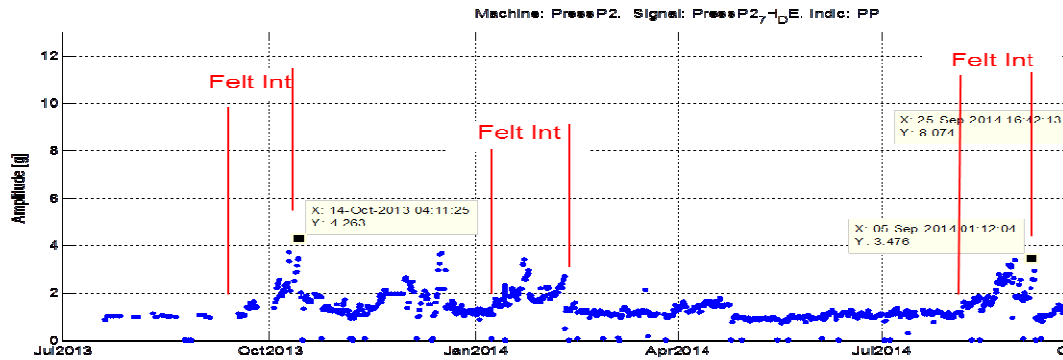
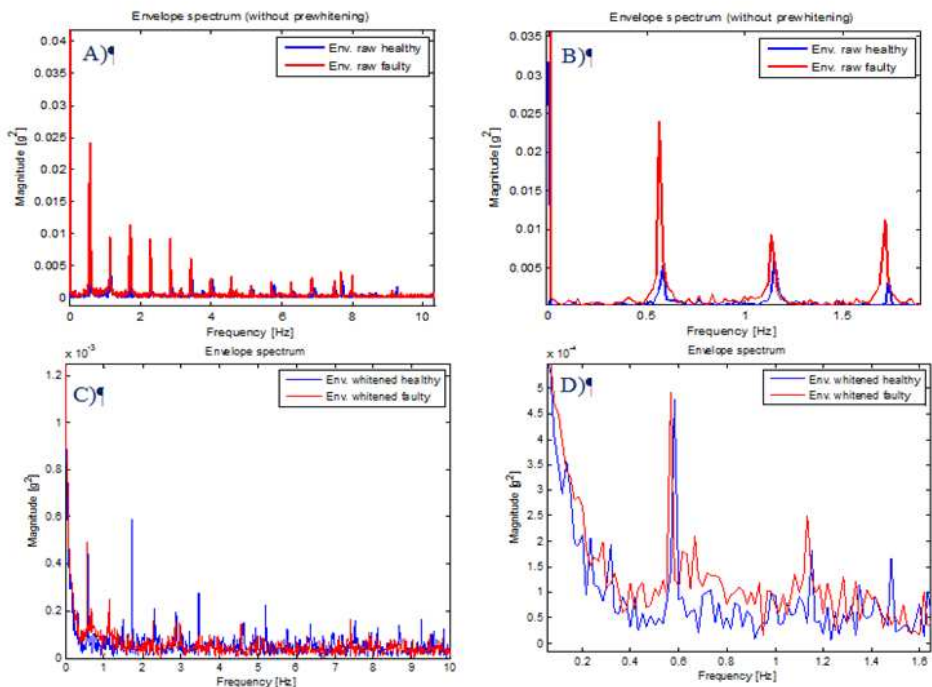


Figure 8. Spectral analysis from the gearbox vibration signal

Spectral analysis show a modulation phenomenon at 0,57Hz around deterministic frequencies (38X roll speed=144Hz). In order to isolate the source of this fault we used the cepstral prewhitening. Figure 9 shows a comparison between envelopes spectra of vibration signal (raw and whitened) and for a healthy and faulty felt. From Figure 9B we notice that the amplitude of the characteristic frequency increases when felt wear appear. From Figure 9D we notice that fault characteristic frequency disappear from the whitened signal. This reveals clearly that fault source is deterministic and occurs periodically due to felt face fault.



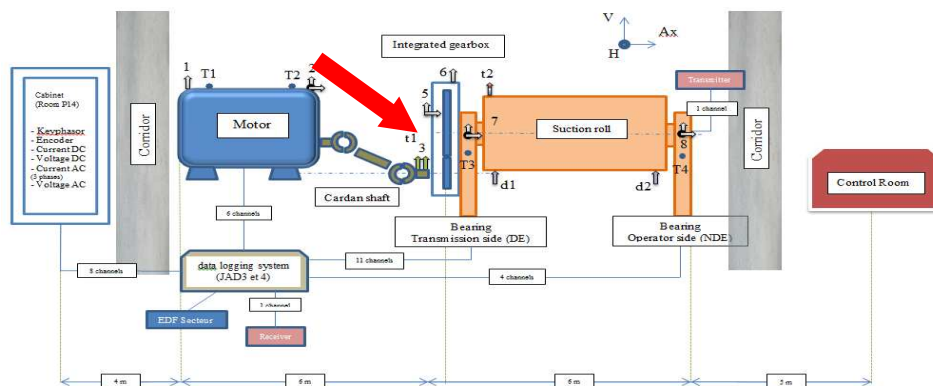
**Figure 9 Cepstral analysis: A) Comparison between envelope spectra of raw vibration signals, B) Zoom of envelope spectra for raw signals. C) Cepstral whitened envelope spectrum comparison, D) zoom of the whitened envelope spectra**

### 3.5 AStrion Results

In this paragraph, two examples on the Condat paper factory, a partner of the SUPREME project, are shown to demonstrate the capability of AStrion in the automatic detection of real-world mechanical faults. The first example is a sensor fault while the second is a mechanical fault of a motor bearing.

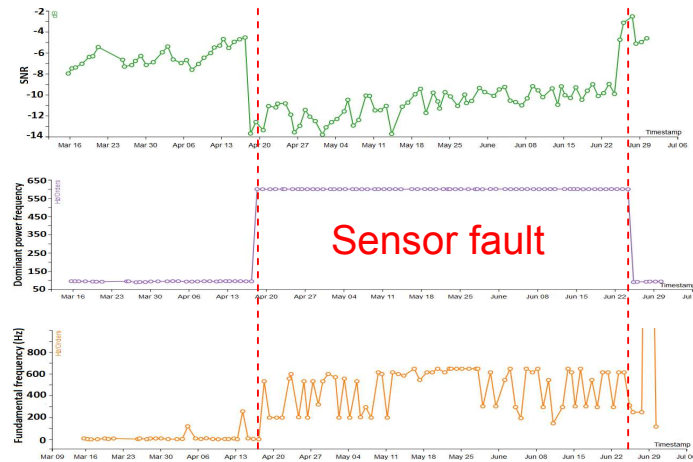
#### 3.5.1 Results on the detection of a cable disconnection of an accelerometer

During April 17<sup>th</sup> and June 25<sup>th</sup> 2014, a cabling problem had been identified at the accelerometer n.5 installed with a 45 degree angle at the gearbox of the suction roll. The sensor location in the overall mechanical configuration is shown as in Figure 10.



**Figure 10. The location of the faulty accelerometer in the suction roll, as marked by the red arrow.**

Without being alerted by a specialist, AStrion is able to autonomously detect the fault. Due to the cabling fault, the accelerometer did not contain the vibration-induced spectrum structure, the dominant spectral content was the instrumentation noise, and some high frequency resonance components, therefore some data validation features provided good indicators of the fault, as presented in Figure 11.



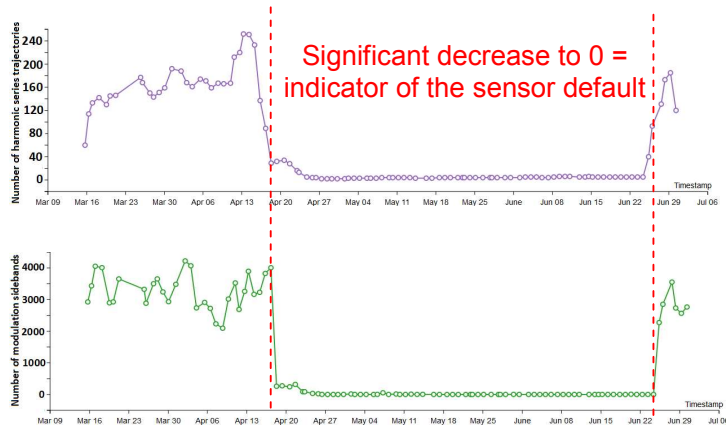
**Figure 11. AStrion-D (data validation) result of the faulty accelerometer of Figure 10 from March 15<sup>th</sup>, 2014 to June 30<sup>th</sup>, 2014. Above: The SNR; Middle: The dominant power periodicity; Bottom: The fundamental frequency.**

In Figure 11, the signals are transformed to order domain using AStrion-A (angular resampling) and the features are computed using AStrion-D (data validation). Since the cable was detached, the accelerometer no longer measured the vibration of the gearbox, therefore the absence of the vibration components significantly suppress the signal power compared to the noise. The Signal-To-Noise (SNR) decreased dramatically compared to the signals under the normal operational condition.

Moreover, the observed signal can be considered as the composition of two types of spectral structure. The first is the vibration components, under normal operational condition they dwell on low frequency range and concentrate high power; the second is the high frequency resonance, which is normally overwhelmed by the vibration components. During the cabling fault, the vibration components were not captured, therefore, the dominant power of the signal will be the high frequency resonance. The significant increase of the dominant power frequency and the fundamental frequency clearly reveal this phenomenon.

Besides the data-validation, the following spectral analysis of the harmonic and sideband structure also provides reliable indicators of the fault, as Figure 12 shows.



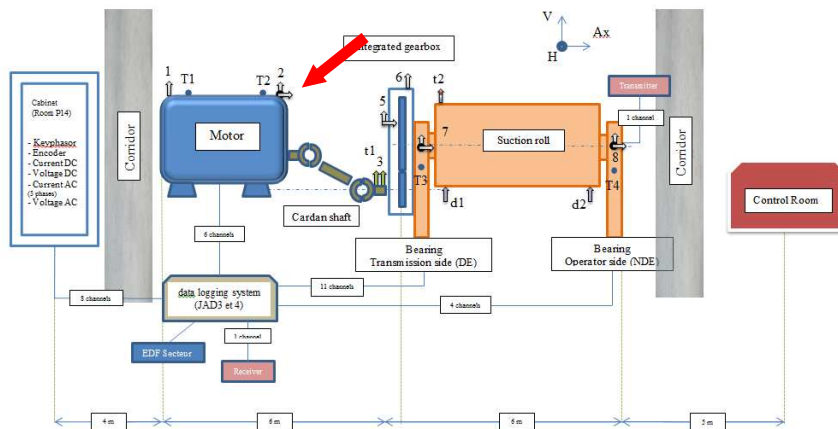


**Figure 12. AStrion-H (harmonic and sideband identification) result of the faulty accelerometer of Figure 10.**

Normally, the harmonics and the sidebands are generated by the vibration of the mechanical parts. When the sensor was disconnected, these spectral structures vanished, the number of the harmonic families and the sidebands also significantly decreased. Moreover, in Figure 12, the number of harmonic series and the sidebands correspond only to those with kinematic associations. Since during the sensor fault, these components were inexistent, both numbers were therefore close to zero.

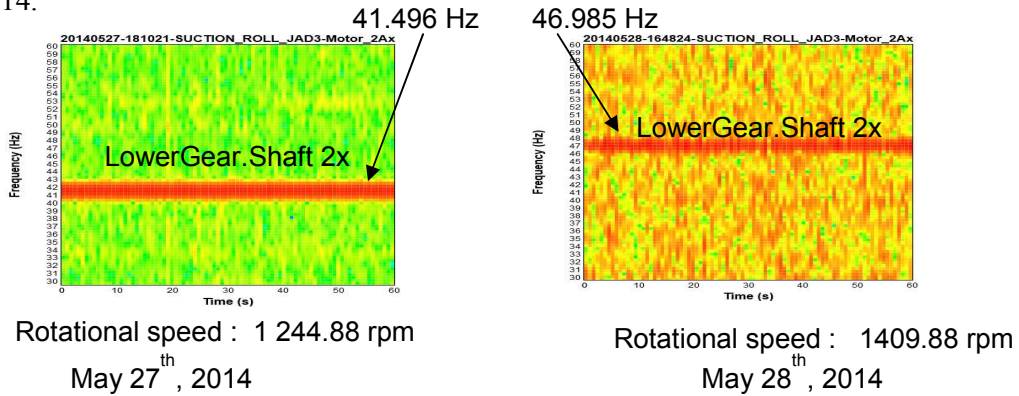
*3.5.2 Results on the detection of a bearing fault in a motor*

It has been reported by a maintenance technician at the end of October 2014 that there had been a failure of the motor in the Suction roll. But the faulty part of the motor had not been identified. However, AStrion carried out continuous surveillance and was capable to automatically detect the fault from the accelerometer signal. The location of the motor and the accelerometer under study are shown in Figure 13.



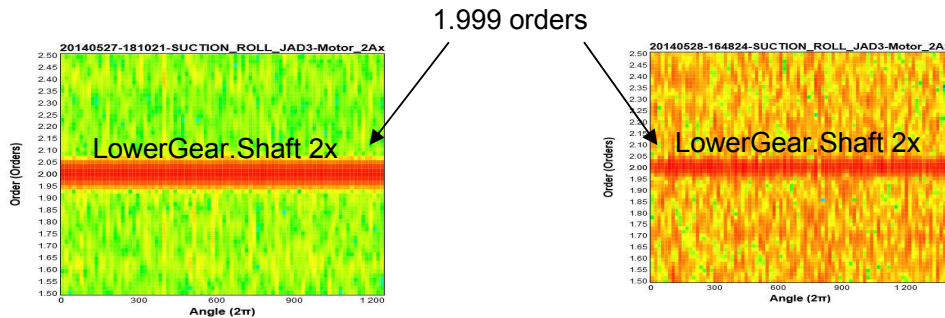
**Figure 13. The location of the faulty motor and the accelerometer (marked by the red arrow) on which AStrion is applied.**

Since the rotational speed of the motor is time-varying, especially over different days, the spectral content of the signal also varied in frequency. It consists of the major difficulty of the tracking of the spectral components by the frequency, as shown in Figure 14.



**Figure 14. The spectrogram of the accelerometer in Figure 13 zoomed around the same kinematic component (2<sup>nd</sup> harmonic of the shaft speed on the low speed gear) at May 27<sup>th</sup> 2014 and May 28<sup>th</sup> 2014.**

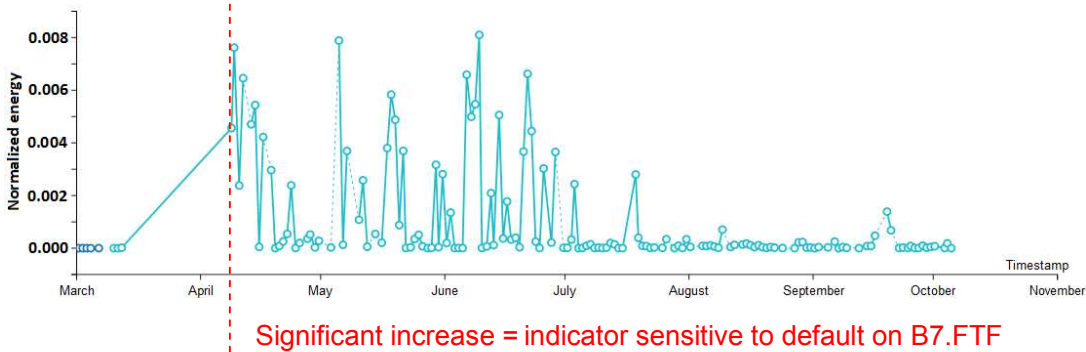
Figure 14 shows the difference in the frequency of the same kinematic component. The frequency shift is proportional to the difference of the rotational speed. After the angular resampling, the signal is synchronized to the angular rotational speed. The frequency spectrum can be transformed to an order spectrum on which the difference of the rotational speed is cancelled, as shown in Figure 15.



**Figure 15. The order spectrogram of the signals under different rotational speed in Figure 13, calculated after being transformed to the order domain by AStrion-A.**

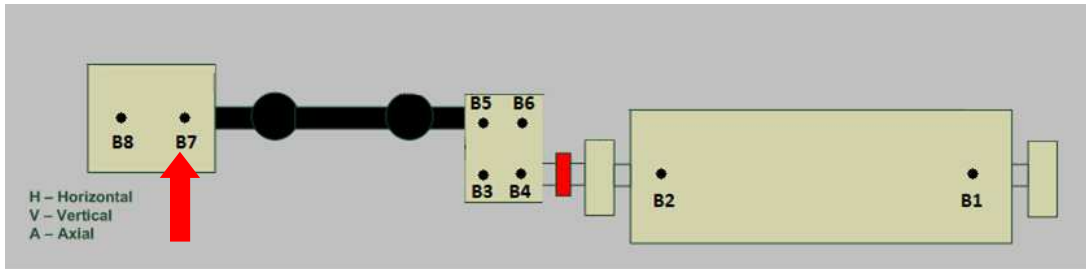
In figure 15, the same kinematic component is aligned at the same order, even if the rotational speed varies. It makes the continuous tracking of the spectral structure easier

and more robust. Over the order spectrum, AStrion-H, the harmonic and sideband identification module, identified a significant increase of the energy of the harmonic family B7.FTF (Fundamental Train Frequency of the bearing 7) of the signal, shown in Figure 16.



**Figure 16. The energy of the harmonic family of B7.FTF of the signals of the accelerometer n.2 of Figure 10.**

The results obtained in Figure 16 are based on the tracking of the harmonic identification of all the signals. The harmonic identification and tracking are carried out in a non-supervised manner: the peaks of the spectrum are detected by AStrion-I, the harmonic families were identified by AStrion-H, the kinematic components were associated by AStrion-K, and the trajectory of the B7.FTF was automatically connected and tracked by AStrion-T. No human intervention was required. The trend of the energy variation clearly indicates the beginning of the fault. After replacing the motor, the trend again stabilized at a low level. The detection results reveal a possible fault at the bearing 7, as shown in Figure 17.



**Figure 17. Location of the bearing 7 in the faulty motor.**

Using Astrion, it is not only possible to detect the fault, but also able to deduce the faulty part before the teardown and the inspection of the motor.

**4. Conclusions**

This work has been done within the SUPREME project, funded by the European Commission, under the FP7 program. In this paper we present condition monitoring methodology applied to the suction roll and the Press roll of a paper machine. Experimental results obtained for the detection and identification of many defects that may occur to different mechanical components are presented. The trends of multiple simple and advanced condition monitoring parameters have shown the effectiveness of indicators to detect and identify the failures that may occur to critical machines.

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## **Vibration condition monitoring in a paper industrial plant: Supreme project**

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### **Abstract**

This paper presents a condition monitoring methodology applied to the suction roll and the Press roll of a paper machine. Experimental results obtained for the detection and identification of many defects that may occur to different mechanical components are presented. To this end, many fault indicators are calculated using a set of signal processing methods. We endeavor to propose robust fault indicators with respect to the variations of the operation parameters as the speed variation. Cyclostationary and cepstral approaches are used in order to make vibration source separation and to extract pertinent indicators closely related to the health of the paper machine. AStrion strategy, a stand-alone, data-driven and automatic tracking analyzer, is applied in order to characterize a sensor failure on the suction roll and a fault on the motor that drives the press roll. The trends of these parameters have shown the effectiveness of these methods to detect and identify the failure modes of the equipment thus allowing the reduction of the overall maintenance cost. This work has been done within the SUPREME project, funded by the European Commission, under the FP7 program.