Detection and diagnosis of fault bearing using wavelet packet transform and neural network

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ABSTRACT. Bearings, considered crucial components in rotating machinery, are widely used in the industry. Bearing status monitoring has become an essential step in the deployment of preventive maintenance policy. This work is part of the diagnosis and classification of bearing defects by vibration analysis of signals from defective bearings using time domain and frequency analysis and wavelet packet transformations (Wavelet Packet Transform WPT) with Artificial Neural Networks (ANN). WPT is used for extracting defect indicators to train the neural classifier. The main goal is the determination of the wavelet generating the most representative indicators of the state of the bearings for better detection and classification of defects. Using the WPT-based neural classifier, the obtained simulation results showed that the db6 wavelet with level 3 decomposition is best suited for diagnosing and classifying bearing defects.

KEYWORDS. Conditional maintenance; Bearing; The wavelet transform; Neural networks.

INTRODUCTION

The goal of maintenance is to detect failures of rotating machinery before a critical failure occurs. Practically, bearings are one of the most widely used elements in rotating equipment, and its failure is one of the main causes of breakdowns in this type of machines [1]. Therefore, of course, the diagnosis of bearing defects has been the

subject of several research studies. Most research related to the diagnosis of bearing defects uses vibration signals because they contain valuable information about defects [2, 3]. In addition, vibration analysis is considered to be the most common and reliable method in this type of analysis [4]. However, ultrasound has also been used appropriately and precisely in the detection of bearing defects [5].

There are different vibration analysis tools to detect and diagnose the appearance of defects in rotating machinery. Many publications synthesize these different methods or tools. They are generally classified into three main categories of vibration data analysis: time analysis, frequency analysis and time-scale analysis. The wavelets transform (TO) be a time-scale analysis technique suitable for both stationary and non-stationary signals [6]. The wavelet transform, offering a multi-resolution analysis, is very suitable for fault diagnosis [7].

The wavelet packet transform (WPT) is an improvement of the Multi-resolution MRA [8] since it allows decomposition of all frequency sub-bands.

In this work, we focus on the diagnosis of rolling defects, using an intelligent classification system based on Artificial Neural Networks (ANN) and Wavelet Packet Transformation.

The coefficients of the WPT will be used for the extraction of the indicators, in this case, the energy, and the kurtosis, which will drive the network of neurons [9]. Thus, the main objective of our work is the determination of the wavelet generating the most representative indicators of the state of the bearings for better detection and a good diagnosis of the defects.

WAVELET TRANSFORM

Wavelet packet transform

The wavelet packet method is a generalization of wavelet decomposition that offers a range of possibilities for signal analysis in wavelet analysis; a signal is broken down into approximations and details. The approximation is then itself cut into approximation and second-level detail, and the process is repeated. For decomposition of "n" levels, there are (n + 1) possible ways to decompose or encode the signal [10].

In wavelet packet analysis, details, as well as approximations, can be decomposed.

This yields more than (2n + 1) of different signal decompositions. The wavelet packet decomposition tree is shown in Fig .1. In the case of the detection of bearing defects, this technique makes it possible to obtain the same analysis fineness regardless of the frequencies investigated.
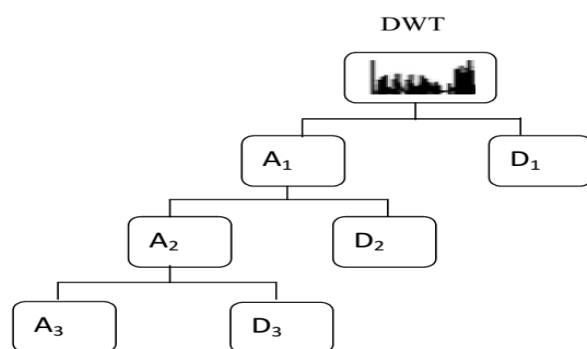

Figure 1: Representation in filter banks of the DWT at N = 3 level.

The extraction of indicators

Due to the complex nature of the machines and the complexity of the associated parameters, it is generally difficult to evaluate the state of a machine directly from the time data. The advent of the wavelet transform has provided an efficient tool for feature extraction of various time signals. As an extension to the discrete wavelet transform, the DWPT, in comparison with the DWT, provides more flexibility in time-frequency decomposition, especially in the high- frequency region. In particular, the DWPT allows the extraction of the indicators (for example, energy or kurtosis) from the frequency sub-bands where the indicators are concentrated[11].

Since the energy content of a signal provides a strong indicator of the signal but is not sensitive enough to incipient defects, kurtosis, on the other hand, is very sensitive to incipient defects but has low stability. Therefore, these two

indicators, energy, and kurtosis can be combined, instead of using one, to better characterize the vibratory signal and improve fault detection [12].

BEARING DATA CENTER

Vibration signals (accelerations) are obtained by exploiting the data made available on the Case Western Reserve University (CWRU, Bearing Data Center) site [13]. The signals are measured at a sampling frequency Fe = 12 kHz for   10 sec on a three-phase 1.5 kW (2 hp: horsepower) electric machine coupled to a load that determines its speed. The data were acquired from the rolling bearings under different loads (0, 1, 2 and 3 loads) and under different rolling conditions: normal condition, ball defect (BF), inner race defect (IRF), and defect in the outer race (ORF). As illustrated in Fig 2.
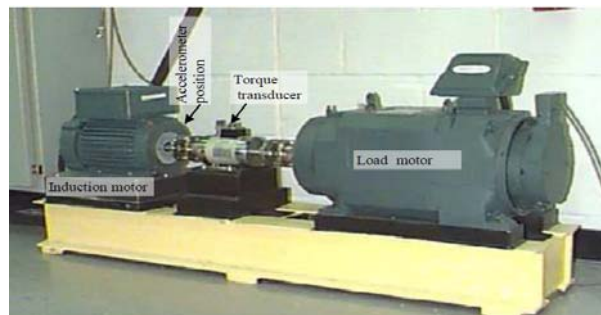

Figure 2: Bearing Test Stand

The bearings used in this work are SKF 6205 type ball bearings. Internal ring, outer ring, and ball defects are introduced into the bearings by Electrical Discharge Machining (EDM). The defect diameters are 0.1778 *mm* (0.007 *inches*), 0.3556 *mm* (0.014 *in*), 0.5334 *mm* (0.021 *in*) and 0.7112 *mm* (0.028 *in*) corresponding to incipient, moderate, severe and very severe defects respectively.

DIAGNOSIS OF DEFECTS BY METHODS OF ANALYSIS USING A CLASSIFIER ON NEURAL NETWORKS

Detection of bearing defects by time analysis

For temporal analysis, the input vector of the neural network is formed by the 7 temporal indicators already mentioned and are given by:

$$[Peak \quad RMS \quad Ku \quad ImF \quad CF \quad TALAF \quad THIKAT]^T \tag{1}$$

Two cases are considered according to the number of outputs. As shown in Fig. 3, we have 4 output neural network and 10 output neural network is shown in Fig. 4.
The performance of the fault diagnosis is evaluated by the recognition rate which is defined as

$$t_{r\%} = \frac{N_c}{N_t} \times 100 \tag{2}$$

N_c : Number of correct decisions

N_t : Total number of tests
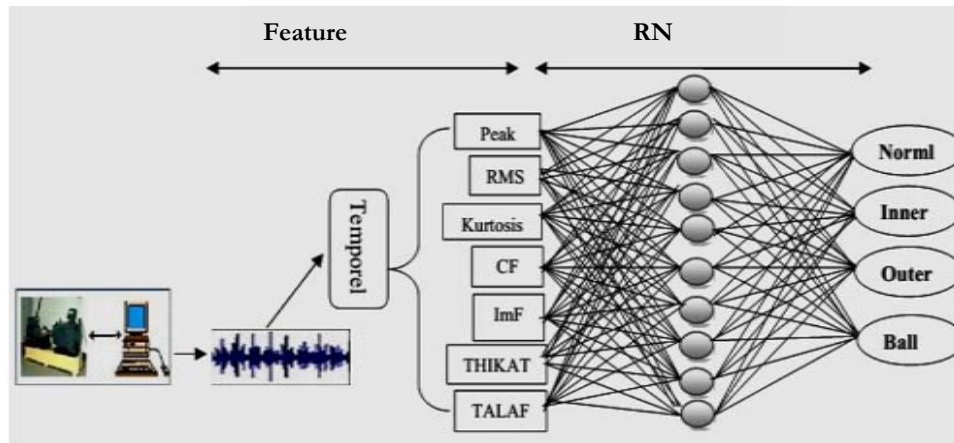
Case_1: 4 output neural network

Figure 3: RNA structure {7 10 4 }

Case 2: 10 output neural network

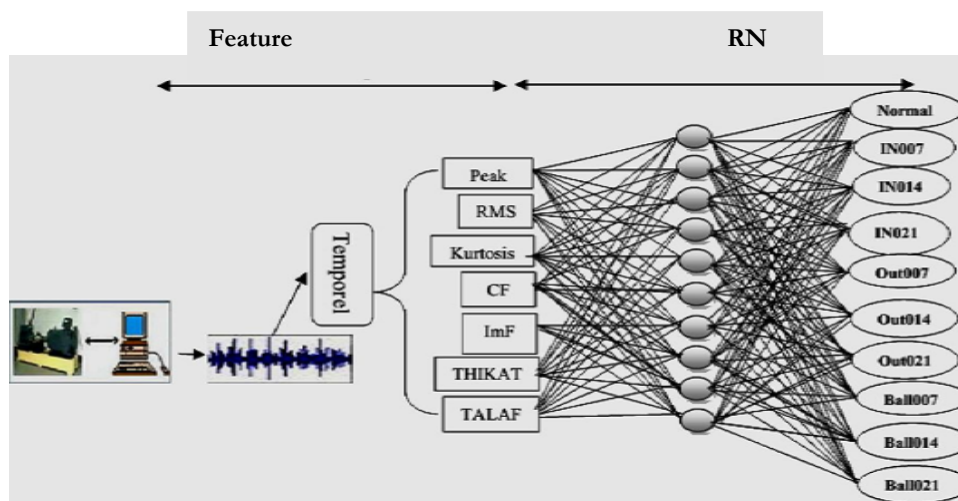Figure 4: RNA structure {7 10 10 }

Tab. 1 presents the classification performance of the single-layer hidden neural network with 10 neurons using time indicators for the two structures, 4 and 10 outputs:

Neural network Structure		
Number Of input	Number Of outputs	Performance Rate %
7	4	91.10
7	10	85.34

Table 1: Classification performance of time indicators.

Diagnosis of defects by time and frequency analysis

Seven time indicators $\begin{bmatrix} peak & RMS & Ku & ImF & CF & TALAF & THIKAT \end{bmatrix}^T$

Three spectral descriptors

$$\begin{bmatrix} x_{fouter} x_{finner} x_{fball} \end{bmatrix}^T \tag{3}$$

Hence, the input vector of the RNA, composed of 10 indicators, is given by

$$\begin{bmatrix} peak & RMS & Ku & ImF & CF & TALAF & THIKAT & x_{fouter} & x_{finner} & x_{fball} \end{bmatrix}^T \tag{4}$$
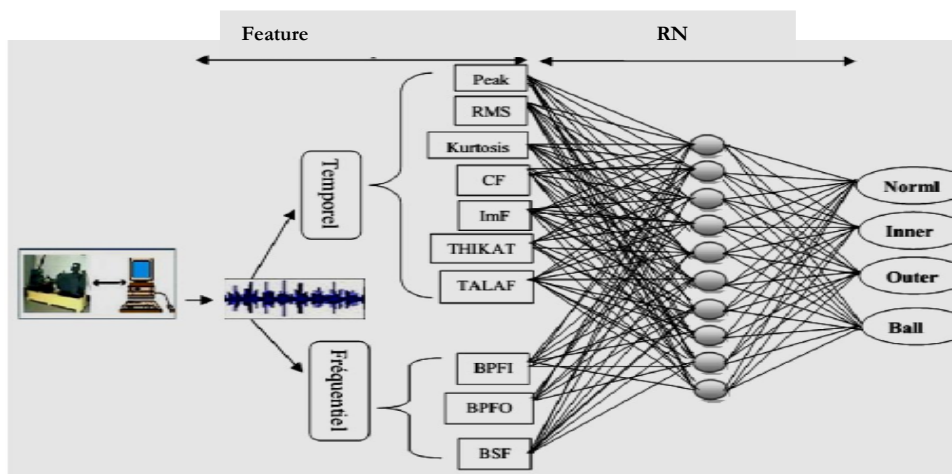
Case 1: 4 output neural network

Figure 5: RNA structure {10 10 4 }.

Case 2: 10 output neural network
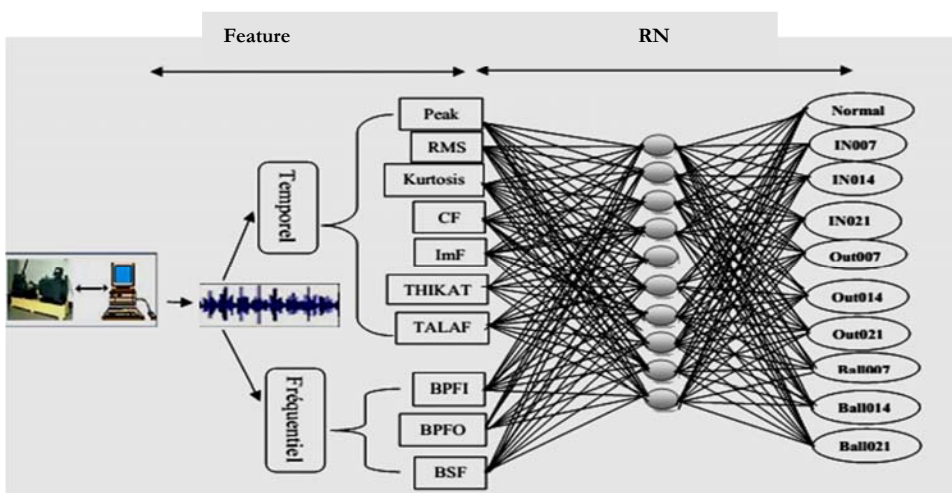
Figure 6: RNA structure {10 10 10 }.

Neural network Structure		
Number Of input	Number Of outputs	Performance Rate %
10	4	97.21
10	10	92.67

Table 2: Classification rate with time and frequency indicators.

From the results shown in Tab. 2, the neuronal classifiers {10 10 4 } and {10 10 10 } which is shown in Fig. 5 and Fig. 6 respectively, have classification rates of 97.21% and 92.67%, respectively. This confirms the contribution of frequency descriptors to the improvement of the classification rate and the diagnosis of defects.

DIAGNOSIS OF DEFECTS BY THE WAVELET TRANSFORM

Optimal choice of wavelet and decomposition level

In practice, unfortunately, there is no wavelet that is better than the others for all cases; it all depends on the intended application. For vibratory analysis based on the wavelet transform, the selection of the mother wavelet depends on its properties or the similarity between the signal and the mother wavelet. Based on the DWPT, this step consists of determining the best mother wavelet (type and order) and the optimal decomposition level best suited to our application. The wavelets chosen for this study are:

- The wavelets of Daubechies: db1, db2, db3, db20, db30, db40 and db44
- Coiflets: coif1, coif2, ..., coif5
- Symlets: sym2, ⋯, sym10 and sym15

For the search of the decomposition level by the wavelet packet transform, we have considered the levels $j = \{3, 4, 5, 6, 7\}$. These characteristics can be expressed in a vector such as:

$$F_v = \begin{bmatrix} E_j^1 & E_j^2 & \cdots & E_j^{2^j} & K_j^1 & K_j^2 & \cdots & K_j^{2^j} \end{bmatrix} \qquad (5)$$

Fig. 7 shows the classification is based on artificial neural networks.
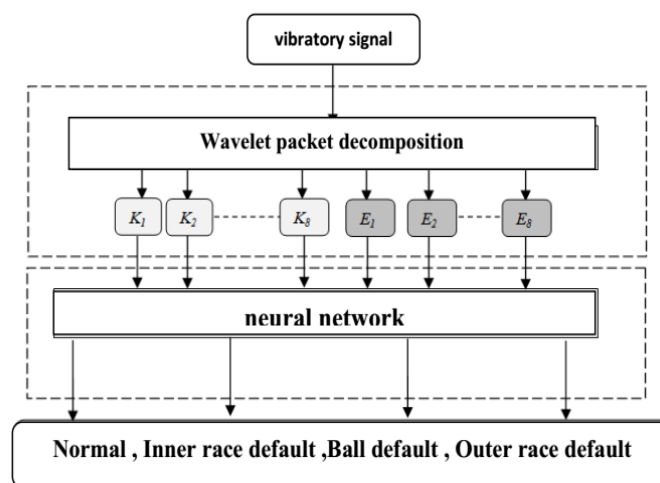

Figure 7: Classification scheme by RNA-based DPWT with a level of decomposition j = 3, 4, 5, 6, 7

Configuration Neural network

The configuration chosen is the following:

- 3-layer network: 1 single hidden layer;
- 10 neurons in the hidden layer;
- Performance error = 10^{-8}.

We have the database has 180 signals for each rolling condition Among the 720 signals, 60% and 40% are exploited for learning the RNA test respectively.

The results showed in Tab. 3, for the three families of wavelets, which the best classification rates are obtained with the classification rate, are obtained with the level 3 of decomposition. In addition, Daubechies wavelets db1, db2, db3, db6, db7 and db8 have the best performance in terms of fault classification rates.

Using the wavelets db1, db2, db3, db6, db7 and db8, with which the best performances are obtained, were performed the neuron classification algorithm 100 times and the results obtained are reported in Tab. 4.

wavelet	Level				
	3	**4**	**5**	**6**	**7**
db1	**99.21**	98.17	97.91	90.88	79.68
db2	**99.21**	96.61	97.13	88.80	83.33
db3	**99.21**	97.39	98.17	89.84	86.45
db4	97.91	97.39	95.83	92.70	88.80
db5	98.17	97.13	97.39	90.88	79.94
db6	**99.21**	97.91	95.57	93.48	86.19
db7	**99.21**	96.87	96.61	90.62	89.58
db8	**99.21**	96.61	97.39	91.66	88.80
db9	96.87	98.17	97.39	90.36	76.04
db10	97.39	97.39	97.13	90.10	82.81
db11	98.43	96.61	96.61	92.18	80.20
db12	98.95	97.91	96.35	89.32	86.45
db13	98.43	97.65	97.91	91.40	85.93
db14	98.17	99.21	96.61	89.58	87.50
db15	97.65	98.69	97.39	91.92	89.84
db16	97.39	97.39	95.57	91.66	84.11
db17	98.17	97.91	98.17	90.36	82.81
db18	96.09	97.91	97.65	89.84	90.66
db19	98.69	97.39	97.31	92.96	75.00
db20	98.17	96.35	97.65	91.40	83.66
db30	98.17	97.39	97.65	90.88	87.50
db40	98.69	97.91	98.43	95.50	80.20
db44	98.17	98.17	97.39	96.09	85.84
Coif 1	98.69	97.39	94.27	89.48	79.16
Coif 2	98.17	97.13	97.13	91.66	84.63
Coif 3	97.91	97.39	95.57	86.13	85.93
Coif 4	98.17	96.09	94.01	85.15	82.81
Coif 5	99.21	96.09	93.22	86.45	75.00
Sym 2	98.43	97.13	97.39	89.06	76.04
Sym 3	97.65	98.43	97.13	93.22	85.93
Sym 4	98.95	98.43	97.39	90.62	87.50
Sym 5	98.95	98.43	97.13	92.44	89.84
Sym 6	98.17	97.65	95.57	90.62	83.07
Sym 7	98.69	96.87	95.83	89.06	80.20
Sym 8	98.17	96.09	96.61	91.92	84.11
Sym 9	98.95	98.43	96.35	92.44	80.20
Sym 10	98.17	96.61	94.27	82.03	75.00
Sym 15	98.17	97.65	97.13	93.22	76.04

Table 3: Classification rates for different types of wavelet and different levels of decomposition

Wavelet	db1	db2	db3	db6	db7	db8
Performance %	98.95	98.95	99.21	**99.47**	98.69	99.21

Table 4: Classification rate with decomposition level N = 3

We conclude that the optimal wavelet most appropriate to fault diagnosis of bearings is the Daubechies wavelet of order 6 "db6" with a level of decomposition, N = 3, has proven its performance in several works dealing with the diagnosis of defects [14,15,16].

Reduction of the vector of indicators
The application of the wavelet packet transform (DWPT) to the vibratory signal, using the wavelet db6 with decomposition level N = 3, generates $2^3 = 8$ frequency sub-bands. Recall that the 16 indicators used in this work are based on energy and kurtosis calculated for each frequency sub-band and are given by:

$$F_v = \begin{bmatrix} E_3^1 & E_3^2 & \cdots & E_3^8 & K_3^1 & K_3^2 & \cdots & K_3^8 \end{bmatrix} \tag{6}$$

In order to see which of the 16 indicators are sensitive to the state of rotation, the diagrams representing the energies and kurtosis of each sub-band are plotted and shown in Fig. 8 and 9 respectively.

From Fig. 8, we can easily see that the two indicators, in this case, E_3^5 and E_3^6 are almost invariant. For kurtosis, represented by Fig. 9, we can note that the 8 indicators $K_3^1, K_3^2, K_3^3, K_3^4, K_3^5, K_3^6, K_3^7,$ and K_3^8 are sensitive to changing the state of the bearing. As a result, we have maintained the 14 most relevant indicators for the classification of bearing defects that are given by:

$$F_{vr} = \begin{bmatrix} E_3^1 & E_3^2 & E_3^3 & E_3^4 & E_3^7 & E_3^8 & K_3^1 & K_3^2 & \cdots & K_3^8 \end{bmatrix} \tag{7}$$
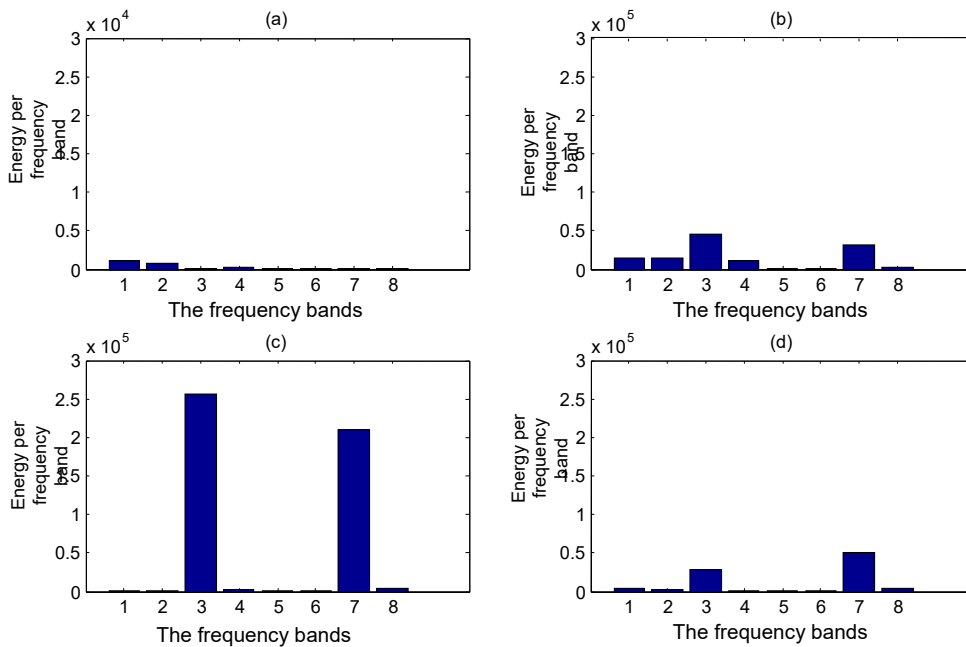

Figure 8: Energy of each sub-band for the four states of the bearing: (a) no fault, (b) defect in the inner race, (c) defect in the outer race, (d) defect in the ball.

DIAGNOSIS OF DEFECTS BY TRANSFORM WAVELET PACKETS

The diagnosis and classification of bearing defects are performed by an artificial neural network (ANN) whose inputs are energy indicators and kurtosis calculated using coefficients derived from the decomposition level 3 transform wavelet packet (DWPT) using the db6 wavelet.

We kept the same configuration of the RNA used before. Thus, the structure of the RNA takes the form:

- 3-layer network: 1 single hidden layer;
- 10 neurons in the hidden layer;
- The number of nodes at the input is equal to the number of indicators that is 14;
- The number of nodes in the output layer is:
    - **Case 1:** 4 outputs (see Fig. 10) corresponding to the four bearing states.
    - **Case 2:** 10 outputs (see Fig. 11) for detecting the severity of the fault. Corresponding the different defects as well as their diameters:
        - Normal.
        - Fault in the inner race (0.007 and 0.014 and 0.021 *inches*).
        - Fault in the inner race (0.007 and 0.014 and 0.021 *inches*).
        - Fault in the ball (0.007 and 0.014 and 0.021 *inches*).
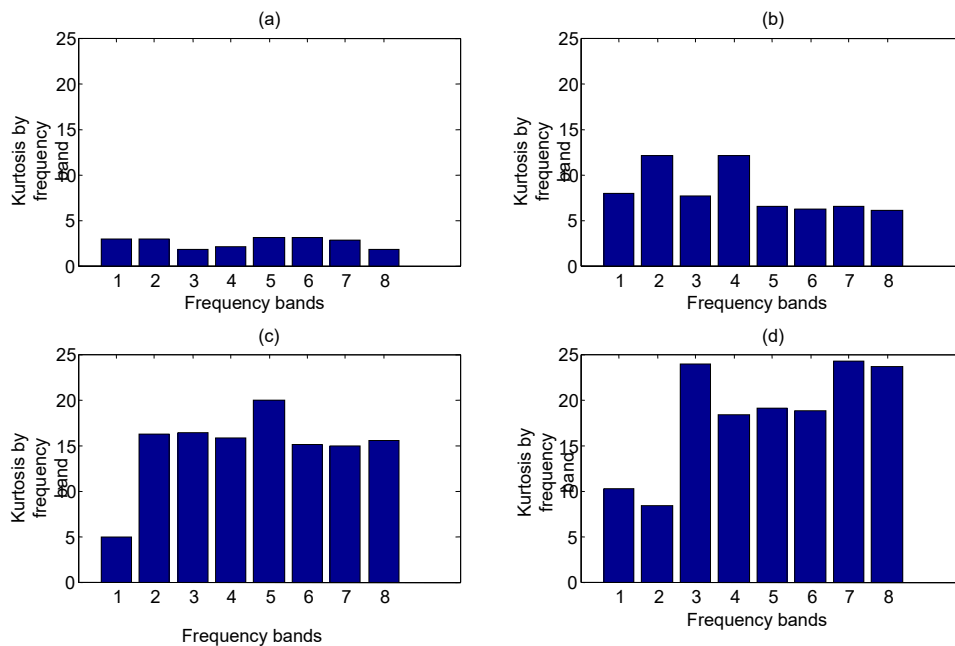

Figure 9: Kurtosis of. each sub-band for the four states of the bearing: (a) no fault, (b) fault in the inner race, (c) fault in the outer race, (d) fault in the ball.

Tab. 5 shows the RNA classification rates based on the wavelet packet transform for both the 4 and 10 output configurations.

Neural network Structure		
Number Of input	Number Of outputs	Performance Rate %
14	4	99.47
14	10	99.33

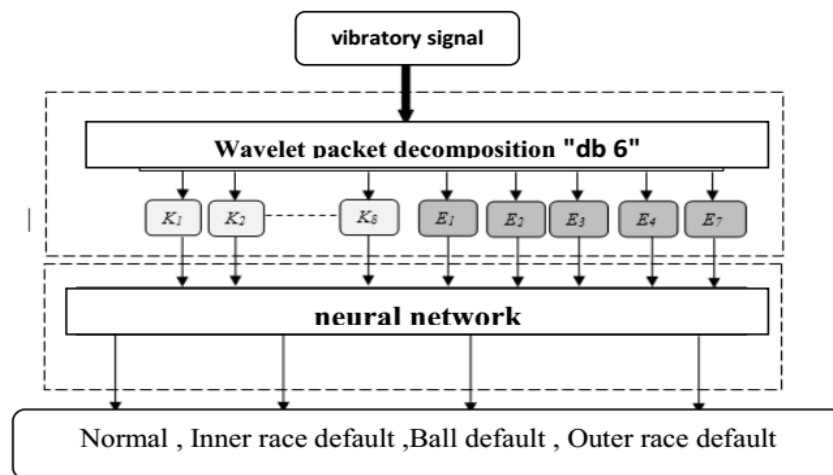Table 5: Classification Rate with indicators based on wavelet db6

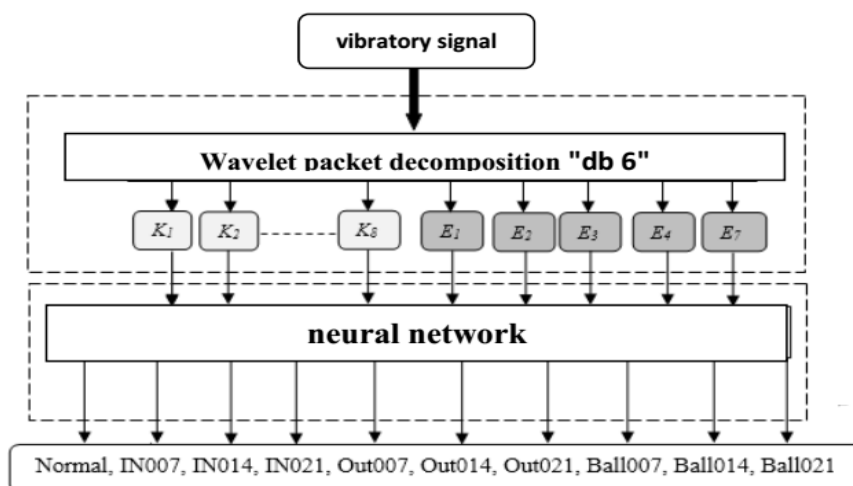Figure 10: Structure of RNA classifier 4 outputs

Figure 11: Structure of RNA classifier 10 outputs

The results shown in Tab. 5 show a classification rate of 99.47% for the detection of the fault location (four outputs), and a rate of 99.33% for the detection of the diameter (severity) of the fault (ten outputs). These results confirm the efficiency of the use of the wavelet packet transform (with the db6 wavelet) for the extraction of indicators sensitive to the variations of the state of the bearing to be monitored.

CONCLUSIONS

The work presented in this article is part of the preventive maintenance of rotating equipments and particularly the detection of defects bearings by vibration analysis. The temporal and frequency analysis is used to improve the classification rate and the diagnosis of bearing failure and the time and frequency analysis is used to determining its diameter and location. This objective was mostly achieved with a precision of about 92.67% when determining the diameter of the defect, and 97.21% when locating.
Next, we have tried to determine the optimal wavelet best suited to the diagnosis and classification of bearing defects using the wavelet packet transform and Artificial Neural Networks (ANN).
The main objective was to determine the wavelet that generates indicators in this case energy and kurtosis best reflecting the state of the bearings. We could show that the wavelet db6 with decomposition level 3 is the most appropriate diagnosis and classification of bearing fault. This wavelet db6 and decomposition level 3 improve our result at 99.33 % when determining the diameter of the defect, and 99.47 % when locating

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