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INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR)

Article DOI: 10.21474/IJAR01/19718
DOI URL: http://dx.doi.org/10.21474/IJAR01/19718

RESEARCH ARTICLE

DESIGN OF COMBINED SCALAR INDICATORS FOR FAULT DETECTION OF ROTATING MACHINES

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Manuscript Info

Manuscript History
Received: 24 August 2024
Final Accepted: 28 September 2024
Published: October 2024

Key words:-
Monitoring, Vibration Analysis, Fault Detection, Scalar Indicator, Combined Scalar Indicator

Abstract

The machine health monitoring becomes crucial for any company using rotating machines. A rotating machine is subject to developments that induce changes in its vibration behaviour. These changes can be due either to a change in its parameters (load or speed), or to degradations, or to defects affecting its intrinsic characteristics and behaviour. Several maintenance methods are currently used to detect defects in rotating machines. Time-domain analysis is one of the methods for detecting defects that use well-known scalar indicators such as Root Mean Square (RMS), Kurtosis, peak-to-peak value, crest factor etc. However, these indicators may have limitations when it comes to detecting multiple defects in machines. In this article, we propose new innovations in the field of the monitoring of rotating machine by vibration analysis, specifically in time-domain analysis. We propose new indicators for detecting defects by linear combination of scalar indicators We evaluate these indicators in order to assess their capacity to detect a single or multiple defects, their capacity to assess the severity of a defect, and their capacity to detect a healthy gear or a defective gear in different configurations of defects created on the gear and on the bearing mounted on an experimental test bench.

Introduction:-

Conditional maintenance is efficient and essential to keep machines in working condition and increases productivity. It consists of monitoring the machine from data regularly collected and analyzed, in order to intervene at the opportune time to avoid an incident. It is based on several scientific and technical analysis methods which are for example vibration analysis presented by Zezz et al., 2004, oil analysis by Wartsilla, 2016, infrared thermal imaging or sound perception by Younes et al., 2015 and Hamzaoui et al., 2015. In our case, we limit ourselves to vibration analysis. In this field, work has been carried out by the authors Djebala et al., 2007, Djebala et al., 2012 and Djebala et al., 2006. Moreover, a synthesis of their work was made by Djebala, 2012. In this work, they proposed a method based on multiresolution wavelet analysis and the Hilbert transform to detect single and multiple gear defects. They showed from an experimental result and from a signal simulation containing a phase and amplitude modulation, that on the one hand, small defects are neither detected by the spectrum nor by the cepstrum as presented by El Badaoui, 1997, but that the envelope spectrum has made it possible to highlight the modulating frequency and several of its harmonics, even in the case of combined pinion-wheel defects. On the other hand, they show that Kurtosis is a tool that better detects defects in shock signals compared to the crest factor. They also show that detection is better when

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the bearing is greased or when the gears are loaded, and that Kurtosis increases according to the size of the defect. In parallel with their work, in this paper, we show that Kurtosis is not able to detect the severity of a bearing defect compared to another defect on the bearing, but as in their case, it is sensitive to shocks, especially to gear defects. Other criteria are also evaluated in this work. The authors, Antoni and Sidahmed briefly presented different methods for fault diagnosis in acoustic and vibration signals, applicable to stationary or non-stationary signals. In the case of non-stationary signals, especially cyclostationary signals where the speed is variable, a direct analysis of the signal would not give a correct result, because the number of points is not the same in each period of the signal. Specific signal processing techniques are required to complement or improve the presented methods as presented by Abboud, 2015. To analyze signals in this context, one approach is to resample the signal (angular resampling), apply synchronous averaging to eliminate first-order components of the signal, apply filtering (Antoni and Randall, 2006), and finally apply spectral correlation to detect second-order faults. Lejeune et al. 1997 also present work on first- and second-order cyclostationarities applied to gear vibration signals. In the following sections, we present our approach for the work.

Materials and Methods:-

Materials:-

For the experiments, a vibration test bench is used on which the tests are carried out. For the recording of vibration signals, seven channels were connected with seven accelerometers at the input of the OROS analyzer-recorder. Five channels such as channel 2, 3, 4, 5 and 6 are connected to the accelerometers placed at different points of the bench, one channel (channel 1) records the signals of the tachometer placed near the primary shaft, and which measures the number of tops/rev and finally one channel (channel 7) connects the brake mounted on the secondary shaft to the OROS brand recorder as shown in Figure 1.

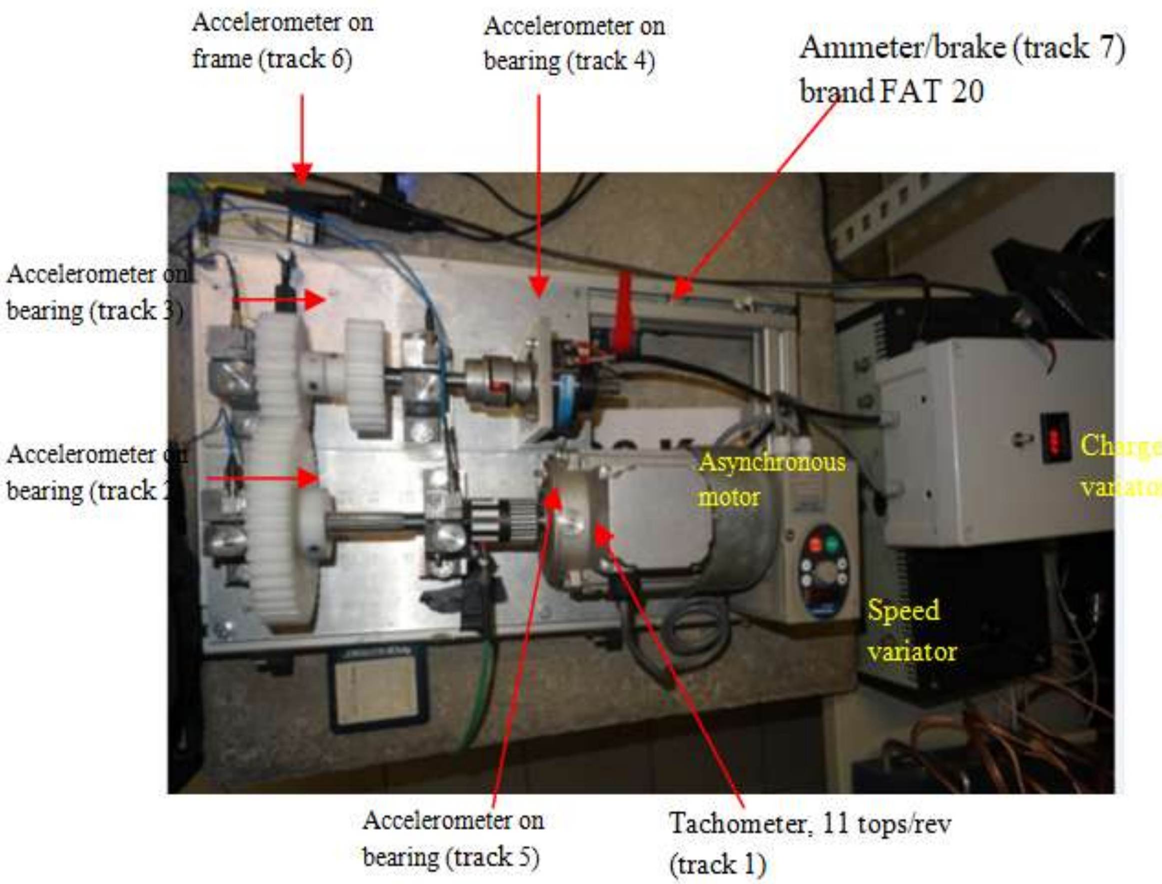

Fig. 1:- Vibration test bench.

For this work, the signals delivered by the sensor of channel 3 are used. Table 1 below shows the tests carried out and the typology of the defects.

Tableau 1:- Experimental tests with different defect configurations.

Twelve (12) Gear and Bearing Fault Configurations		
Outer ring fault	Cage fault	Gear fault (1 tooth broken)
		
Test 1: Healthy bearing (Rs)		
Test 2: Healthy bearing and healthy gear (Rs_Es)		
Test 3: Healthy Bearing and Defective Gear (Rs_Ed)		
Test 4: Defective outer ring bearing (Rd_bext)		
Test 5: Defective outer ring bearing and healthy gear (Rd_bext_Es)		
Test 6: Defective outer ring bearing and defective gear (Rd_bext_Ed)		
Test 7: Defective inner ring bearing (Rd_bint)		
Test 8: Defective inner ring bearing and healthy gear (Rd_bint_Es)		
Test 9: Defective inner ring bearing and defective gear (Rd_bint_Ed)		
Test 10: Defective cage bearing (Rd_cage)		
Test 11: Defective cage bearing and healthy gear (Rd_cage_Es)		
Test 12: Defective cage bearing and defective gear (Rd_cage_Ed)		

Methods:-

Method 1: Fault detection by traditional scalar indicators

In this work, we use the temporal analysis of vibration signals, which is a method of analyzing stationary signals in the time domain. The temporal analysis makes it possible to highlight the presence of faults in machines. In this analysis, the presence of faults and, if necessary, their severity in rotating machines are detected. The temporal methods are based on the statistical analysis of the collected signal and use well-known scalar indicators to follow the evolution of a quantity derived from the power or peak amplitude of the signal. These indicators include, among others, the RMS (effective value), the Kurtosis, the crest factor, the peak-to-peak and the K factor presented below.

The Effective Value (RMS):-

The effective value or RMS (Root Mean Square) is one of the first scalar indicators used in industry. It allows measuring the average energy of the signal; it is used to detect abnormally high energy dissipations accompanying the birth of a defect. The RMS is the square root of the quadratic mean of the discrete time vibration signal x(n) of length N and empirical mean $\bar{x}$ and is given by equation (1):

$$RMS = A_{CC.eff} = \sqrt{\frac{\sum_{i=1}^{N} X(i)^2}{N}} \quad (1)$$

Where xi is the amplitude of the acceleration of the signal of sample i and N is the number of samples of the signal.

The Crest Factor:-

The crest factor is a more specific indicator, which allows observing the vibration signal more closely. Monitoring the crest factor allows earlier detection by measuring the ratio between the maximum value of the signal modulus (peak value) and the effective value (see equation 2):

$$FC = \frac{\text{Acc crete}}{\text{Acc eff}} = \frac{\text{valeur crête}}{\text{RMS}} = \frac{\text{Sup}\,|X(i)|}{\sqrt{\frac{\sum_{i=1}^{N} X(i)^2}{N}}} \quad (2)$$

The crest factor has the advantage of detecting defects before the effective value. This comes from the fact that for a bearing without defects, the ratio remains approximately constant and increases when degradation appears, whereas the crest value increases while the effective value remains approximately constant.

The Kurtosis:-

Kurtosis is an indicator that characterizes shocks in mechanical organs. It is a statistical quantity that allows us to analyze the "pointy" or "flat" character of a distribution and therefore to observe the shape of the signal. Kurtosis is defined as the ratio of the mean value of the signal raised to the power of 4 to the square of its energy (see equation 3):

$$\text{Kurt} = \frac{\frac{\sum_{i=1}^{N}(X(t)-\bar{x})^4}{N}}{\left(\frac{\sum_{i=1}^{N}(s(i)-\bar{x})^2}{N}\right)^2} \quad (3)$$

A bearing in good condition generates a vibration signal with a Kurtosis close to 3. For a degraded bearing, presenting flaking, indentations or significant mechanical error or irrespective of tolerances, the shape of the distribution of the signal amplitude is modified and the Kurtosis is greater than 3.

The K Factor:-

K factor of a signal is defined as the product of the peak value by the effective value. It is an indicator specific to bearings. It is expressed by equation (4):

$$K = \text{Acc crete} * \text{Acc eff} = \text{Sup}|X(i)| \times \sqrt{\frac{\sum_{i=1}^{N} X(i)^2}{N}} \quad (4)$$

The interpretation of the crest factor is done through its evolution as the bearing deteriorates. The value of K increases with bearing wear.

The Peak-to-peak value (PP):-

The peak-to-peak (PP) value is given by the difference between the maximum value of the acceleration signal and its minimum value (see equation 5):

$$PP = A_{CC\ max} - AC_{C\ min} \quad (5)$$

The Peak value (P):-

The peak value (P) is the maximum value of the acceleration signal (see equation 6):

$$P = A_{CC\ max} \quad (6)$$

Method 2: Detection by new indicators (combined scalar indicators):-

The new indicators proposed in this work that we call "combined scalar indicators" are obtained by linear combination of two scalar indicators among the six indicators given by equations (1), (2), (3), (4), (5) and (6) above. Thanks to a simple combinatorial analysis $\binom{6}{2} = \frac{6!}{2!(6-2)!}$, we thus obtain fifteen (15) combined scalar indicators named I1 to I15.

For example, the indicator (I1) obtained by linear combination of Root Mean Square (RMS) value and crest factor (FC) is given by equation (7):

$$I_1 = a * RMS + b * FC + c \quad (7)$$

With a, b et c are constants to be determined.

For all indicators, we can write the system of equations in the following matrix form (equation 8):

$$[I] = [H].[X] \quad (8)$$

Where $[I]$: Column matrix of combined indicators, with:

$$[\mathbf{I}] = \begin{Bmatrix} \mathbf{I_1} \\ \mathbf{I_2} \\ \mathbf{I_3} \\ \vdots \\ \vdots \\ \mathbf{I_N} \end{Bmatrix}$$

$[H]$: Matrix of scalar indicators, with:

$$[\mathbf{H}] = \begin{Bmatrix} \mathbf{RMS} & \mathbf{FC} & \mathbf{1} \\ \mathbf{RMS} & \mathbf{KURT} & \mathbf{1} \\ \mathbf{K} & \mathbf{FC} & \mathbf{1} \\ \vdots & \vdots & \mathbf{1} \\ \vdots & \vdots & \mathbf{1} \\ \mathbf{PP} & \mathbf{KURT} & \mathbf{1} \end{Bmatrix}$$

$[\mathrm{X}]$: Column matrix of constants a, b and c, with:

$$[\mathbf{X}] = \begin{Bmatrix} \mathbf{a} \\ \mathbf{b} \\ \mathbf{c} \end{Bmatrix}$$

The coefficients a, b and c are determined using equation (9). Since the matrix [H] is not square, there is no exact solution to this system of equations. The pseudo-inverse of Gauss (see Boukar et al., 2014 and Bernard G-B., 1967) or the least square minimization of multilinear regression is given by equation (10), it allows to find a better solution for a, b and c.

$$[\mathrm{X}] = [\mathrm{H}^*].[\mathrm{I}] \qquad (9)$$

With: $[\mathrm{H}^*] = ([\mathrm{H}^t.\mathrm{H}])^{-1}.[\mathrm{H}^t]$ the Pseudo-inverse of Gauss.

This gives equation (10):

$$\begin{Bmatrix} \mathrm{A} \\ \mathrm{B} \\ \mathrm{C} \end{Bmatrix} = \left[\begin{Bmatrix} \mathrm{RMS} & \mathrm{RMS} & \mathrm{K} \ldots & \ldots & \mathrm{PP} \\ \mathrm{FC} & \mathrm{KURT} & \mathrm{FC} \ldots & \ldots & \mathrm{KURT} \\ 1 & 1 & 1 \ldots & \ldots & 1 \end{Bmatrix} \mathrm{x} \begin{Bmatrix} \mathrm{RMS} & \mathrm{FC} & 1 \\ \mathrm{RMS} & \mathrm{KURT} & 1 \\ \mathrm{K} & \mathrm{FC} & 1 \\ \vdots & \vdots & 1 \\ \vdots & \vdots & 1 \\ \mathrm{PP} & \mathrm{KURT} & 1 \end{Bmatrix} \right]^{-1} \mathrm{x} \begin{Bmatrix} \mathrm{RMS} & \mathrm{RMS} & \mathrm{K} \ldots & \ldots & \mathrm{PP} \\ \mathrm{FC} & \mathrm{KURT} & \mathrm{FC} \ldots & \ldots & \mathrm{KURT} \\ 1 & 1 & 1 \ldots & \ldots & 1 \end{Bmatrix} \mathrm{x} \begin{Bmatrix} \mathrm{I}_1 \\ \mathrm{I}_2 \\ \mathrm{I}_3 \\ \vdots \\ \vdots \\ \mathrm{I}_N \end{Bmatrix} \qquad (10)$$

The coefficients of the matrix [H] are the scalar indicators such as RMS, Kurtosis, FC… determined using the vibration measurements carried out on the experimental test bench in Figure 1. The measurement results were analyzed using MATLAB®. For detecting defects with the combined scalar indicators I, initial values were imposed on these indicators depending on the severity of the defects. Equations (11) and (12) make it possible to decide whether or not a defect is present:

If $\mathrm{I}_{\text{calculed}} \le \mathrm{I}_{\text{initial}}$, no fault (11)

If $\mathrm{I}_{\text{calculed}} > \mathrm{I}_{\text{initial}}$, there is a fault (12)

Validation de la valeur des constantes a, b et c par R² :-

Indeed, to validate the values of a, b and c calculated from scalar indicators, it is necessary to search for their optimal values by determining the correlations that exist between the scalar indicators (Kurtosis, RMS, FC …). For that, we use R^2, the statistical correlation model with two (2) parameters. R2 is an indicator used in statistics to judge the quality of a linear regression. R^2 is between 0 and 1 and increases with the adequacy of the regression to the model. We consider that an R^2 is better when it is between 0.85 and 1. Thus, we use R^2 to check the correlation that exists between Kurtosis and RMS, between RMS and FC, between Kurtosis and FC, between FC and PP, … which would allow us to find the optimal value of a, b and c.

In our case, we calculate several R^2 between the scalar indicators (2-parameter correlations). The best R^2 is obtained between the peak value and the crest factor as presented in Figure 2. The values of the six scalar indicators studied (Kurtosis, RMS, FC, P, PP, and K) are close to the regression line in Figure 2(a) presented below.

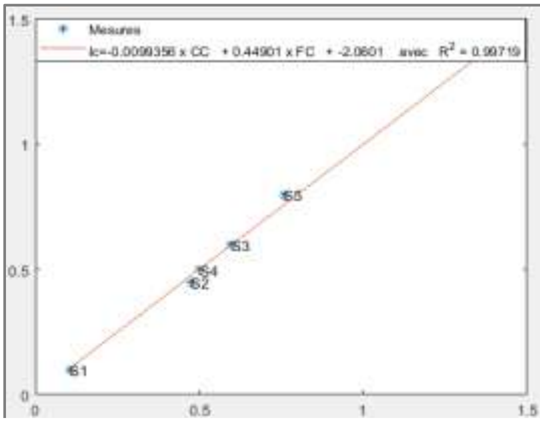

Fig. 2b-R^2 between PP and FC

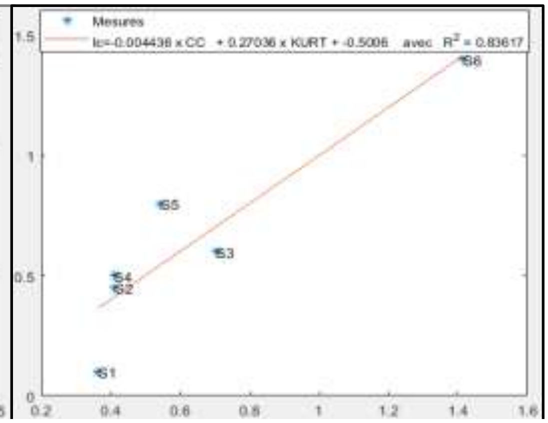

Fig. 2a-R^2 between PP and FC

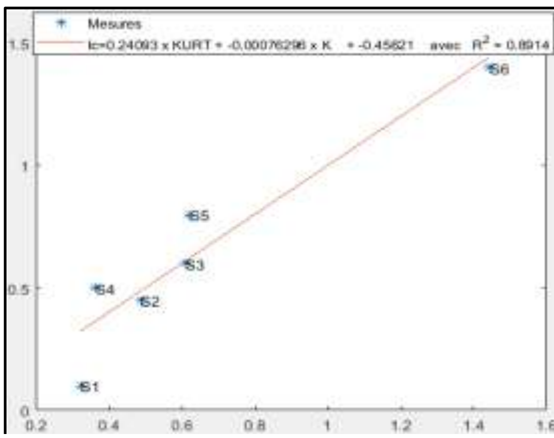

Fig. 2c-R^2 between Kurtosis and K

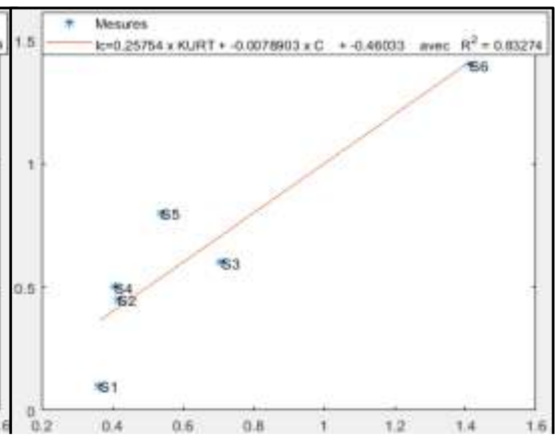

Fig. 2d-R^2 between Kurtosis and P

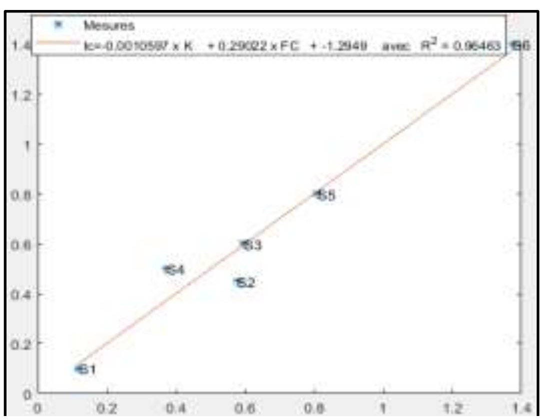

Fig. 2f-R^2 between K and FC

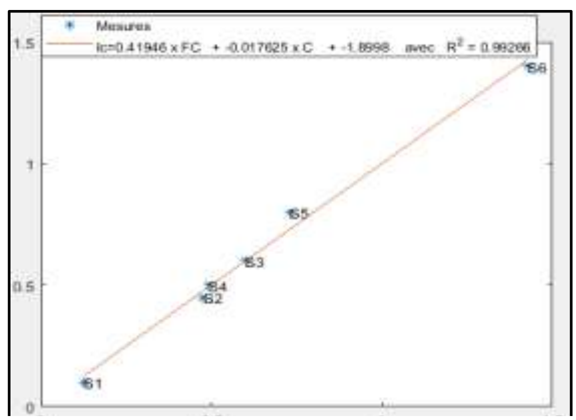

Fig. 2e-R^2 between FC and P

Fig. 2:- Some values of R^2 and constants a, b and c.

Figure 1 above shows the results of some values of R^2 allowing to obtain the values of a, b and c. Among these results, we retain the best **R^2 = 0, 99719** obtained between the peak-to-peak value of the acceleration and the crest factor. Which gives the constants **a = - 0, 0099356** and **b = 0, 44901** et **c = - 2.0601**.

To obtain these results of R^2, a, b and c, the simulations were carried out with the signals from the tests of six (6) fault configurations among the twelve (12) presented in Table 1. The six signals chosen to calculate these parameters are those from the following tests:

- Test 1: Healthy bearing (Rs);

- Test 2: Healthy bearing and healthy gear (Rs_Es);
- Test 3: Healthy Bearing and Defective Gear (Rs_Ed);
- Test 7: Defective inner ring bearing (Rd_bint);
- Test 8: Defective inner ring bearing and healthy gear (Rd_bint_Es);
- Test 9: Defective inner ring bearing and defective gear (Rd_bint_Ed).

Indeed, there are fifteen (15) combined scalar indicators obtained by linear combination of the six traditional scalar indicators. These constants will therefore be used to calculate the remaining fourteen (14) combined scalar indicators in order to determine the best combined scalar indicator among the fifteen. The results are presented in the following section.

Results and Discussion:-

Results and discussion on scalar indicators:-

We present in Figures 3(a) to 2(f) below the results of the scalar indicators for the 12 tests carried out at the rotation frequency of 40 Hz. The indicator K is specific to bearings, no tests with gear for K.

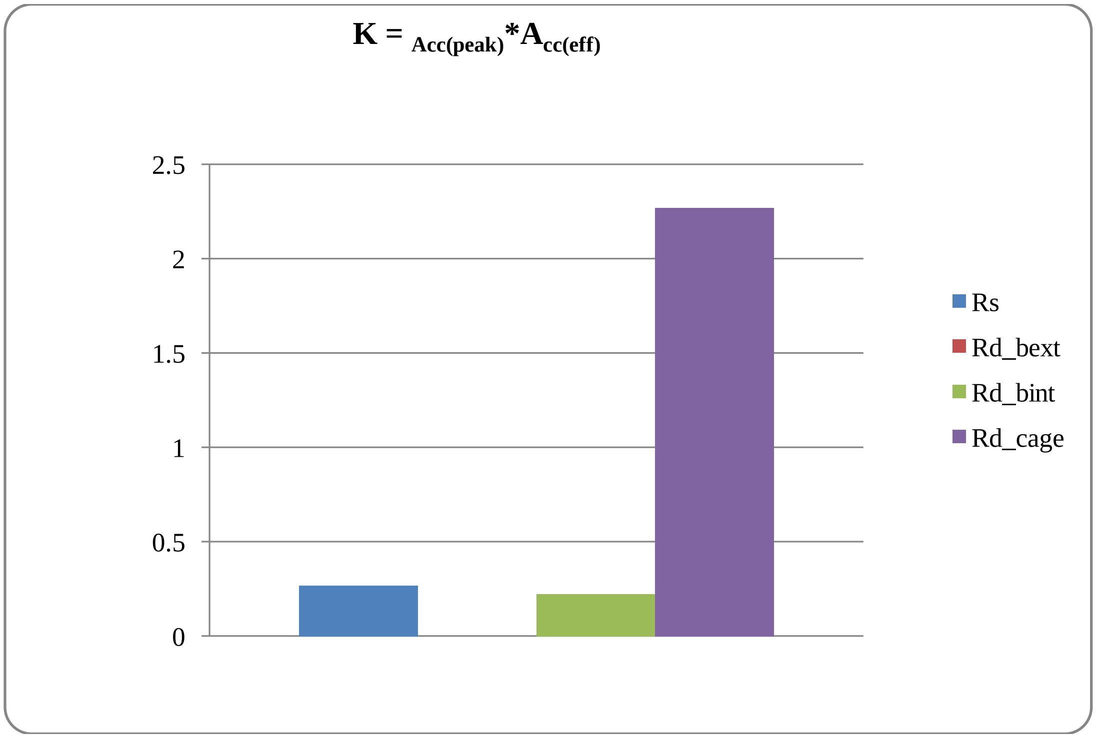

Fig. 3a:- Detection by K indicator .

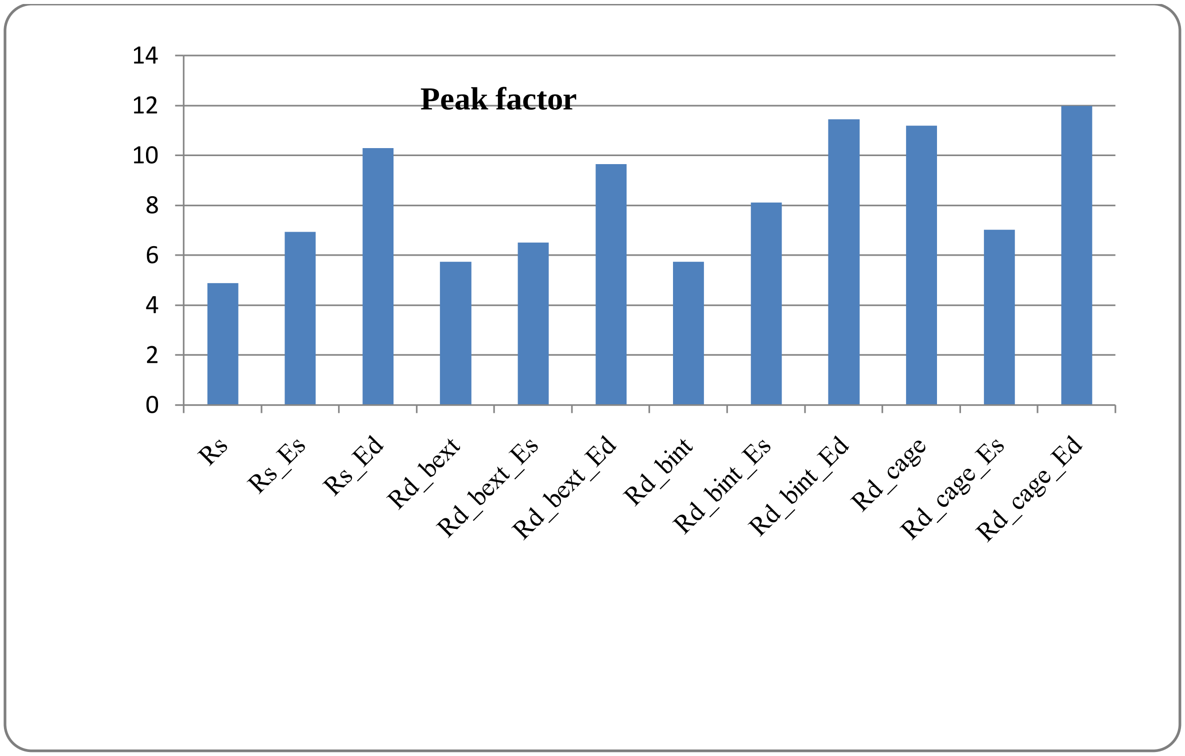

Fig. 3b:- Detection by the Crest factor.

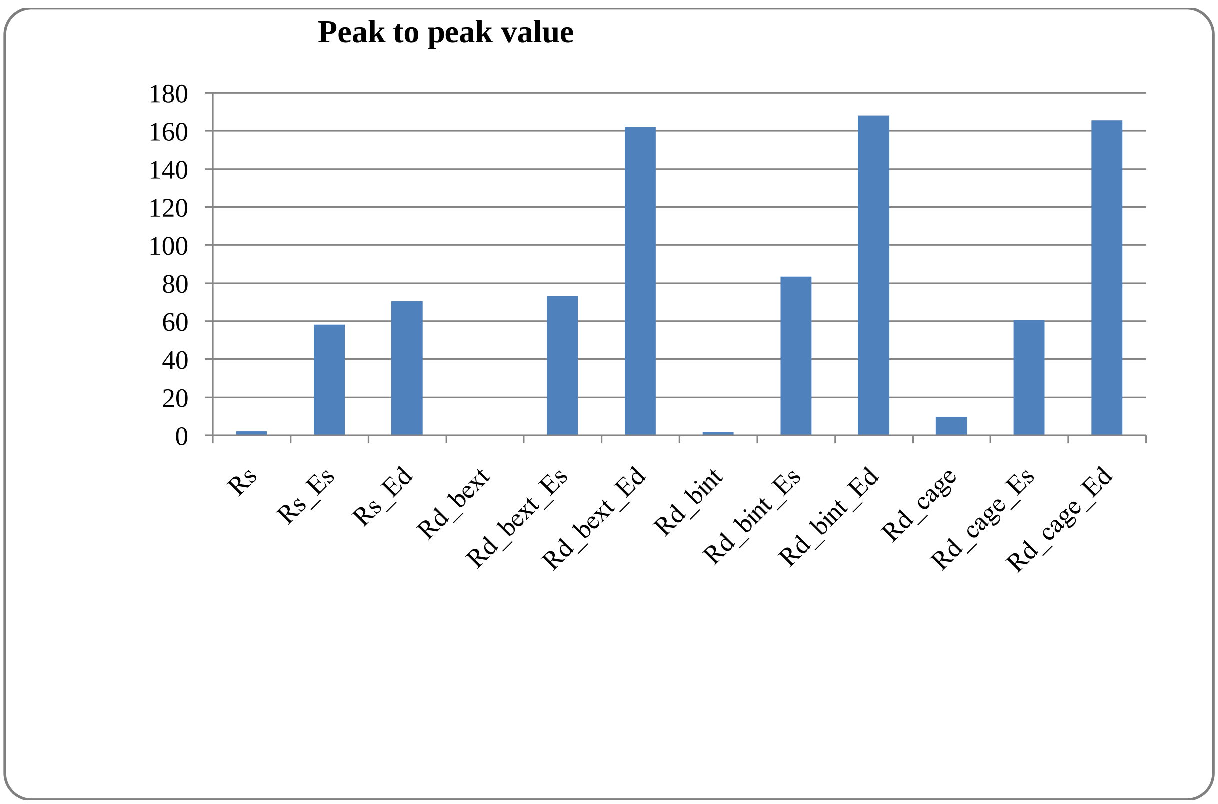

Fig. 3c:- Detection by peak-to-peak value.

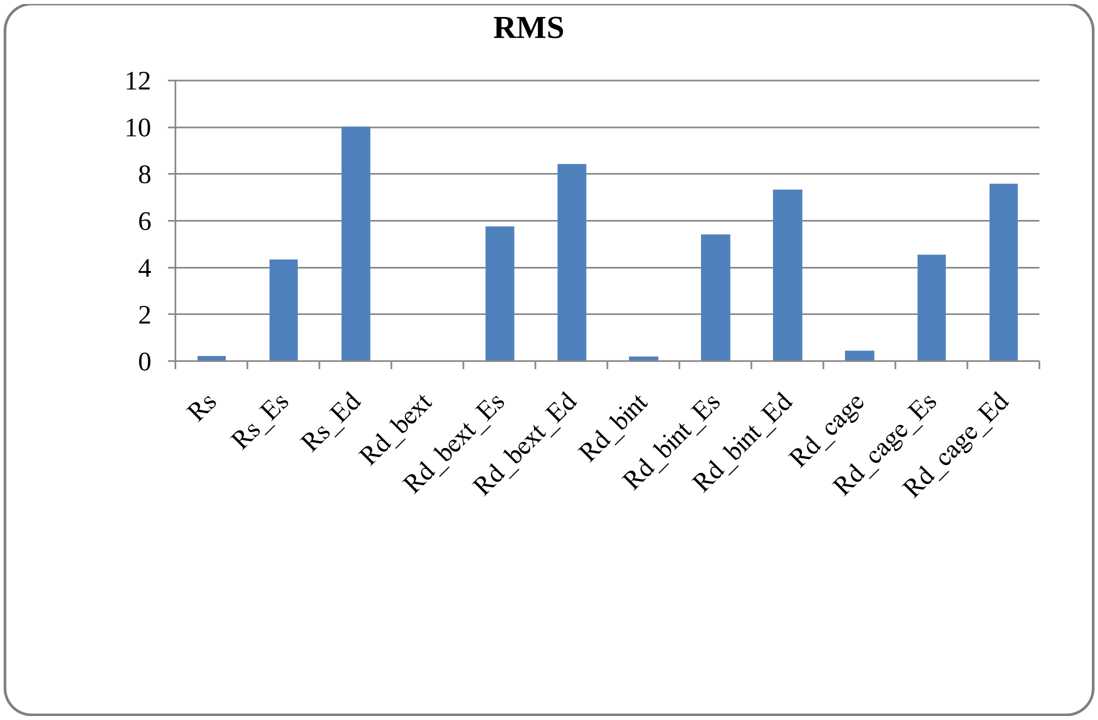

Fig. 3d:- Detection by RMS.

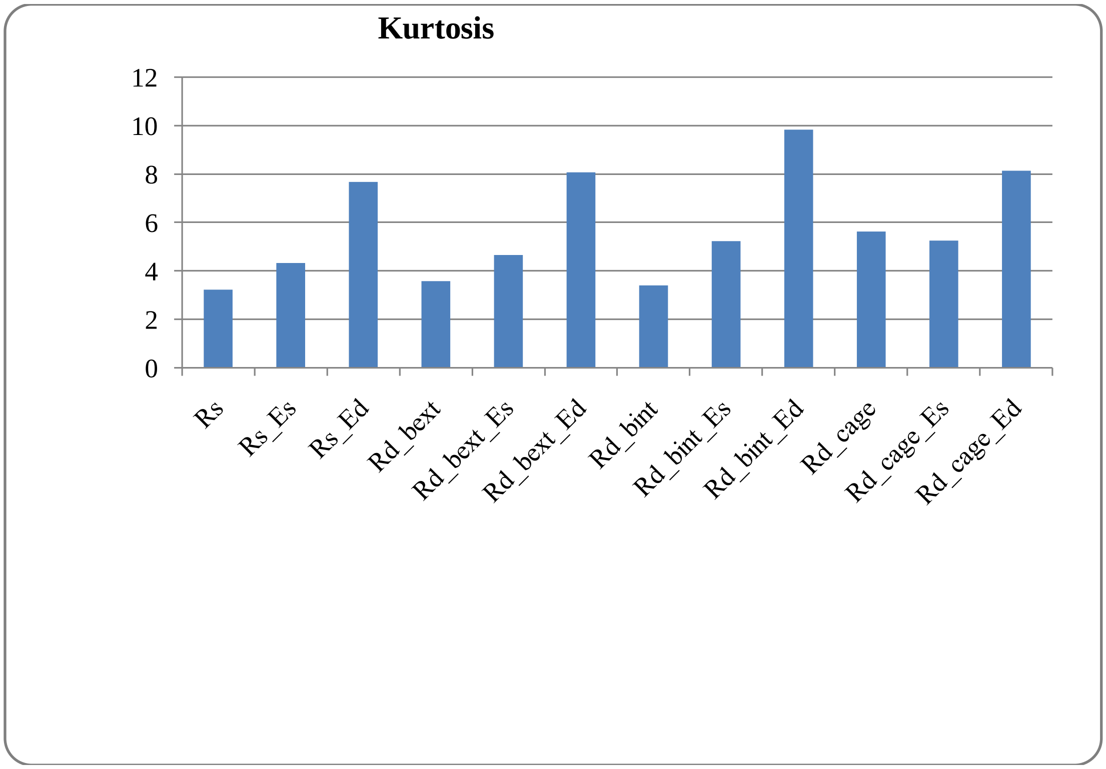

Fig. 3e:- Detection by Kurtosis.

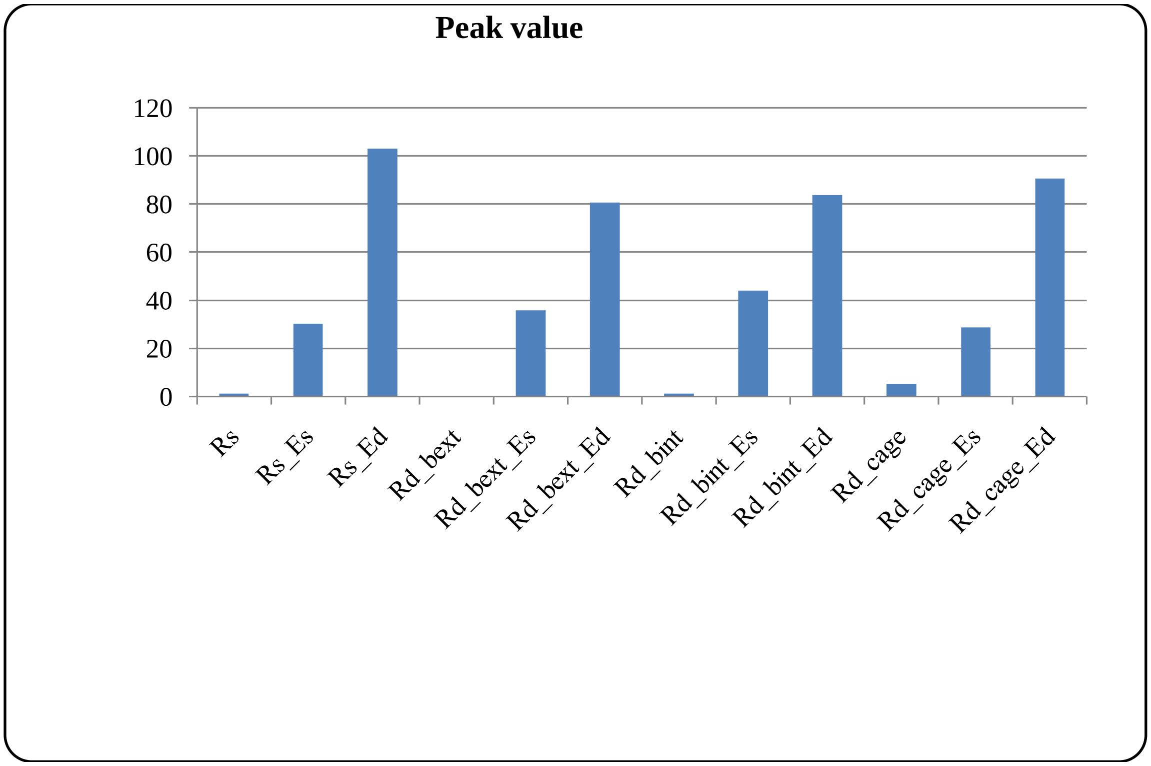

Fig. 3f:- Detection by peak value.

Fig. 3:- Results of traditional scalar indicators for the 12 tests carried out.

The results presented in Figure 3(a) – 3(f) show that:

- The K factor better detects shock defects in the cage defect example, rather than low amplitude defects (see Fig. 3a);
- The crest factor detects defects well in the first nine (9) tests, but is limited to visibly detect bearing defects with shocks. This is the case for tests 10, 11 and 12; in these cases, we should find a low value for a simple bearing defect (test 10), a value for test 11 close to that of test 10 and a value for test 12 greater than those of test 10 and test 11. On the other hand, the gear defect which is a shock defect is better detected by the crest factor, because its value has clearly varied compared to the case of healthy bearing and healthy mesh (see Fig. 3b);
- The peak-to-peak indicator is more sensitive to gear defects than the crest factor (see Fig. 3c), its value increases considerably in the case of multiple bearing and gear defects;
- The RMS is also very sensitive to gear defects (see Fig. 3d). The RMS shows that there is more shock in the case of gear defects, because its value is greater. On the other hand, in the case of multiple bearing and gear defects, it shows an attenuation of vibrations, because its value decreases but there is a clear variation compared to the healthy case, without bearing and gear defects;
- The Kurtosis is also sensitive to gear defects (see Fig. 3e). However, like the crest factor, it does not give a satisfactory result in the case of single bearing defects (test 10), single bearing defects with healthy mesh (test 11) and multiple bearing and gear defects (test 12). Logically, its value should increase progressively from test 10 to test 12;
- Like the peak-to-peak indicator, the peak indicator is very sensitive to gear defects (see fig. 3f).

Results and discussion on combined scalar indicators:-

In the following paragraphs, we present the results of the combined scalar indicators. As mentioned above, the combined scalar indicator that gives the best correlation R^2 (0.99719) is obtained between the peak-to-peak value and the crest factor, with **I = – 0, 0099356*PP + 0, 44901*FC – 2.0601.**

So, a = - 0, 0099356;
b = 0, 44901 et
c = - 2.0601.

As mentioned above, these constants are used to calculate the other fourteen (14) combined scalar indicators. To calculate these values, we arbitrarily imposed in the simulation an initial value for each combined scalar indicator (see equation 10). This initial value is set according to the severity of the defect for the six (6) tests used to calculate R^2, a, b and c.

Thus, for:

Test 1 (Rs) : I_initial = 0,1 ;

Test 2 (Rs_Es) : I_initial = 0,45 ;

Test 3 (Rs_Ed) : I_initial = 0,6 ;

Test 7 (Rd_bint) : I_initial = 0,5 ;

Test 8 (Rd_bint_Es) : I_initial = 0,8 ;

Test 9 (Rd_bint_Ed) : I_initial = 1,4.

To know whether there is a defect or not, the decision is given by equations (11) and (12) above.

To better evaluate the method, we proceeded to the tests in the following manner: a test is carried out with a healthy bearing or a defective bearing, then a healthy mesh is added, then a defective gear so as to have a single defect or a multiple defect. Of the fifteen (15) combinations of the combined scalar indicators, fourteen (14) do not give the expected results. In the 14 calculated indicators, at least one test out of twelve is not verified. Only one combined indicator gives satisfactory results in the twelve configurations of defects tested. This is the following combined scalar indicator:

I = – 0,0099356***RMS** + 0,44901***FC** – 2,0601

The results obtained by this indicator (see Fig. 4c) show that when a healthy gear is added, it is detected, because the value of the indicator I increases compared to the case without gear. When a defective gear is added, its value increases further. This shows the sensitivity of this indicator to shocks, and therefore its sensitivity to gear defects. In the context of the detection of bearing defects, the result is also satisfactory. Indeed, the initial value of the indicator chosen for test 1 (Healthy bearing) is almost the same as the calculated one, this means that it is able to recognize when there is no bearing defect ($I_{initial}$ = 0,1 et $I_{calculed}$ = 0,1246).

From all of the above, we logically retain for the temporal analysis, the monitoring indicator I obtained by linear combination of RMS and FC.

Figure 4c below shows the results of this indicator. We can see that the values of the indicator calculated for the tests with defects are higher than their initial values. When there is no defect, its two values are close. Also, as we can see in this figure, the defects of low amplitude are less highlighted, for example tests 4 (Rd_bext) and 7 (Rd_bint).

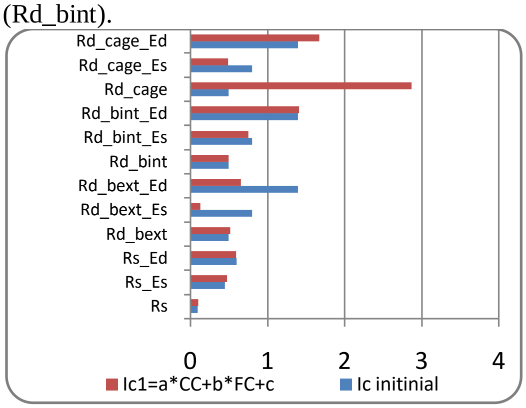

Fig. 4a-I1 = f (CC, FC)

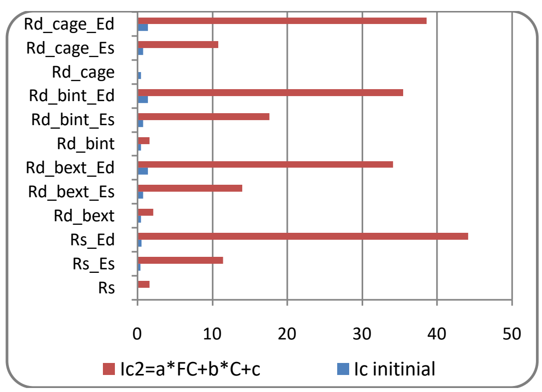

Fig. 4b -I2 = f (FC, C)

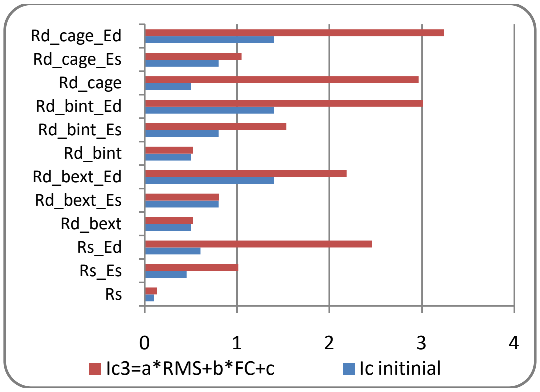

Fig. 4c-I3 = f (RMS, FC)

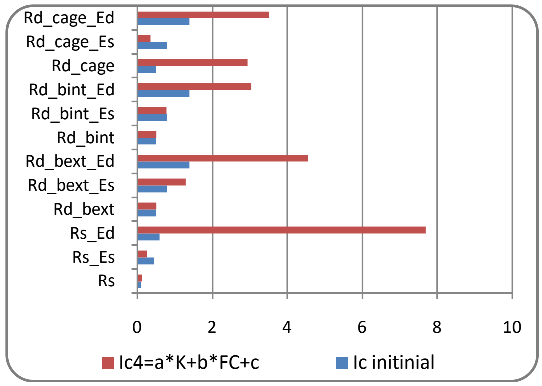

Fig. 4d-I4 = f (K, FC)

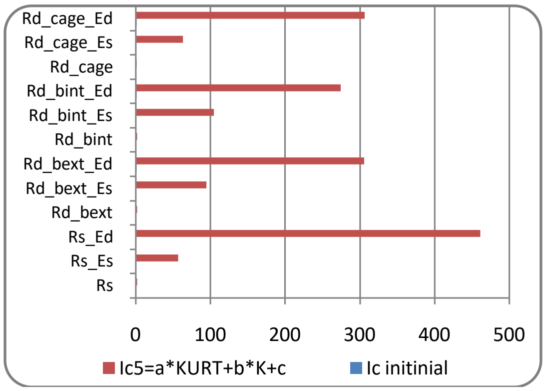

Fig. 4e-I5 = f (KURT, K)

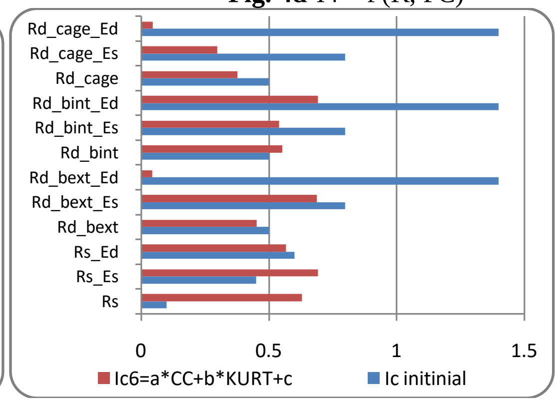

Fig. 4f-Ic6 = f (CC, KURT)

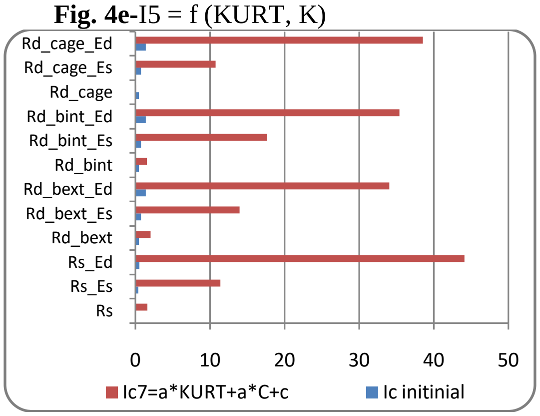

Fig. 4g-I7 = f (KURT, C)

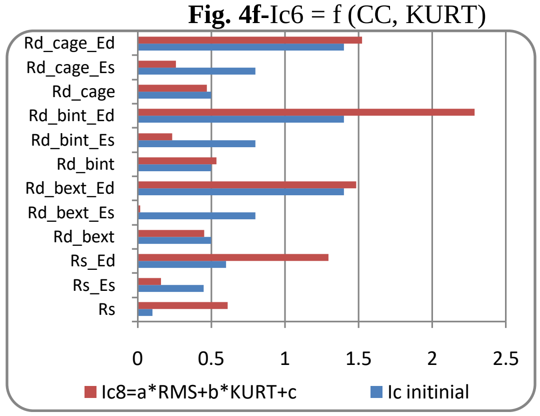

Fig. 4h-I8 = f (RMS, KURT)

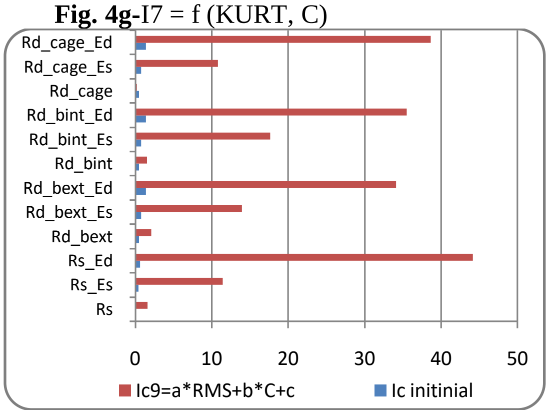

Fig. 4i-I9 = f (RMS, C)

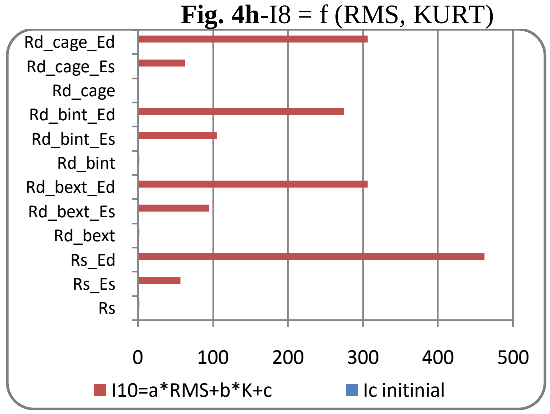

Fig. 4j-I10 = f (RMS, K)

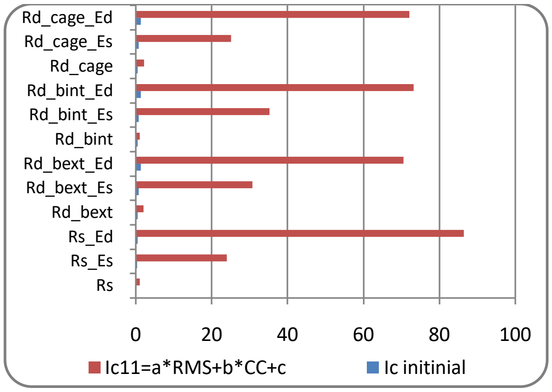

Fig. 4k- I11 = f (RMS, CC)

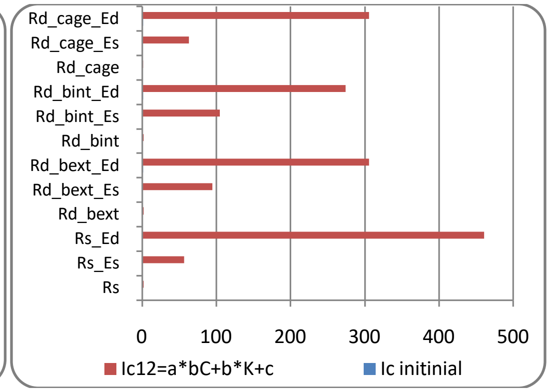

Fig. 4l- I12 = f (C, K)

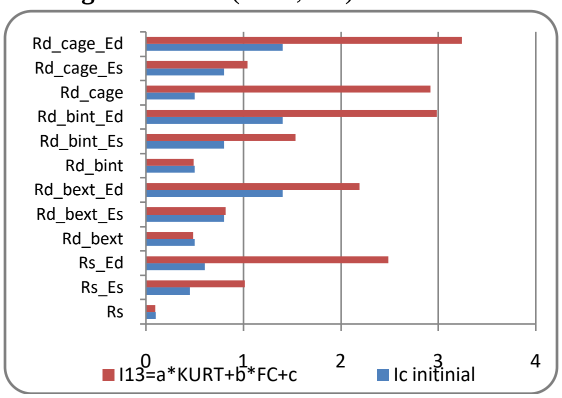

Fig. 4m-I13 = f (KURT, FC)

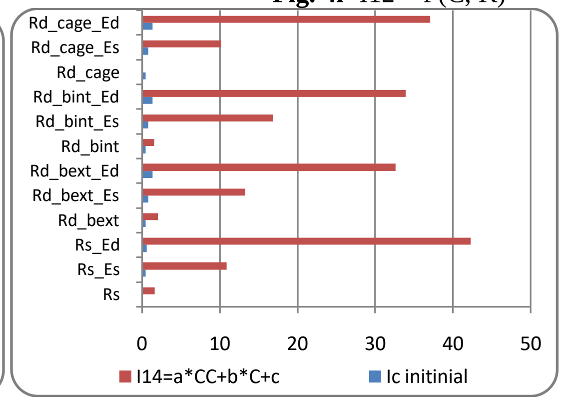

Fig. 4n-I14 = f (C, K)

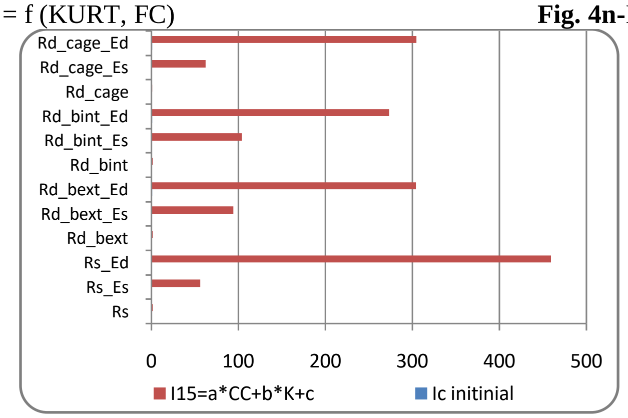

Fig. 4o- I15 = f (CC, K)

Conclusion:-

In this article, we proposed a new indicator for monitoring rotating machines by vibration analysis, based on the linear combination of scalar indicators commonly used in maintenance by time analysis. Fifteen different indicators are studied and evaluated on twelve tests, with different fault configurations performed on a vibration test bench. Only one combined indicator out of the fifteen studied gives satisfactory results on all the tests performed, namely the indicator obtained by linear combination of RMS and FC. This is what we now retain for the detection of faults in the time domain. However, to definitively validate this indicator, full-scale tests would have to be carried out, because we identified a misalignment of shafts on the experimental setup using spectral analysis, which is not presented here in this work.

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