Automatic Generation of Fuzzy Inference Diagnosis System for Industrial Plant

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Abstract. *There are several methods that can be used for automatic fault detection in mechanical plants, such as, neural network, RMS level alarms and fuzzy system, among others. The fuzzy inference system has some advantages when compared with others methods the main of these advantages being the possibility of working with many different types of industrial plant fault characteristics and of being implemented in a user-friendly way. On the order the repetitive and exhaustive work required from an expert in maintenance to create pertinent functions and inferences rules that describe the mechanical plant is clearly a disadvantage. This article deals with overcoming this problem, presenting a methodology to automatically create a fuzzy inference system using statistical information from an available database. Some examples of fuzzy system to detect and to classify localized and distributed defects in rolling bearing, generated with this methodology, are presented.*

Keywords*: predictive maintenance, fuzzy system, defect detection, rolling bearing*

1. Introduction

The fault diagnosing task is normally accomplished by an expert team in industrial plant. However, in an industrial plant where monitoring systems deliver a huge amount of information to be analysed for diagnostic purpose, the importance of automatic defect diagnoses in predictive maintenances is clear. This is particularly the case of rolling bearing health condition monitoring, since such component is widely distributed in industrial machines.

There are several ways to automate diagnostic task. As examples, one can mention the RMS level alarm (Shin, 1992), widely used for fault detection in industrial plants, and diagnoses system based on neural network (Li, 2000; Padovese, 2002). The first one is simple to implement and use, but its diagnostic reliability is weak (Vicente, 2001). The second can present a higher reliability, but is a black-box model, and does not allow the user of heuristic knowledge (Ayoubi, 1997).

A way to overcome the black-box model limitation of neural networks is by the use of a system based on fuzzy logic. In this context the most employed tool is the fuzzy inference system (Tsoukalas, 1997). In the past years fuzzy system has been employed for failure diagnosis of rolling bearings (Liu, 1996; Mechefske, 1998; Vicente, 2001a; Vicente, 2001b), gear boxes (Joentgen, 1999) and industrial plants (Jeffries, 2001; Tarifa, 1997). It has also been used in industrial control, dynamic system models, pattern recognition, among others (Cox, 1994; Mathworks, 1995; Kartalopoulos, 1996; Shaw, 1999).

In the specific case of rolling bearing fault diagnosis, fuzzy systems presented in literature have several limitations, such as: the use of heuristic information solely (Vicente, 2001a; Vicente, 2001b); the use of a single fault descriptor parameter (Liu, 1996); and the diagnostic of few types of defects (pit in outer and inner raceways and rolling element) (Mechefske, 1998).

A disadvantage of fuzzy inference system is that it requires the repetitive and exhaustive work from an expert in maintenance to create pertinent functions and inferences rules that describe the mechanical plant (Ayoubi, 1997). This article proposes a methodology to overcome these difficulties by automatically creating membership functions and inference rules, by using statistical information from an available database. However, this methodology does not totally eliminate the necessity of the maintenance expert, since his knowledge is necessary to specify the best signal parameters that describe the diagnostic problem, as well as to verify the reliability of the diagnostic results. In order to exemplify this methodology some diagnostic results obtained from an automatically generated fuzzy inference system, for a rolling bearing fault detection problem is presented

2. Fuzzy Inference System

Fuzzy inference systems are based on fuzzy logic. It is possible to understand fuzzy logic by comparison with classic logic. While in classic logic an element must belong to either a set or its complement, in fuzzy logic this same element can belong to a set and its complement, depending on a membership degree. A way to represent this membership degree is (Tsoukalas, 1997):

$$A = \{x, \mu_A(x) \mid x \in X\} \tag{1}$$

Let A be the fuzzy set, X the universe of discourse of this set, x an element in the universe of discourse and μ_A the membership function in the interval [0,1]. In this case, 0 represents the total not-belong condition and 1 the total belong.

A fuzzy inference system has the structure showed in Fig. (1).

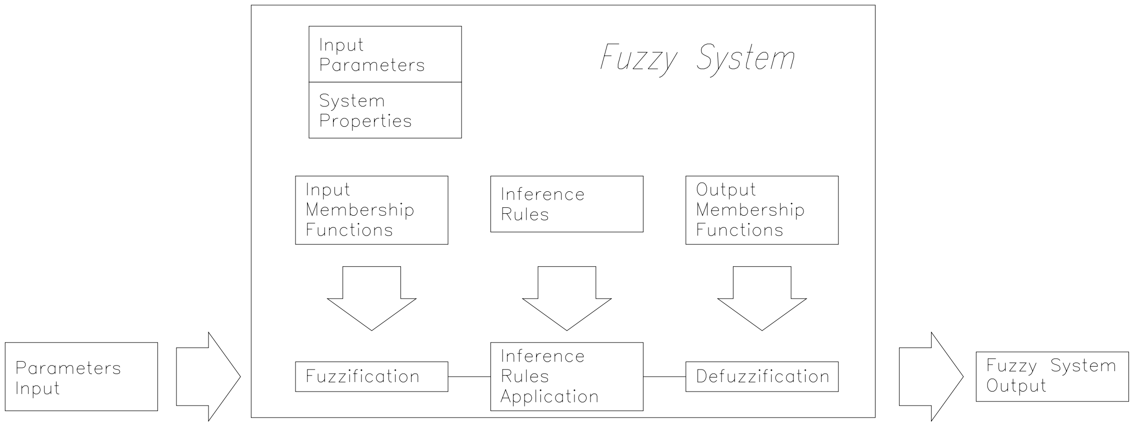

Figure 1 – Fuzzy Inference System structure

As can be seen in Fig. (1), to describe or create a fuzzy inference system one must define several characteristics system. These characteristics are presented as follow:

1. Input Parameters – numeric data which describe the studied system;
2. (Input) Membership function – relation between the numeric value of input and its membership degree in a fuzzy set;
3. (Output) Membership function – relation between a membership degree in a fuzzy set and an output numeric chosen value;
4. Inference rules – IF – THEN – ELSE rules which relate input sets with output sets. These rules can be represented by: ***IF*** *x is A* ***AND/OR*** *y* ***NOT*** *is B* ***AND/OR****... ...w is F* ***THEN*** *u = k* ***ELSE IF****...;*
5. System properties (for more details and options of these properties see Cox,(1994)):
    a. Logic Operators (***OR/AND/NOT***);
    b. Implication Operator ***THEN***;
    c. Aggregation Operator ***ELSE*** and
    d. Defuzzification Operator.

Fig. (2) presents an example of fuzzy inference system application. The purpose of this fuzzy system is to evaluate the amount of the tip given by a restaurant client to the staff, according to the quality of the food and services. The characteristics used in this example are:

1. Input Parameters – the service and food quality grades;
2. (Input) Membership function – Service: Poor, Good and Excellent; Food: Rancid and Delicious;
3. (Output) Membership function – Tip: Cheap, Average e Generous;
4. Inference rules –
    - IF service is poor OR food is rancid THEN tip = cheap ELSE
    - IF service is good THEN tip = average ELSE
    - IF service is excellent OR food is delicious THEN tip = generous
5. System properties –
    a. Logic Operators: OR (max. function) and AND (min. function);
    b. Implication Operator THEN (min function);
    c. Aggregation Operator ELSE (max function);
    d. Defuzzification Operator (centroid)

Fuzzy inference system features are the following (Mathworks, 1995):

- It is conceptually easy to understand;
- It is flexible;
- It is tolerant of imprecise data;
- It can model systems of arbitrary complexity;
- It can be built on top of the experience of experts;
- It is based on natural language.

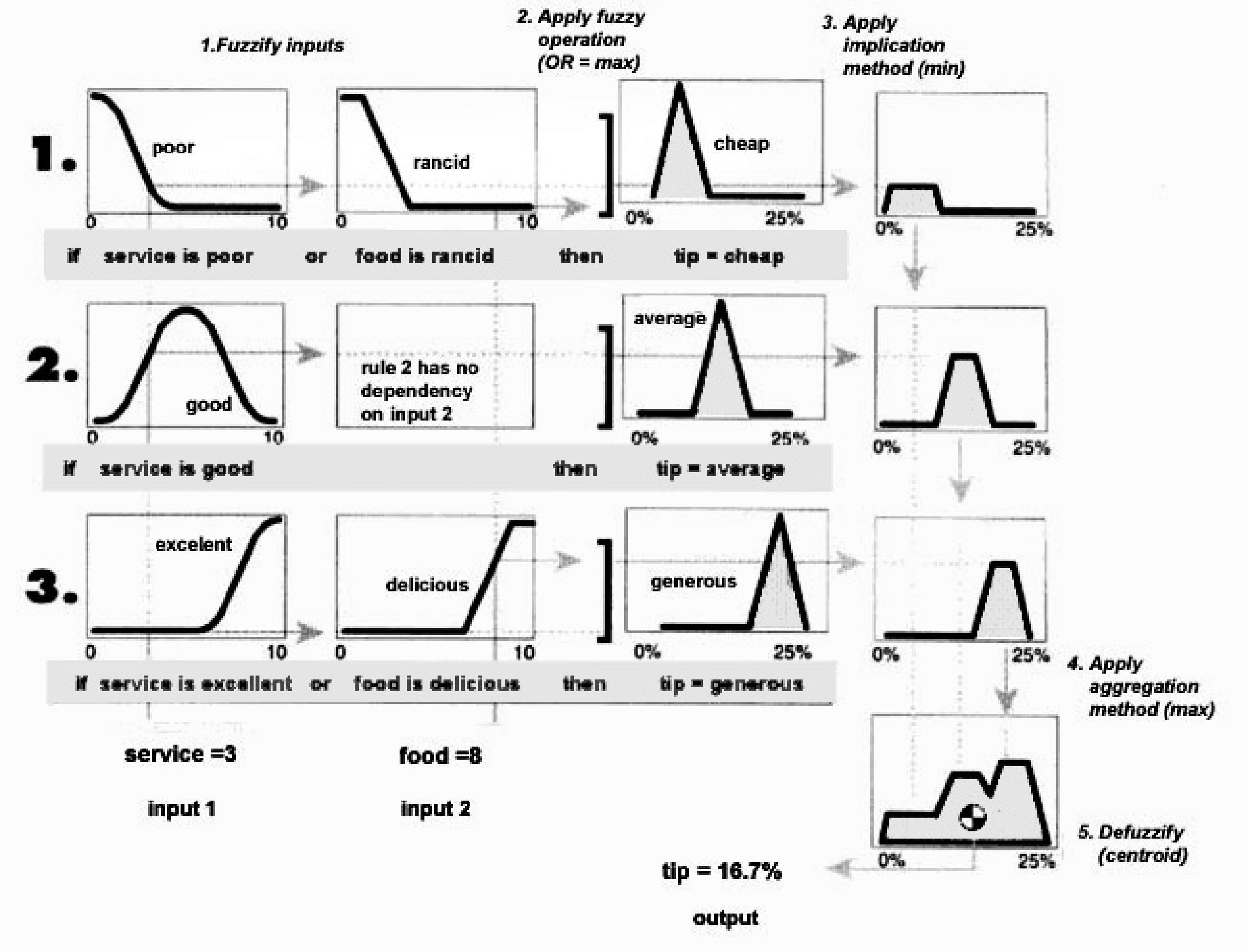

Figure 2 – Fuzzy Inference Process Example (Mathworks, 1995).

Moreover, others fuzzy systems advantages are: allowing the use of heuristic knowledge; analyzing and verifying knowledge in fuzzy system; and managing a lot of information of different natures.

Among fuzzy system limitations we can cite (Ayoubi, 1997):

- It works in a highly abstract and heuristic way;
- A maintenance expert is required to determine inference rules and membership function of fuzzy system (relationship between input and output).
- It does not have self-organization and self-regulation mechanisms as is the case for neural networks.

Tab. (1) shows a comparison between fuzzy systems and another widely used methodology for automatic diagnosis, the neural networks.

Table 1– Basic features of fuzzy inference systems and neural networks (Tsoukalas, 1997)

Fuzzy Systems	***Neural Systems***
Linguistic Representation	Black Box Representation
Expert Knowledge Required	Example Data or Performance Function Required
Some Adaptation	Adaptation Mechanisms Available
Fault Tolerant	Fault Tolerant
Application-Dependent Computational Cost	Rather High Computational Cost
Multiple Descriptions Possible	Multiple Descriptions Possible

3. Automatic Generation of Fuzzy Inference System

The main difficulty for creating fuzzy system is to establish the membership functions and the inference rules. In this paper it is proposed to accomplish these two processes automatically. Inference rules and membership functions statistically created by this methodology can later aggregate others rules and functions gotten heuristically.

Although this fuzzy system creation process is being automate regarding input membership functions and inference rules, other characteristics, such as, output membership functions, logic operator, implication operator, etc. still need to be defined by user.

3.1. Membership Function

Firstly one defines parameters (e. g., RMS, Kurtosis, etc.) which describe the studied system and system outputs (e. g. normal bearing, bearing with pit, corrosion, etc.) Secondly, it is built a database composed of several conditions descriptors related to an output.

Using this database, it is calculated the mean and the standard deviation of each descriptor related to an output. In this case, there are several descriptors associated with the same output (e. g. considering a bearing defect as an output and RMS as the input, there is a RMS value related to each shaft speed considered in the fuzzy system). Each descriptor is represented by its mean and standard deviation.

The next step is the choice of the membership function shape (Trapezoidal, Triangular, Pi, Beta, Gaussian, etc.) (Cox, 1994). In this work, it was used the Beta shape of membership function (Fig. (3)). This function is described by:

$$\mu_{BETA}\left(x;m,\Delta\right)=\frac{1}{1+\left(\frac{x-m}{\Delta}\right)} \tag{2}$$

In equation above, the Beta shape is defined by a mean *(m)* and dispersion (*Δ*). The dispersion (*Δ*) is equal to the standard deviation calculated in the database multiplied by a dispersion proportional factor (in this case, it was used the value 1 for this factor, value obtained by trial and error).

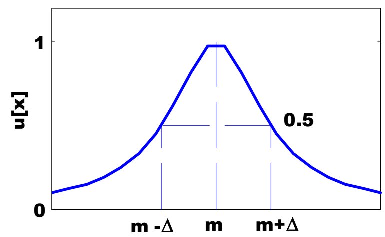

Figure 3 –Beta's Function Parameters

Using means and standard deviations, obtained from the database, to shape the membership function previously defined, one generates one membership function group related to each output. We can divide this membership functions in groups that are related to outputs. Therefore, the number of membership functions groups is equal to the number of outputs.

Therefore, the shape (type) of membership function is chosen by user but its final shape is defined by statistical properties (mean and standard deviation) contained in database.

3.2. Inference Rules

The inference rules used in the current methodology are predefined fuzzy rules. In order to present them, each possible output is written as *Def(i)*, each input parameter as *X(j)*, each membership function related to an output as *N(i,j,k)* and final result as *Y(i)*, where:

i=1...*n* (number of possible outputs);

j=1...*m* (number of input parameters) and;

k=1...*p(i,j)* (number of membership functions related to possible output and input parameter)

The standard rules are:

IF *{[X(1)] is [N(i,1,1)]* ***OR*** *[X(1)] is [N(i,1,2)]* ***OR ... OR*** *[X(1)] is [N(i,1,p(i,1))]}* ***AND*** *{[X(2)] is [N(i,2,1)]* ***OR*** *[X(2)] is [N(i,2,2)]* ***OR ... OR*** *[X(2)] is [N(i,2,p(i,1))]}* ***AND ... AND*** *{[X(m)] is [N(i,m,1)]* ***OR*** *[X(m)] is [N(i,m,2)]* ***OR ... OR*** *[X(m)] is [N(i,m,p(i,1))]}* ***THEN*** *[Y(i)] is [Def(i)]* ***ELIF***

IF *{[X(1)] is [N(i+1,1,1)]* ***OR*** *[X(1)] is [N(i+1,1,2)]* ***OR ... OR*** *[X(1)] is [N(i+1,1,p(i+1,1))]}* ***AND*** *{[X(2)] is [N(i+1,2,1)]* ***OR*** *[X(2)] is [N(i+1,2,2)]* ***OR ... OR*** *[X(2)] is [N(i+1,2,p(i+1,1))]}* ***AND ... AND*** *{[X(m)] is [N(i+1,m,1)]* ***OR*** *[X(m)] is [N(i+1,m,2)]* ***OR ... OR*** *[X(m)] is [N(i+1,m,p(i+1,1))]}* ***THEN*** *[Y(i+1)] is [Def(i+1)]* ***ELIF***

IF ...

Figure 4 – Standard inference rules

The fuzzy inference system has *n* (number of possible output) rules similar to the standard one, shown in Fig. (4).
This inference rules can be interpreted as follows: if the fuzzy system input is near to a condition (e.g. bearing with pit, normal bearing, etc) used in the creation step then the phenomenon of this input is related to that condition. The measure of nearness is done comparing the input values with every centres (or means) of membership functions defined in fuzzy system. The nearness value is obtained through the membership function which is related with the standard deviation (or dispersion) obtained from database.

4. Creating Fuzzy System

In this article, the procedure described above is applied to generate a fuzzy inference system which diagnoses and classifies defects in rolling bearings.
Initially, a rolling bearing fault database is required. This database was built from acceleration vibration signals gotten from failed rolling bearings. The rolling bearings used are of FAG B015TVP type. The experimental conditions used are shown in Tab. (2). The faults located in inner and outer raceways are: pit, corrosion 1 (exposition of a strip of the race to synthetic sea water for 8 hours), corrosion 2 (idem for 24 hours) and a scratched race.
Six different shaft speeds (400 to 1400 rpm) were employed by using motor frequency control, and 3 different radial loads (200, 400 and 600 N) were applied for each shaft speed.
The vibration signals were measured in the experimental rig (Fig. (5)), using a sample rate of 5 kHz and period of 10 seconds. For each system condition showed in Tab. (2), 20 samples were collected.

Table 2 –Experimental Conditions

Defect/Normal	*Defect Location*	*Shaft Speed (rpm)*	*Load (N)*
Normal		400 600 800 1000 1200 1400	200 400 600
Scratch Corrosion 1 Corrosion 2 Pit	Inner Raceway Outer Raceway		

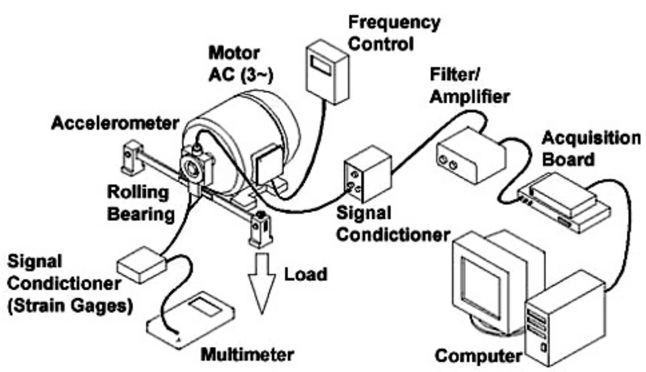

Figure 5 – Experimental rig scheme

In what follows, for each database vibration signal its frequency spectrum was calculate. Fig. (6) shows the used procedure.

Figure 6 – Procedure for frequency spectrum calculation

Fig. (7) shows a frequency spectrum obtained with this procedure.

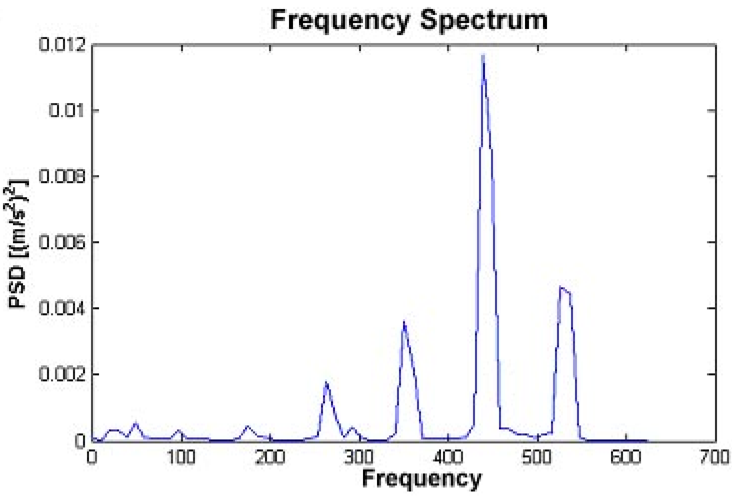

Figure 7 – Frequency spectrum example (Defect: Corrosion 1, Defect on Inner Raceway; Shaft Speed: 1400 rpm; Load: 600 N)

The spectrum amplitudes (as exemplified in Fig. (7)) were taken as the fuzzy system input parameters. Thus, 65 parameters are used as fuzzy systems input, e.g. each point of the spectrum vector is considered a parameter. In this work, the first spectrum point was denominated PSD_F1, the second was denominated PSD_F2, and so on.

Next, it was calculated the mean and standard deviation of 15 samples collected with the same experimental condition (in this article, we considered four experimental conditions: load, shaft speed and defect type). These values were used to create the input membership functions. The five others samples were used only to test the fuzzy system. A computer code was implemented (by using MatLab (Mathworks, 1995)) to generate (according the proposed methodology) and test the fuzzy system. Some of the 165 input membership functions resulting from the system generation (Number of Defect x Number of Load x Number of Shaft Speed) are shown in Fig. (8). In this figure, each graphic has a function set related to a defect (Normal, Scratches_Outer, etc). The Universe of Discourse is defined in [-2.1,3.2].

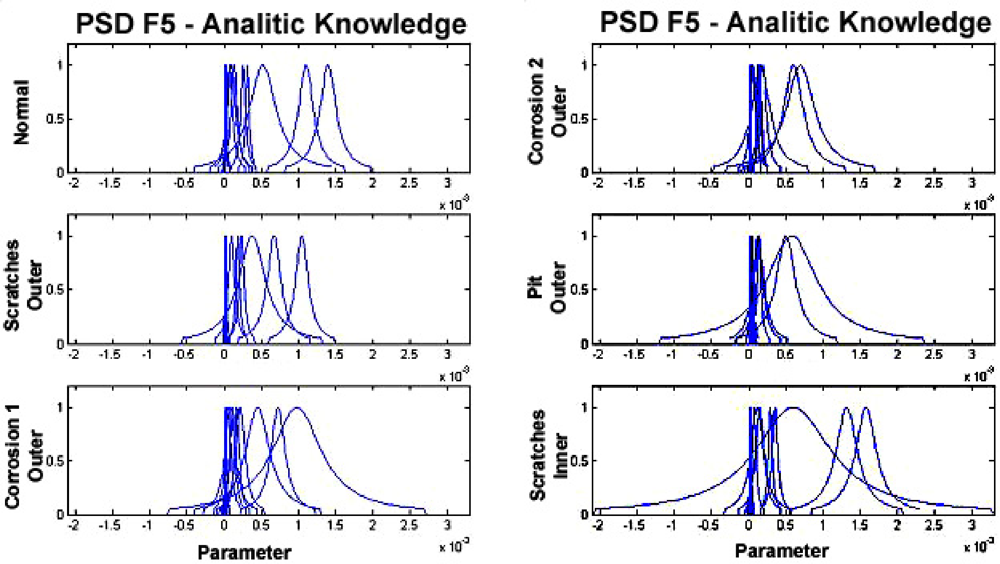

Figure 8 – Input membership functions examples related to a parameter (PSD_F5).

In this practical example, nine inference rules (Number of Faults), similar to rule shown in Fig. (9) are created.

IF *{[PSD_F1_Sample is PSD_F1_Pit_BD1]* ***OR*** *[PSD_F1_Sample is PSD_F1_Pit_BD2]* ***OR ... OR*** *[PSD_F1_Sample is PSD_F1_Pit_BD18]}* ***AND*** *{[PSD_F2_Sample is PSD_F2_Pit_BD1]* ***OR*** *[PSD_F2_Sample is PSD_F2_Pit_BD2]* ***OR ... OR*** *[PSD_F2_Sample is PSD_F2_Pit_BD18]}* ***AND ... AND*** *{[PSD_F65_Sample is PSD_F65_Pit_BD1]* ***OR*** *[PSD_F65_Sample is PSD_F65_Pit_BD2]* ***OR ... OR*** *[PSD_F65_Sample is PSD_F65_Pit_BD18]}* ***THEN*** *[Sample has Pit]*

Figure 9 – Inference rule example.

In Fig. (9), PSD_F1_Pit_BD1 is the first membership function which describes the PSD_F1 parameter of defect Pit, PSD_F1_Pit_BD2 is the second membership function which describes the PSD_F1 parameter of the same defect, PSD_F2_Pit_BD3 is the third one, and so on.

The membership functions chosen as the output ones of the fuzzy system are present in Fig. (10). It is possible to observe that each type of faults has a different output membership functions. The value of defuzzification output (graphic abscissa) obtained from this function relates a non-dimensional scale to failure intensity. In this scale the degree 10 is the defect used to generate the database. The only exception is the corrosion cases, where Corrosion 2 has higher intensity (degree 10) than Corrosion 1.

Finally, the other system properties required are defined as fellow:

- Logic Operators: OR (maximum function) and AND (minimum function);
- Implication Operator THEN (minimum function);
- Aggregation Operator ELSE (maximum function);
- Defuzzification Operator (centroid)

Details of these parameters and functions can be seen in Cox (1994).

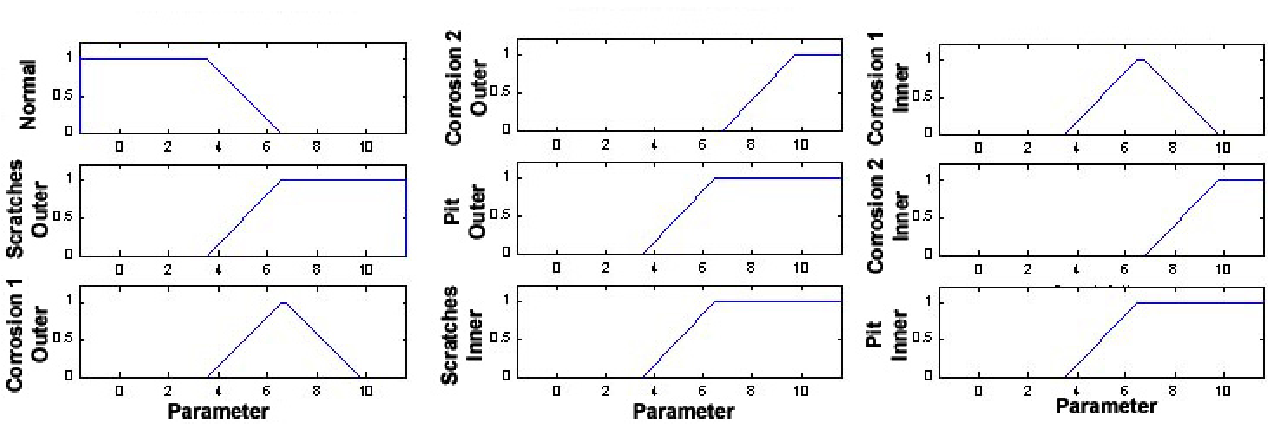

Figure 10 – Output membership functions of fuzzy system

5. Results

In order to analyse the diagnostic performances of the fuzzy system developed, two basic indexes were used: detection and classification indexes. The detection index express the ability of differentiating between a defected rolling bearing (does not caring about defect type) and a normal rolling bearing. The classification index express the ability of diagnose the defect type.

The results from the tested fuzzy system are shown in Tab. (3).

Table 3 – Fuzzy inference system results

Index	*% of Hints*
Detection of Defect	90%
Classification of Defect	62%
	Time (s)
Time to Create	150 s.
Time to test (per sample)	16 s.

It is important to emphasize that the objective of this work was to demonstrate the viability of the methodology and not to optimize the fuzzy system properties and parameters. This means that better results can be reached, if a more detailed study is carried out. Such study could improve diagnosis reliability of the system.

The implemented fuzzy system presents a worse performance than several systems based in neural network (Li, 2000; Padovese, 2002) where detection hints are higher than 90%. Li (2000) obtained 100% of detection and classification hints using MLP (Multi Layer Perceptron), but using only three classes of faults: fault in the rolling element, in the inner and outer raceways. He did not that account of different types of faults. He also optimized the neural network parameters (number of neurons in hidden layer and learning rate). Padovese (2002) used a database similar to that used in this work and obtained 100% of detection and classification hints using PNN (Probabilistic Neural Network), seeking as well for optimal neural network parameters.

It is worth noting that the detection and classification tasks in the present study is more complex (with vary shaft speed and load) than that of the two previous cited papers. Another advantage of the fuzzy system is its open architecture when compared to the Multilayer Perceptron neural network. Moreover, the input parameters used here have much redundancy what interferes in the final performance. This redundancy could be optimizes.

6. Conclusion

In this work, we proposed a methodology to create automatically fuzzy inference system using statistical information from available database. This methodology automatically accomplishes the fuzzy system development steps of creation and implementation of membership function and inference rules.

Using this methodology, a diagnostic system was created in order to detect and classify rolling bearing defects. The parameters which describe the 9 types of defects are the spectrum amplitudes of vibration signals. The developed system led to good results for fault detection but not so good for fault classification. This situation could be expected since we were worried about demonstrating the viability of the methodology and not about attaining the best results by optimization of parameters and properties of the diagnostic fuzzy system.

The main contribution of this work is emphasizing the benefits of automatically generating diagnostic fuzzy inference system, by the use of statistical information. With this methodology the necessity of a maintenance expert does not disappear, but his knowledge is reduced to the choice of the input parameters (which best describe the fault phenomenon) and to verify the results reliability.

7. Acknowledgements

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8. References

AYOUBI, M.; ISERMANN, R., 1997. "Neuro-fuzzy systems for diagnosis". Fuzzy Sets and Systems, v. 89, p. 289-307.

COX, E., 1994. "The Fuzzy Systems Handbook". Ed. AP Professional, 615 p..

JEFFRIES, M.; LAI, E.; PLANTENBERG, D. H.; HULL, J. B., 2001. "A fuzzy approach to the condition monitoring of a packaging plant". Journal of Materials Processing Technology, v. 109, p. 83-89.

JOENTGEN, A.; MIKENINA, L.; WEBER, R.; ZEUGNER, A.; ZIMMERMANN, H.-J., 1999. "Automatic fault detection in gearboxes by dynamic fuzzy data analysis". Fuzzy Sets and Systems, v. 105, p. 123-132.

KARTALOPOULOS, S. V., 1996. "Understanding Neural Networks and Fuzzy Logic: Basic Concepts and Applications". IEEE Press.

LI, B.; CHOW, M.; TIPSUWAN, Y.; HUNG, J. C., 2000. "Neural-Network-Based Motor Rolling Bearing Fault Diagnosis". IEEE Transactions on Industrial Electronics, v. 47, n. 5, October, p. 1060-1069.

LIU, T. I.; SINGONAHALLI, J. H.; IYER, N. R., 1996. "Detection of Roller Bearing Defects using Experts System and Fuzzy Logic". Mechanical Systems and Signal Processing, v. 10 n. 5, p. 595-614.

MATHWORKS, THE, 1995. "Fuzzy Logic Toolbox: For Use With MATLAB, User's Guide". Version 2., MathWorks Inc., 227 p.

MECHEFSKE, C. K., 1998. "Objective Machinery Fault Diagnosis Using Fuzzy Logic". Mechanical Systems and Signal Processing, v. 12 n. 6, p. 855-862.

PADOVESE, L. R. "Automatização de Diagnóstico de Falhas em Plantas Industriais", 2002, 142 p., Tese de Livre Docência, EP-USP.

SHAW, I. S.; SIMÕES, M. G., 1999. "Controle e Modelagem Fuzzy". Ed. Edgard Blücher.

SHIN, Y. S.; LIU, C. S.; JEON, J. J., 1992. "Determination of Vibration Alert Level in Condition Monitoring of Rotating Machinery". Proc. of Intern. Modal Analysis Conference - IMAC, v. 2, p. 1483-1490.

TARIFA, E. E.; SCENNA, N. J., 1997. "Fault Diagnosis, Direct Graphs, and Fuzzy Logic". Computers Chem. Engng., v. 21, p. S649-S654.

TSOUKALAS, L. H.; UHRIG, R. E., 1997. "Fuzzy and Neural Approaches in Engineering". John Wiley & Sons Inc..

VICENTE, S. A. V.; FUJIMOTO, R. Y.; PADOVESE, L. R., 2001a. "Rolling Bearing Fault Diagnostic System Using Fuzzy Logic". The 10th IEEE International Conference on Fuzzy Systems, v. 2.

VICENTE, S. A. da S.; MASOTTI, P. H. F.; ALMEIDA, R. G. T. de; TING, D. K. S.; PADOVESE, L. R., 2001b. "Automatic Diagnosis of Defects in Bearings Using Fuzzy Logic". Anais do COBEM 2001.