# Sleeve Bearing Fault Diagnosis and Classification

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*Abstract:* Sleeve bearing is a bearing without any rotating element but with a sliding component, it is an expensive component in special machinery elements. Their faults can damage other principal machinery parts like shafts and cause very important production lost and high maintenance cost. Because those bearings are a special case just a few researchers studied detection and classification of sleeve bearing faults by data vibration analysis.
In this paper we present a diagnosis and a classification methodologies applied to different kind of sleeve bearing damages. We develop a two-lobe bore sleeve bearing vibration database from a set of large induction machine equipment, then we use temporary and frequency process to diagnose faults, in the final step we classify those sleeve bearings by different methods based on entropy extraction and fault classifiers fusion.

*Keywords:* Condition monitoring, Machine vibration, Diagnosis, Fault classification, Sleeve bearing.

## 1. Introduction:

A sleeve bearing also known as a plain bearing or journal bearing is a bearing in which a shaft rotates freely in a supporting metal sleeve or shell with a layer of oil or grease separating the two parts due to fluid dynamic effects. Journal bearings are used to support high radial loads and are used for low to high speeds. Typical applications include large milling systems, engine crankshafts, gearboxes, and shaft bearing supports. There are five basic types of journal bearings: plain cylindrical bore, lemon shape (two-lobe bore), four-lobe bore, four pad tilting pad, and five pad tilting pad bearing [1]. In this paper the second type two-lobe bore (see Fig.1) is considered.

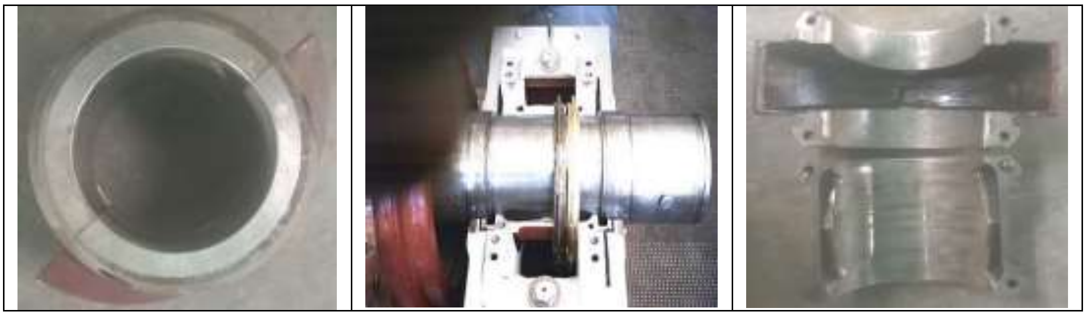


**Fig. 1: Sleeve bearing lemon shape with two oil ring**

Induction machines can be purchased with antifriction or sleeve bearings. The sleeve bearing is in many cases the unique bearing type to utilize on larger motors and generators in excess of 2000 Hp (Horse power) and for some special design requirements on medium motors (ships, draglines …). In general sleeve bearing motors are significantly more expensive than the anti-friction bearings but this may not be as significant when the total life cycle cost is taken into account. Theoretically, sleeve bearings have infinite life and they guaranty more process reliability [1]. The sleeve bearings operate under the principal of hydrodynamic lubrication. As the shaft rotates, it builds up a wedge of oil between the shaft and bearing by using oil ring (see Figure1). Flood lubrication can be used where additional cooling is required as a redundant feature.

The sleeve bearing faults detection and diagnosis was studied using vibration analysis [2, 3], the spectral methods are developed to perform this diagnosis [4, 5]. The statistical approach was recently used for journal bearing fault classification by several techniques such as fisher linear discriminant, K-nearest neighbor and support vector machine [6, 7, 8].

This paper addresses fault diagnosis and automated classification of sleeve bearings with different defects types. The feature extraction is done with entropy methods, the temporal and frequency analysis are used for sleeve bearing diagnosis and the fault classification is performed with many classifiers.

In Section 2, the adopted approach -is exposed. Section 3 presents signal vibration acquisition, treatment and classification based feature extraction, while section 4 gives an account of obtained results. Finally, the conclusion is presented in section 5.

## 2. Proposed fault detection process

The bearing diagnosis proposed method is a tree steps process (see Fig. 2). The first step is vibration signal measurement, the second step is a time-frequency analysis and the third step deals with fault classification using feature extraction. We develop a vibration database measured by accelerometers, then we treat the input signal by filtering and interpreting graphs in time and frequency domain, after that we extract entropy features for each sleeve bearing/direction, and finally we detect the best classification using learned models and some classifier algorithms.

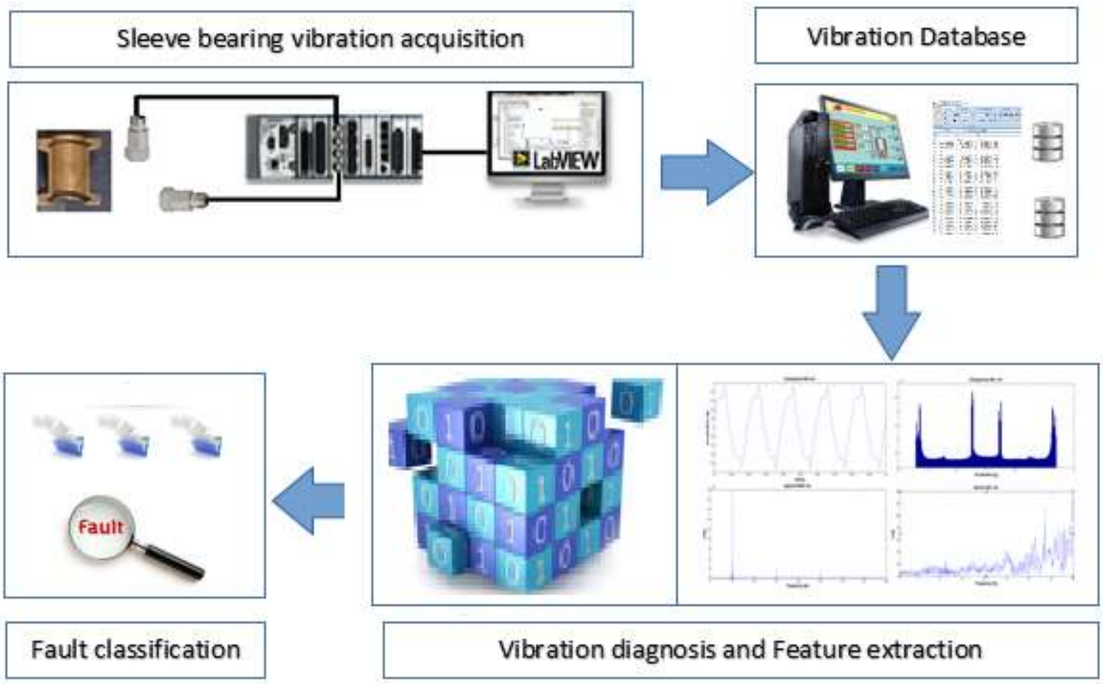


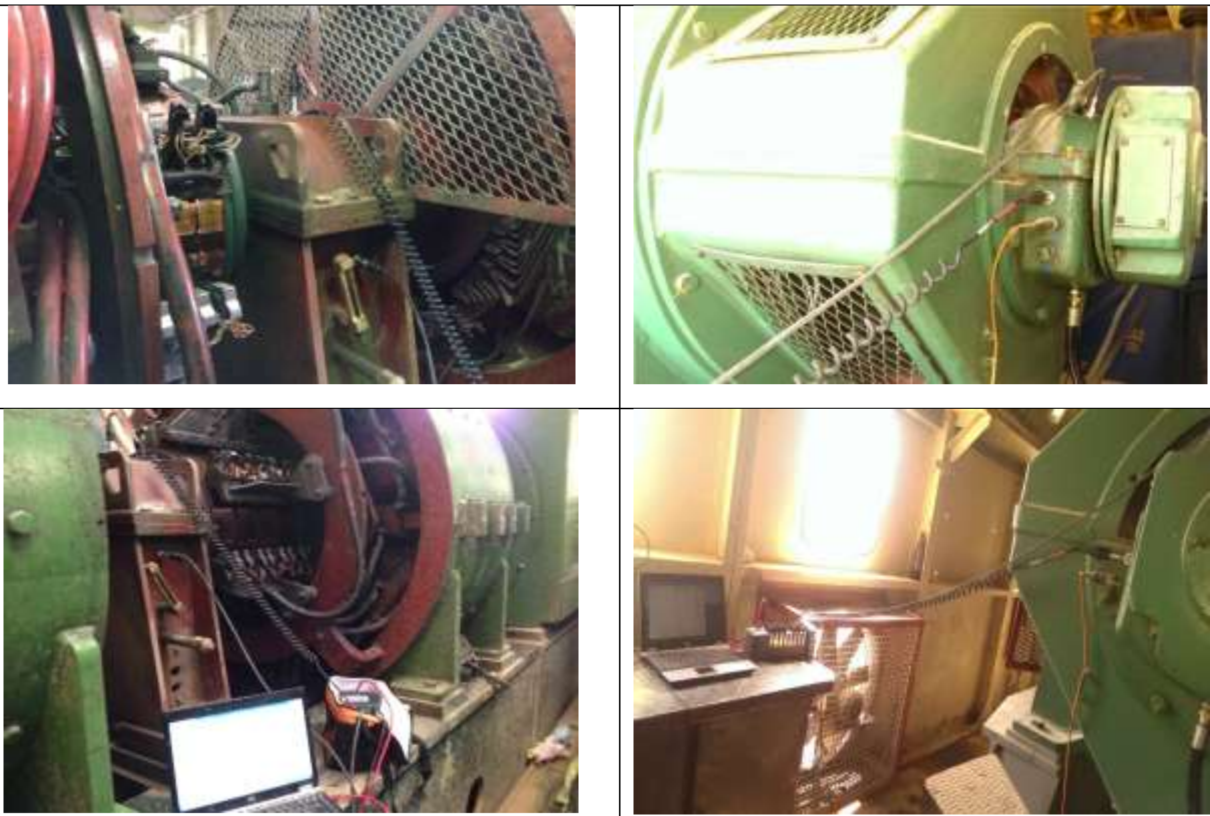

**Fig. 2: Sleeve bearing fault classification**

We considered four sleeve bearing default states: Normal, Friction fault, Excessive wear fault, and abnormal lubricating fault. Each classifier estimates bearing state with a recognition accuracy rate. The entropy extraction theory estimates the complexity of time series through the comparison of neighboring values as detailed in [9, 10]. This extraction is characterized by 51-parameter family corresponding to probability density, asymmetry and concentration measurement. Those parameters can completely represent the statistical signal characteristics. We use them in fault diagnosis of sleeve bearings and we hope that they can give a good separation between different classes. We use as traditional statistical technique classifiers, the Linear Discriminant Analysis (LDA) as linear dimension reduction method by performing in parallel the maximization of the between-class scatter and the minimization of the within-class scatter [11, 12], the multi-class Support Vector Machine (SVM) applies structural risk minimization learning method for regression and classification [13, 14], The Principle Component Analysis (PCA) is using for reduce data dimension and complexity based on a transformation of some possibly correlated variables into a smaller number of uncorrelated variables to perform a satisfying accuracy [15, 16].

## 3. Experimental phase

### 3. 1 Sleeve bearing vibration acquisition:

The experiment was carried on 26 sleeve bearings. The used induction motors and generators are three phases 400 Hp to 2250 Hp with 1000 rpm and full load running as operating conditions. Vibration signals of those sleeve bearings are obtained by magnetic base accelerometers mounted on horizontal and vertical direction and taking from bearing housing.



| Pedestal mounted sleeve bearing | Flange mounted sleeve bearing |
|---|---|

**Fig. 3: Sleeve bearing acceleration acquisition**

In this paper we study and diagnose the sleeve bearing vibration in two large motors/generators with different mounted model [17] (see Fig. 3):

- Pedestal mounted sleeve bearings are used for the first set of motors/generators (850Hp to 2250Hp). Motors/generators with integral pedestal bearings are as easy to mount and align as motors/generators with flange mounted bearings. Separate pedestal bearing are mounted on a common base frame.

- Flange mounted sleeve bearings are used for the first set of motors/generators and they are mounted on the end-shields of the motor/generator (400Hp to 1225Hp).

The vibration data was collected from sleeve bearing housing trough two piezoelectric accelerometers ICP 603C01 with frequency range up to 10 kHz and a 1mv/m/sec$^2$ sensitivity. The signals are transferred to the vibration module NI 9234 as inputs then the NI controller CompactRIO- 9022 records and communicates complete data to the computer by exploiting LABVIEW software [18]. The capture duration for each sleeve bearing is set to 30 seconds with 25.6 kHz sampling rate. We apply a low pass band filter Fc=500 Hz to all signals and we analyze the vibration data in both time and frequency domains to detect characterized bearing defects.

## 3. 2 Sleeve bearing vibration diagnosis:

The diagnosis of sleeve bearings is characterized by the specifications [19] listed in Fig. 4.

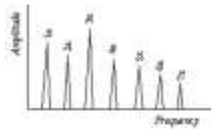
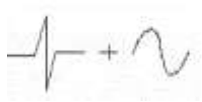
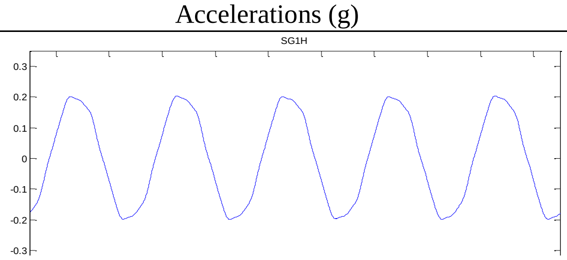
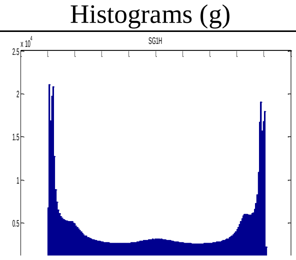
| | Spectral signal form | Temporal signal form |
|---|---|---|
| Excessive Clearance defect |  |  |
| Friction defect | |  |
| Abnormal lubricating | Noisy spectrum | Noisy signal |

**Fig. 4: Sleeve bearing excessive clearance, friction and lubricating defects**

The vibration captured signals by horizontal and vertical accelerometers are analyzed for defect diagnosis. Then sleeve bearing can be classified after applying some algorithms and methods to the feature extraction data. Four different states: (1) Sleeve bearing N°1: Normal healthy, (2) Sleeve bearing N°2: Friction defect, (3) Sleeve bearing N°3: Excessive clearance defect, (4) Sleeve bearing N°4: Abnormal lubricating and friction defects. Fig. 5 and Fig. 6 present acceleration and spectrum based horizontal accelerometer data for those different bearings classes.

| | Accelerations (g) | Histograms (g) |
|---|---|---|
| Sleeve bearing N°1: Normal healthy |  |  |

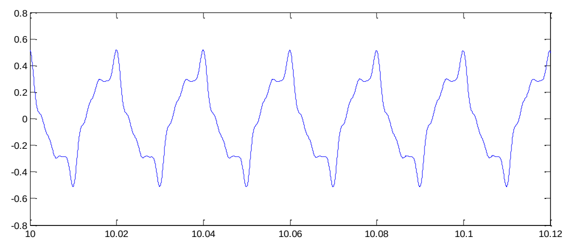
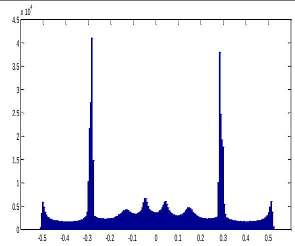
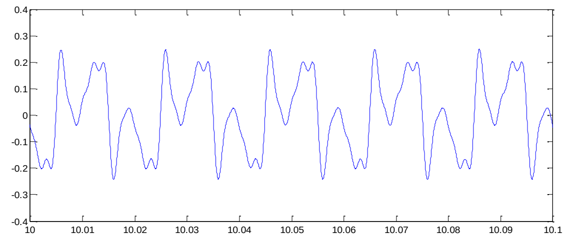
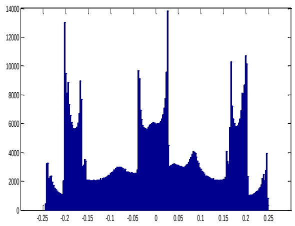
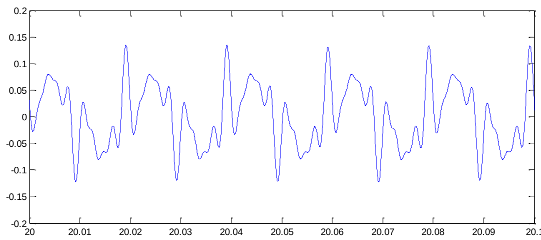
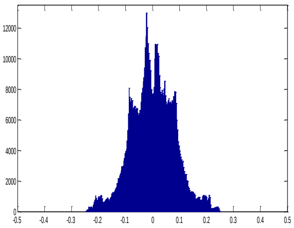
| | | |
|---|---|---|
| Sleeve bearing N°2 : Friction defect |  |  |
| Sleeve bearing N°3: Excessive clearance defect |  |  |
| Sleeve bearing N°4: Abnormal lubricating and friction defects |  |  |

**Fig. 5: Sleeve bearings Acceleration/Histogram based horizontal data**

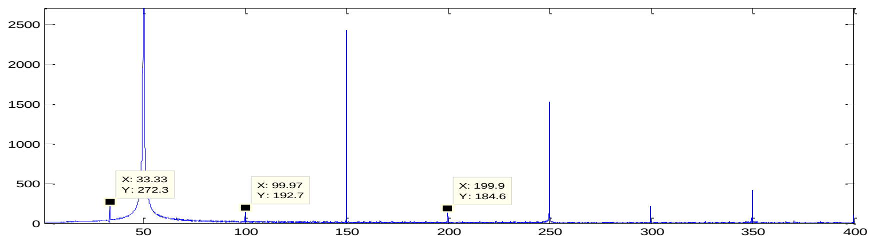
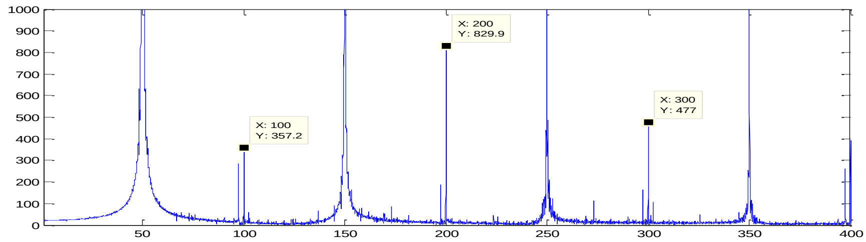
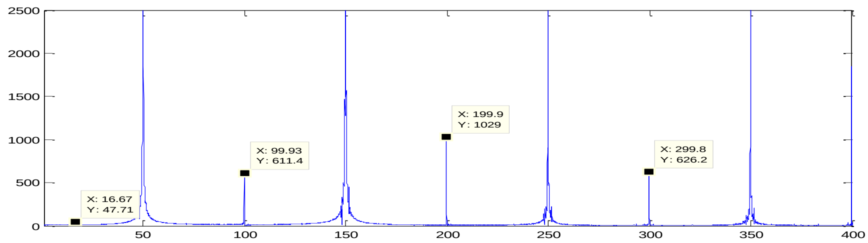
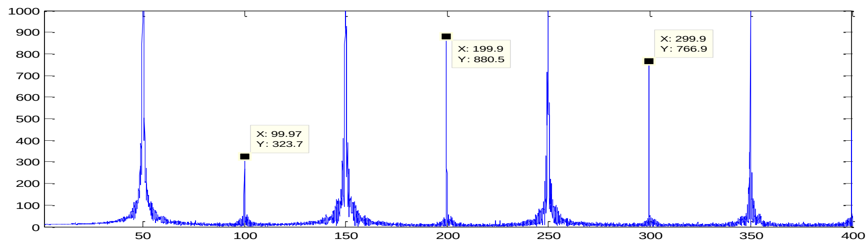
| | |
|---|---|
| Sleeve bearing N°1: Normal healthy |   |
| Sleeve bearing N°2 : Friction defect |   |
| Sleeve bearing N°3: Excessive clearance defect |   |
| Sleeve bearing N°4: Abnormal lubricating and friction defects |   |

**Fig. 6: Sleeve bearing FFT Spectrums based horizontal data**

According to figures 5 and 6, we can see that the acceleration and FFT spectrum depend to the bearing defect, the healthy normal bearing presents a good temporal signal with some peaks in his FFT spectrum (in the natural frequency of structure at 50Hz and its harmonics), in the lubricating defect case we can detect a noisy acceleration spectrum, the friction and excessive clearance defects were characterized by the temporal acceleration forms and by some spectrum peaks with medium or high level.

## 4. Results and Discussions

We present in Table 1 a comparison between several classifications methods using entropy extraction feature as input, the recognition accuracy rate with same experimental data is influenced by the chosen classifier. We use different amount of vibration data learning: 10%, 20% and 30% windows of training were taken for each sleeve bearings in the horizontal and vertical axis to calculate the statistical features. Then we use them as input to different classifier process based entropy extraction (LDA, PCA and SVM). For the testing purpose the vibration data is split into two sets, the first composed by 10 to 30% of the total inputs is used for training, and the second one composed by 90 to 70% is used for validation and testing classification using LDA, PCA, SVM algorithms based entropy extraction. The result of SVM classification was satisfactory (see Table 1). Then, in Table 2, we expose the classification results for the studied sleeve bearings.

**Table 1: Recognition sleeve bearing classification accuracy based accelerometer data**

| Amount of training windows | 10% | | 20% | | 30% | |
|---|---|---|---|---|---|---|
| | Horizontal | Vertical | Horizontal | Vertical | Horizontal | Vertical |
| LDA | 80,56% | 72,22% | 62,50% | 90,63% | 71,43% | 97,62% |
| PCA | 71,30% | 71,30% | 88,54% | 88,54% | 89,29% | 94,05% |
| SVM | 75,00% | 73,15% | 90,63% | 96,87% | 92,86% | 100% |

**Table 2: Recognition accuracy based flange sleeve bearing classification**

| | | Class Normal healthy | | Class 2 Friction defect | | Class 3 Excessive clearance defect | | Class 4 Abnormal lubricating, and | |
|---|---|---|---|---|---|---|---|---|---|
| | | H | V | H | V | H | V | H | V |
| S. Bearing 1b | | 100 | 100 | 0 | 0 | 0 | 0 | 0 | 0 |
| S. Bearing 2b | | 0 | 0 | 100 | 100 | 0 | 0 | 0 | 0 |
| S. Bearing 3b | | 0 | 0 | 0 | 0 | 100 | 100 | 0 | 0 |
| S. Bearing 4b | | 0 | 0 | 0 | 0 | 0 | 0 | 100 | 100 |
| Pedestal mounted sleeve bearing | S. Bearing 1a | 0 | 0 | 100 | 100 | 0 | 0 | 0 | 0 |
| | S. Bearing 2a | 0 | 0 | 0 | 0 | 100 | 90 | 0 | 10 |
| | S. Bearing 3a | 0 | 0 | 0 | 6,67 | 0 | 0 | 100 | 93,33 |
| | S. Bearing 4a | 0 | 0 | 100 | 100 | 0 | 0 | 0 | 0 |
| | S. Bearing 5a | 0 | 0 | 0 | 0 | 100 | 100 | 0 | 0 |
| | S. Bearing 6a | 0 | 0 | 0 | 0 | 86,67 | 96,67 | 13,33 | 3,33 |
| | S. Bearing 7a | 0 | 0 | 0 | 0 | 100 | 100 | 0 | 0 |
| | S. Bearing 8a | 0 | 0 | 20 | 0 | 63,33 | 96,67 | 16,67 | 3,33 |
| | S. Bearing 9a | 0 | 0 | 100 | 100 | 0 | 0 | 0 | 0 |
| | S. Bearing 10a | 0 | 0 | 100 | 100 | 0 | 0 | 0 | 0 |
| | S. Bearing 11a | 0 | 0 | 0 | 0 | 96,67 | 100 | 3,33 | 0 |
| | S. Bearing 12a | 0 | 0 | 0 | 0 | 93,33 | 93,33 | 6,67 | 6,67 |
| | S. Bearing 13a | 0 | 0 | 0 | 0 | 93,33 | 96,67 | 6,67 | 3,33 |
| | S. Bearing 14a | 0 | 0 | 90 | 86,67 | 6,67 | 13 ,33 | 3 ,33 | 0 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | S. Bearing 15a | 0 | 0 | 100 | 100 | 0 | 0 | 0 | 0 |
| Flange mounted sleeve bearing | S. Bearing 5b | 0 | 0 | 0 | 0 | 86,67 | 90 | 13,33 | 10 |
| | S. Bearing 6b | 0 | 0 | 0 | 0 | 100 | 93,33 | 0 | 6,67 |
| | S. Bearing 7b | 0 | 0 | 0 | 0 | 96,67 | 100 | 3,33 | 0 |
| | S. Bearing 8b | 0 | 0 | 0 | 0 | 93,33 | 96,67 | 6,67 | 3,33 |
| | S. Bearing 9b | 0 | 0 | 0 | 0 | 93,33 | 100 | 6,67 | 0 |
| | S. Bearing 10b | 0 | 0 | 0 | 0 | 93,33 | 100 | 6,67 | 0 |
| | S. Bearing 11b | 0 | 0 | 0 | 0 | 76,67 | 90 | 23,33 | 10 |

In table 2, recognition accuracies classification results were acceptable.

# 5. Conclusion:

In this study we diagnosed sleeve bearings and we classified them in four different fault classes for both pedestal and flange mounted bearings, one healthy and three with different defects type. The analysis of the vibration acceleration signal, obtained using horizontal and vertical accelerometers, was used to detect the specific damage. The treatment of the feature extraction was, then, applied to characterize each class with acceptable accuracy recognition for the 26 studied sleeve bearings.

It was seen that the percentage of correct classification was between 92 and 100% for our approach based entropy extraction and SVM classifier algorithm.

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