JNRID || ISSN 2984-8687 || © April 2024, Volume 2, Issue 4

Algorithm To Detect Defects In Ball Bearings

SumantKumar Kavadi Rajkumar (CH.EN.U4ECE21054), Dr.VenkataSubramanian

Department of ELECTRONICS AND ENGINEERING

AMRITA VISHWA VIDYAPEETHAM

Chennai Campus

Abstract - Acoustic emission sensors were used to find problems with certain kinds of ball bearings. There were different types of sensors used: one called R6a, another called WSa, a wide band sensor, and a small one called Pico. Each sensor has its own way of working and how well it can pick up signals. Researchers looked at the signals from these sensors and found four different kinds of problems with the bearings. They used a special computer program called an artificial neural network to figure out what kind of problem was happening and how big it was. When they compared the signals from all the sensors, they found that R6a was the best at picking up the signals from the bearings.

Keywords - Flaw detection, Sound emission sensor variations, angular contact ball raceways, Neural Network

I. INTRODUCTION

Non-destructive testing methods are really important for finding problems in parts. Right now, sound emissions are a big deal for checking things without damaging them. The good thing about sound emissions is they help us see how things are breaking, especially when it comes to cracks getting bigger.

When things are pushed or heated, they let out strong energy that travels through them as waves. Acoustic emission happens when these waves are made quickly and the stored energy is let out fast in solid objects. Sensors on the object's surface can catch and study these waves, helping us understand where the sound is coming from, which might show a problem. This study looks into the waves made by things rolling over and cracks that were made on purpose.

The features of the acoustic emission method, is its passive nature, contrasting with the active nature of most other methods. To gather information about a component, methods such as ultrasonic or radiographic testing often require the application of external energy or material alteration. On the other hand, the acoustic emission method uses energy that's naturally released from inside the component itself for analysis.

Many research projects have looked into how acoustic emission can help find faults in different areas. Some scientists have looked at how acoustic emission behaves in hydrodynamic bearings, finding connections between how much power the bearing loses and the sounds it makes. Other studies have looked into sorting out different types of sounds from journal bearings, figuring out the different ways they rub against each other when conditions change.

The utilization of acoustic emission alongside vibration methods has been revealed in further investigations to identify and classify contamination levels in bearings, including the detection of particle contaminants. Efforts have been made to create models and programs that help understand how acoustic emissions are made, showing how different things happening during operation affect the sound energy made by rolling element bearings.

In addition to experimental research, computational approaches such as deep learning neural networks were significant for fault diagnosis using acoustic emission signals. These methods show they're really good at finding and sorting out different problems accurately. They could be handy for keeping an eye on things as they happen and planning ahead for maintenance.

This research builds on what others have done before by using many sensors to find problems and figure out how big they are over time. It's a thorough way of figuring out what's wrong with parts of machines that spin.

The precision of the three sensors was examined to diagnose the imperfections of super-precise angular contact ball bearings. Dynamometers are utilized to determine the dynamic traits of a motor being examined and assess aspects such as strength, twisting moment, oscillation, and so forth. Consequently, the malfunction of the apparatus due to a defective bearing would not only incur expenses but also impact the information gathered from the apparatus.

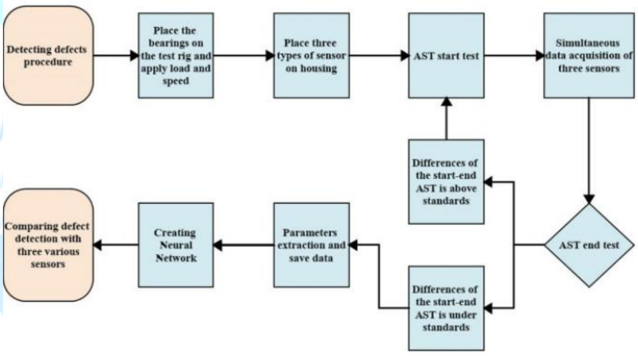


Fig. 1. A visual representation simplifies the understanding of the defect diagnosis process

- In contrast to this study's angular contact ball bearing, previous research focuses on deep groove ball bearings.
- The application of loading on the bearing involves tightening four screws using a torque meter, which forces a disc onto the inner surface, resulting in simultaneous changes to radial and axial loading.

II. TYPES OF SENSORS

Examinations into defects were conducted using a single sensor. Consequently, it must be ensured that the selection of the optimal sensor is validated (obtaining superior energy from the acoustic emission and aiding in the detection and diagnosis of defects more effectively than others). We compared three types of sensors to see which ones can find problems in things and measure things like how fast they move.

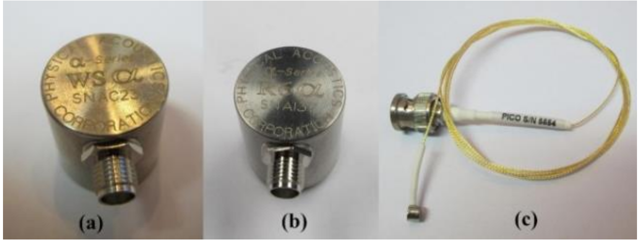
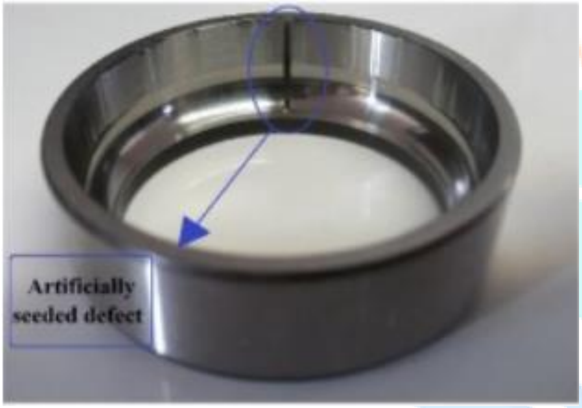


Fig. 2. (a) WSa sensor (b) R6a sensor and (c) Pico sensor

III. EXPERIMENTAL TEST RIG AND TEST BEARING

The ball bearing chosen for this experiment is made by SKF. Four stages of bearings were used: regular, small problem, medium problem, and big problem bearings. Fig. 3 shows the defect in the bearing, which is an artificial problem created in a straight line with the bearing's middle and made on the outer part of the bearing using a special machine. The experiments were done at different speeds: slow, medium, fast, and very fast, with different levels of weight applied using four screws.



(a)

Size(mm)	Defect Type
0.1	Small defect
0.4	Medium defect
0.7	Large defect

(b)

Fig. 3 (a) Image of the defective ball bearing (b) Classification of defects based on dimensions

IV. DATA PROCESSING

MATLAB software was employed to analyze the data. Following thorough testing, MATLAB was utilized to extract all relevant statistical and standard acoustic emission measurements. Table 1 includes key parameters crucial for identifying defects.

Parameters	**Equation**
RMS	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} y_i^2}$
Peak	$y_{max} - y_{min}/2$
Peak to Peak	$(y_{max} - y_{min})$
Absolute energy	v^2/r
ASL	$20\,log_{10}\left(\sum_i^N y_i/N\right)$
Crest Factor	y_{peak}/y_{rms}
Kurtosis	$N\sum_{i=1}^{N}(y_i-\bar{y})^4/\left[\sum_{i=1}^{N}(y_i-\bar{y})^2\right]$
Skewness	$\frac{1}{N}\sum_{i=1}^{N}(y_i-\bar{y})^3$

Table 1. Parameters extracted from ultrasound radiating signals

- RMS shows how big something is when it keeps changing.
- Skewness tells us if the data is lopsided, either leaning more towards the left or right from the average.
- Kurtosis indicates how sharp or flat the data's peaks are, and how much it deviates from the norm.
- Crest Factor indicates how far apart the peaks are in datasets.
- Energy and absolute energy are different in how they're calculated. Absolute energy is the real measure of energy in a signal, while energy is about adding up the voltages over time.

V. TYPES OF DEFECTS

Based on different types of application of the ball bearings, due to various mechanical wear and tear, various types of defects have been classified.

i. Crazing
ii. Inclusion
iii. Patches
iv. Pitted
v. Rolled
vi. Scratches

VI. BEARING DEFECT FREQUENCY

Table 2 displays the particular sounds linked to problems in every turning part holder, which are associated with how swiftly the holder spins.

In this study, F shows how fast the bearing spins, B is for the size of the ball, and P is for the diameter. The q value represents the contact angle, which is 25 degrees in the bearings used here. It's important to note that all the bearings tested in this study are of the same type and under the same conditions. This means that the frequencies of defects only change based on how fast the bearing is spinning.

VII. NEURAL NETWORK

A neural network with two layers was employed to spot defects. It had ten hidden neurons using sigmoid functions and linear functions for the output. Fig. 10 displays four results: one for a good bearing and three for defective ones of varying sizes. The network was trained using the Margaret-Levenberg backpropagation algorithm, considering key parameters from previous studies. Energy, Crest Factor, Skewness, Kurtosis, and RMS were utilized individually as inputs, with separate neural networks for healthy and faulty states.

Sensor	**WSa**	**R6a**	**Pico**
Energy	56.1%	64.9%	55.6%
Crest Factor	70.5%	75.5%	24.8%
Kurtosis	49.9%	82.0%	54.6%
RMS	57.2%	57.2%	78.6%
Skewness	37.2%	51.8%	57.4%

Table 2. Accuracy of sensors in detecting defects

Based on the table, it's clear that both Pico and R6a sensors showed higher accuracy across all parameters, except for crest factor, when compared to WSa. As a result, using WSa for diagnosing defects and classifying sizes with just one parameter as input wouldn't be effective. Additionally, Pico and R6a generally demonstrated better accuracy in most instances.

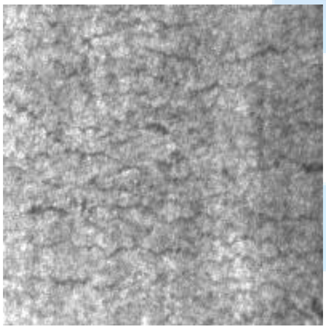
VIII. RESULTS

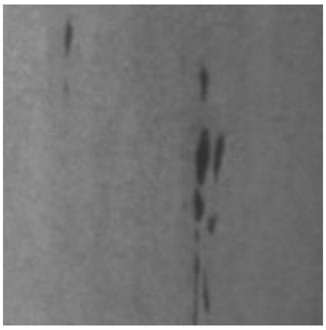
After concluding the Pico and R6a sensors to having the most accurate results, choosing the working code model of R6a sensor and integrating it in MATLAB, implementing the 2 - layer neural network algorithm to identify the following defects by categorizing the errors based on the size of the defects, the accuracy is tested for 5 distinct-defective ball bearings (crazing, inclusion, patches, rolled and scratches), each for 10 iterations.

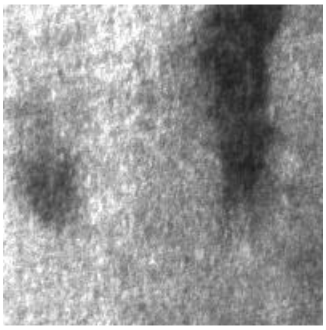
The result showed a 90% success rate in spotting defects and determining their type correctly. This high accuracy was mainly because of using RMS and skewness parameters in separate neural networks, where RMS had the highest accuracy of 78.6%, and skewness followed with 57.4% accuracy when used individually as inputs.

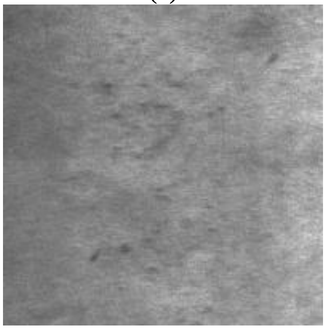
While performing the result accuracy using a Pico sensor, the “crest factor” parameters impacted the probability of an accurate result. Therefore, R6a was considered is to be the best sensor for this application.

The implementation of the R6a sensor into the 2 - layer neural network also pays a tribute to the improvement in the accuracy of the output results.


(a)


(b)


(c)


(d)

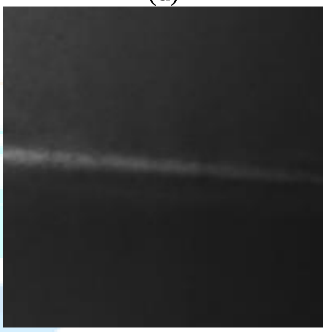

(e)

Fig .4. Types of defects (a) Crazings, (b)Inclusions, (c) patches, (d) rolled, (e) scratches

The algorithm (2 - layer neural network) which was trained with these defects, was run to find the defects of these 5 ball bearings.

- The ball bearings with crazings and inclusion defects were traced accurately and were declared the same in all the iterations.
- Whereas for the ball bearings with patch defects, the algorithm was accurate for 7 of the 10 iterations
- In case of rolled ball bearings, 8 of the 10 iterations were accurate and
- For the scratches, 9 of the 10 iterations were accurate.

IX. CONCLUSION

This study compared three types of acoustic sensors to find defects and classify their sizes. Initially, signals from the sensors showed that the R6a sensor captured acoustic energies better because it operates at a lower frequency. For the neural network, parameters like skewness and RMS were chosen, and including the R6a sensor model in the algorithm led to positive results, with a success rate of 90%.

X. REFERENCES

[1] S.A. Mirhadizadeh, E. Moncholi, D. Mba
Influence of operational variables in a hydrodynamic bearing on the generation of acoustic emission

[2] N. Mokhtari, C. Gühmann
Classification of journal bearing friction states based on acoustic emission signals

[3] H. Sadegh, A.N. Mehdi, A. Mehdi
Classification of acoustic emission signals generated from journal bearing at different lubrication conditions based on wavelet analysis in combination with artificial neural network and genetic algorithm

[4]S. Martin-del-Campo, et al.
Detection of particle contaminants in rolling element bearings with unsupervised acoustic emission feature learning

[5] S. Poddar, N. Tandon
Detection of particle contamination in journal bearing using acoustic emission and vibration monitoring techniques

[6] H. Towsyfyan, et al.
Modelling acoustic emissions generated by tribological behaviour of mechanical seals for condition monitoring and fault detection