

WAVELET ZERO CROSSINGS AND PARACONSISTENT FUZZY LOGIC IN THE DIAGNOSTIC OF ROLLING BEARINGS

Paulo Henrique Ferraz Masotti and Daniel Kao Sun Ting

Instituto de Pesquisas Energéticas e Nucleares - IPEN-CNEN/SP
Av. Lineu Prestes 2.242 – Cidade Universitária
05508-000 São Paulo, SP, Brasil

ABSTRACT

A new defect characteristic extraction method for rolling bearings vibration signals based on Wavelet Transform is presented. A more robust automated diagnostic system for defects in bearings based on Paraconsistent Fuzzy Logic is also presented which deals with inconsistent and ambiguous information. There is a need for the optimization of diagnosis systems in order to increase precision and to reduce human errors. Automatic diagnosis systems should be robust to a point where it must operate with a diversified source of information allowing for analysis of different equipment and existing defects. The Paraconsistent Fuzzy Logic is applied in the present work. This technique is a flexible tool which allows the modeling of uncertain and ambiguous data frequently found in real situations. Experimental data were used to test the methodology. The results obtained by using wavelet zero crossings for characteristic extraction and Paraconsistent fuzzy logic for defect classification were conclusive showing that the system is capable to identify and to classify defects in bearings.

Keywords: diagnoses, bearings, automatic, wavelet zero crossing, paraconsistent.

I. INTRODUCTION

The present state of the art in the industry regarding monitoring and diagnosis of rolling bearing is limited to the use of Root Means Square (RMS) values of acceleration signals measured at the bearing housing [1,2,3].

Many vibration monitoring 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 will then depend solely on user knowledge about the behavior of the spectral parameters. No standardization is yet available.

However, there is a significant effort in the scientific community, in the research and development of new defect characteristic extraction techniques [5,6,18] such as the use of kurtosis, time-frequency transforms and higher order statistics as well as expanding the validity of existing characteristics through further experimental work. Another important research topic is in the development of automatic systems for defect diagnosis. Most of such automated systems are based in artificial intelligence techniques such as fuzzy logic inference machines, and neural networks [7,8,9,10,11]. In this present work we studied two new methods applied to rolling bearing condition monitoring in defects characteristic extractions well as in automating the diagnosis. We propose the use of the Wavelet Transform to generate the number of wavelet zero crossings [12] which

represents the number of inflection points per unit time in the original acceleration signal. We observe that this characteristic is related to the existence of defect and also to the type of defects.

One important limitation in existing diagnosis automation systems developments is that whatever information is supplied to the system, it is assumed valid and consistent "a priori" with other information which is gathered. However, a diagnosis system should be robust being able to generate a reliable output even with diversified source of information. It should also be able to deal with ambiguous and sometimes contradictory data. To deal with the treatment of diversified source of information, ambiguity and contradictory data we studied and applied a new non-classical logical theory named Paraconsistent Fuzzy Logic [13,14,15,16,18]. This type of inference system allows us to have several inputs from different sources, to automatically combine these data even if contradiction and ambiguity are present and to produce a broader range of possible output states.

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

II. THEORY

Characteristics Extractions 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), *Kurtosis*, which are statistical parameters of the signal [17] and the wavelet zero crossing (WZC) as defined below [12]:

By using $Y(t)$ as mother wavelet, the wavelet transform of a function $f(t)$ at the scale s and time t is defined by:

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

The wavelet transform of a signal $W_s^y f(t)$ is proportional to its first derivative weighted by a function $q(t)$, if the mother wavelet is the first derivative of the weighting function. And the transform will be proportional to the second derivative of the signal weighted by $q(t)$ if the mother wavelet is the second derivative of the weighting function. These two transformation are presented below:

$$W_s^\psi f(t) = [f * (s \frac{d}{dt} \theta_s)](t) \quad (2)$$

$$W_s^\lambda f(t) = [f * (s^2 \frac{d^2}{dt^2} \theta_s)](t) \quad (3)$$

The local extremes of $W_s^y f(t)$ correspond the **wavelet zero crossing** (WZC) of $W_s^I f(t)$ and the inflection point of $f * q_s(t)$.

$$WZC = \frac{W_s^\psi}{\Delta t} \quad (4)$$

where, Δt = time length of the signal.

In other words, the number of wavelet zero crossing represents the number of point where the signal has zero derivative values.

Paraconsistent Fuzzy Logic The basic assumption which is also a limitation of the classical Boolean logic, basis for the 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 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 Jaskowski 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 $0 \leq \mu_A \leq 1$ means the degree of credibility of P while the degree of non-credibility of P is $0 \leq \mu_B \leq 1$. The domain defined by this pair is called the square of true values. 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. This domain is illustrated in Figure 1 below and it is called the Hasse diagram.

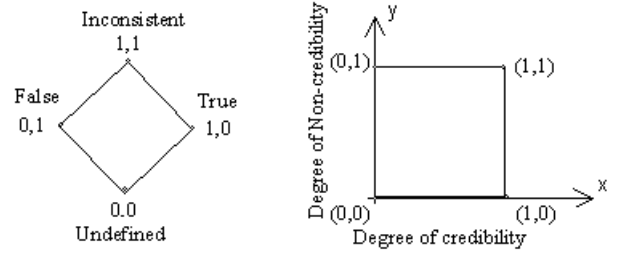


Figure 1. The Hasse Diagram and its Cartesian Form.

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

$$\text{Degree of Contradiction: } G_{ct} = \mu_1 + \mu_2 - 1 \quad (5)$$

$$\text{Degree of Certainty: } G_c = \mu_1 - \mu_2 \quad (6)$$

$$\text{where: } \mu_1 = \mu_A \quad (7)$$

$$\mu_2 = 1 - \mu_B \quad (8)$$

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:

$$A = \int_X \mu_A(x_i) / x_i \quad (9)$$

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:

$$A = \int_X \mu_A(x_i)/x_i + \mu_B(x_i)/x_i \quad (10)$$

The symbol '+' as well as the integration symbol represents here either the logical operators 'AND' or 'OR'. The implementation of the equation 10 can be easily done adapting the Fuzzy Logic toolbox in the MATLAB software.

III. 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 loadings for each type of defect.

The statistical parameters (*RMS* and *Kurtosis*) are calculated from the acquired signals. Also, the number of Wavelet Zero Crossings were calculated using the algorithms defined above.

Once the parameters are well defined, these will be used to generate membership functions for the processing in a paraconsistent fuzzy logic inference system. As input to the system the membership functions are inserted for each one of the selected parameters and by means of the inference rules it is obtained a diagnosis able to indicate the status which classifies the defects of the rolling bearing.

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 of the component, faults in the assembly of the rolling bearing, etc.

We can classify the defects by the size of the defect at the surface. To simulate different sizes and kinds of defects, 4 types were introduced in the outer race of the rolling bearing: a pit (punctual size), a localized corrosion produced by synthetic sea water for 8 hours (medium size), other enhanced corrosion produced by synthetic sea water for 24 hours (large size) and a scratched surface (distributed evenly throughout the outer race). A rolling bearing in good condition (no fault) was also used to represent the reference signal. Each one of these faults will be named by a code, which are: *N* for normal, *S* for scratched, *P* for pit, *C1* for the corrosion and *C2* for enhanced corrosion.

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 2 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 5,12 kHz and 2048 points files to

represented each signal. The rotation control of the shaft and the loading system were calibrated before beginning the measurements.

Three experimental runs for every loading, speed and defect type were conducted. The experimental variables were: five types of defects (*N*, *S*, *P*, *C1*, and *C2*), six different speeds (400 to 1400 rpm) and three different conditions of radial loading (200, 400 and 600N). Consequently 270 acceleration signals form the database.

Membership Functions From the acceleration signals obtained in the experimental set up we calculated the *RMS*, *kurtosis* and *WZC* index for every type of defects and every operating condition. If one chose a given shaft speed, e.g. 100 rpm and analyze the behavior of these parameters one can construct the correspondent membership function as shown in Figure 2, 3 and 4.

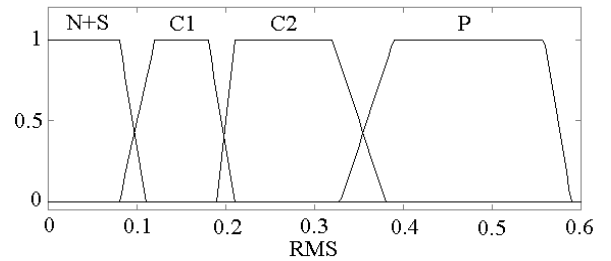


Figure 2. RMS Membership Function.

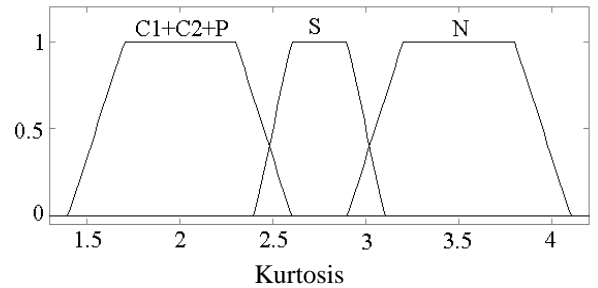


Figure 3. Kurtosis Membership Function.

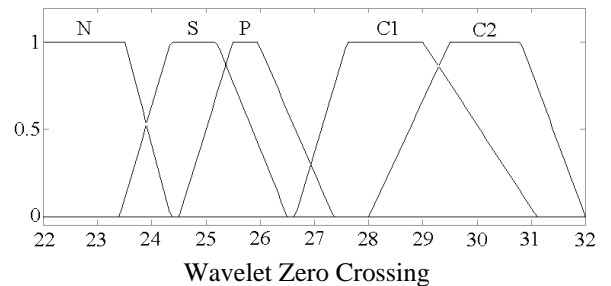


Figure 4. Wavelet Zero Crossing Membership Function.

IV. APPLYING PARAconsistent FUZZY LOGIC IN THE DIAGNOSIS OF ROLLING BEARINGS

The algorithm (10) developed 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:

$P(\mu_1, \mu_2)$: The bearing being analyzed has a defect of type “x”, with degree of credibility μ_1 and degree of non-credibility μ_2 .

The types of defects “x” considered in this present work are: normal (N), scratched (S), pitting (P), incipient corrosion (CI) and enhanced corrosion (C2). The membership functions μ_A and μ_B for each type of defect are obtained from Figure 2, 3 and 4, for *RMS*, *Kurtosis* and *Wavelet Zero Crossings* values, respectively. Presently, the industrial standard for diagnosis of defect in bearings uses the *RMS* value [1,2,3] 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, either the *Kurtosis* membership function μ_B or the *WZC* membership function μ_C will be used to calculate the degree of non-credibility ($\mu_2 = I - \mu_B$) or ($\mu_2 = I - \mu_C$).

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 $G_{ct} = \mu_1 + \mu_2 + I$, both defined in the domain [-1,1] [13]. Two membership functions for each defect are then constructed, totaling 10 input membership functions. To illustrate this, in figure 5 is shown the degree of credibility μ_1 based on *RMS* membership function (μ_A) for the pitting type defect and in the Figure 6 is shown the corresponding degree of non-credibility μ_2 based on *WZC* membership function (μ_B), which as calculated considering one scale level and normalized to the number of points.

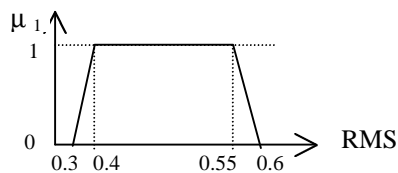


Figure 5. Degree of Credibility (RMS).

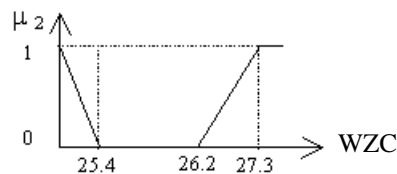


Figure 6. Degree of Non-Credibility (WZC).

The diagnostic system is shown in Figure 7 below where the input function blocks, the inference rules and the output functions are depicted.

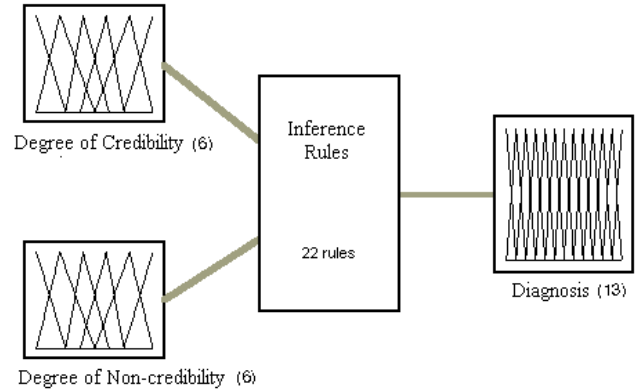


Figure 7. Diagnosis System Block Diagram.

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 8. The legends are defined in Figure 9, which illustrates in all possible output states (10) and their definitions.

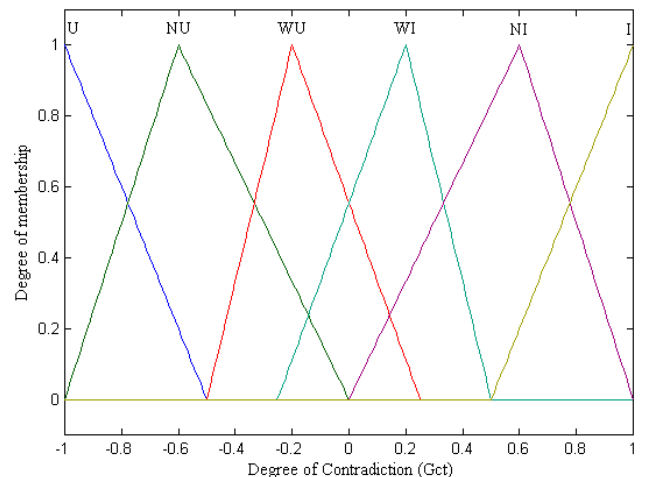
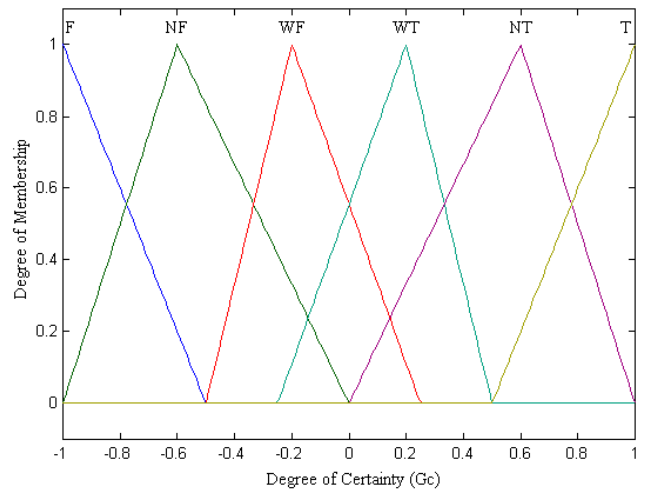


Figure 8. Fuzzified Input Membership Functions.

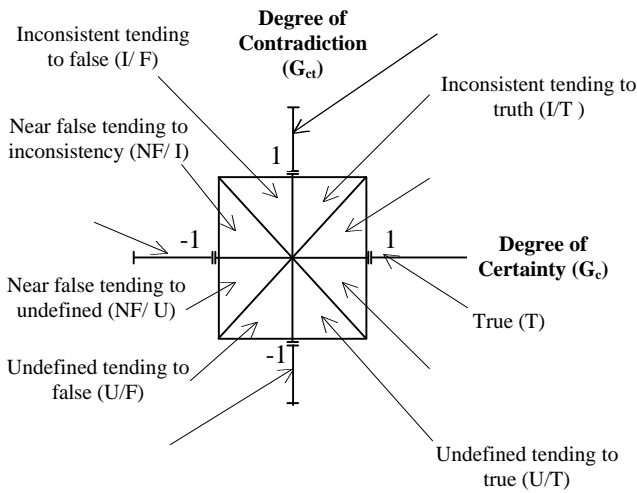


Figure 9. Degree of Certainty and Contradiction Logical Domain.

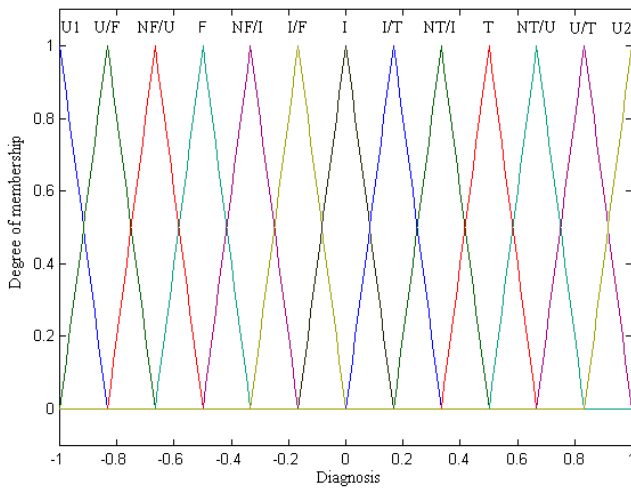


Figure 10. Output States Membership Functions.

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

$G_{ct} \backslash G_c$	T	NT	WT	WF	NF	F
U	*	*	U	U	*	*
NU	*	NT/U	U/T	U/F	NF/U	*
WU	V	NT/U	*	*	NF/U	F
WI	V	NT/I	*	*	NF/I	F
NI	*	NT/I	I/T	I/F	NF/I	*
I	*	*	I	I	*	*

In this present work, in view of not being a complete extensive assessment of rolling bearings defects diagnosis but instead we wish to demonstrate the

applicability of these tools using a limited experimental database we will reduce the number of output states from 12 states to 4 states 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, NT/I, NT/U]: The test is valid and the defect is of the type being investigated.

[F, NF/I, NF/U]: The test is valid and there is no defect.

[I, F/I, F/U]: 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.

Check whether the defect characteristics used are adequate.

Check whether the instrument channel is appropriate, e.g., filters set-points, amplifier gains, sensors sensibility, sensors positioning.

[U, U/T, U/I]: The test is not valid and the equipment used is out of order. Fix the equipment or change by another set.

We can summarize the procedure to apply this methodology as follows:

- 1) Acquire the acceleration signal at the bearing housing with the proper instrumentation and data acquisition parameters.
- 2) Calculate the signal *RMS*, *kurtosis* and *WZC* values.
- 3) Calculate their correspondent credibility μ_1 and non-credibility μ_2 membership function values.
- 4) Calculate their degree of contradiction G_{ct} and certainty G_c .
- 5) Input these values into the automated diagnosis system and obtain an output state indicating the diagnosis.

V. CONCLUSIONS

1- Calculating the number of wavelet zero crossing (*WZC*) for the accelerations signals for bearings with different type of defects and operational conditions showed that *WZC* can be a new characteristic for defects detection. The reason why *WZC* 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.

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.

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.

4- As far as future activities goes, we plan to extend our experimental database in order to improve our knowledge base. In other words, we plant to improve de applicability of our membership functions

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REFERENCES

- [1] INTERNATIONAL STANDARD ISO 10816-1; **Mechanical vibration – Evaluation of machine vibration by measurements on non-rotating part 1**, First edition, 1995
- [2] INTERNATIONAL STANDARD ISO 281; **Rolling Bearing – Dynamic Load Ratings and Rating Life** STD.ISO 281: 1990/Amd2:2000(E).
- [3] ANS, ANSI/ABMA STD 11; **Load Ratings and Fatigue Life for Roller Bearing**.
- [4] SKF **Early Warning Fault Detection In Rolling Element Bearings Using Microlog Enveloping**, SKF Condition Monitoring – Application Note – CM 3021 Revised 2-96, 1996. Article from the "site" www.skfcm.com.
- [5] TANDON, N.; CHOUDHURY, A.; **A Review of Vibration and Acoustic measurement methods for the detection of defects in rolling elements bearing** Tribology International 32, pp 469 - 480, 1999; Elsevier Science 2000
- [6] BROTHERTON, TOM; and POLLARD, TOM; **Application of Time-Frequency and Time-Scale Representation to Fault Detection and Classification**, Proceeding IEEE 4-6 October, pp 95 - 99, 1992.
- [7] LIU, T.I. SINGONAHALLI; and IYER, N.R.; **Detection of Roller Bearing Defects Using Expert System and Fuzzy Logic** Mechanical System and Signal Processing 10 (5), pp. 595 - 614, 1996; Elsevier Science 1996.
- [8] PAYA, B.A.; ESAT, I.; **Artificial Neural Network Based Fault Diagnostics of Rotating Machinery Using Wavelet Transform as a Preprocessor** Mechanical Systems and Signal Processing 11 (5), pp. 751 - 765, 1997; Elsevier Science 1997.
- [9] TSOUKALAS, LEFTERI H., UHRIG, ROBERT E.; **Fuzzy and Neural Approaches in Engineering** John Wiley & Sons Inc 1997.
- [10] UPADHYAYA, BELLE R.; **Hybrid Digital Signal Processing And Neural Networks For Automated Diagnostics Using NDE methods** – Annual Progress Report 9/30/91 – 9/29/92, Nuclear Engineering Department The University of Tennessee Knoxville, September de 1992
- [11] PADOVESE, LINILSON, R.; **Comparison Of Neural Networks Performance For Fault Classification In Rolling Bearing**, Proceedings of the IASTED International Conference Applied Modeling and Simulation, September 1-3 1999, Australia.
- [12] UPADHYAYA, B. R.; ERBAY, ALI S.; HÁZI G.; SUNG, KEY Y.; **Eddy Current Test Data Analysis For Steam Generator Tubing Diagnosis Using Artificial Intelligence Methods**. Nuclear Engineering Department The University of Tennessee Knoxville, Annual Report, February 1999.
- [13] Da SILVA FILHO, JOÃO I.; **Métodos de Aplicações da Lógica Paraconsistente Anotada de Anotação com Dois Valores-LPA2v com Construção de Algoritmo e Implementação de Circuitos Eletrônicos**, PHD Thesis - Universidade de São Paulo, São Paulo 1999.
- [14] Da COSTA, N. C. A., ABE J.M., SILVA FILHO J.I., MUROLO A.C., LEITE C. F. S.; **Lógica Paraconsistente Aplicada**, Editora Atlas S.A. – São Paulo, 1999.
- [15] Da SILVA FILHO, JOÃO I. and ABE, JAIR M.; **Para-Fuzzy Logic Controller I – A Hybrid Logical Controller Indicated for Treatment of Inconsistencies Designed with the Junction of the Paraconsistent and Fuzzy Logic** Proceedings of the International ICSC Congress on Computational Intelligence Methods and Applications CIMA 99 Rochester Institute of Technology, Rochester, NY, USA, June 22-25, 1999.
- [16] Da SILVA FILHO, JOÃO I. and ABE, JAIR M.; **Para-Fuzzy Logic Controller II – A Hybrid Logical Controller Indicated for Treatment of Fuzziness and Inconsistencies** Proceedings of the International ICSC Congress on Computational Intelligence Methods and Applications CIMA 99 Rochester Institute of Technology, Rochester, NY, USA, June 22-25, 1999.
- [17] PROAKIS, J. G.; MANOLAKIS, D. G.; **Digital Signal Processing**, 3rd. Ed., Prentice Hall, 1996
- [18] Ting, D.K.S.; Masotti, P.H.F.; Mesquita, R.N.; **Teste de Validade para um Ensaio por Eddy Current em Tubos Geradores de Vapor Usando Lógica “Fuzzy” Paraconsistente**, I Congresso de Lógica Aplicada à Tecnologia, LAPTEC 2000, 11 à 15 de Setembro de 2000.