THE PARACONSISTENT FUZZY LOGIC USING WAVELET ZERO CROSSINGS FOR THE DIAGNOSTIC OF DEFECTS IN ROLLING BEARINGS

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ABSTRACT A automated diagnostic system for defects in bearings based on Paraconsistent Fuzzy Logic is presented which deals with inconsistent and ambiguous information and a new defect characteristic extraction method for rolling bearings vibration signals based on Wavelet Transform is presented. There is a need for the optimization of diagnosis systems in order to increase precision and to reduce human errors. Experimental data were used to test the methodology. The results of paraconsistent fuzzy logic for defect classification using wavelet zero crossings for characteristic extraction were conclusive showing that the system is capable to identify and classify defects in bearings.

1. INTRODUCTION

The present industrial technology for the monitoring and diagnosis of defects in rolling bearings is limited to the use of root means square (RMS) values and spectral analysis of the acceleration signals measured at the bearing housing [1, 2, 3].

The use of vibration analysis in monitoring the operational condition of rotating machinery with safety functions, such as the primary pump of a nuclear power plant, present additional challenges, namely, the monitoring system must have a degree of reliability compatible with the equipment which is being monitored.

Many companies are manufacturing and selling systems with spectral analysis capabilities such as power spectrum density and envelope techniques built in [4]. In these cases, the diagnosis of bearing defects depend on previous user knowledge about the behavior of the spectral parameters. No standardization is yet available.

However, significant effort in the scientific community has been spent, in the research and development of new and more reliable defect characteristic extraction techniques [5, 6, 18] and in the automation of diagnosis systems. Most of the systems are based in artificial intelligence techniques such as fuzzy logic inference machines and neural networks [7, 8, 9, 10, 11]. In this work we studied two new methods applied to rolling bearings condition monitoring, one for defects characteristic extraction and another for automating the diagnosis. We propose the use of the discrete wavelet transform and the wavelet zero crossing [12], which represents the number of inflection points in the original acceleration signal. We observe that this characteristic is related to the existence of a defect and to the type of defect.

A diagnosis system should be robust, being able do generate a reliable output and should also be able to deal with ambiguous and sometimes contradictory data. To deal with the treatment of diversified source of information, we studied and applied a new non-classical logical theory named Paraconsistent Fuzzy Logic [13, 14, 15, 16, 18].

These proposed new methods are then applied to a database obtained from an experimental set up where rolling bearings with different types of implanted controlled defects and operating in different conditions. The results obtained inside the domain of this experimental data showed that the proposed methods are valid.

2. THEORY

Characteristics Extraction: The vibration behavior of a machine is the main phenomena used to monitor its condition. The vibration signature is obtained by acquiring and processing acceleration signals from piezoelectric sensors. These signals are processed to extract characteristics that can be correlated to existing defects. The characteristics analyzed in this work are the *RMS* (Root Mean Square), which is a statistical parameters of the signal [17] and the wavelet zero crossing index (*WZCI*).

This new index was developed for the extraction of additional information of a signal, which goes beyond the usual techniques based on spectral analysis, using the wavelet transform and the wavelet zero crossing. Below, we introduce some basic concepts with regard to wavelet transforms, wavelet zero crossing and wavelet zero crossing index.

The wavelet transform is a linear operation that decomposes a signal into components that appear at different scales [19]. By using $\psi(t)$ as the mother wavelet, the wavelet transform of a function $f(x)$ at the scale s and position x is defined by:

$$W_s^{\psi} f(x) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} f(u)\psi\left(\frac{u-x}{s}\right)du \qquad (1)$$

If $s = 2^j$ and $x = k*2^j$ with $(j, k) \in z$, we have the dyadic wavelet transform.
Mallat [19] has proposed that: We define as the smoothing function, the impulse response of a low-pass filter. The convolution of a function $f(x)$ with the smoothing function attenuates part of its high frequencies without modifying the lowest frequencies and hence smooths $f(x)$. Let us show that if the wavelet is the second derivative of a smoothing function, the zero-crossing of a wavelet transform indicate a location of the signal sharper variation points.

Let $\theta(x)$ smoothing function, and

$$\psi(x) = \frac{d^2\theta(x)}{dx^2} \qquad (2)$$

We denote

$$\theta_s(x) = \frac{1}{s}\theta\frac{x}{s} \qquad (3)$$

The dilation of $\theta(x)$ by a factor s. Since

$$W_s f(x) = f * \psi_s(x) \qquad (4)$$

we derive that

$$W_s f(x) = f * \left(s^2 \frac{d^2\theta_s}{dx^2}\right)(x) = s^2 \frac{d^2}{dx^2}(f * \theta_s)(x) \qquad (5)$$

Hence, $W_s f(x)$ is proportional to the second derivative of $f(x)$ smoothed by $\theta_s(x)$. The zero-crossings of $W_s f(x)$ correspond to the inflection points of $f * \theta_s(x)$.

The wavelet zero-crossing index can therefore be defined by:

$$WZCI = \frac{W_s^{\psi} f(x)}{\Delta l} \qquad (6)$$

where, $\Delta l = f_a * n^o$ *points of the signal.*

This index is also associated to a threshold value that can be varied as well as to the number of levels of the discrete wavelet transform.

Paraconsistent Fuzzy Logic: The basic assumption which is the basis for the classical fuzzy logic, is that an element "x" of the universe of discourse "X" must be chosen as being part of the fuzzy set "A". This element "x" is considered valid and consistent 'a priori'. The only quantification associated to it, is the degree of membership in the fuzzy set "A", expressed through a membership function $\mu_A(x)$ [13]. No other quantification or verification of either the validity nor the credibility of the information, as well as of its consistency is possible later on, resulting only in an output set between [0, 1] representing all possible states between the truth and the false.

In the fifties, a new non-classical logic was introduced named Paraconsistent Logic, which is an evolution of the classical Boolean logic with its fuzzy form. This new logic was created simultaneously and independently by the polish logician Jáskowosli and by the brazilian logician Costa [14]. We will present below a free form, short summary without completeness, the basic concepts used in this work.

In this work the first order double notation paraconsistent logic will be used [13]. A given proposition P is associated to a pair (μ_A, μ_B) where $0 \le \mu_A \le 1$ means the degree of credibility of P while the degree of non-credibility of P is $0 \le \mu_B \le 1$. The domain defined by this pair is called the square of true values as shown in figure 1. In this square, the point (1,0) represents the total credibility or truth, (0,1) indicates the total non-credibility or false, the point (1,1) indicates total inconsistency and (0,0) totally undefined.

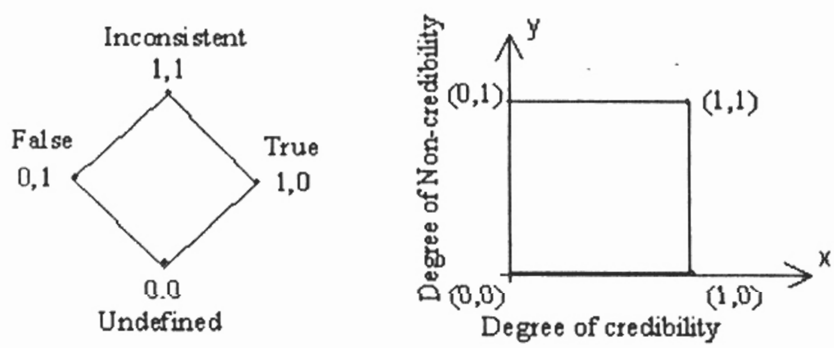


Figure 1 – The Hasse Diagram and its cartesian form

A better representation can be obtained using two new logical variables named Degree of Contradiction and Degree of Certainty defined as follows:

Degree of Contradiction: $G_{ct} = \mu_1 + \mu_2 - 1$ (7)

Degree of Certainty: $G_c = \mu_1 - \mu_2$ (8)

where: $\mu_1 = \mu_A$ (9)

$\mu_2 = 1 - \mu_B$ (10)

The Degree of Contradiction represents the distance between two extreme states namely: Totally Undefined and Totally Inconsistent while de Degree of Certainty represents the distance between two other extreme states named Totally True and Totally False.

In the classical fuzzy set theory, an element x of the universe of discourse X is associated to the fuzzy set A through the membership function $\mu_A(x)$ with values in the interval [0, 1]. In its continuous form, the fuzzy set can be represented by:

$$A = \int_X \mu_A(x_i)/x_i \qquad (11)$$

However, considering the paraconsistent logic form where a given proposition is characterized by a pair of membership function $[\mu_A, \mu_B]$, one can demonstrate that the fuzzy set A is expressed by:

$$A=\int_X \mu_A(x_i)/x_i + \mu_B(x_i)/x_i \qquad (12)$$

The symbol '+' as well as the integration symbol represents here either the logical operators *'AND'* or *'OR'*. The implementation of the equation 12 can be easily done adapting the Fuzzy Logic toolbox in the MATLAB software.

3. APPLICATION

Rolling bearings with different kinds of defects were studied. Experimental measurements were performed to obtain a database composed of vibration signals at several different speeds and radial loading for each type of defect. The statistical parameters (*RMS*) and Wavelet Zero Crossings Index are calculated using the algorithms defined above using the acquired signals. Once the parameters are well defined, these will be used to generate membership functions for the processing in a paraconsistent fuzzy logic inference system.

Experimental Setup and Measurements An AC motor that drives a shaft in which the rolling bearing was assembled composes the experimental apparatus. Connected to the bearing there is a mechanism that loads radially the rolling bearing. The speed of the AC motor is controlled by an electronic frequency inverter.

Faults can appear in rolling bearings as consequence of many problems such as: incorrect lubrication, contamination through dust or external particles, use of an inadequate lubricant, incorrect storage, faults in the assembly of the rolling bearing, etc. To simulate different sizes and kinds of defects, 4 types were introduced in the rolling bearing: a pit *P1* (punctual size), a low severity corrosions *CL*, a advanced corrosion *CE*, all of them running with low and high loading, distributed evenly in the outer race. A pit type defect *IR* in an inner race was also studied. A rolling bearing in good condition (no fault) *N* was also used to represent the reference baseline signal.

Vibration signals of a rolling bearing were sampled using a piezoelectric accelerometer mounted vertically on the top of the bearing housing. The accelerometer was connected to an amplifier with a low pass filter with 10 kHz cut-off frequency. The filtered signal was digitized by an A/D acquisition card installed in a personal computer, with a sampling frequency of 30kHz and 120000 points files to represented each signal.

Three experimental runs for every loading, speed and defect type were conducted. The experimental variables were: five types of defects (*N, CL, CE, IR,* and *P1*), five different speeds (900, 1200, 1500 2100 and 2460 rpm) and two different conditions of radial loading (5 and 30N). Consequently 50 acceleration signals form the database.

Membership Functions From the acceleration signals obtained in the experimental set up we calculated the *RMS* and *WZCI* for every type of defects and every operating condition. If one chose a given shaft speed, e.g. 1500rpm and analyze the behavior of these parameters one can construct the correspondent membership function as shown in Figure 2 and 3.

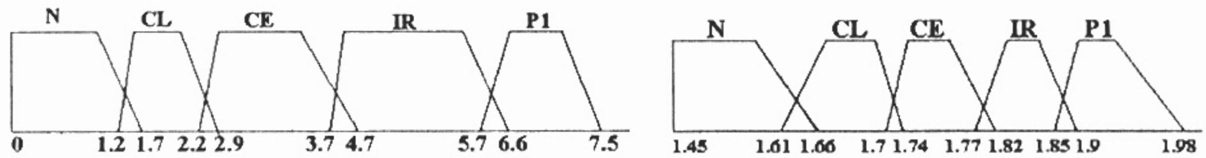


Figure 2. RMS and Wavelet Zero Crossing Index Membership Function

4. APPLYING PARACONSISTENT FUZZY LOGIC IN THE DIAGNOSIS OF ROLLING BEARINGS

The developed algorithms (12) were implemented using MATLAB. Particularly, the Paraconsistent Fuzzy Logic diagnosis system was implemented by adapting existing functions in the Fuzzy Toolbox. For every possible defect, a proposition and the corresponding membership functions must be defined. In this present case the propositions will be:

***P*(μ_1, μ_2)** : *The bearing being analyzed has a defect of type "x", with degree of credibility μ_1 and degree of non-credibility μ_2.*

The type of defects "*x*" considered as an example in this present work is *P1*. The membership functions μ_A and μ_B for each type of defect are obtained from Figure 2 and 3, for *RMS*, and Wavelet Zero Crossings Index, respectively. Presently, the industrial standard for diagnosis of defect in bearings uses the *RMS* value [1, 2, 3] or with some refinement using spectral analysis like power spectrum density and envelope techniques. Since *RMS* value of acceleration signals is a well-established industrial characteristic, we will use it to define the degree of credibility ($\mu_1 = \mu_A$). In this way, the *WZCI* membership function μ_B will be used to calculate the degree of non-credibility ($\mu_2 = 1 - \mu_B$).

Having defined the degree of credibility and the degree of non-credibility one can transform to the new logical variables: degree of certainty $G_c = \mu_1 - \mu_2$, and the degree of contradiction $G_{ct} = \mu_1 + \mu_2 - 1$, both defined in the domain [-1, 1] [13]. Two membership functions for each defect are then constructed. To illustrate this, in figure 3 is shown the degree of credibility μ_1 based on *RMS* membership function (μ_A) for the pitting type defect and degree of non-credibility μ_2 based on *WZCI* membership function (μ_B), which as calculated considering one scale level and normalized to the number of points.

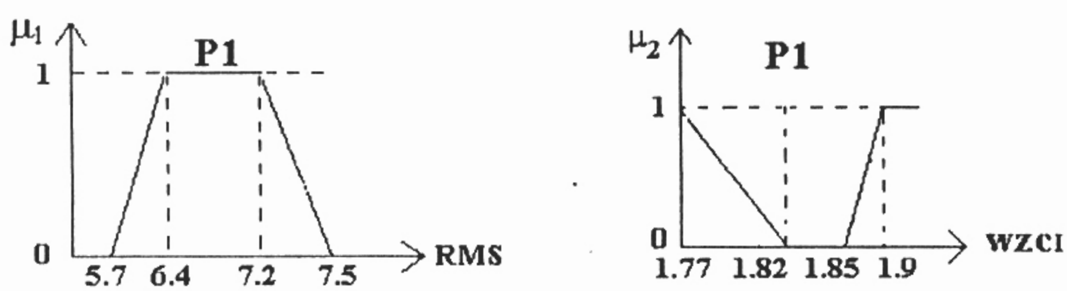


Figure 3.Degree of Credibility (RMS) and Degree of Non-Credibility (WZCI)

The diagnostic system is shown in Figure 4 below where the input function blocks, the inference rules and the output functions are depicted.

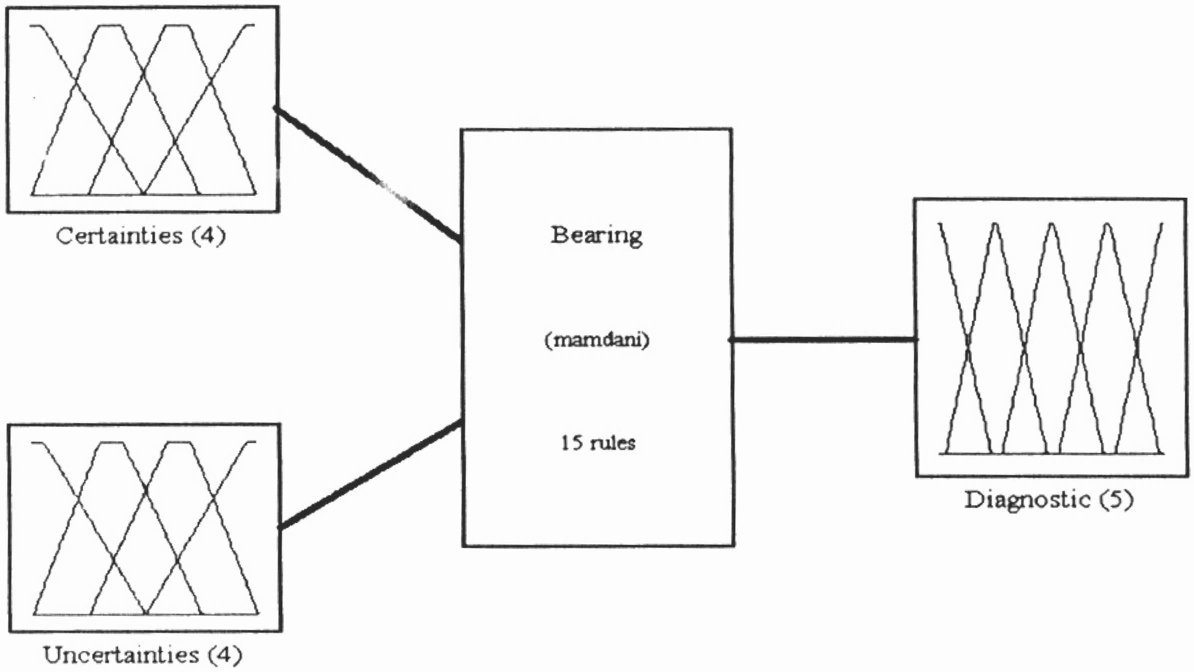
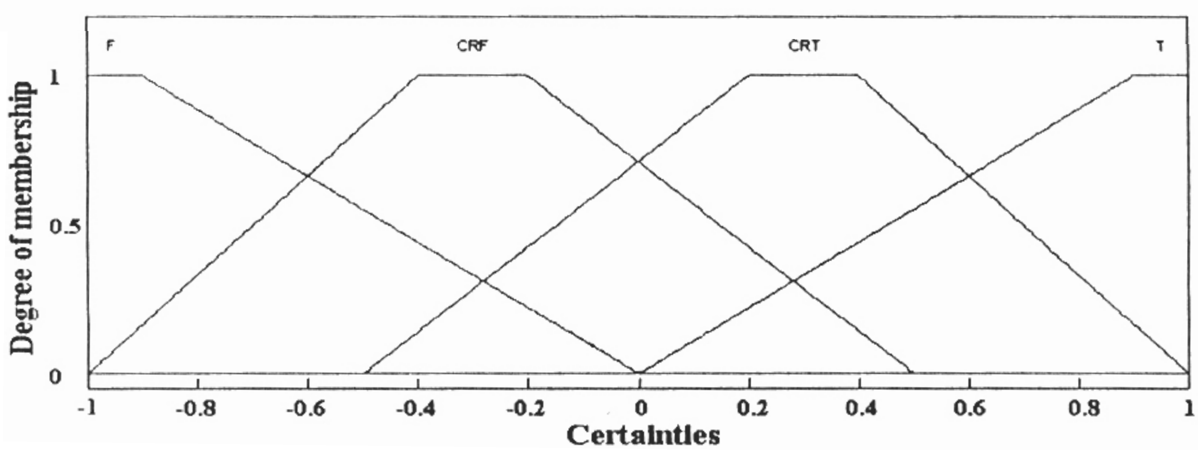


Figure 4. Diagnosis System Block Diagram

The two input membership functions, namely the degree of certainty and the degree of contraction are fuzzified and two new input membership functions are generated for each of them and they are shown below in Figure 5. The legends are defined in Figure 6, which illustrates in all possible output states Figure 7 and their definitions.



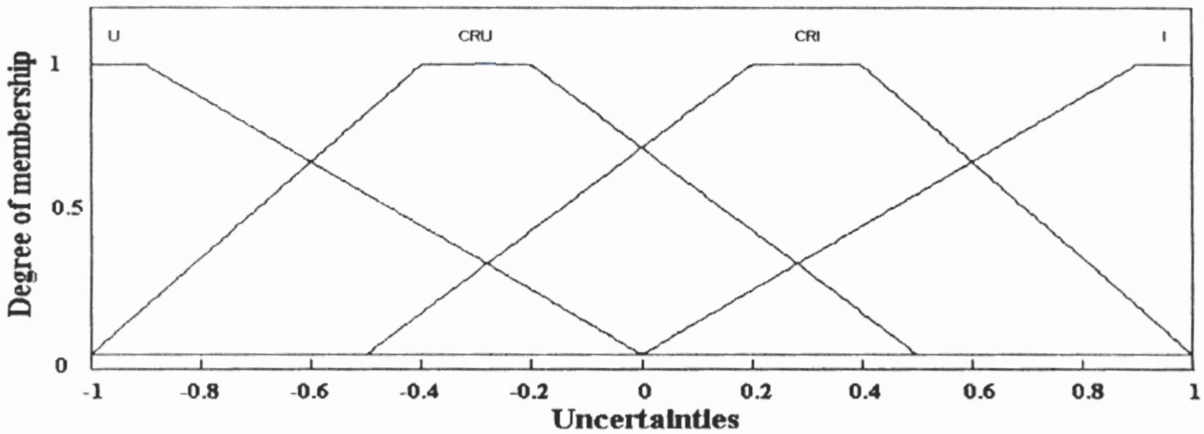


Figure 5. Fuzzified Input Membership Functions

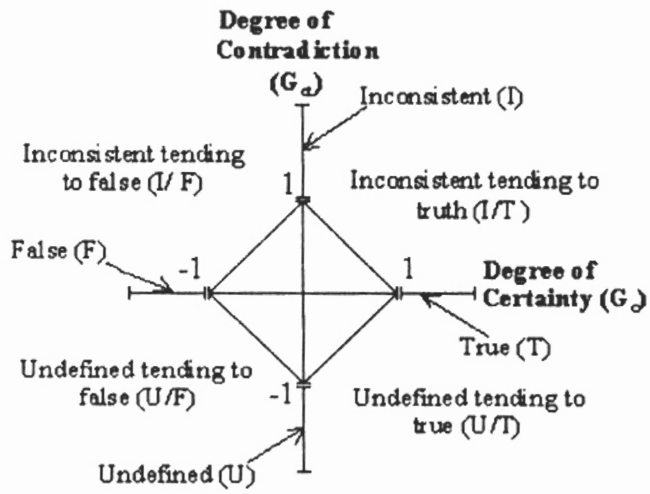


Figure 6. Degree of Certainty and Contradiction Logical Domain

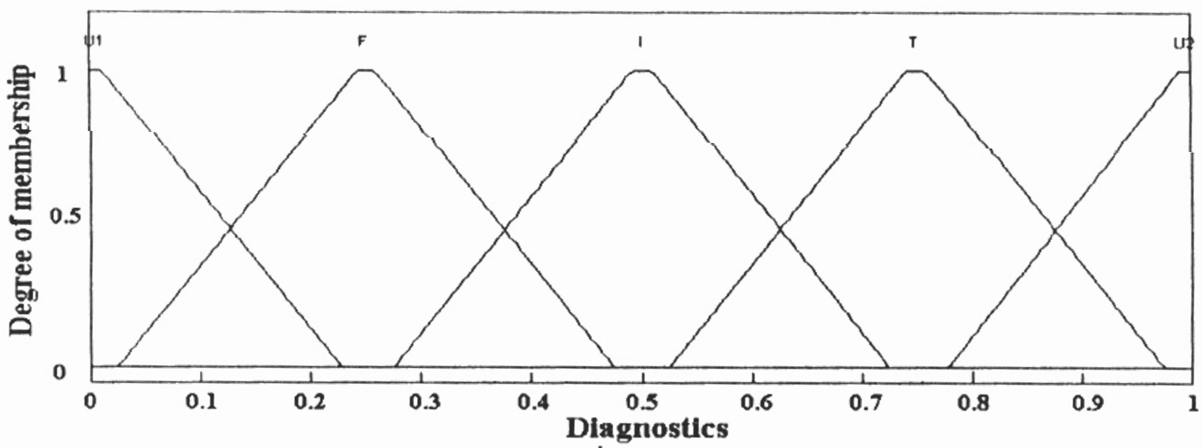


Figure 7. Output States Membership Functions

The Table 1 below defines the inference rules between the input membership functions degree of contradiction and the degree of certainty and their correspondent output states.

Table 1: Inference rules and output states.

G_c \ G_{ct}	T	CRT	CRF	F
U	*	U1, U2	U1, U2	*
CRU	T	*	*	F
CRI	T	*	*	F
I	*	I	I	*

Examples of some typical inference rules used in this work:

1. If (Degree of Certainties is CRT) and (Degree of Uncertainties is U) then (Diagnostic is U2) (1)
2. If (Degree of Certainties is CRF) and (Degree of Uncertainties is U) then (Diagnostic is U2) (1)
3. If (Degree of Certainties is T) and (Degree of Uncertainties is CRU) then (Diagnostic is T) (1)

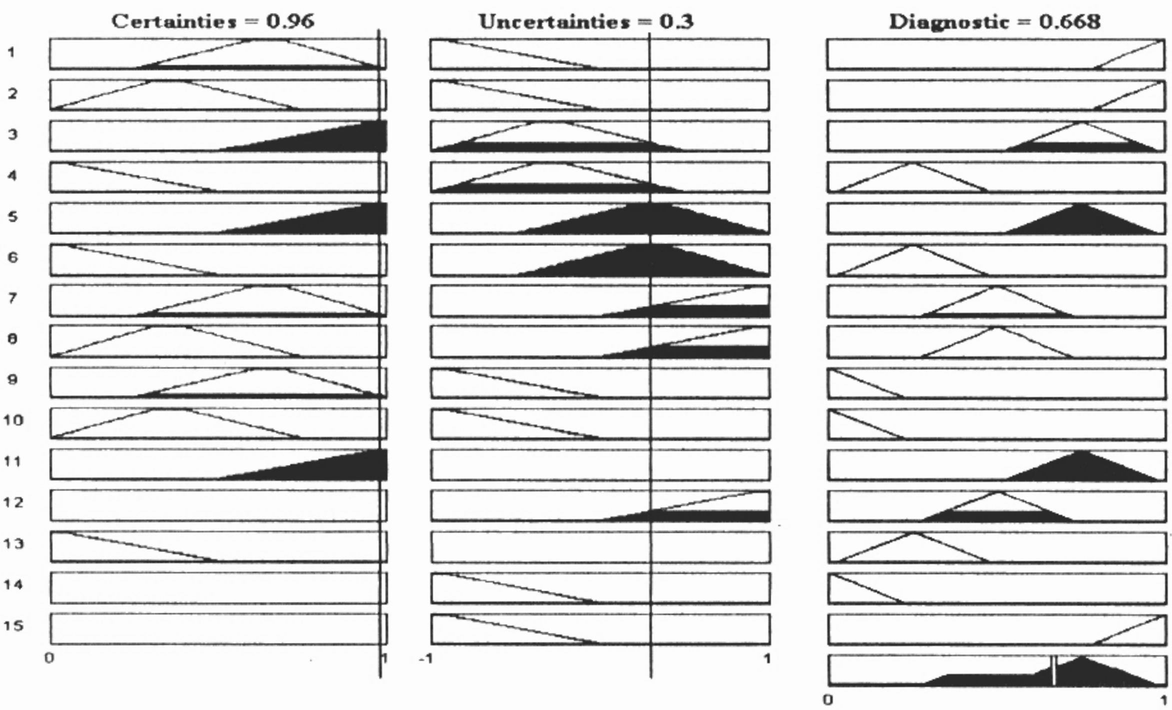


Figure 8 example of use of ruler view of toolbox Matlab

In this present work, in view of not being a complete and extensive assessment of rolling bearings defects diagnosis but instead we only wish to demonstrate the applicability of these tools using a limited experimental database. Therefore, at the moment it suffices the use of only 6 output states [T, F, I, U, (T→I, F→I), (T→U, F→U)] for diagnosis as defined below.

As we extend our knowledge to a broader range of database, we can expand the number of possible output states for refining the diagnosis. The logical output states and their correspondent diagnosis are listed below:

[T]: The test is valid and the defect is of the type being investigated.

[F]: The test is valid and there is no defect.

[I]: The test is not valid even though the equipment is operational. The following maintenance procedure are recommended before proceeding to a new testing:

Check equipment calibration and check whether the parameters used in defect characteristics extraction are adequate and check whether the instrument channel is appropriate, e.g., filters set-points, amplifier gains, sensors sensibility, sensors positioning.

[U]: The test is not valid and the equipment used is out of order. Fix the equipment or change by another set.
[T →I] or [F →I]: If the diagnosis it true tending to inconsistent [T→I] or false tending to inconsistent [F→I], the parameters used in the defect characteristics extraction or the monitoring equipment adjustments are not appropriate. Run the measurement again readjusting the characteristic extraction parameters and the monitoring equipment set points.
[T →U] or [F →U]: If the diagnosis is true tending to undefined [T→U] or false tending to undefined [F→U], the monitoring equipment is starting to present problems and a maintenance for this equipment should be programmed, i. e., it can present in the near future problems in set-points, filters, gain on amplifiers, sensors, etc.. Drifting may be present and calibration might be necessary and should checked.

5. CONCLUSIONS

5.1- Calculating the number of wavelet zero crossing Index (*WZCI*) for the accelerations signals for bearings with different type of defects and operational conditions showed that it can be a new and very effective characteristic for defects detection and classification. The reason why *WZCI* represents a different approach is because contrary to energy, statistics or spectral type parameters, it reveals another phenomenological aspect of vibration, which is the number of times that the acceleration changes direction for a given frequency band.
5.2- Although our database is not broad enough, the applications of Paraconsistent Fuzzy Logic for automating the diagnosis in this database domain, proved to be a valid tool and an improvement upon existing diagnosis automation methods. This is because the present method allowed us to combine diverse information inputs to form a diagnosis, even if the information is ambiguous or inconsistent.
5.3- The methods proposed in this work were properly implemented in the Matlab environment and it is running efficiently allowing the generation of diagnosis once an acceleration signal is supplied to the program.
5.4- As far as future activities goes, we plan to extend our experimental database in order to improve our knowledge base.

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