DIAGNOSIS OF BEARING DEFECTS BY ANFIS IN THE INDUCTION MOTOR

Nabil **TALBI**[1], Abderrezak **METATLA**[1], Toufik **SEBBAGH**[1], Nadir **BOUTASSETA**[2], Mohamed **HASSANI**[2]

[1] *Department of Mechanical Engineering, Faculty of Technology, Université 20 août 1955 Skikda BP 26 Road of El hadaiek,Skikda, Algeria.*

[2] *Research Center in Industrial Technologies CRTI, P.O.Box 64, Cheraga, Algeria.*

n.talbi@ univ-skikda.dz, a.metatla@ univ-skikda.dz, t.sebbagh@ univ-skikda.dz, boutasseta@gmail.com, moha82.hassani@hotmail.fr

Keywords: Fault diagnosis, ANFIS, parameter extraction, induction motor, fault classification.

Abstract*: In this paper, we developed a robust technique for fault classification in the induction motor, which was used by the Adaptive Network Reference Information System (ANFIS). A robustness and precision test of the proposed method was performed on a small database. To speed up the response and minimize the calculation time, the most sensitive indicators have been used to ensure the learning of the classifier. The database used was carried out at the University of Case Western, this database has two modes of healthy operation and with rolling defects located side coupling. The objective of the technique used in this paper is to extract the indicators and to test them to select the most sensitive to the apparition of defects. The obtained results show the effectiveness and sensitivity of the proposed approach to identify the nature of the defect even at the birth stage.*

1. INTRODUCTION

The asynchronous motor sometimes called induction motor is the most used motor in the industrial world because of its robustness. In addition, its cost is low as well as the cost of the maintenance and its simplicity [1]. During its operation the induction motor subjected to constraints generates defects which negatively affect the profitability of the drive systems and consequently the productivity of the installations. To ensure the proper functioning of the drive systems therefore the continuity of productivity, it is necessary to ensure a policy of maintenance to detect and identify the occurrence of defects at the birth stage and to avoid the unexpected shutdown of the installations that causes significant economic losses.

Several categories of methods are proposed for the diagnosis of defects in the literature, surveyed recently in [2], from data processing perspective. We can divide those methods in to three types of methods, namely model-based, signal-based and knowledge-based methods.

The first family of methods that uses a mathematical model describing the normal operating state of the induction motor, model-based methods of fault diagnosis algorithms are developed to monitor the consistency between the measured results of practical systems and model predictions, such as state observing methods, parametric estimation, and parity space utilization. The advantage of this type of method is that the fault diagnosis is very simple since one carries out a direct mapping with the physical coefficients [3].

The methods based on prior knowledge that can be divided into two groups: qualitative methods based on symbolic intelligence and quantitative methods using artificial intelligence. Qualitative methods include failure trees, logging and expert systems, while quantitative methods such as unsupervised learning systems like K-means, C-means, and principal component analysis (PCA) and supervised learning systems including Fuzzy logic, support vector machines (SVM), shallow and deep neural networks, also some hybrid systems like PCA and autoencoder [4], [5], [6].

A study was carried out by Bonnettet. al [7], in the context of diagnosis of various rolling defects in the induction motor. Diallo et.al [8], presented an analysis by shape recognition, were defects created on the rotor and on the stator of the induction motor. Decision procedures based on the k-nearest neighbor rule and direct limit calculation, were used to detect defects. Another work was developed by [9], the authors proposed a technique for detecting and identifying the defects of the induction motor based on the analysis of structured residues of the stator currents. The simulation results obtained by this technique are satisfactory since it is able to detect and identify the defects of breaking bars, ring portions and eccentricity with a good estimate of their tripping time. In [10], the author has developed a method for pattern recognition based on a Multi-Layer Perception Artificial Neural Network (MLPANN) in order to detect and identify eccentricity defects and demagnetization of the synchronous machine. In the study presented in [11], where the author used an approach which based on the classical spectral analysis and a method of classification, inspired by the supervised learning theory of supported vector machines (SVM), enable the detection and identification of the ball bearing defect in the induction motor. In [12], the author proposed a technique of diagnosis of rotor electrical defects in the induction motor based on the analysis of acoustic signals; three motor states have been analyzed.

In addition, the work proposed by [13] presents a fault diagnosis technique in the single-phase induction motor based on acoustic signals. The authors use three classifiers namely the closest neighbor, the closest average and the Gaussian mixing models. Despite the low operating cost of the proposed technique, the last remains non-invasive since it is sensitive to interference from environmental noise while the classification rate is relatively low.

Reference [14] has proposed an appropriate approach to diagnose rotor imbalance defect in rotating machinery. It’s used as a technique of the two classifiers k-nearest neighbor (KNN) and (SVM). Features were taken from the FFT amplitude of the vibratory signals. The classification results obtained by this approach show that the SVM rate of 95.87% is significantly higher than the KNN rate of 77.51%. SVM has been the subject of many applications, this technique has already been exploited by [15] to ensure an automatic classification of bar break defects in induction motors. This technique was also used by [16] and [17] to detect and diagnose the real-time rolling defect and it was very successful. Good bibliographic research was presented by [18] from 2001 to 2014, the purpose of SVM in various data mining tasks such as classification, clustering and forecasting, etc. Despite the effectiveness and good quality of the results obtained by this method, some problems related to this method were mentioned. In the same sense [19] is developed diagnostic technique based on Artificial Neural Networks (ANN) to classify roller bearing defects. The results obtained by this technique give a fault classification accuracy of 93%. In the works of [20] and [21] a fairly efficient technique called adaptive network-based fuzzy inference system (ANFIS) was used to identify the bearing fault in the induction motor. Through this study, we develop a new approach for detecting and classifying induction motor defects using ANFIS.

It allows the identification of the majority of faults from birth precisely and in real time. In order to allow early classification of defects using limited samples, which facilitates online diagnosis, the approach has been optimized.

Our goal is to synthesize a new diagnostic approach and establish criteria of choice for their use in order to make a very advanced practical contribution to the diagnosis of induction motor defects. Our contribution is structured as follows:

• In the literature, many works use vibration signal processing with different approaches to signal processing. In our study, instead of using the vibration signal, we propose an approach based on an ANFIS algorithm to classify induction motor defects.

• In a second step, a fault diagnosis approach based on an efficient classifier formed on a small dataset was proposed.

This work is organized as follows. In section 2 we present a statistical study of defects that affect the induction motor. A detailed description of the test bench used in this work is presented in Section 3. The fourth section was devoted to the architecture of the developed approach. First, we presented the vibratory signals, this step will be followed by a pre-processing step which consists of extracting the characteristics related to the evolution of defects in order to give a reduced representation of the vibratory signals before performing the identification and classification of defects. The fifth section was devoted to the presentation of the ANFIS classifier used for the classification of defects. In the last section contains an experimentation phase and discussion of obtained results. The study was terminated by conclusion and perspective.

2. DEFECTS IN INDUCTION MOTOR

Any extraordinary stress that penalizes and causes total or partial paralysis and disrupts the good functioning of the engine is considered as a defect. The induction motor fault is original: electrical, mechanical and magnetic. It can occur on one of the organs that constituted them namely: the bearing, the stator, the rotor and the shaft. According to the recent statistical study presented in [22], the default rate for each component of the motor is shown in the figure below:

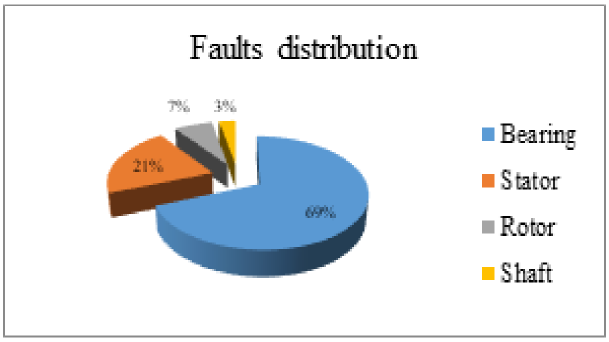

Fig. 1. Statistical study of induction motor defects [23]

In this study, the bearing failure rate has a large range compared to other defects, for this reason, it is recommended to guide our study into bearing defaults and this to show its influence on the dynamic behavior of the induction motor.

The causes and consequences of rolling fault are presented in the following table:

Table 1. Faults description in the induction motor.

Defects	Illustration	Causes	Effects
Rolling fault		The rolling fault is generally related to the wear of the bearingand more specifically a degradation of the balls, or the tread, caused by: ➢ Wear due to aging, ➢ High operating temperature, ➢ Loss of lubrication, ➢ Contaminated oil.	Oscillation of the load torque, ➢ Appearance of additional losses, ➢ Vibration by the displacement of the rotor around the longitudinal axis, ➢ Generates additional harmonicson the signature of power supplies.

3. DATABASE DESCRIPTION

The effectiveness of the proposed method cannot be definitively validated until the real conformity of the obtained data that is why one refers to the data acquired on the test bench available which are posted on the website of University Case Western Reserve [23]. This test bench illustrated in *figure 2* is a very simple design, it allows the assembly and disassembly of the two bearings tested, it consists essentially of a 2-horse induction motor and a dynamometer that allows applying different loads (in this case the applied loads are of the order 0, 1, 2 and 3 Hp). The latter is connected to the motor by an elastic coupling. In order to measure the vibrations of the motor, two accelerometers were placed at the level of the bearing on one side drive and the other side fan. There is also a speed sensor to measure the actual speed of rotation of the motor.

Fig.2. Test bench [24].

Defects are inserted separately on the three elements of the bearing as follows: the outer ring, inner ring and rolling elements. The defects studied on the turnover of the coupling end (drive side) are characterized by the following parameters:

- Number of holes = 1
- Diameter of the defect = 0.07, 0.14 and 0.21 inches.
- Depth of defect = 0.0118 inches.

The defect realized is well explained in the *figure 3*:

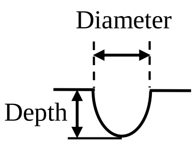

Fig. 3 Point defect on a bearing

4. ARCHITECTURE OF THE DEVELOPED APPROACH

The principle of the approach developed in this work is based on the use of a rather robust technique for classifying rolling defects from the vibratory signals that characterize each mode of operation.

The proposed approach has been divided into three stages. In a first step, we have represented the vibration signals for each mode of operation. In the next step, a data preprocessing operation was performed; firstly, the calculation of the fifteen statistical indicators was performed on the dataset. Among which, the most sensitive to defects have been taken into consideration. Finally, the ANFIS classifier was used with different operating scenarios of the induction motor. The different stages of the approach developed were presented in *figure 4*.

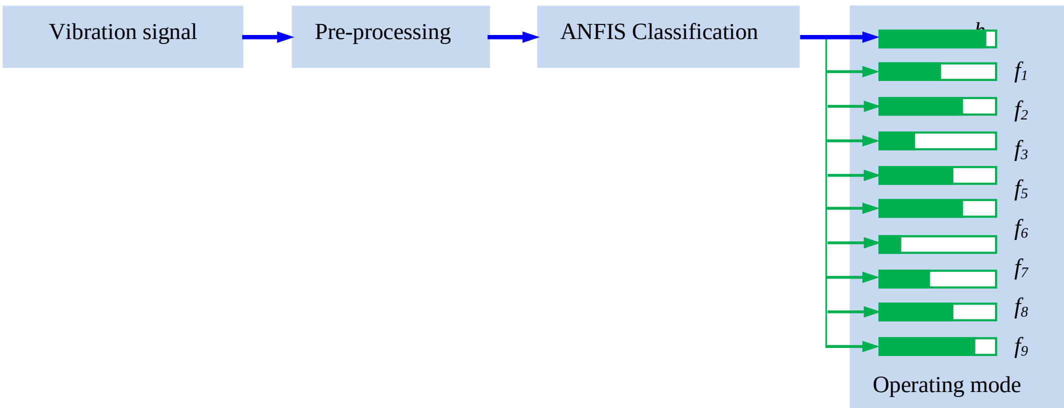

Fig.4. Breakdown Different stages of the approach.

5. VIBRATION SIGNAL

In this study, only ten (10) operating states were used for classification because of the availability of information needed for these cases. *Figure 5 (a - j)* shows the vibratory signals measured at the level of the rolling bearing on the coupling side in a normal state, then in a failed state. The fault state is divided into three types of defects occurring on the inner ring, the outer ring and the balls, each of which is expressed by three drill sizes of the order of 0.07, 0.14 and 0.21 inches. Knowing that the sampling frequency is 12000Hz.

It is found that at each state of operation of the bearing presented by a signal which is characterized by a very large number of points (N = 24000) which is difficult to exploit. For this purpose, it is necessary to minimize this number by means of the statistical indicators which make it possible to characterize each signal.

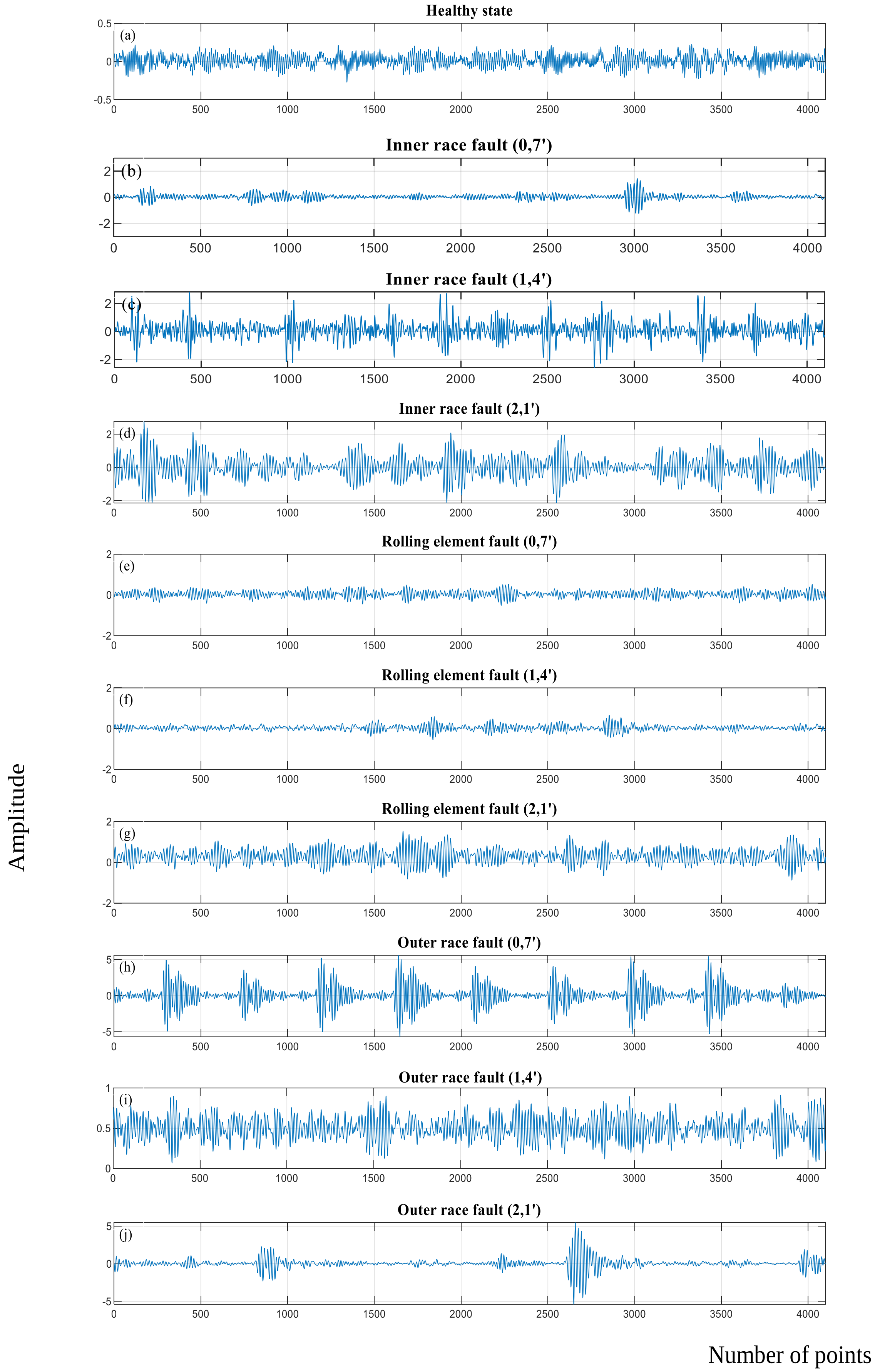

Fig.5. Vibratory signals of different rolling states.

6. PRETREATMENT (PRE-PROCESSING)

This step involves the extraction of the indicators that characterize the vibratory signals. First, the calculation of the statistical indicators on the dataset was done. Second, among these indicators those most sensitive to defects were selected.

Several statistical indicators exist in literatures, more or less efficient and adequate to characterize a given signal. The most used indicators are described in Table 2.

Table 2. Statistical indicators

Statistical parameters	**Equation**
Average	$X_{\text{var}} = \sum_{k=1}^{N} x(n)/N$
Standard deviation	$\sigma' = \sqrt{\sum_{n=1}^{N} (x(n) - x_m)^2 / N}$
Variance	$X_{\text{var}} = \sum_{k=1}^{N} (x(n) - x_m)^2 / N$
RMS value	$\text{X}_{\text{eff}} = \sqrt{(1/N)\sum_{n=1}^{N} x((n))^2}$
Maximum amplitude	$X_{\max} = \max\lvert x(n)\rvert$
Minimum amplitude	$X_{\min} = \min\lvert x(n)\rvert$
Skewness (biais)	$X_{ske} = \sum_{n=1}^{N} (x(n) - x_m)^3 / (N-1)\sigma^3$
Kurtosis	$x_{kur} = \sum_{n=1}^{N} (x(n) - x_m)^4 / (N-1)\sigma^4$
Crest factor CF	$\text{CF} = x_{\max} / x_{eff}$
Clearance factor CLF	$CLF = x_{\max} / \left(\frac{1}{N} \sum_{n=1}^{N} \sqrt{\lvert x(n)\rvert} \right)^2$
Shape factor SF	$SF = x_{eff} / \frac{1}{N} \sum_{n=1}^{N} \lvert x(n)\rvert$
Impulse factor IF	$IF = x_{\max} / \frac{1}{N} \sum_{n=1}^{N} \lvert x(n)\rvert$
Mean absolute deviation MAD	$MAD = \sum_{n=1}^{N} \left(\left\lvert \sum_{n=1}^{N} (x(n) - x_m) \right\rvert / N \right)$
Central Moment CM	$CM = \sum_{n=1}^{N} \left(\sum_{n=1}^{N} (x(n) - x_m)^p / N \right)$
Range	$x_{range} = \lvert x_{\max} - x_{\min}\rvert$

For extracting the most effective indicators, we tested their sensitivity to the detection of defect. The choice was made on the most sensitive among the samples. We found that RMS, standard deviation, minimum, maximum and Skewness are the most sensitive; their evolution is influenced by the presence and size of the defect.

Figures. 6 and *7* respectively illustrate the shape of the time signals and the variation of the indicators for N samples, in a healthy state of rolling afterwards in a state where it turns out that the fault comes from the outer ring with three drilling sizes different (i.e. with a drilled diameter of 0.7, 0.14 and 0.21).

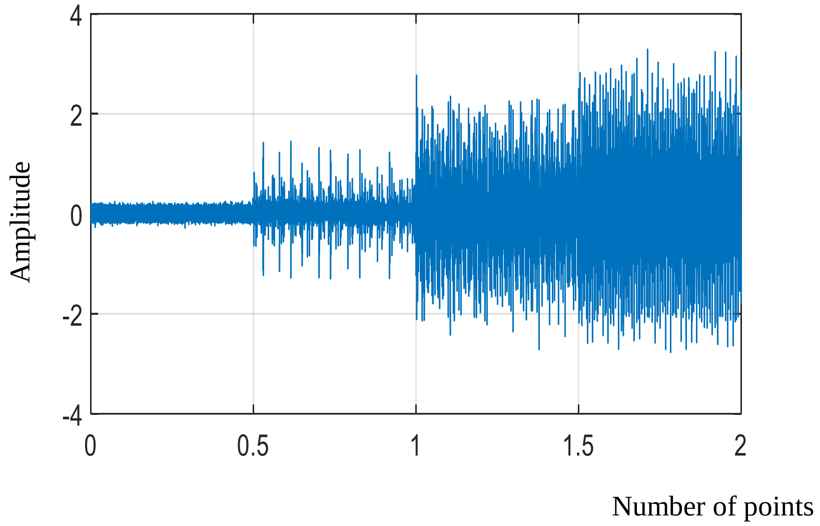

Fig.6. Succession of vibratory signals.

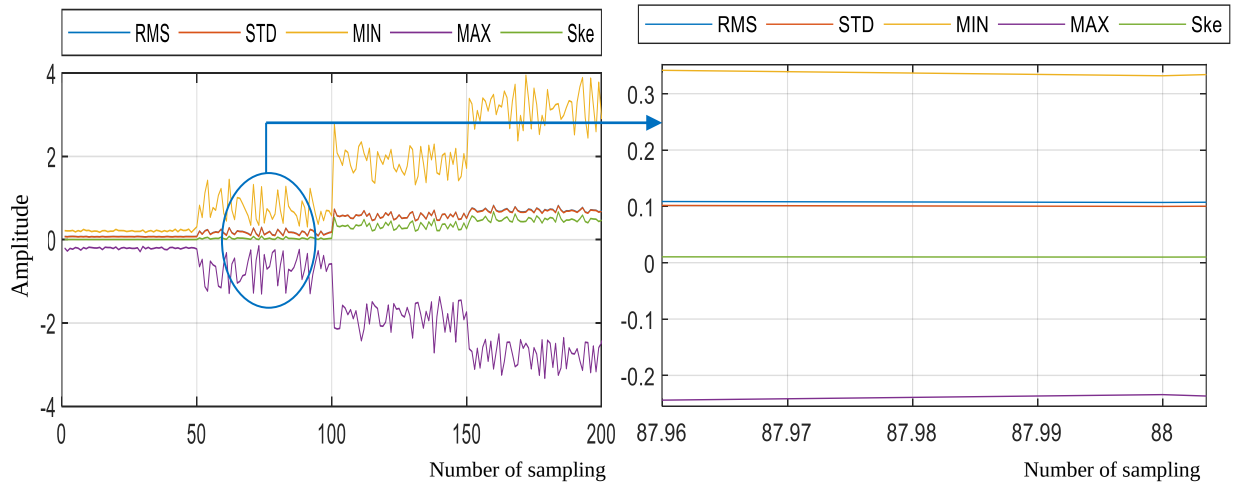

Fig.7.Evolution of the most sensitive indicators.

After selecting the most significant indicators, the classification step is followed to identify the nature and size of defects generated.

7. GENERAL INFORMATION ABOUT ANFIS

An adaptive network-based fuzzy inference system (ANFIS) is an improved type of artificial neural network based on the fuzzy inference system. The method was developed by Jang in 1993 [24]. ANFIS is the result of the fusion of the two combined methods. It simultaneously integrates hybridization of the neural network and fuzzy logic. Its inference system corresponds to a set of fuzzy (if - then) rules with the ability to learn nonlinear functions.

In this article, the classification of defects has been modeled by a new concept, it exploits the set of results obtained from the computation of the relevant temporal indicators (f_1, f_2 ...) on vibratory signals. *Figure 8* is the architecture of the adaptive fuzzy inference system, where: A_1, A_2, B_1, B_2 are fuzzy sets and the terminology of the three nodes are: *M*: multiplication, *N*: normalization, *S*: summation.

The output function *F* is expressed as follows:

$$F = \frac{w_1}{w_1 + w_2}\left(p_1.f_1 + q_1.f_2 + r_1\right) + \frac{w_2}{w_1 + w_2}\left(p_2.f_1 + q_2.f_2 + r_2\right) \tag{1}$$

where w_1, w_2 are the synaptic weights.

If we ask that: $W_1 = \frac{w_1}{w_1 + w_2}$ and $W_2 = \frac{w_2}{w_1 + w_2}$ these last two are called the standardized versions.

The linear combination of the design parameters p_1, q_1, p_2, q_2 obtained during the learning process makes us rewrite the output function as follows:

$$F = W_1\left(p_1.f_1 + q_1.f_2 + r_1\right) + W_2\left(p_2.f_1 + q_2.f_2 + r_2\right) \tag{2}$$

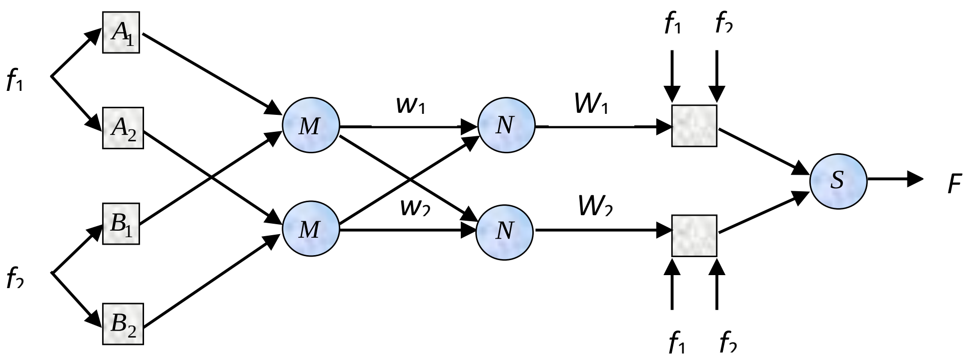

Fig.8.Architecture of ANFIS

To validate the proposed technique, we have taken ten rolling operation scenarios in different states (normal functional, defected for three size cases) that are presented in *figure 3*. This study therefore becomes a classification problem. where the number of classes is equal to the number of cases. Each signal is fragmented into several sections of the same size (N = 4100 samples). On each section the five selected indicators are calculated. The total of all data is equal to 590 samples, which are divided into two groups of data, one for the training that contains 490 samples and the other for the test that contains 200 samples that will be inserted into the sample ANFIS classifier. The data sets as well as the different states of the bearing are illustrated in detail in Table 3.

Table 3. Description of the database

Rolling condition	**Diameter of the defect (in inches)**	**Charge (Ch)**	**Number of samples for learning**	**Number of samples for the test**	**Class**
Healthy (*h*)		0, 1, 2, 3	49	10	1
Outer race (f_1)	0.07	0, 1, 2, 3	49	10	2
Outer race (f_2)	0.14	0, 1, 2, 3	49	10	3
Outer race (f_3)	0.21	0, 1, 2, 3	49	10	4
Inner race (f_4)	0.07	0, 1, 2, 3	49	10	5
Inner race (f_5)	0.14	0, 1, 2, 3	49	10	6
Inner race (f_6)	0.21	0, 1, 2, 3	49	10	7
Rolling element (f_7)	0.07	0, 1, 2, 3	49	10	8
Rolling element (f_8)	0.14	0, 1, 2, 3	49	10	9
Rolling element (f_9)	0.21	0, 1, 2, 3	49	10	10
Total			590		

8. EXPERIMENTS

To be able to quickly diagnose faults, it is necessary to make a compromise between learning speed, memory utilization, accuracy and interoperability. This is why we chose to use an ANFIS classifier in this work, with the extraction of the indicators directly from the data signals already made during the pre-processing phase.

Our algorithm is essentially written in MATLAB. We used Image Processing Toolbox TM as well as Statistics and Machine Learning Toolbox TM. The application is run on a Core i5 processor with a clock of 2.70 GHz and 8 GB of RAM.

Once the learning process is functional in a suitable manner, the test step validates the effectiveness of the proposed method, and this through the illustrated confusion matrix as follows:

$$C = \begin{bmatrix} 10 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 10 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 10 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 10 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 10 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 10 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 10 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10 \end{bmatrix}$$

Fig.9.Confusion matrix obtained by the classifier ANFIS

The confusion matrix, in the terminology of supervised learning, is a tool for measuring the quality of a classification system. Each column of the matrix represents the number of occurrences of an estimated class, while each row represents the number of occurrences of an actual (or reference) class. The data used for each of these groups must be different. One of the interests of the confusion matrix is that it quickly shows whether the system is able to classify correctly or not.

We consider a classification system whose purpose is to classify e-mail into two classes: normal e-mails and spam. We will want to know how many normal emails will be falsely estimated as spam (false alarms) and how many spam will not be estimated as such (no detections).

All the classification results obtained by the ANFIS are summarized in the table.

Table 4: Score with execution time

Type of classifier	Classification score %	Execution time (s)
ANFIS	100%	24,364

From the results displayed by the confusion matrix, we find that among the set of classes tested, it turns out that all the states are well assigned to their classes. Especially since this approach is able to classify large and small size defects.

A perfect classification rate is only the sum of the diagonal elements.

We clearly notice that the three low gravity defects were perfectly assigned to their appropriate classes, and this reinforces our belief that this system is viable. In the continuation of our work and for the good decision of the reliability of the proposed method, one uses a large database.

9. ACCURACY OF DEFECT CLASSIFICATION

To ensure the safety of people and equipment in the world of industry, a system is needed to know the occurrence of a failure in real time. This type of system is affected by two main factors:

1- The time needed to make a good prediction,

2- The time needed to make a good decision.

We test our method by reducing the number of samples needed to create a discriminant descriptor in order to obtain a good classification (minimization of execution time or fast response speed).

To evaluate the minimum number of samples needed to obtain a good classification of defects. *Figure 10* illustrates the number of samples necessary to give a good decision with the classifier used.

From the appearance of the variation of the error as a function of the number of iterations, we find that at the 6th iteration the error decreases to the value zero.

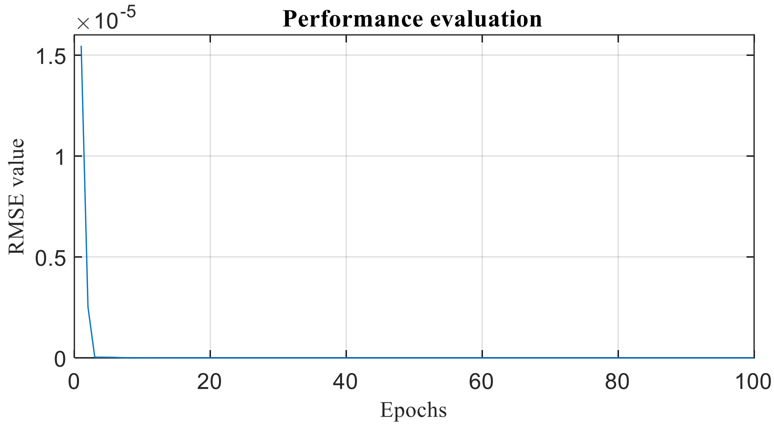

Fig.10.Performance of the ANFIS

10. CONCLUSION

In this paper, a new approach based on the use of ANFIS as a modern technique is developed. It makes possible to diagnose the nature of defect as well as, its gravity; the learning of this technique is also based on the indicators most sensitive to defects. The test results clearly show that there are five most sensitive indicators that are RMS, standard deviation, minimum, maximum and Skewness.

To obtain the classification rate of rolling defects the ANFIS classifier previously formed by the most defect-sensitive indicators is used. The results obtained show that the proposed technique has made it possible to classify the nature of the defect as well as its size with great precision.

REFERENCES

[1] N. Bessous, S.E.Zouzou, W.Bentrah, S.Sbaa, and M. Sahraoui, *Diagnosis of bearing defects in induction motors using discrete wavelet transform*, International Journal of System Assurance Engineering and Management, vol. 15, no. 4, pp. 1-9, Jul. 2015.

[2] Y. Merizalde, L. Hernandez,-Callejo and O. Duque-Perez, *State of the art and trend in the monitoring detection and diagnosis of failures in electric induction motors*, Energies, Vol, 10, 1056, 2017.

[3] X. Dai and Z. Gao, *From Model, Signal to Knowledge: A Data- Driven Perspective of Fault Detection and Diagnosis*, IEEE Transactions on Industrial Informatics, vol. 9, no. 4, pp. 2226–2238, 2013.

[4]. Y. Qi, S. Changquing, D. Wang, J.Shi, X. Jiang and Z. Zhu, *Stacked space auto encoder based deep network for fault diagnosis of rotating machinery*, IEEE Access, doi, 10, 1109/Access, 2728010,volume 5,pp: 1506-15079, 2017.

[5] G.E. Hinton, *Learning multiple layers of representation*, Trends in cognitive sciences, vol. 11, no. 10, pp, 428-434, 2007.

[6] Y. Kim, *Convolutional neural networks for sentence classification*, arXiv preprint arXiv : 1408.5882, 2014.

[7] A. H. Bonnett, *Cause and analysis of anti-friction bearing failures in A.C induction motors*, IEEE Transactions on Industry Application., pp. 14-23, Sept/Oct, 1993.

[8] D. Diallo, M. E.Benbouzid, D.Hamad, and X. Pierre, *Fault detection and diagnosis an induction machine Drive: A pattern recognition approach based on Concordia stator mean current vector*, IEEE Transactions on energy conversion, Institute of electrical and Electronics engineering, vol. 20, no. 3, pp. 512-519. 2005.

[9] A. Metatla, S.Benzahioul, and S. Haddad, *Induction Motor Failure Identification by Analyzing Structured Residues*, Proceeding of the 9th International Conference on Ecological Vehicles and Renewable Energies (EVER). 2014.

[10] K. Guota,and A.Kaut,*A review on fault diagnosis on induction motor using artificial neural networks, International journal of science and research*, vol. 3. 2014.

[11] F. Ta_nine, F.Mokrani, K. Antoni, J.Kabla, and Z. Asradj, *Introduction des SVM en MCSA*, 4th International conference, Sciences of electronic, technologies of information and telecommunications. March 25-29, Tunisia 2007.

[12] A. Glowacz, *Recognition of acoustic signals on induction motors with the use of MSAF10 and byes classier*, Arc. Metall. Mater., vol. 60, no. 1, pp. 153-158. 2016.

[13] A. Glowacz, W.Glowacz, Z.Glowacz, and J.Kozik, *Early fault diagnosis of bearing and stator faults of thesingle-phase induction motor using acoustic signals*, Measurement. vol. 113, pp. 1-9. 2018.

[14] M. Moosavian, H.Ahmadi, B.Sakhaei, R.Labbafi, *Support vector machine and K-nearest neighbour for unbalanced fault detection,* J. Q. Maint. Eng, vol. 20, pp.65–75. 2014.

[15] N. Hamdad, and K. Hammouche, *Hilbert Huang Transform and Pattern Recognition to detect defects in induction motor,* 4th International Conference on Electrical Engineering (ICEE). 13-15 Dec. 2015.

[16] J. S. L. Senanayaka, S. T. Kandukuri, Huynh Van Khang, and K. G. Robbersmyr, *Early detection and classification of bearing faults using support vector machine algorithm*. IEEE Workshop on Electrical Machines Design, Control and Diagnosis (WEMDCD) (Nottingham: UK). pp. 250-255. 2017

[17] W. Jie, T. Tang, C. Ming, and H. Tianhao, *Self-Adaptive Spectrum Analysis Based Bearing Fault Diagnosis*, Sensors, vol.18, 2018

[18] J. Nayak, B. Naik, and H. S. Behera,*A comprehensive survey on support vector machine in data mining tasks: Applications and challenges*. International Journal of Database Theory and Application, Vol.8, no. 1, pp.169-186.2015.

[19] J. B. Ali, N. Fnaiech, L. Saidi, B. Chebel-Morello,F. and Fnaiech, *Application of empirical mode decomposition and artificial neural network for automatic bearing fault diagnosis based on vibration signals*, Applied Acoustics, vol. 89, pp. 16–27, 2015.

[20] I. Attoui, N. Fergani, N. Boutasseta, B. Oudjani, and A. Deliou, *A new time–frequency method for identification and classification of ball bearing faults*, J. Sound Vibrat., vol. 397, pp. 241–265, Jun. 2017.

[21] I. Attoui, N. Boutasseta, N. Fergani, B. Oudjani, A. Deliou, *Vibration-based bearing fault diagnosis by an integrated DWT-FFT approach and an adaptive neuro-fuzzy inference system*, 3rd International Conference on Control, Engineering & Information Technology, IEEE, pp. 1–6. 2015.

[22] MA. Khan, Y. Kim, J. Choo, *Intelligent fault detection via dilated convolutional neural networks*, IEEE International Conference on Big Data and Smart Computing (Big Comp), pp 729–731. 2018.

[23] Case Western Reserve University Bearing Data Center Website (http://csegroups.case.edu/bearingdatacenter/home).

[24] J.-S.R.Jang,*ANFIS: adaptive-network-based fuzzy inference system*, IEEE Transactions on Systems, Man, and Cybernetics, Vol. 23, no. 3 , pp. 665 – 685, 1993.