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AUTOMATION OF MECHANICAL FAULTS DIAGNOSIS OF ROTATING MACHINES BY APPLICATION OF THE FUZZY LOGIC (FL)

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ABSTRACT

This work deals with the application of the fuzzy logic to automate diagnosis of bearing defects in rotating machines based on vibration signals. The classification tool used is a fuzzy inference system (FIS) of Mamdani type. The vector form of (input) contains parameters extracted from the signals collected from the test bench studied. The output vector contains the classes for the different operating modes of the experimental study. The results show that; pretreatment data (filtering, decimation,..), the choice of parameters of fuzzy inference system (input variables and output, types and parameters of membership functions associated with different variables input and output of the system, the generation of fuzzy inference rules, ...) are of major importance for the performance of fuzzy inference system used as a tool for fault diagnosis of rotating machinery.

Keywords: Rotating machines, Mechanical vibration, fuzzy logic, fuzzy inference, Fault diagnosis, signal processing

INTRODUCTION

Despite the Progress and technological advances in the distributed control and automation of complex processes, monitoring processes remains a very important task which is still largely a manual activity, carried out by operators, especially when it comes to respond to abnormal events. This activity is based on the nature and criticality of defects or malfunctions, affect economic, environmental and security more or less significant, not only in equipment but also operators. Especially the fact that managing a large amount of information and need to act quickly can lead operators to make incorrect decisions, further degrading the situation. Thus, the monitoring systems that integrate tools for monitoring, detection and diagnosis are needed to provide the operator with sufficient criteria for decision-making.

In this context, many approaches are developed for fault detection and diagnosis, by the different scientific communities. The methods differ in the type of a priori knowledge about the process they require. Thus they may be classified, in general, as model-based methods, and methods based on historical data. Methods based models consider a structural model of the behavior of the process based on fundamental physical principles. These models can be quantitative, expressed as mathematical equations or a qualitative, expressed for example in

the form of logical relationships. Methods based on historical data seek to extract information, such as examples or trends within steps from the sensors and actuators, which can identify the behavior of the process. These methods include, among others, statistical methods and classification (or pattern recognition). Among the methods based on historical data, there are methods of pattern recognition based on fuzzy logic. The contribution of fuzzy logic is the possibility of a simulation of the expertise of an operator or designer in the monitoring and process control. From the mid-90s (Liu and sing 1996), (Mechefske 1998), (Lou and loparo 2004), (Sugumaran and ramachandran 2007), applications of fuzzy logic in maintenance of rotating machines begin to appear progressively with the use of different classification methods fuzzy. It was found that several applications in recent years use of inference systems based on fuzzy rules, as a tool for classification of faults for diagnosis (Boutros and liang2007), (wu and hsu 2009), (Saravanan and cholairajan 2009), (Wu and hsu 2009), (Aliustaoglu and metin 2009). In our work we try to apply fuzzy logic to detect and diagnose faults in rotating machines (application to bearings). We will use a classification method with a fuzzy inference system (FIS).

IMPLEMENTATION OF FUZZY INFERENCE SYSTEM (FIS)

There are three functional steps in the implementation of a fuzzy inference system (FIS) for the diagnosis, as shown in the diagram (see Figure.1)
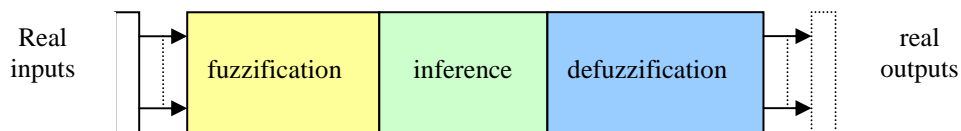

Fig.1 Stages of the implementation of a
fuzzy inference system (FIS)

A. Step of Fuzzification

The fuzzification step is to define fuzzy sets for input variables and output for each of these variables must be known a priori definition of the interval, the number of fuzzy sets and the shapes of the functions of belonging.

B. Step Inference

This is the stage where we establish the fuzzy rules which allow to reach the exit by the values of the input variables. Each rule consists of premises linked by AND, OR and gives rise to an implication by the operator THEN.
After editing the rules, it remains to calculate the membership degrees of the output variable to all fuzzy sets associated with it.
The aggregation of these rules is an operation that should lead to a single value of the variable output after defuzzification.

C. Defuzzification Stage

This step is to transform the linguistic variable outcome of fuzzy inference system to a digital value. For this, there are three main methods:
- The method of maximum corresponding to the minimum horizontal axis of the ordinate up to the surface. It is little used.
- The method of weighted average.

- The method of centroids is the best. It is simply to calculate the centers of gravity of surfaces.

TEST BENCH

The website*" www.eecs.cwru.edu\laboratory\bearing\welcome_overview.htm»* (loparo 2004); Provides access to the database testing of ball bearings or bearings normal or defective. As shown in figure.2 below, the test bench consists mainly of an engine "2HP" (left), a coupling transducer / encoder (center), a generator (right) and control circuits (not shown).

Fig.2 Bearing test rig

The bearings tested support the motor shaft at both ends (drive side and side fan). Simple defects in the form of points have been created on the bearing test, using electro-discharge machining.

The signals were recorded using accelerometers, which were attached to the cage of the motor magnet. These sensors were placed at the 12 o'clock position "vertical", both sides and fan coupling of the cage motor.

The signals were recorded examined for defects of the inner side coupling under the following conditions:

- The shaft rotates at a speed of 1730 rpm.
- The power of the load torque is 3HP.
- Three defects of diameters 0007, 0021, and 0.028inch were created on the inner race.
- The four signals (states) are drawn on the side studied mating signal without defects and with other defects (defects in three sizes 0007, 0021, and 0.028inch).

The Figure.3, Represents the time signals collected on the side of the coupling, for different diameters of defects produced on the inner ring to a torque of 3HP. (HP: Horse Power)

Fig.3 Representation of time signals for different
diameters of the defect on the inner ring

CONSTITUTION OF THE DATABASE

The database contains four available signals, a signal without defects and three with defects. As the fuzzy inference systems (FIS) require a large database for the classification, and to have enough data, we divided each signal Kt slices N_M points provided that the number of samples for each slice must be large enough to cover a sufficient number of the largest cycle corresponding to the greatest period (the lowest speed). We have the signals of length 120 800 points. The shaft rotates at a speed of 1730 rpm.

$$fr_{shaft} = \frac{1730}{60} = 28.83 HZ$$

It has four characteristic frequencies corresponding to the various elements of the bearing (cage, inner and outer race and rolling elements). The greatest period corresponds to the smallest frequency. In our case, the greatest period is the period of the cage:

$$f_{cage} = 0.9382 \times 28.83 = 11.48 HZ$$

- The period:

$$T_{cage} = \frac{1}{f_{cage}}$$

- The sampling frequency:

$$f_s = 12 KHZ = 12000 HZ$$

- The sampling period:

$$\Delta t = \frac{1}{f_s}$$

- The number of points per period:

$$Np = \frac{T_{cage}}{\Delta t} = \frac{f_s}{f_{cage}} = \frac{12000}{11.48} = 1045,29 pts \cong 1046 pts$$

If we take a factor of 5. The length will be required for each portion:

$$N_{po} = N_p \times 5 = 5230 pts.$$

If we take a value greater than 2^n

$$N_M = 2^{13} = 8192$$

While the number of slices in the case of a recovery of 50%, $s1 = \frac{N_M}{2}$ then:

$$K_t = \frac{N_s - s1}{N_M - s1} = \frac{120800 - 4096}{4096} \cong 28$$

So, we got 112 signals, 28 signals for each class.

A. Pretreatment and Calculation of Indicators

A signal preprocessing is required to remove all kinds of useless information, and facilitate the task of extracting indicators for monitoring the most relevant formants database. We chose initially to calculate the following indicators: the STDEV (ET), the crest factors (Fc), the crest- crest (Acc), the factor dissymmetry (skewness (Ks)) and the flattening factor (Kurtosis (Ku)) (Lou and loparo 2004), (Sugumaran and ramachandran 2007), and the energy from the

spectrum envelope. These indicators can be good indicators for monitoring in the case of the bearings. After a preliminary analysis, we chose to calculate these indicators as follows:

A.1. Temporal Indicators
The time indicators mentioned above are calculated in five frequency bands from the band analysis '6 KHZ ', 4 in adjacent bands of width 1500Hz, plus the total band. The indicators are the averages of the indicators calculated in the five bands. The bands are then calculated: [0-1500Hz], [1500-3000Hz], [3000-4500HZ], [4500-6000Hz] and [0-6000Hz]. The signal from each portion has been centered and filtered by filters like band pass.

A.2. Frequency Indicators
The indicators (energy from the spectrum envelope) are calculated in the five (5) frequency band and total frequency bands of width of 1000Hz, from the spectrum envelope of the different tranches. Frequency indicators are calculated; EBT in the band [0-6000Hz], EB1 in [0_1000HZ], EB2 in [1000-2000Hz], EB3 in [2000-3000Hz] EB4 in [3000-4000Hz] and EB5 in [4000 -5000Hz].

- Notes

- For the division of signals into slices, and the calculation of time and frequency indicators, a program in Matlab is designed for this purpose.

- Figures, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, and 14 graphically represent the variation of the 11 indicators based on 112 observations (number of slices). Note that the numerical values of the three indicators ET, EB2 and EB5 corresponding to Figures 4, 11, and 14 are divided into 4 levels completely separated from each other, these levels correspond to the four operating conditions studied, and therefore the three indicators ET, EB2 and EB5 are most relevant for classification.
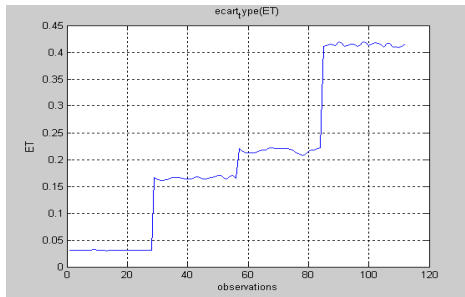

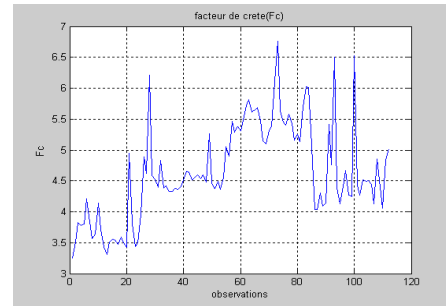
Fig.4 Variation indicator (ET).
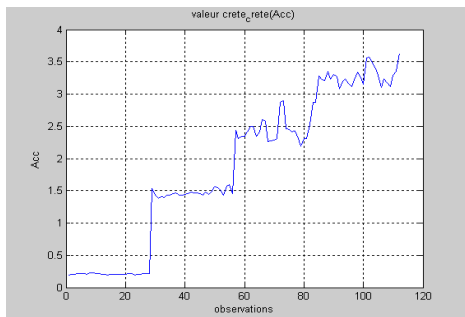

Fig.5 variation   indicator (FC)
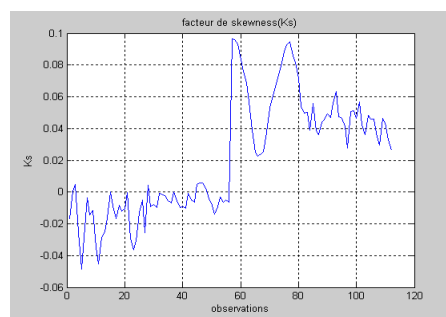

Fig.6 Variation indicator (Acc).
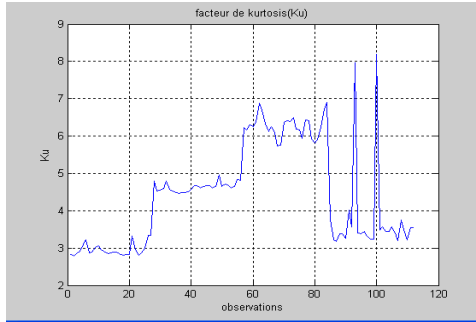

Fig.7 variation Indicator (Ks).

Fig.8 Variation indicator (Ku).
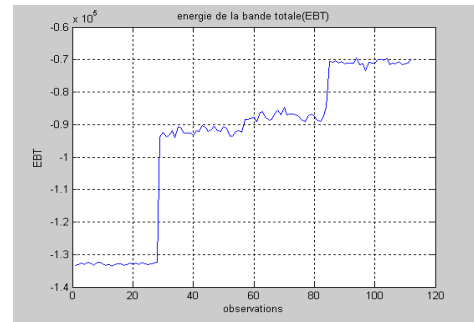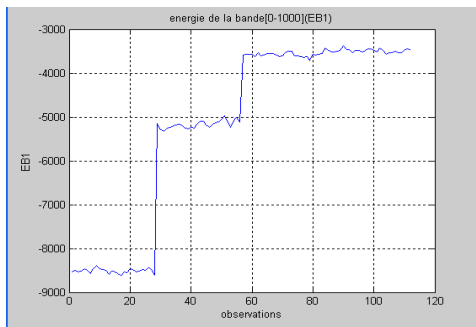

Fig.9 variation Indicator (EBT).

Fig.10 Variation indicator (EB1).
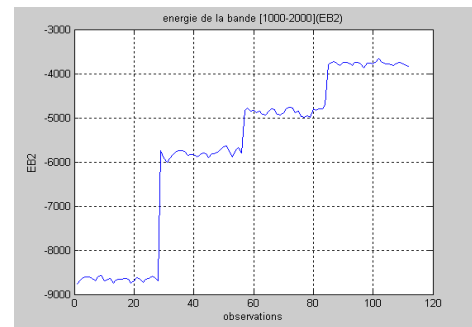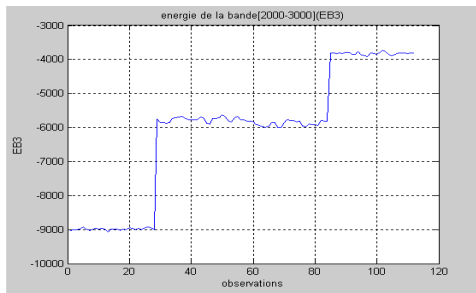

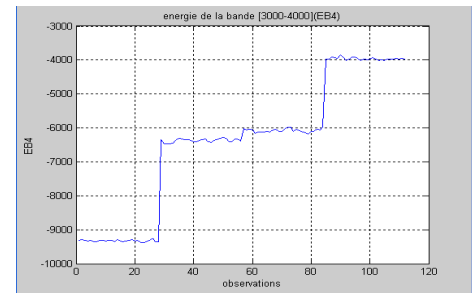Fig.11 variation indicator (EB2).

Fig.12 Variation indicator (EB3).

Fig.13 variation indicator (EB4).

Fig.14 Variation indicator (EB6).

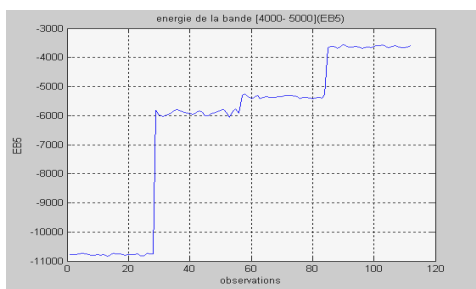### *B.   Constitution of Vector Form*

The vector form consists of a number of indicators selected from the previously calculated indicators. The components of the vector form representing the input variables of the fuzzy inference system (FIS) chosen for the classification of defects in bearings. The data that must classify and treat is stored in an array of type observations / variables of the form:

$$database = \begin{pmatrix} x11 \, x12 & \cdots & x1M \\ x21 \, x22 & & x2M \\ \vdots & \ddots & \vdots \\ xN1 \; xN2 & \cdots & xNM \end{pmatrix} = \begin{bmatrix} X1 \\ X2 \\ \vdots \\ XN \end{bmatrix}$$

Where $\begin{cases} \text{N is the number of observations} \\ \text{M is the number of indicators} \end{cases}$

We then have:

M: indicators, shown in columns, and N observations represented on line will be divided into Nc classes (w1, w2, ... W$_{NC}$) or operating modes, each class w_i has N_i observations.

For our work:

N = 112 observations (28 slices per 4 signals).

M =3; the number of indicators that represent the input variables of the fuzzy inference system, we chose three most relevant indicators calculated from the 11 indicators (this choice is justified in A previous section, and in addition this number is sufficient because every time we increase the number of input variables and the number of membership functions associated with each variable, we will have a complexity for the generation of fuzzy inference rules . for example: for two input variables and four membership functions for each of the two variables, we have (4^2 = 16) fuzzy inference rules, and for three input variables and four membership functions, we have (4^3 = 64) rules. the three indicators selected, a type of statistic: the STDEV (ET) (this indicator is widely used for fault monitoring bearings), and the other two types of frequency (EB2) and (EB5) that represent the outcome of the energy bands [1000-2000Hz], [4000-5000Hz] (these indicators are also selected for the reason that they are very sensitive to the variation of energy (in our case was an increase the size of the defect and therefore an increase in energy)).

C. Choice of Classes (Output of Fuzzy Sets (FIS))

We opted for the system output (FIS) a single output variable, which represents the health of the studied device (state), for this variable we chose four fuzzy sets corresponding to different diameters of default. Table 1 shows the different fuzzy sets (classes) associated with the output variable.

Table.1: fuzzy sets (classes) of the variable output (state).

Fuzzy sets (classes) associated with the output variable	Diameter of the Fault (inch)
N1	No fault
N2	0.007
N3	0.021
N4	0.028

CONDUCT OF CLASSIFICATION BY FUZZY INFERENCE SYSTEM (FIS)

The methodology chosen for the classification of different states of machine faults by a fuzzy inference system (FIS) for the diagnosis is represented by the flowchart in figure15.
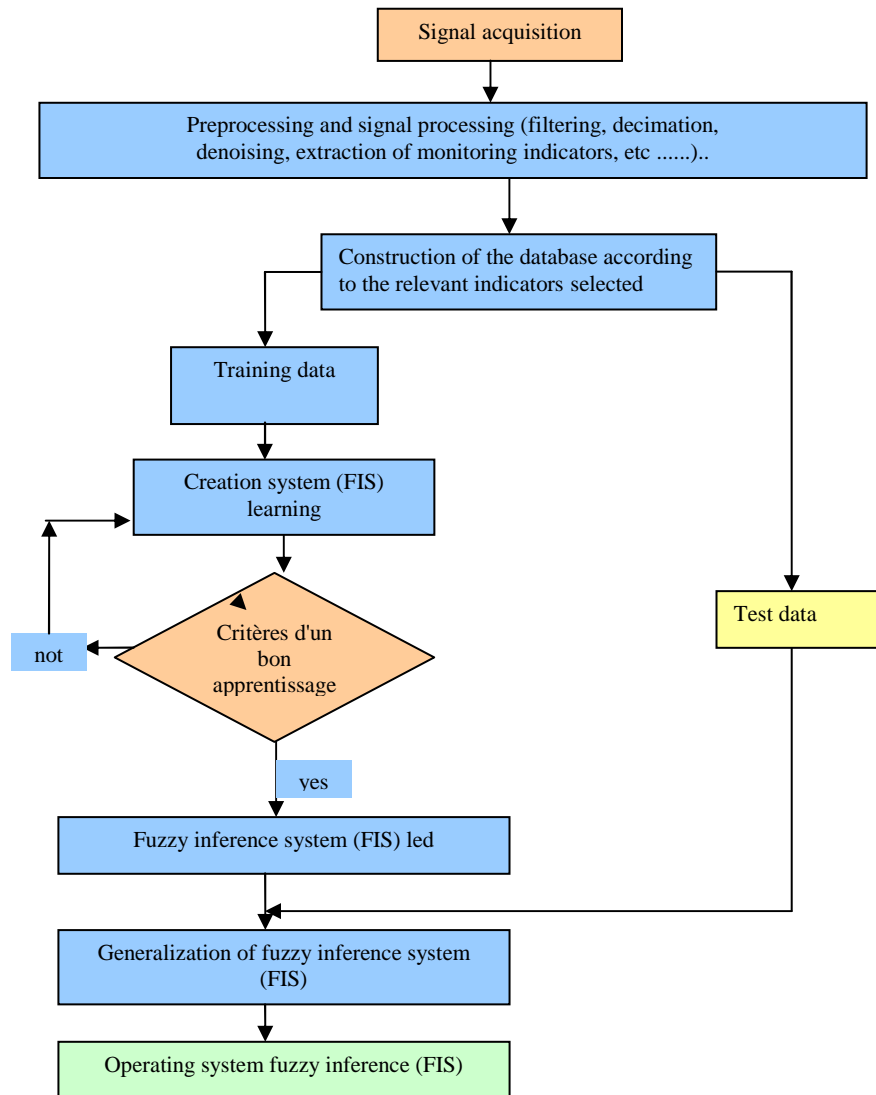
Fig.15 Flowchart of implementation of the fuzzy inference system (FIS) for the classification of defects.

IMPLEMENTATION OF FUZZY INFERENCE SYSTEM (FIS) IN MATLAB

The implementation of fuzzy inference system in Matlab can be achieved by two different methods, either using the controls toolbox (Fuzzy Logic) or the graphical user interface of the latter (Mathworks 2000).

A. Implementation System (FIS) Through the Graphic Interphace
A.1. Structure of the Fuzzy Inference System (FIS)
We have chosen a fuzzy inference system of Mamdani type with three variables at the input and a variable to the output. Figure 16 shows the block diagram of our system. We chose a fuzzy inference mechanism that works with the methods shown on Figure 16, which should lead to a single value of the variable output (state).
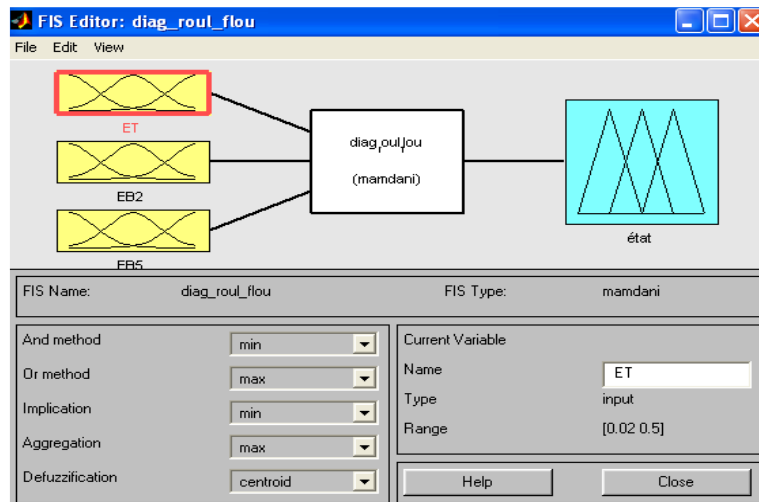
Fig.16. Block diagram of (FIS).

A.2. *Fuzzification of the Input Variables and Output*

Figures, 17, 18, 19, and 20 respectively represent the fuzzification of the three input variables (ET, EB2, EB5) and the output variable (state)
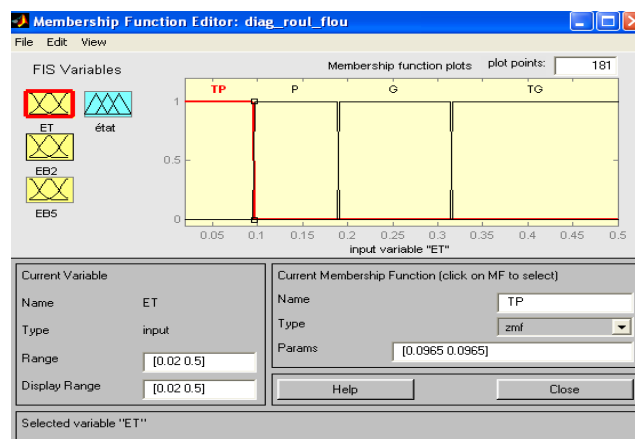

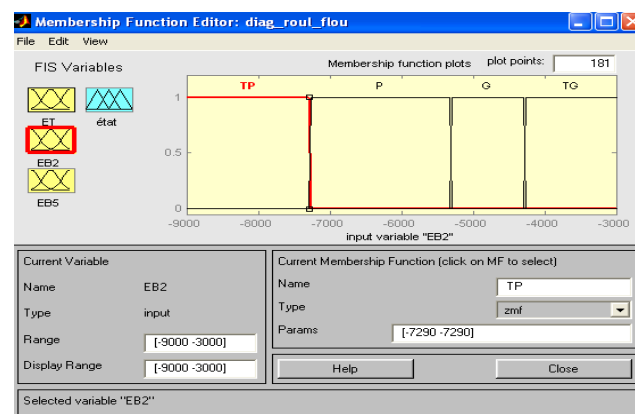Fig.17 Fuzzification of the input variable "the STDEV (ET)."

Fig.18. Fuzzification of the input variable "energy band [1000-2000Hz] (EB2)."
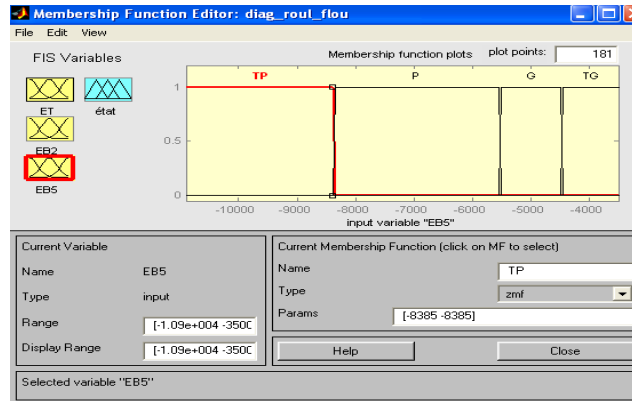
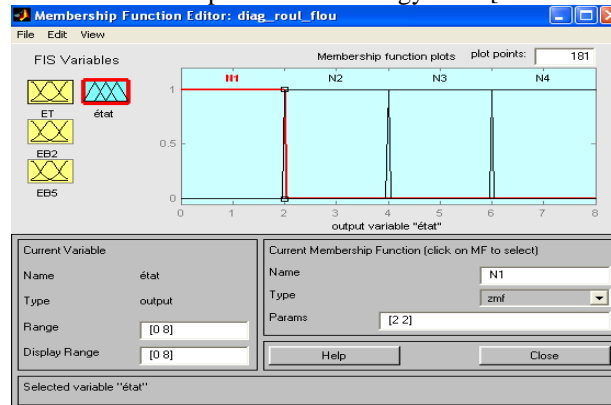Fig.19. Fuzzification of the input variable "energy band [4000-5000Hz] (EB5)."

Fig.20. Fuzzification of the output variable   "Device status (state)."

A.3. Inference Rules

The different possible rules according to the fuzzification of input variables and output are selected (three input variables and 4 functions for each variable, we obtain 64 rules of inference ($4^3 = 64$)) are presented some rules of the 64 rules.

1. IF [(ET is TP) and (EB2 is TP) and (EB5 is TP)] THEN (condition is N1) (1)
2. IF [(ET is TP) and (EB2 is TP) and (EB5 is P)] THEN (condition is N2)   (1)
3. IF [(ET is TP) and (EB2 is TP) and (EB5 is G)] THEN (condition is N3)   (1)
4. IF [(ET is TP) and (EB2 is TP) and (EB5 is TG)] THEN (condition is N4) (1)
5. IF [(ET is TP) and (EB2 is P) and (EB5 is TP)] THEN (condition is N1)   (1)
6. IF [(ET is TP) and (EB2 is P) and (EB5 is P)] THEN (condition is N2)   (1)
7. IF [(ET is TP) and (EB2 is P) and (EB5 is G)] THEN (condition is N3)   (1)
8. IF [(ET is TP) and (EB2 is P) and (EB5 is TG)] THEN (condition is N4)   (1)
9. IF [(ET is TP) and (EB2 is G) and (EB5 is TP)] THEN (condition is N3)   (1)
10. IF [(ET is TP) and (EB2 is G) and (EB5 is P)] THEN (condition is N3)   (1)

55. IF [(ET is TG) and (EB2 is P) and (EB5 is G)] THEN (condition is N4)   (1)
56. IF [(ET is TG) and (EB2 is P) and (EB5 is TG)] THEN (condition is N4) (1)
57. IF [(ET is TG) and (EB2 is G) and (EB5 is TP)] THEN (condition is N4) (1)
58. IF [(ET is TG) and (EB2 is G) and (EB5 is P)] THEN (condition is N4)   (1)
59. IF [(ET is TG) and (EB2 is G) and (EB5 is G)] THEN (condition is N4)   (1)
60. IF [(ET is TG) and (EB2 is G) and (EB5 is TG)] THEN (condition is N4) (1)

61. IF [(ET is TG) and (EB2 is TG) and (EB5 is TP)] THEN (condition is N4) (1)
62. IF [(ET is TG) and (EB2 is TG) and (EB5 is P)] THEN (condition is N4)   (1)
63. IF [(ET is TG) and (EB2 is TG) and (EB5 is G)] THEN (condition is N4) (1)
64. IF [(ET is TG) and (EB2 is TG) and (EB5 is TG)] THEN (condition is N4) (1)

B.   *Classification of the database by the Fuzzy Inference System (FIS)*

We have designed a program in the Matlab environment using the controls in the toolbox "fuzzy logic" for the implementation of fuzzy inference system (FIS), developed the program also allows to classify the observations database. The Appendix presents the results of the classification database.

RESULTS AND DISCUSSION

A.   *Graphical Representation of Results Classification*

The figure21, graphically represents the result of classification, we note that:
-   The observations considered at the start of class 1 (no defects) that correspond to the line1on line28 in the data matrix, all these observations are classified by the system at N1, that is to say in the class1.
-   The observations considered at the start of class 2 (diameter of the defect (0.007inch)) that correspond to the line29 on line 56 in the data matrix, all these observations are classified by the system at N2, that is to say in the class2.
-   The observations considered starting from the class3 (diameter of the defect (0.021inch)) that correspond to the line57 on line84 in the data matrix, all these observations are classified by the system at N3, it is say in class3.
-   The observations considered starting from the classe4 (diameter of the defect (0.028inchh)) that correspond to the line 85 on line 112 in the data matrix, all these observations are classified by the system at the N4, that is, say in class 4.

Fig.21 classification of the database (bearings).

B.   *Interpretation of Results Classification*

The result obtained by the classification system (FIS) is coincident with the hypothesis that we considered in section (3.3), and the distribution of the database into four classes, Class 1: no default, Class 2: with defect (0.007inch of Φ), class 3: with default (0.021inch of Φ), and Class 4: with default (0.028inch of Φ). Note that all observations of the database are classified correctly, which gives a correct classification rate of 100%. The high rate of good classification system may be due to:
-   The right choice of system parameters (input variables and output, number and type of membership functions chosen for the different variables, rules of inference,

defuzzification method), especially the three input variables system (ET, EB2, EB5), these variables (indicators) are most relevant for classification among 11indicateurs initially calculated.

- The preprocessing applied to the various slices of the signals studied, and the calculation of indicators in frequency bands neither too wide nor too narrow, it provides the indicators sensitive to changes that may occur on the system studied.
- the total separation of the four classes may also be due to the size of the defects created on the system, which are relatively spaced apart (the spacing of the dimensions of the defects produced energy nival separated) In the end, we can say that the fuzzy inference system (FIS), with this configuration, designed to clearly separate the four classes.

CONCLUSION

- The difficulty is always in this type of diagnosis by fuzzy inference systems in the choice of parameters, starting with the choice of input variables (vector form), through the number of fuzzy sets associated with each variable input and output arriving in the edition of the rules especially if the number of fuzzy sets associated with different input variables is large enough. It can be said here that there are no rules for choosing the parameters of the inference system, which vary depending on the problem studied. Only the user experience can overcome this difficulty. The implementation of fuzzy inference system (FIS) in the Matlab environment is characterized by its simplicity, Just choose the parameters of the system, and then implement either using GUI or from command Matlab this box.

ANNEX
Classification result of the database of bearings by the classifier based on fuzzy inference
- Note:
This appendix contains the actual values of the output variable that represents the state of the device studied. So we have:
Line: one line, which represents the real value of output variable.
Column: 1 to112 of the columns are labeled observations of the database.

1	2	3	4	5	6	7	8	9	10	11
1	1	1	1	1	1	1	1	1	1	1
12	13	14	15	16	17	18	19	20	21	22
1	1	1	1	1	1	1	1	1	1	1
23	24	25	26	27	28	29	30	31	32	33
1	1	1	1	1	1	3	3	3	3	3
34	35	36	37	38	39	40	41	42	43	44
3	3	3	3	3	3	3	3	3	3	3
45	46	47	48	49	50	51	52	53	54	55
3	3	3	3	3	3	3	3	3	3	3
56	57	58	59	60	61	62	63	64	65	66
3	5	5	5	5	5	5	5	5	5	5
67	68	69	70	71	72	73	74	75	76	77
5	5	5	5	5	5	5	5	5	5	5
78	79	80	81	82	83	84	85	86	87	88
5	5	5	5	5	5	5	7	7	7	7
89	90	91	92	93	94	95	96	97	98	99
7	7	7	7	7	7	7	7	7	7	7
100	101	102	103	104	105	106	107	108	109	110
7	7	7	7	7	7	7	7	7	7	7
111	112									
7	7									

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