Internal combustion engine gearbox bearing fault prediction using J48 and random forest classifier

Nithin Somehalli Kapanigowda[1], Hemanth Krishna[1], Shamanth Vasanth[1], Ananthapadmanabha Thammaiah[2]
[1]School of Mechanical Engineering, REVA University, Bangalore, India
[2]School of Engineering, Mysore University, Mysuru, India

Article Info

Article history:

Received Sep 13, 2022
Revised Feb 1, 2023
Accepted Feb 4, 2023

Keywords:

Artificial neural network
Bearing
Internet of things
Machine learning classifier
Petrol engine
Random forest

ABSTRACT

Defective bearings in four-stroke engines can compromise performance and efficiency. Early detection of bearing difficulties in 4-stroke engines is critical. Four-stroke gasoline engines that vibrate or make noise can be used to diagnose issues. Using time, frequency, and time-frequency domain approaches, the vibrational features of healthy and diseased tissues are examined. Problems are only detectable by vibration or sound. The fault is identified through statistical analysis of seismic and audio data using frequency and time-frequency analysis. Vibration must be minimized prior to examination. Adaptive noise cancellation removes unwanted noise from recorded vibration signals, boosting the signal-to-noise ratio (SNR). In the first of the experiment's three phases, vibrational data are collected. To reduce noise and boost SNR, adaptive noise cancellation (ANC) is applied to vibration data from the first stage. In the second stage, ANC-filtered vibration data is subjected to three studies to detect bearing failure using J48 and random forest classifiers for online, real-time monitoring. In this experiment, one healthy and two faulty bearings are used. According to a current study, the internet of things (IoT) is a promising alternative for online monitoring of remote body health.

Corresponding Author:

Nithin Somehalli Kapanigowda
School of Mechanical Engineering, REVA University
Bangalore, India
Email: nithinsk67@gmail.com

1. INTRODUCTION

One of the essential machine parts in mechanical parts such as centrifugal pumps, turbines, and engine gearboxes. is the ball bearing. Bearings in internal combustion (IC) engine gearboxes play an important role in carrying the shaft and spinning at different speeds depending on the engine's operating conditions. The gearbox's vibration signals reveal features of the bearing's state. Many researchers rely extensively on vibration analysis while trying to diagnose problems with IC engines and other machinery. With the increased use of computing technology and its upcoming advancement in conjunction with the internet of things (IoT), as well as data science algorithms to online monitor and predict the health of mechanical equipment, in recent years, several sensors, such as those relating to vibration, acceleration, temperature, and air pressure, have been employed, or multiple sensors of the same type have been combined, to collect real-time operational status data pertaining to various mechanical equipment components.

The research in the area of IC engine and rotating machine condition monitoring is described in the following publications. The literature has a great deal of work on failure detection and diagnostics in rolling element bearings. Nithin *et al.* [1] illustrate the applicability of the continuous wavelet transform (CWT) for detecting bearing defects and a machine learning approach with vibrational loads [2]. Joshuva and Sugumaran [3] use it in a separate publication. Use the vibration signal as a measurement parameter for diagnosing a failure in rolling element bearings. Saini *et al.* [4] proposed methodologies for wind turbine monitoring and fault detection systems.

According to Neto *et al.* [5], wavelet decomposition is used to assess bearing health. The literature indicates that wavelet transformations have also been applied to machine condition monitoring. An artificial neural network (ANN)-based model to classify the machine faults was developed using statistical data and speed, which yields better results [6], and Tiboni *et al.* [7] used the current signature to determine the error. Bastami and Vahid [8] the statistical data is very important to differentiate between vibrations and faults, and for accurate data extraction, it has been discovered that an adaptive Morlet wavelet can be utilized [9]. Gligorijevic *et al.* [10] decomposes the signal and optimally analyses it with the help of scatter matrices and quadratic classifiers. A large-scale wind turbine state-of-the-art monitoring model was presented [11]. Wang *et al.* [12] commented on the need for monitoring devices in wind turbine generator sets and also presented a detailed review of the classification procedure and various techniques in different stages that are associated with it. Nithin *et al.* [13] demonstrates the analysis of vibration signals from IC engines by carrying out feature extraction. An efficiency of 100% is achieved by Brkovic *et al.* [14] in early fault detection of rotating machines using quadratic classifiers. Hou *et al.* [15] presented a novel optimized technique for detecting faults early, as well as a technique known as the chirp Z-transform, which is used to improve resolution and obtain accurate results. Amini *et al.* [16] details the peculiarities of wavelet analysis for feature extraction in defect diagnostics. This research also involves filtering the noise from the acquired noisy signal to increase its signal to noise ratio (SNR) before analyzing it to identify the issue [17]. For noise filtration, an adaptive noise cancellation (ANC) strategy is used [18]. Ghemari *et al.* [19] utilized a finite impulse responsive-based adaptive algorithm and enhanced the ANN approach [20] to address early fault detection and control. The least mean square method is used for error convergence in adaptive filters [21]. As a result, the ANC technique was used to reduce noise during the preprocessing phase of this investigation. The filtered (noise-free) acoustic and vibration signals are then utilized to identify the bearing problem.

In the experiment [22], one healthy and two defective bearings were used. Using wireless devices, the measured parameters of machine elements located in a remote location can be monitored. For this reason, the IoT is utilized. Along with Wi-Fi devices, IoT-compatible sensors are used to collect and transmit measured data from machine elements to the cloud. The measured data is collected from the cloud and used to identify machine component failures. Huang *et al.* [23] multi source sensing data fusion model using IoT and big data processing technology to diagnose and predict the mechanical fault in two steps, and the proposed technique is compared with other popular techniques found in the literature. The machine learning (ML) technique is also extended to diagnose and prognose mechanical faults in the manufacturing industry, the Fernandes *et al.* [24] also highlighted the need for these technologies and its advancement in predicting the mechanical faults. Ravikumar *et al.* [25], the classification of IC engine faults based on vibration data using the ML algorithm is proposed and for loading eddy current dynamometer is used and achieved 97.5% accuracy.

The proposed work describes the experimental setup that was conceived and constructed to diagnose bearing faults. The system for collecting vibrational data is described. The performance of adaptive filtering techniques used in the preprocessing phase to reduce background noise is then evaluated and chosen. Then, various signal processing techniques, such as frequency and time-frequency analysis, are utilized to determine bearing faults. Each rotating element bearing in good condition has its own unique vibration characteristic. Nonetheless, if it develops a defect, the vibrational properties will alter. Using time and frequency analysis, this shift is discernible. However, noise generated by other machinery components may have an effect on the diagnostic operation. Before analyzing the gathered, measured signal, it is necessary to eliminate the noise. Due to the non-stationary nature of noise, an adaptive noise cancellation approach is employed to reduce it.

The following is the organization of the manuscript: section 1 introduces details and emphasizes the significance of the problem statement. Section 2 explains the recommended approach to the problem, followed by section 3's description of the experimental setup and data gathering system. Section 4 includes a graphical representation of the results and discussion, while section 5 concludes.

2. PROPOSED METHOD

The proposed method involves three different stages: the first stage is to collect the graphical engine data from the vibration sensor. The acquired waveforms are subjected to wavelet analysis in the second stage to extract their features. In the next stage, the extracted data is stored in the cloud, and the same is used to train the machine learning model to classify the faulty and healthy bearings of a 4-stroke engine. Utilizing effective and cutting-edge signal processing techniques, the current work's goal is to identify and classify problems in rotating machine components (bearings and gears), as mentioned in Figure 1. Furthermore, when ThingSpeak is used as an IoT platform to visualize and analyze data, the observed data is saved in the cloud and can be retrieved on demand.

A vibration sensor (accelerometer) and an appropriate data collection system for the acquisition of vibration data make up the experimental bearing fault diagnostic setup used for fault diagnosis in bearings. Using a portable sound analyzer that consists of a sound sensor (microphone) and an appropriate data collection device, the acoustic data from this experimental setup for bearing failure diagnosis is collected. Both healthy and damaged (faulty) spinning machine elements are collected as measurement signals from the experimental setup. The captured signal is then pre-processed to eliminate the background noise. At this point, the de-noising approach is used with the obtained signals to use an adaptive filter to filter out the noise. In the following stage, the analysis procedure uses the filtered measuring signals (vibration and acoustics) to find problems in rotating machine components. A comparison between the healthy element signal (signal obtained from healthy elements) and the defective element signal is done to find problems in the machine elements (signal acquired from defective elements). On acquired signals, time, frequency, and time-frequency analyses are performed for this purpose. Different classifiers are then employed to categorize bearing defects. Algorithms for machine learning classifiers are employed for this purpose. The classifiers are fed with statistical information from the measured vibration signals, which is used as a training component to hone the system's ability to identify bearing defects.

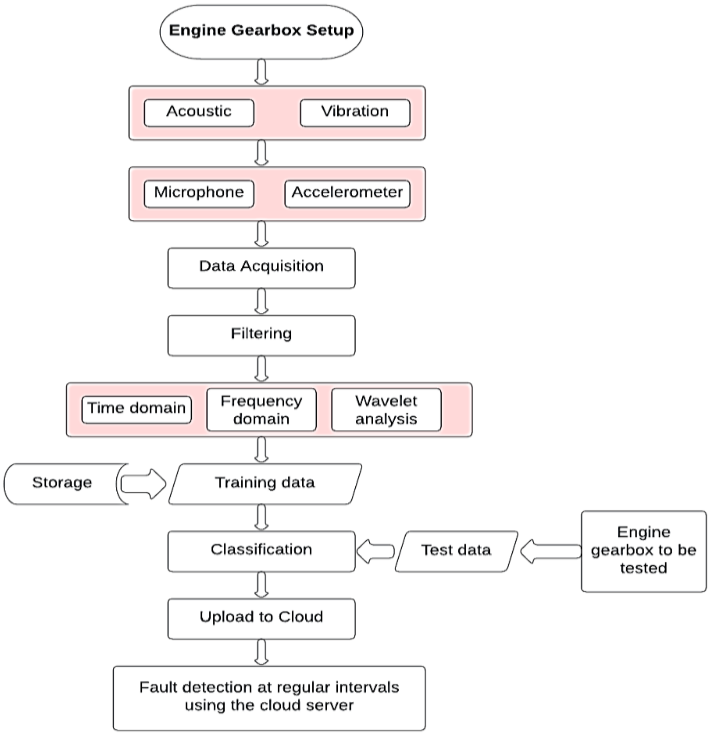

Figure 1. Data acquisition and ML classifier working model

2.1. Feature extraction using CWT

The statistical parameter data is fed into the classifiers for training. Table 1 lists the five statistical parameters that were used for this purpose. The crest factor, kurtosis, root mean square (RMS), variance, and mean are the five features chosen. The signals are split into 0.1-second windows with 1,000 samples for each data point. Each set of samples has six features that are retrieved and used in the categorization process.

Table 1. Statistical parameter data used for classification

Static Parameters	Healthy bearings	Defect bearing type I	Defect bearing type II
Root mean square	0.0124	0.0264	0.0204
Mean	0.6632	1.625	1.04
Crest factor	5.741	6.628	7.0231
Kurtosis	3.854	9.0123	5.741
Variance	0.0743	6.825	4.213

2.2. Machine learning model as classifier

In this study, a method for identifying faults in rotating machine bearings using machine learning classifiers was presented. The statistical characteristics used in the defect categorization technique are feature vectors. Kurtosis, mean, variance, RMS, and crest factor are all studied in all 17 samples using a 1-s window with 167 training samples and 56 healthy bearings with type I and type II defects, respectively. The algorithms are trained on the testing sample using 9-fold cross-validation. The statistical data is computed and retrieved from the observed vibration signal and provided as an input to the classifiers in the first stage. The classifier algorithms are trained using the statistical parameters provided and then use the training data to classify bearing faults.

Here J48 Classifier is preferred to analyze the extracted features, which split the data into subsets to make the analysis easy and also helps in filling the missing attributes with a very low error rate, which improves the overall performance of the model. Because the data is so large, the random forest technique is also used to classify the bearing faults, and the expected accuracy is higher than that of other techniques found in the literature. The steps for fault categorization in bearings are as follows: i) the vibration measurement signal is provided by the bearings; ii) from the detected vibration signal, statistical statistics (transient parameters) are computed (feature extraction); iii) the training data for the classifiers is limited to a few statistical factors; iv) these statistical parameters are used to teach the system or algorithm how to use the machine learning classifiers; and v) the training data are used to classify faults, and the confusion matrix is used to figure out how well the faults were classified.

2.3. Interface to ThingSpeak

The Arduino IDE is used to accept sensor data from a variety of sensors. The ESP8266 Wi-Fi module is designed to store data via ThingSpeak in the cloud. The data is retrieved from the sensors every 15 seconds. In addition, the ThinkTweet application is used to link a Twitter account to the ThingSpeak so that an alarm message can be sent to the user if the vibration level increases.

3. EXPERIMENTAL SET-UP AND DATA ACQUISTION SYSTEM

The constructed experimental setup as well as the instrumentation system are presented in this part. The designed instrumentation system is used to measure the vibration signatures of healthy and faulty bearings. A 4-stroke petrol engine is mounted over the experimental table to attach the bearings under test, and the rolling shaft of the bearing is stretched. The test bearings are attached to the engine shaft, reducing undesired vibrations. The accelerometer is attached to the top of the gearbox to prevent undesirable jerky movement during the high-speed rotation. An accelerometer (PCB 325C03), as well as an NI data acquisition (DAQ) card (Ni9234), and a computer interface are used to collect the signals from the sensors. A data acquisition card with signal conversion and amplification capabilities is known as a DAQ card. LabVIEW and MATLAB are installed on the computer.

The signals that are being measured are captured and recorded, and the signals that have been recorded are then used in LabVIEW and MATLAB to analyze and diagnose problems. The bearings from the 6203-ZZ series were utilized in the experiment for testing and analysis. The bearing specifications can be found in Table 2. To facilitate understanding, each tested bearing has been assigned a bearing number, as shown in Table 3.

Table 2. Specification of ball bearing

Contact angle (α)	00
Ball diameter (d)	6 mm
No. of balls (Nb)	8
Pitch dia (D)	30 mm

Table 3. Type of bearings and defects

Bearing No	Type of Fault	Type of Defect
B1	Healthy Bearing	No defect
B2	Outer race fault	Cut
B3	Inner race fault	Hole

3.1. Adaptive noise cancellation algorithm selection and performance comparison

In this section, the experimental setup's noisy vibration signal is treated with three ANC techniques. SNR and mean square error (MSE) are used to compare the three ANC methods. The best ANC algorithm is used to preprocess experimental vibration data. Least mean square (LMS), wavelet, and EMD were tested as ANC techniques. Using good bearing vibration signals as a reference, damaged bearing noise is minimized.

Figure 2 shows the filtered vibration signal before and after using the three ANC techniques. Table 4 compares the results. For ANC, 150 filters and 0.01 steps were used. ANC approaches are evaluated using the vibration signal from a Type-1 defective bearing. The graph shows the vibration signal before and after ANC installation. SNR and MSE compare performance. Calculating SNR and MSE uses MATLAB. EMD is the best of the three ANC algorithms in the table. EMD de-noises experimentally recorded vibration information for more accurate problem diagnosis. Noise is removed before signal processing begins.

Table 4. Performance comparison of de-noising techniques

ANC	SNR	MSE
Wavelet	11.084	0.0241
learning management system	13.145	0.0364
Empirical mode decomposition	14.896	0.0164

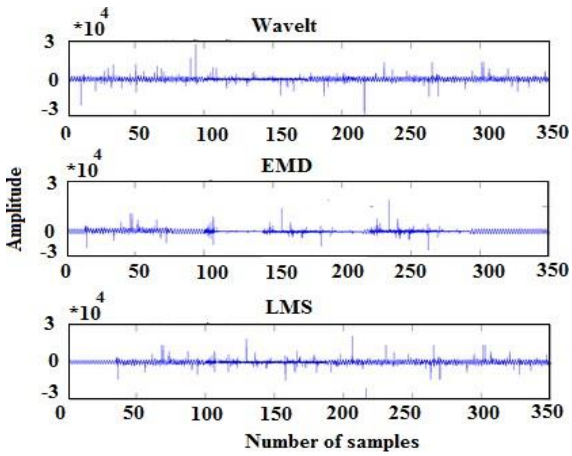

Figure 2. A judgement of advance noise cancellation performance

4. RESULTS AND DISCUSSION

The vibration signal of an IC engine is analyzed in this part so that problems with the bearings may be diagnosed and the various types of problems are classified. In this section, the vibration signal of an IC engine with type-I and type-II flaws is isolated from the vibration signal of the healthy bearing so that it can be analyzed in both the time and frequency domains, as shown in Figures 3 to 5, respectively. The statistical data that is produced is then saved in the cloud so that it can be analyzed in the future.

4.1. Time analysis using vibration signal

Figure 3 depicts one of the vibration signal samples that were recorded in the time domain for each of the different conditions of the bearing. It has been determined, by analysis of signals in the time-domain, that the level of acceleration rises as the fault becomes more severe. A time-domain technique for vibration signal analysis gives the overall vibration level but does not provide any diagnostic information.

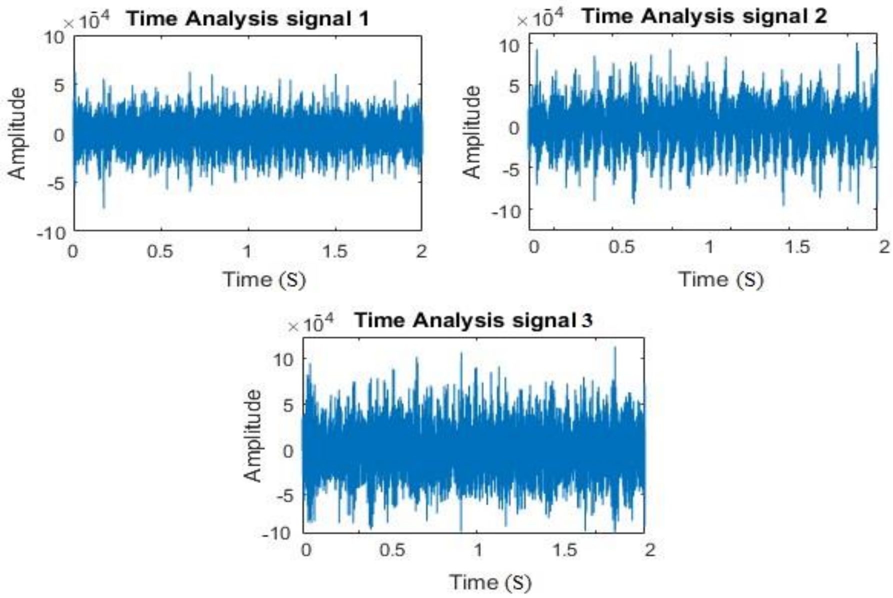

Figure 3. Vibration filtered signal from healthy bearing, type 1 defect and type-2 defect condition

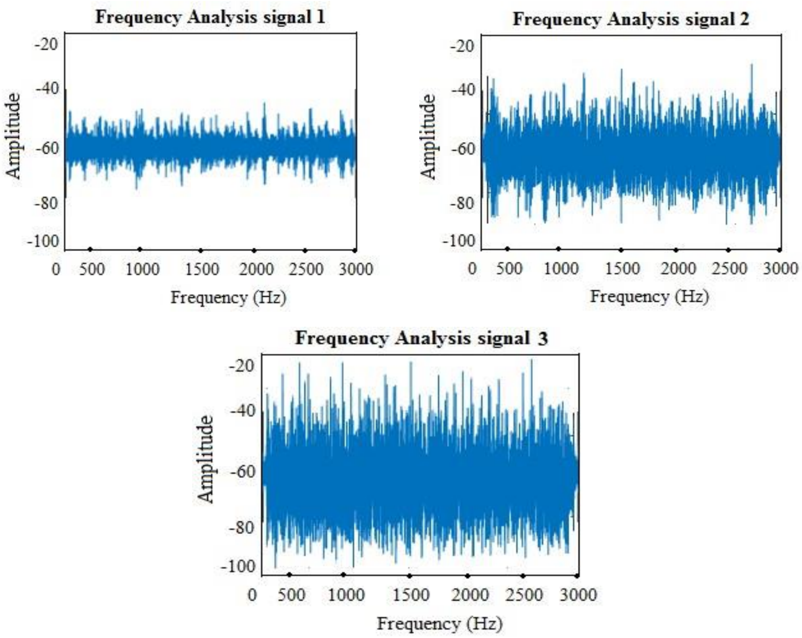

Figure 4. Frequency of vibration signal condition from healthy, type I defect and type II defect bearing

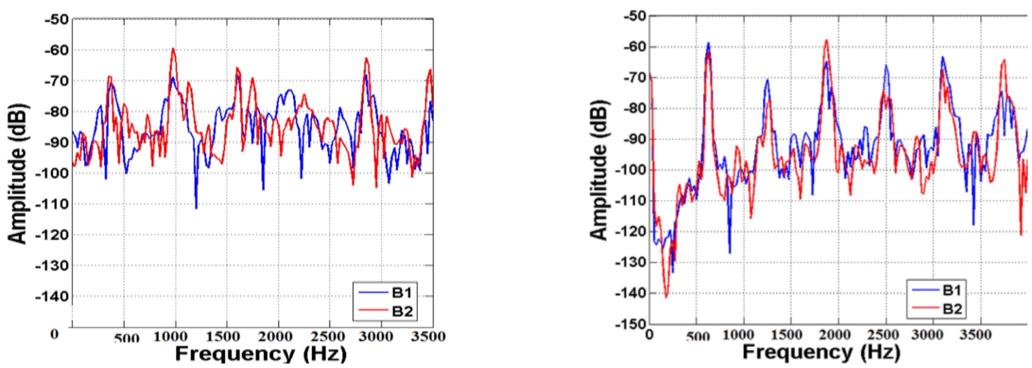

Figure 5. FFT comparison of vibration signal from healthy bearing (B1), type-1 and type-2 defect bearing (B2)

4.2. Statistical analysis using vibration signal

The statistical parameters are calculated using mathematical methods using filtered vibration and acoustic signals from good and defective bearings. According to the comparison in Table 5, in defective bearings, vibration signal data statistical parameter values differ from those in healthy bearings. This tool detects irregularities in faulty bearings.

Table 5. Statistical parameter comparison for vibration signal

Sl No	Statistical parameter	Good Bearing Condition	Type 1 Fault bearing condition	Type 2 Fault bearing condition
1	RMS	0.0135	0.0262	0.0235
2	Peak Value	0.0774	0.1745	0.2658
3	Mean	0.6614	1.6258	1.038
4	Skewness	0.0054	0.8524	0.1278
5	Crest Factor	5.7485	6.6259	7.149
6	Variance	0.0788	6.8451	4.2784
7	Kurtosis	3.8546	9.0234	5.893
8	Clearance Factor	716.323	665.23	624.35
9	Standard Deviation	0.0125	0.0265	0.0287
10	Shape factor	1.326	1.7895	7.458
11	Impulse Factor	7.4522	10.235	9.5687

4.3 Frequency analysis using vibration signal

Another method for detecting bearing faults is to use a frequency analysis methodology that uses vibration signals. The fast Fourier transform (FFT) is used to analyze faults in this method. The FFT is used to convert a time-domain vibration signal technique to a frequency-domain vibration signal technique. As a result, the frequency spectrum of collected vibration signals is compared using FFT. Figures 4 illustrate the FFT of good, type I, and type II faulty bearings, respectively. Figure 5 shows a comparison of the vibration signal from a good bearing (B1) and a type-1 defective bearing (B2) in terms of frequency range (B2) and also compares the frequency spectra of a good bearing (B1) and a type-2 defective bearing (B3).

At the bearing characteristic frequency (BCF), the difference in the frequency spectrum between healthy and problematic bearings can be detected. The BCF is also known as the outer race defects frequency (ORDF). The BCF is calculated using the formula:

$$ORDF = \frac{N_b}{2}\left(\frac{N}{60}\right)\left(1 - \frac{d}{D}cos\alpha\right)$$

where Nb is total number of balls, N is speed of rotational in rpm, d is bearing ball dia, D is Pitch dia of bearing and α is contact angle of the bearing. 74.67 Hz is the calculated BCF. As a result, the FFT of vibration signals is compared at a frequency of 74.67 Hz. At BCF, Figure 6 compares the frequency spectrum of good and a Type 1 faulty bearing.

In Figure 6, the presence of a defect is indicated by the presence of an amplitude difference at the ORDF. Since the ORDF is calculated based on how the bearings are shaped, any difference in amplitude measured at this frequency indicates a problem.

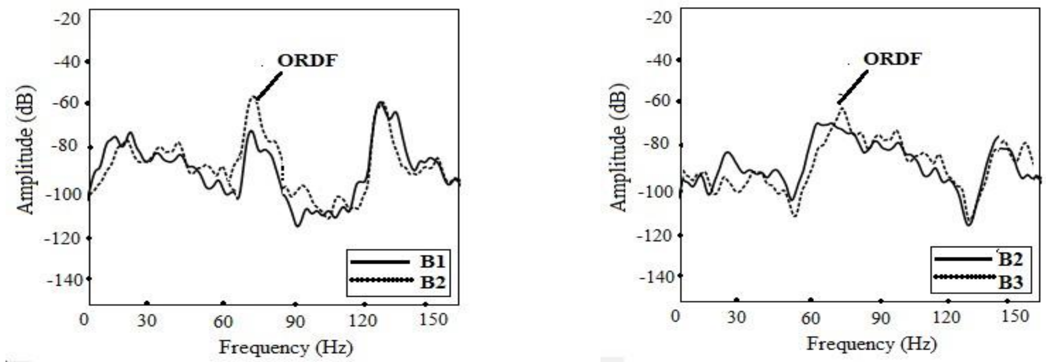

Figure 6. FFT contrast of vibration signals from good bearings (B1), type-1 and type-2 fault bearings (B2)

4.4. The corresponding value of scale with respect to BSF

The scale value for a 74.66 Hz vibration signal is 277. Consequently, vibration signal scalograms are observed in about 277 samples. The difference is clear around this scale value. The scalogram intensities of defective and healthy bearings differ. Scalograms around expected scale values change colors and patterns. Variations in intensity indicate bearing difficulties, and the details are tabulated in Table 6. FFT analysis of vibration waveforms can reveal bearing issues.

Table 6. The corresponding value of scale with respect to BCF

Bearing No	Type of fault	BCF	Calculated frequency in Hz	Scale value for acoustics
B2	Defect of outer race type I bearing	Defect of outer race frequency (ORF)	74.66	277
B3	Outer fault type-2	Outer race defect frequency (ORF)	74.66	277

4.5. FFT analysis of data stored in ThingSpeak cloud server

The transistor stores the vibration data of a healthy bearing and a defective bearing. The FFT is applied to both healthy and defective bearings. The frequency spectra for both bearings are shown in Figure 7. Though this work shows the on-line monitoring of measuring parameters from the bearing set-up, the fault analysis and diagnosis are done off-line.

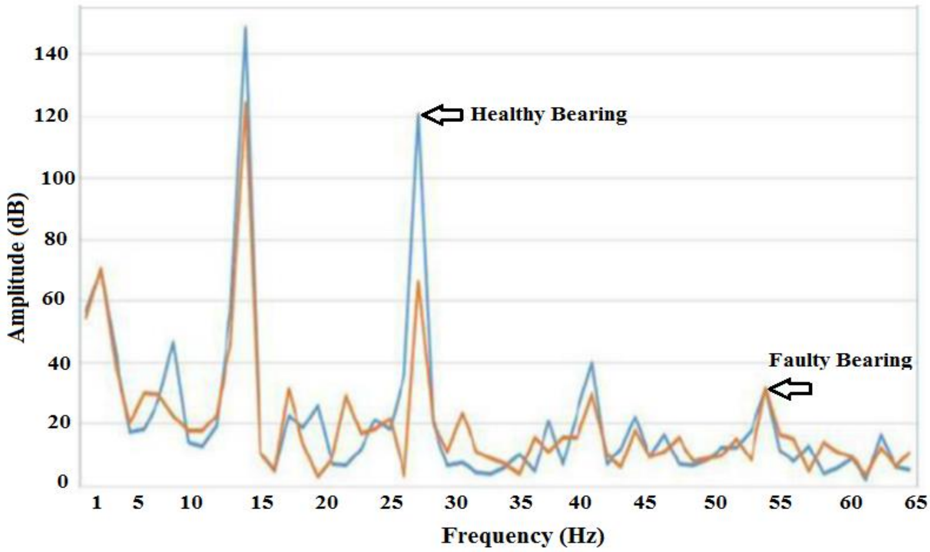

Figure 7. Comparison of FFT of vibration signal from healthy and defective bearings

5. CONCLUSION

Adaptive noise cancellation is used to improve bearing failure analysis and identification in the current experimental study's preprocessing step. This study uses vibrations to detect bearing defects. At first sight, the statistical data comparison reveals the time analysis problem. The ORDF FFT comparison in frequency analysis shows the problem. Wavelet analysis gives temporal and frequency information. This research produced a more effective and reliable bearing fault detection method. Machine learning algorithms classify bearing problems using statistical markers. Random Forest outperforms J48 in detecting bearing flaws. The experiment shows the necessity for IoT to monitor bearing measurement parameters online. This paper shows that spinning machine components can be checked remotely using IoT. This study shows how to use cloud-based vibration data to discover bearing issues. ThingSpeak is used to alert users when measured data exceeds a threshold. Despite showing online monitoring of bearing parameters, fault investigation and diagnosis were done offline using ThingSpeak data. In order to make this system capable of online fault diagnosis, the work can be upgraded.

ACKNOWLEDGEMENT

Author would like to acknowledge the support from REVA University for the facilities provided to carry out the research.

REFERENCES

[1] S. K. Nithin, K. Hemanth, V. Shamanth, R. Shrinivas Mahale, P. C. Sharath, and A. Patil, “Importance of condition monitoring in mechanical domain,” *Materials Today: Proceedings*, vol. 54, pp. 234–239, 2022, doi: 10.1016/j.matpr.2021.08.299.
[2] A. M. Umbrajkaar, A. Krishnamoorthy, and R. B. Dhumale, “Vibration analysis of shaft misalignment using machine learning approach under variable load conditions,” *Shock and Vibration*, vol. 2020, pp. 1–12, Jul. 2020, doi: 10.1155/2020/1650270.
[3] A. Joshuva and V. Sugumaran, “A lazy learning approach for condition monitoring of wind turbine blade using vibration signals and histogram features,” *Measurement*, vol. 152, Feb. 2020, doi: 10.1016/j.measurement.2019.107295.
[4] S. Saini, M. Raj, S. Fatima, and N. Tandon, “Condition monitoring of a centrifugal pump by vibration and motor current signature analysis,” in *10th International Conference on Industrial Tribology (IndiaTrib-2019)*, 2019.
[5] J. M. de Oliveira Neto, A. G. Oliveira, J. V. L. de C. Firmino, M. C. Rodrigues, A. A. Silva, and L. H. de Carvalho, “Development of a smart system for diagnosing the operating conditions of a helicopter prototype via vibrations analysis,” *Research, Society and Development*, vol. 10, no. 12, Sep. 2021, doi: 10.33448/rsd-v10i12.20546.
[6] A. Alzghoul, A. Jarndal, I. Alsyouf, A. A. Bingamil, M. A. Ali, and S. AlBaiti, “On the usefulness of pre-processing methods in rotating machines faults classification using artificial neural network,” *Journal of Applied and Computational Mechanics*, vol. 7, no. 1, pp. 254–261, 2021, doi: 10.22055/JACM.2020.35354.2639.
[7] M. Tiboni, G. Incerti, C. Remino, and M. Lancini, “Comparison of signal processing techniques for condition monitoring based on artificial neural networks,” in *Applied Condition Monitoring*, 2019, pp. 179–188. doi: 10.1007/978-3-030-11220-2_19.
[8] A. Rohani Bastami and S. Vahid, “A comprehensive evaluation of the effect of defect size in rolling element bearings on the statistical features of the vibration signal,” *Mechanical Systems and Signal Processing*, vol. 151, Apr. 2021, doi: 10.1016/j.ymssp.2020.107334.

[9] V. Sharma, "A review on vibration-based fault diagnosis techniques for wind turbine gearboxes operating under nonstationary conditions," *Journal of The Institution of Engineers (India): Series C*, vol. 102, no. 2, pp. 507–523, Apr. 2021, doi: 10.1007/s40032-021-00666-y.
[10] J. Gligorijevic, D. Gajic, A. Brkovic, I. Savic-Gajic, O. Georgieva, and S. Di Gennaro, "Online condition monitoring of bearings to support total productive maintenance in the packaging materials industry," *Sensors*, vol. 16, no. 3, Mar. 2016, doi: 10.3390/s16030316.
[11] Z. Liu and L. Zhang, "A review of failure modes, condition monitoring and fault diagnosis methods for large-scale wind turbine bearings," *Measurement*, vol. 149, Jan. 2020, doi: 10.1016/j.measurement.2019.107002.
[12] T. Wang, Q. Han, F. Chu, and Z. Feng, "Vibration based condition monitoring and fault diagnosis of wind turbine planetary gearbox: A review," *Mechanical Systems and Signal Processing*, vol. 126, pp. 662–685, Jul. 2019, doi: 10.1016/j.ymssp.2019.02.051.
[13] S. K. Nithin, K. Hemanth, and V. Shamanth, "A review on combustion and vibration condition monitoring of IC engine," *Materials Today: Proceedings*, vol. 45, pp. 65–70, 2021, doi: 10.1016/j.matpr.2020.10.093.
[14] A. Brkovic, D. Gajic, J. Gligorijevic, I. S. Gajic, O. Georgieva, and S. Di Gennaro, "Early fault detection and diagnosis in bearings for more efficient operation of rotating machinery," *Energy*, vol. 136, pp. 63–71, Oct. 2017, doi: 10.1016/j.energy.2016.08.039.
[15] D. Hou, H. Qi, H. Luo, C. Wang, and J. Yang, "Comparative study on the use of acoustic emission and vibration analyses for the bearing fault diagnosis of high-speed trains," *Structural Health Monitoring*, vol. 21, no. 4, pp. 1518–1540, Jul. 2022, doi: 10.1177/14759217211036025.
[16] A. Amini, Z. Huang, M. Entezami, and M. Papaelias, "Evaluation of the effect of speed and defect size on high-frequency acoustic emission and vibration condition monitoring of railway axle bearings," *Insight - Non-Destructive Testing and Condition Monitoring*, vol. 59, no. 4, pp. 184–188, Apr. 2017, doi: 10.1784/insi.2017.59.4.184.
[17] D. Ibarra-Zarate, O. Tamayo-Pazos, and A. Vallejo-Guevara, "Bearing fault diagnosis in rotating machinery based on cepstrum pre-whitening of vibration and acoustic emission," *The International Journal of Advanced Manufacturing Technology*, vol. 104, no. 9–12, pp. 4155–4168, Oct. 2019, doi: 10.1007/s00170-019-04171-6.
[18] F. Castellani, L. Garibaldi, A. P. Daga, D. Astolfi, and F. Natili, "Diagnosis of faulty wind turbine bearings using tower vibration measurements," *Energies*, vol. 13, no. 6, Mar. 2020, doi: 10.3390/en13061474.
[19] Z. Ghemari, S. Saad, and K. Khettab, "Improvement of the vibratory diagnostic method by evolution of the piezoelectric sensor performances," *International Journal of Precision Engineering and Manufacturing*, vol. 20, no. 8, pp. 1361–1369, Aug. 2019, doi: 10.1007/s12541-019-00154-5.
[20] C. R. Soto-Ocampo, J. M. Mera, J. D. Cano-Moreno, and J. L. Garcia-Bernardo, "Low-cost, high-frequency, data acquisition system for condition monitoring of rotating machinery through vibration analysis-case study," *Sensors*, vol. 20, no. 12, Jun. 2020, doi: 10.3390/s20123493.
[21] D. A. Papathanasopoulos, K. N. Giannousakis, E. S. Dermatas, and E. D. Mitronikas, "Vibration monitoring for position sensor fault diagnosis in brushless DC motor drives," *Energies*, vol. 14, no. 8, Apr. 2021, doi: 10.3390/en14082248.
[22] S. Lu, P. Zhou, X. Wang, Y. Liu, F. Liu, and J. Zhao, "Condition monitoring and fault diagnosis of motor bearings using undersampled vibration signals from a wireless sensor network," *Journal of Sound and Vibration*, vol. 414, pp. 81–96, Feb. 2018, doi: 10.1016/j.jsv.2017.11.007.
[23] M. Huang, Z. Liu, and Y. Tao, "Mechanical fault diagnosis and prediction in IoT based on multi-source sensing data fusion," *Simulation Modelling Practice and Theory*, vol. 102, Jul. 2020, doi: 10.1016/j.simpat.2019.101981.
[24] M. Fernandes, J. M. Corchado, and G. Marreiros, "Machine learning techniques applied to mechanical fault diagnosis and fault prognosis in the context of real industrial manufacturing use-cases: a systematic literature review," *Applied Intelligence*, vol. 52, no. 12, pp. 14246–14280, Sep. 2022, doi: 10.1007/s10489-022-03344-3.
[25] K. N. Ravikumar, C. K. Madhusudana, H. Kumar, and K. V. Gangadharan, "Classification of gear faults in internal combustion (IC) engine gearbox using discrete wavelet transform features and K star algorithm," *Engineering Science and Technology, an International Journal*, vol. 30, Jun. 2022, doi: 10.1016/j.jestch.2021.08.005.

BIOGRAPHIES OF AUTHORS

Nithin Somehalli Kapanigowda has received the B.E. degree in Mechanical Engineering from VTU University, India, in 2013 and M.Tech degree in Mechanical Machine Design from VTU, in 2015, respectively. Currently, he is an Assistant Professor at the Department of Biomedical and Robotics Engineering, Mysuru University School of Engineering, Mysuru. His research interests include condition monitoring, IoT, machine learning. He can be contacted at email: nithinsk67@gmail.com.

Hemanth Krishna has awarded by B.E., M.Tech and PhD degree. Currently he is working as Associate Professor, School of Mechanical Engineering, Reva University, Bengaluru. He has Published 25+ Journal papers in peer reviewed Journals, 5+ Conference Publications and Book Chapter. His research interests include vibration, vehicle dynamics, condition monitoring, composites and additive manufacturing. He can be contacted at email: hemanth.k@reva.edu.in.

Shamanth Vasanth has awarded by B.E, MTech and PhD degree. Currently he is working as Associate Professor, School of Mechanical Engineering, Reva University, Bengaluru. He has Published 14+ Journal papers in peer reviewed Journals, 7+ Conference Publications and Book Chapters. His research interests include additive manufacturing. He can be contacted at email: shamanth.v@reva.edu.in.

Ananthapadmanabha Thammaiah has awarded B.E, M.E and PhD degree. Currently he is working as Director, School of Engineering, Universiity of Mysore, Mysuru. He has published 300+ papers in international conferences and peer reviewed journal. His research area includes power systems, machine learning, distributed generators. He can be contacted at email: drapn2015@gmail.com.