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Location and evaluation of bearings defects by vibration analysis and neural networks

M. E. Boukhobza*, Z. Derouiche, Z. Ahmed Foitih*****
**Signals, Systems and Data Laboratory, Electronics department, USTO, Algeria*
***Signals, Systems and Data Laboratory, Electronics department, USTO, Algeria, E-mail: zianeder@yahoo.fr*
****Power Electronic and Automation Laboratory, Electronics department, USTO, Algeria, E-mail: zfoitih@yahoo.fr*

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1. Introduction

The bearings are one of the weaknesses of a rotary machine for their support of the dynamic forces of a shaft. They are the most critical elements and therefore the elements to watch for the most [1, 2].

Much research has been performed in this field to determine at an early stage any form of cracks leading to chipping and then to ruin the bearing [3, 4]. In general three approaches are used for detection of bearing defects. The first is based on scalar measurements such as root mean square (RMS), crest factor and the kurtosis [5] which gives a reasonably global defect indication without the possibility of its location in the bearing.

The second approach is based on the application of the algorithm of fast Fourier transform. However the total spectrum of the vibration signal (shaft and bearings) obtained does not show an obvious characteristic frequency of pulses trains generated by the defects. This problem was overcome by the high frequency resonance technique (HFRT) [6] which use a band pass filter to isolate one of the resonant frequencies of a structure and then to eliminate unwanted vibrations from other sources (e.g. the rotation shaft). We then apply to a filtered signal a demodulation by envelope detection. Finally we calculate the spectrum of the demodulated signal and low frequency lead to the characteristic frequency of defect. However, the latter method has some drawbacks.

The user has to accurately know the position of the band pass filter around one resonance frequency. In addition this method is ineffective in the presence of a high noise levels.

The third approach combines techniques based on time frequency demodulation with wavelets [7]. Pulses signal can be detected by high frequencies of the wavelet with good resolution [8]. Due to its complexity this technique is still very rarely applied in industry compared to the Fourier transform.

In this paper we apply neural networks to locate and quantify the size of a defect on one element of a bearing. The network's inputs are time indicators from a vibration signal measured on a mechanical component in progressive wear. It has two outputs one indicates the position of the defect and the other the size.

It is critical to know the position of defect: the inner ring, the outer ring or the bearing balls. This localization and monitoring of flaw size is used to estimate the remaining operating life before replacement. This life time is different depending on each bearing element load [9].

With such tool, maintenance technicians will avoid stopping a machine too early to change a bearing, as it can still work without damaging equipment. This condition ensures the best performance of machinery while minimizing the cost of spare parts [10].

The ongoing monitoring of variables indicative of damage is tedious, as it a repetitive procedure established to interpret each iteration level of the selected indicators. Otherwise it is easier to the use of neural networks enable the automation of the defect monitoring process, easily providing the operator automated results [11].

2. Measurement of defects ball bearing

"Case Western Reserve University (CWRU), Cleveland Ohio's" has such an appropriate test bench for experiments necessary for detection and monitoring of bearing defects [12]. Thanks to the computer center which provides access to data stored on tests ball bearing for normal and defective bearings. Vibration measurements were conducted using the test set-up pictured in Fig. 1.

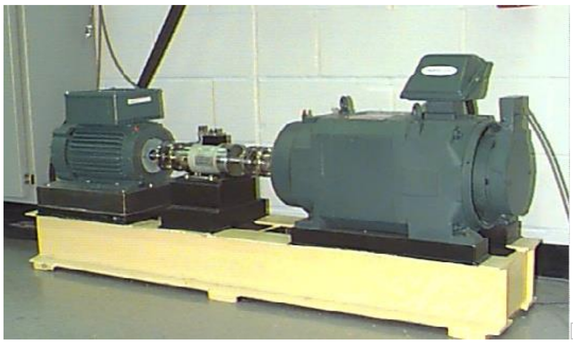


Fig. 1 Bearing test rig

Accelerometers are used to measure vibration in a radial plane. They are arranged on bearings on which are sewn, by electro-erosion, characterized point defects of a certain diameter and a certain depth (Fig. 2).

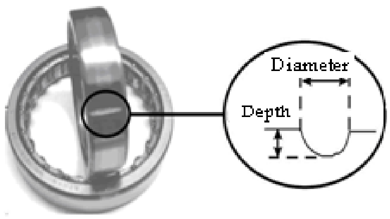


Fig. 2 Point defect on a bearing

The defects were inserted on the bearings of the motor shaft. A single point of failure is produced by each operation bearing with a depth of 0.30 mm and diameters of default variables.

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:

- diameter of the defect = 0.20 and 0.50 mm;
- depth of defect = 0.30 mm.

3. Diagnostic system and bearing tracking defects

Our project consists in developing a system to trace the source of the fault to estimate its severity and location, or to assess the absence of defect.

Several studies have been made in the field. Researchers have developed a system that can provide an output only capable of identifying the severity of the defect on a bearing using neural networks and genetic algorithms [13]. Other researchers have developed a neural network using time and frequency input variables as indicators associated with defects of the bearing.

Three frequency parameters were selected:

- the defect frequency of the outer ring;
- the defect frequency of the inner ring;
- the defect frequency of the rolling element.

To these frequency parameters were added time indicators to form a neural network for locating the site and to determine the diameter of the defect [14].

From an experimental study on time indicators, it was observed that they vary with the size of the defect and its position on the bearings. They can therefore be used to monitor the development of the fault and locate its location on the bearing. This task of identification may also be obtained using spectral indicators.

This system has the distinction of being simple to prepare as it uses time indicators calculated vibration signals directly without any treatment of temporal frequency which reduces computation time. In addition, this system is more easily adoptable in industry because its application is very simple.

It was observed during our experimental study that the temporal indicators associated with defects of rolling elements (balls) are proportionally lower compared to the indicators associated with defects of rings. For this reason we have divided our system into two neural networks. The first network is used to diagnose faults of rings, and indicate their diameter, and may also indicate the presence of non defective rings. The second network treats the case of the rolling elements (balls), it has to diagnose the presence of the defect and indicate its diameter. It can also confirm the lack of defects.

4. Configuration of neural networks

The configuration of neural networks has been the crucial step in developing our system for locating and assessing the severity of the defect. It must be based on data inputs and outputs. The literature review on studies conducted in this area suggests the adoption of a multilayer neural network [11, 13]. Not to unnecessarily increase the complexity of the network, we decided to use a single hidden layer.

The implemented neural network is composed of three layers: an input layer, a hidden layer and an output layer.

Input layer: the number of neurons in input layer depends on the number of time indicators used in our case we have four and they are:

- The RMS value given by the following expression:

$$V_{RMS} = \sqrt{\frac{1}{N_e}\sum_{n=1}^{N_e}\left[x(n)\right]^2}\,, \tag{1}$$

where $x(n)$ is the time measured vibration signal, N_e represents the number of samples from the signal. This value provides information on the overall level of vibration but provides no information on the defective mechanical component.

- The peak value.

$$V_{peak} = sup_{1\le n\le N_e}\left|x(n)\right| \tag{2}$$

- The crest factor *CF* of the vibration signal is defined as the ratio between the peak and RMS value.

It provides timely information on the degradation of the bearing, while remaining independent of the operating characteristics (the bearing size, load, speed, etc).

The *CF* presents a drawback because it decreases as the defect develops.

$$CF = \frac{V_{peak}}{V_{RMS}} \tag{3}$$

- The *Kurtosis*: the vibration types or sinusoidal impulse generate all gaits of curves with different densities. The *Kurtosis*, which quantifies the difference, is given by:

$$Kurtosis = \frac{\frac{1}{N_e}\sum_{n=1}^{N_e}\left(x(n)-\bar{x}\right)^4}{\sigma_x^4} \tag{4}$$

with: $\bar{x}$ the average value and σ_x the standard deviation. The Kurtosis quantifies the flattening of the curve of probability density of the recorded signal. It gives great importance to the high amplitudes while weighting the isolated events, unlike the crest factor.

Output layer: the number of neurons is set to 2. A first output *DC* indicates the severity of the defect by calculating its diameter. A second output E_i indicates its location on the bearing if the defect exists; otherwise E_i indicates the absence of defect. Index i is assigned as:

$i = 1$, for the output corresponding to the rings: E_1;
$i = 2$, for the output corresponding to the balls: E_2.

Hidden layer: The numbers of neurons in hidden layer and activation functions were selected experimentally; we chose the best performing model.

This system takes into account the defect tracking in the database of neural networks based on measurements of various diameters for different defects.

Neural networks are developed using vibration data recorded on healthy bearings and bearings with defects.

4.1. Design of neural network specialized in the defects of rings

The developments of neural networks are done experimentally. Such a network would have 4 input neurons corresponding to the number of indicators used in the temporal network input and two output neurons since we want to calculate the diameter of the defect *DC*, and identify the defect type E_1 , such as:

if $E_1 \approx 1 \Rightarrow$ defect on the outer ring;
if $E_1 \approx 2 \Rightarrow$ defect on the inner ring;
if $E_1 \approx 0 \Rightarrow$ no defect ring.

Network experiments were performed with the number of neurons in hidden layer ranging from 1 to 10. Three transfer functions were considered: a linear function “purelin”, and two sigmoid functions, one for positive and negative output 'tansig', the other to output only positive “logsig”.

Learning is performed for each configuration, with the following parameters:

Maximum number of iterations (Epochs) = 100.
Maximum gradient = $1e^{-10}$.
Learning is stopped if any of these conditions is satisfied.

Performance criteria of the neural network are to examine the performance of each neural network. The sum of squared errors (*SSE*) and the mean square error modeling (*MSE*) [13] associated with the diameter of the defect were derived as described below.

The SSE is given by the following equation [15]:

$$SSE = \sum_{k=1}^{N_T} \left[y_m(k) - y_c(k) \right]^2 , \tag{5}$$

where N_T is the number of elements of the test set; y_m is the actual measured values of the process to be modeled; y_c is the values calculated by the model.

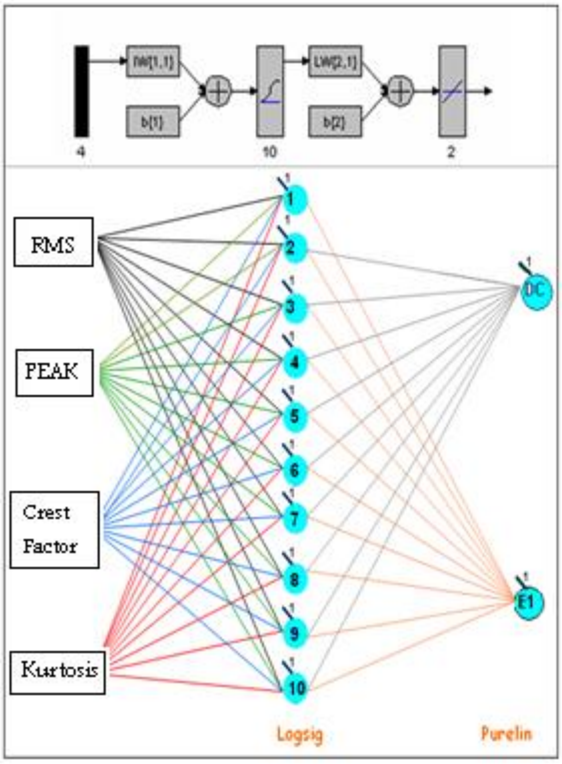


Fig. 3 ANN specialized in defects in rings

The *MSE* is written as follows:

$$MSE = \sqrt{\frac{1}{N_T} \sum_{k=1}^{N_T} \left[y_m(k) - y_c(k) \right]^2} . \tag{6}$$

The *SSE* and the *MSE* are calculated during the test phase, there decreasing is synonym that the neural network is performing. These two parameters are associated with the diameter of the defect because it is its size which strongly influences the decision of changing the ball bearing. Fig. 3 shows the selected ANN.

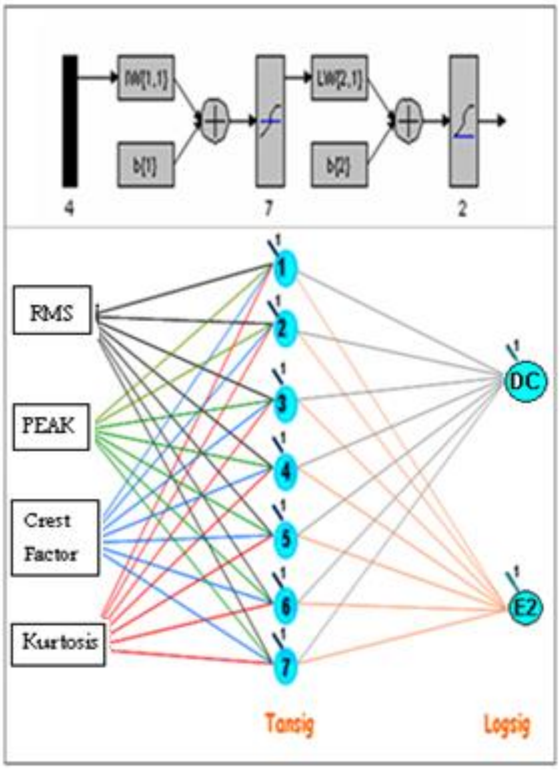


Fig. 4 ANN specialized in defects of rolling elements

4.2. Design of neural network specialized in the defects of rolling elements (BALL)

The dedicated network defects in rolling elements has 4 input neurons which correspond to the number of time indicators used at the entrance of the network, and two output neurons since we want to calculate the diameter of the defect *DC* and identify the defect type E_2, such as:

if $E_2 \approx 1 \Rightarrow$ defect on the rolling element;
if $E_2 \approx 0 \Rightarrow$ healthy bearing ball.

The design of a neural network specific to the defects of rolling elements is performed in the same way that the previous network shown. Figure 4 shows the selected ANN.

4.3. Vibratory signals used for diagnosis and monitoring of drive end and fan end bearing defects

The signals used in the applications of table 4 and table 5 originate from the database of CWRU. The signals were respectively collected from SKF 6205 drive end bearing (Table 1) and SKF 6203 fan end bearing (Table 2) with different severities of inner race and outer race faults (Table 3). Drive end bearing specifications, including bearing geometry and defect frequencies are listed in the bearing specifications.

Vibration data was collected using accelerometers, which were attached to the housing with magnetic bases. Accelerometers were placed at the 12 o'clock position at both the drive end and fan end of the motor housing.

Data was collected for normal bearings, single-point drive end and fan end defects. Digital data was collected at 12000 samples/second for fan end bearing and at 48000 samples/second for drive end bearing experiments. Data files are in Matlab format.

Table 1

Drive end bearing: 6205-2RS JEM SKF, deep groove ball bearing, size in mm

Inside diameter	Outside diameter	Thickness	Ball diameter	Pitch diameter
25	52	15	8	39

Defect frequencies (multiple of running speed in Hz)

Inner ring	Outer ring	Cage train	Ball
5.4152	3.5848	0.39828	4.7135

Table 2

Fan end bearing**:** 6203-2RS JEM SKF, deep groove ball bearing, size in mm

Inside diameter	Outside diameter	Thickness	Ball diameter	Pitch diameter
17	40	12	6.75	28.5

Defect frequencies (multiple of running speed in Hz)

Inner ring	Outer ring	Cage train	Ball
4.9469	3.0530	0.3817	3.9874

Table 3

Diameters and depths of the defects located on the drive end and fan end bearings

Position of bearing	Location fault	Diameter, mm	Depth, mm
Drive end bearing	Inner and outer ring and ball	0.20	0.30
Drive end bearing	Inner and outer ring and ball	0.35	0.30
Drive end bearing	Inner and outer ring and ball	0.50	0.30
Fan end bearing	Inner ring	0.20	0.30
Fan end bearing	Inner ring	0.35	0.30
Fan end bearing	Inner ring	0.50	0.30

4.4. Application system for diagnosis and monitoring of drive end bearing defects

Table 4 below provides an example on how to implement the system to diagnose and monitor the condition of bearings, with:

DR means the diameter of the actual defect;

DC means the calculated diameter of the defect;

ER is the location of the actual defect;

E_1 is the location of the defect found by the network specializing in defects rings;

E_2 is the location of the defect found by the network specializing in defects of rolling elements.

We considered the following cases of measures:

Case a: Healthy bearing.

The four inputs of neuron networks, RMS, peak, crest factor and kurtosis, are calculated from the temporal signal vibratory. Both networks, rings defect and rolling elements defect, give the output $E_1 = E_2 = DC = 0$ indicating that the bearing is healthy.

Case b: Bearing with inner ring defect.

The four time indicators listed before are calculated in this case on a vibratory signal measured on a bearing with a point defect on the inner ring. We find that the location parameter E_1 is very close to 2 meaning that the defect is in the inner ring and the calculated diameter corresponds to the actual diameter.

Case c: Bearing with outer ring defect.

The point defect is located in the third case on the outer ring; its diameter is 0.50 mm. Shocks appear clearly through the temporal signal that is used to calculate the time indicators. This case shows positive results as the calculated diameter $DC = 0.53$ mm is very close to the actual diameter of 0.50 mm. The defect location is also justified by the output $E_1 = 3$.

Case d: Bearing with rolling element defect.

In the latter case the defect is made by electro-erosion on a ball bearing. The first application of neural network, defect ring, provided for defect location $E_1 = 0.1325$. We can consider that this result is close to zero and therefore we can assume that the defect is not on the outer ring or on the inner ring.

4.5. Application system for diagnosis and monitoring of fan end bearing defects

The location of the defect has an important influence on the lifetime of the defective mechanical element. A statistical study [11] showed that 45 % of the bearings affected by a defect on the internal ring were replaced against 25% of the bearings affected on the external ring.

This finding implies that the propagation of a fault on the inner ring is almost twice as fast as a defect on the outer ring. For these reasons, we are interested in locating in what part of the bearing the defect is.

Figs. 5, a-c illustrate three vibration signals measured on the bearings having respectively inner ring defects, made by electro-discharge, of 0.20, 0.35 and 0.50 mm diameter. As seen in the following figures the vibration amplitude increase with the size of the defects.

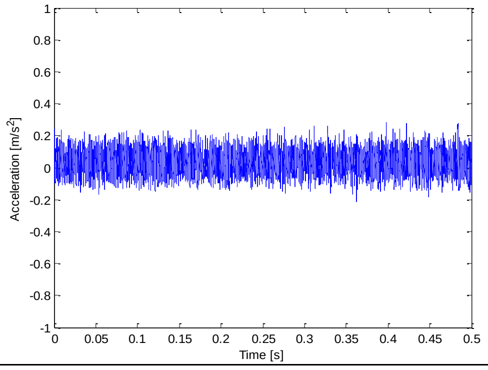
From these three signals are determined the following scalar indicators: RMS value, Peak Value, Crest Factor and Kurtosis. The values of these indicators supply the neural networks whose outputs provide information on the location and size of the various defects (Table 5).

The informations collected are decisive in the monitoring of the mechanical state of rotating machines and in particular the bearings. If the defect appears on the inner ring the monitoring will be done at close intervals.

Table 4

Diagnosis examples on ball bearings (a, b, c, d)

a - Healthy bearing	
DR = 0 mm	*ER* = 0



RMS value = 0.07 m/s^2
Peak value = 0.25 m/s^2
Crest factor = 3.4
Kurtosis = 2.82

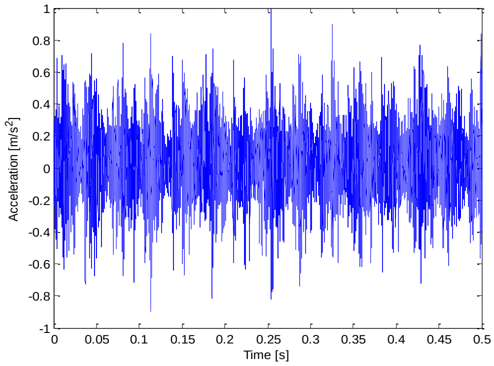
DC = 0 mm	E_1 = 0

Since E_1 = 0 => no default ring.
We must check for any failure of rolling element by the 2nd neural network.

DC = 0 mm	E_2 = 0

Since E_2 = 0 => bearing without defect

b - Inner race defect	
DR = 0.20 mm	*ER* = 2

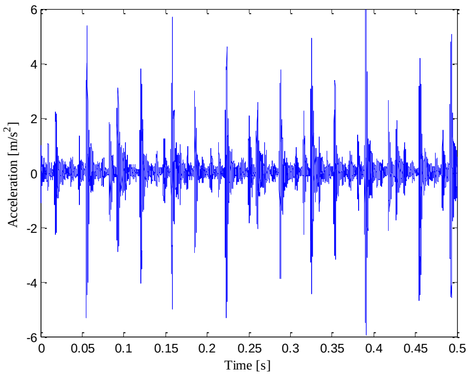


RMS value = 0.29 m/s^2
Peak value = 1.60 m/s^2
Crest factor = 5.50
Kurtosis = 5.54

DC = 0.20 mm	E_1 = 1.9996

Since E_1 = 1.9996 ≈ 2 => defect of the inner ring with a calculated diameter of the defect:
DC = 0.20 mm

c - Outer race defect	
DR = 0.50 mm	*ER* = 3

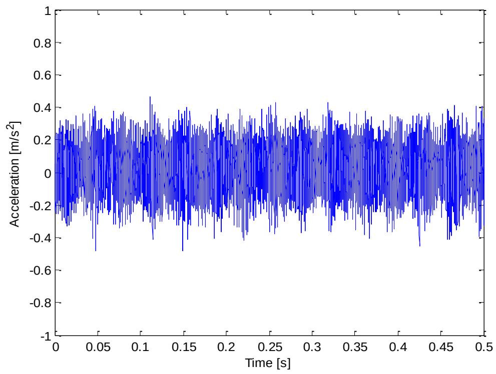


RMS value = 0.56 m/s^2
Peak value = 5.51 m/s^2
Crest factor = 9.78
Kurtosis = 21.17

DC = 0.53 mm	E_1 = 3

Since E_1 = 3 => defect of the outer ring with a calculated diameter of the defect: *DC* = 0.53 mm.

d - Ball defect	
DR = 0.20 mm	*ER* = 0



RMS value = 0.14 m/s^2
Peak value = 0.52 m/s^2
Crest factor = 3.69
Kurtosis = 3.04

DC = 0.13 mm	E_1 = 0.1325

Since E_1 = 0.1325 ≈ 0 => No defect ring. We must check for any failure of rolling element by the 2nd network.

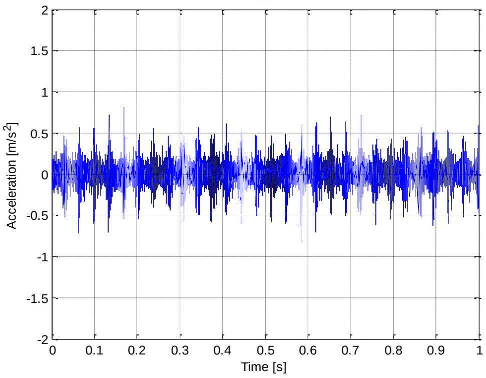
DC = 0.20 mm	E_2 = 1.00

Since E_2 = 1 => defect in a rolling with a calculated diameter of the defect: *DC* = 0.20 mm

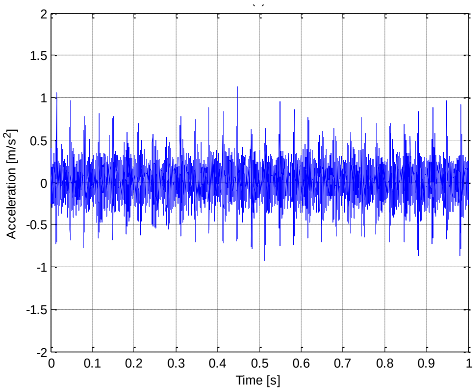
Table 5

Diagnosis examples of Inner race defects

Actual diameter of inner race defect DR, mm	Scalar indicators				ANN results		
	RMS value	Peak value	Crest factor	Kurtosis	Calculated diameter of the defect DC, mm	Type of defect	
						E_1	E_2
0.20	0.14	0.81	5.78	5.40	0.18	very close to 2 so defect in inner ring	Close to 0 no ball defect
0.35	0.18	1.12	6.22	5.65	0.36		
0.50	0.32	1.90	5.94	6.96	0.53		



a



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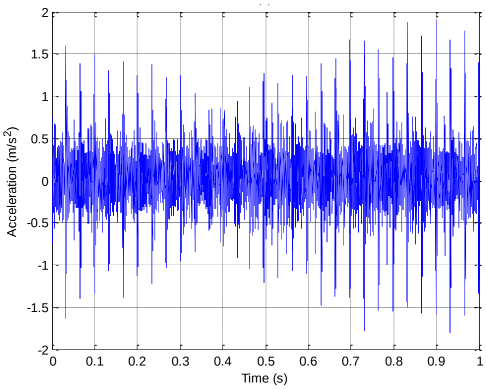

c

Fig. 5 Bearing inner race fault waveforms a- 0.20 mm, b- 0.35 mm and c- 0.50 mm

5. Conclusion

The application of neural networks and vibration signal processing were used in locating and monitoring the progress of a defect on a ball bearing.

The sum of squared errors and mean squared error are used as a benchmark of different ANN.

Our system has demonstrated the efficacy of ANN for the diagnosis and monitoring of the progression of defects on a ball bearing. With the help of ANN, an operator may decide to intervene in a timely manner.

This project also allowed us to verify the effectiveness of ANN from the choice of the number of neurons and transfer functions used. The main advantage of neural networks is their ability to machine-learn, which allows solve complex problems without having to write complex rules.

The system is developed by the pairing of time indicators from the vibration signals with neural networks. These indicators have the advantage of being very simple to use and highly effective in the diagnosis and monitoring of defects in ball bearings.

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M. E. Boukhobza, Z. Derouiche, Z. Ahmed Foitih

GUOLIŲ DEFEKTŲ VIETOS APTIKIMAS IR ĮVERTINIMAS VIRPESIŲ ANALIZĖS IR NEURONINIŲ TINKLŲ METODU

R e z i u m ė

Mašinų priežiūros kokybė turi didelę įtaką firmos darbui. Mašinų defektų vystymosi įvertinimas ir stebėsena gali sumažinti priežiūros sąnaudas minimizuojant neplanines prastovas ir užtikrinant ekonomiškai pagrįstus nuostolius. Mašinos būsena labai priklauso nuo besisukančių elementų, taigi ir nuo guolių. Virpesių matavimai padeda nustatyti, ar mašina yra tinkama naudoti, ir laiku atlikti priežiūros darbus. Šio darbo tikslas sukurti dirbtiniu intelektu pagrįstą sistemą, kuri leistų nustatyti guolių elementų defekto radimosi pradžią ir pagal virpesių signalų pokyčius nustatyti, ar tai didelis defektas.

M. E. Boukhobza, Z. Derouiche, Z. Ahmed Foitih

LOCATION AND EVALUATION OF BEARINGS DEFECTS BY VIBRATION ANALYSIS AND NEURAL NETWORKS

S u m m a r y

The quality of maintenance has an important influence on firm performance. Detection and monitoring of the progression of the defects of machines can reduce maintenance costs by minimizing the number of unplanned shutdowns and ensuing economic losses.

The state of a machine depends largely on the condition of rotating elements that compose it and especially bearings.

The vibration measurements are used as indicators of the health status of machines and timeliness of maintenance. The objective of this work is to establish a system based on artificial neural networks to know precisely the position of an incipient defect on the bearing elements and quantify its severity, using indicators from vibration signals.

Keywords: maintenance, vibration, temporal indicators, Bearing, Artificial Neural Network (ANN).

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