DYNAMO

Laboratoire en dynamique des machines, structures et procédés

ÉTS

Le génie pour l'industrie

Bearing monitoring: from modelling to experiments: feature selection for fault diagnosis

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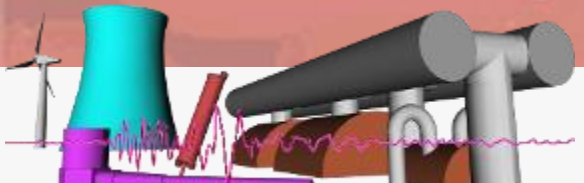
ETS, Montreal



Surveillance 8

International Conference - October 20-21, 2015

Roanne Institute of Technology, France

Outline

- Introduction (ETS, Dynamo)
- Bearing models
- Defect severity
- Time indicators of defects
  - Statistic indicators
  - Shock indicators
    - Shock Filter
    - Minimum Entropy Deconvolution
- Peak Hold Down Sampling (low speed operation)
- Envelop
- Empirical Mode Decomposition (EMD-EEMD)
- Teager Kaiser Energy Operator (TKEO)
- Cyclostationnarity

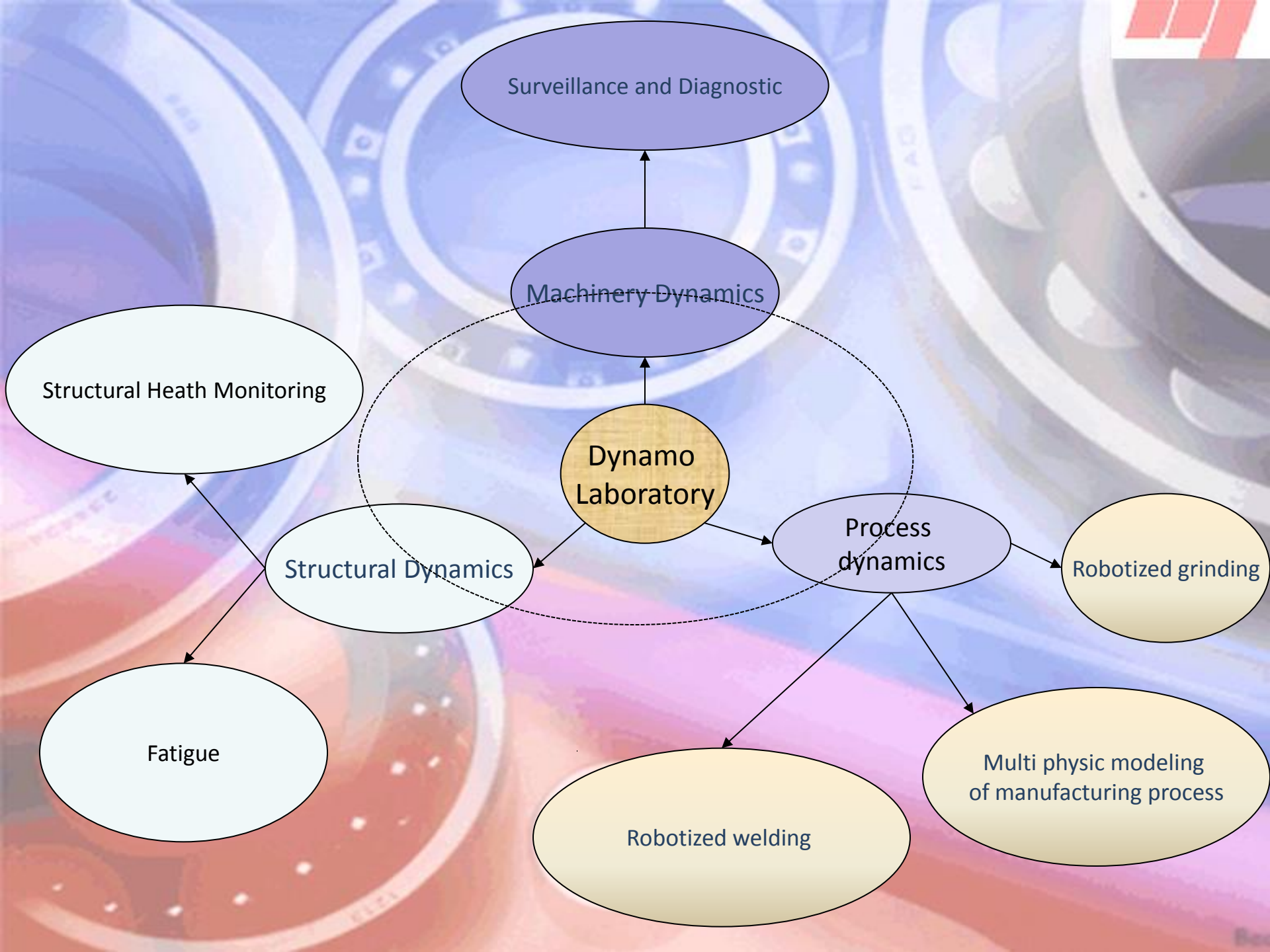
Outline

- Frequency indicators
- Time (Scale)-Frequency indicators
  - STFT
  - Wavelet Paquet
    - Application to electric current measurement
  - Empirical Wavelet Transform (EWT)
- Complexity indicators

L'École de Technologie Supérieure

180 professors
360 staffs
6000 students
400 Ph.D. students
800 Masters

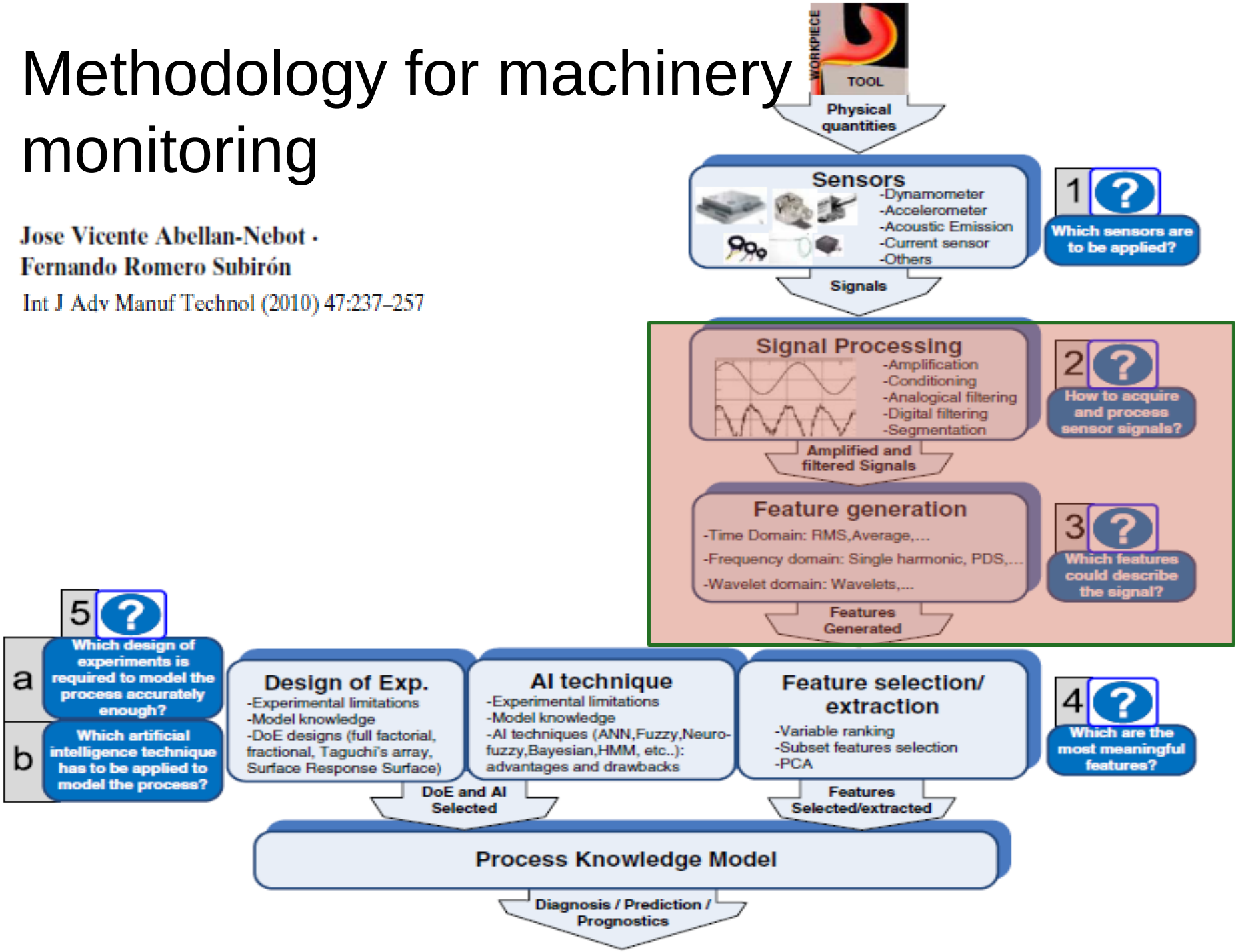
- *7 engineering programs (B.Ing.)*
- *5 certificate programs*
- *12 master programs (M. Sc. A.)*
- *1 Ph. D. program*


Surveillance and Diagnostic
Machinery Dynamics
Structural Heath Monitoring
Dynamo Laboratory
Structural Dynamics
Process dynamics
Robotized grinding
Fatigue
Robotized welding
Multi physic modeling of manufacturing process

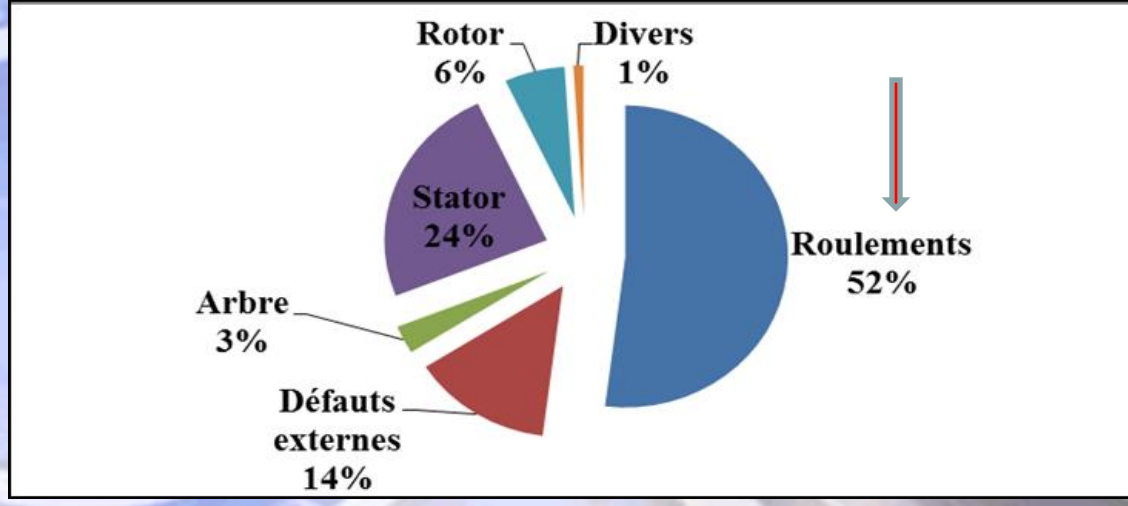
Methodology for machinery monitoring

Jose Vicente Abellan-Nebot ·
Fernando Romero Subirón

Int J Adv Manuf Technol (2010) 47:237–257



Introduction

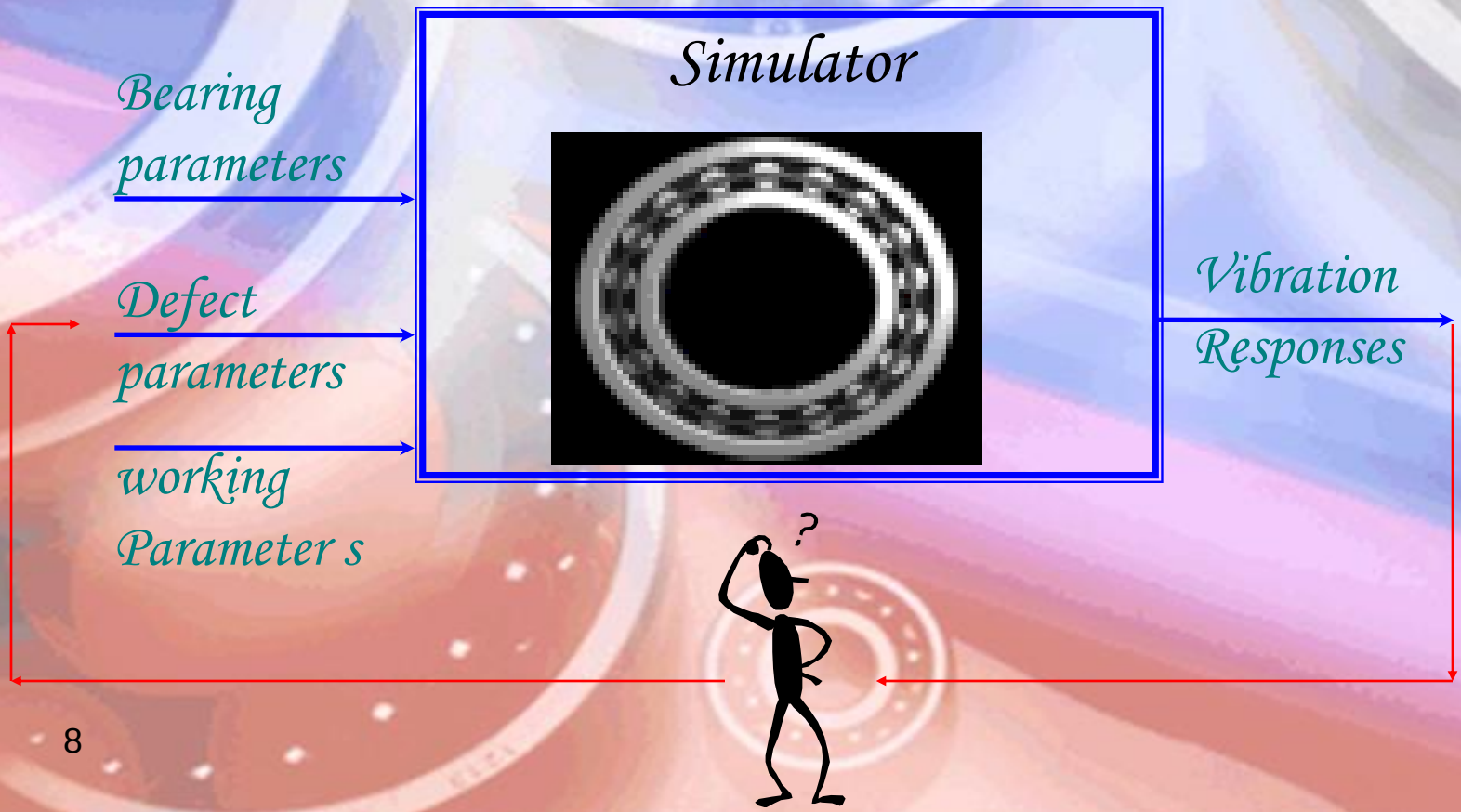


- In order to better understand the dynamic behavior of mechanical components such as bearings subjected to defects, it may be necessary to **develop dynamic models**.
- These models (after experimental calibration) allows for evaluating the sensitivity and **efficiency of features** for detecting faults both in time and frequency domains, before to apply them experimentally.
- Various experimental applications of signal processing methods are described.

Thorsen, O. V., and M. Dalva. 1999. « Failure identification and analysis for high-voltage induction motors in the petrochemical industry ». *Industry Applications, IEEE Transactions* vol. 35, nº 4, p. 810-818

TARGET

Develop a numerical simulator of bearing dynamics with localized defects to generate vibration responses according to all the functionning parameters .

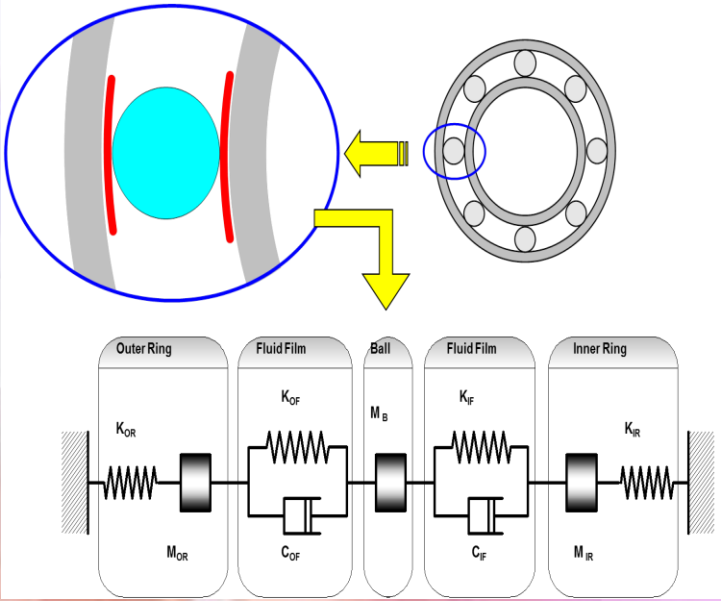


Theoretical, Discrete and FE models

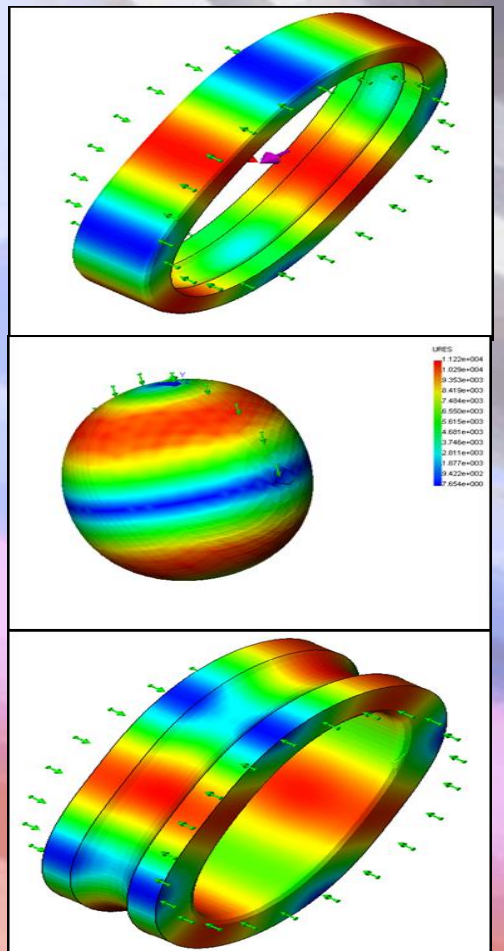
Theoretical models based on assumptions about expected results

Example:
Assumption that defect produces amplitude and phase modulations with harmonics

Discrete models based on simplified physical behavior
Example: bearing model



Finite Elements models
Example: Continuous bearing model

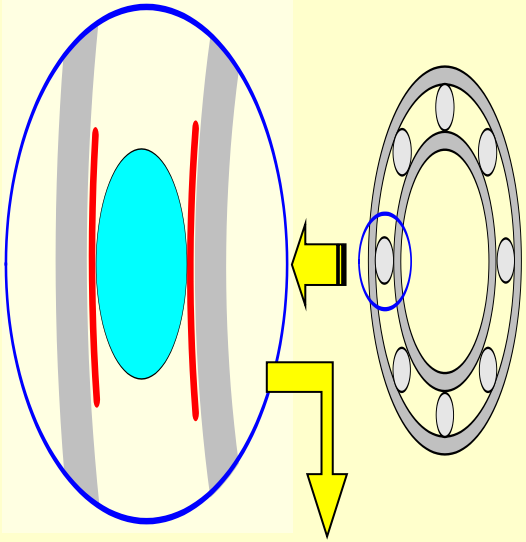


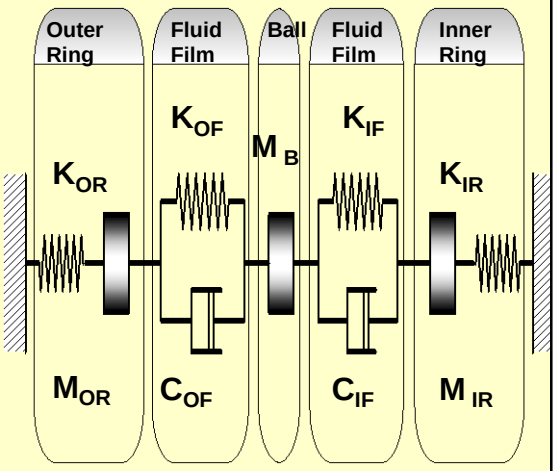
$$x(t) = \left[\sum_{m=0}^{M} A_m [1 + a_m(t)] \cos\{2\pi f_m t + \beta_m + b_m(t)\} \right]$$

$$+ A_i e^{-\zeta w_0 t} \cos(w_0 \sqrt{1-\zeta^2}\, t + \varphi) u(t - iT_r) + e_0$$

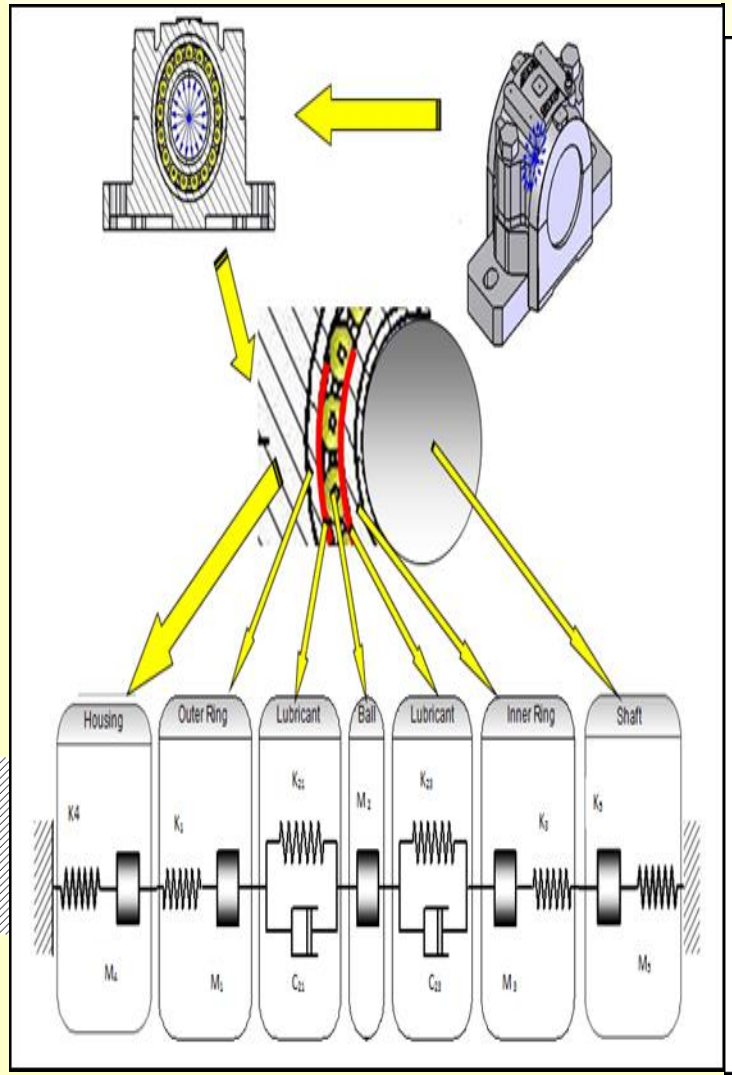
Discrete models of bearing in a Radial Direction

3 D.O.F: Only consider the bearing

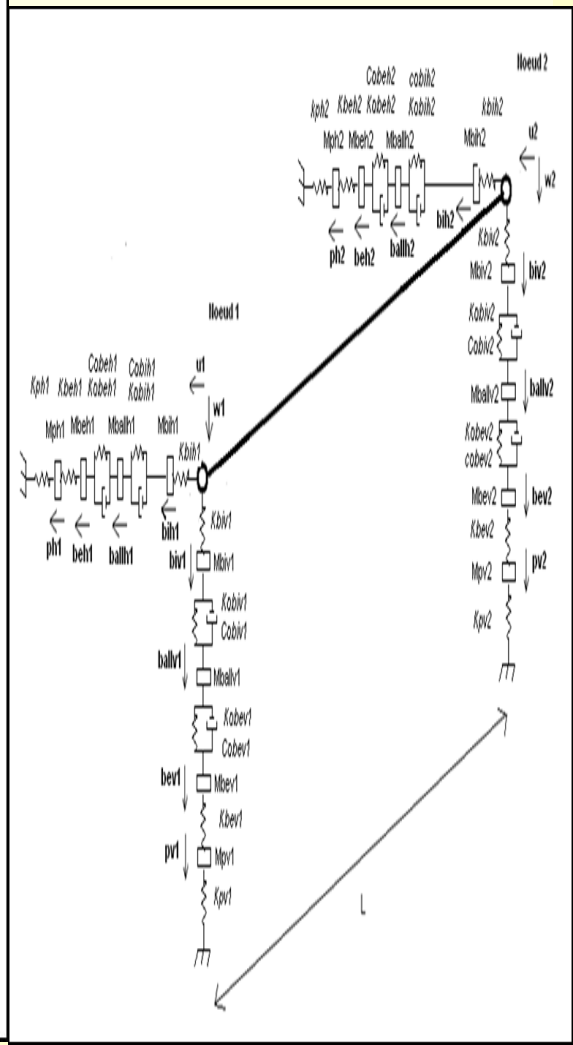




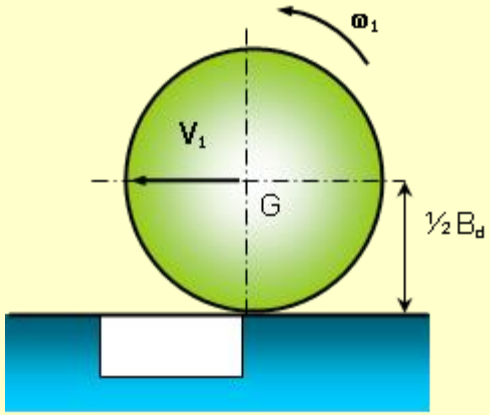
5 D.O.F.: Consider the housing, bearing and shaft

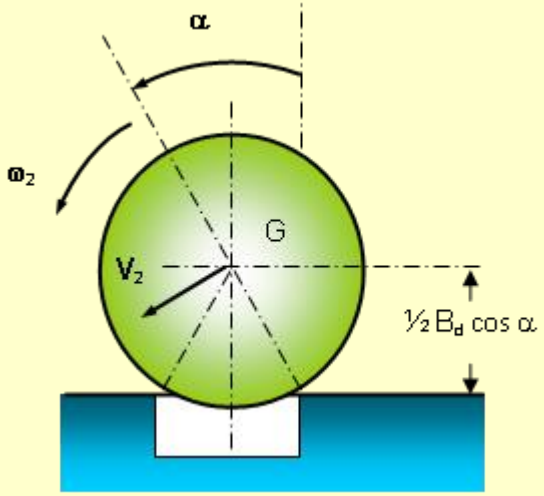


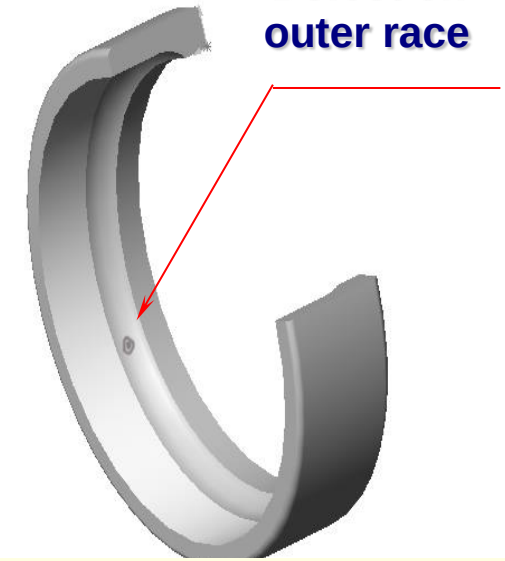
20 D.O.F.: allows for considering gyroscopic effect (high speed operations)

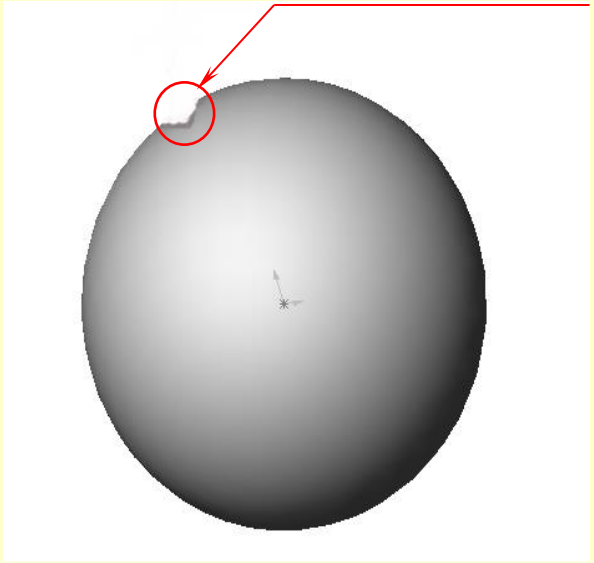


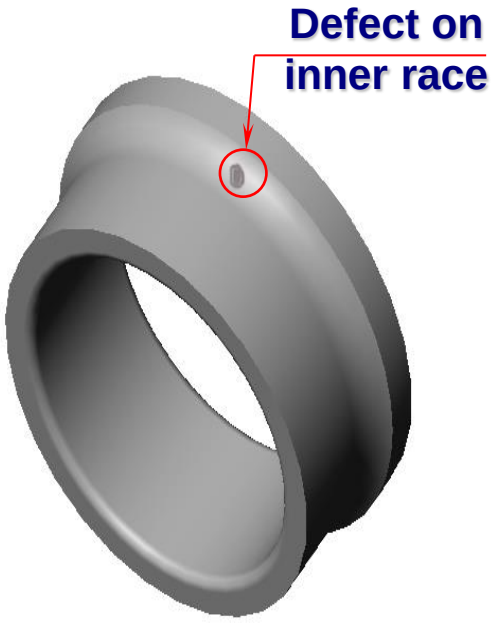
Simulation of bearing defects









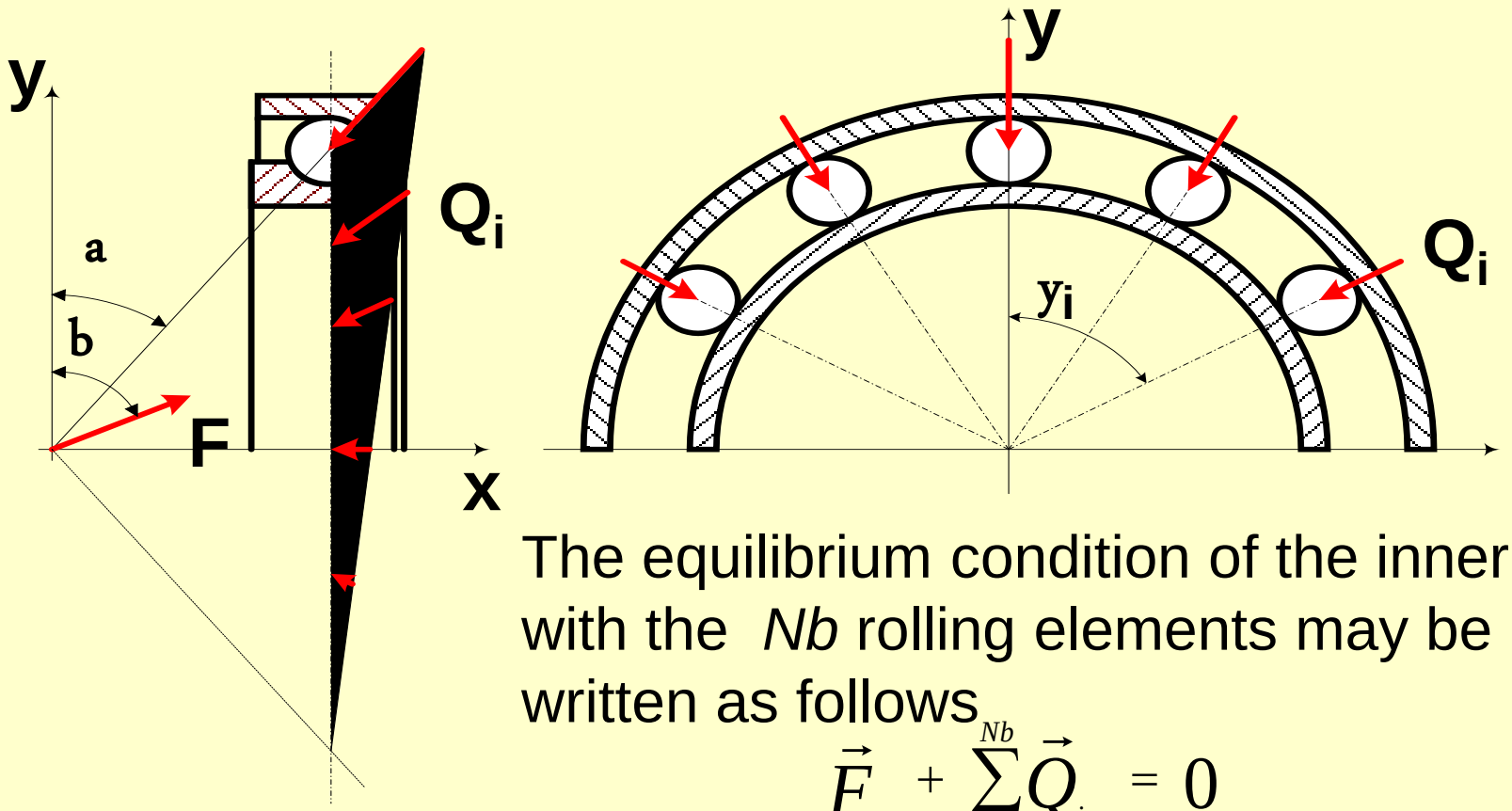


S. Sassi, B. Badri, M. Thomas, (2007), A Numerical Model to Predict Damaged Bearing Vibrations, Journal of Vibration and Control. vol. 13 no. 11, 1603-1628.

Loading Forces

The bearing may be subjected to external forces with radial and axial components

$$\vec{F} = F_a \vec{x} + F_r \vec{y} = F_r \left(\tan\beta \, \vec{x} + \vec{y} \right)$$



The equilibrium condition of the inner race with the *Nb* rolling elements may be written as follows

$$\vec{F} + \sum_{i=1}^{Nb} \vec{Q}_i = 0$$

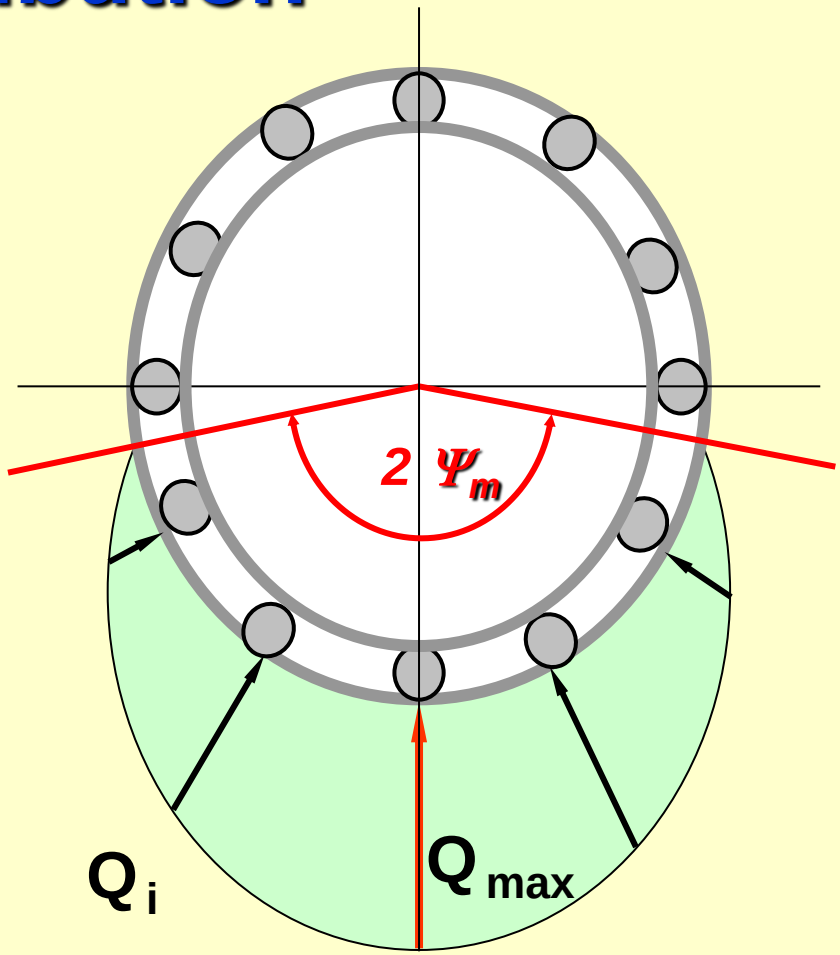
Load Distribution

The load applied on any rolling element located at angle ψ_i measured from the maximum load direction Q_{max}, is given by :

$$Q_i = Q_{max}\left(1 - \frac{1-\cos\psi_i}{2\varepsilon}\right)^t$$

When : $-\psi_m \le \psi_i \le \psi_m$

Elsewhere : $Q_i = 0$



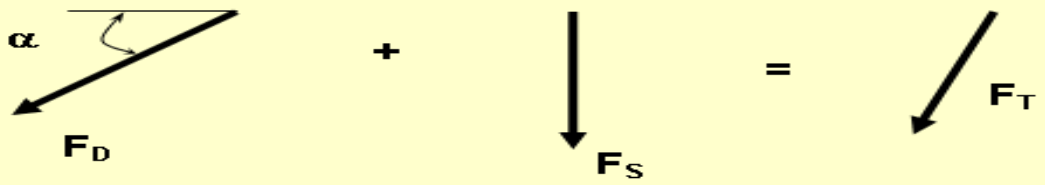
ε is the load distribution factor. $\varepsilon = \frac{1}{2} \cdot \left[1 + \frac{\delta_a}{\delta_r} . tg\,\alpha\right]$

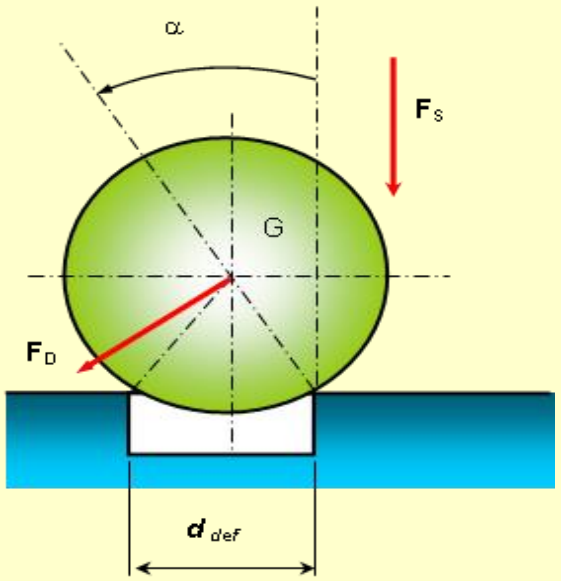
which is function of the axial and radial displacement components

t is a constant that depends on the contact nature.

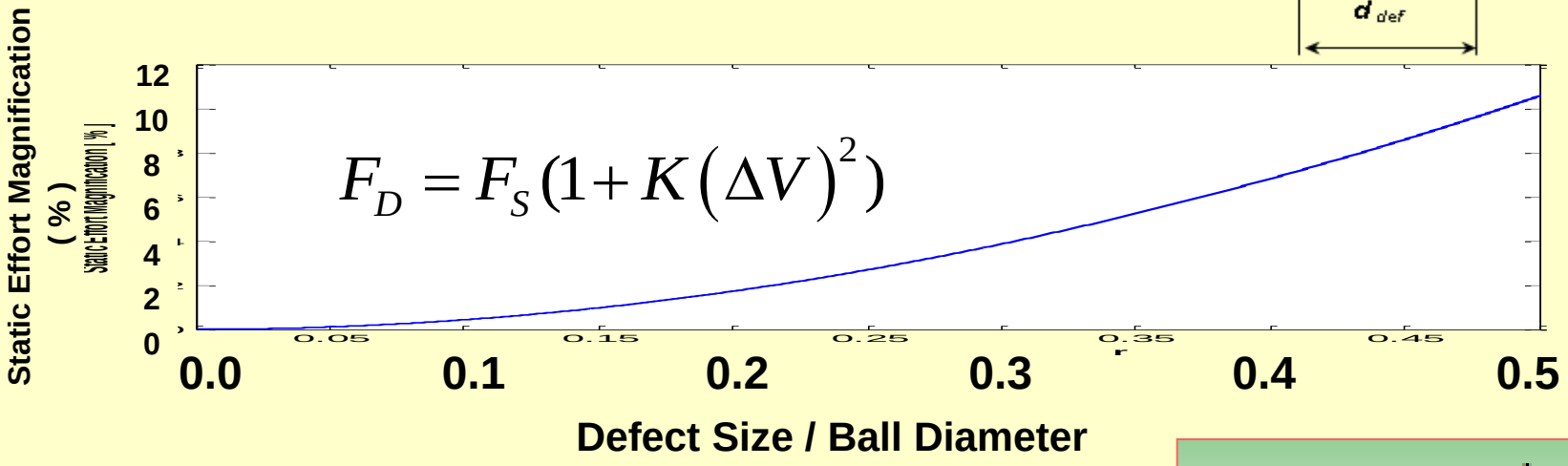
Impact Force During the Shock Versus Defect Size-Ball Diameter Ratio

The motion over the failed areas produces impacts which result in shock pulses.





The strength of impact felt by the bearing components when the ball is traversing a defect area depends on the relative speeds and on the external load.



$$F_D = F_S\left(1 + K\left(\Delta V\right)^2\right)$$

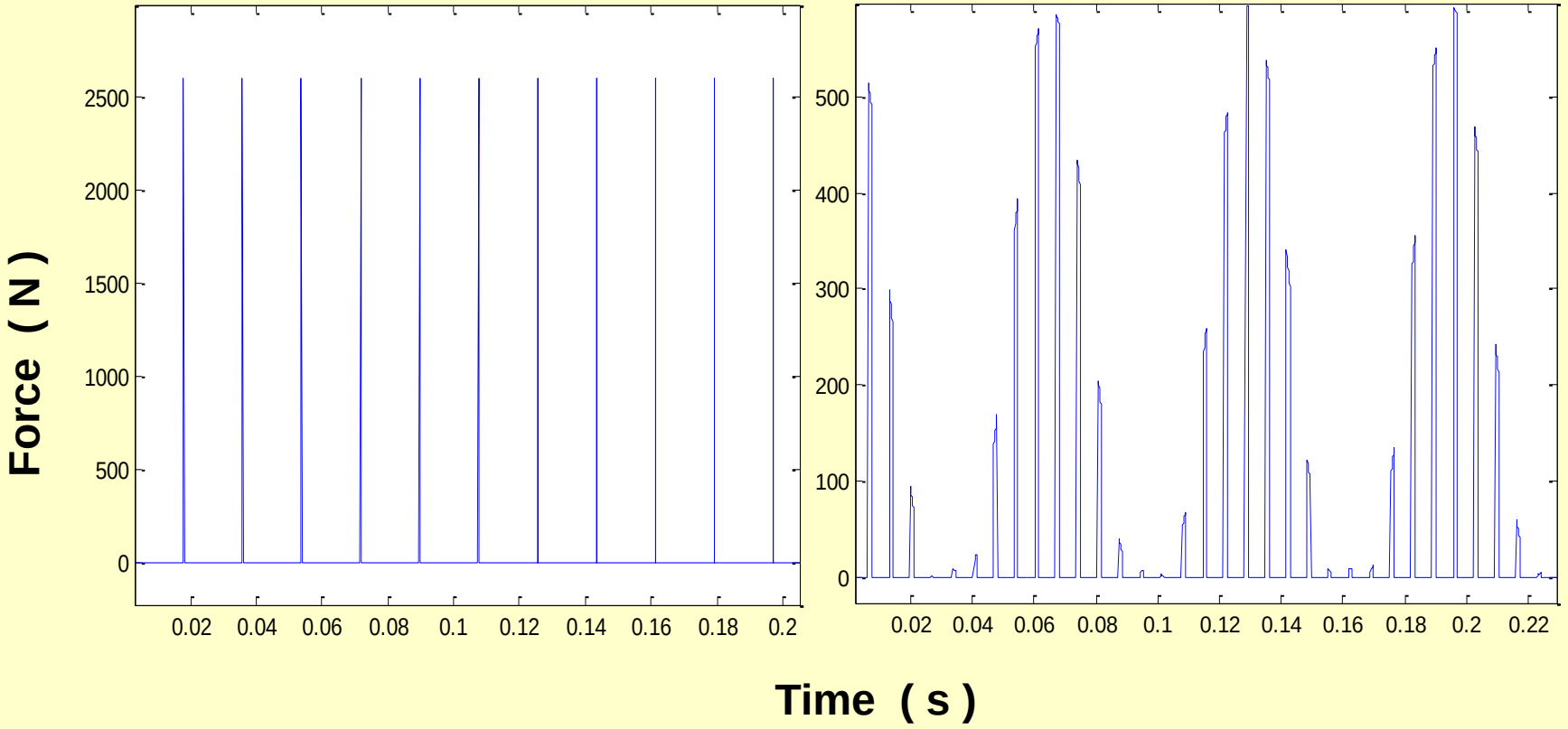
ΔV is the **variation of speed** before and after shock.

K is an impacting material coefficient

$$\omega_2^2 - \omega_1^2 = \frac{20}{7} g \frac{1-\cos\alpha}{B_d}$$

Exemples of constant Shock pulses generated by a defect

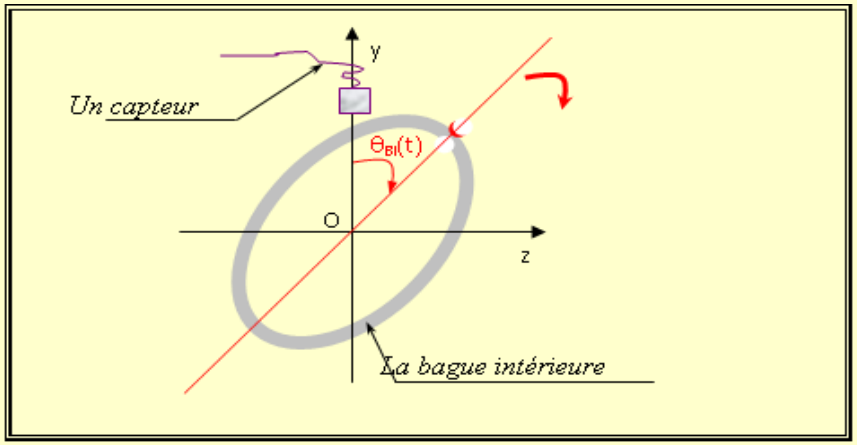
(a) on Outer Race, (b) on Inner Race

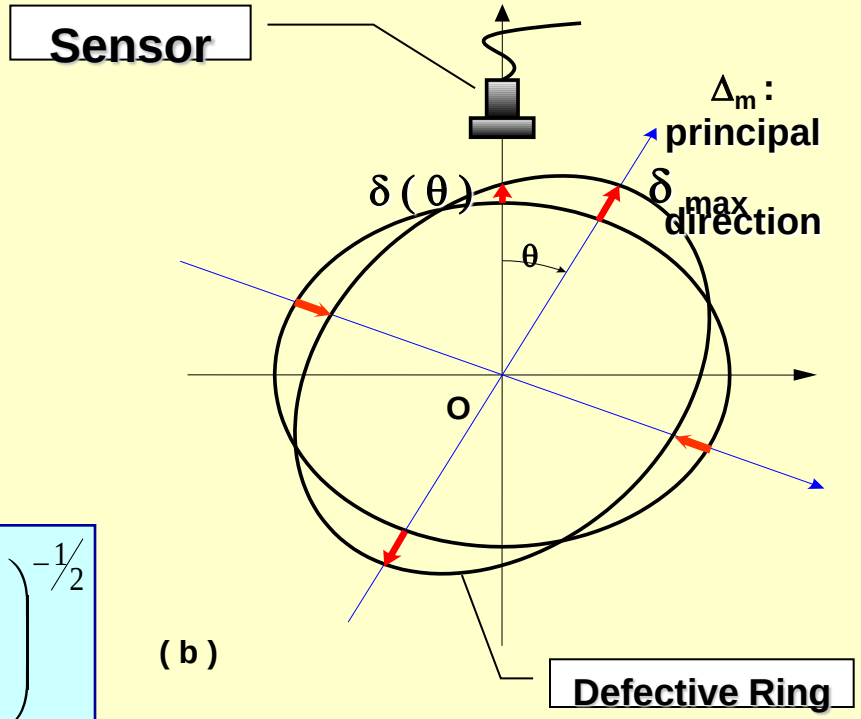


Geometric correction of the numerical response

The model has been designed to generate a response according to a radial line of maximum deformation (turning), whereas the response measured by the sensor (fixed) is given according to a different radial line of measurement.

A correction must be added to the numerical response of the model to correlate the numerical response with the response delivered by a fixed sensor.





(b)

$$\delta(\theta) = R - \left(\frac{\sin^2(\theta)}{\left[R - \delta_{max} \right]^2} + \frac{\cos^2(\theta)}{\left[R + \delta_{max} \right]^2} \right)^{-1/2}$$

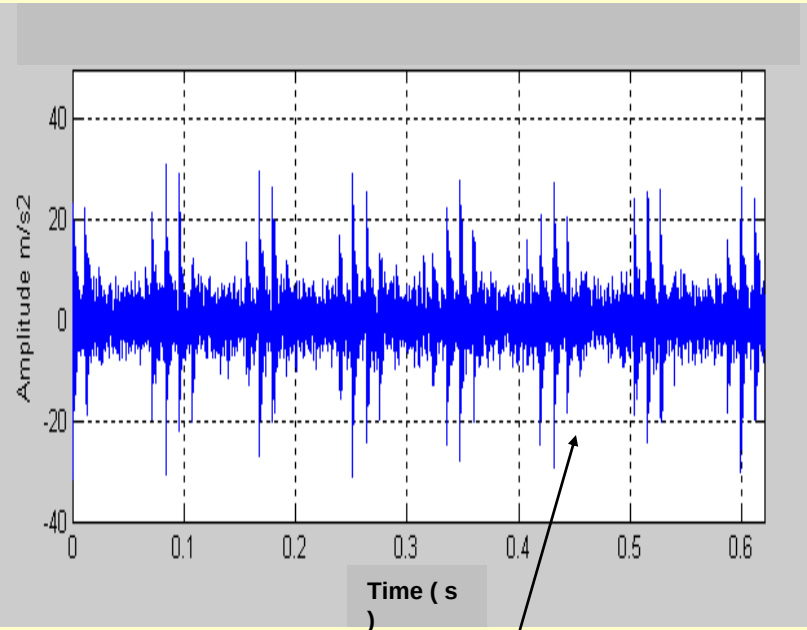
Effects of Random Perturbations

As the relative motion between the rolling elements and the races is composed of rolling and slipping, friction-induced vibration must be added in the total computed response.
Friction-induced vibration produces random type vibration.

$$\delta(\text{random}) = K_{AN}\, V^{\frac{1}{2}} \left[\frac{Q_{max}}{S}\right]^2 f\left(d_{def}/B_d\right)$$

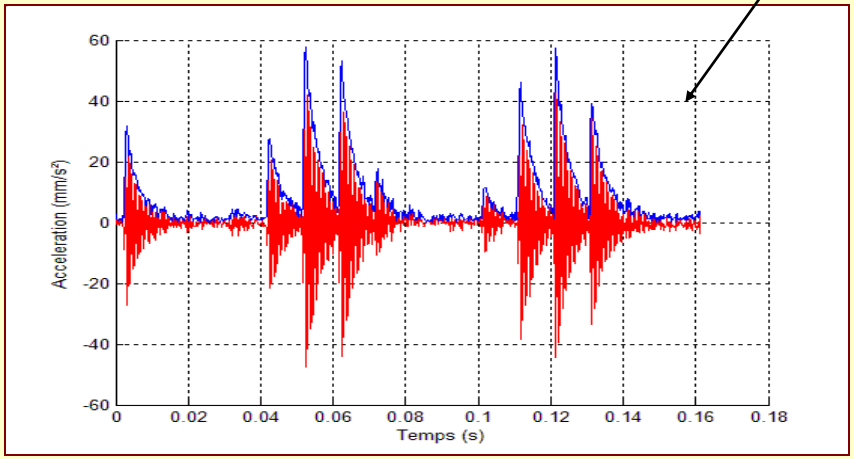
K_{AN} is a constant,
V is the relative slip speed between the ball and the race,
Q_{max} is the maximum loading value (applied on the most loaded ball),
S is the ball/race elliptic contact surface,
$f\,(d_{def}/B_d)$ is a weighting polynomial function.

Effects of Random Perturbations



The relative movement between elements = mixture of ROLLING and SLIP

$$\delta(\text{ Total }) = \delta(\text{ impact }) + \delta(\text{random })$$



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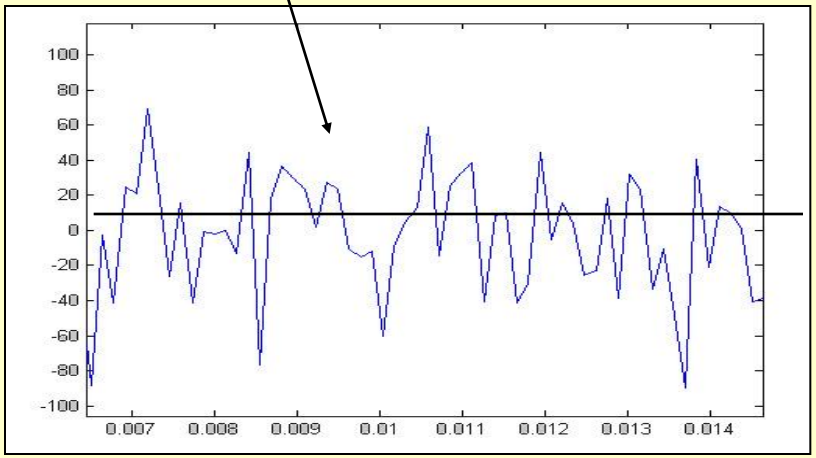
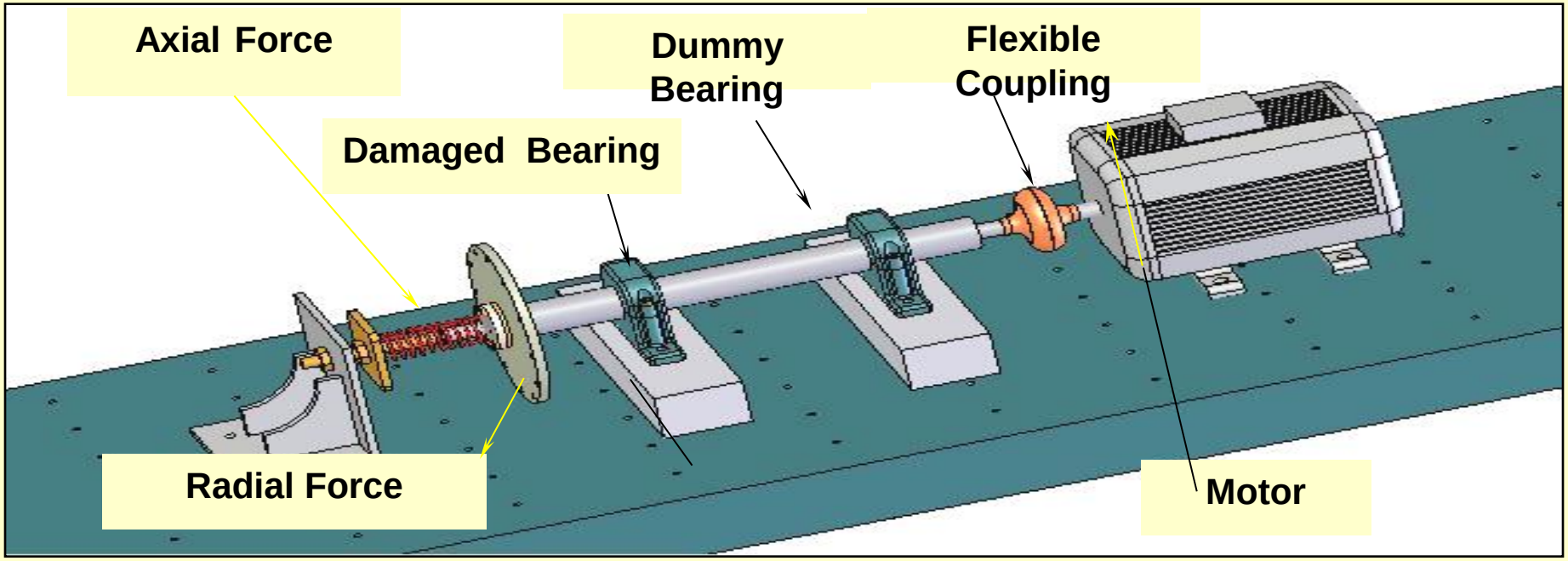
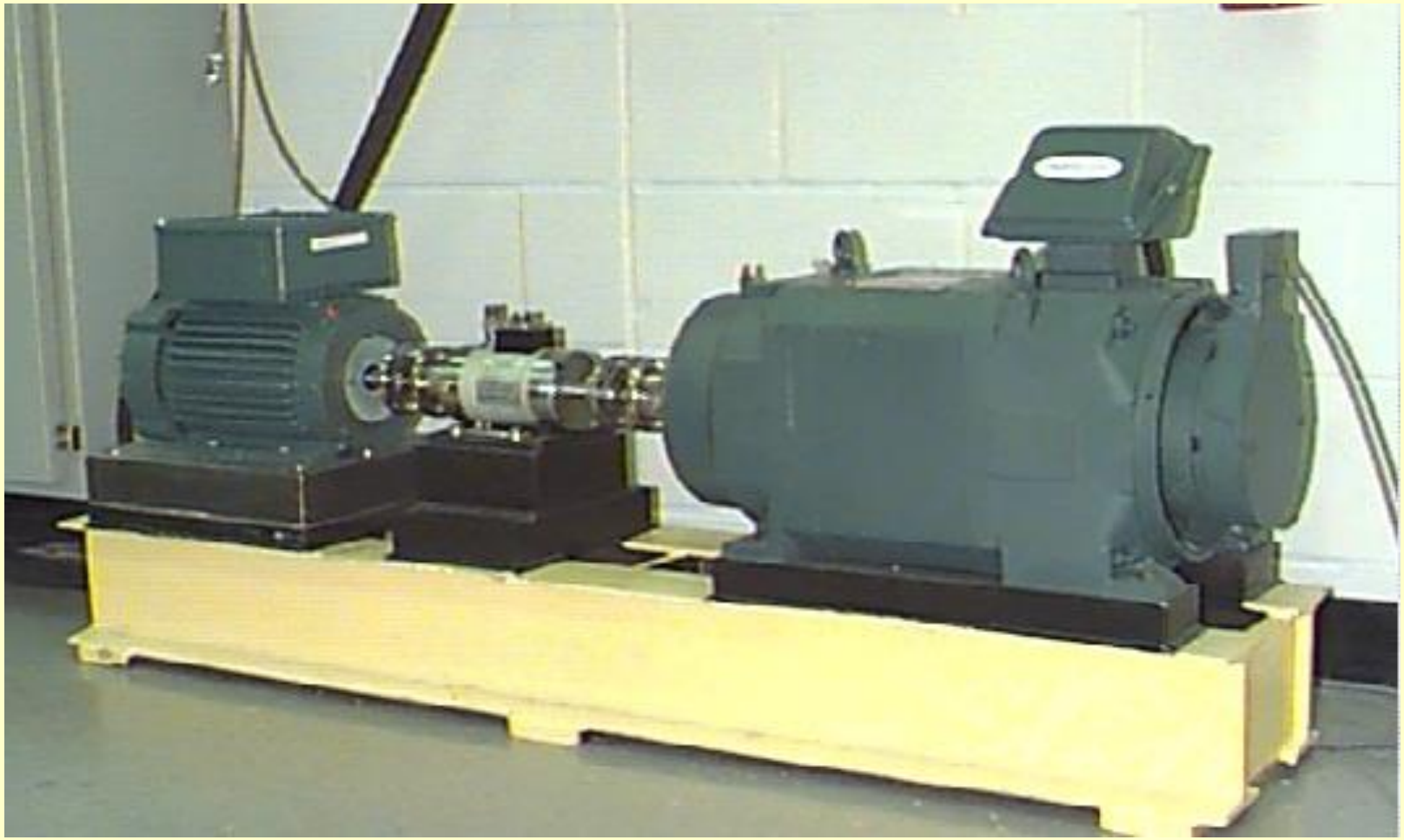


Calibration with experimental testing

The test rig is composed of a shaft supported by two bearings driven by a motor. The forces comes from an inertial wheel and an axial force.



Test bench from Case western reserve University: Bearing data center

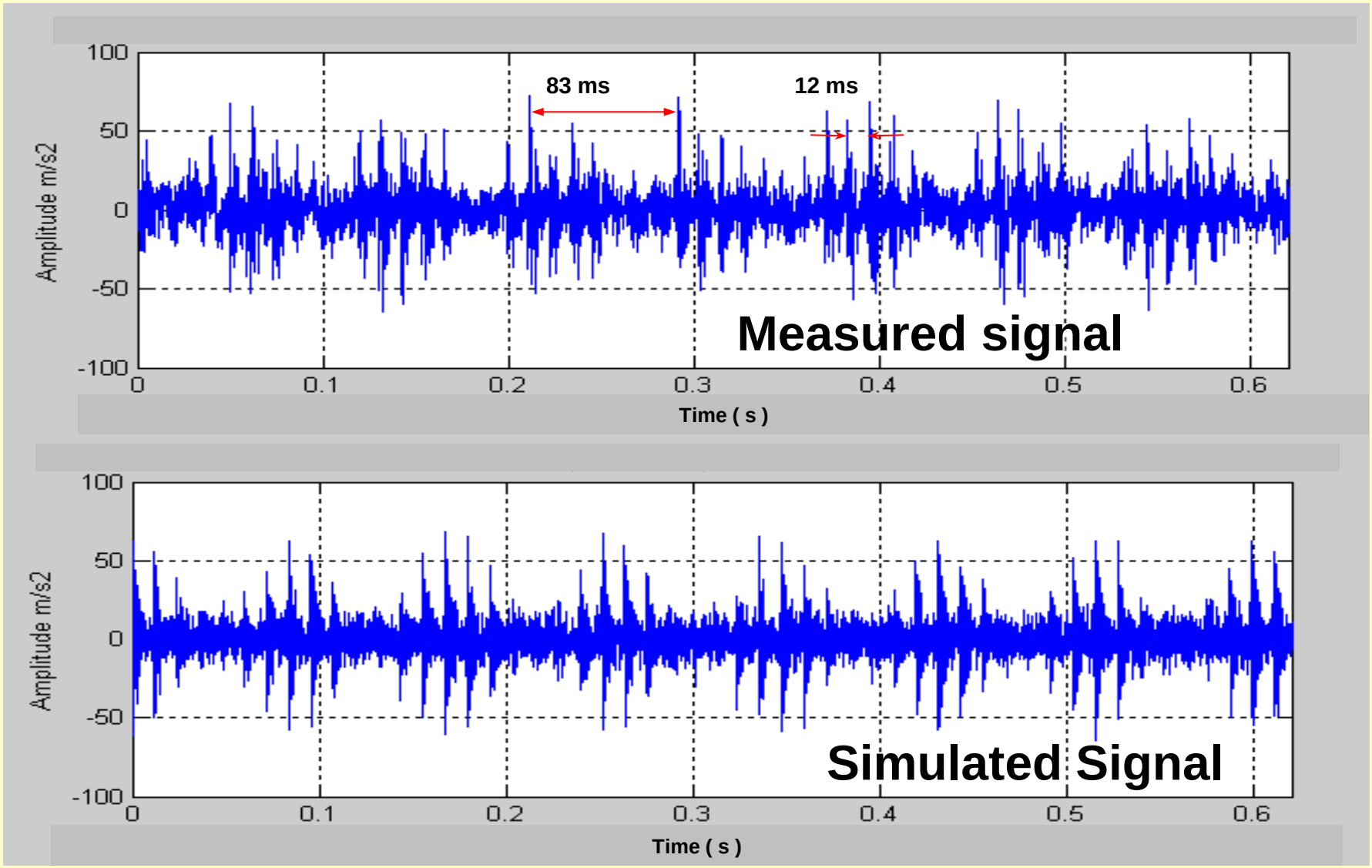


Signals from defective rolling-element bearings available on site
http://csegroups.case.edu/bearingdatacenter/pages/apparatus-procedures

Comparison of time responses (simulated and measured)

Damage Size = 1270 μm.

[*Frequency Rotation = 11.6 Hz ; Loading Amplitude = 1242 N ; Loading Orientation = 22 degrees*]

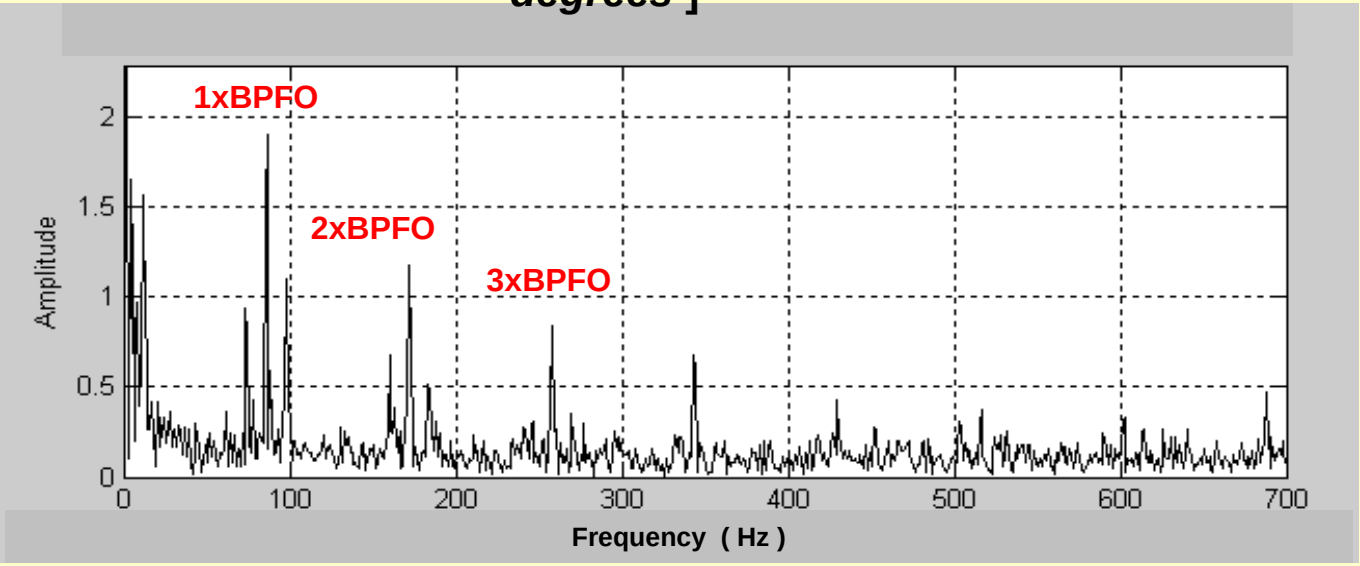


Comparison in Frequency Domain

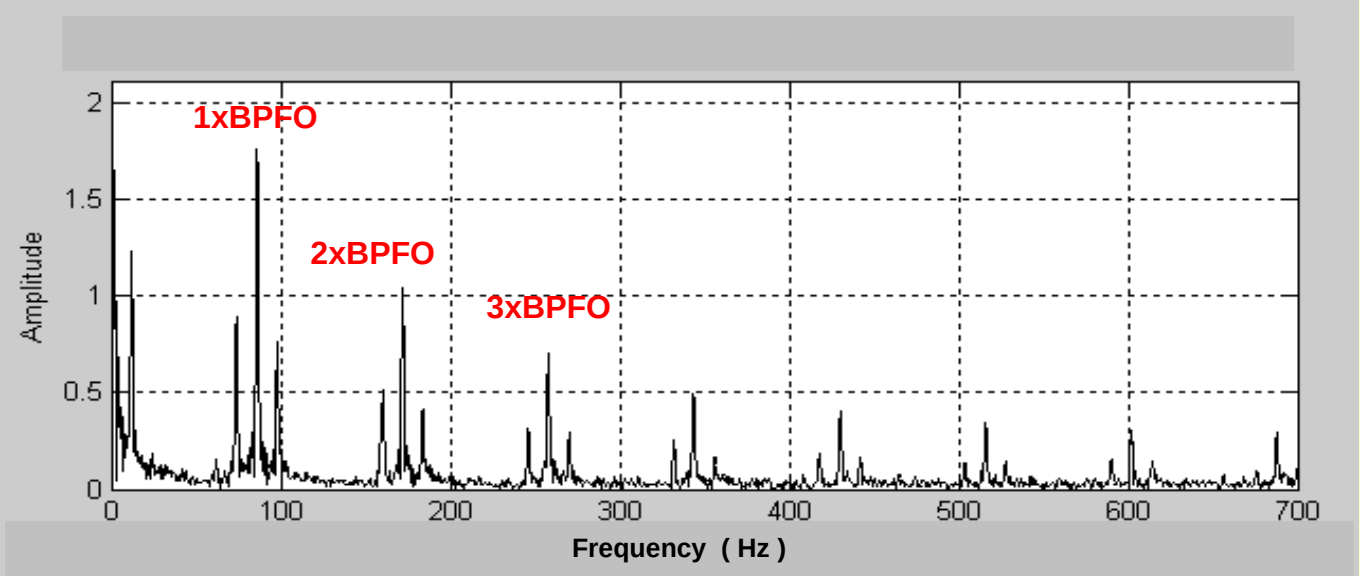
Damage Size = 1270 μm on outer race

[Frequency Rotation = 11.6 Hz ; Loading Amplitude = 1242 N ; Loading Orientation = 22 degrees]

Measured signal

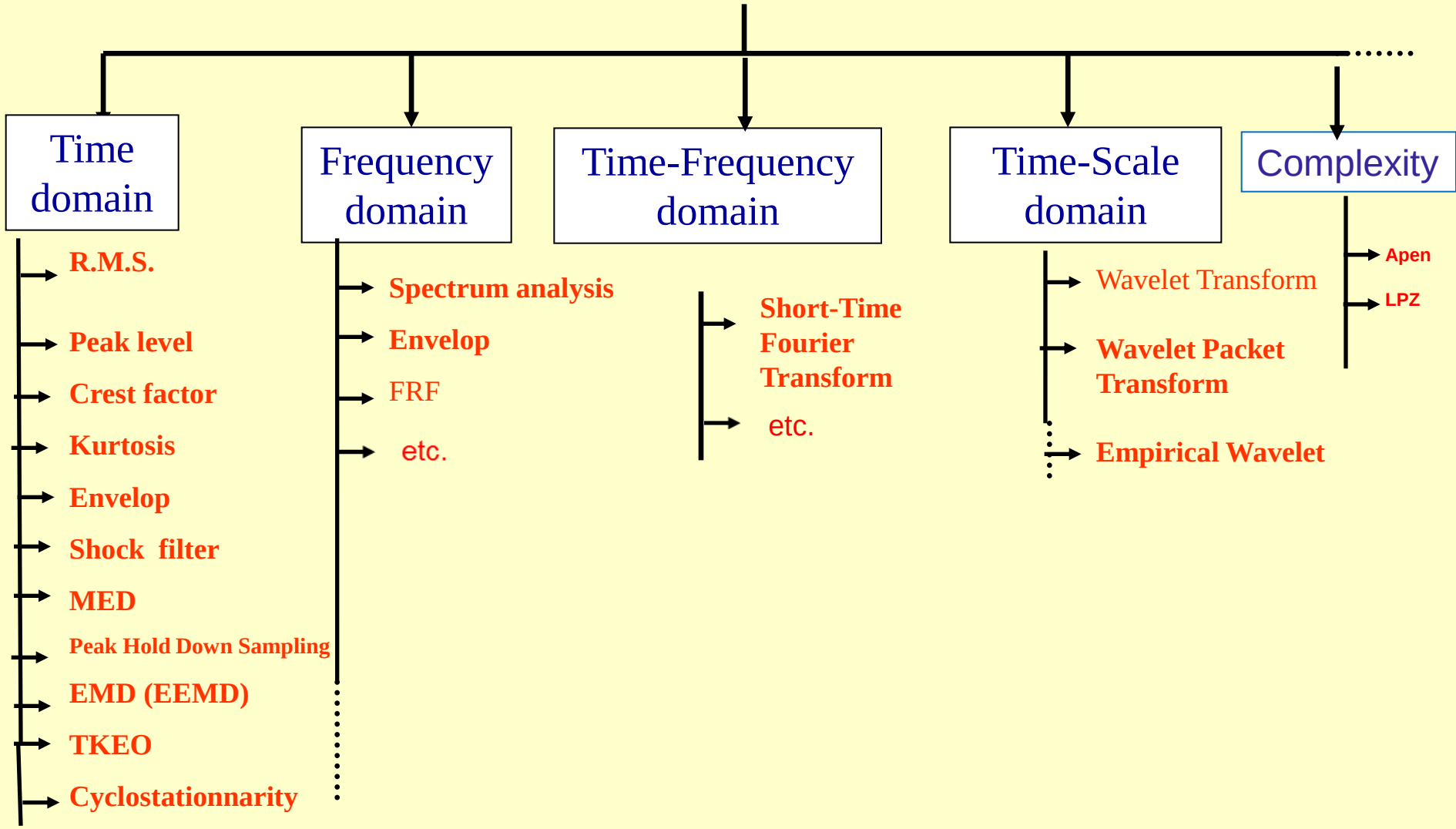


Simulated Signal



Vibration Signal Analysis → *Diagnostic*

Signal Analysis



Time indicators of machinery defects

Scalar indicators

Peak to Peak

$$PP = a_{max} - a_{min}$$

Peak

$$a_{peak} = \sup_{1 \le k \le N} |a_k|$$

or $$a_{peak} = \frac{PP}{2}$$

Average

$$\bar{a} = \frac{1}{N} \sum_{k=1}^{N} a_k$$

Redressed Average

$$|\bar{a}| = \frac{1}{N} \sum_{k=1}^{N} |a_k|$$

Crest Factor

$$CF = \frac{a_{peak}}{a_{RMS}}$$

K-Factor

$$K = Peak * RMS$$

Root Mean Square

$$a_{RMS} = \sqrt{\frac{1}{N} \sum_{k=1}^{N} a_k^2}$$

Skewness

$$Sk = \frac{\frac{1}{N} \sum_{k=1}^{N} (a_k - \bar{a})^3}{\left(\frac{1}{N} \sum_{k=1}^{N} (a_k - \bar{a})^2 \right)^{3/2}}$$

Impulse Factor

$$IF = \frac{a_{peak}}{|\bar{a}|}$$

Standard Deviation

$$a_{STD} = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (a_k - \bar{a})^2}$$

Kurtosis

$$Ku = \frac{\frac{1}{N} \sum_{k=1}^{N} (a_k - \bar{a})^4}{\left(\frac{1}{N} \sum_{k=1}^{N} (a_k - \bar{a})^2 \right)^2}$$

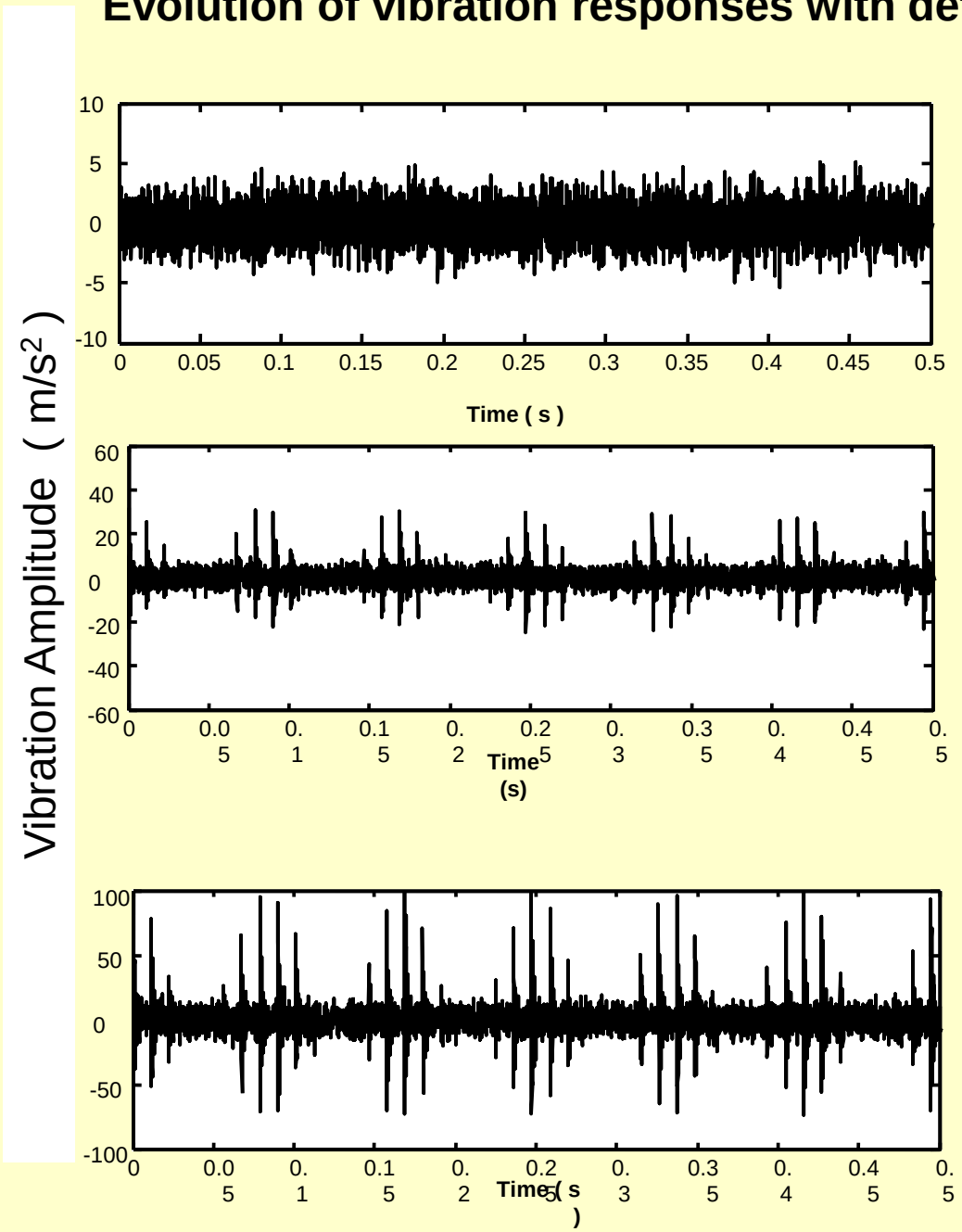
Shape Factor

$$SF = \frac{a_{RMS}}{|\bar{a}|}$$

Once calibrated, the aim of the simulator is :

- to analyze the sensitivity of fault scalar indicators extracted from time domain signals to bearing damage manifested through an increase in size and in the number of localized defects.

Evolution of vibration responses with defect sizes



a) healthy bearing

Peak	5.1	CF	3.8	SF	1.2
RMS	1.4	KU	3	IF	4.6

b) small defect of 0.55 mm

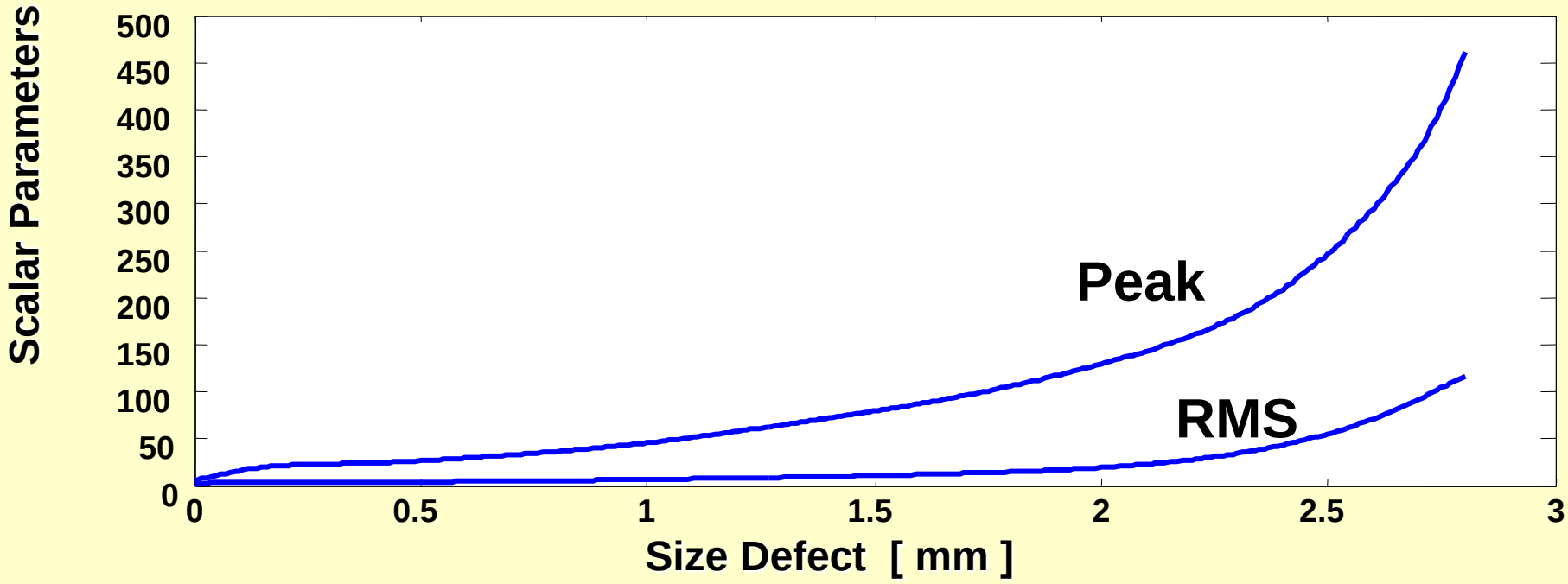
Peak	26.6	CF	6.4	SF	1.4
RMS	4.3	KU	10.2	IF	9.3

c) defect of 1.52 mm

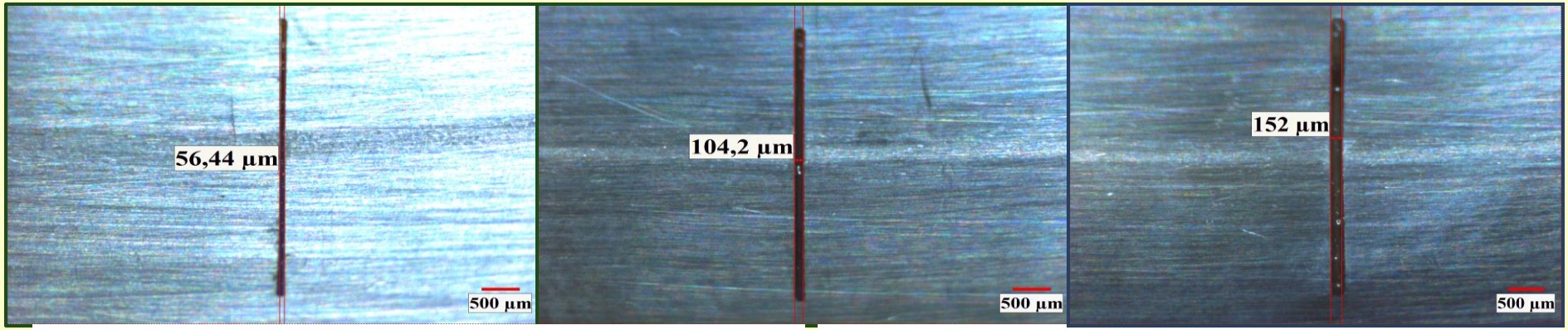
Peak	75.7	CF	7.2	SF	1.6
RMS	10.4	KU	15.8	IF	11.5

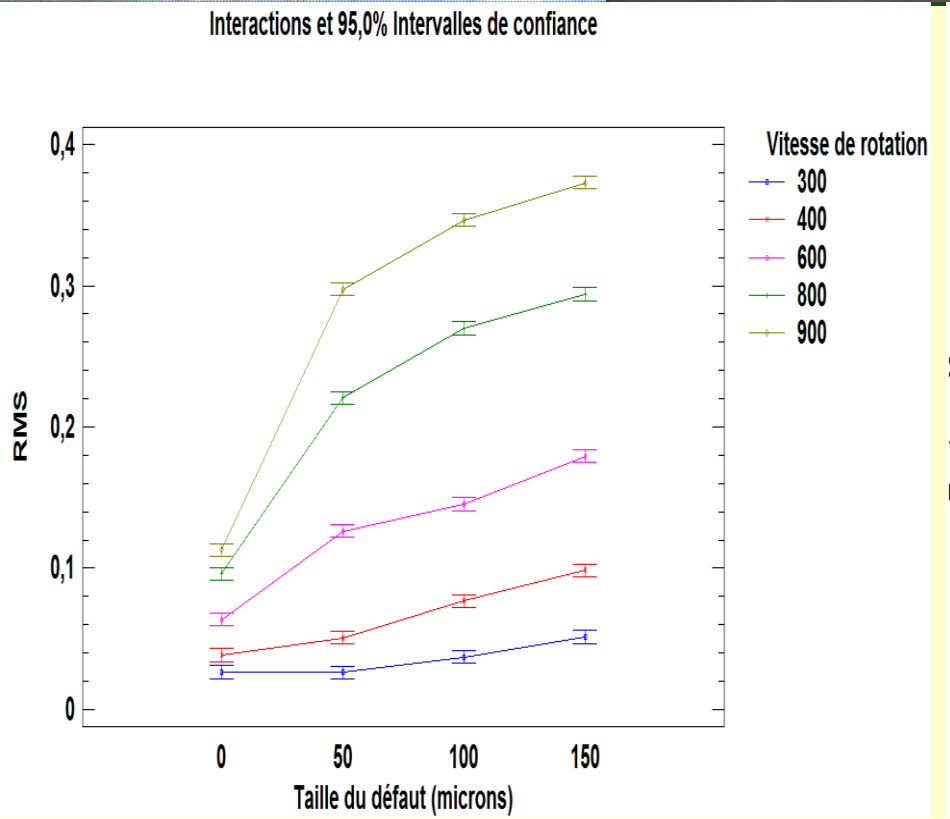
Evolution of Scalar Parameters (Peak, RMS) according to the size of a defect on the Outer race

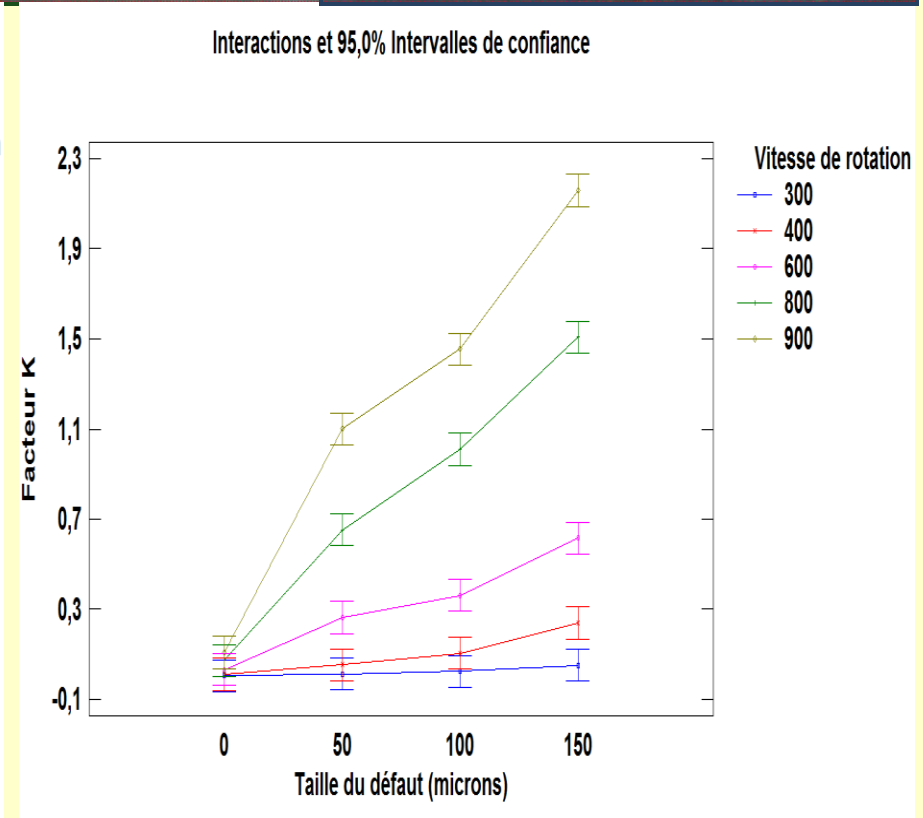
After calibration, the model allows for investigating the sensitivity of features to damage size.



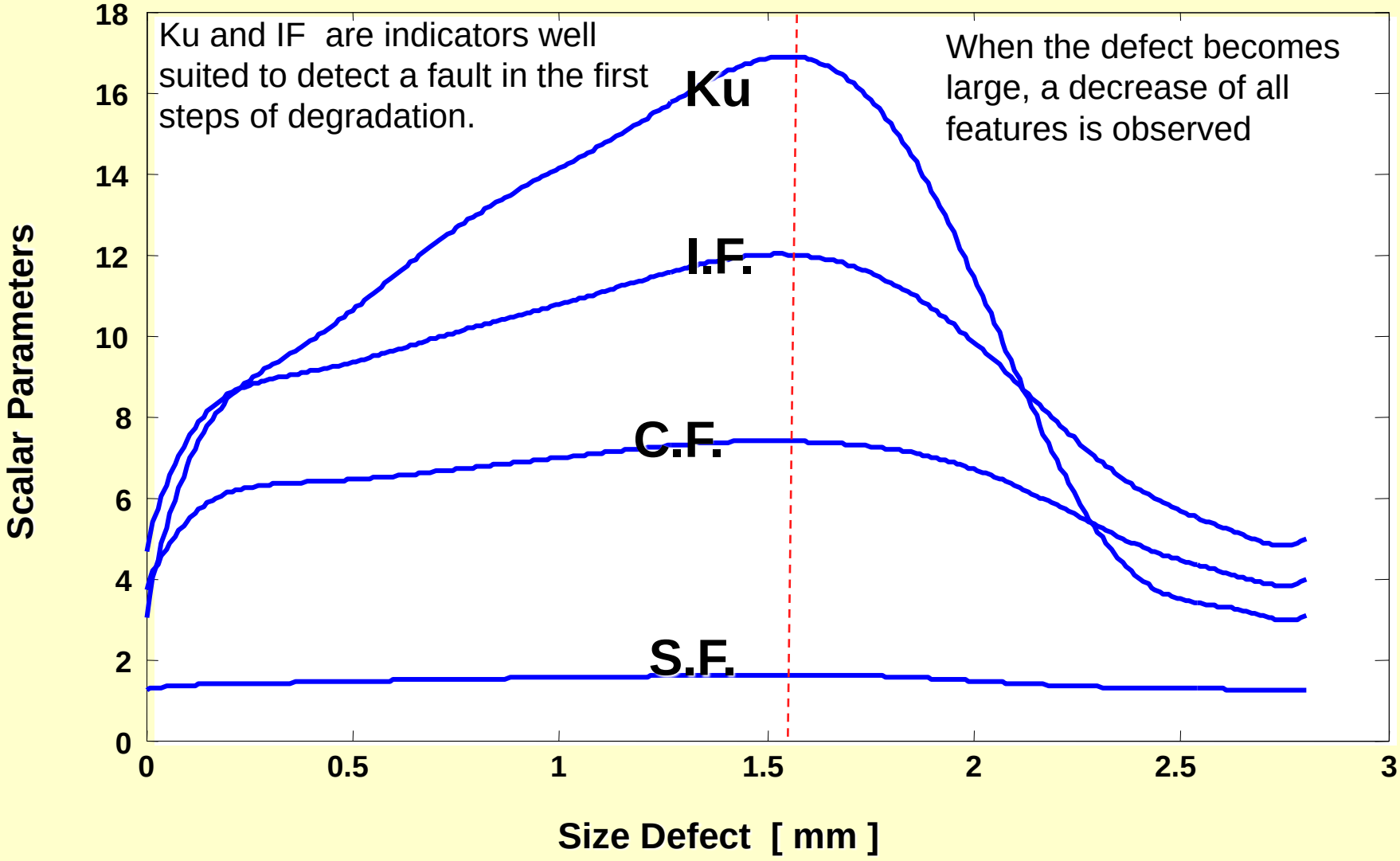
Design of experiments: 5 speeds, 3 forces, 4 defects, 3 repetitions= 180 experiments





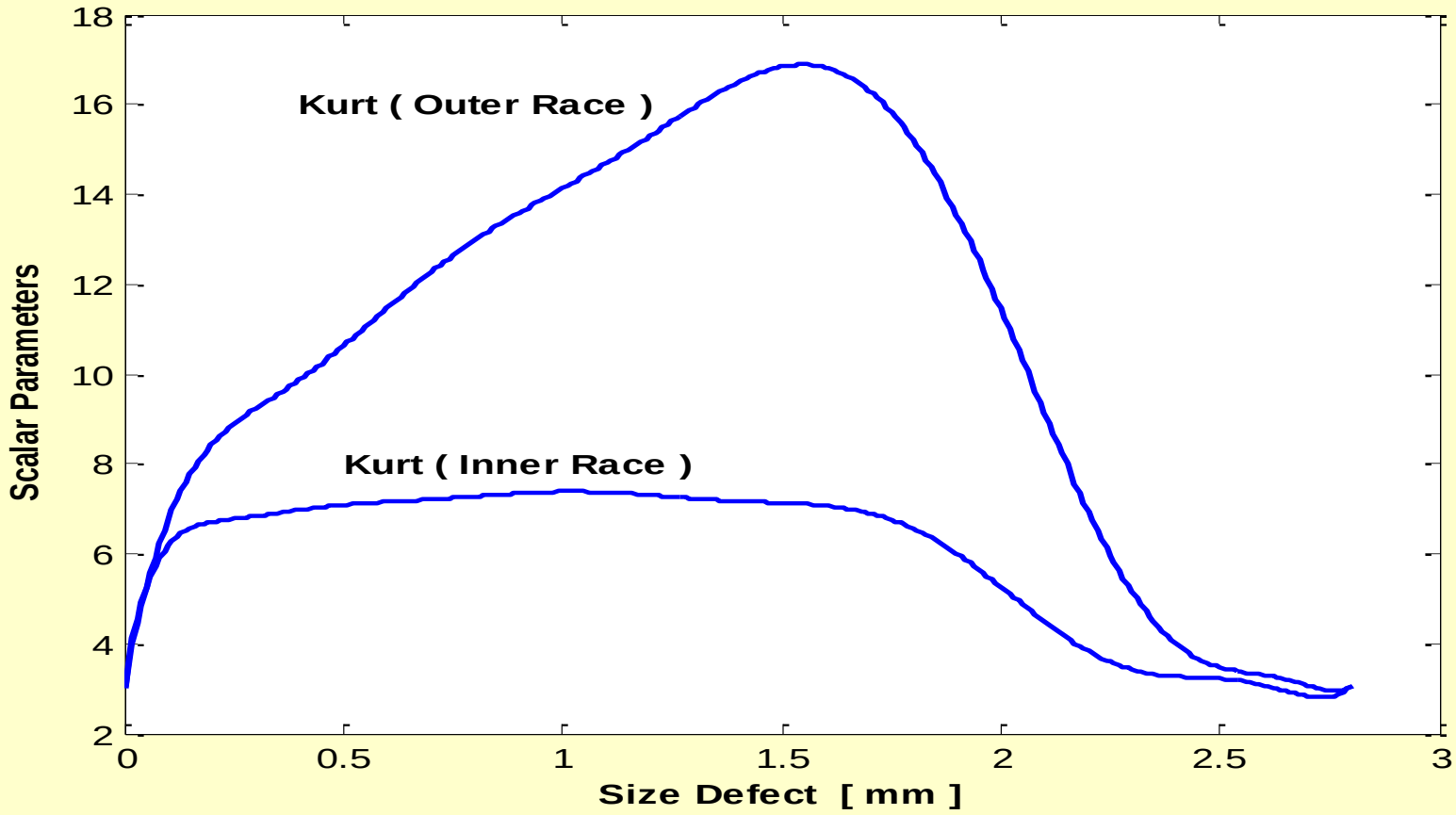


Evolution of Scalar Parameters (Ku, CF, IF, SF) according to the size of a defect on the Outer race



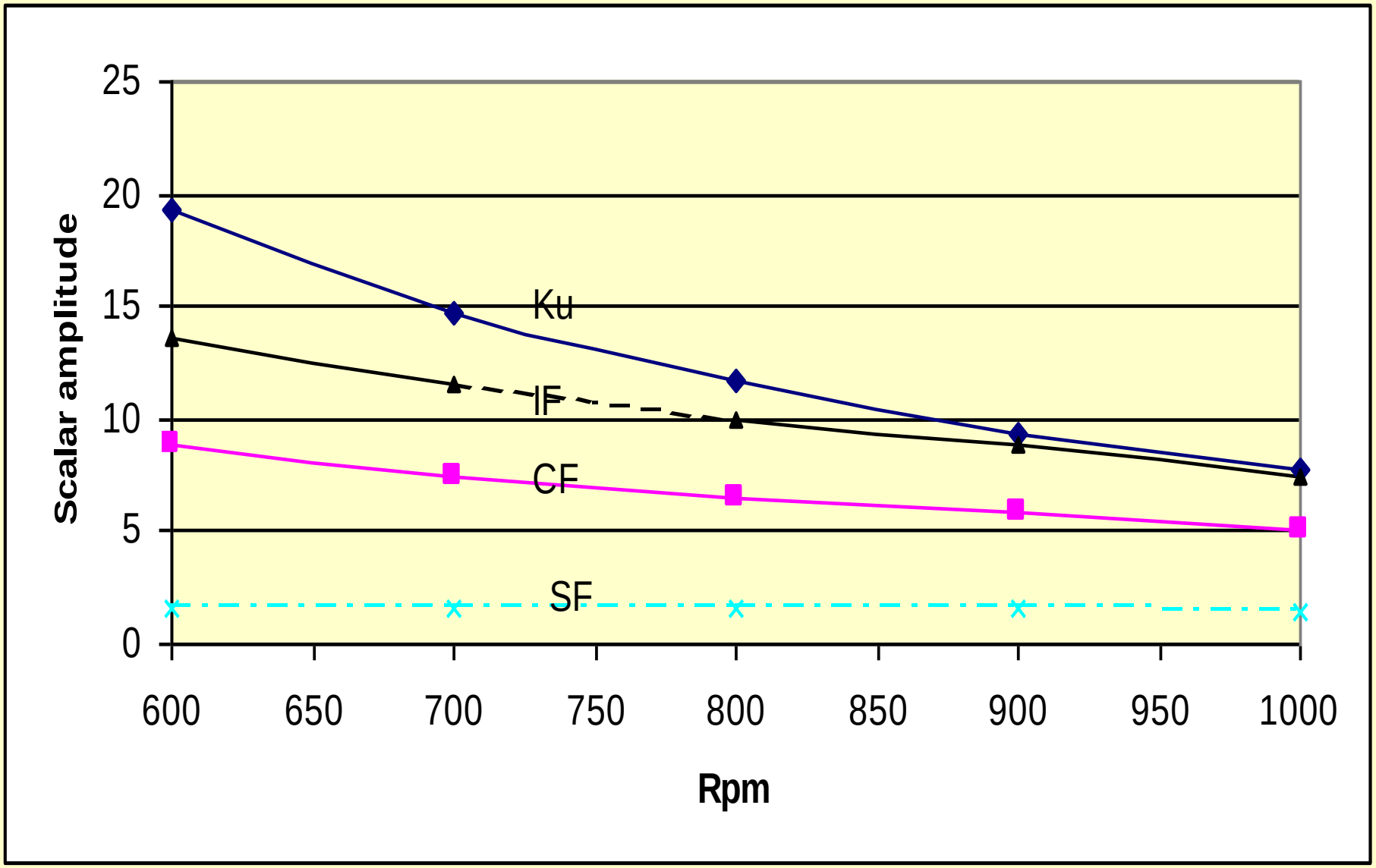
Comparison between Kurtosis values, for defects located on Outer and Inner Races

- **When the defect is affecting the inner race, numerical simulation shows that the sensitivity of Kurtosis is less pronounced than when the defect is located on the outer race.**



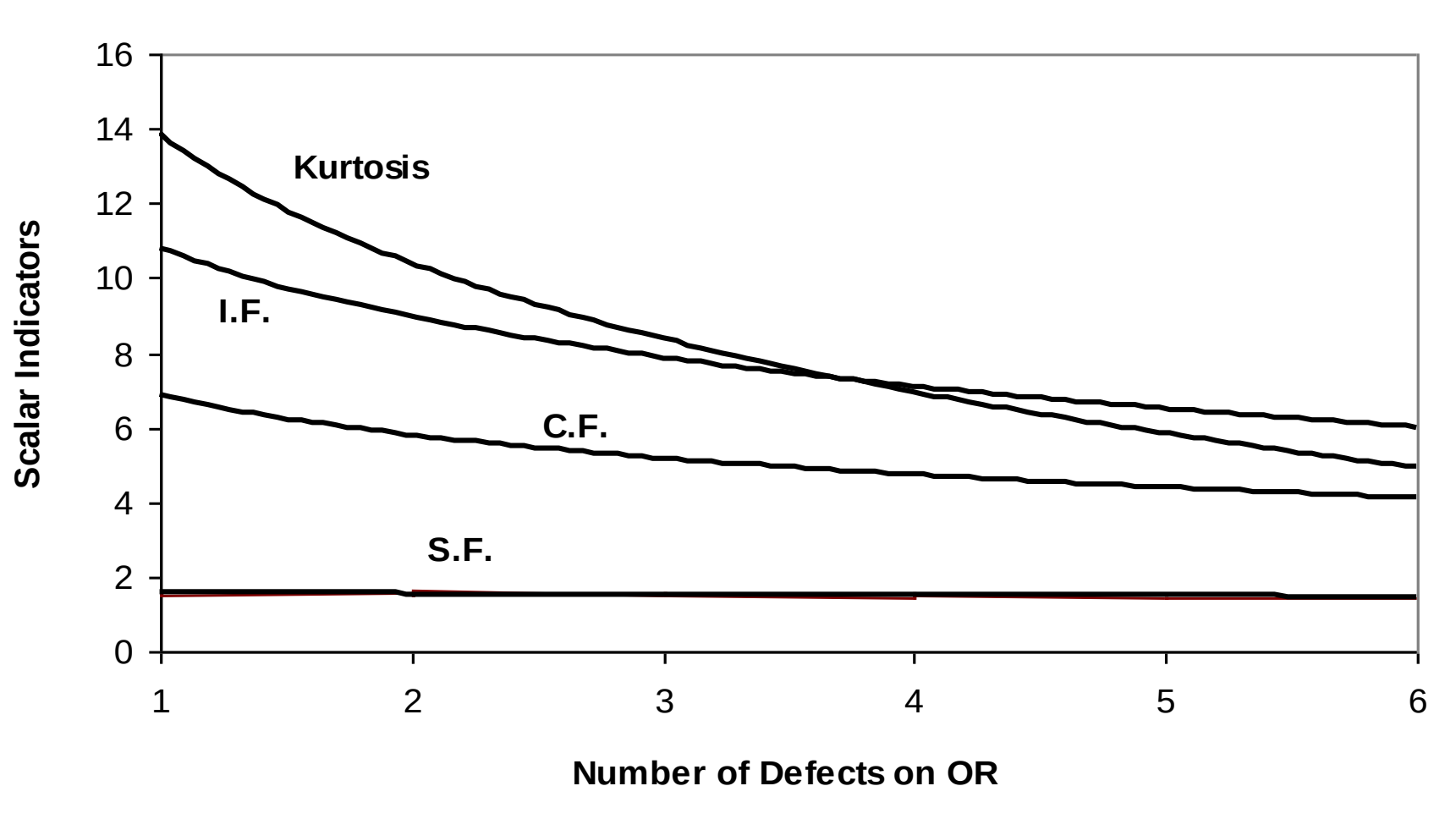
Effect of rotor speed

Numerical simulations show that the features are less sensitive at higher speeds



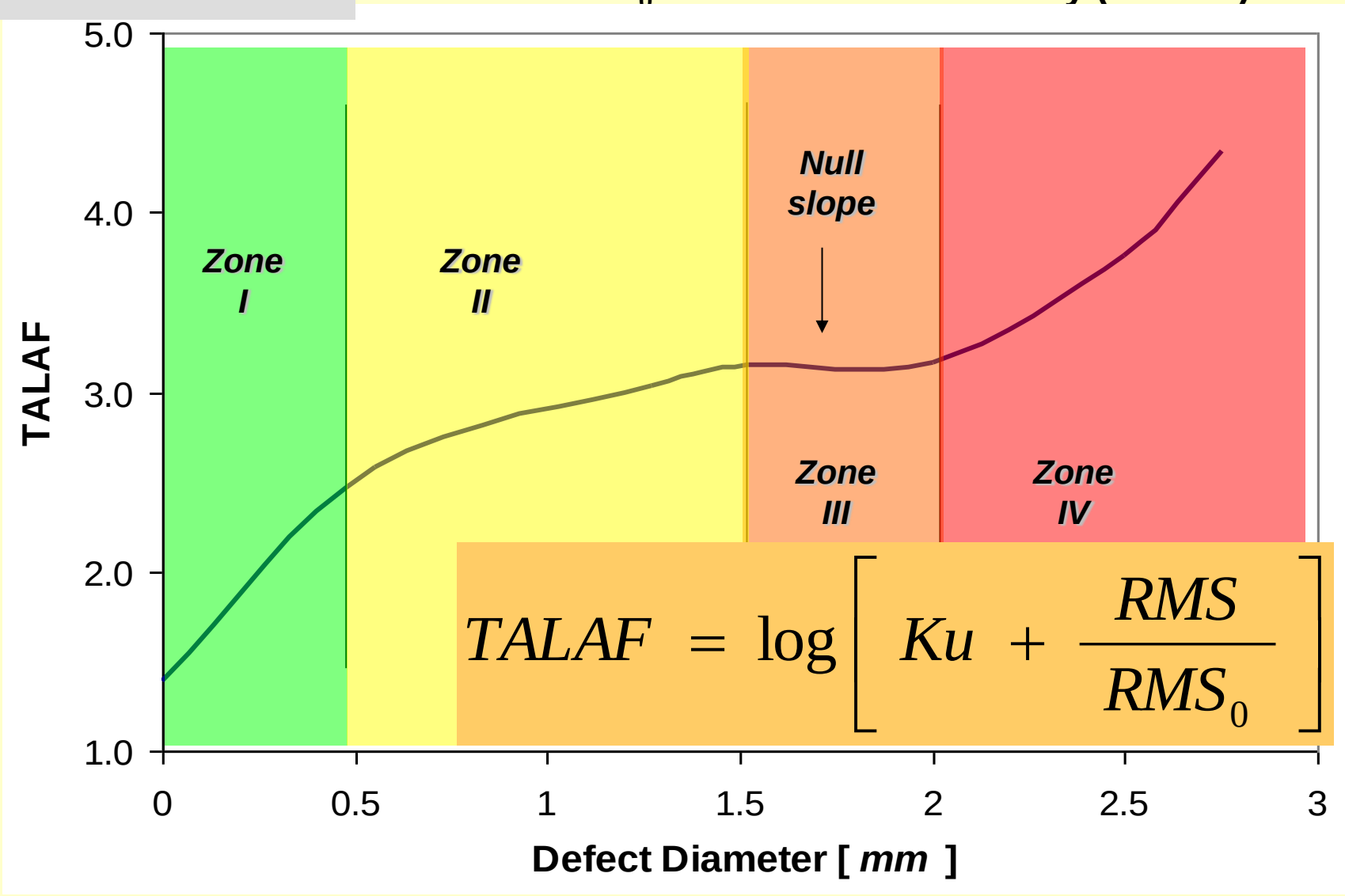
Bearing affected by multiple defects

- **The numerical simulations show that all features decrease with the number of defects.**



TALAF

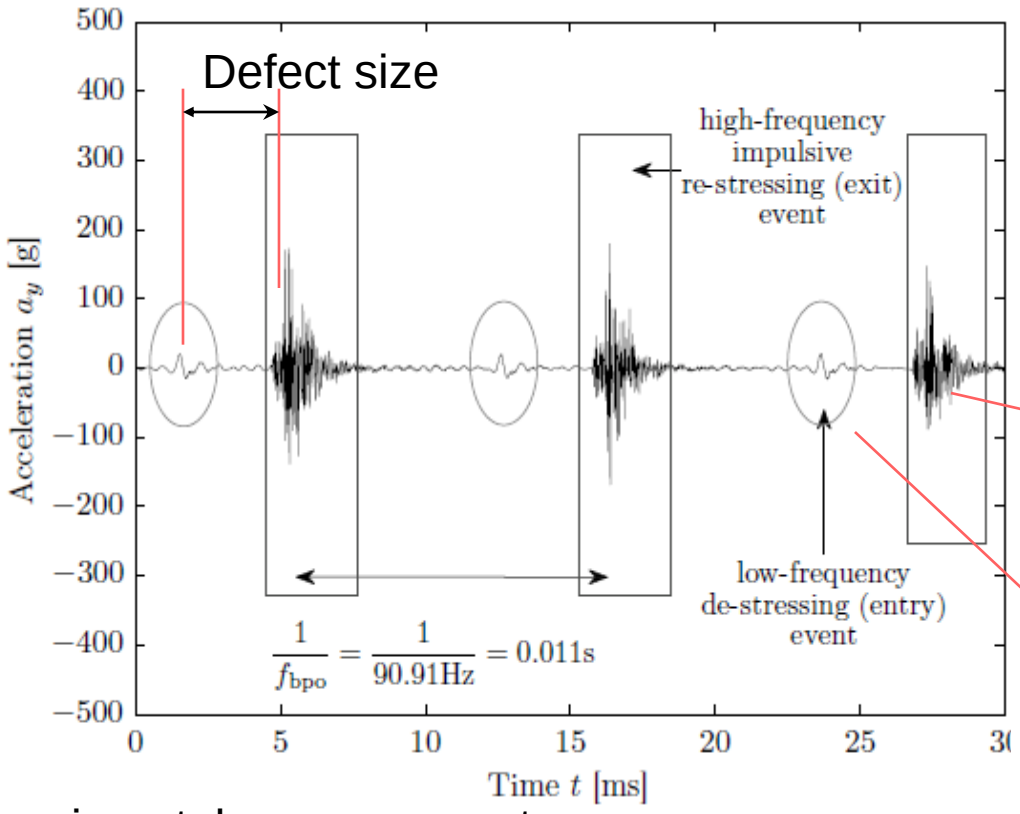
Development of a new indicator based on Ku and RMS, which always increases with the defect size .
It needs a RMS_0 reference when healthy (zone 1).

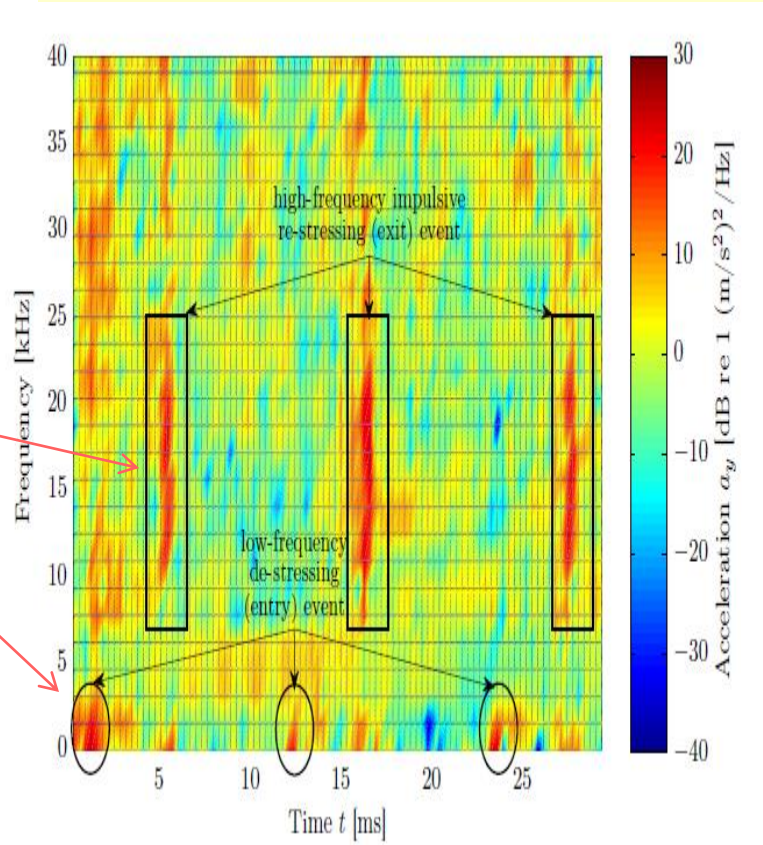


Sassi S., Badri B. and Thomas M., 2008. *Tracking surface degradation of ball bearings by means of new time domain scalar descriptors*, Internat. journal of *COMADEM*, ISSN1363-7681, 11 (3), 36-45

Detection of defect severity

There is a double impact: one at entry and one at the exit of the defect.
The time between both allows for detecting the defect size.





Experimental measurement

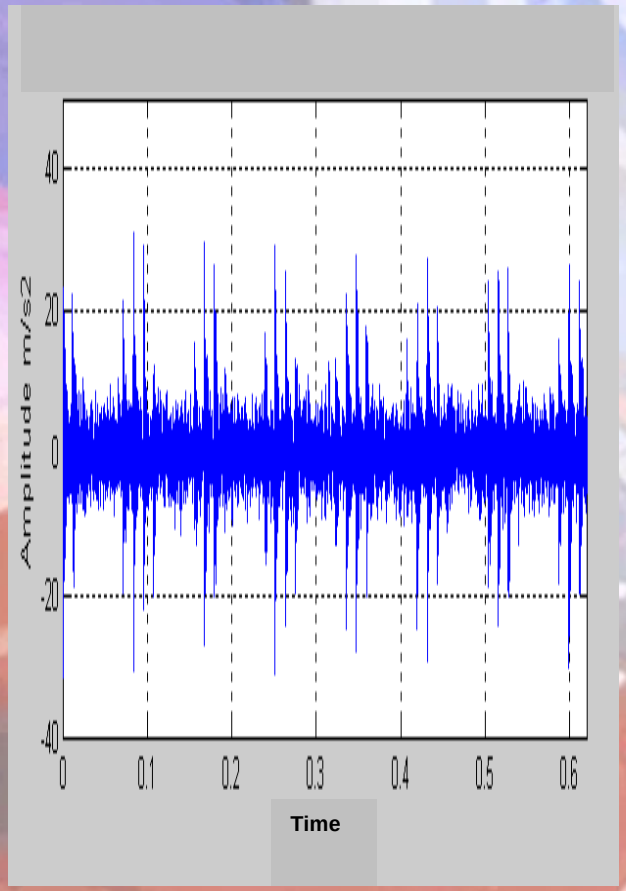
Ref: Singh S., Explicit dynamic finite element modelling of defective rolling element bearing, 2014, U. Adelaide (Au)

The shock filters

- **The Shock filter**
- **Minimum Entropy Deconvolution (MED)**

TARGET of Shock Filter

Extract the shock response from the other sources of perturbation



Random vibration (slip, friction)

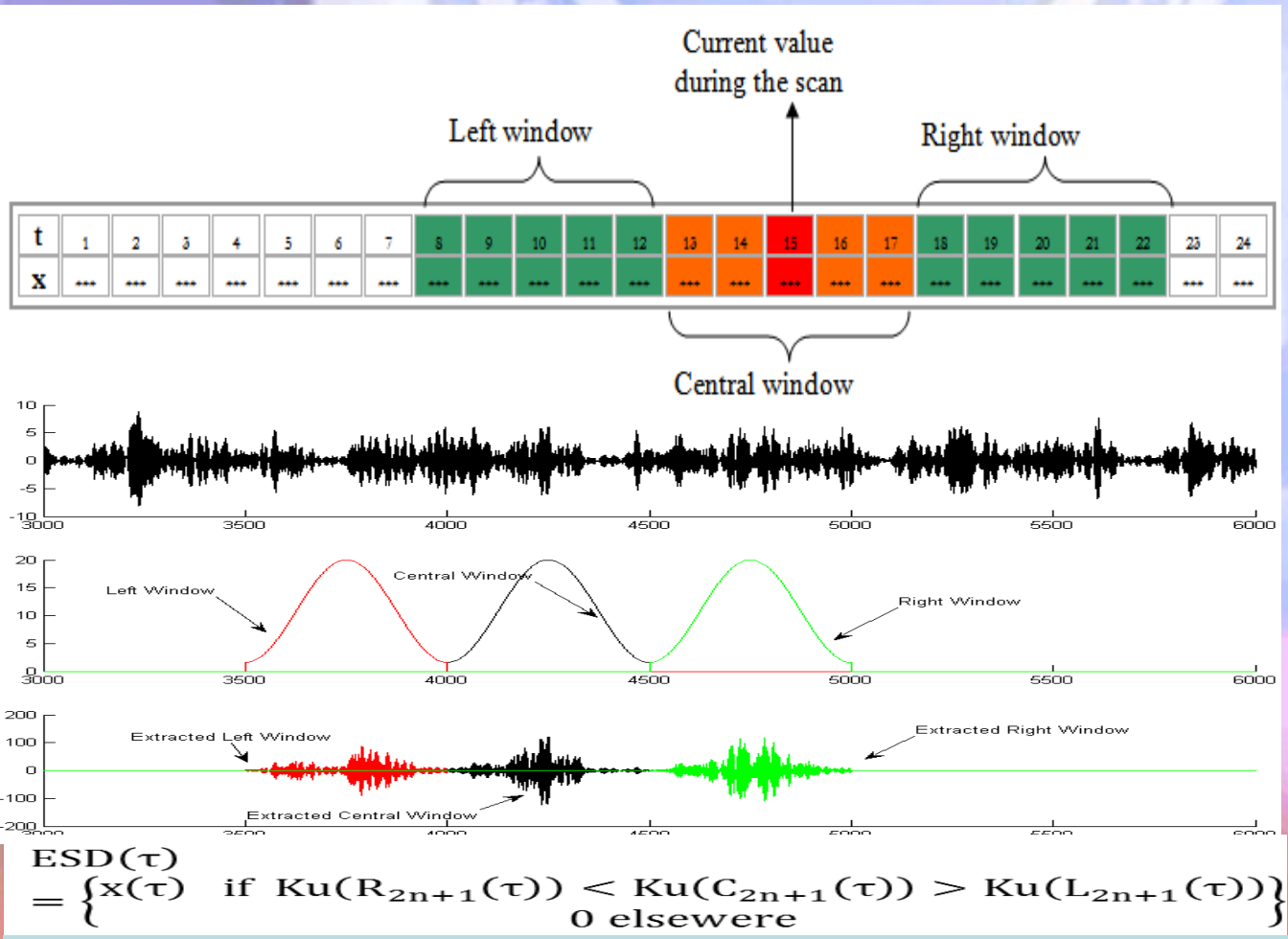
Shocks (defects)

Harmonic vibration (unbalance, misalignment)

Filtered Vibration Response

The Shock filter

At each sample (i) of the time signal, the Kurtosis of a window C centered on i (i-n; i+n) is computed and compared to the ones calculated on windows located to the left L (i-3n; i-n) and right R (i+n; i+3n) of the current sample (i).



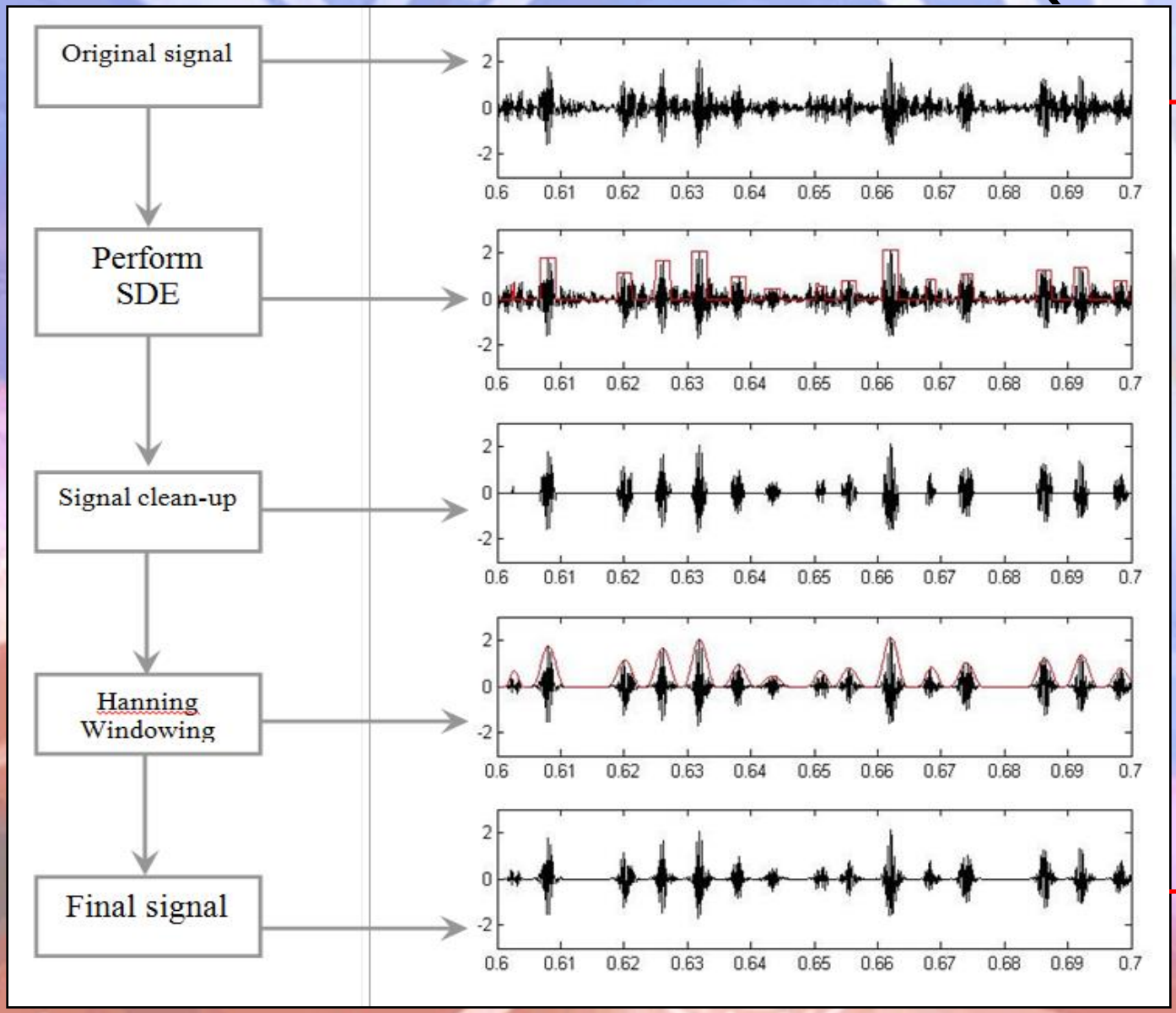
$$ESD(\tau) = \begin{cases} x(\tau) & \text{if } Ku(R_{2n+1}(\tau)) < Ku(C_{2n+1}(\tau)) > Ku(L_{2n+1}(\tau)) \\ 0 & \text{elsewere} \end{cases}$$

Once the Kurtosis has been evaluated for each of the three windows, a selection is conducted:

- If the energy of the central window is greater than the two others into the left and right window, we declare the presence of a shock and the peak amplitude of the signal at position (i) is assigned to the shock extractor.
- Otherwise, there is no shock and the shock extractor takes a null value.

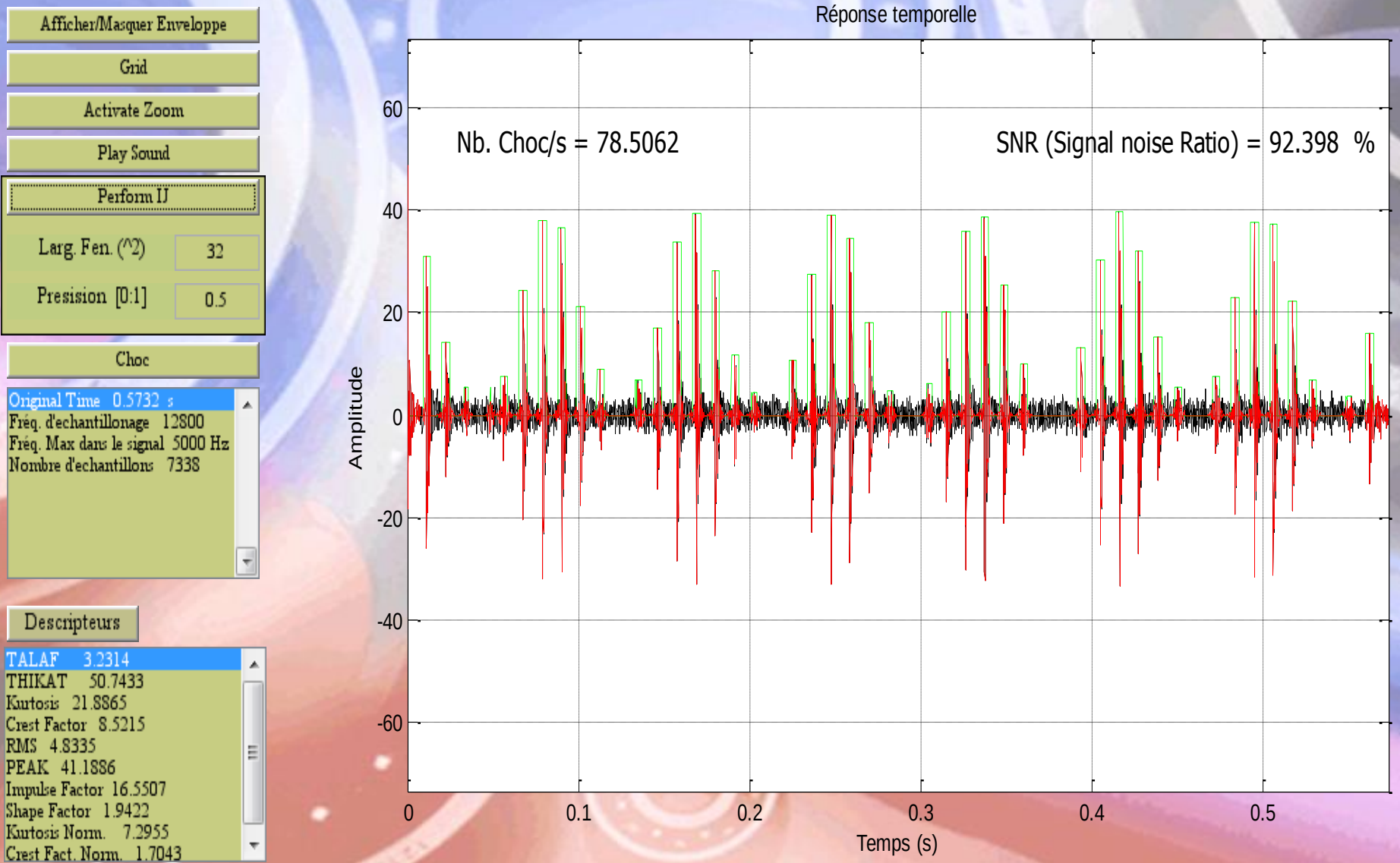
Badri B., Thomas M. and Sassi S., July 2012. The envelop Shock detector: a new method to detect impulsive signals, International journal of COMADEM.13 p.

Shock Detector (SD)



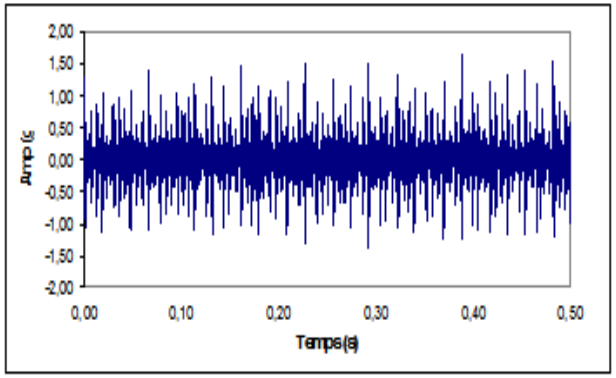
$$SNR = \frac{rms\,[ESD(t)]}{rms\,[\,x(t)]}$$

The Shock Filter



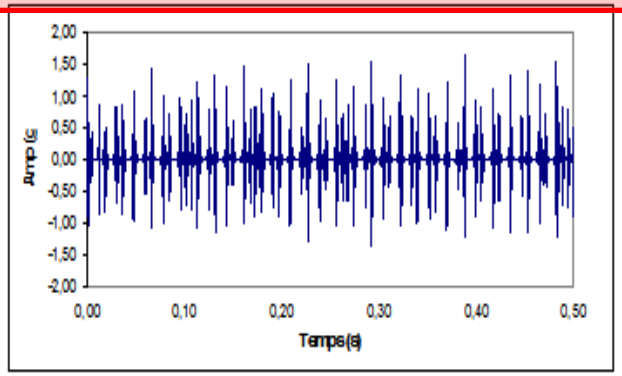
Evaluation of defect severity with SD signals

Defect =0,18mm SNR 63%



a) Original signal for a defect size = 0.18 mm

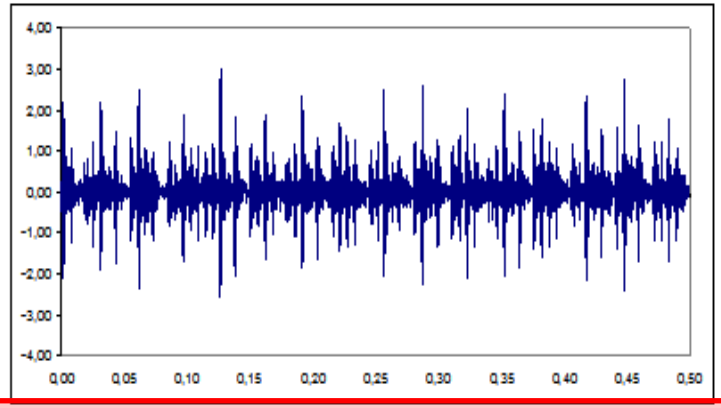
Peak	RMS	CF	Kurtosis
1.51	0.33	4.57	5.57



b) Signal modified by TJR for a defect size = 0.18 mm

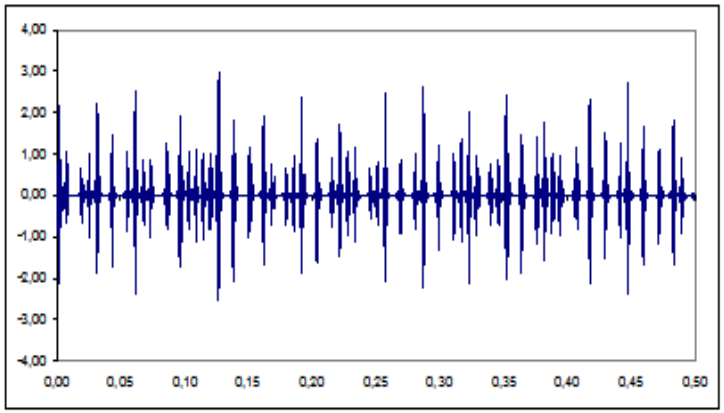
Peak	RMS	CF	Kurtosis
1.51	0.21	7.21	11.45

Defect =0,56mm SNR 82%



Original signal for a defect size = 0.56 mm

Peak	RMS	CF	Kurtosis
2.87	0.46	6.14	7.88

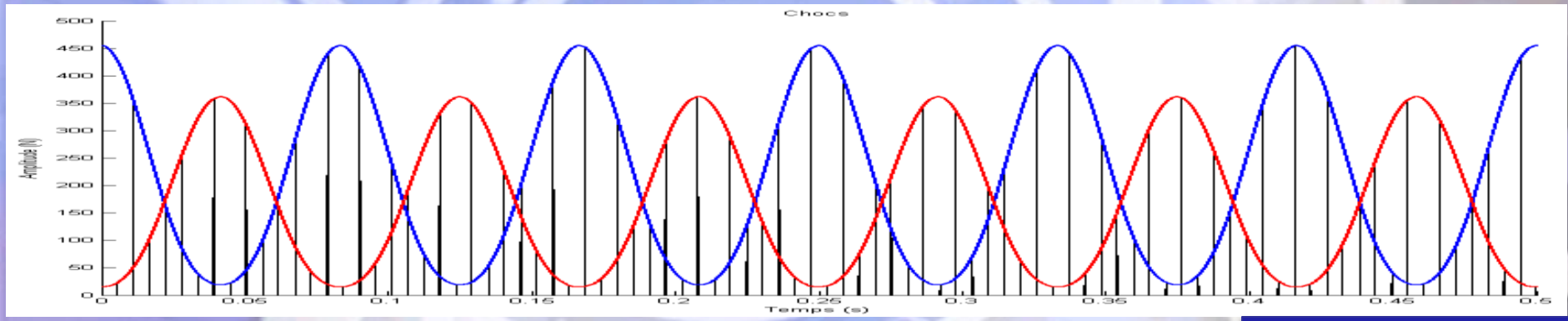


Signal modified by TJR for a defect size = 0.56 mm

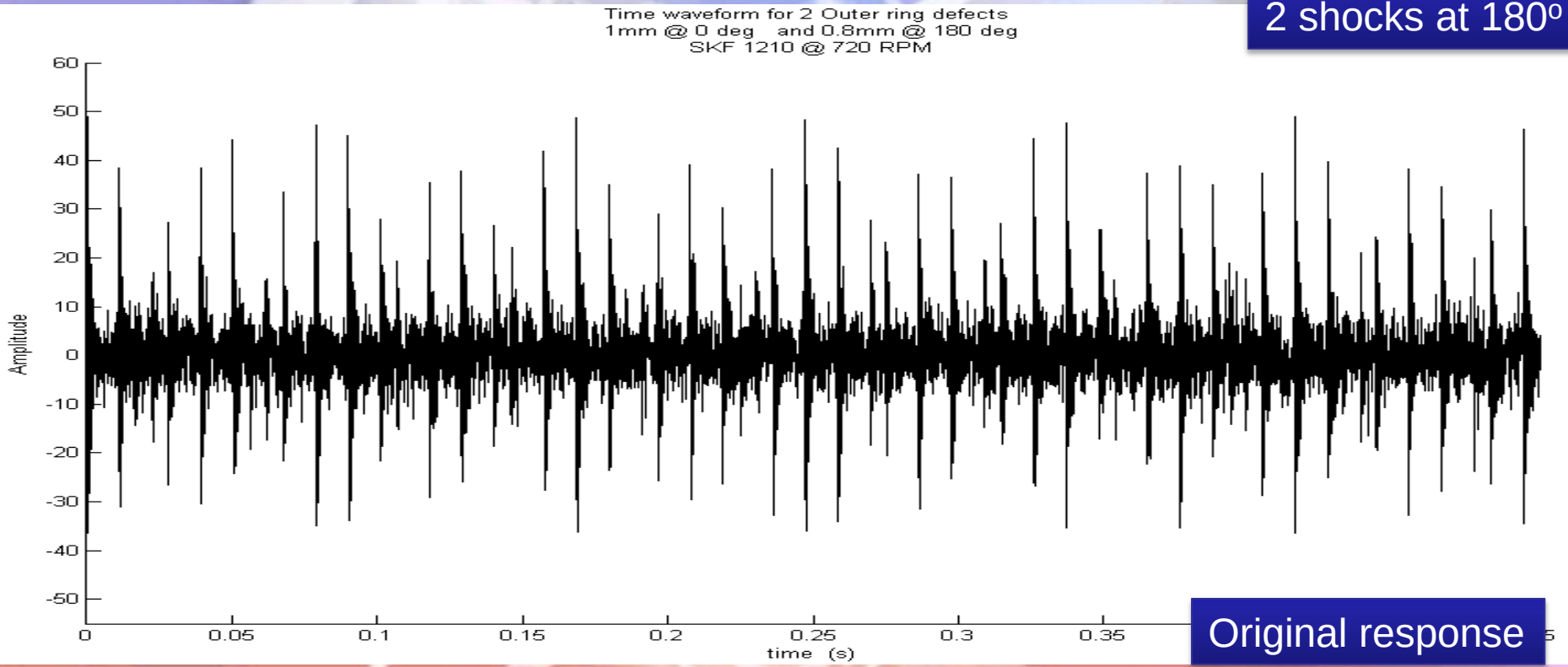
Peak	RMS	CF	Kurtosis
2.87	0.38	7.49	14.87

Comparing the RMS level of the filtered signal with the original signal gives an indication on the severity of damage.

Detection of multiple defects



2 shocks at 180°



Original response

Bearing SKF 1210 ETK9 operating at 720 RPM
with 2 defects on outer race:1mm @ 0deg and 0,8 mm @ 180deg

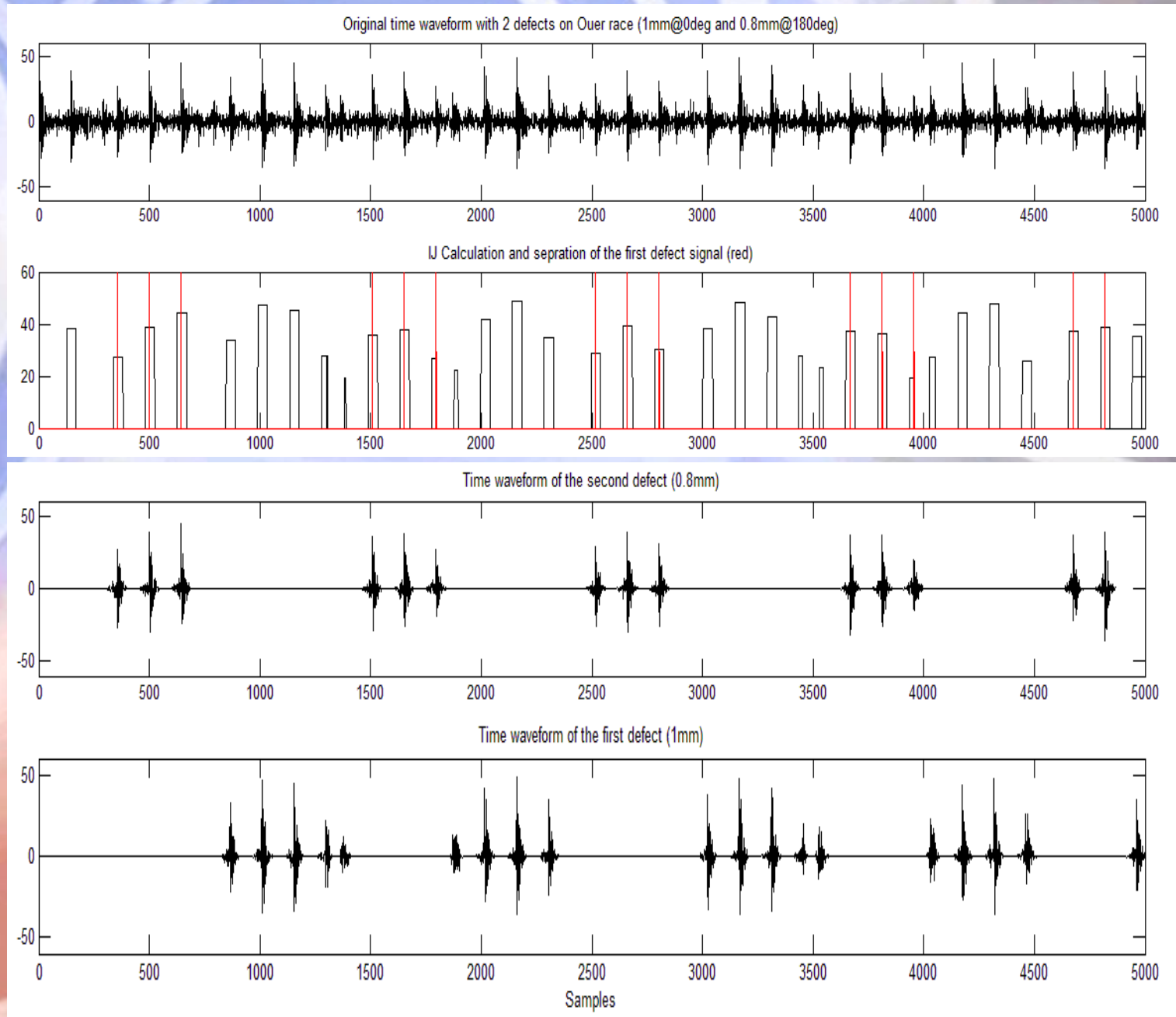
Identification of shock sources

Original signal

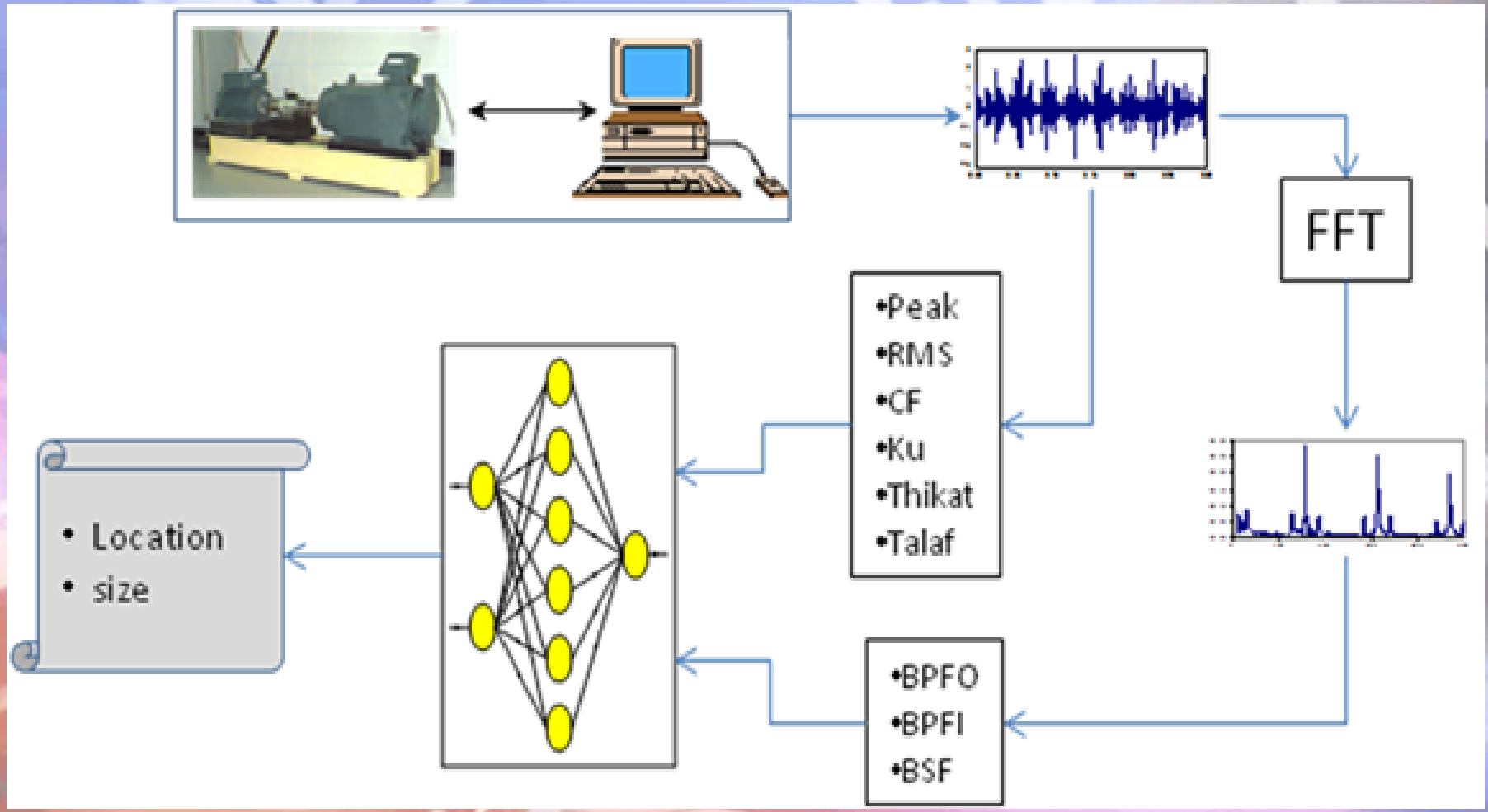
SD Filtered signal

1st shock signal

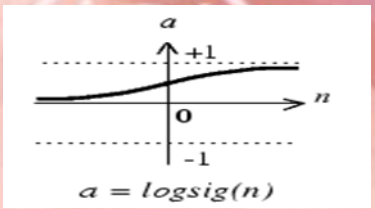
2nd shock signal



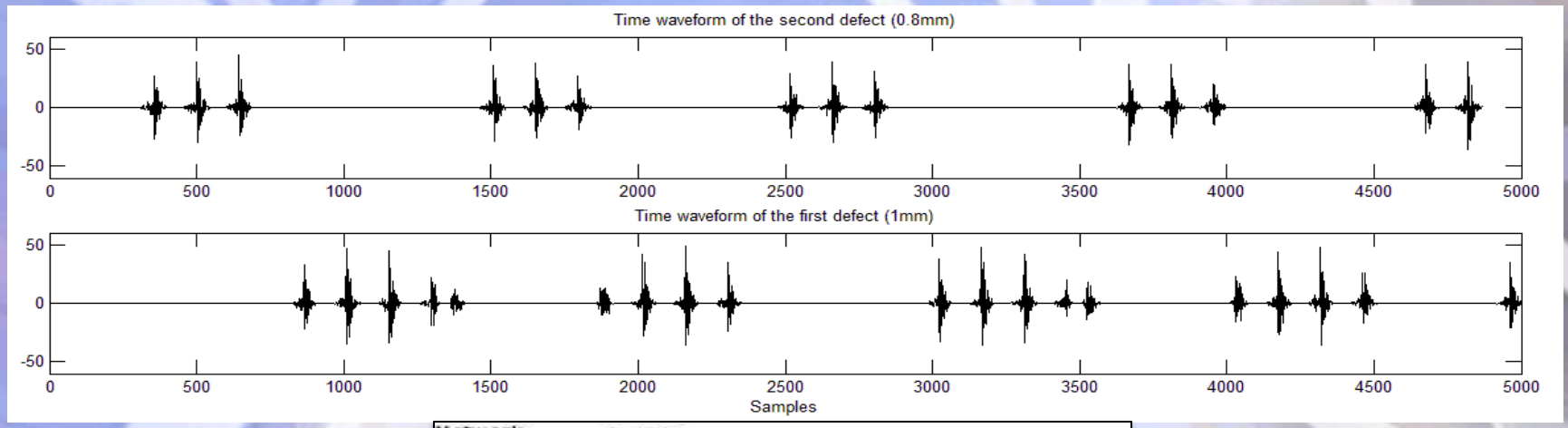
Detection of defects by neural network

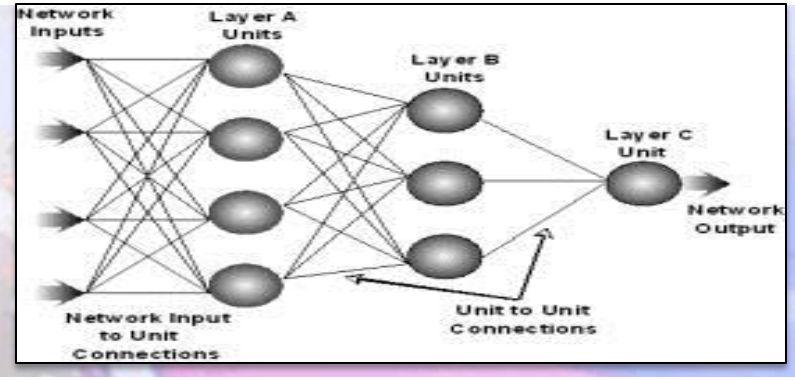


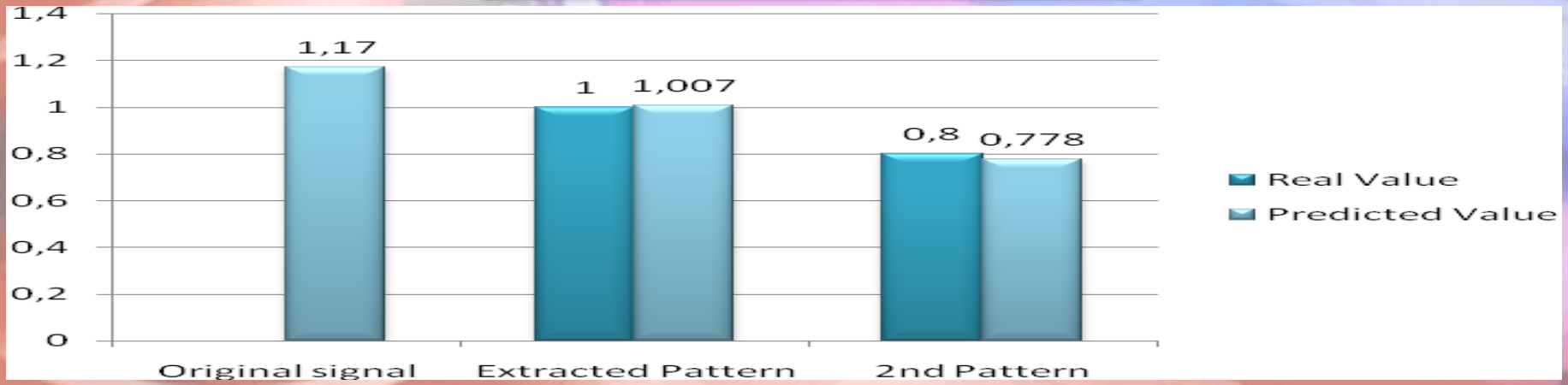
Three layers
5 Neurons into the hidden layer
Activation with log-Sigmoïde



Identification of damage severity by neural network

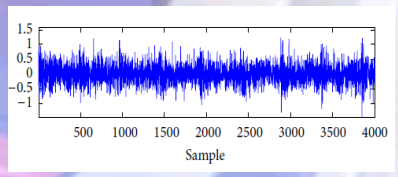




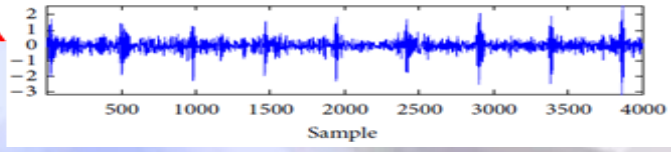


Maximizing the Kurtosis with the Minimum Entropy Deconvolution (MED)

- A minimum entropy is aimed to reduce the disorder.
- **Minimum Entropy Deconvolution:** The method allows for highlighting the shocks present into the original signal



$$y(n) = h(n) * x(n) + e(n)$$



Filtre optimal

$$x(n) = w(n) * y(n)$$

We must optimize the filter in order to maximize the Kurtosis:

Maximise The Kurtosis of x(n)

$$O_2^4(w(n)) = \frac{\sum_{i=1}^{N} x^4(i)}{\left[\sum_{i=1}^{N} x^2(i)\right]^2}$$

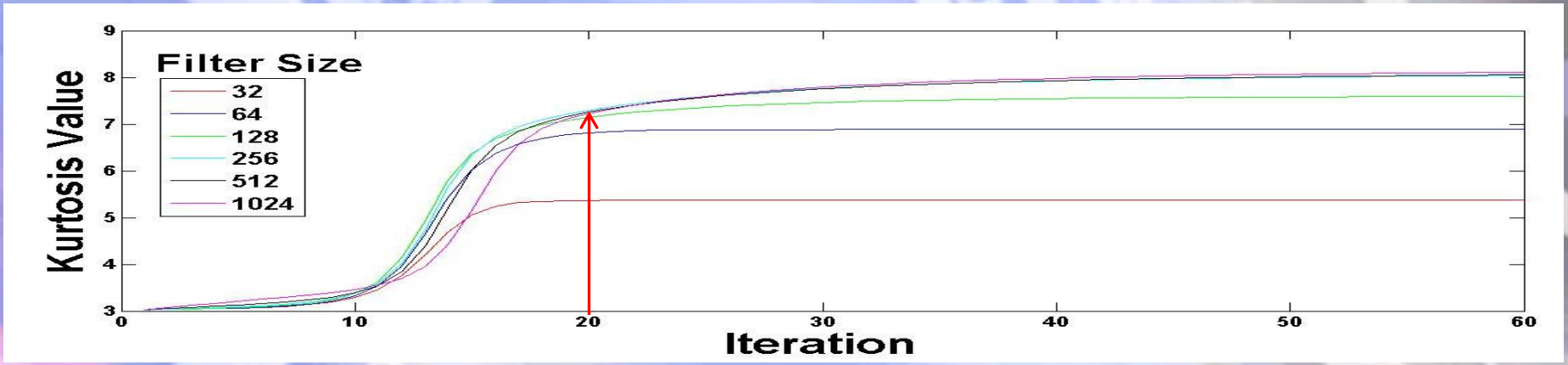
$$\frac{\partial O_2^4(w(n))}{\partial w(n)} = 0$$

June-Yule Lee et A.K. Nandi, *Extraction of impacting signals using blind deconvolution.* Journal of Sound and Vibration 1999. **232**(5): p. 945-962.

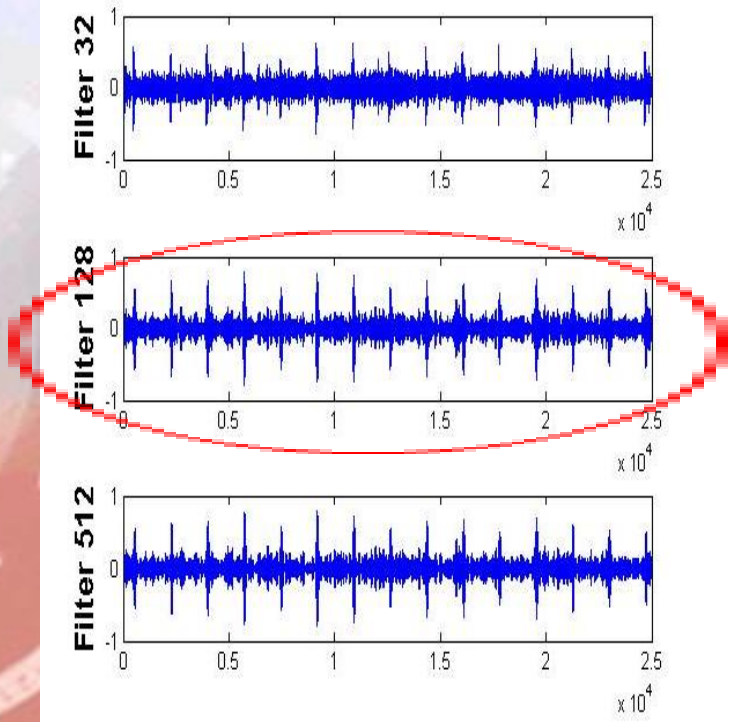
Endo H., Randall R.B. (2007), *Application of a minimum entropy deconvolution filter to enhance Autoregressive model based gear tooth fault detection technique*, Mechanical Systems and Signal processing, 21, 906,919.

Tomasz B. Nader S. (2012), *Fault Detection Enhancement in Rolling Element Bearings Using the Minimum Entropy Deconvolution*, Archives of Acoustics, Vol 37, No. 2, pp. 131-141.

When using MED, the filter size and number of iterations must be selected



In this example, N=128 with 20 itérations was selected

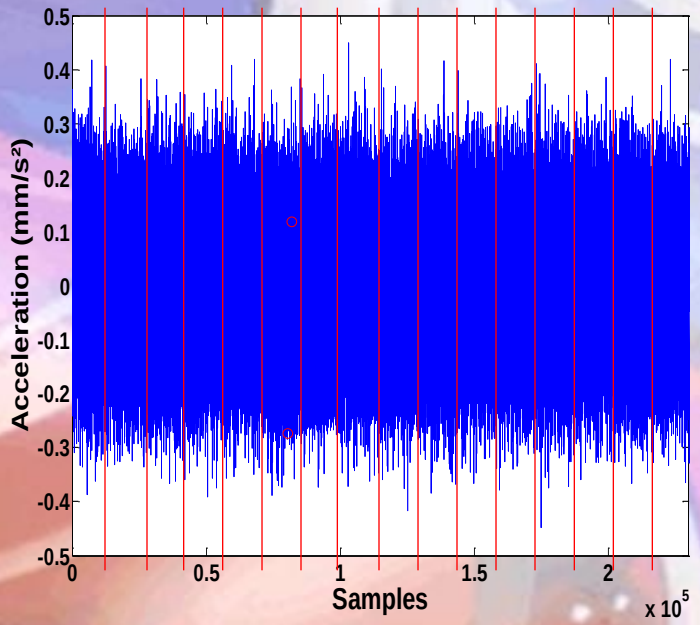


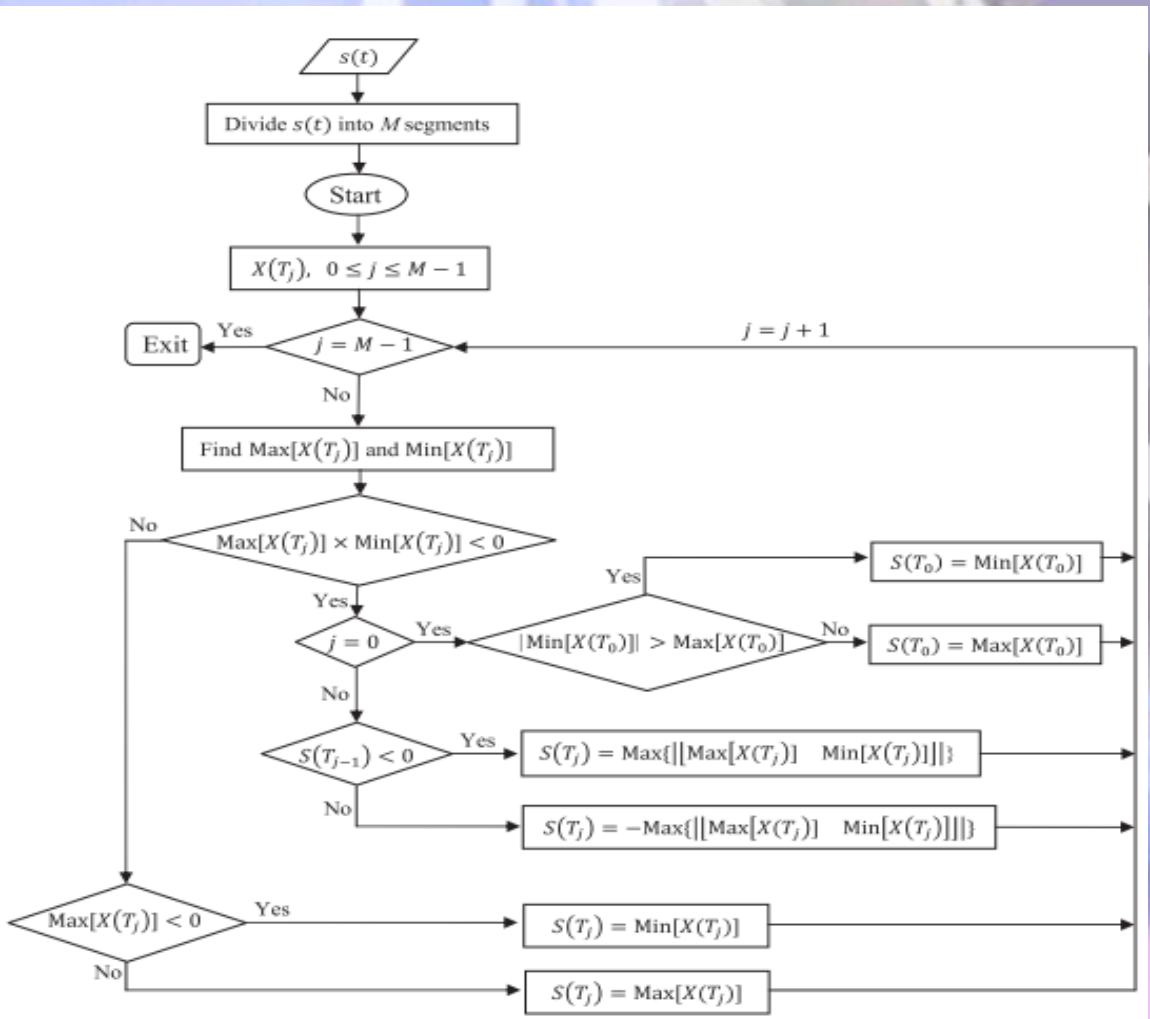
Application to low speed operations

In low speed operations, the periods are very long and the length of signals very big.

- **Peak Hold Down Sampling**

help to reduce the length of signal by segmentation



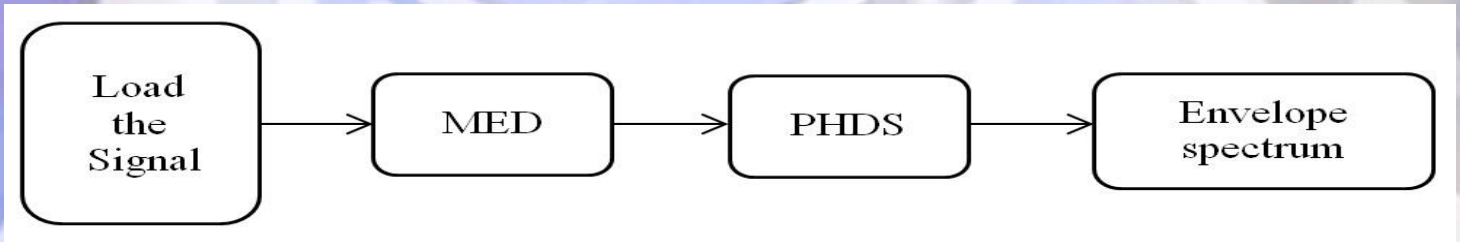


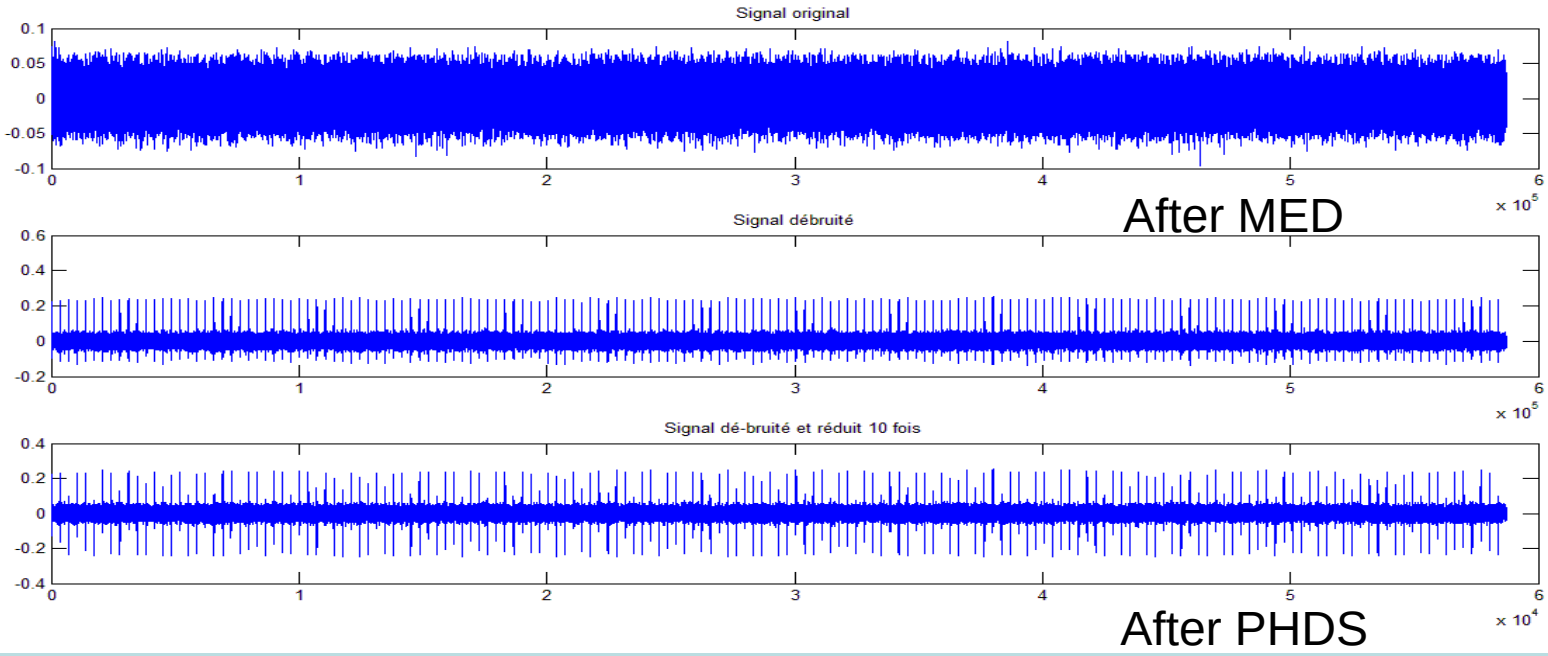
Tian Ran Lin, Eric Kim, Andy C.C. Tan. (2013) A practical signal processing approach for condition monitoring of low speed machinery using Peak Hold Down Sample algorithm, MSSP 36, 256-270.

Bearing faults diagnosis using PHDS and MED when operating at low speeds

Using directly PHDS is too much noisy. The signal needs to be previously unnoised.

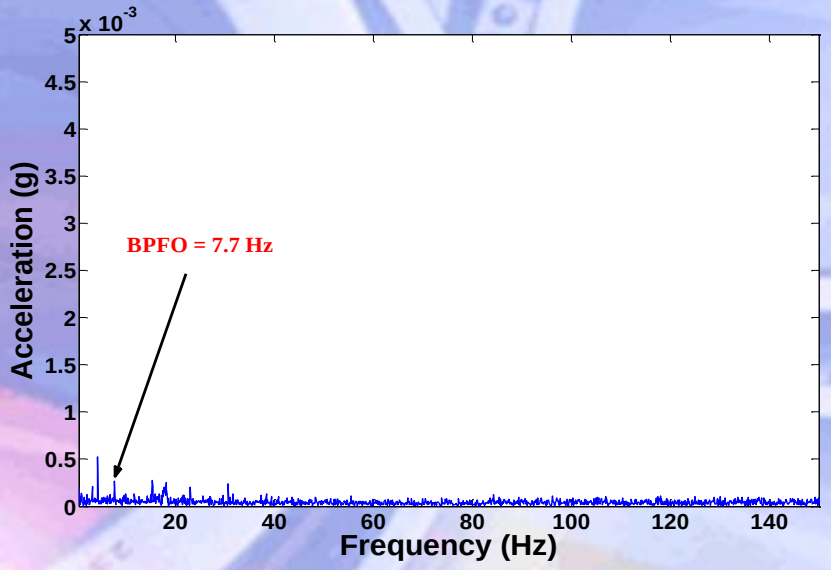
- The method first uses MED to maximize the Kurtosis, and then uses the PHDS to reduce the signal length. The enveloppe is then applied.



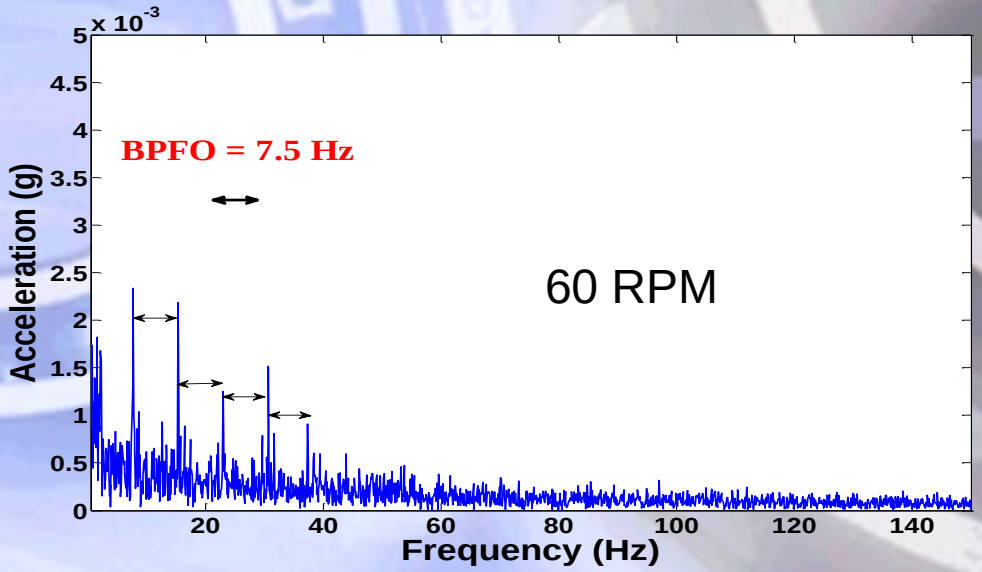


Melki O., Kedadouche M., Badri B. and Thomas M. October 2014. *Monitoring bearing operating at very low speeds*. Proceedings of the 32e CMVA, Montreal, 14 p

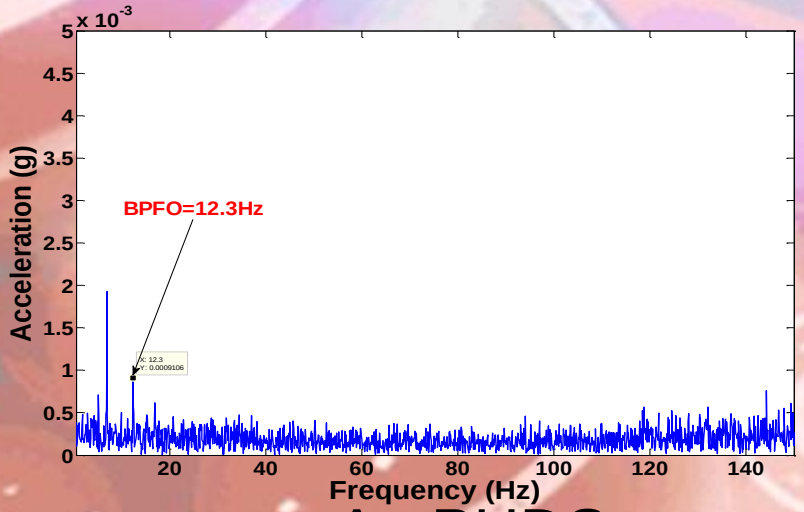
Experimental applications on test bench
Defect size 50 microns



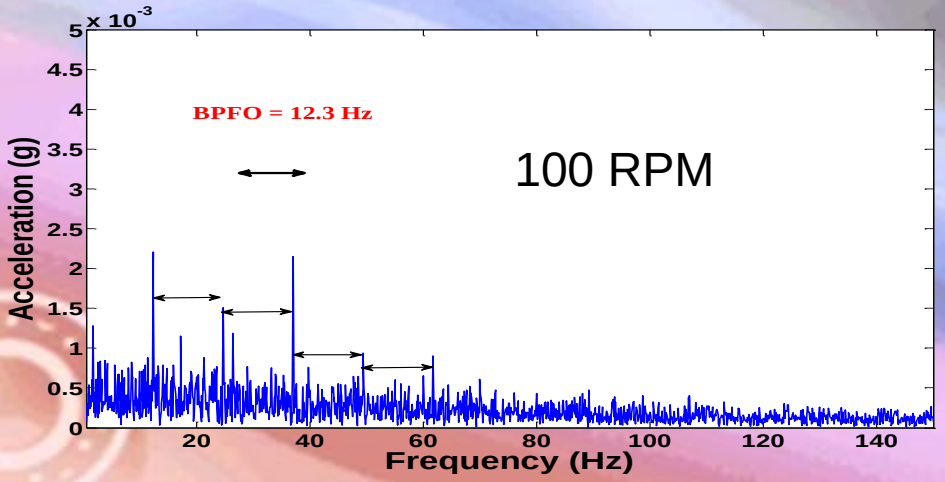
A - PHDS



B - MED +PHDS



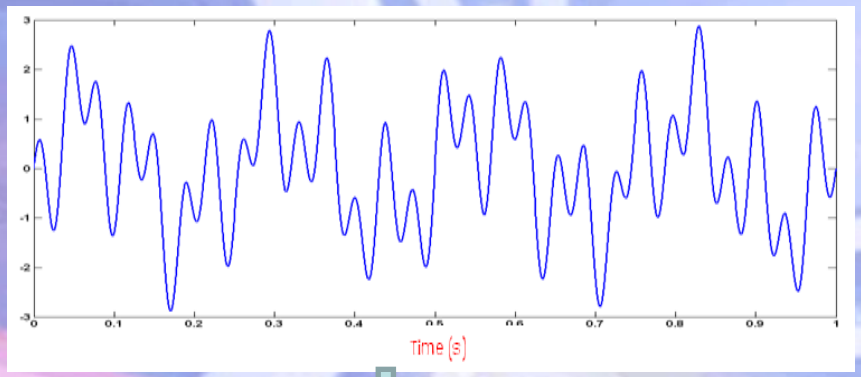
A - PHDS



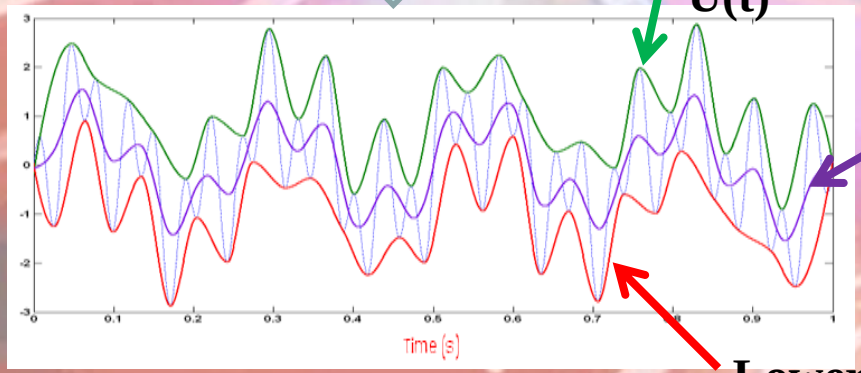
B - MED +PHDS

EMD (Empirical Mode Decomposition)

SIGNAL



EMD



UPPER Envelop: U(t)

Mean: m(t)

Lower Envelop:(L(t)

The empirical mode decomposition assumes that any real signal s(t) can be divided into "a local average" m(t) and "a strongly oscillating component" $h_1(t)$ as follows:

$$s(t) = h_1(t) + m(t) = \sum_i h_i(t) + r(t)$$

The mean of the upper and lower envelopes is defined as:

$$m(t) = \frac{U(t) + L(t)}{2}$$

Huang, N. E., Shen, Z., and Long, S. R., The Empirical Mode Decomposition and Hilbert Spectrum for Nonlinear and Non-Stationary Time Series , *Proc. R. Soc. London, Ser*. (1998)

EMD Method

- The mean is subtracted from the signal, leading to the first component, until it is the first Intrinsic Mode Function(IMF_1):

IMF_1 contains the highest frequency band.

$$d_1(t) = s(t) - m_1(t)$$

$$d_{11}(t) = d_1(t) - m_{11}(t)$$

$$IMF_1 = d_{1k}(t) = d_{k-1}(t) - m_{1k}(t)$$

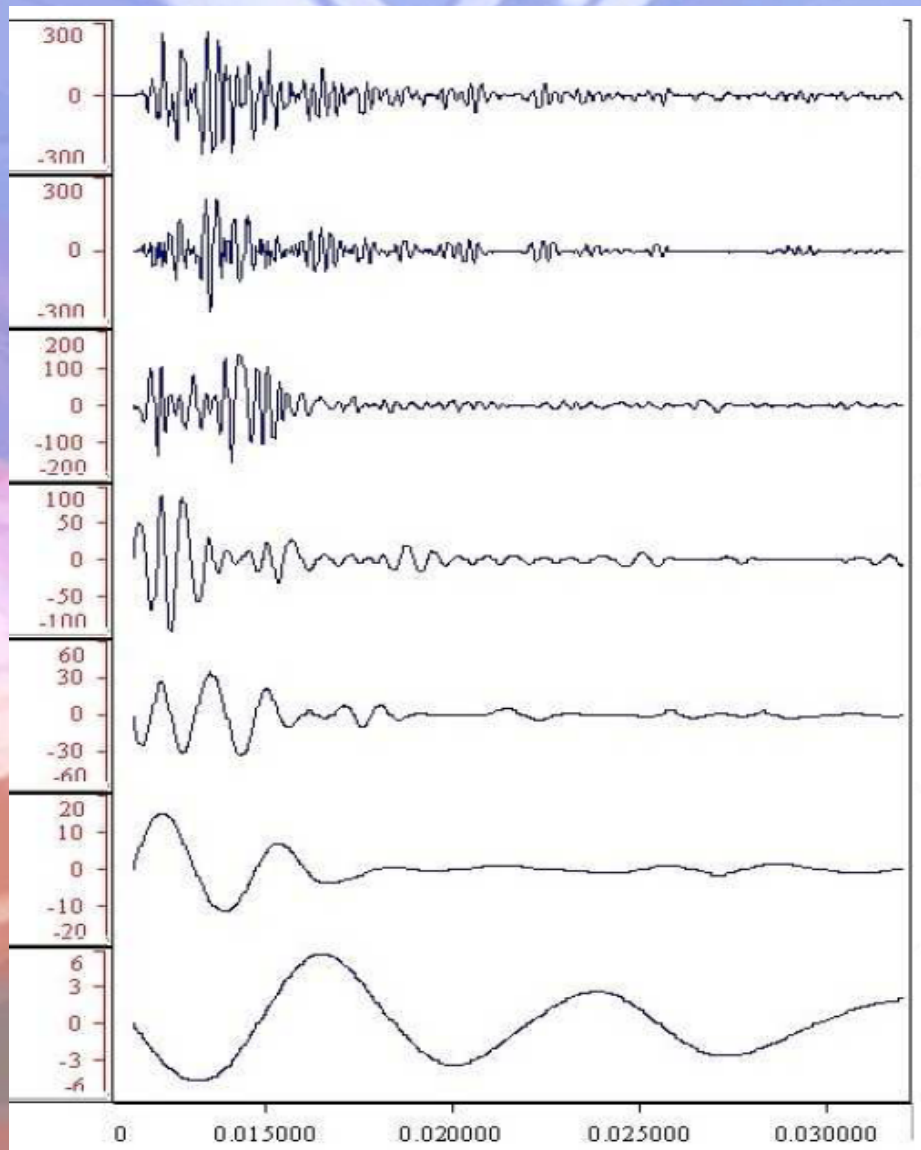
- An IMF is a function respecting the following conditions:
  - The number of extrema and the number of zero crossings are either equal or differ at most by 1;
  - The value of the moving average between the superior envelope (defined by local maxima) and the inferior envelope (defined by local minima) is zero.
- **Iterative steps**: the same procedure is applied by removing IMF_1 to the signal, etc..

$$r_1(t) = s(t) - IMF_1(t)$$

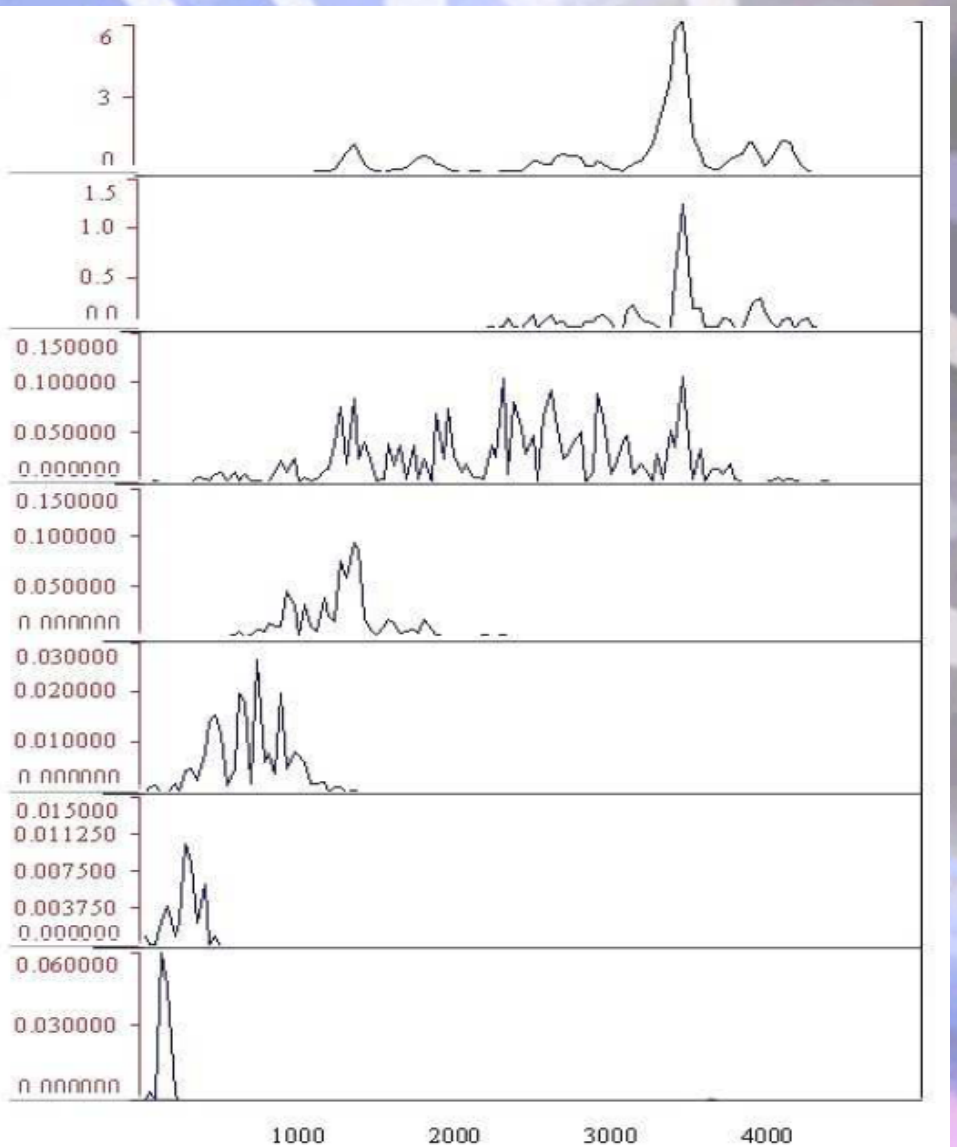
$$r_2(t) = r_1(t) - IMF_2(t)$$

$$r_n(t) = r_{n-1}(t) - IMF_n(t)$$

E.M.D



IMFs

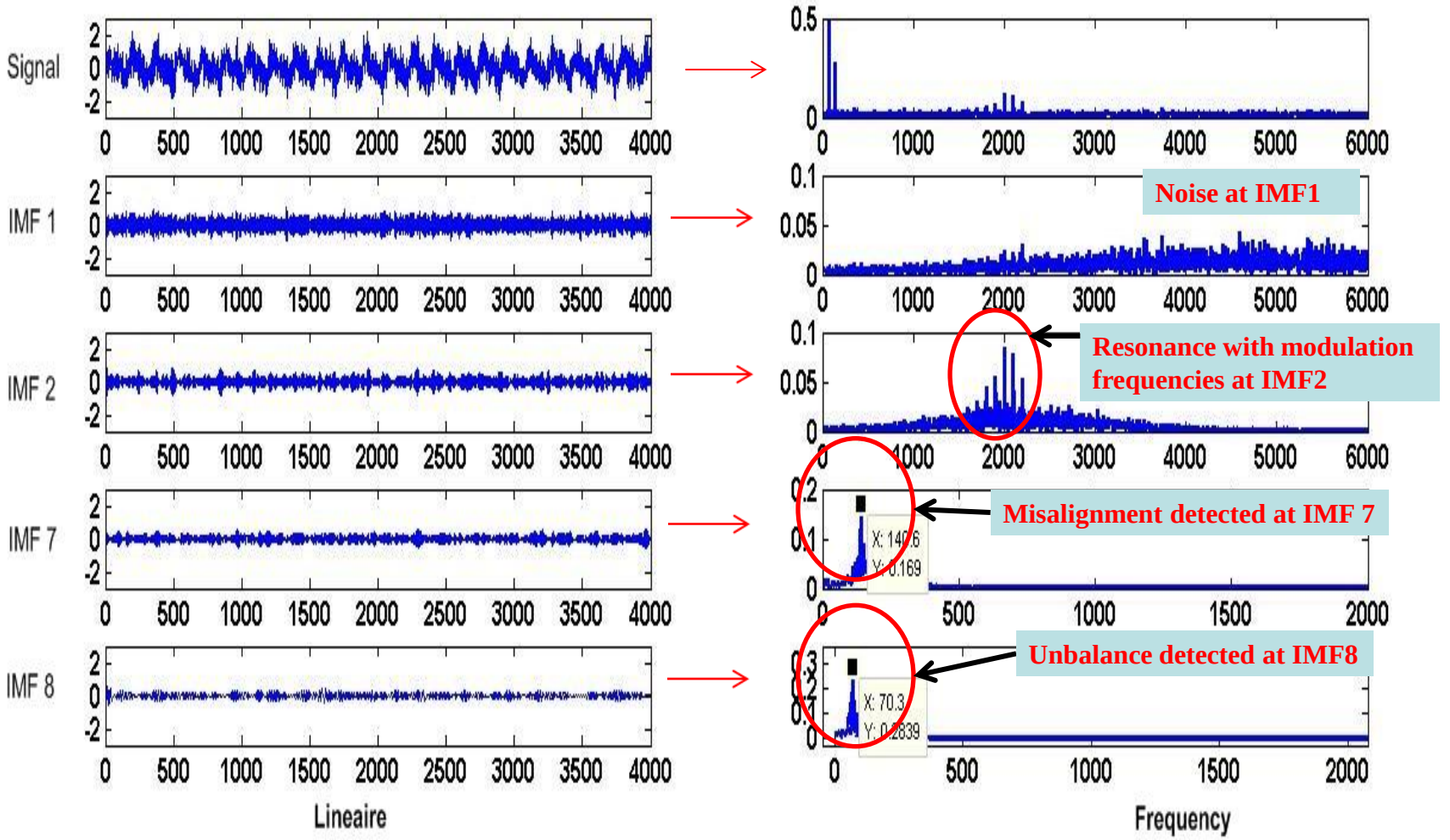


Spectre of IMFs: from highest to lowest

❑ Example: Simulated Signal of bearing defect

The simulated signal (assumptions about expected results) contains:

- excitation at the resonance (2000 Hz) modulated by BPFO +
- unbalance (70 Hz)+
- misalignment (140 Hz)+
- noise (50%)

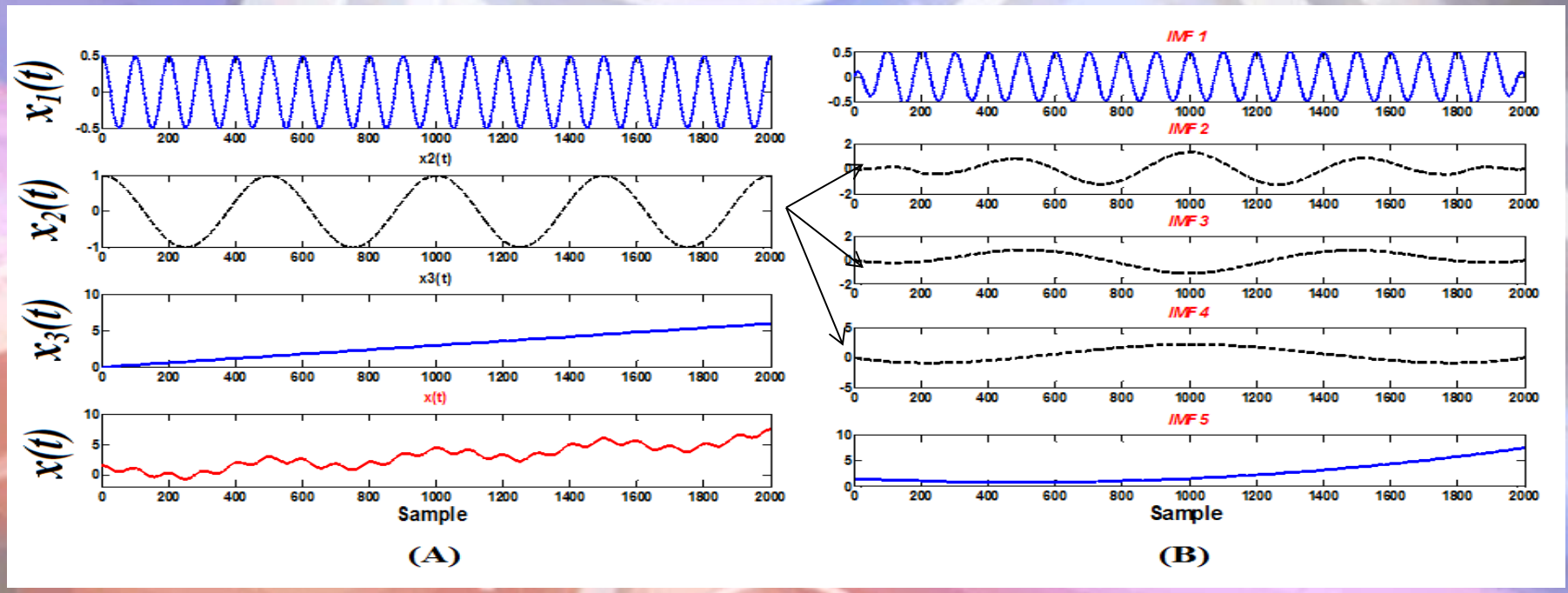


Mode mixing problem with EMD

Example:

$$x(t) = x_1(t) + x_2(t) + x_3(t)$$

$$\begin{cases} x_1(t) = 0.5\cos(40\pi t) \\ x_2(t) = \cos(8\pi t) \\ x_3(t) = 6t \end{cases}$$



The EMD decomposition may give erroneous results

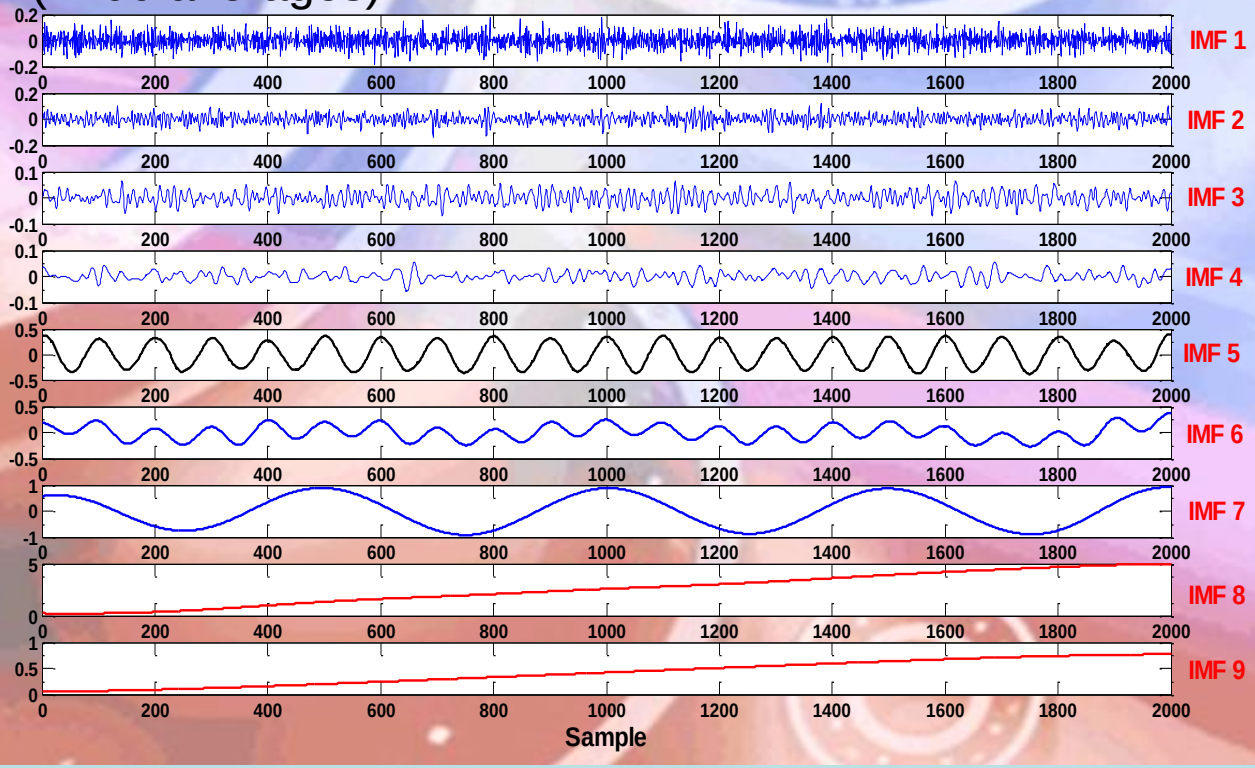
→ **Ensemble EMD**

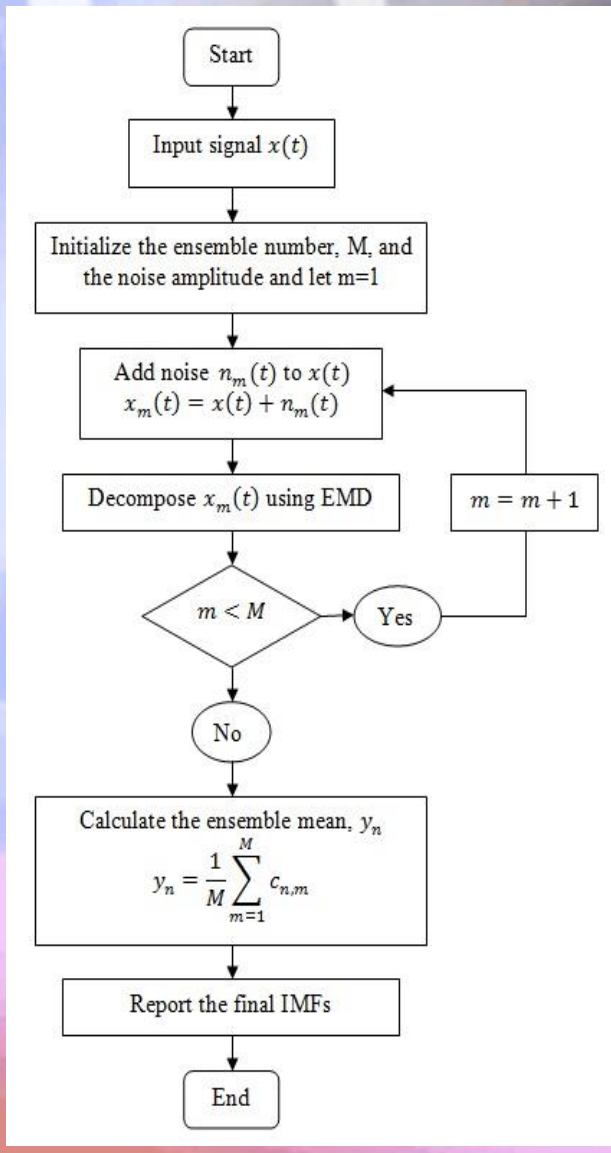
Usual EEMD

A noise must be added to the signal

- The noise level to add is unknown
- Usually **20% of the RMS signal** is arbitrary selected

This method takes time (>100 averages)



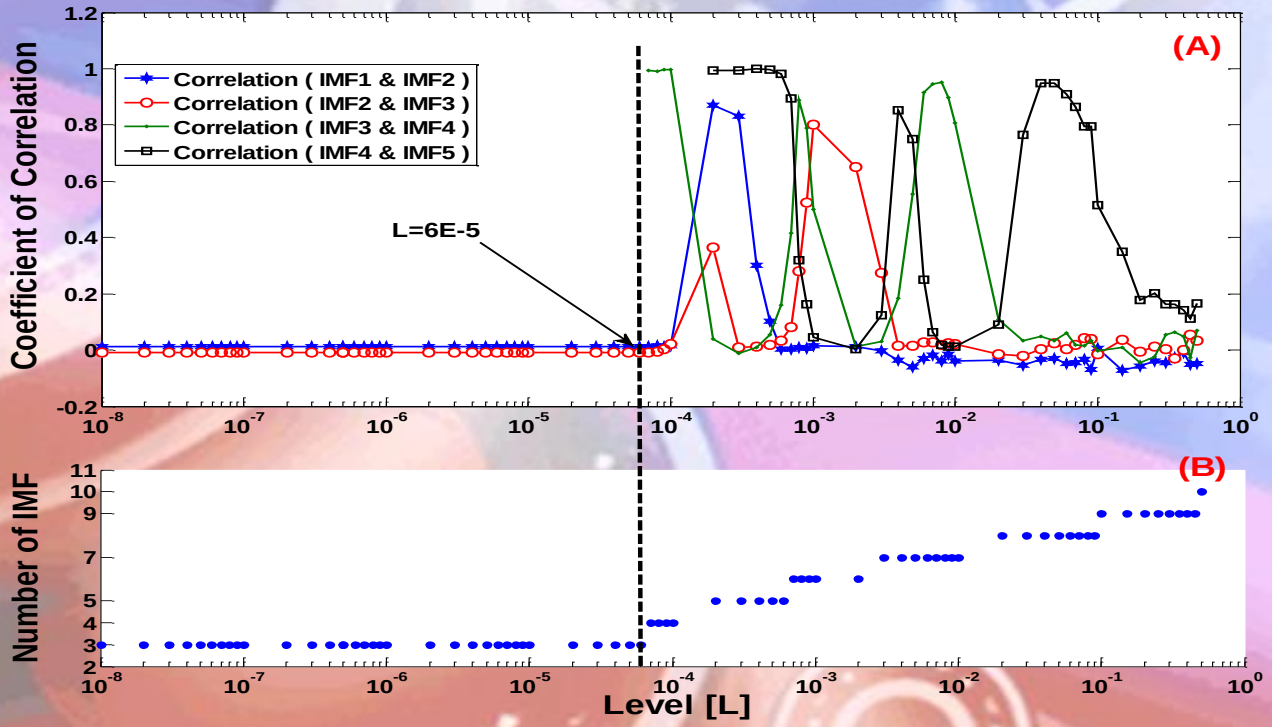


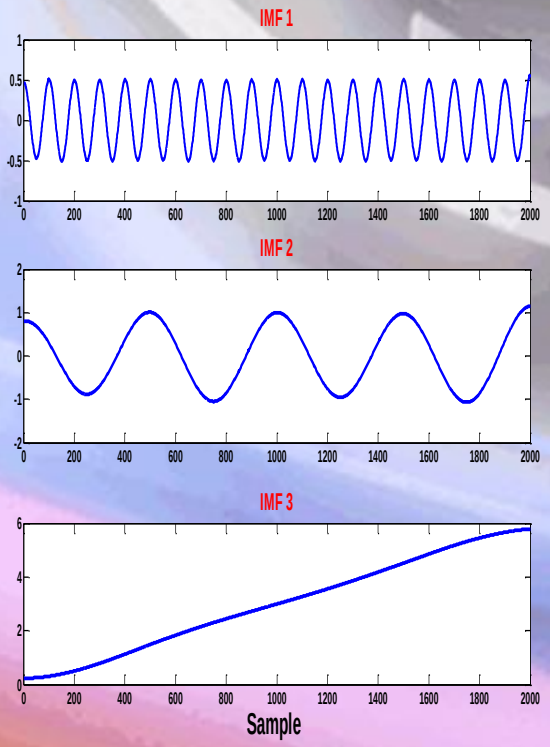
Wu Z H and Huang N E. Ensemble empirical mode decomposition: a noise assisted data analysis method Adv. Adapt. Data Anal (2009). 1 1–41

Optimum EEMD

The correlation between each subsequent IMF is computed with the noise level in order to find the optimal noise level.

$$r(k) = \frac{\sum_{i=1}^{N}(IMF_k(i) - (\overline{IMF_k})(IMF_{k+1}(i) - (\overline{IMF_{k+1}})}{\sqrt{\sum_{i=1}^{N}(IMF_k(i) - (\overline{IMF_k})^2}\ \sqrt{\sum_{i=1}^{N}(IMF_{k+1}(i) - (\overline{IMF_{k+1}})^2}}$$





The IMF (3) is identified in this case

M. Kedadouche, M. Thomas and A. Tahan. 2015. A comparative study between Empirical wavelet transforms (EWT) and Empirical Mode Decomposition methods: Application to bearing defects , submitted to MSSP

Complementary Ensemble Empirical Mode decomposition (CEEMD)

- The method consists in adding and removing the noise in order to generate two series.

$$x_1(t) = x(t) + w_n(t)$$
$$x_2(t) = x(t) - w_n(t)$$

The resulting IMF is the mean of the two results: $\mathrm{IMF}_j(t) = \frac{1}{2N_e}\sum_{i-1}^{N_e}\left[c_{ij}^{+}(t) + c_{ij}^{-}(t)\right]$

- The methis is faster than EEMD

Yeh J. R., Shieh J. S. et Huang N. E., Complementary Ensemble Empirical Mode Decomposition: A novel noise enhanced data analysis method, Advances in Adaptive Data Analysis, 2 (2) (2010) 135-156.

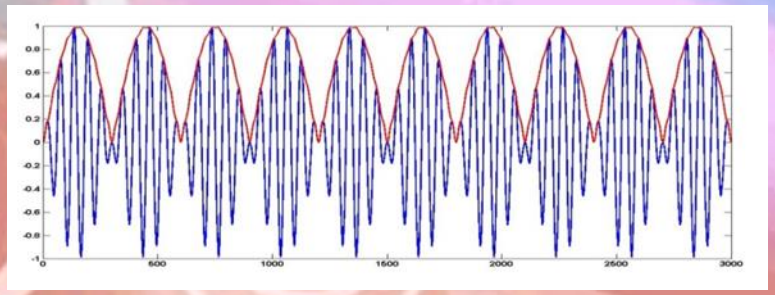
Teager Kaiser Energy Operator (TKEO)

$$\Psi\big(x(t)\big) = [\dot{x}\,(t)]^2 - x(t)\ddot{x}(t)$$

$$\Psi\big(x(n)\big) = [x(n)]^2 - x(n+1)x(n-1)$$

TKEO extracts the amplitude modulation and the frequency modulation from the signal.
TKEO has a great time resolution since the operator **only needs three samples** into the signal to be computed.
TKEO is very easy to implement efficiently**.**

$$|a(t)| \approx \frac{\Psi(x(n))}{\sqrt{\Psi(\dot{x}(n))}},$$



$$f(t) \approx \frac{1}{2\pi}\sqrt{\frac{\Psi(\dot{x}(n))}{\Psi(x(n))}}$$

Maragos, P., J. F. Kaiser et T. F. Quatieri. 1993. « *On amplitude and frequency demodulation using energy operators* ». Signal Processing, IEEE Transactions on, vol. 41, no 4, p. 1532-1550.

Numerical application of TKEO

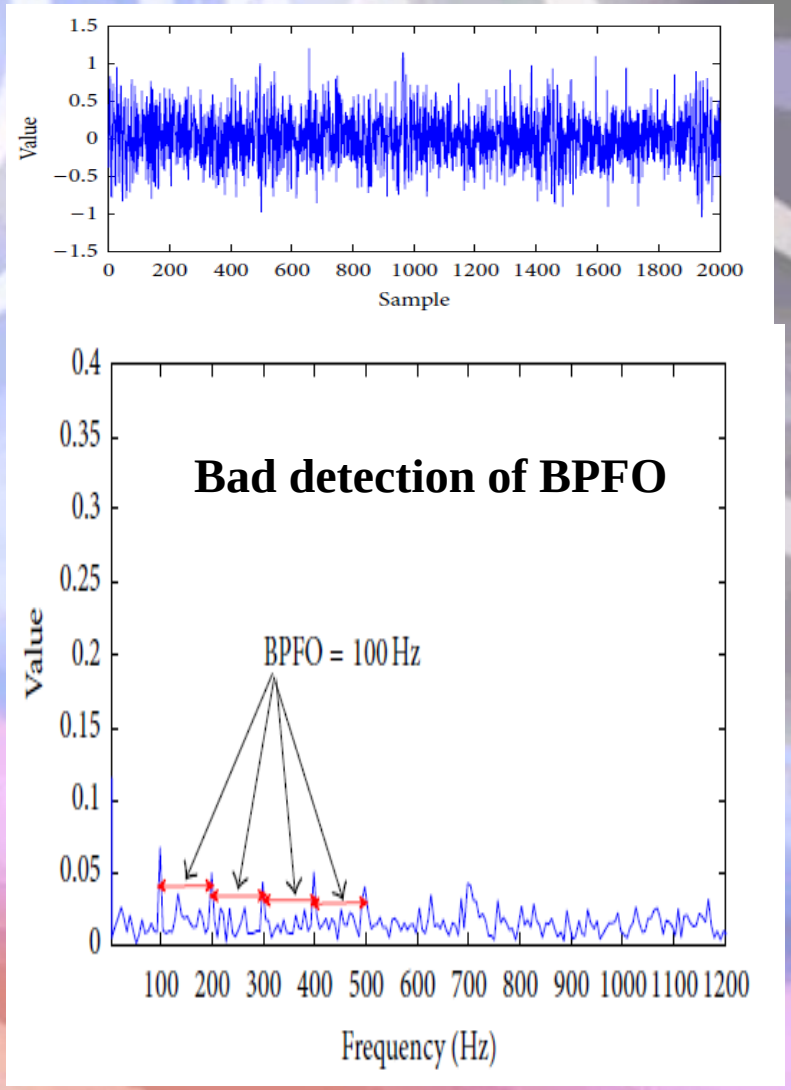
$$x(t) = e^{-\alpha \grave{t}}(A\sin(2\pi f_1 t) + B\sin(2\pi f_2 t)) + n(t)$$

$$\grave{t} = mode\left(t, \frac{1}{F_m}\right)$$

$$n(t) \sim N(0, 0.3)$$

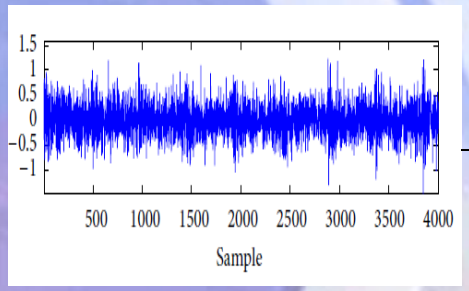
Fm=BPFO	*f1*	*f2*	A	B
100 Hz	1800 Hz	4000 Hz	0,1	0,8

- **The signal needs to be mono component and must be previously filtered.**
- **TKEO is very sensitive to noise and the signal needs to be previously unnoised**

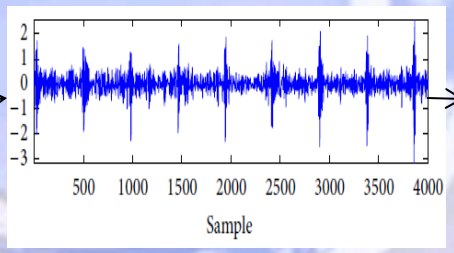


Sheen, Yuh-Tay. 2004. « A complex filter for vibration signal demodulation in bearing defect diagnosis ». Journal of Sound and Vibration, vol. 276, no 1–2, p. 105-119.

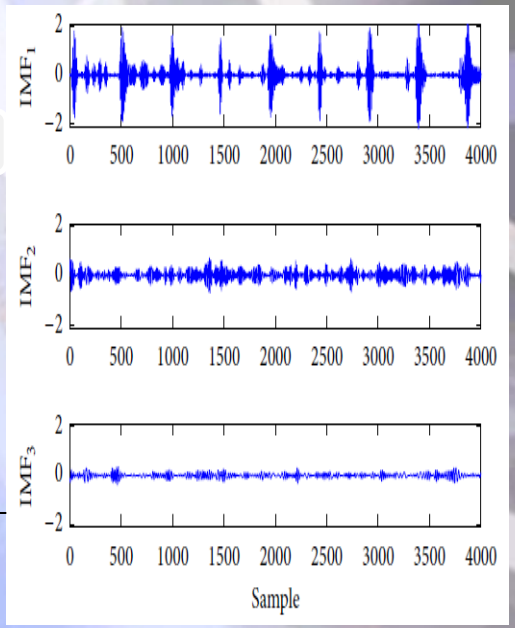
Monitoring Machines by Using a Hybrid Method Combining MED, EMD, and TKEO



MED



EMD



Multi-components and noisy signal

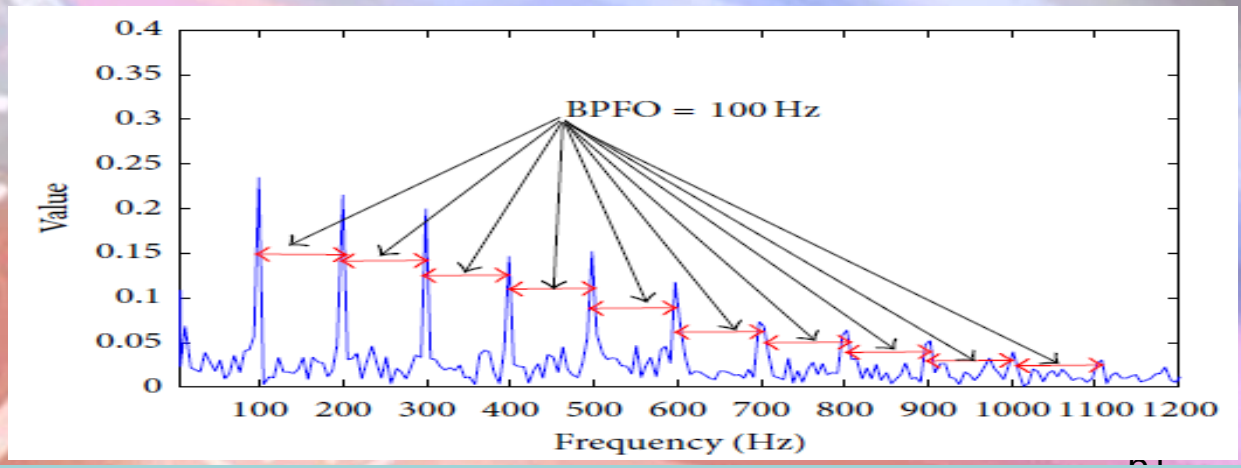
Denoising the signal

IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	IMF 6	IMF 7	IMF 8	IMF 9	IMF 10	IMF 11
0.86	0.53	0.16	0.22	0.17	0.12	0.07	0.06	0.04	0.03	0.01

Correlation

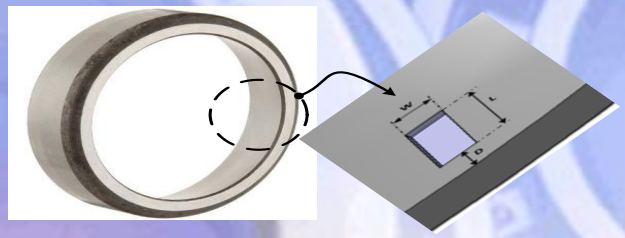
Selection of the most correlated IMF to the signal

TKEO of IMF1

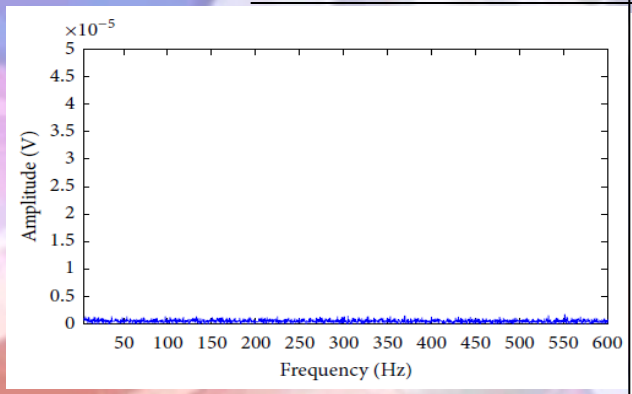
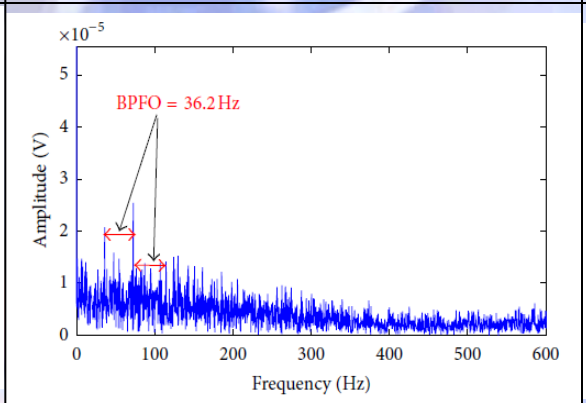
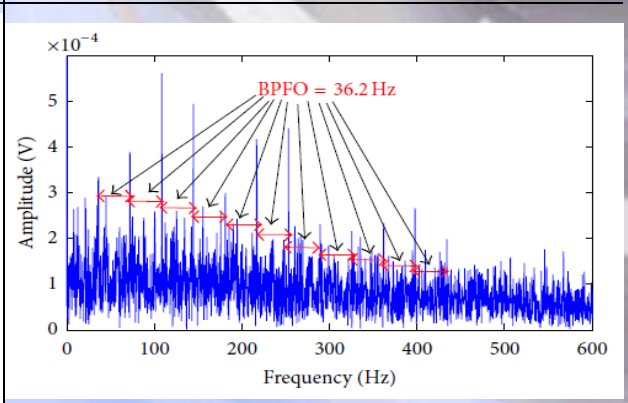
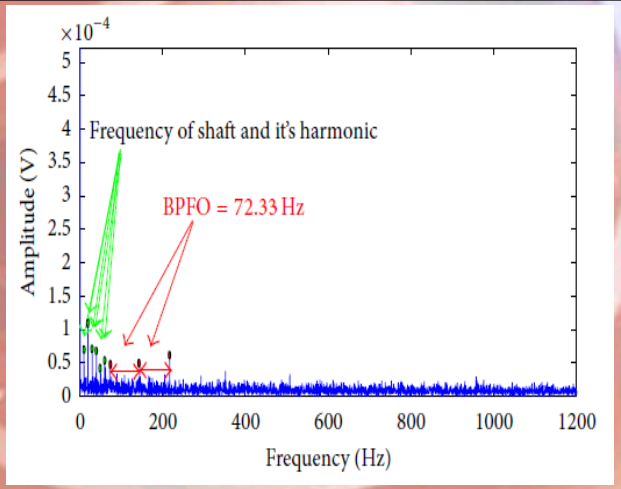
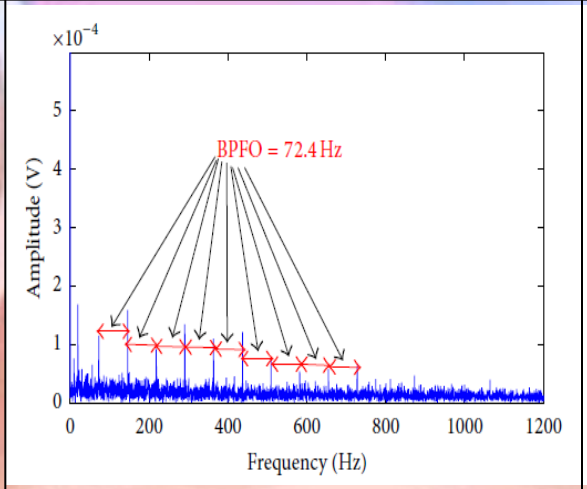
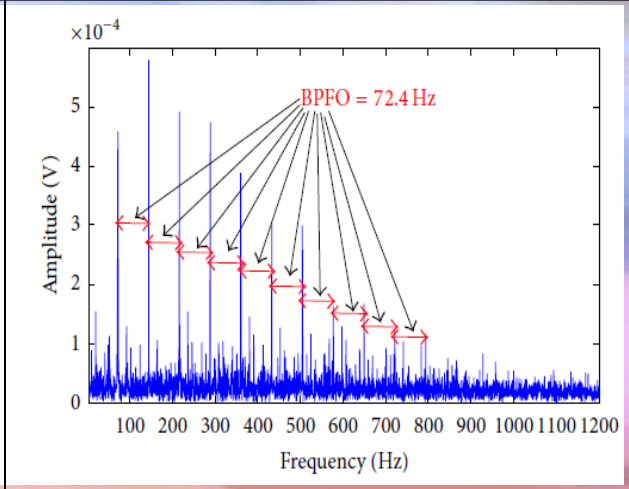


M. Kedadouche, M. Thomas and A. Tahan, 21 april 2014. *Monitoring bearing defects by using a method combining EMD, MED and TKEO*. Advances in Acoustics and Vibration., Vol 2014, ID 502080,10 p.

Experiments on test bench of bearing fault detection by mixing MED, EMD, and TKEO from acoustic emission



Bearing	W
Healthy	0
Defect 1	50 µm
Defect 2	100 µm

	D0	D1	D2
300 rpm			
600 rpm			

Envelope-Derivative Operator (EDO)

- The EDO is given by:

$$\Gamma[x(t)] = \left|\dot{x}(t) + jH[\dot{x}(n)]\right|^2 = \dot{x}^2(t) + H[\dot{x}(n)]^2$$

- For a discrete signal x(n), the EDO is defined in discrete format by (6)

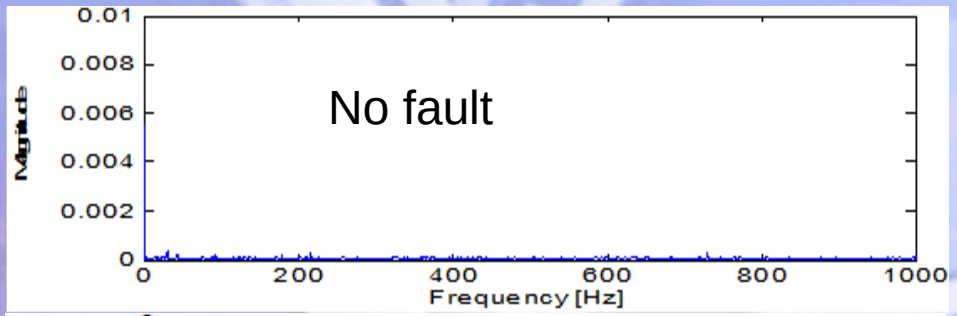
$$\Gamma[x(t)] = \frac{1}{4}\left[x^2(n+1) + x^2(n-1) + h^2(n+1) + h^2(n-1)\right]$$

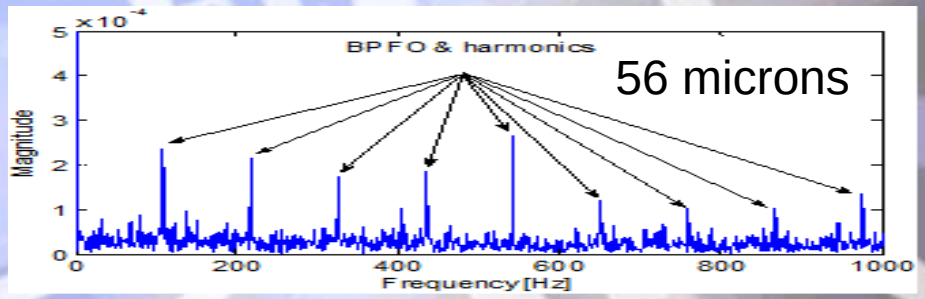
$$+ \frac{1}{2}\left[x(n+1) + x(n-1) + h(n+1) + h(n-1)\right]$$

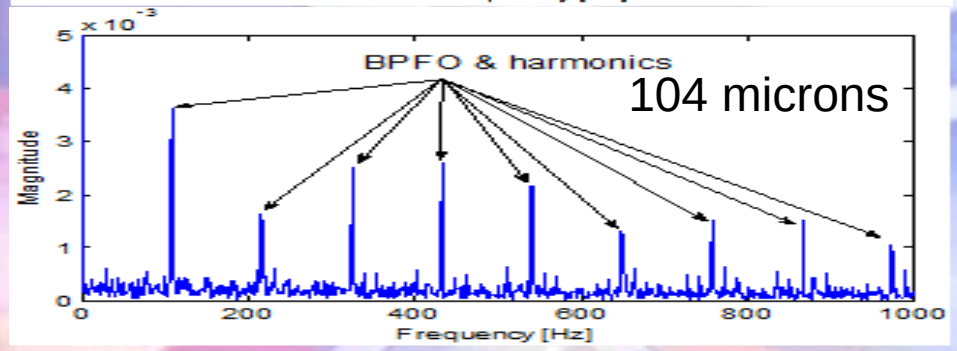
where h(n) is the discrete Hilbert transform and defined as h(n) = H[x(n)].

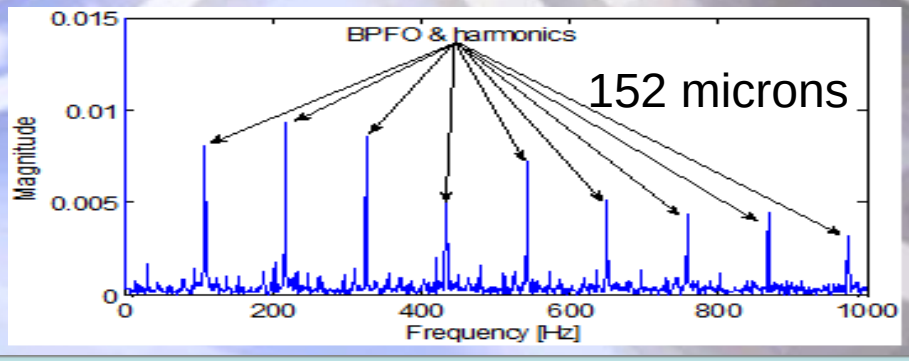
J.M.O. Toole, A. Temko and N. Stevenson, *Assessing instantaneous energy in the EEG: a non-negative, frequency-weighted energy operator*, IEEE conference proceedings, (2014) 3288–3291.

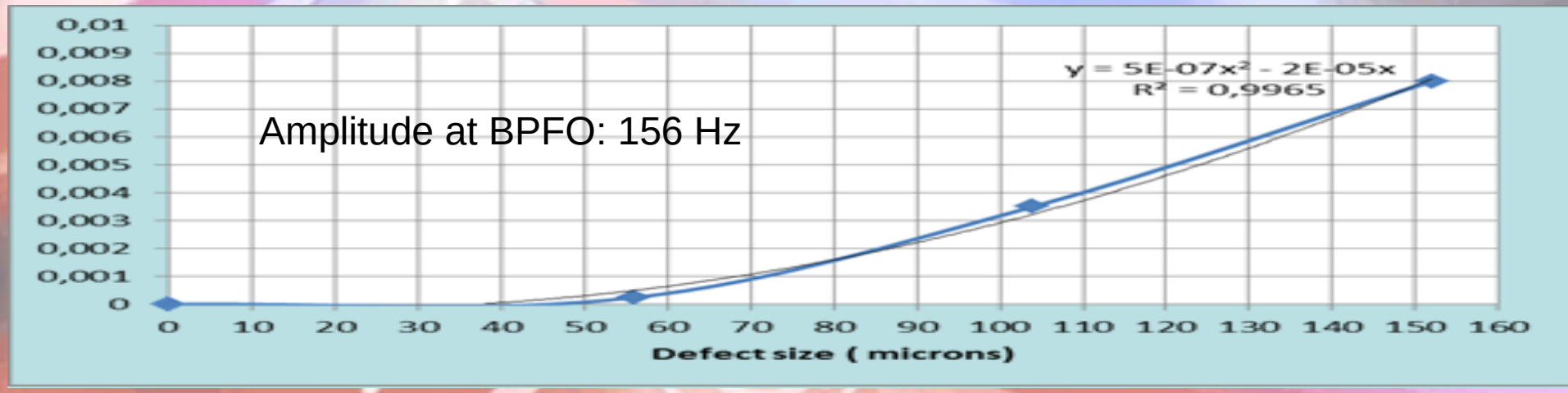
4 experiments of EDO: No fault, 56, 104 and 152 microns







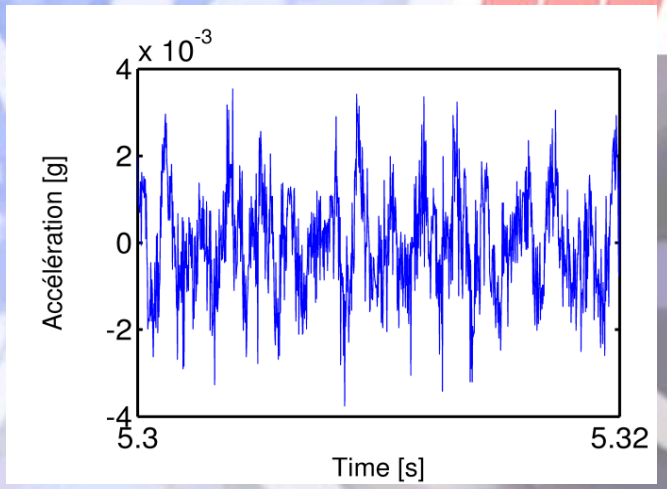




Y. IMAOUCHEN, M. KEDADOUCHE, R. ALKAMA and M. THOMAS, The Envelope-Derivative Operator for Bearing Fault Detection, Surveillance 8

Cyclostationnarity: Computation of angular statistics

1. **Data acquisition (pre-recorded vibration signals)**



2. **Re sampling in the angular domain**

3. **Computation of the angular statistics**

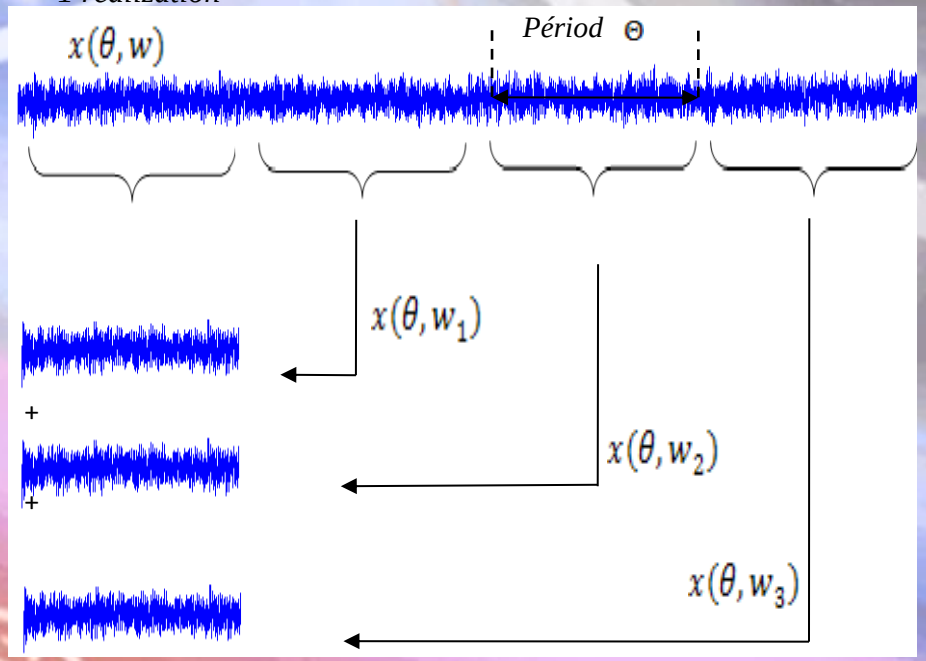
$$m_x(\theta)]_\Theta^K = \frac{1}{K}\sum_{k=0}^{K-1} x[mod(\theta + k\Theta, K\Theta)]$$

$$V_x(\theta)]_\Theta^K = \frac{1}{K}\sum_{k=0}^{K-1} (x[mod(\theta + k\Theta, K\Theta)] - m_x(\theta)]_\Theta^K)^2$$

$$P_x(\theta)]_\Theta^K = \frac{1}{K}\sum_{k=0}^{K-1} (x[mod(\theta + k\Theta, K\Theta)])^2$$

$$Kur_x(\theta)]_\Theta^K = \frac{1}{K}\sum_{k=0}^{K-1} \{(x[mod(\theta + k\Theta, K\Theta)] - m_x(\theta)]_\Theta^K)^4\}/(V_x(\theta)]_\Theta^K)^2$$

1 réalization

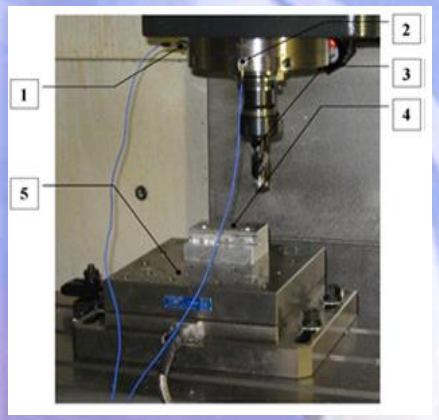


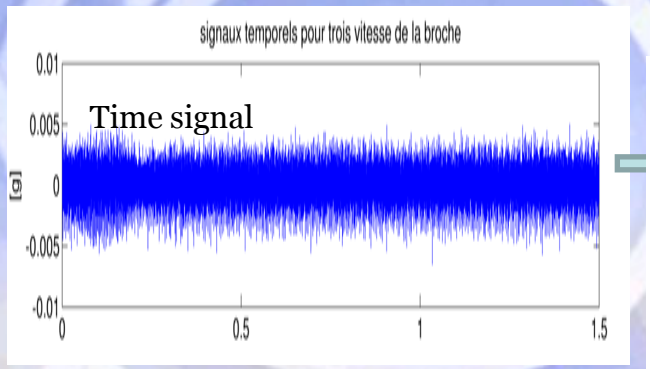
Angular statistics= angular mean, variance, power, Kurtosis

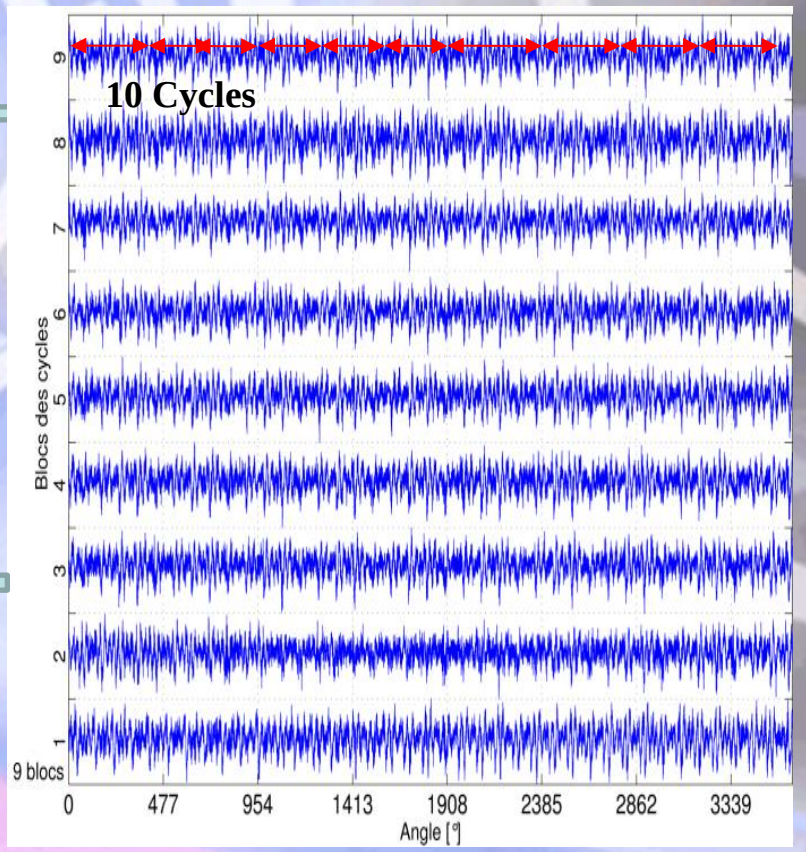
4) **Angular analysis (FFT, Angle-frequency, etc.)**

Lamraoui M., Thomas M., El Badaoui M. et Zaghbani I., Juin 2010. *Le kurtosis angulaire comme outil de diagnostic*, Vibration, Choc et bruit (VCB2010), Lyon, France, article AC 29, 21 p.

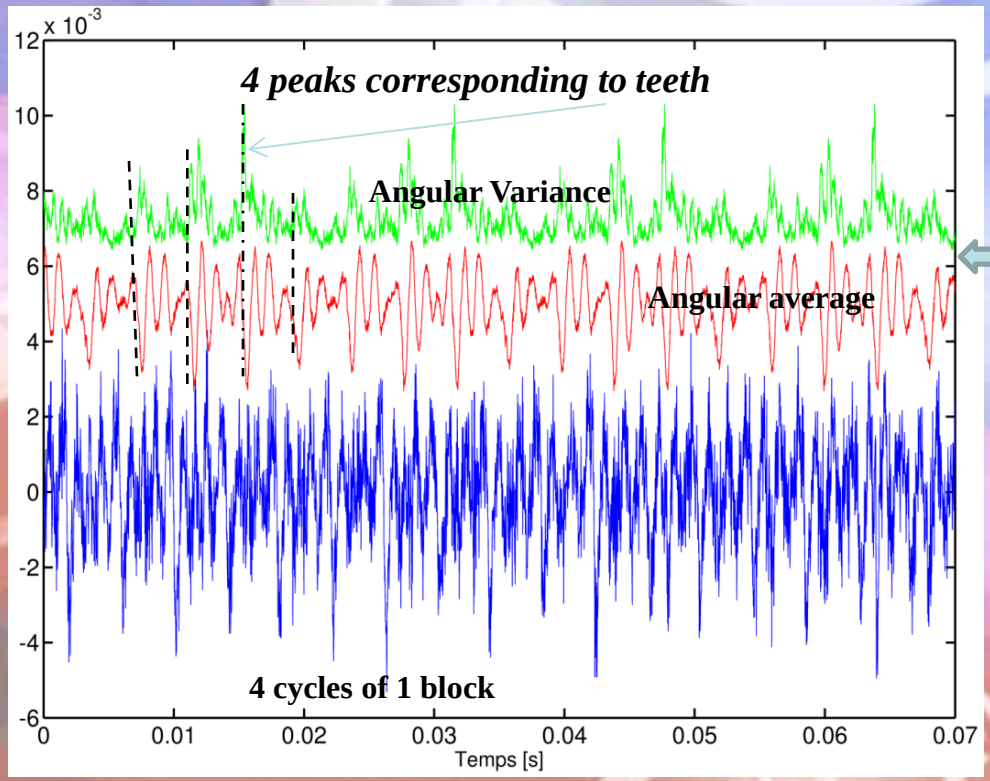
Applying cyclostationnarity to machining







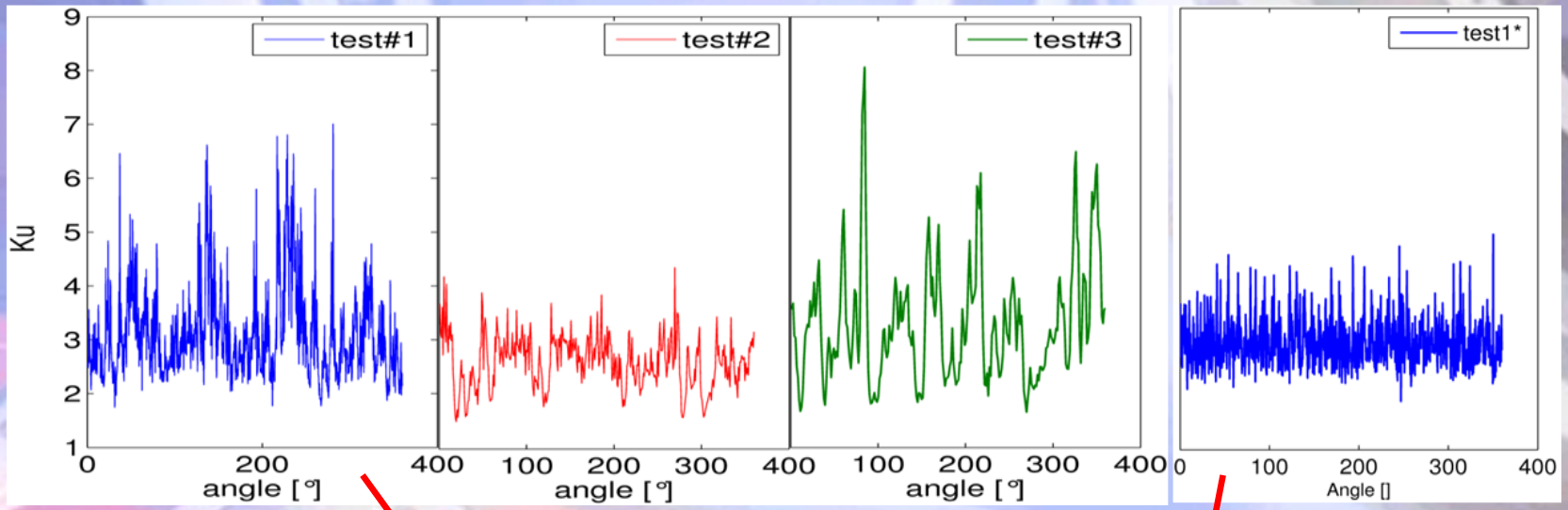
Blocks of cycles after synchronization, (10 cycles by block)



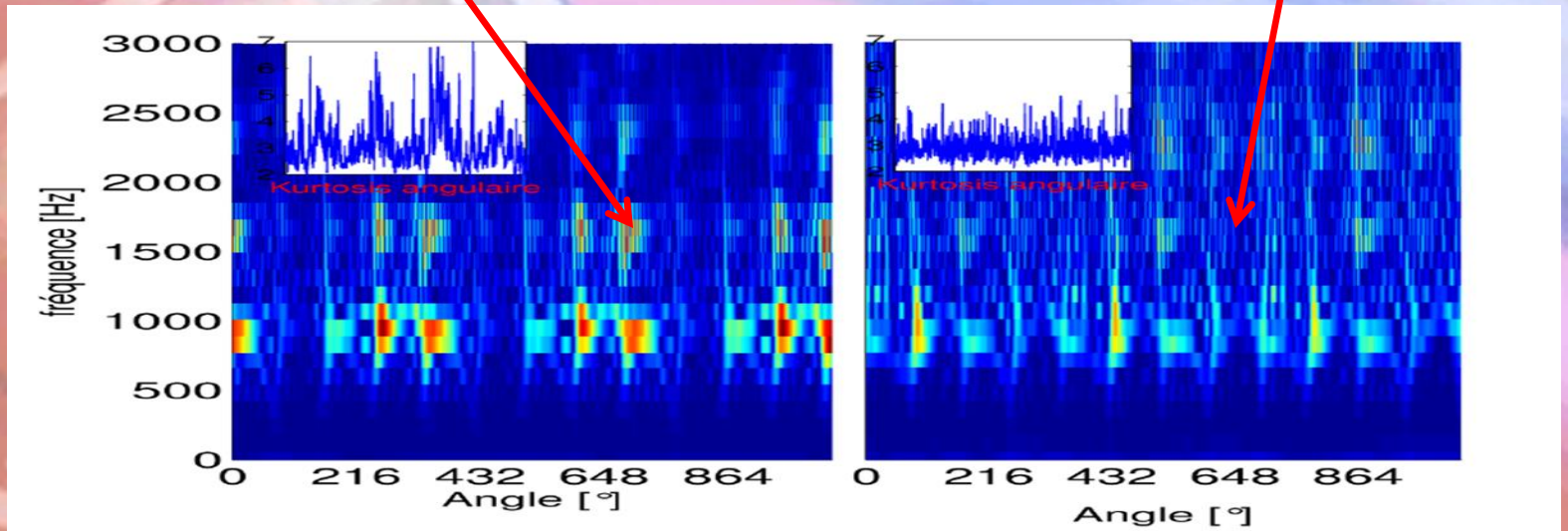
Signal (blue) with its mean (red) and angular variance (green)

Lamraoui M., Thomas M., El Badaoui M. et Zaghbani I., Juin 2010. *Le kurtosis angulaire comme outil de diagnostic*, Vibration, Choc et bruit (VCB2010), Lyon, France, article AC 29, 21 p.

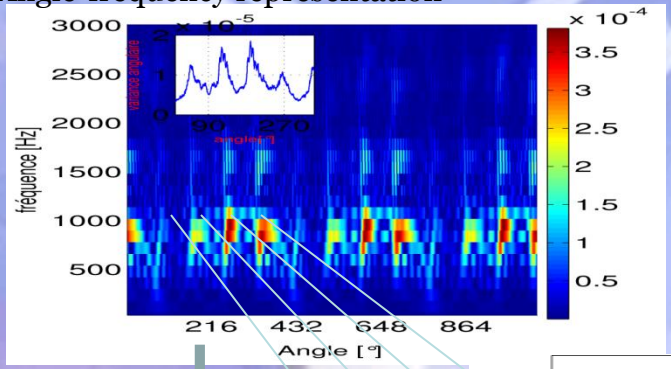
The Angular Kurtosis decreases when chatter or tool wear



Healthy tool Chatter In resonance After tool wear



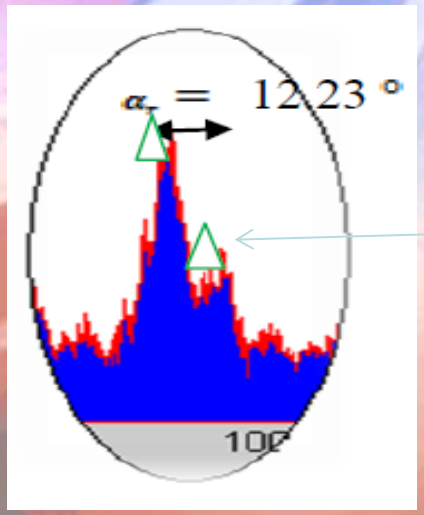
Angle-frequency representation



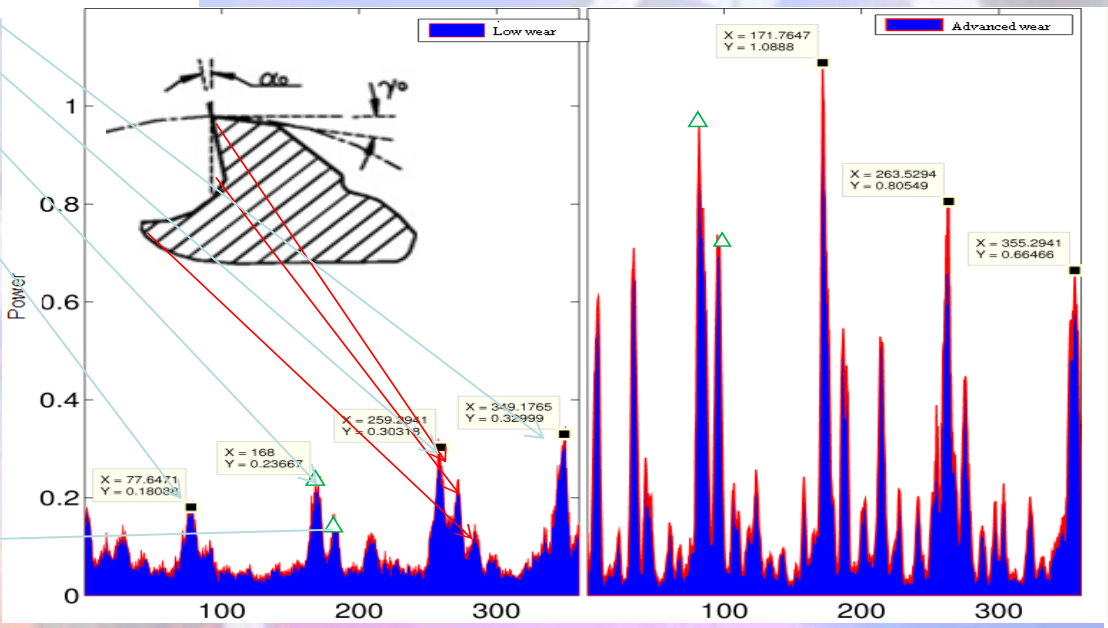
Effect of tool wear on the angular power

For an important wear, a strong increase of the angular power amplitude is detected

The 4 peaks are corresponding to the passage of every tooth.

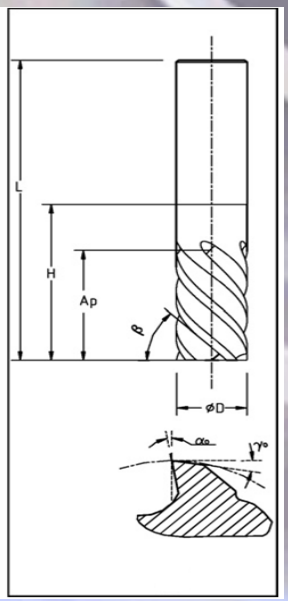


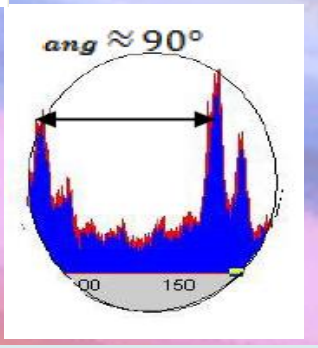
Measurement of rake angle α_γ



Test 1: before wear

Test 4: after wear



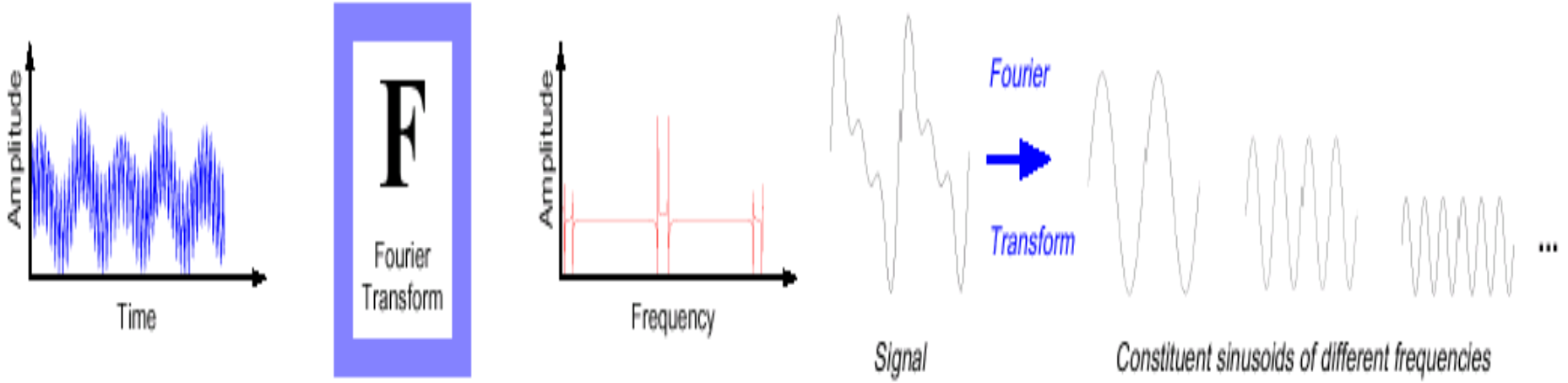


Angle between two teeth

Lamraoui M., Thomas M., El Badaoui M. et Zaghbani I., Juin 2010. *Le kurtosis angulaire comme outil de diagnostic*, Vibration, Choc et bruit (VCB2010), Lyon, France, article AC 29, 21 p.

Frequency Analysis: FFT

- Fourier analysis breaks down a signal into constituent sinusoids of different frequencies.



Bearing frequencies if both races are rotating

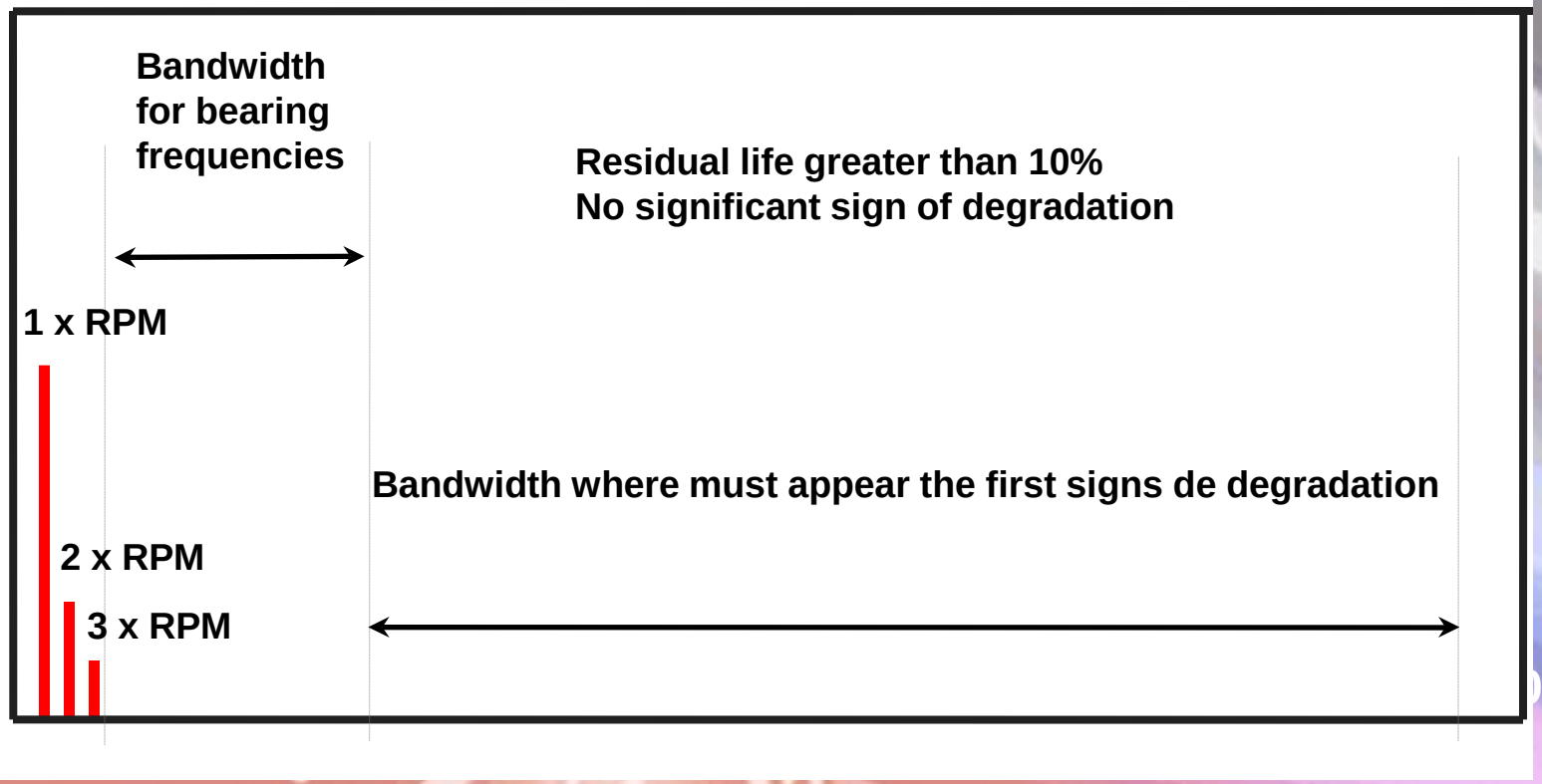
$$FTF = \frac{1}{2}\left[\omega_i\left(1-\frac{B_d\cos\theta}{P_d}\right)+\omega_o\left(1+\frac{B_d\cos\theta}{P_d}\right)\right]$$

$$BPFO = N_B\left(\omega_o - FTF\right)$$

$$BPFI = N_B\left(\omega_i - FTF\right)$$

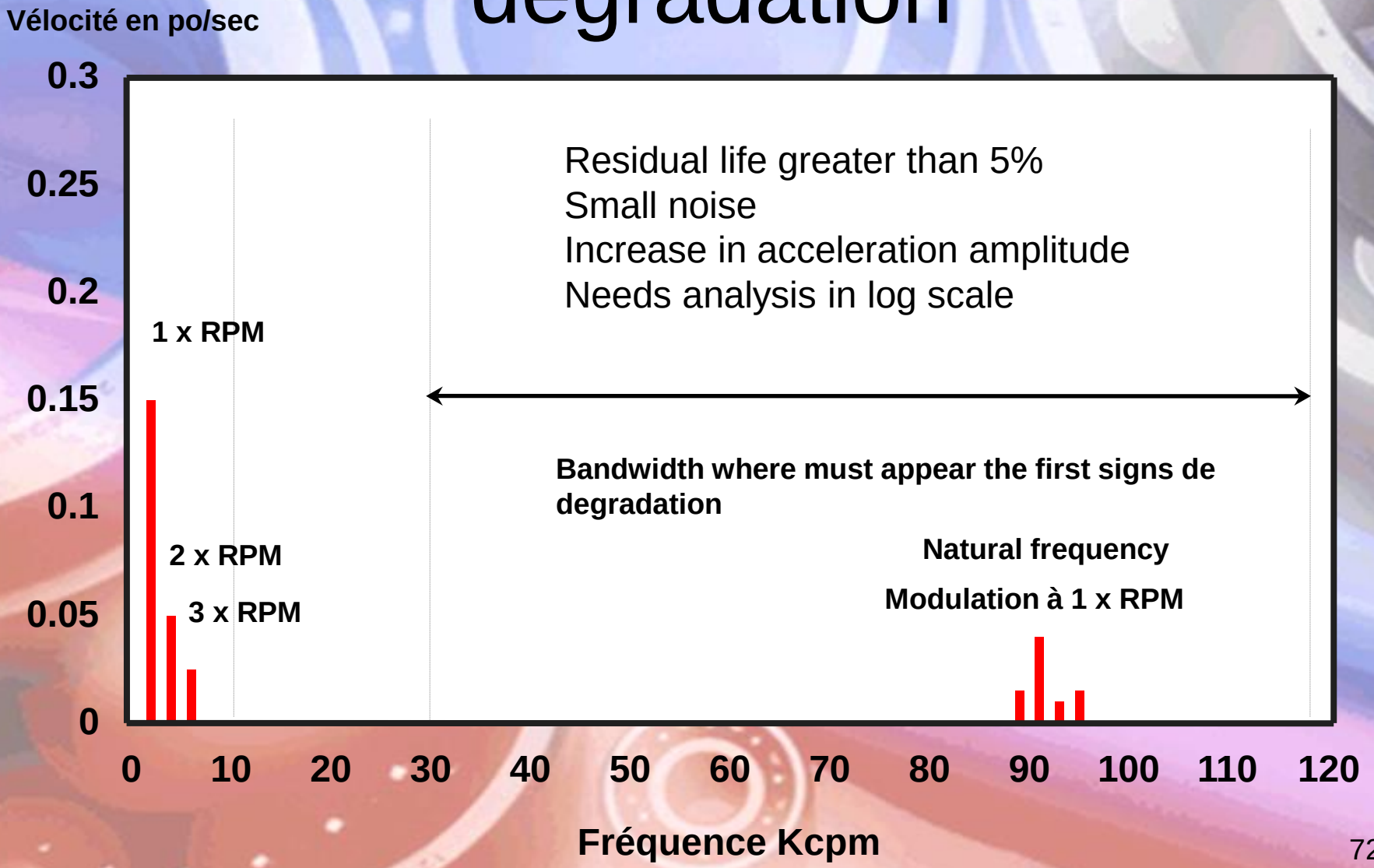
$$BSF = \left(\omega_i - FTF\right)\frac{\left(P_d - B_d\cos\theta\right)}{Bd}$$

First step of bearing degradation



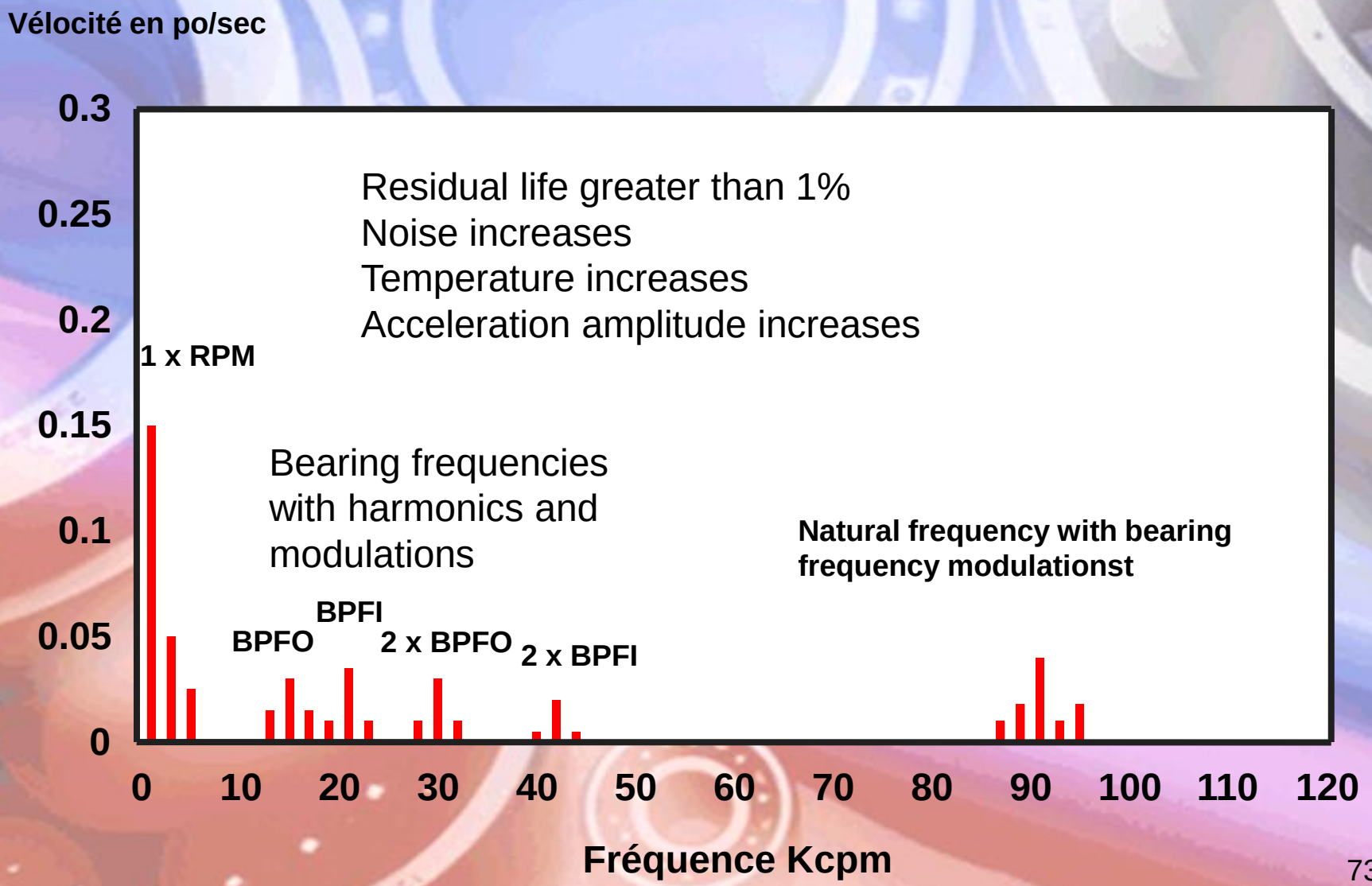
Berry. 1991. « How to track rolling bearing health with vibration signature analysis ». Sound and Vibration, p. 24-35

Second step of bearing degradation



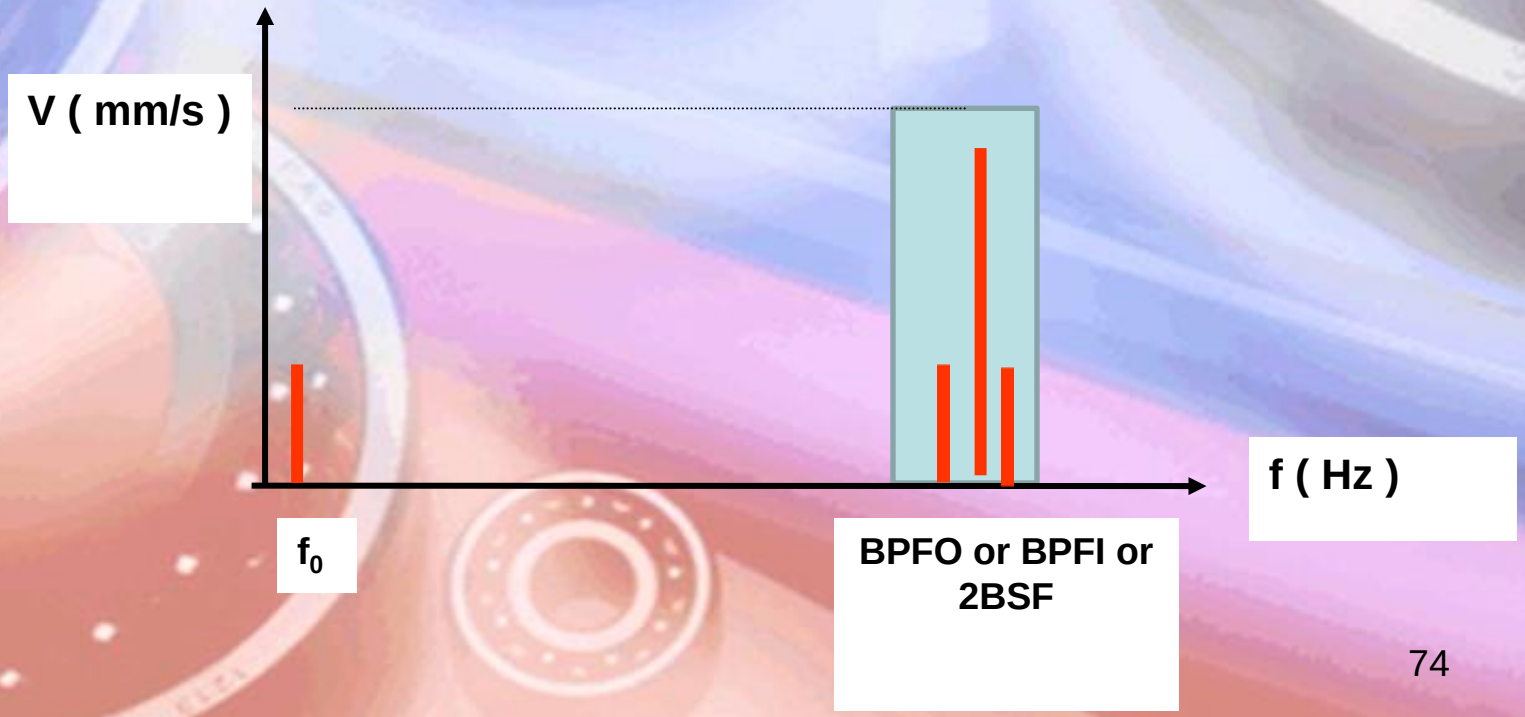
Berry. 1991. « How to track rolling bearing health with vibration signature analysis ». Sound and Vibration, p. 24-35

Third step of bearing degradation

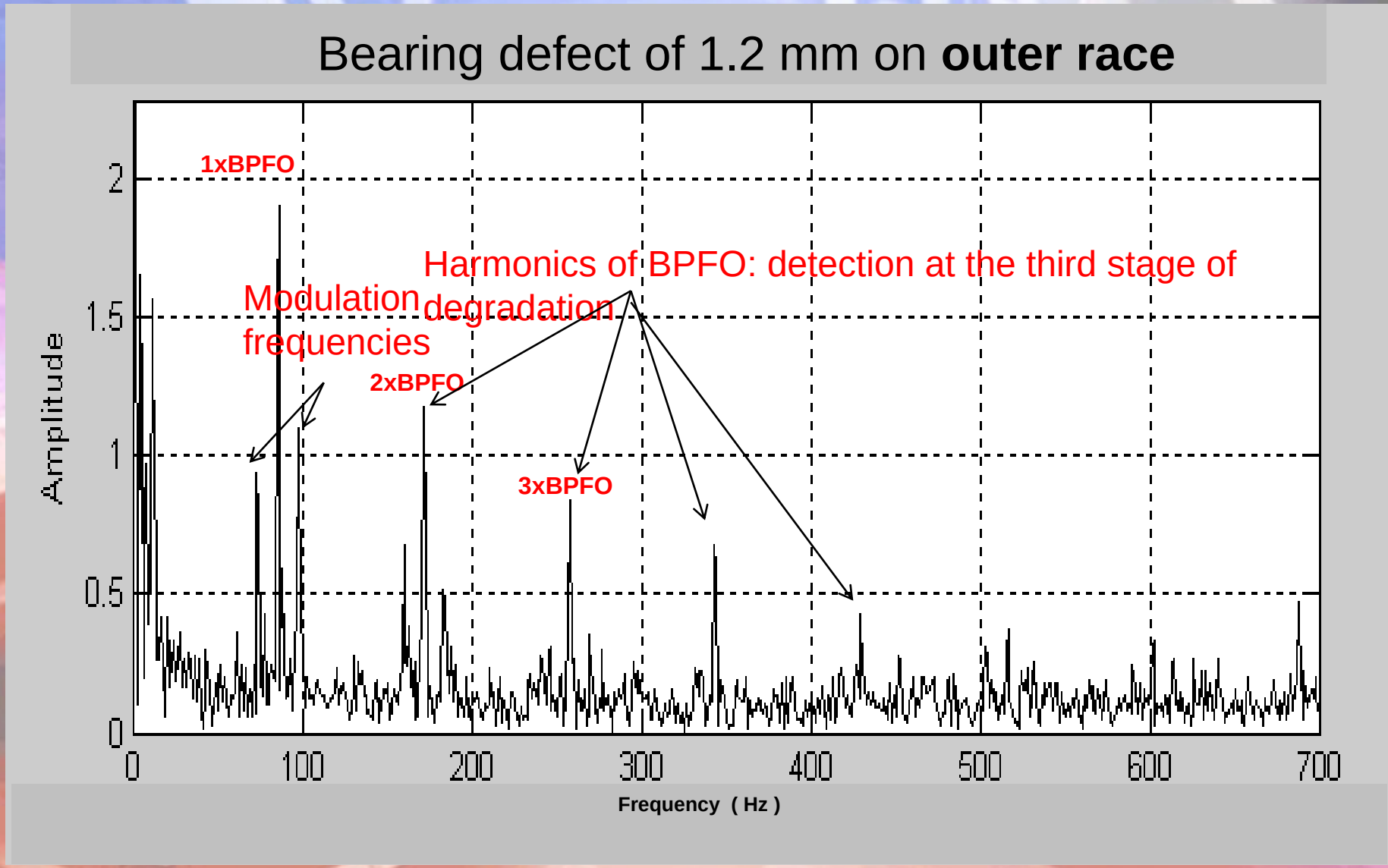


Berry. 1991. « How to track rolling bearing health with vibration signature analysis ». Sound and Vibration, p. 24-35

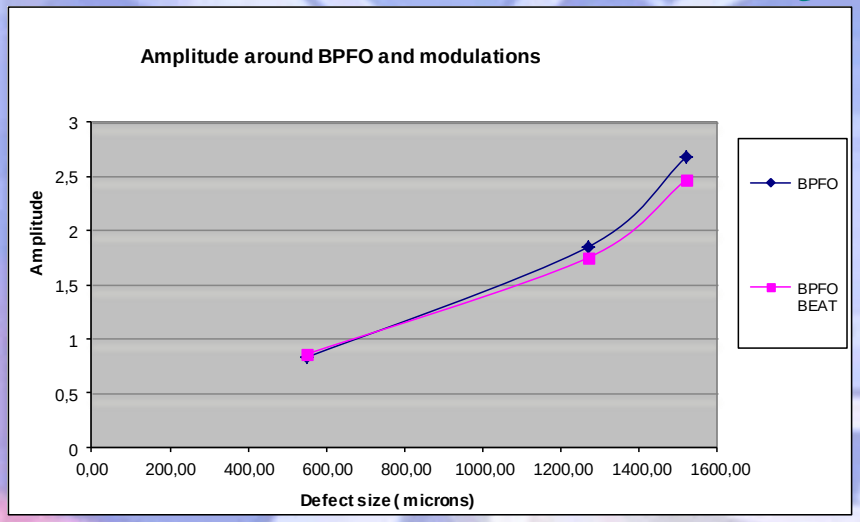
Severity based on amplitude at the bearing frequency



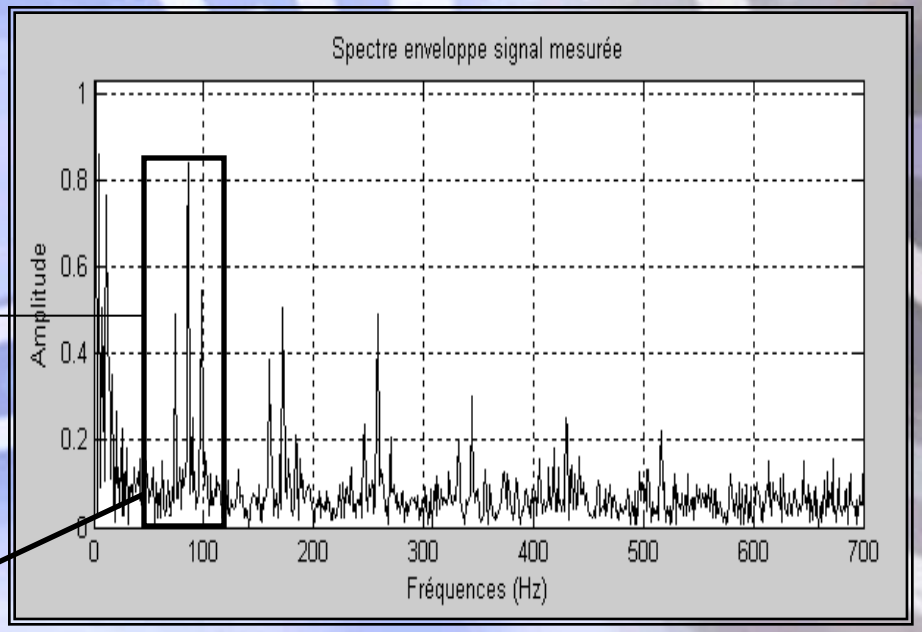
Frequency analysis (FFT) from numerical bearing model

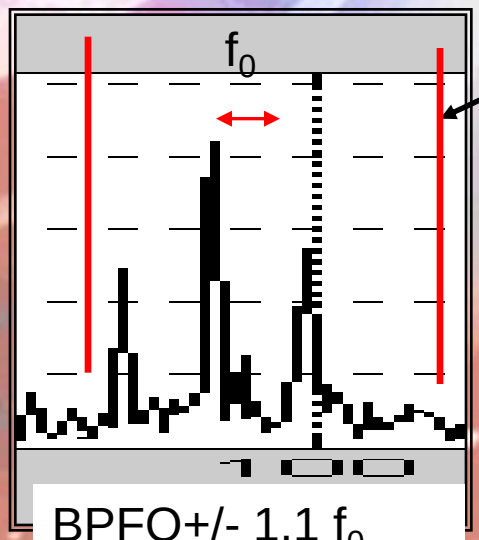


Features in frequency domain



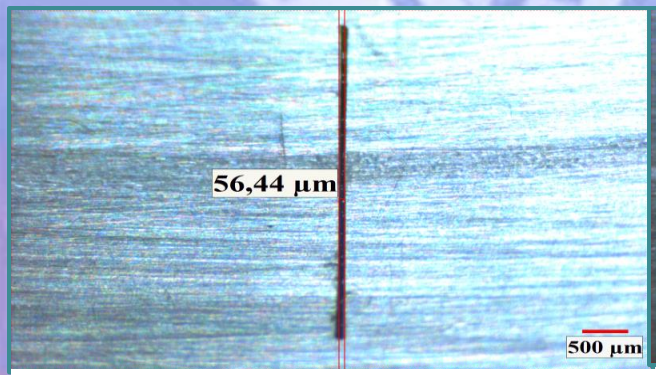
Numerical simulation

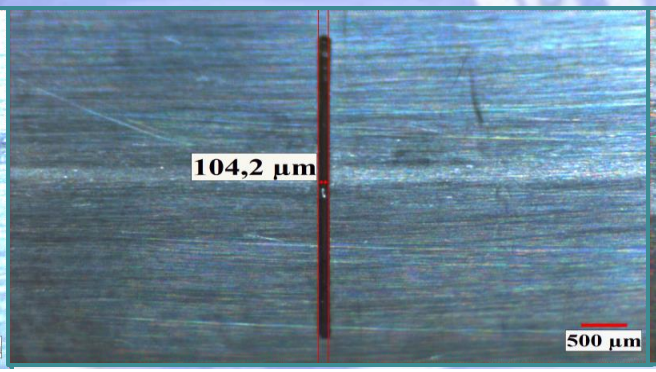


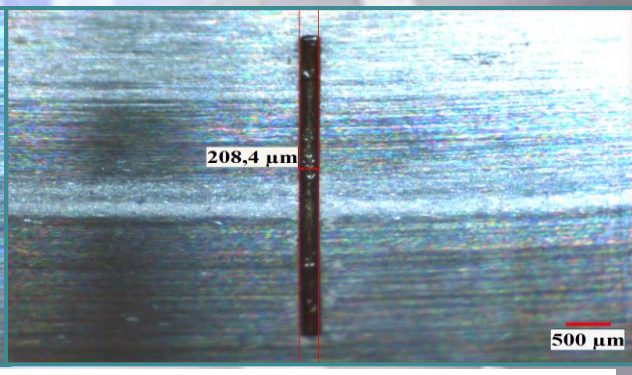


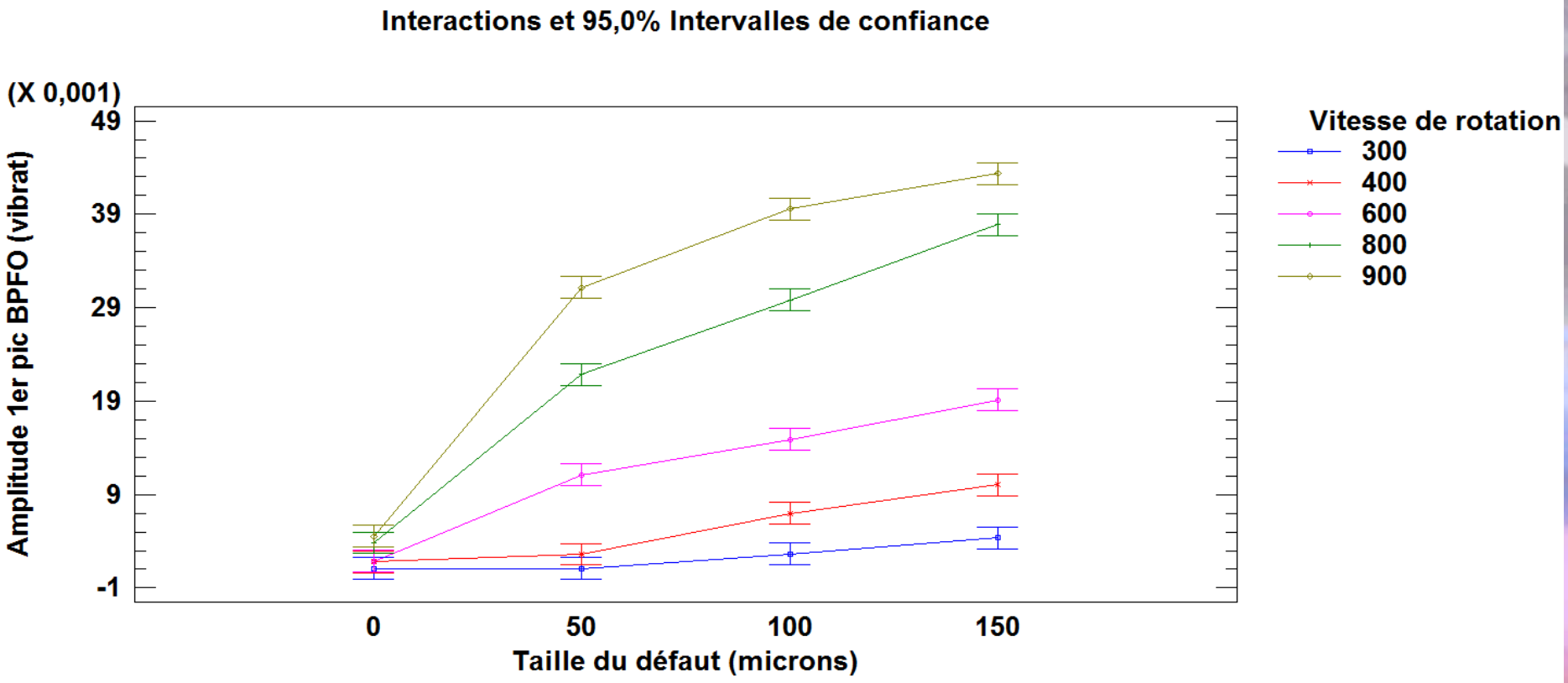
*The features in the frequency domain consider the amplitude at the bearing frequencies and the harmonics (n*BPFO) including the modulations (f_0)*

Design of experiments: 5 speeds, 3 charges, 4 defects, 3 repetitions= 180 experiments

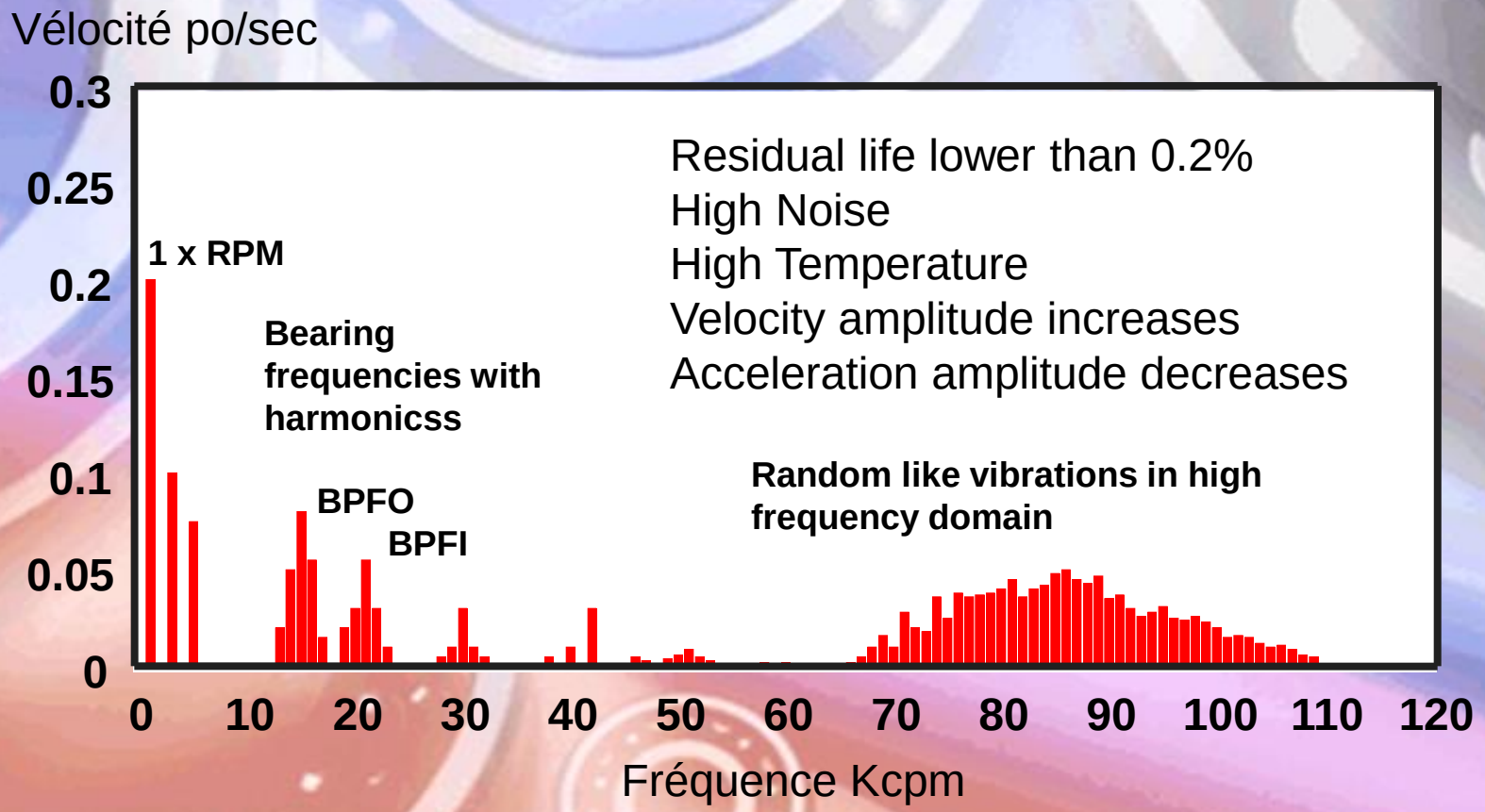








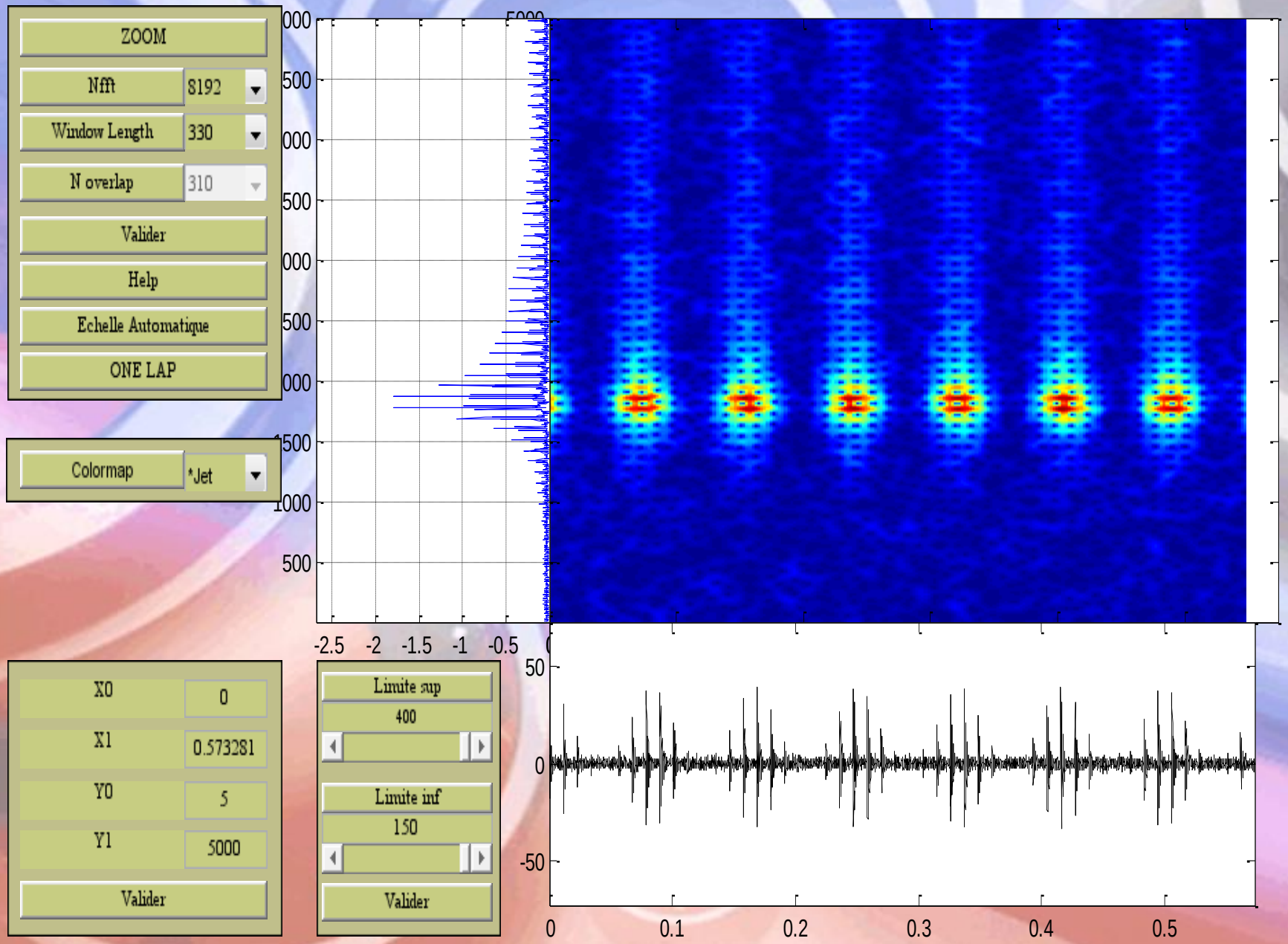
Last stage of bearing degradation



Berry. 1991. « How to track rolling bearing health with vibration signature analysis ». Sound and Vibration, p. 24-35

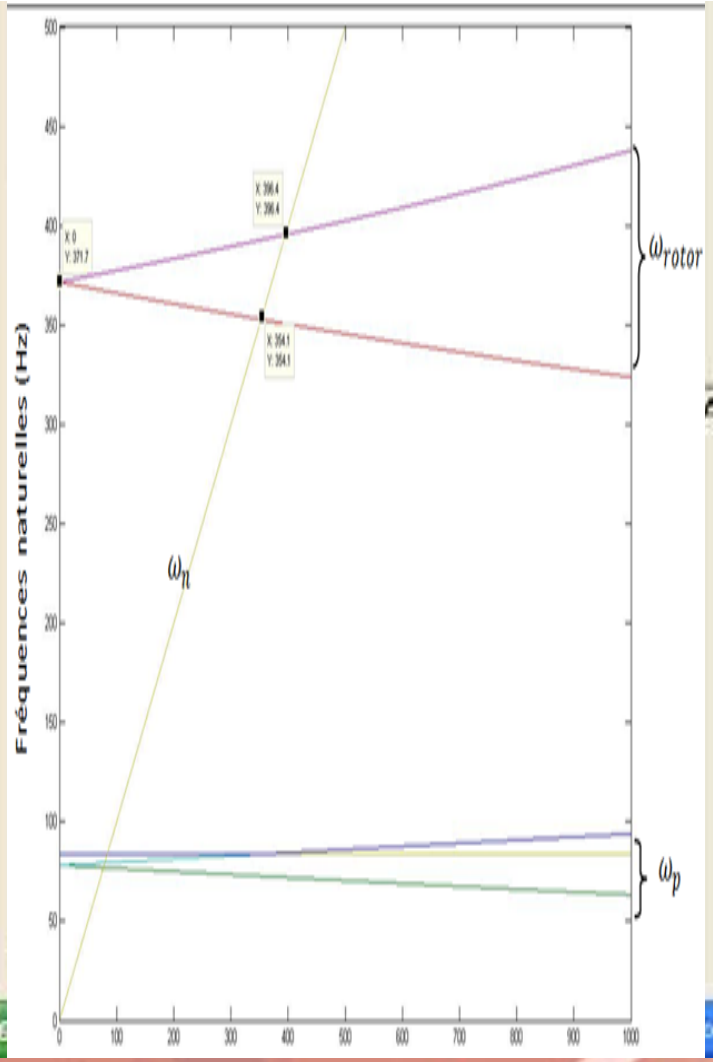
Time-frequency analysis

STFT from numerical bearing model

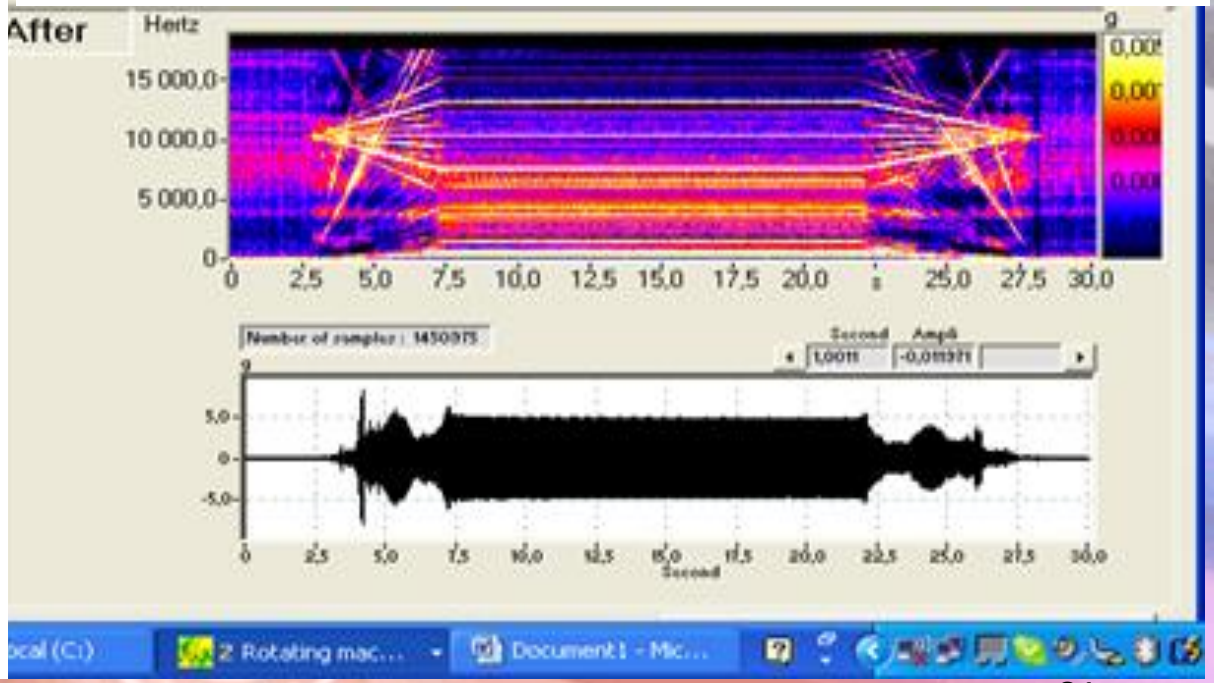


Increase and decrease of speed up to 30 000 rpm on machining center

Computation of variation of natural frequencies with speed due to gyroscopic effect.

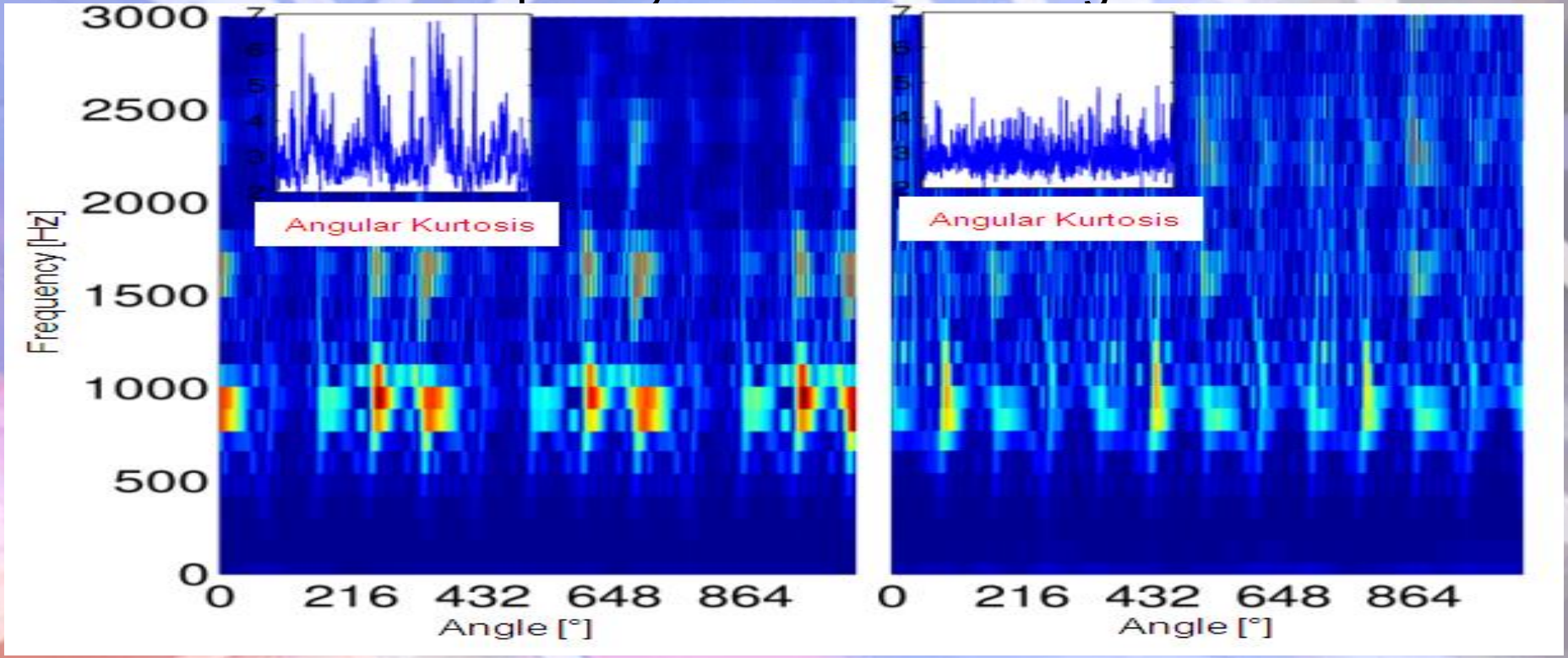


STFT Measurement (after denoising): high vibration observed at 23 000 rpm during transients (up, stable and down speed) due to coincidence between: <u>harmonics of spindle bearing</u> and <u>natural frequencies</u>



Badri B., M. Thomas; S. Sassi; I. Zaghbani; V. Songméné, Juin 2010, *Étude du comportement des roulements dans les rotors tournant à haute vitesse*, Revue Int. sur l'Ingénierie des Risques Industriels, 3(1), 1-16

Application in machining: Cyclostationnarity and Angle-Frequency of the residual signal



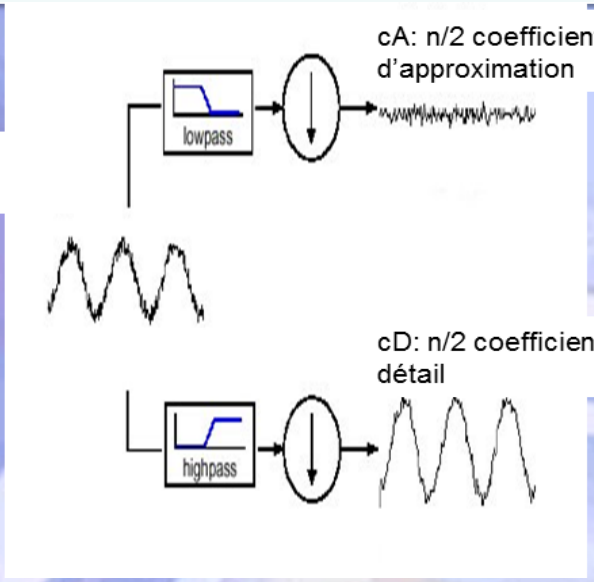
Low wear **Advanced wear**

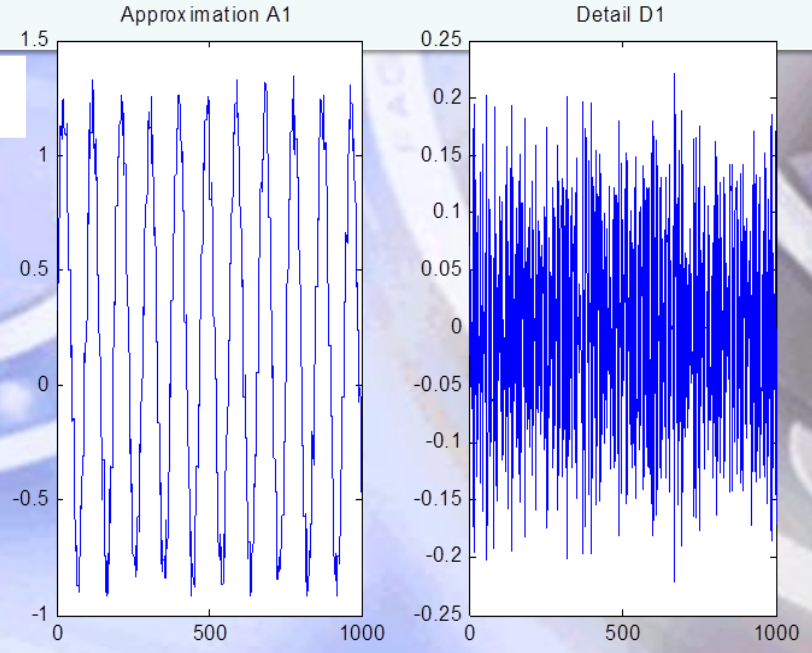
- The peaks corresponding to the four teeth are very well defined when there is no wear.
- When the wear becomes important, the spikes of the angular Kurtosis disappeared and it is less easy to distinguish the frequencies of the residual signal.
- The wear involves a decrease of impulses, and thus a flattening of angular Kurtosis.

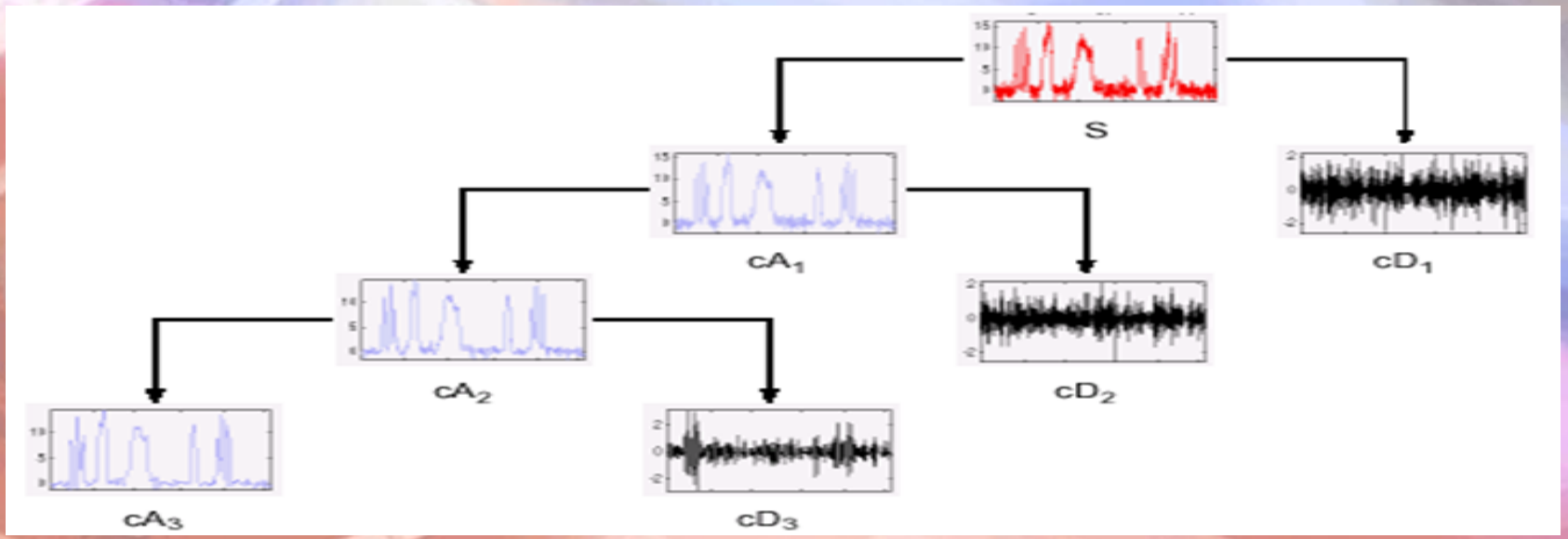
Lamraoui M., Thomas M., El Badaoui M. et Zaghbani I., Juin 2010. *Le kurtosis angulaire comme outil de diagnostic*, Vibration, Choc et bruit (VCB2010), Lyon, France, article AC 29, 21 p.

Wavelet decomposition

Signal s: n échantillons

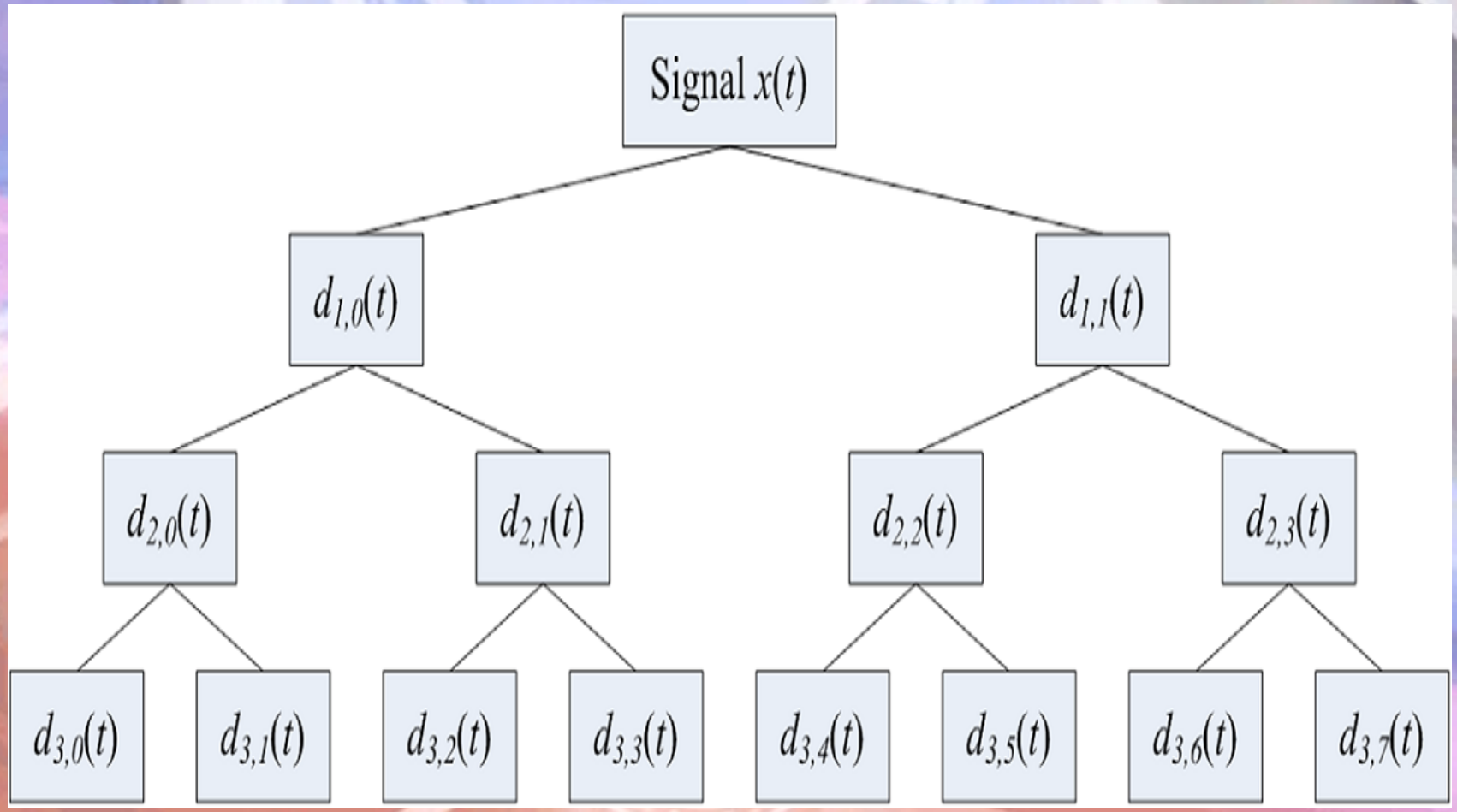




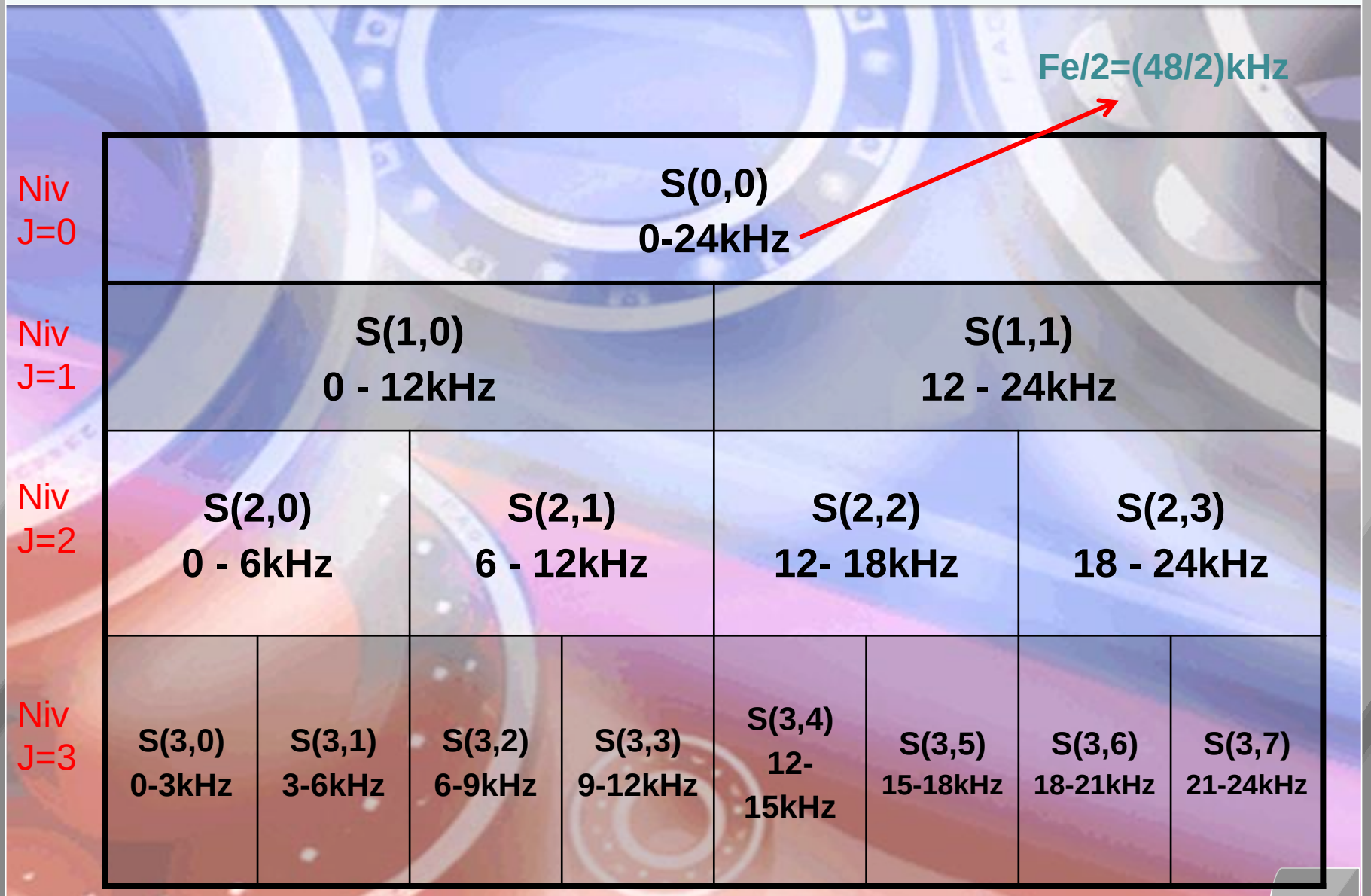


Wavelet Packet Decomposition

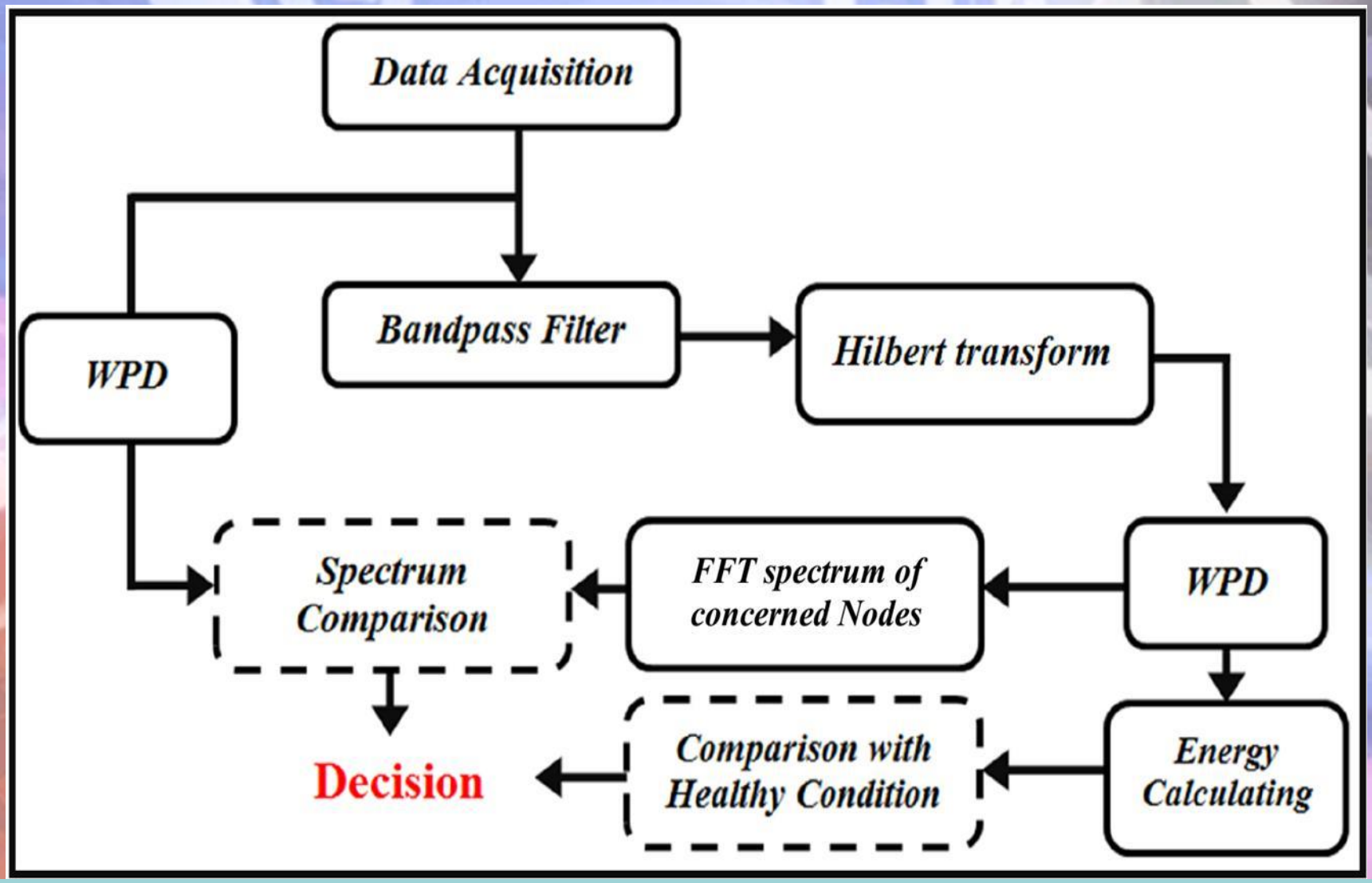
Example: Three-level Wavelet Packet Decomposition tree



WPD Wavelet Packet Decomposition

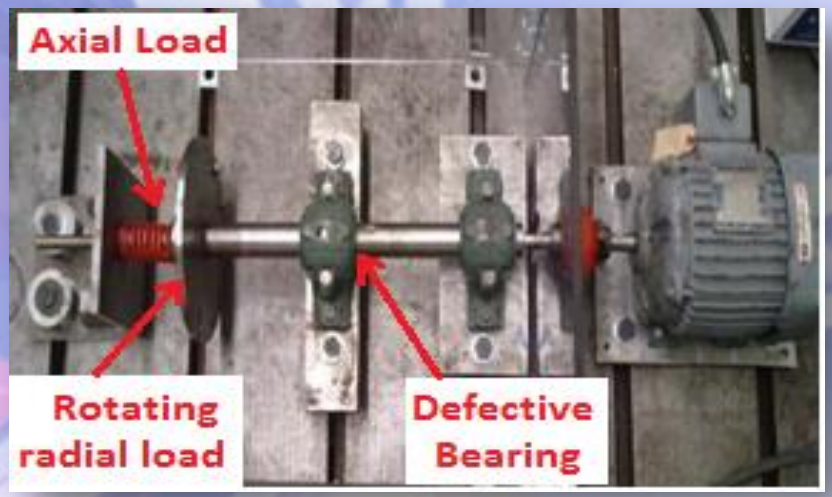


Comparison between WPD and HT+WPD



Y. Imaouchen, R. Alkama and M. Thomas. October 2014. Bearing Fault Detection Using Motor Current Signal Analysis Based on Wavelet Packet Decomposition and Hilbert Envelope. 2e AVE, Blois (Fr)

Materiel and Test Bench: application to electric current measurement



Experimental Test Bench

Bearing SKF : 1210 EKTN9

Acoustic Emission

Vibration Sensor

Current probe (Hall effect)

Sampling Frequency 48kHz

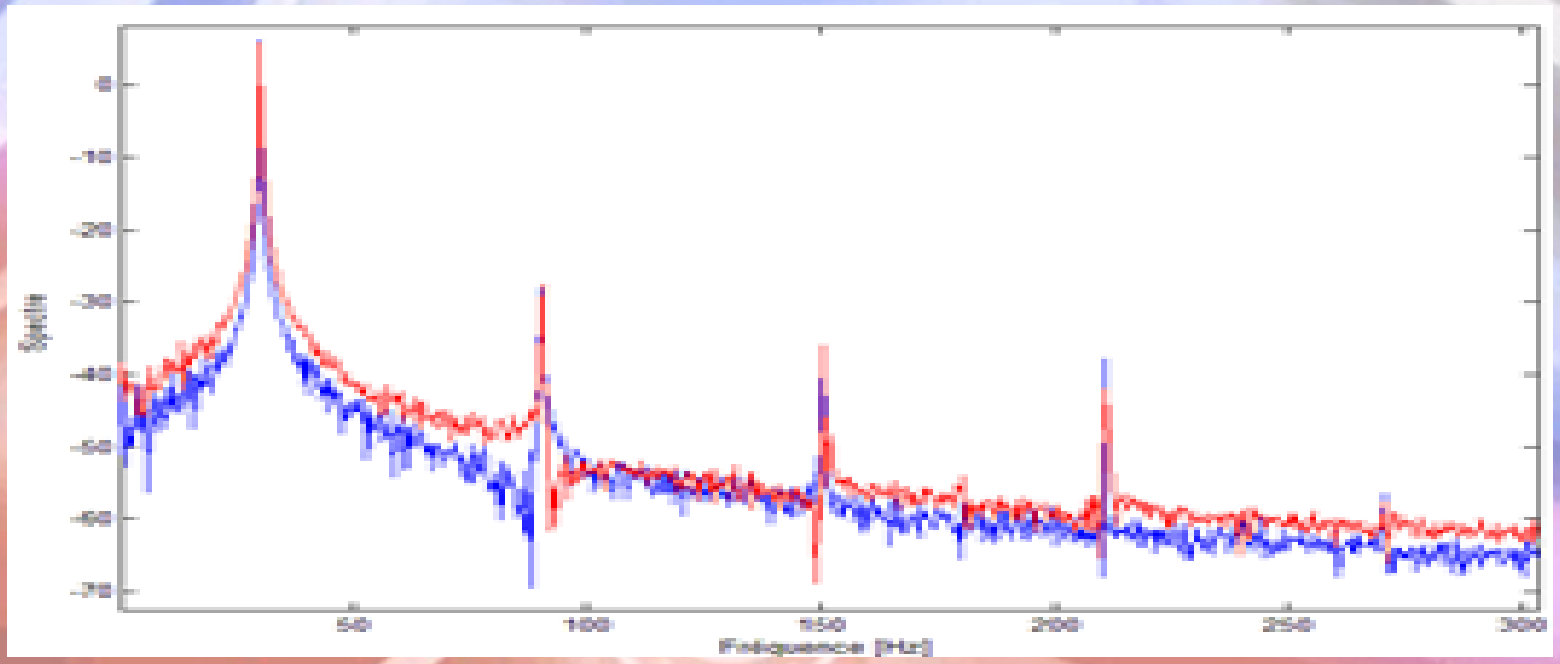
Data acquisition system

Bearing defect

- The bearing is SKF1210.
- Two experiments:
  - healthy
  - 1.06 mm on the outer race
- The electric signal (Canada) is 30 Hz (120 Hz/4 pôles).
- At 900 RPM (15 Hz), BPFO is 116.6 Hz.
- The supply voltage frequency is modulated by the bearing defect .
- The envelope of the current signal contains thus the fault-related frequencies.

Conventional spectral analysis

- The healthy bearing is in blue
- The defective bearing is in red
- We only notice an amplitude increase at each frequency: difficulty for diagnosing a defect.



Bearing frequencies into the current signal

The bearing frequencies into the current signal may be identified by :

$$f_{\text{fault}} = \left| f_a \pm m.BPFO \right|$$

f_a	f_r	Modulation effect on stator current	Related nodes
		$\lvert f_a$-BPFO$\rvert$ = 86.6 Hz	(11 – 04) : [82.03-93.75Hz]
30Hz	15Hz	$\lvert f_a$+BPFO$\rvert$ = 146.6 Hz	(11 – 10) : [140.6-152.3Hz]
		$\lvert f_a$-2*BPFO$\rvert$ = 203.26 Hz	(11 – 25) : [199.2-210.9Hz]
		$\lvert f_a$+2*BPFO$\rvert$ = 263.26 Hz	(11 – 29) : [257.8-269.5Hz]

Energy Comparison

The energy is compared around the defect frequencies for the healthy and the defective bearing.

ENERGY COMPARISON AROUND 86.6HZ

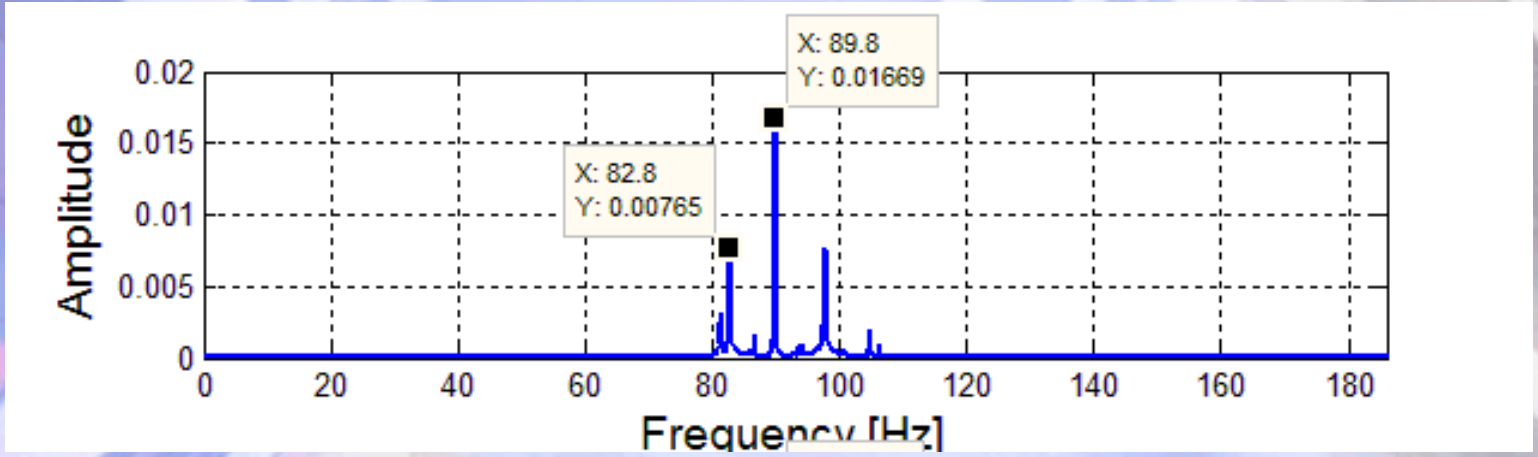
Condition	Frequency range		
	Node (11 – 5) (70.31-82.03Hz)	Node (11 – 4) (82.03-93.75Hz)	Node(11 – 12) (93.75-105.46Hz)
Healthy	0.47	0.22	2.17
outer race defect	0.9	5.16	2.38

ENERGY COMPARISON AROUND 146.6HZ

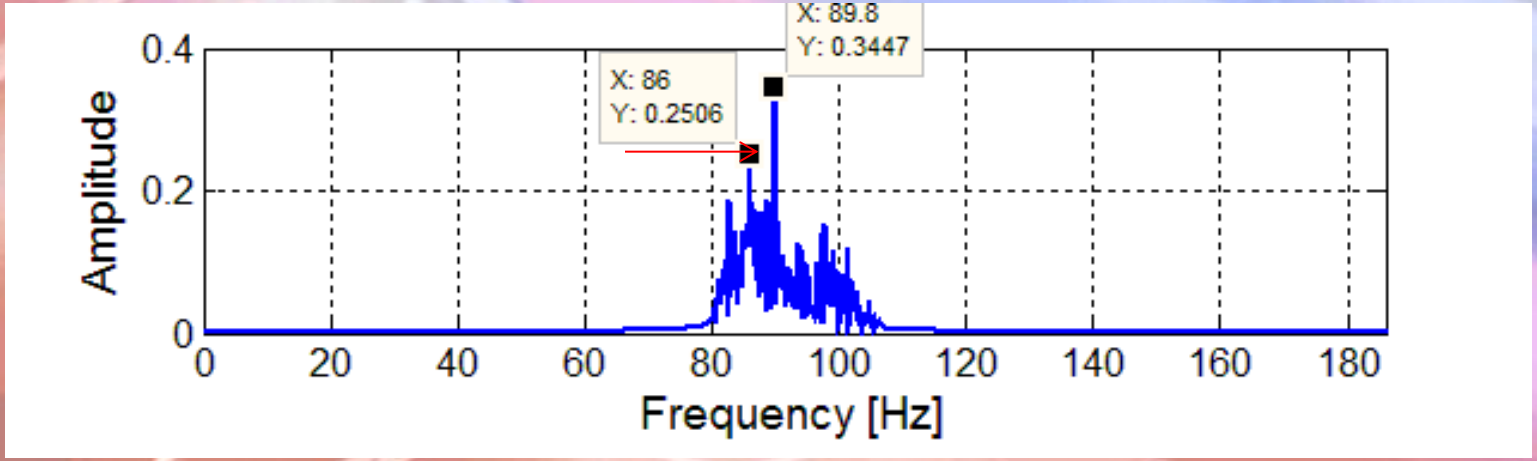
Condition	Frequency range		
	Node (11 – 14) (128.9-140.6Hz)	Node (11 – 10) (140.6-152.3Hz)	Node(11 –11) (152.3-164.1Hz)
Healthy	0.023	0.016	0.17
outer race defect	0.23	0.84	0.28

Spectrum Comparison between WPD and HT+WPD

WPD applied on the node containing 86,6 Hz

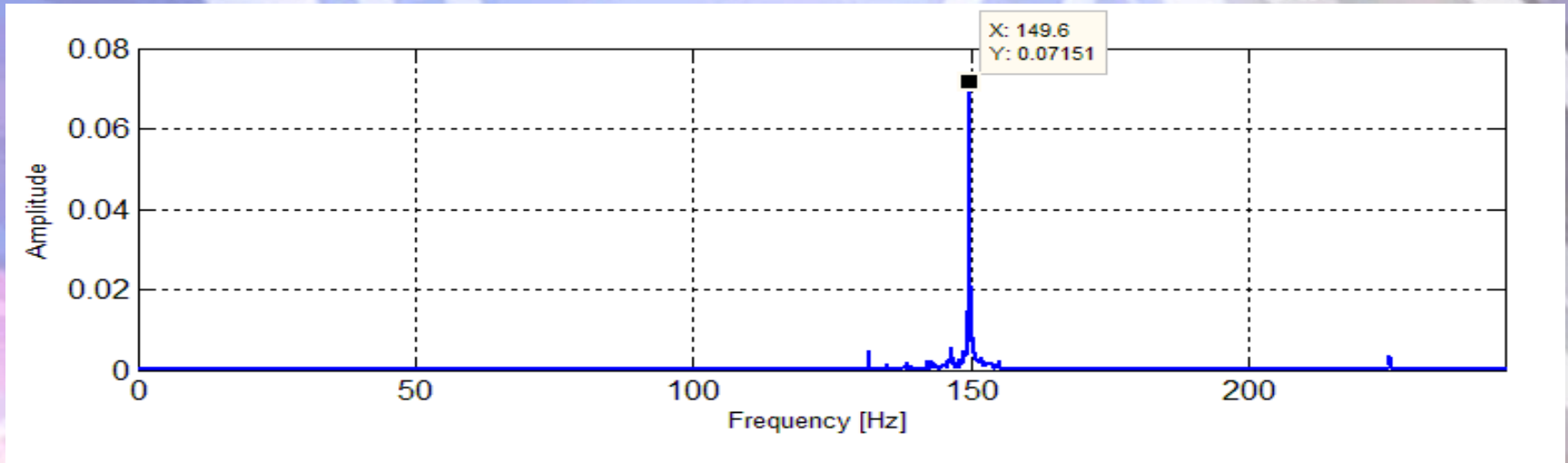


HT+ WPD applied on the node containing 86,6 Hz

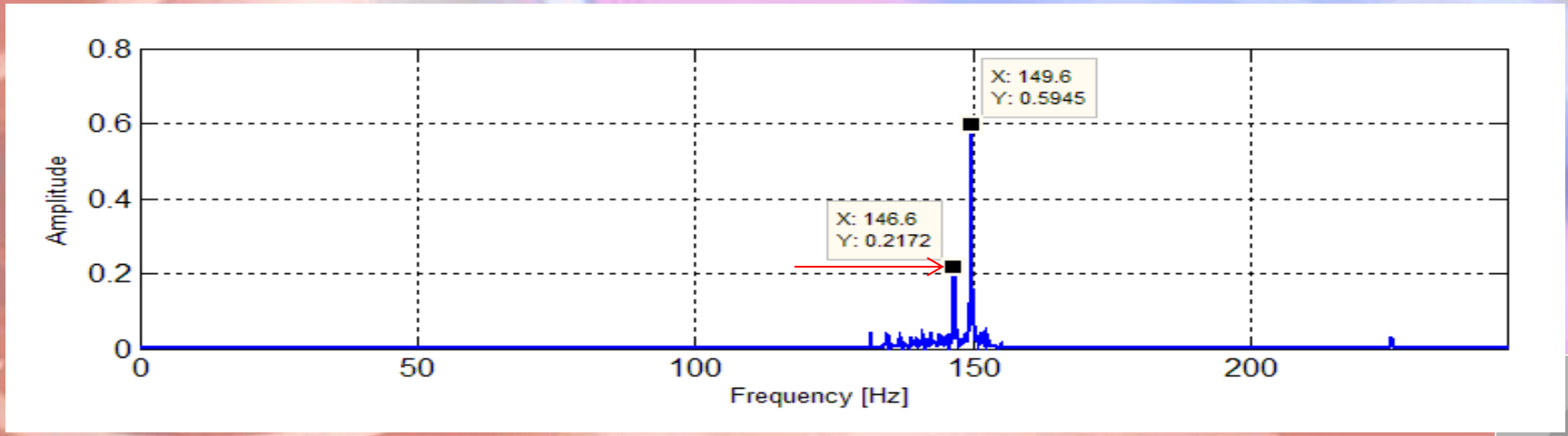


Spectrum Comparison between WPD and HT+WPD

WPD applied on the node containing 146,6 Hz



HT+ WPD applied on the node containing 146,6 Hz



The Empirical Wavelet Transform

The main idea of EWT is to extract different modes by designing appropriate wavelet filter banks adapted to the signal.

Scaling function: low pass Filter

$$\varnothing_n(w)=\begin{cases}1 & if\ |w|\le(1-\gamma)w_n\\ \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma w_n}\left(|w|-(1-\gamma)w_n\right)\right)\right] & if\ (1-\gamma)w_n\le|w|\le(1+\gamma)w_n\\ 0 & otherwise\end{cases}$$

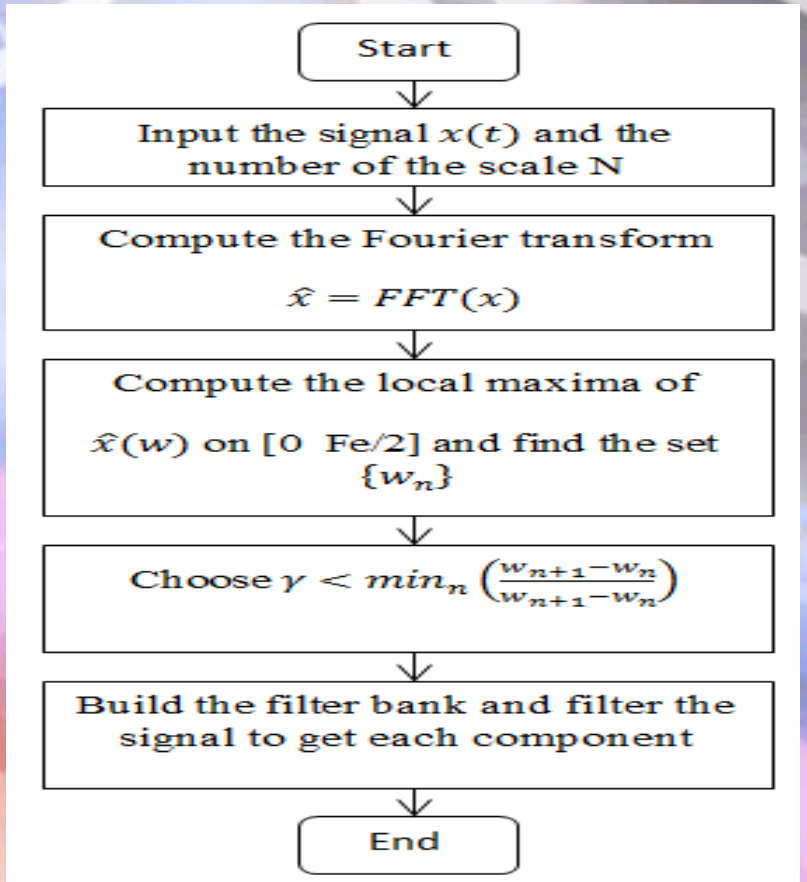
Wavelete function: band pass filter

$$\hat{\varphi}_n(w)=\begin{cases}1 & if\ (1+\gamma)w_n\le|w|\le(1-\gamma)w_{n+1}\\ cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma w_{n+1}}\left(|w|-(1-\gamma)w_{n+1}\right)\right)\right] & if\ (1-\gamma)w_{n+1}\le|w|\le(1+\gamma)w_{n+1}\\ sin\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma w_n}\left(|w|-(1-\gamma)w_n\right)\right)\right] & if\ (1-\gamma)w_n\le|w|\le(1+\gamma)w_n\\ 0 & otherwise\end{cases}$$

Spectral segmentation

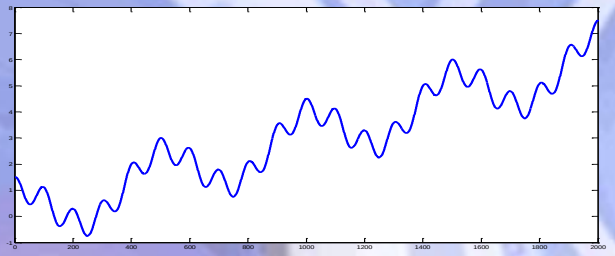
The filter supports are defined accordingle the frequential content

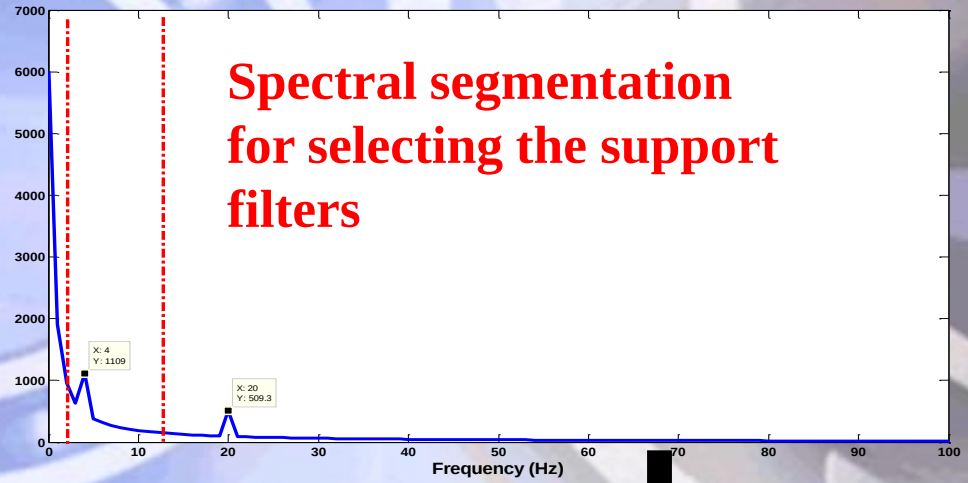
Adaptative Filter



Numerical simulation of EWT

$$x(t) = x_1(t) + x_2(t) + x_3(t)$$





The detail coefficients are

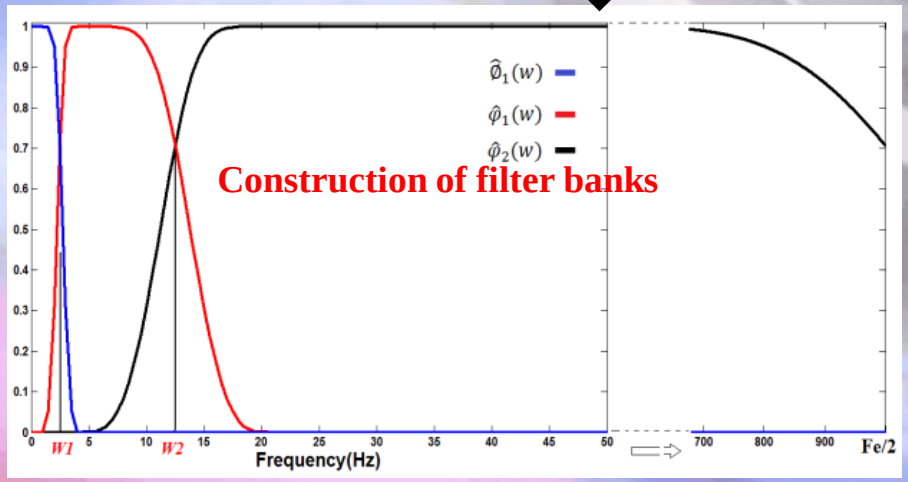
$$W_x(n,t) = \langle x(t), \varphi_n \rangle = \hat{x}(w).\overline{\hat{\varphi}_n(w)}$$

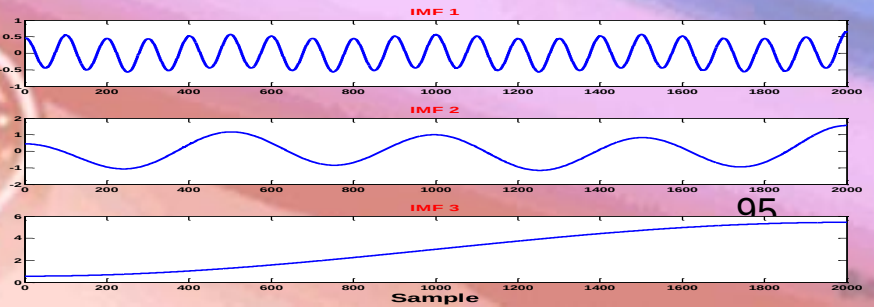
The approximation coefficients are

$$W_x(0,t) = \langle x(t), \varnothing_1 \rangle = \hat{x}(w).\overline{\hat{\varnothing}_1(w)}$$

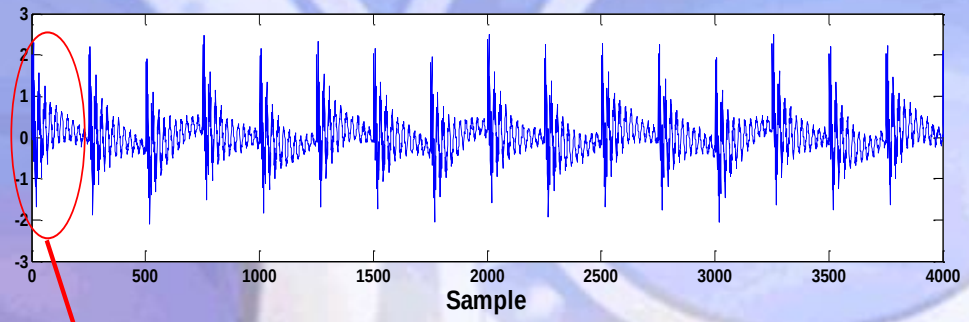
The signal is given by:

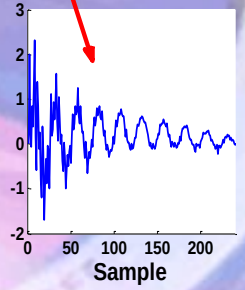
$$x(t) = \hat{W}_x(0,w)\hat{\varnothing}_1(w) + \sum_{n=1}^{N} \hat{W}_x(n,w)\hat{\varphi}_n(w)$$



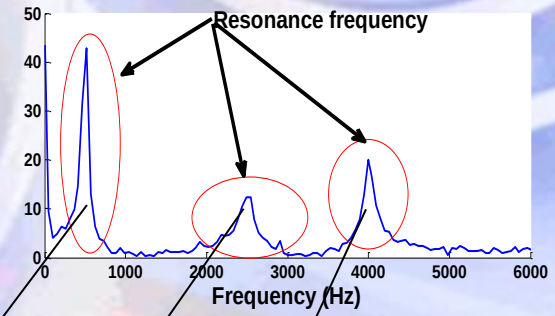


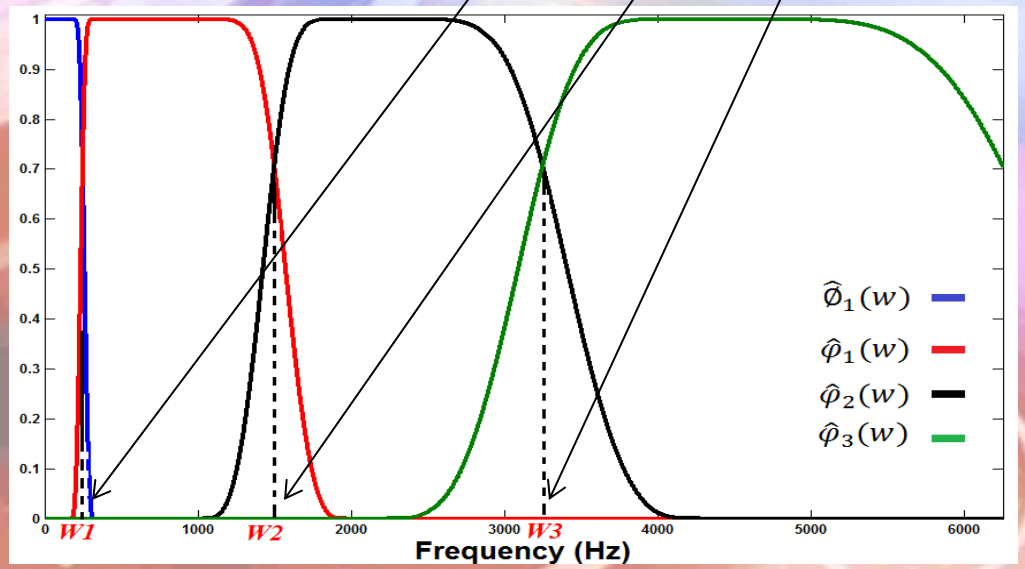
Empirical Wavelet Transforms : application to bearing defect

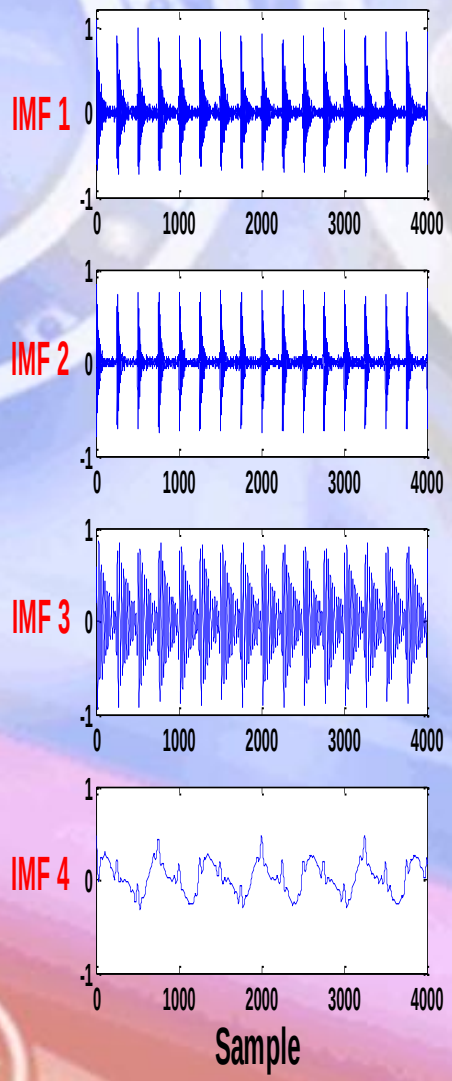


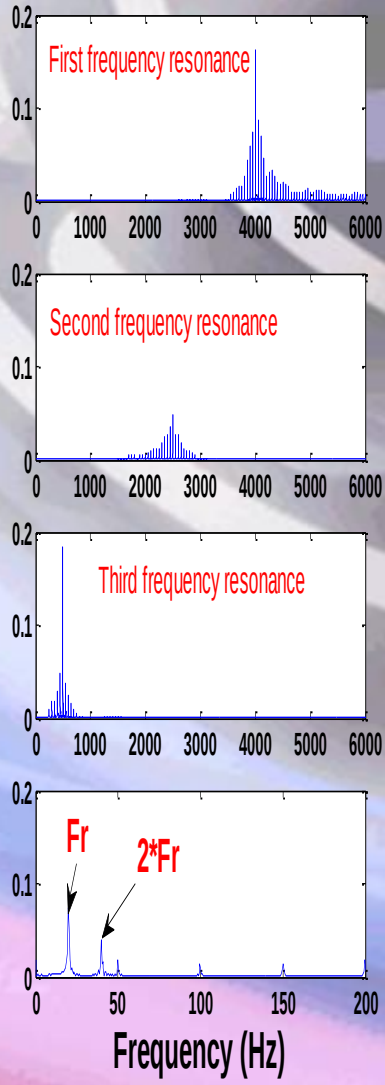


FFT





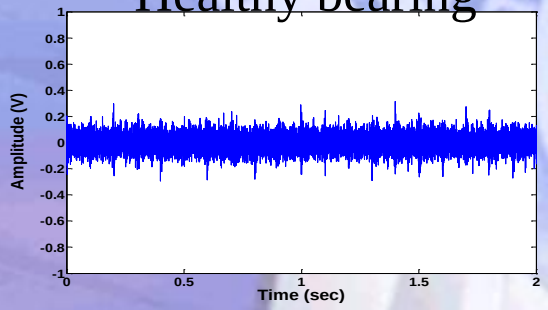


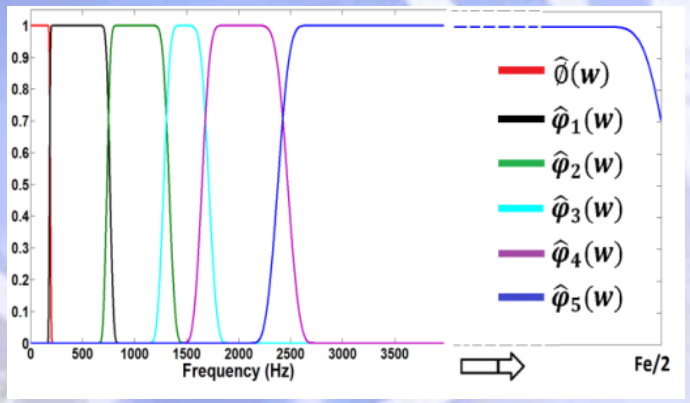


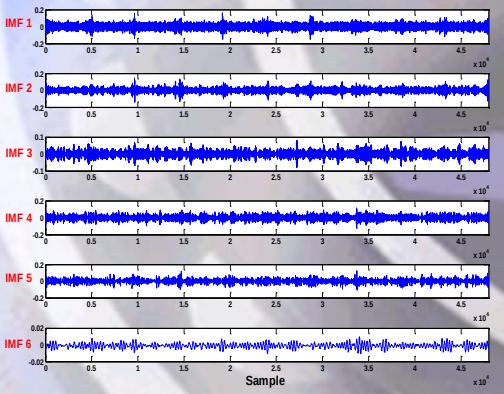
(A) (B)

Experimental application of EWT

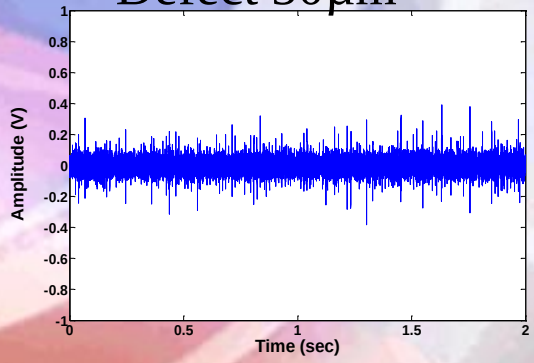
Healthy bearing

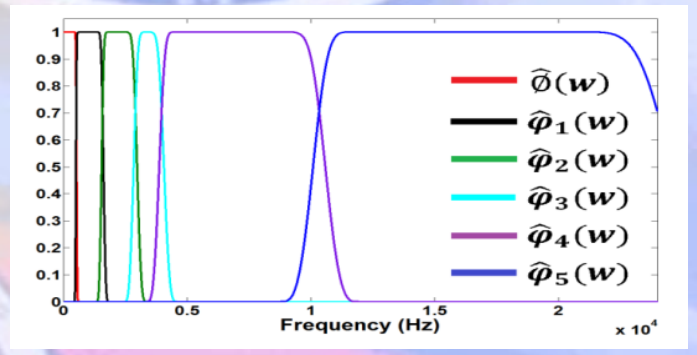


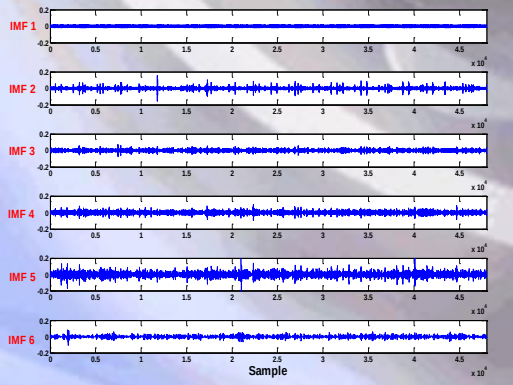




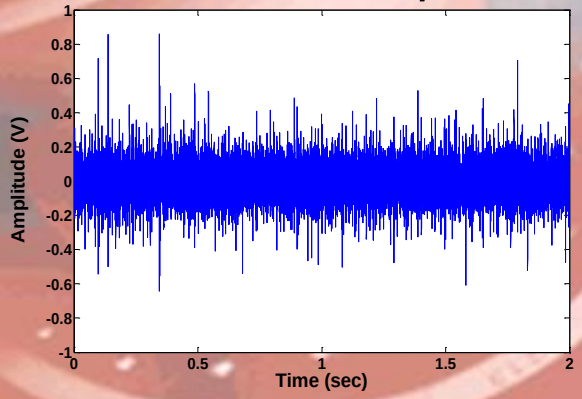
Defect 50µm

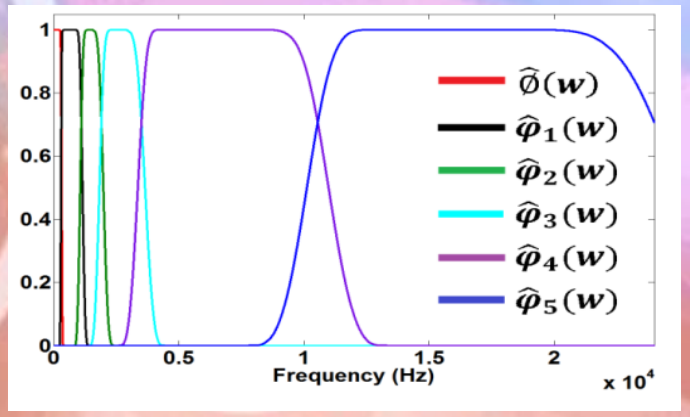


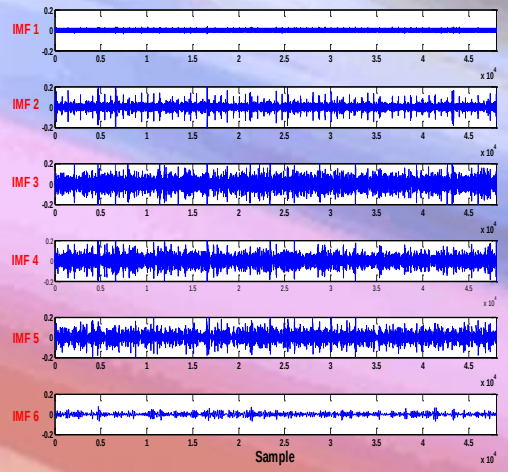




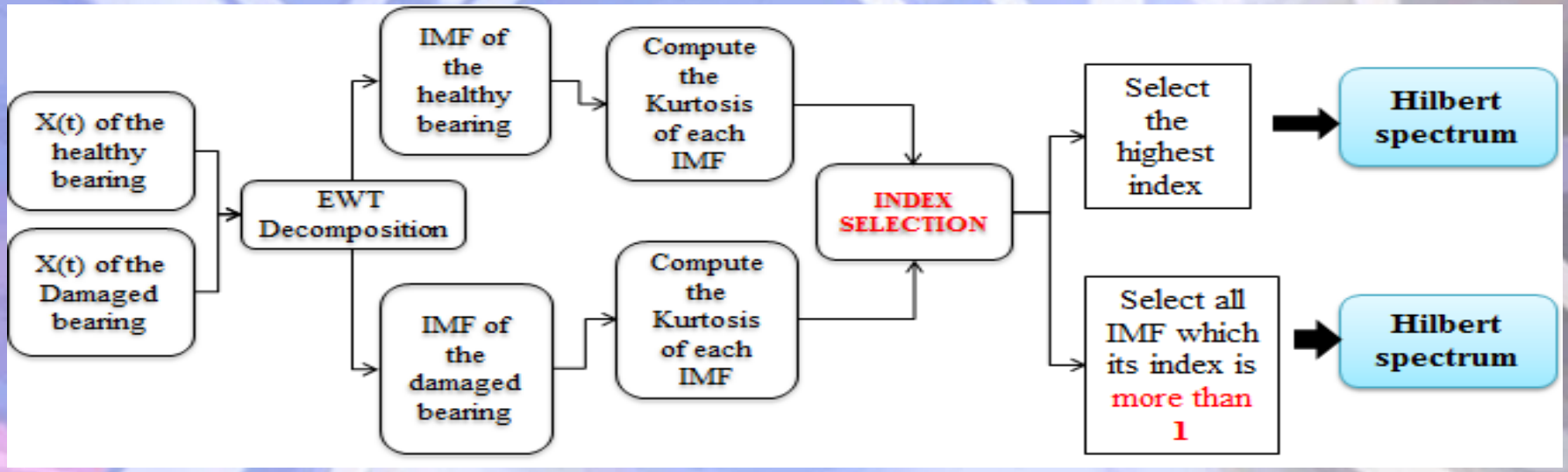
Defect 100µm







Empirical Wavelet Transforms: Index selection,

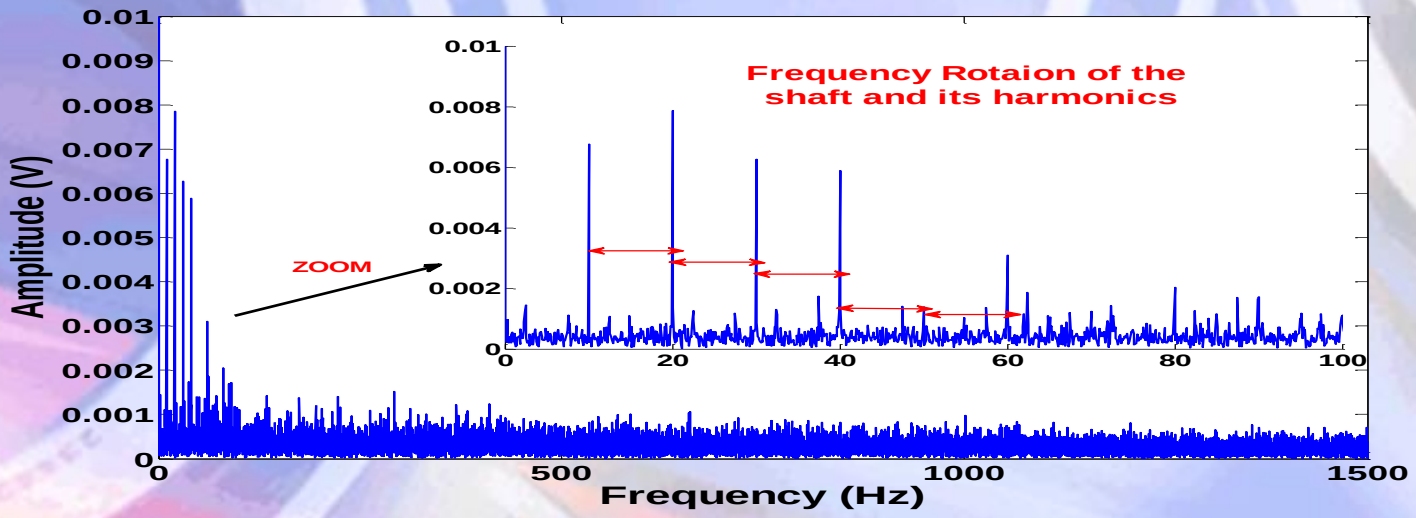


$$index_selection = \frac{kurtosis(IMF_i)_{damaged} - kurtosis(IMF_i)_{Healthy}}{kurtosis(x)_{damaged} - kurtosis(x)_{Healthy}}$$

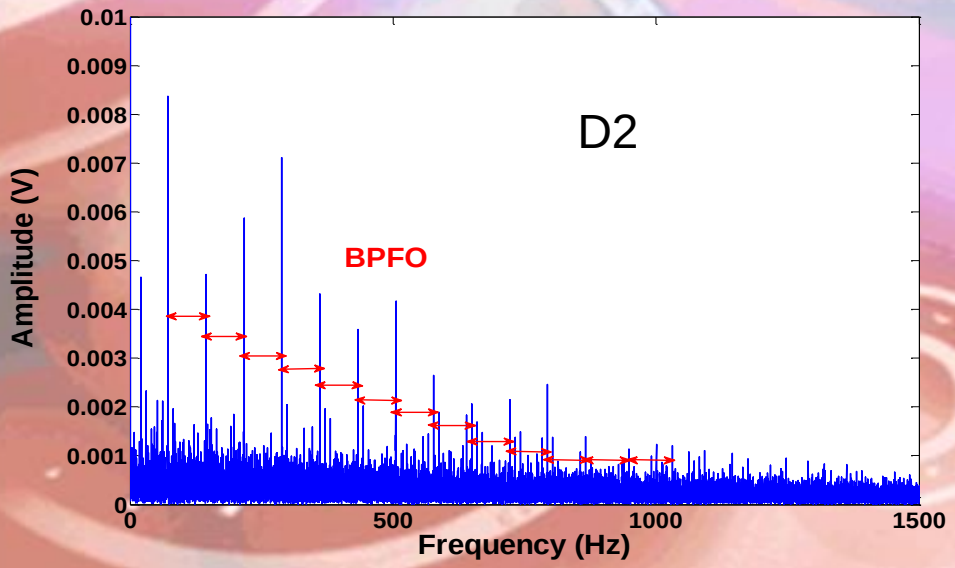
	Decision
<1	The is not selected
=1	The difference between the distribution of amplitude of the both IMF (healthy & damaged) is the same as the raw signal (healthy & damaged)
>1	The IMF is more impulsive than the raw signal. It is selected

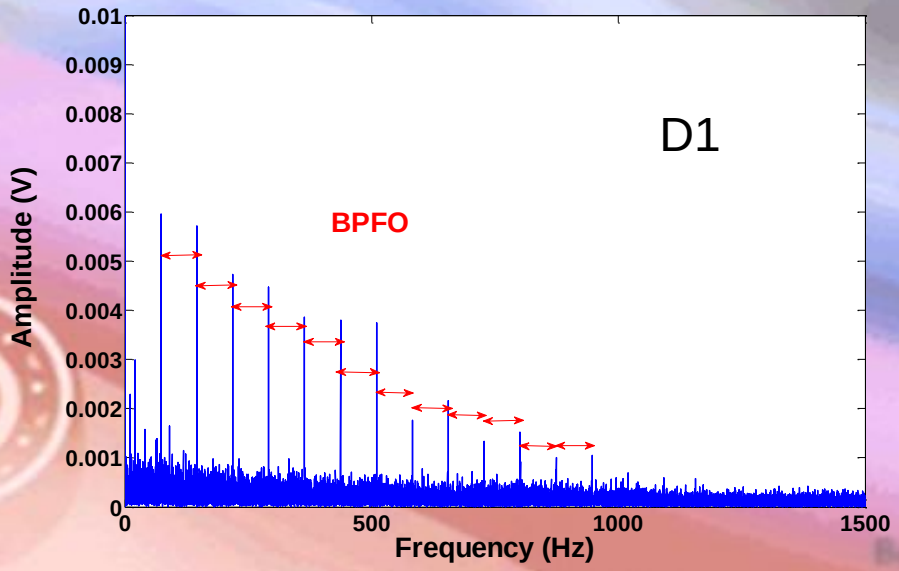
Empirical Wavelet Transforms, IMF > 1

D1=50 µm	-0,68	3,77	1,47	1,27	1,17	0,36
D2=100 µm	-1,23	4,13	1,35	0,85	0,33	0,31

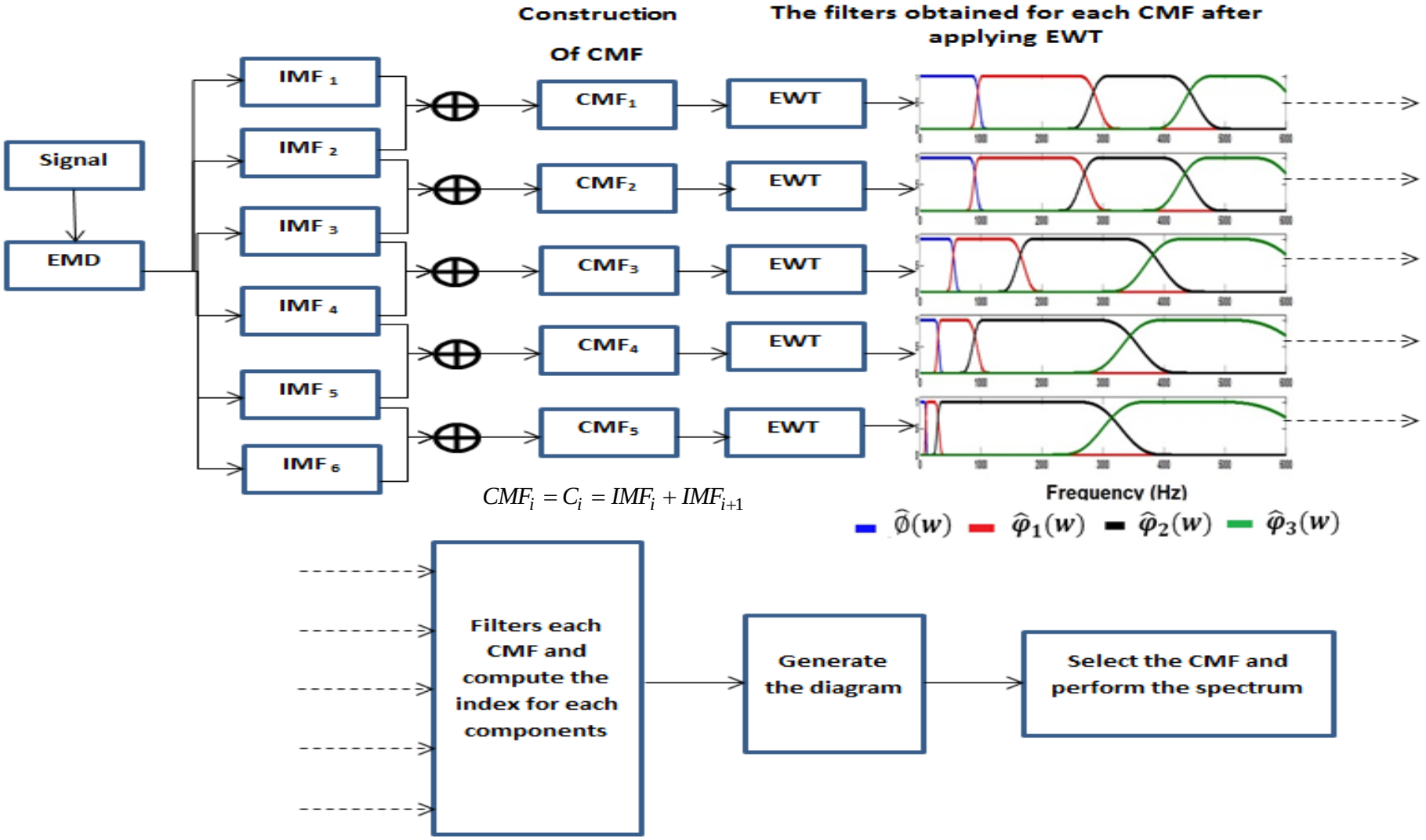


Index selection greater than 1



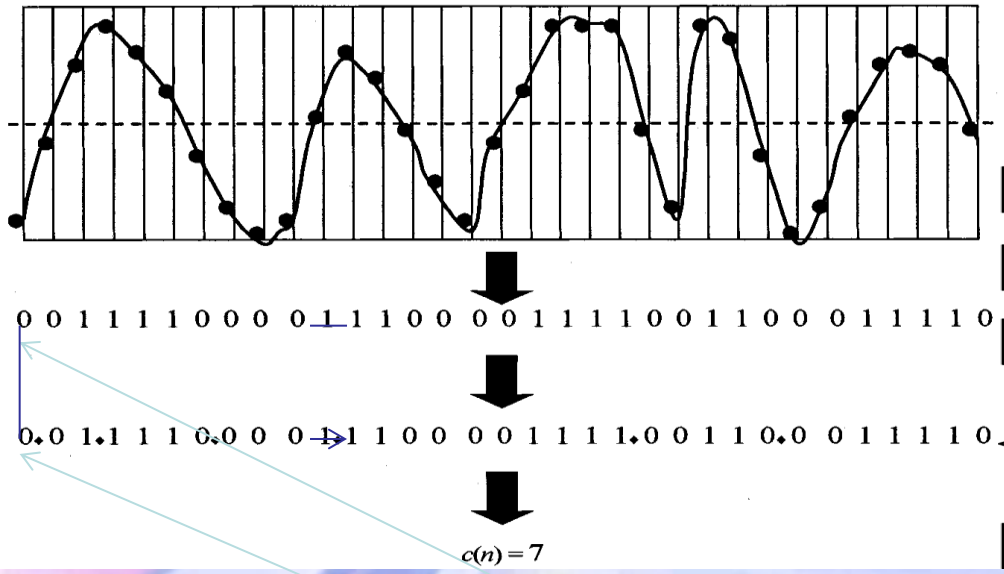


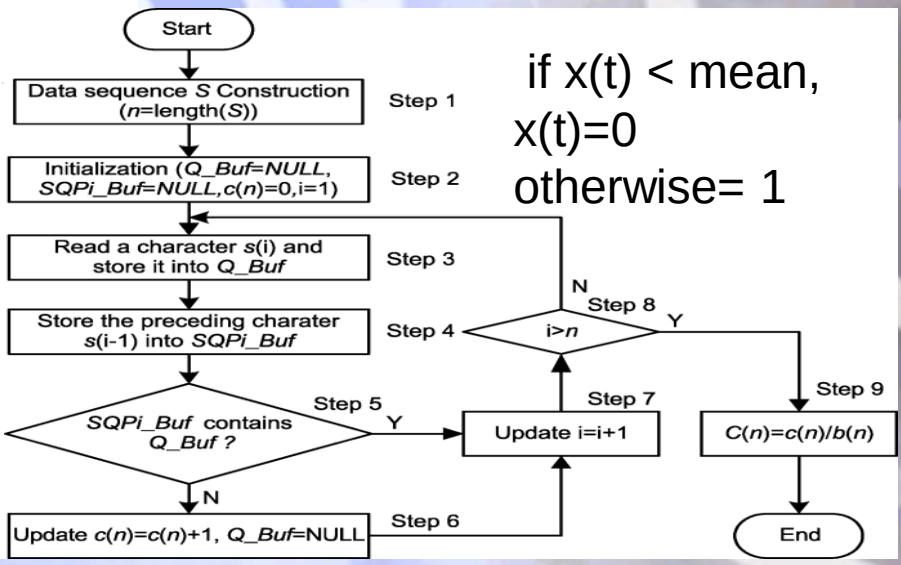
Improvement: The selection will be easier if the signal is monocomponent



Kedadouche, M., Thomas, M., Tahan, A. (2014) « An effective method based on empirical mode decomposition and empirical wavelet for extracting bearing defect». 4th International Conference on Condition Monitoring of Machinery in Non-Stationary Operations (CMMNO), December 15-16, Lyon, France.

Lempel-Ziz Complexity





if x(t) < mean, x(t)=0
otherwise= 1

i=1 S=0 Q_Buff=0 SQ_Buff=00 SQπ_Buff=0 **SQπ _Buff contain Q_buff**

0◊01

i=2 S=0 Q_Buff=**01** SQ_Buff=001 SQπ _Buff=00 **SQπ _Buff doesn't contain Q_buff**

New subsequence : 0◊01◊1 **c(n)=c(n)+1**

i=3 S=**001** Q_Buff=**1** SQ_Buff=**0011** SQπ _Buff=001 **SQπ _Buff contain Q_buff**

0◊01◊11

i=4 S=**001** Q_Buff=**11** SQ_Buf=**00111** SQπ _Buff=0011 **SQπ _Buff contain Q_buff**

.

Ruqiang Yan and Robert X. Gao,Complexity as a Measure for Machine Health Evaluation, IEEE transactions on instrumentation and measurement, vol. 53, no. 4, august 2004

Complexity :Approximate entropy (ApEn)

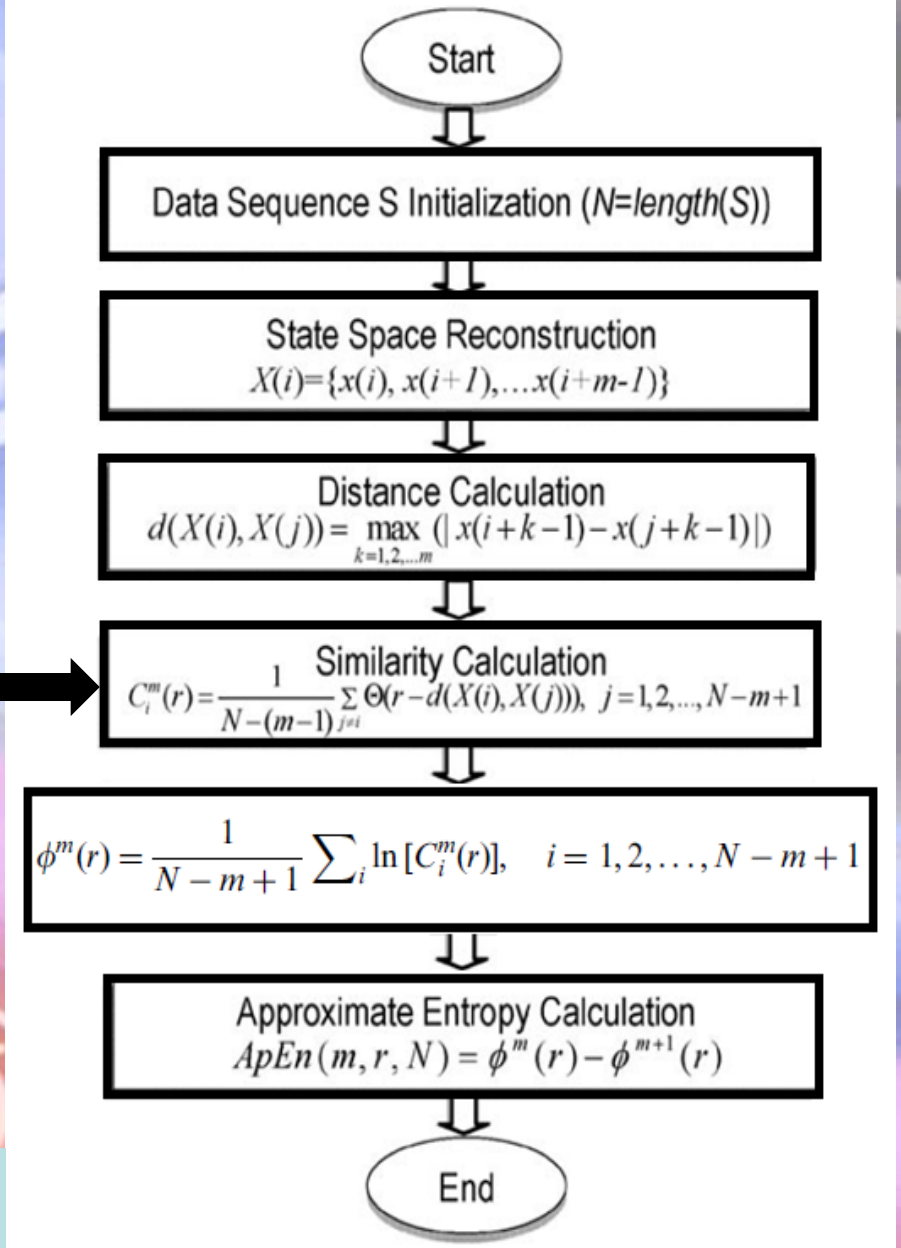
Complexity ApEn represents a quantification of regularity in sequences and time series data.

Complexity increases with the noise

$$\Theta\{x\} = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

r=k*standard deviation of the x(t)

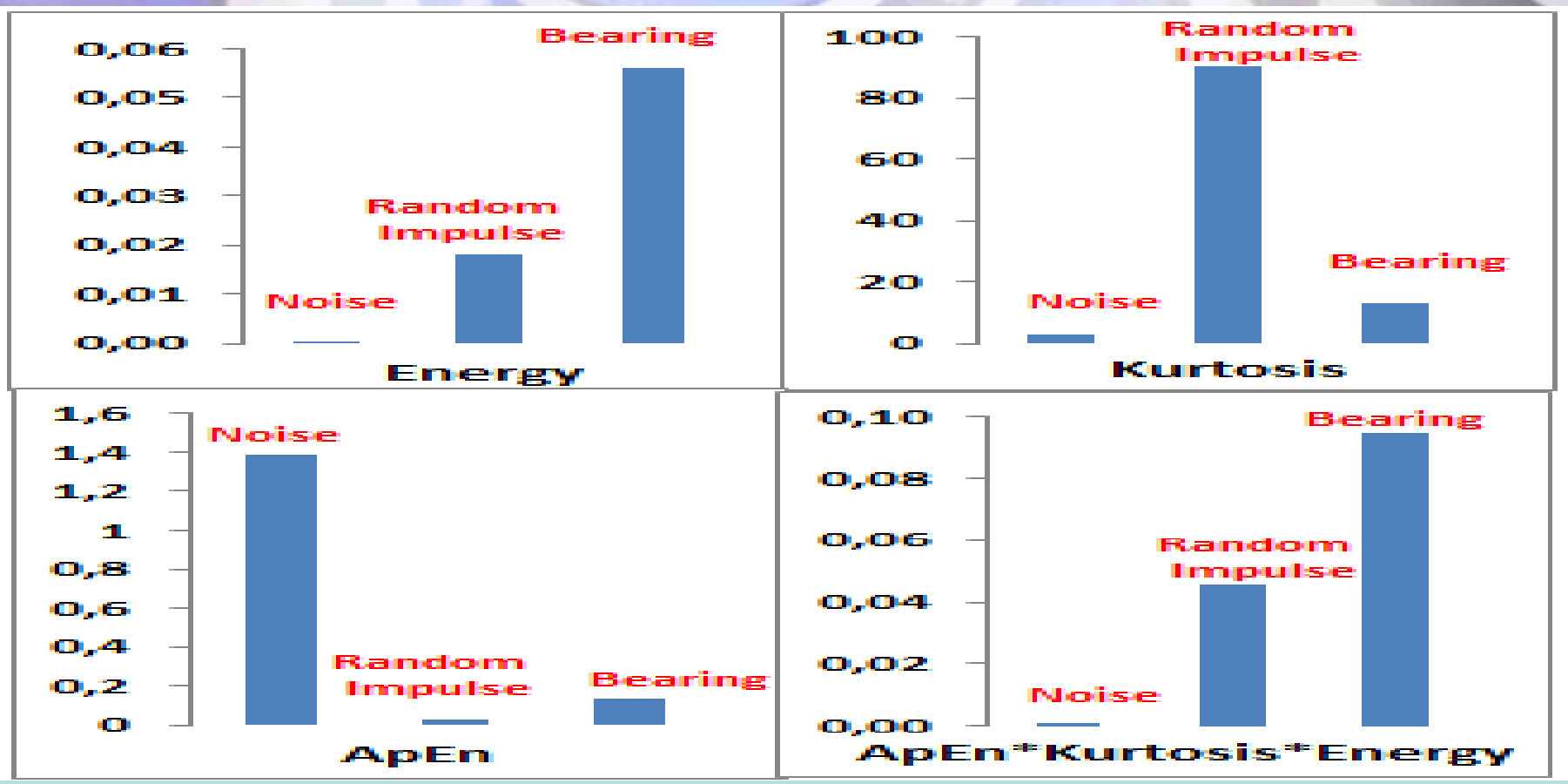
It is an effective tool to distinguish between the random and the cyclic shocks since ApEn of noise is high.



Yan, R. and R. X. Gao. 2007. « Approximate Entropy as a diagnostic tool for machine health monitoring ». *Mechanical Systems and Signal Processing,* vol. 21, nº 2, p. 824-839.

Index for defect severity

$$INDEX = \left(Kurtosis = \frac{\frac{1}{N}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^4}{RMS^4} \right) * \left(Energy = \sum x(f)^2 \right) * (ApEn)$$

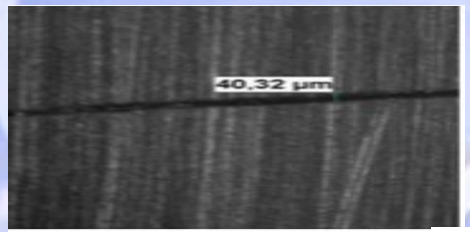


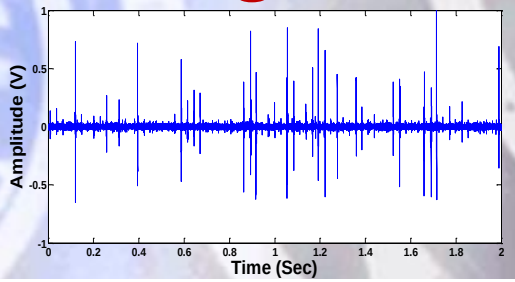
M. Kedadouche, M. Thomas and A. Tahan. 2015. A comparative study between Empirical wavelet transforms (EWT) and Empirical Mode Decomposition methods: Application to bearing defects , submitted to MSSP

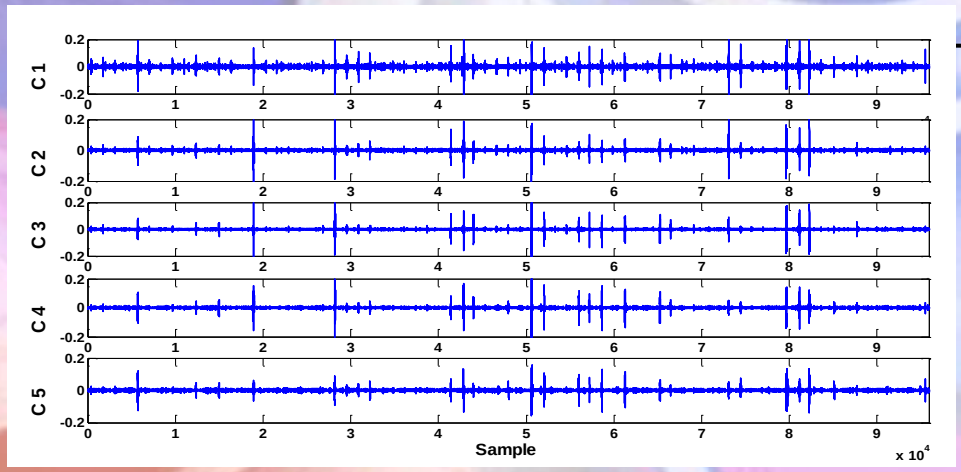
Early detection with EMD+EWT+Index: experiments of acoustic emission on bearing test bench

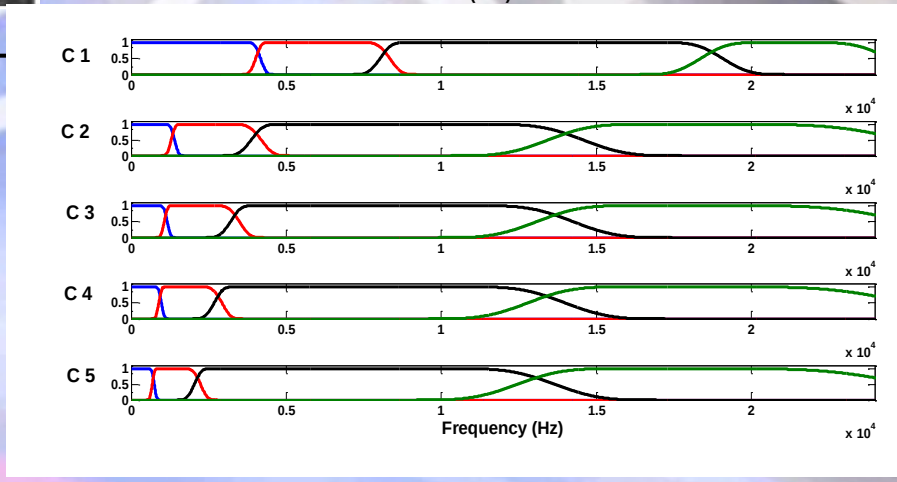
Velocity: 300 rpm

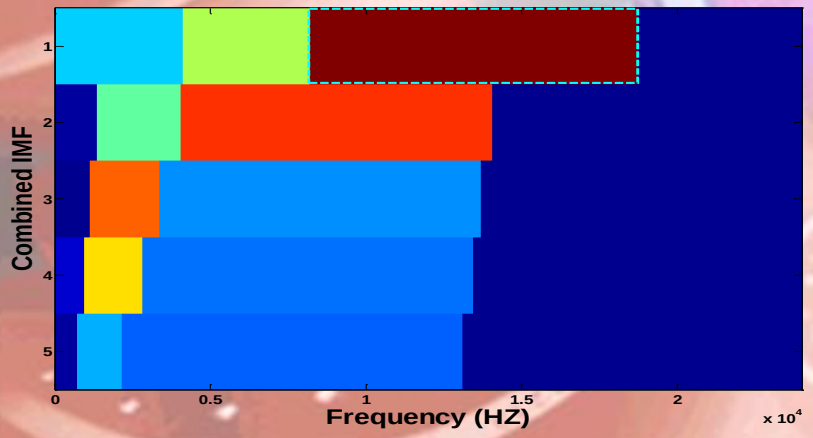
BPFO: 36.6 Hz

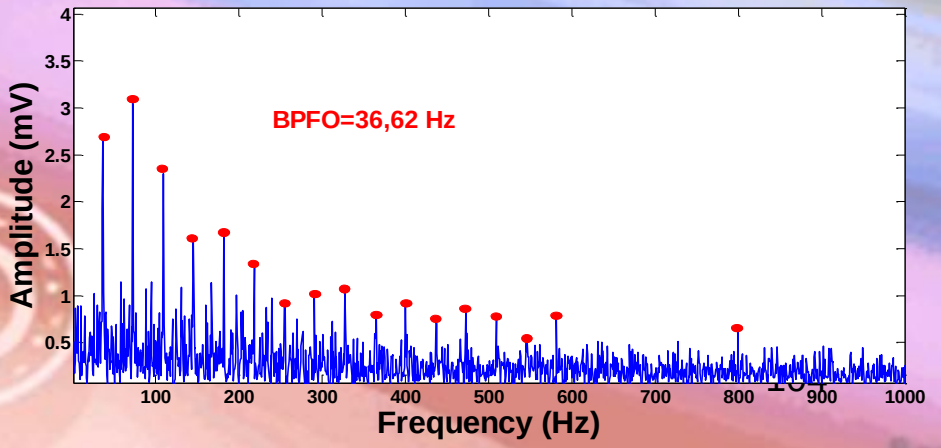












You do things right because you have experience
You have experience because you did things wrong

Thank you for your attention