

# Early Fault Detection in Bearing with Fault Seeded on Outer Raceway at Three Different Position: Orthogonal, Centered and Opposite



Abdoulhdi A. Borhana Omran, Yasir Hassan Ali, Uma Shankar, Fareg Saeid Ali, Saleh Gareh, Omar Suliman Zaroog, N. A. Mardhiah

**Abstract:** Rotating machine such as a small low voltage motor or a power plant generator is an essential asset to the industrial applications. The execution and efficiency of these rotating machines are being reduced due to faulty rotating machinery parts. The faulty parts also generate various forces, thus increases the amplitude of vibration as well as energy consumption. Early fault detection and diagnosis have been widely used with various methods as they were able to reduce accidents and machine breakdowns along with economic losses. This study aims to present the faulty bearings which were seeded in the bearings. The fault size are ranging from 0.007 inches to 0.021 inches in diameter. Among the methods, vibration signal data is one of the champions. In this study, early fault detection was focused on bearing using the time domain technique and the data were analyzed. Particularly, the fault was introduced on the outer raceway at three different positions; orthogonal (3 o'clock), centered (6 o'clock) and opposite (12 o'clock). The MATLAB software was used to determine the time domain parameters, comprising of the standard deviation, Root Mean Square (RMS), skewness and shape factor as the representation of the best reflection of the failure. The time domain parameters for healthy and faulty bearing were plotted and compared in graphical presentation. The result shows all the four parameters have greater value in contrast with the healthy bearing value except for skewness data in the opposite (12 o'clock) position.

**Keywords:** Bearing, Early fault detection, Time domain technique, Outer raceways

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## I. INTRODUCTION

Rapid growth in this recent industry has delivered increasingly complex machines. Diagnosis and checking of fault for current mechanical machinery is progressively more crucial in order to maintain a strategic distance from financial loss [1, 2, 3]. One of the major causes in machinery failure is defects in rolling element bearings and have gotten extensive interest [4].

The efficiency of an electro-mechanical system such as induction motors, rotating machines, is determined by its structural design [5]. Rotary machines with induction motor uses bearing to adequately reduce energy losses due to friction. However, unfriendly operating condition environments and cyclic stuffing can lead to extensive wear in bearings, leading to formation of surface cracks [6]. If these surface cracks were not detected early, it can cause unexpected shutdowns, resulting in financial inefficiency, as well as human injuries [1, 7, 8, 9].

In addition, nowadays, high levels of precision and automation are requested simultaneously in recent rotating. Hence, the capability of detecting faults at a very early stage must also exist for reliability [10]. When the machine is being used, every rotating machine produces a vibration. Rotating machine covers a wide range of mechanical machinery and plays an important function in the applications of industry. In general, it works under intense workplace and is hence subject to faults, which could be analyzed and distinguished by utilizing signal handling systems [11].

A rotating machine is usually powered by mechanical, chemical, thermal and electronics. These machines help human in everyday life as well as increase the productivity of an industry by speeding the production rate and maintaining the quality at the very same time. A sudden failure, including major and minor faults, have a massive impact on economic losses due to the unexpected breakdown and downtime time for repairing the machine. In the long run, incessant usage of a faulty machine may risk human life to death. Thus, advanced technologies are needed to monitor the health status of parts efficiently and effectively [12].

Many methods have been developed for early fault detection and diagnosis such as vibration measurements, acoustic measurements, temperature measurements and wear debris analysis [13].



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Early fault detection is able to minimize the significant effect of the faulty machinery which in long-term are profoundly cost-effective and are safe for human well-being along with high production efficiency. Vibration analysis is among the most widely recognized technique utilized in the observing applications since an imperfection produces progressive driving forces at each contact of deformity [14]. Time domain analysis, frequency domain analysis, and spike energy analysis have been employed to identify different defects in rotating bearings [15, 16, 17].

In addition, one of the powerful tool signal processing, techniques in known as Empirical Mode Decomposition (EMD). It has been widely studied and extensively applied in fault diagnosis of rotating machines [11]. Even though EMD is the great apparatus for this technique, it has a few disadvantages, for example, the lack of a mathematical base, no criterion of robust stopping for the sifting process, mode mixing and the border effect problem. The frequency of the extreme detection which refers to the various components in the main reason for mode mixing [10].

The main mechanical parts in a rotating machinery are gears, bearings, spindles, shaft, and mechanical coupling elements and the common faults of rotating machinery are shaft misalignment, gear faults, and bearings [18]. The main purpose of this studies is to present the healthy and faulty bearing seeded on the outer raceway within the range of 0.007 to 0.021 inches in diameter using time domain technique at three different positions; orthogonal (3 o'clock), centered (6 o'clock) and opposite (12 o'clock). The outer raceway defects were artificially introduced to the bearing using Electrical Discharge Machining (EDM). The diverse and distinct conduct of vibration signals from bearings on the outer raceway fault helps in recognizing the defects in bearings.

## II. METHODOLOGY

For analyzing and diagnosing the various fault detections of bearings, features are extracted according to this plan; after obtaining vibration signals of each class, firstly, these signals are divided into time-series widow blocks, followed by their feature extraction, which include mean, median, variance, standard deviation, Skewness, min value, max value, kurtosis value, Root Mean Square (RMS), crest factor, impulse factor and shape factor. Figure 1 below shoes the flowchart of fault diagnosis.

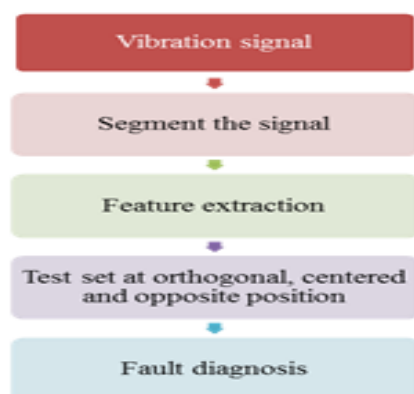


Fig. 1 Flowchart of fault diagnosis

Various parameters are elucidated in regard to time in time domain technique [19]. The amplitude of signals at a quick time is given by the procedure at which it is being tested. Comparing to alongside the time domain technique, statistical parameters are a portion of mathematical functions and physical signals.

For these studies, the vibration signal information was acquired from the online web site of the Case Western Reserve University Bearing Data Center [20]. A deep groove ball bearing of 6205-2S JEM SKF was used for this studies and further information of the bearing are as shown in Table 1 [21]. The fault seeded in the bearings ranges from 0.007 inches to 0.021 inches in diameter. The fault was introduced at the outer raceway at three different positions; orthogonal (3 o'clock), centered (6 o'clock) and opposite (12 o'clock).

Table. 1 Bearing information [21]

| Ball Diameter | Pitch Diameter | Inside Diameter | Outside Diameter | Thickness     |
|---------------|----------------|-----------------|------------------|---------------|
| 0.3126 inches | 1.5370 inches  | 0.9843 inches   | 2.0472 inches    | 0.5906 inches |

Then, using an accelerometer, the vibration signals were gathered [20]. It is joined to the housing with a magnetic base positioned at 12 o'clock. A 16 channel of DAT recorder was utilized to gather all the vibration signals and it is processed using Mat Lab software. All the information were acquired at 12,000 sample for every second and 48,000 sample for each second for drive end bearing faults. The position of the bearing fault respect to the load zone of the bearing directly affects the vibration response of the bearing system. In this manner, the experiments were conducted for bearing with faults located at orthogonal (3 o'clock), centered (6 o'clock) and opposite (12 o'clock) position. Figure 2 demonstrates the experimental setup comprise of two horsepower motor, torque transducer, dynamometer and control electronics.



Fig. 2 Experiment setup [20]

Data were collected for both healthy and faulty bearings. The vibration signal was obtained from four different speed which is 1730 rpm, 1750 rpm, 1772 rpm, and 1797 rpm. The signals vary for each speed. Once the vibration signal data was obtained, the time domain parameters were calculated using the Mat Lab software. The length of faults was seeded on the bearing outer raceway at three different positions of orthogonal (3 o'clock), centered (6 o'clock) and opposite (12 o'clock), relative to the load zone. It was induced on

bearings ranges from 0.007 inches to 0.021 inches. The faults on the bearing were seeded with the help of Electro-Discharge Machining (EDM). Each faulty bearings were reinstalled into the test motor and the vibration signal data was recorded at each different motor speed.

### III. RESULTS AND DISCUSSION

All parameters were calculated for both healthy and faulty bearings as well as to detect the failure of the bearing. The differences in the parameters were observed and the parameter with the best reflects on the bearing failure were selected. The graph was plotted dependent on the time domain parameter calculated. The faulty bearings parameters were compared with the healthy state bearings. All the parameter value changes when the speed of the motor increases and also when the fault inches increases.

#### 3.1 Statistical Analysis on Healthy & Faulty Bearing Seeded at Orthogonal (3 o'clock)

The best reflects the parameter on the outer raceway fault at orthogonal (3 o'clock) position in a bearing were standard deviation, RMS, skewness and shape factor.

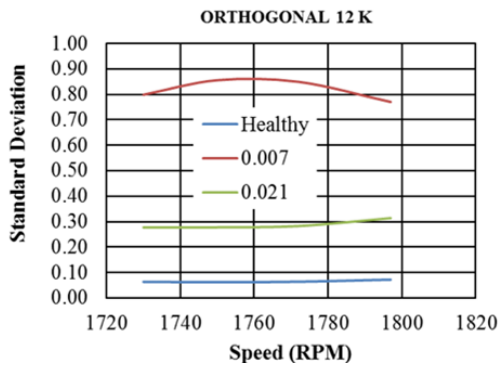


Fig. 3 Standard deviation value against speed

Figure 3 demonstrates that the healthy bearing has minimal value for standard deviation and obviously the values in various speed are around comparative. Low standard deviation value mirrors that a large portion of the values is especially near to the average. All the fault bearing have consistent standard deviation all through the speed yet as the fault diameter increase, the values increases as well. For faulty bearing of 0.007 inches in diameter, the standard deviation value at 1730 rpm speed is 0.7976 and this value increases to 0.8544. At speed of 1797 rpm, it gradually decreases to 0.7694.

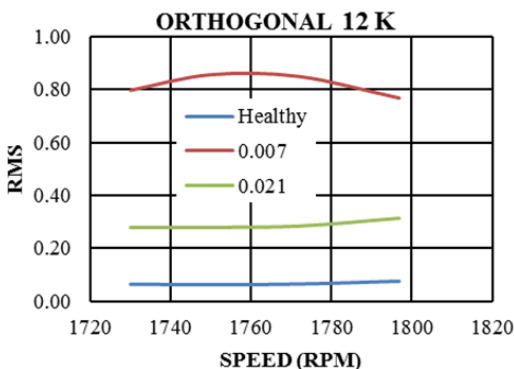


Fig. 4 RMS value against speed

Figure 4 displays a comparable graph trend as in Figure 3. So also, the healthy bearing has the littlest RMS value, trailed by the faulty bearing of 0.007 inches in diameter and the most elevated RMS value by the faulty bearing of 0.021 inches in diameter. RMS speaks the energy content in the vibration signal and has been generally utilized in distinguishing progressive failures [22]. It is a discovery instrument by and large demonstrate that lower value implies the better condition state of the parts [23].

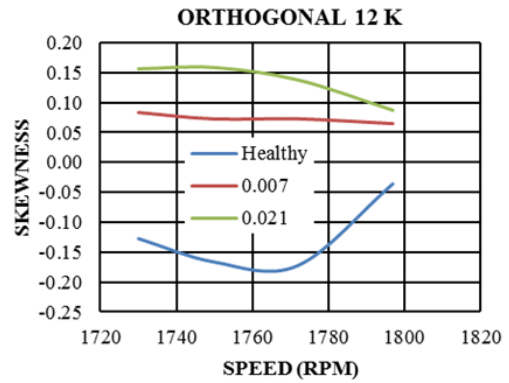


Fig. 5 Skewness value against speed

Skewness is portrayed as the measure of asymmetry in statistical distribution where the curve created in a misshaped way. The graph can be either skewed to one side or to the other side. In the meantime, skewness value can be both positive and negative. In light of Figure 5, the healthy bearing have negative skew value and the faulty bearing of 0.007 and 0.021 inches in diameter have positive skew value. The healthy bearing is alluded to as negative skew as it has a long tail in the negative direction.

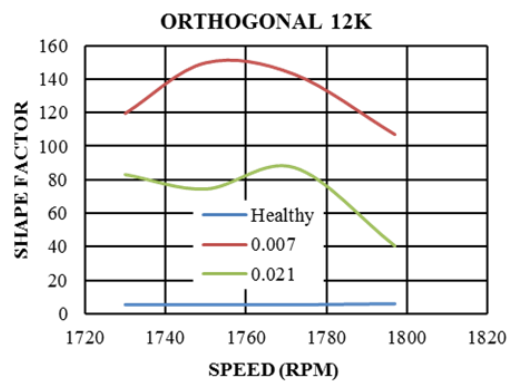


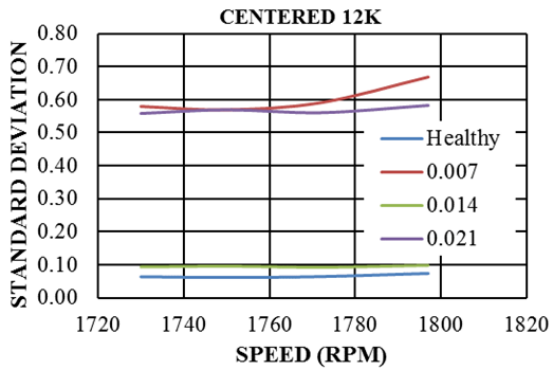
Fig. 6 Shape factor value against speed

#### 3.2 Statistical Analysis on Healthy & Faulty Bearing Seeded at Centered (6 o'clock)

The best reflects the parameter on the outer raceway fault at centered (6 o'clock) position in a bearing were standard deviation, RMS, skewness and shape factor.

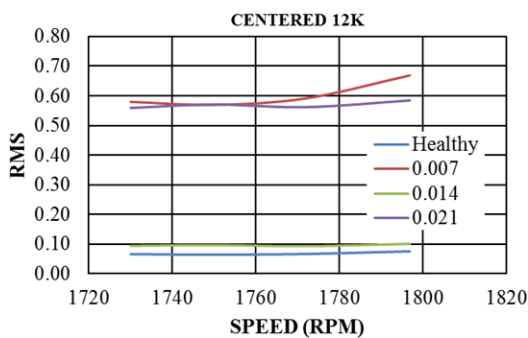


## Early Fault Detection in Bearing with Fault Seeded on Outer Raceway at Three Different Position: Orthogonal, Centered and Opposite



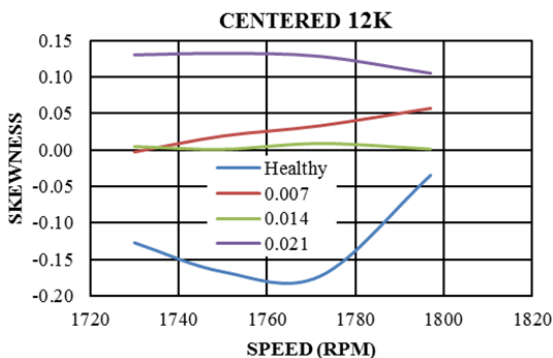
**Fig. 7 Standard deviation value against speed**

From the perception in Figure 7, the healthy bearing has the slightest standard deviation value with relatively steady value all through the distinctive speeds. Healthy bearing and faulty bearing of 0.014 and 0.021 inches in diameter shows almost a straight line and the standard deviation values do not differ too much as the speed increases. It was observed faulty bearing of 0.007 inches in diameter means the most elevated standard deviation value of 0.6691 at 1797 rpm speed. At speed of 1730 rpm, the standard deviation value was 0.5804 and it decreases to 0.5702 at 1750 rpm speed. Standard deviation is descriptors of the state of the amplitude distribution of vibration signal data gathered from a bearing [24].



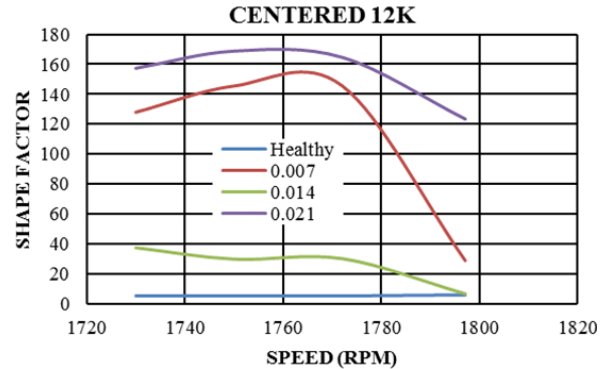
**Fig. 8 RMS value against speed**

Figure 8 exhibits a comparable graph trend as in Figure 7. So also, the healthy bearing has the littlest RMS value, trailed by the faulty bearing of 0.014, 0.021, and the most noteworthy RMS value by the faulty bearing of 0.007 inches in diameter which is 0.6695 at 1797 rpm speed. At speed of 1730 rpm, the RMS value was at 0.5804 and decreases to 0.5702 at 1750 rpm speed. Fault bearing of 0.007 and 0.021 inches in diameter differs a lot from the healthy RMS value.



**Fig. 9 Skewness value against speed**

A graph was plotted between skewness value and speed as Figure 9. The skewness value changes for every state as the speed increases. The skewness values differ a lot from a healthy state for every fault diameters. The fault bearing of 0.021 inches in diameter has the highest skewness value from another state. The skewness value at 1730 rpm speed is 0.1301 and this value decreases gradually as the speed increases.

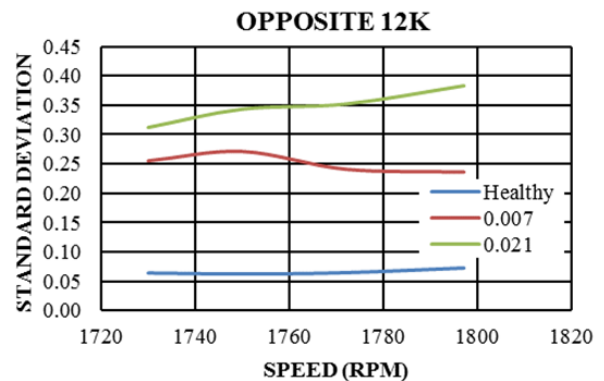


**Fig. 10 Shape factor value against speed**

From the observation of Figure 10, healthy state bearing shows almost constant value for every speed. When the fault was introduced to the bearing, the shape factor value differs quite a lot from the healthy state value. The faulty bearing of 0.021 inches in diameter has the highest shape factor value from the other state.

### 3.3 Statistical Analysis on Healthy & Faulty Bearing Seeded at Opposite (12 o'clock)

The best reflects the parameter on the outer raceway fault at opposite (12 o'clock) position in a bearing were standard deviation, RMS, skewness and shape factor.



**Fig. 11 Standard deviation value against speed**

As observed from the plotted graph as Figure 11 between standard deviation and speed, faulty bearings' standard deviation values are higher than the value of healthy state bearing. The most noteworthy standard deviation value was conveyed by the faulty bearing of 0.021 inches in diameter and it increases as the speed increases. The healthy bearing shows slight diverse value contrasted with the faulty bearing of 0.007 and 0.021 inches in diameter and additionally have about consistent value all through the speed range.

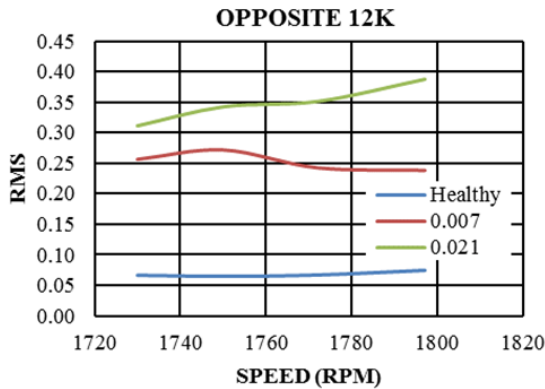


Fig. 12 RMS value against speed

Graph for RMS against speed was plotted as Figure 12. It is observed that the healthy state bearing has the lowest RMS value and almost same for every speed. RMS values of healthy state are 0.0659 at 1730 rpm speed. These value increases slightly as the speed of rotation increases. The RMS value for faulty bearing of 0.021 inches in diameter at 1730 rpm speed is 0.3118 and the value increases to 0.3881 at 1797 rpm speed. As observed from the graph, the bigger the fault diameter, the higher the RMS value. The RMS of vibration signals provided the best parameter at almost all speeds.

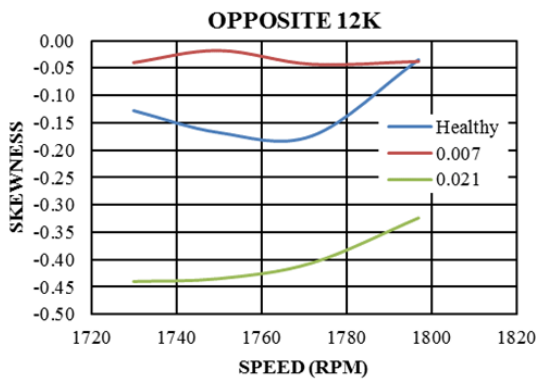


Fig. 13 Skewness value against speed

Skewness is described as the measure of asymmetry in statistical distribution where the curve developed in a distorted manner. The graph can be either skewed to the left or to the right. At the same time, skewness value can be both positive and negative. Based on Figure 13, the faulty bearing of 0.007 and 0.021 inches in diameter as well as the healthy bearing have both negative skew value. It is referred as negative skew because it has a long tail in the negative direction.

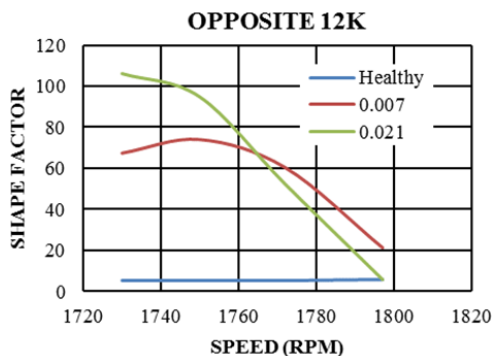


Fig. 14 Shape factor value against speed

From the observation of Figure 14, the healthy state bearing shows almost constant value for every speed. When fault was introduced to the bearing, the shape factor value differs quite a lot from the healthy state value. The faulty bearing of 0.021 inches in diameter has the highest shape factor value than the other state at the speed of 1730 rpm. However, both faulty bearing of 0.007 and 0.021 inches in diameter decrease as the speed increases and faulty bearing of 0.021 inches in diameter reaches to near same value as healthy bearing at speed of 1797 rpm.

#### IV. CONCLUSION

This paper reports on the comparison between the healthy bearing and the faulty bearing seeded on the outer raceway at three different positions; orthogonal (3 o'clock), centered (6 o'clock) and opposite (12 o'clock). The time domain parameters, comprising of the standard deviation, RMS, skewness and shape factor are as the representation of the best reflection of the failure. Based on the observation, all the four parameters have greater value in contrast with the healthy bearing value except for skewness data in the opposite (12 o'clock) position. For instance, the healthy bearing has a steady value all through the speed range excluding the data for skewness.

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## Early Fault Detection in Bearing with Fault Seeded on Outer Raceway at Three Different Position: Orthogonal, Centered and Opposite

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