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Research Article

Vibration-based fault detection in induced draft fans using unsupervised machine learning approaches

Ramesh BHANDARE[1,*], Pankaj BELDAR[1], Shyam MOGAL[2]

[1]Department of Mechanical Engineering, K K Wagh Institute of Engineering Education & Research, Nashik, 422003, India
[2]Department of Mechanical Engineering, MVPS's K. B. T. College of Engineering, Nashik, 422013, India

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ABSTRACT

Induced draft (ID) fan is a crucial member to carry our hot flue gases and always subjected to high temperature and pressure. Flue gases carry higher temperature than atmospheric so, ID fan always works under elevated temperature 24x7. Supporting members such as by bearing and coupling also have to work under significant temperature more than atmospheric condition which leads create unbalance, misalignment or unexpected failures. Predictive maintenance has its own advantages to avoid this, Vibration analysis is a best tool for this. Vibration analysis clearly indicate the unbalance and misalignment fault in induce draft fan and coupling respectively as earliest. Vibration data has been collected on machine in paper mill and statistical features has been extracted. Machine learning techniques has its own significance for checking fault accuracies. Proposed study suggested unsupervised machine learning approach to separate 2 different faults like unbalance and misalignments faults in ID fan.

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INTRODUCTION

The induced draft (ID) fan finds in thermal power plants, cement plants, paper mills, steel mills, chemical plants, etc. In a paper mill plant, the ID fan is typically located after the boiler and before the chimney or stack. Specifically located within the flue gas system, and it plays a vital role in the process of exhausting the flue gases from the boiler. ID fan subjected to high temperature and pressure needs continuous monitoring otherwise faults are created in ID fan or in support system. As a vital member of plant, accurate investigation of faults in the ID fan is the need. Defect in an ID fan can leads to decrese in performane and rise in energy usage. Timely identification and rectification of these faults ensure an increase in the life of a fan, minimize energy costs, and also enhance overall efficiency. Issues like imbalance, bearing faults, misalignment, looseness, or a bent shaft can escalate significantly in ID fan due to vibrations may caused unanticipated shutdowns. Predictive maintenance plays vital role in such situation. Vibration based condition monitoring is essential and reliable technique for identifying multiple faults in such system. Maintaining system in a healthy condition is crucial for their long-term proficiency and to enhance the overall efficiency of a plant.

*Corresponding author.
*E-mail address: rvbhandare@kkwagh.edu.in

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A case study on ID fan by Jagtap et al. [1] reveals how vibration analysis techniques provide insights for earlier fault findings. Author located fault severity by wear, noise and ultrasound level. In addition to this Kurien and Srivastava [2] done motor signature and wear debris analysis in their research. Vibration based condition monitoring for auxiliary equipment's like feed pump, fan, turbine in thermal power plants used by some researchers [3-6]. Li [7] in their case study conducted vibration analysis for forced draft fan and found unbalance in system and also explain the dynamic balancing process. Some researcher's comments on the effectiveness of vibration analysis techniques in their literature [8-9,]. Faults within the such system have a direct impact on the safety of a thermal power plant and the overall reliability and economy of the system. By extracting the vibration signal, faults within the auxiliary components such as ID fan can be identified and categorized using a set of specific features. The fast fourier transform (FFT) or discrete methods are applied to extract valuable features from the vibration signal.

Statistical features selection approach has been employed by some investigators [10,11] from time domain and frequency domain signal. By extracting Statistical features like kurtosis, skewness, variance, standard deviation etc. improve the locate faults in the system. Machine learning (ML) techniques one more area open for scholars to deeply explain the faulty cases. Supervised ML approach has been employed by Liu et al. [12] to investigate the fault accuracy for steam turbine in nuclear power plant. verify the fault severity and accuracy. Classification ML algorithm has potential to significantly distinguish the faulty and healthy cases, which helps the researcher to visualize the anomaly in signals. Support vector machine (SVM), K nearest neighbors (KNN), random forest (RF) such ML algorithms have suggested by researchers in their literature [13-15]. Genetic algorithm-based optimization for vehicle powertrain system has been employed by Genç and Karaduman [16], Deep learning is more powerful tool for fault detection, Kumhar [17] proposed dynamic balancing scheme and applied convolution neural-network (CNN) to extract information. Sarita [18] suggested deep neural network to detect faults in blower of vehicle air conditioner. They also proposed wavelet transform to signal conditioning to improve the performance of signal. Eratlı [19] implemented principal component analysis (PCA) to detect faulty part in the fan motor system. Machine learning helps the scholars to efficiently locating the faulty condition even there is anomality in the available vibration data [20-22]. Many researchers work on thermal or nuclear power plant data [23,24] and few literatures explicitly on paper mill ID fan. Still there is scope to study and reveals the cases arises in this in detail. In the proposed work, data for unbalance and misalignment in ID fan has been carried out in paper mill in real time. Vibration data clearly shows unbalance in ID fan and also locate the misalignment. Unsupervised machine learning approaches has been employed to distinguish between the unbalance and misalignment from vibration signal. Results from vibration analysis and ML algorithms discovers highest accuracy up to 99%.

The present work is divided into three sections, section II covers methodology, the vibration analysis of data collected at paper mill, subsequent section focuses on data conditioning, feature extraction and machine learning approach employed to precisely locate the faults. Section IV, emphasizes on the results and discussion.

MATERIALS AND METHODS

Figure 1 shows methodology for Fault diagnosis of ID fan in paper mill. Vibration data has been collected by using

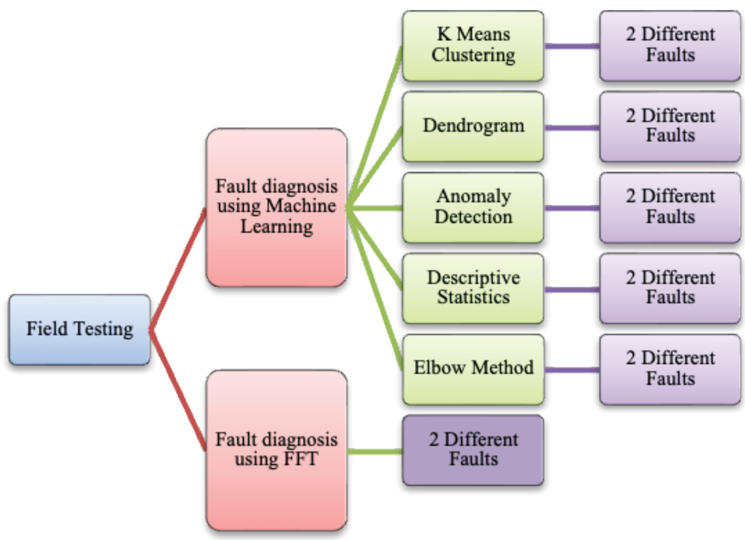


Figure 1. Operational framework.

4 channel FFT analyzer. A vibration signal is obtained in channel 1 (CH1) in vertical (V) and channel 2 (CH2) in horizontal (H) direction at bearing. Time and frequency signal shows the fault frequencies for unbalance and misalignment. To get confirmation of faults machine learning techniques are implemented. Unsupervised machine learning clearly separates the faults and also clustering helps in pattern recognition for anomaly detection.

Induced Draft Fan

Figure 1 shows bearings and shaft of ID fan used in paper mill plant. Specification of ID fan is as tabulated in Table 1.

Experimentation

Vibration data live measured on the bearings of ID fan. The three piezoelectric accelerometers (Sensitivity: 100mv/g) are used to collect the vibration signals in Channel 1 (CH1) in vertical (V), Channel 2 (CH2) in horizontal (H) and Channel 3 (CH3) in axial (A) direction at bearings as shown in Figure 3. Vibration data is collected using vibration analyser (Make: SKF Model: CMXA75).

The overall RMS amplitude of the drive end (DE) bearing in both the vertical and horizontal directions falls within the restricted (alarm) zone, as per ISO 10816-3. Similarly, the overall RMS amplitude of the non-drive end (NDE) bearing is in the critical zone in the vertical direction and in the restricted (alarm) zone in the horizontal direction, as per ISO 10816-3. Consequently, the vibration data from channels CH1 and CH2 are utilized for machine learning-based fault diagnosis.

In this study, The ID fan, as shown in Figure 2, served as the primary focus of the investigation. Vibration measurements carried out at both the drive-end (DE) and non-drive-end (NDE) bearings of the rotor, as shown in Figure 3 data collected in three possible directions. These measurements were critical in diagnosing the misalignment fault at the DE and the unbalance fault at the NDE, based on the vibration spectra obtained.

RESULTS AND DISCUSSION

Case Study: Induced Draft Fan Using FFT

The spectrum at DE bearing in vertical direction CH1 and horizontal direction CH2 are shown in Figure 4. It is observed that axial vibration is less than vertical and horizontal direction. 1X and 2X peak is observed in vertical

Table 1. Specification of induced draft fan

Parameters	Specification
Speed	1440 rev/min
No. of blades	12
Driven	Induction motor
Power	20 Hp
Motor bearing	6203
Fan bearing	22214-EKW-33J

Table 2. Overall amplitude in three directions

Speed (rev/min)	RMS amplitude (mm/s) before alignment and balancing			
	Bearing end	Direction		
		V	H	A
1142	**DE**	5	4.6	2.87
	NDE	8.9	5.8	3.09

DE: Drive-end; NDE: Non-drive-end.

Figure 2. Induced draft fan in a paper mill plant.

Figure 3. Accelerometer mounting on the bearing of the induced draft fan.

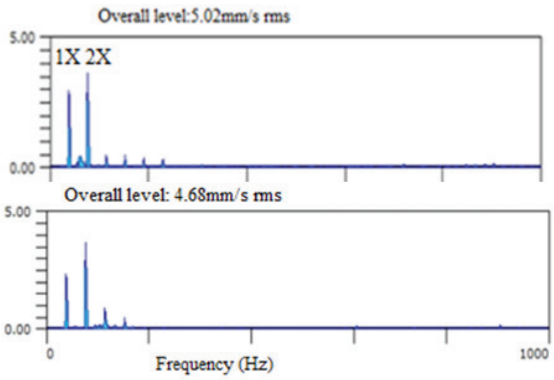


Figure 4. FFT at DE bearing in vertical and Horizontal direction.

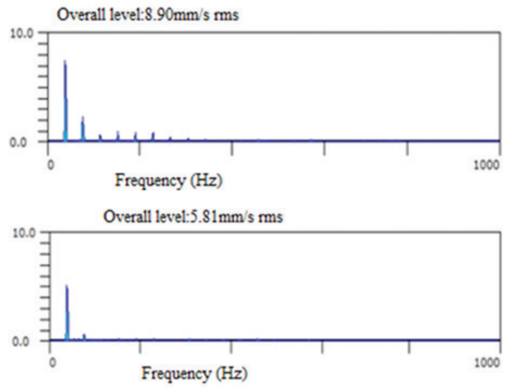


Figure 5. FFT at NDE bearing in vertical and horizontal direction.

and horizontal direction. 2 X peak is higher than 1X. It is cleared that misalignment fault is observed in coupling. The spectrum at NDE bearing in vertical direction and horizontal direction are shown in Figure 5. 1X peak is observed in vertical and horizontal direction. It is clear that unbalance fault is observed in fan. Unbalance fault is developed due to deposition of ash or the wear of the fan blades.

Machine Learning Technique

ML approach now a days very useful in fault detection and categorization. This section covers the unsuprvised ML learning approach contribution in fault findings of ID fans. Vibration signals can be continuously collected by accelerometers placed at critical locations such as DE and NDE bearings. The data preprocessing used various methods to assured high quality data for machine learning models. Unwanted noise can filtered using a band pass filter to eliminate irrelevant low frequency and high frequency noise, to ensure critical frequency ranges related to ID fan faults. FFT applied for feature extraction and time domain signals were transformed into the frequency domain. Frequncy graph gives 1X and 2X harmonics related to faults. Real time signal processing techniques such as FFT and machine learning analysis can be performed on these dataset, ensuring minimal latency. Data need to be normalized to remove the outlier can caused by sensor errors or transient vibrations Z-score normalization has been employed which eliminate extreme anomalies. However, to ensure consistency in variables and enhance clustering accuracy min max scalar has been adopted to normalized the extracted features. In this way, preprocessing steps assured the reliability and suitability of the input data for fault indentification for futher analysis like ML techniques. Various unsupervised ML techniques used for in depth analysis has been covered in next sections.

Number of Faults Detection Using Clustering at Location DE

Machine learning techniques are very useful and popular in collaboration with experimental case study to confirm the fault anomalies in mechanical systems. The present work examines clustering techniques for fault diagnosis in mechanical systems by utilizing vibration data from two channels (CH1 and CH2) at the DE and NDE bearings. The primary faults examined by FFT is "Unbalance" and "Misalignment," which are routine issues in rotating machinery. To evaluate the effectiveness of clustering algorithms based on silhouette score is an essential indicator, specifically when it related to fault anomaly. A high silhouette score means that the samples are well clustered, however a score at or below zero indicates overlapping clusters. The silhouette score runs from -1 to +1. Two components are needed to calculate the silhouettes score for a single sample: the mean nearest cluster distance (b) and the mean intra cluster distance (a). Next, the definition of the silhouette score (s) is given by equation 1.

$$S = \frac{(b-a)}{\max(a,b)} \tag{1}$$

In this case, "a" represents the sample's average distance to every other point in its cluster, and "b" for the sample's average distance to the neighboring cluster. In clustering techniques, silhouette analysis helps to determine the optimal number of clusters that best represent the inherent fault conditions present in the collected data. K-means clustering was selected to identify clusters in vibration signal data collected from DE and NDE of machinery.

The Table 3 indicates that two clusters were formed in both channel readings (CH1 and CH2), correlated with the different fault detected by each channel. The silhouette scores achieved for these clusters were significantly high, CH1 achieves a maximum score of 0.996187 and CH2 reaches to 0.981164 for two clusters. This further supports the importance of the clustering approach in anticipating specific fault conditions. Above analysis aids in validating the clustering results and an invidance

Table 3. Number of clusters at location DE based on silhouette_score

Number of Clusters at Location DE	Silhouette_score	
	CH1	CH2
2	0.996187	0.981164
3	0.980444	0.967254
4	0.918261	0.926722
5	0.87416	0.810565
6	0.873087	0.811231
7	0.866591	0.659165
8	0.663202	0.576284
9	0.594666	0.586448

to support a robust framework to implement unsupervised machine learning techniques in fault detection scenarios.

Present study applied clustering techniques to the acquired vibration signal at the DE end bearing, with the number of clusters determined based on the silhouette score as indicated in Table 3. Silhouette score of both CH1 and CH2 for DE end cluster wise illustrated in Figure 6. It provides insight into the optimal number of clusters for each channel. Figure 7 shows visualization of cluster for CH1 and figure 8 for CH2 based highest silhouette scores. Which clearly highlights the separation between clusters and confirms the identification of distinct fault patterns at each location.

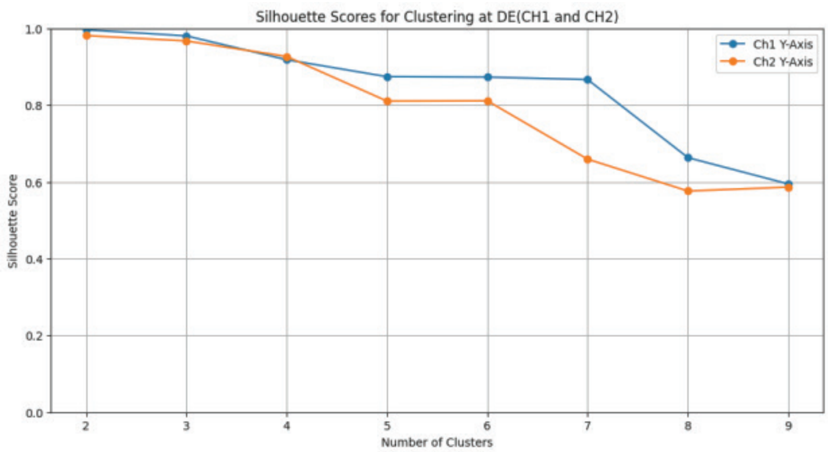


Figure 6. Cluster wise silhouette_score for CH1 and CH2.

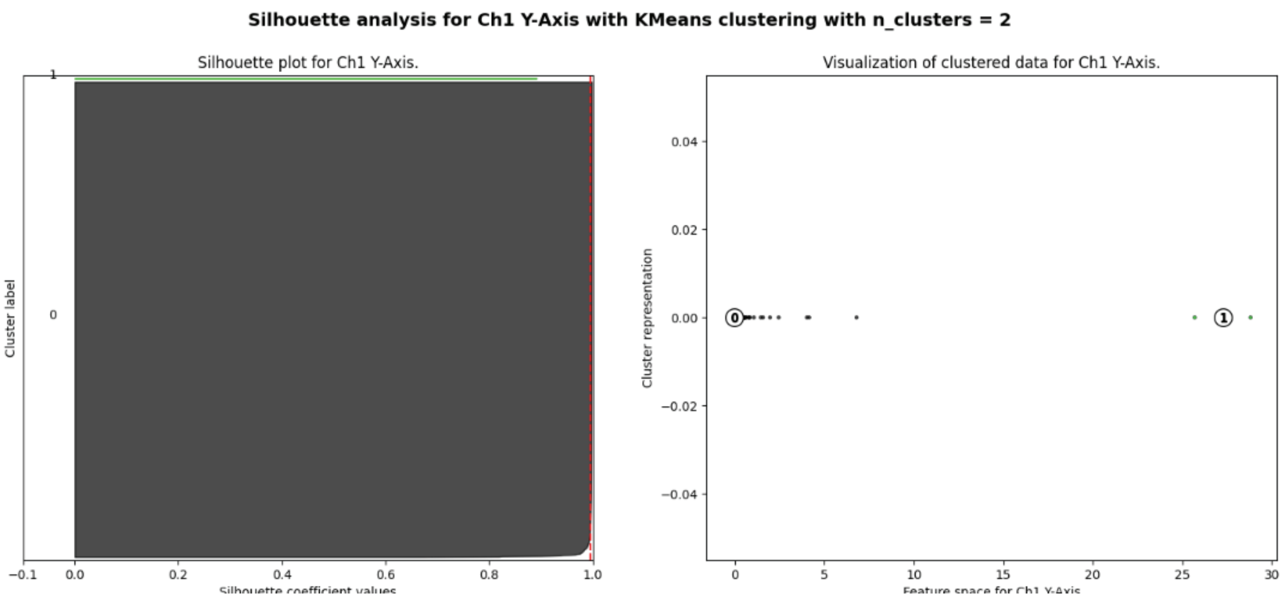


Figure 7. Visualization of Clusters for CH1 based on highest silhouette_score.

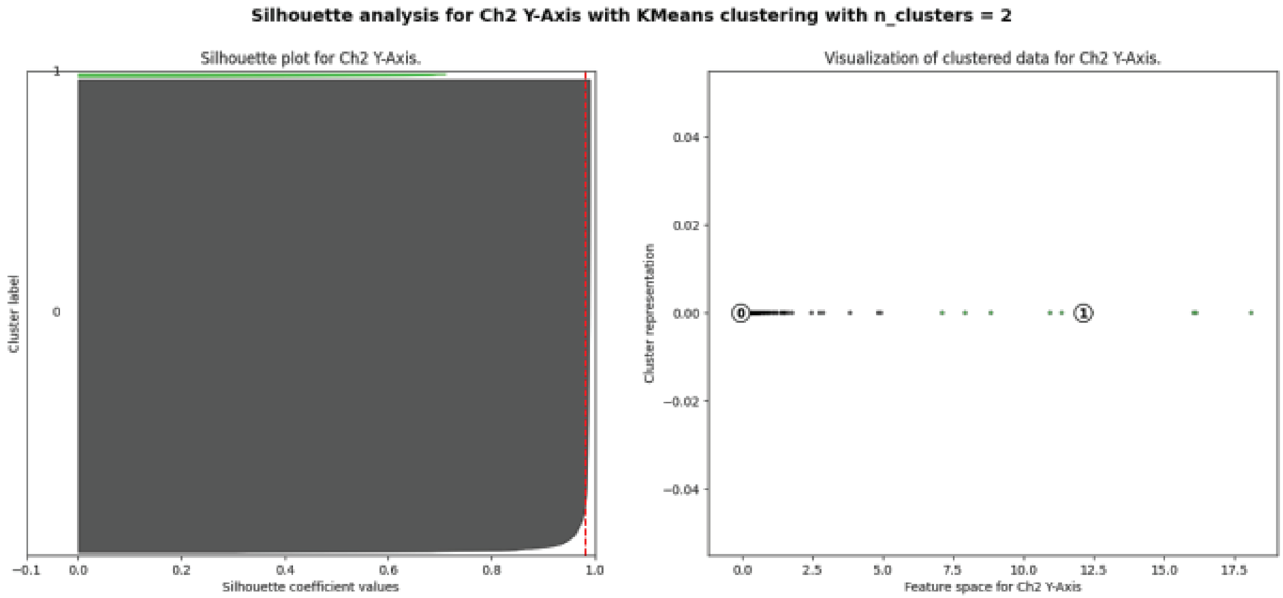


Figure 8. Visualization of Clusters for CH2 based on highest silhouette_score.

Dendrogram for Optimal Clustering

When using hierarchical clustering, a dendrogram is an effective tool that helps visualize the links and cluster structure among data points. It uses a tree shape diagram to show data points joined or seperated according to their relative similarity to produce clusters. Dendrogram determines optimal number of clusters are best for fault identification. A dendrogram is created by starting with every data point as a separate cluster. Clusters are progressively combined according to a predefined distance metric that measures dissimilarity from one another as the algorithm goes on. Iterative process continues till every point in dataset is convert into a cluster and provides a complete picture of the hierarchical structure for whole dataset. Dendrogram indicates that two distinct clusters were formed which reveals that different fault conditions present in the vibration signal data. Through investigation of the dendrogram, it has been quite clear that a point where the vertical line can be drawn to yield two clusters represents an significant level of separation and can distinguished the faults type. In this way, visual representation complements quantitative measures achieved by silhouette score. The confirmation of two clusters through the dendrogram envidence to the findings obtained from other clustering techniques and ensures a robust analysis of fault conditions in machinery.

The dendrogram analysis performed for both CH1 and CH2 confirms the presence of two optimal clusters

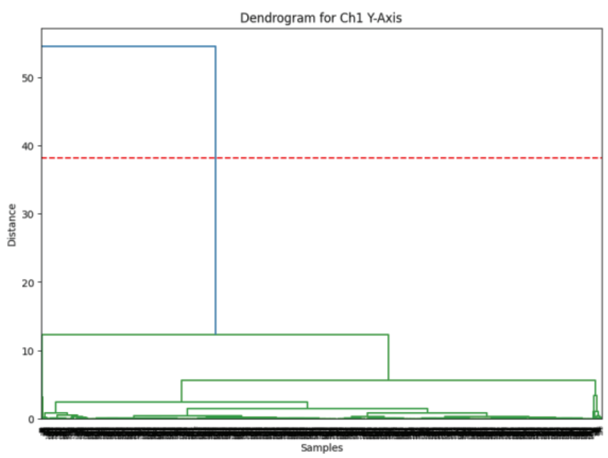


Figure 9. Dendrogram analysis showing 2 optimum clusters for CH1.

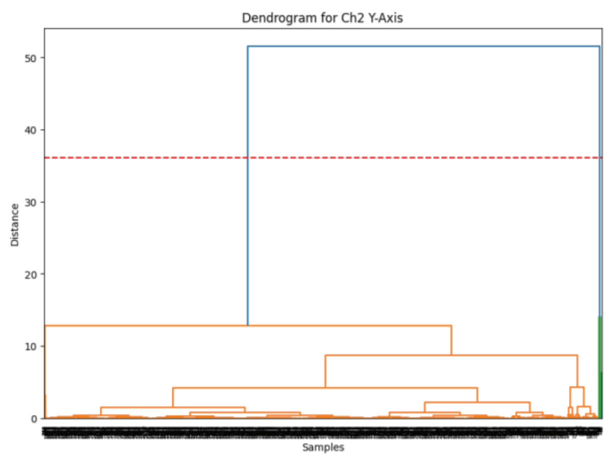


Figure 10. Dendrogram analysis showing 2 optimum clusters for CH2.

at each location. Figure 9 presents the dendrogram for CH1, shows two distinct clusters based on the hierarchical clustering method. Similarly, Figure 10 shows the dendrogram for CH2, reveals two optimal clusters indicates fault detection at both location. These analyses further validate the clustering results obtained through machine learning methods, ensuring accurate fault detection at both locations.

Elbow Method for Optimal Clustering

The author suggested elbow method one more approach to futher authenticate the results obtained through dendrogram a visual technique and silhouette score as quantitative approach. It plots within cluster variance against the total number of clusters is necessary to determine the elbow point or a point at which the rate of variation drastically drops. Ideal balance achieves between model complexity and interpretability by optimal number of clusters. The elbow method was applied to assess various cluster configurations. The results showed a pronounced decline in within cluster variance as the number of clusters increased. However, after reaches two clusters, the reduction in variance became less significant indicates a plateau. Plateau suggests that adding more clusters beyond this point does not significantly enhance the model ability to capture the data structure.

Dendrogram visualizations and silhouette scores results of two clusters further validated by complementary analysis of elbow method. Silhouette analysis indicated high values for two clusters and dendrograms illustrated a clear separation at two clusters, strengthen the conclusion that two distinct fault conditions are present in the data. It ensure that the selected model accurately represents the underlying characteristics of the machinery operational states. The Elbow method has been employed to determine the optimal number of clusters for both CH1 and CH2, as depicted in Figure 11 and Figure 12, respectively.

Anomaly Identification in Fault Diagnosis

Author proposed additional technique like anomaly identification pattern recognition technique serves as a powerful tool in the realm of fault diagnosis, specifically in identify the unusual patterns in signals. Anomaly pattern idetification technique was employed to recognize deviations from normal operational behavior of the vibration signals obtained from channels CH1 and CH2,. This technique aids in pinpointing potential faults that may not be normally noticeable through standard analysis procedure. The application of anomaly detection yielded two distinct patterns for both CH1 and CH2. First pattern aligned with unbalance and the other can line up with misalignment. While analyzed the vibration data, it can possible to isolate these patterns, confirms the presence of two clusters corresponds to the anticipated faults. The incorporation of anomaly detection with clustering techniques intensify the overall diagnostic capabilities. Clustering helps in grouping similar data points and locate general fault types. However, anomaly detection techniques focuses on unusual behavior within clustering groups. This comprehensive analysis with dual approach authenticate realtime machinery condition, leads to plan to more efficient maintenance strategies to improve operational reliability. Thus, the identification of two noticeable patterns strengthen the conclusion that each channel exhibits specific fault characteristics, further validate the importance of the adopted methodologies in fault diagnosis.

Anomaly indentification by pattern recognition has been employed to analyze the fault conditions at CH1 and CH2. Figure 13 demonstrates the anomaly detection at DE end bearing, authenticate clear pattern that aligns with the previously detected misalignment fault condition. Similarly, Figure 14 illustrates the anomaly detection at NDE end bearing, reveals a pattern consistent with the unbalance fault also authenticate by other methods. Above results further confirms the accuracy of the fault diagnosis and provide an additional layer of validation by pattern recognition technique.

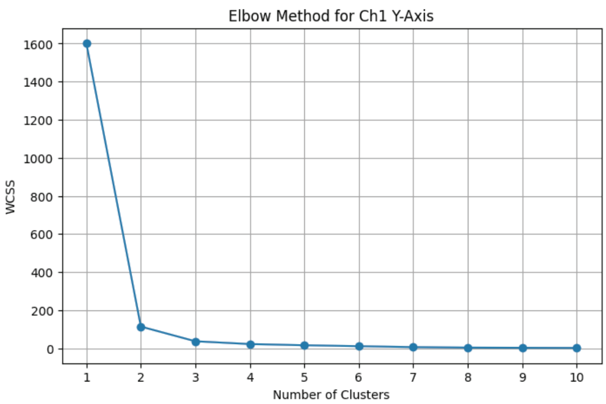


Figure 11. 2 optimal clusters for CH1.

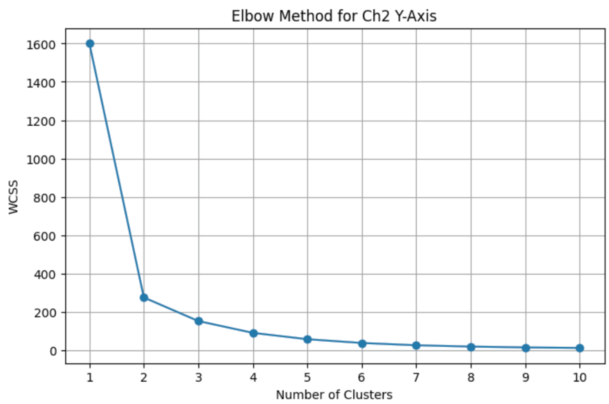


Figure 12. 2 optimal clusters for CH2.

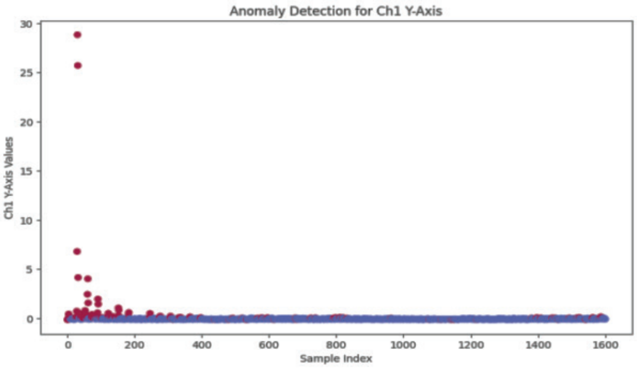


Figure 13. Anomaly detection for CH1 by pattern recognition.

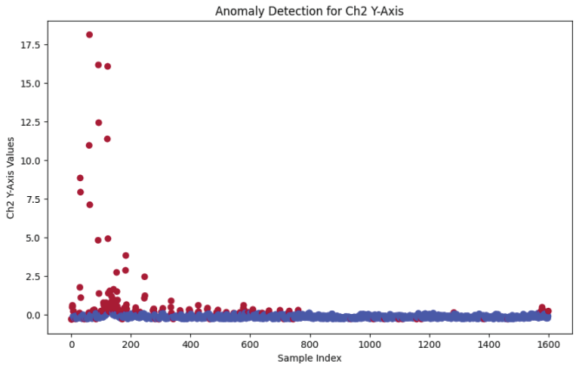
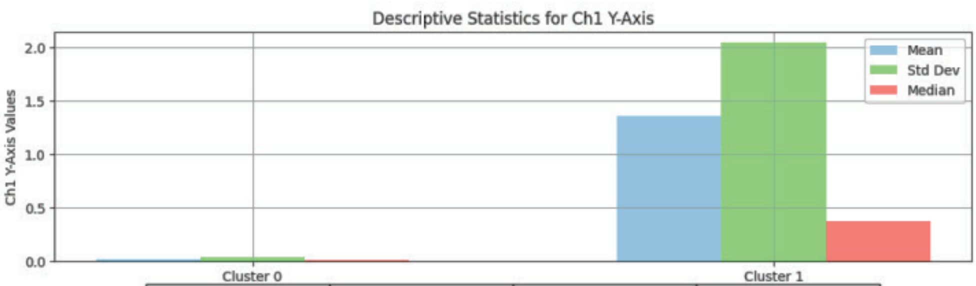


Figure 14. Anomaly detection for CH2 by pattern recognition.

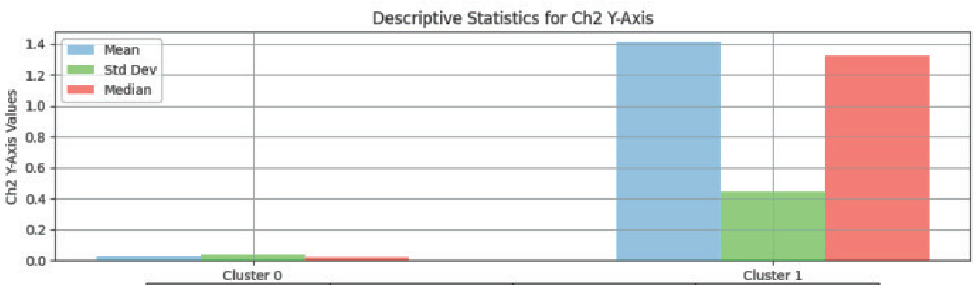
Descriptive Statistics

Current study employed one more analysis technique descriptive statistics play a pivotal role to identify and interpret the clusters within datasets, specifically for fault recognition and monitor through vibration analysis. summarized the characteristics of each cluster, descriptive statistics provides valuable insight into the behavior and properties of the dataset. It measures of central tendency, like the mean and median, indicates the central location of data points, reveals stark contrast between clusters. A mean of 0.0155 for Cluster 0 in Ch1 Y-Axis suggests lower vibration amplitudes compared to a mean of 1.3598 for Cluster 1, underline potential the fault states. Dispersion measures through standard deviation recognize about variability within each cluster; a lower standard deviation for Cluster 0 indicates consistent behavior, while a higher value for Cluster 1 may signal unconsistent presence associated with faults. Additionally, the ability to compare these statistics across clusters underscores their uniqueness, confirms that each cluster represents a distinct operating condition of the



Cluster	Mean	Std Dev	Median
0.0	0.015532166457286433	0.03959707933439678	0.010506
1.0	1.359789888888889	2.038202950162008	0.376439

Figure 15. Clusterwise descriptive statitics for CH1.



Cluster	Mean	Std Dev	Median
0.0	0.023896584170854267	0.03506183411912171	0.017039
1.0	1.406869	0.4453526574289189	1.323255

Figure 16. Cluster wise descriptive statitics for CH2.

machine. Altogether, descriptive statistics not only validate clustering results but also provide actionable insights that can guide to plan maintenance strategies.

Descriptive statistics were performed for each cluster at both DE and NDE end to further analyze the vibration data. Figure 15 shows descriptive statistics for CH1 and representation of statistical parameters such as the mean, median, and standard deviation. It provides detailed insight into the characteristics of each cluster. Figure 16 displays the descriptive statistics for CH2, offers a statistical representation of the clusters. Statistical analysis highlights the difference between clusters and support the detection of distinct fault patterns at each location. Y-axis indicates the presence of two distinct clusters in both the figures, suggests the possibility of two different faults in the system. The CH1 in figure 15 shows mean value of 0.015532 and standard deviation value of 0.039597 without cluster, while the adding cluster shows a significantly rise in mean value reaches to 1.359790 and a standard deviation achives 2.038203 wihich is much higher. This stark contrast implicit that the underlying mechanisms contributing to the measurements, indicates the presence of distinct fault patterns. Similarly, from figure 16, the without cluster has a mean of 0.023897 and a standard deviation of 0.035062, where the second cluster's mean of 1.406869 and standard deviation of 0.445353. Significant differences in both the means and variabilities confirms the hypothesis of different fault conditions. Descriptive statistics approach highlights the potency of clustering techniques to recognize and differentiate faults, ultimately enables more targeted troubleshooting and maintenance strategies.

Histograms and Gaussian curves for both DE and NDE shown in figure 17 and figure 18 provides a visual representation of vibration data within each cluster. Figure 17

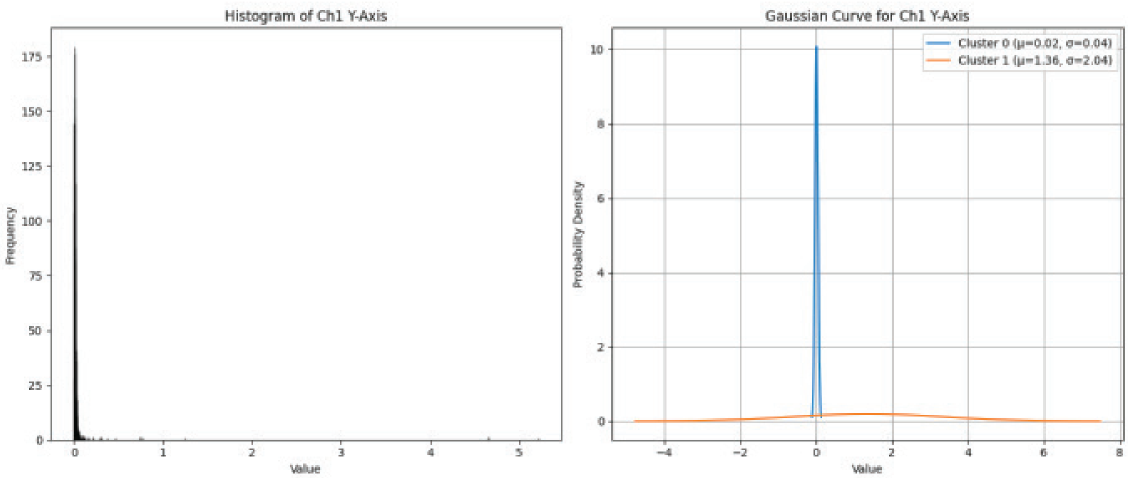


Figure 17. Histogram and gaussian curve for CH1.

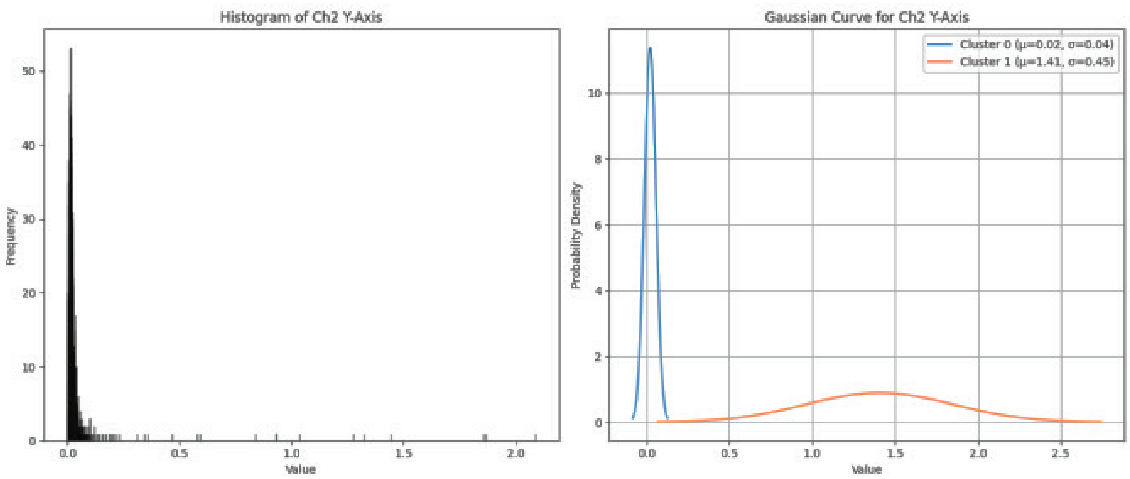


Figure 18. Histogram and gaussian curve for CH2.

Table 4. Cluster wise result analysis

Sr. No.	Channel	Location	Method	Criteria	Number of clusters	Number of possible faults
1	CH1	DE	K means	Max silhouette score	2	1
2			Dendrogram (hierarchical clustering)	Threshold line	2	1
3			Elbow method	Variance	2	1
4			Anomaly detection	Pattern	2	1
5			Descriptive statistics	Mean, mode, median, standard deviation, distribution	2	1
6	CH2	DE	K means	Max silhouette score	2	1
7			Dendrogram (hierarchical clustering)	Threshold line	2	1
8			Elbow method	Variance	2	1
9			Anomaly detection	Pattern	2	1
10			Descriptive statistics	Mean, mode, median, standard deviation, distribution	2	1
11	CH1	NDE	K means	Max silhouette score	2	1
12			Dendrogram (hierarchical clustering)	Threshold line	2	1
13			Elbow method	Variance	2	1
14			Anomaly detection	Pattern	2	1
15			Descriptive statistics	Mean, mode, median, standard deviation, distribution	2	1
16	CH2	NDE	K means	Max silhouette score	2	1
17			Dendrogram (hierarchical clustering)	Threshold line	2	1
18			Elbow method	Variance	2	1
19			Anomaly detection	Pattern	2	1
20			Descriptive statistics	Mean, mode, median, standard deviation, distribution	2	1

illustrates the histogram and Gaussian curve for DE end, shows the frequency distribution and it confirms that data to be normal distribution within the identified clusters. Similarly, figure 18 presents the histogram and Gaussian curves for NDE end bearing and frequncy data distribution visual and further supports the differentiation between the clusters. Visualizations are crucial to interpret the underlying patterns in the vibration signals and to validate the accuracy of fault diagnosis. Detail results for location DE and NDE for CH1 and CH2 are tabulated in Table 4.

The author proposed a novel unsupervised machine learning approach for fault idetification can be effectively implemented in real time industrial settings to strengthen modern data acquisition and processing technologies. K-means clustering algorithm computational efficiency can operate linear time complexity and shows its suitability for deployment on low-power industrial IoT platforms. System can automatically detect anomalies of fault patterns such as unbalance or misalignment based on clustering results and trigger alerts or schedule predictive maintenance to prevent unexpected equipment failures. Integrating unsupervised ML techniques into existing condition monitoring systems, industries can improve operational efficiency, reduce downtime, and optimize maintenance strategies, to enhance overall productivity and reliability.

CONCLUSION

The experimental results with unsupervised machine learning techniques reveals that without the need of label dataset the unspurivised ML techniques can use underlying data patterns to give a valuable insights. Multiple ML algorithms, including K-means clustering, hierarchical clustering, and anomaly detection can successfully identified two distinct faults patterns which also shown by FFT for CH1 and CH2 at two both DE and NDE bearing location. Accelerometers at DE end bearing mounted for both vertical (CH1) and horizontal (CH2) directions, characterized by FFT a higher 2X peak in both directions indicates a misalignment fault. Similarly, at NDE end CH1 and CH2 FFT signifies a significant 1X peak can be intimated as a unbalance fault, likely due to ash deposition or fan blade wear. To validate the result by FFT current study employed various unsupervised machine learning algorithms. Clustering techniques has been adopted and findings reveals the effectiveness of the ML approaches to detect and distinguish between misalignment and unbalance faults. Dendrogram used to visualize the clustering results, elbow method for optimal clustering and descriptive statistics for statistical analysis, ensures more precise fault diagnosis and system reliability. Above all methods can accurately distinguish misalignment and unbalance faults. The present study used a novel unsupervised ML approaches for fault diagnosis can be used to optimize maintenance strategies.

AUTHOR CONTRIBUTIONS

All authors contributed to the study conception and design. material preparation, data collection and analysis were performed by [Ramesh Bhandare and Pankaj Beldar]. The first draft of the manuscript was written by [Ramesh Bhandare], review and editing done by [Shyam Mogal].

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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