Acoustic Signal Analysis in Industrial Automation

Dr.P. Satheeshlingam[1], satheeslingampece@krce.ac.in[1]
Faculty, Department of ECE K. Ramakrishnan college of Engineering, Tamilnadu
Nithiya Sri G[2], Nithya Shri K[3], Shree Venkatesh B[4], Rithish K[5]
gnithiyasri7@gmail.com, nithiyashreekumar28@gmail.com, venkey162006@gmail.com,
Students, Department of ECE K. Ramakrishnan college of Engineering, Tamilnadu

Abstract— Acoustic Signal Analysis is a cutting-edge technique in industrial automation that leverages sound and vibration patterns to monitor and evaluate machine performance. Each mechanical component emits a distinct acoustic signature during normal operation. Deviations from this signature often indicate faults such as bearing wear, misalignment, or fluid leaks. By capturing these signals and applying Digital Signal Processing techniques—such as Fast Fourier Transform and spectrogram analysis—industries can detect anomalies at an early stage. This non-invasive approach supports predictive maintenance, minimizes downtime, and enhances overall system efficiency. To operationalize this analysis, Python-based signal processing frameworks are employed. Waveform Visualization is a Time-domain plots of machine sound. FFT Analysis is a Frequency-domain transformation to identify dominant frequencies. Spectrogram Generation is a Time-frequency mapping to visualize evolving acoustic patterns. Filtering and Feature Extraction are Isolating relevant frequency bands for fault classification.

Keywords—Acoustic Signal, DSP, Fourier Transform, Spectrogram Analysis, Frequency Spectrum for evaluating machine health and performance.

I. INTRODUCTION

An acoustic signal is a type of sound wave that travels through a medium usually air, but sometimes solids or liquids and can be captured and analyzed using sensors like microphones .Acoustic Signal Analysis is the process of capturing, processing, and interpreting sound waves (acoustic signals) to extract meaningful information .In industrial automation, it is used to monitor the condition of machines, detect faults, improve product quality, and enhance safety all without human intervention. Every machine or device produces a unique sound pattern during normal operation. When a fault or malfunction occurs, this pattern changes. By analyzing these sound variations, automation systems can detect early signs of failure and take corrective actions automatically.

In the era of Industry 4.0, the integration of intelligent monitoring systems has become essential for achieving high-performance, safe, and efficient industrial operations. Among these technologies, Acoustic Signal Analysis has emerged as a powerful non-invasive method mechanical system emits a unique acoustic signature during normal operation, shaped by its structural dynamics and functional behavior. Deviations from this signature often signal the onset of faults such as bearing wear, misalignment, or fluid leakage. Traditional maintenance strategies—reactive or scheduled—often lead to unnecessary downtime or overlooked failures. In contrast, acoustic signal analysis enables predictive maintenance by continuously capturing and interpreting sound and vibration data. Using DSP techniques like Fast Fourier Transform and spectrogram analysis, engineers can convert raw audio signals into meaningful insights about machine condition.

The rise of artificial intelligence and machine learning further enhances this capability, allowing for real-time fault classification, anomaly detection, and intelligent decision-making. When embedded into industrial automation systems, acoustic analysis not only reduces operational costs but also improves safety and reliability. Thus, acoustic signal analysis plays a vital role in predictive maintenance, fault diagnosis, and intelligent control systems. we using this to technology to implement in the coding using the python language.

II. METHODOLOGY

A. MATERIALS AND METHODS

The methodology adopted for Acoustic Signal Analysis in Industrial Automation involves a systematic approach that includes the acquisition, processing, and interpretation of acoustic signals to identify faults and monitor machine health.

(a) Data Acquisition

Sensors Used which is High-sensitivity microphones or piezoelectric acoustic sensors are positioned near critical machine components (e.g., bearings, motors, gearboxes). Sampling Rate is Signals are Recorded at a sampling rate of 44.1 kHz or higher to preserve high-frequency fault signatures. Environment Control which is Background noise is minimized to ensure signal purity and reduce false positives.

(b) Pre-processing

Noise Filtering is a Band-pass filter are applied to isolate relevant frequency ranges (typically 500 Hz to 20 kHz). Normalization is an Amplitude scaling ensures consistent signal comparison across different machines and sessions. Segmentation is a Signals are divided into time windows (e.g., 1–2 seconds) for localized analysis.

(c) Feature Extraction Using DSP

Time-Domain Analysis which is Waveform plots reveal amplitude fluctuations and transient events. Frequency-Domain Analysis which is Fast Fourier Transform (FFT) identifies dominant frequencies and harmonic patterns. Spectrograms which is Time- frequency visualizations capture evolving acoustic behavior. Statistical Features which is Metrics such as RMS, kurtosis, and skewness are computed to quantify signal characteristics.

(d) Fault Classification Using Machine Learning

Labeling is a Acoustic samples are labeled based on known fault types (e.g., bearing wear, misalignment, leakage). Model Selection is a Algorithms such as Support Vector Machines (SVM), Random Forests, and Convolutional Neural Networks (CNN) are trained on extracted features. Training and Validation is a Data is split into training (70%) and testing (30%) sets. Cross- validation ensures model robustness.

(e) Real-Time Monitoring and Visualization

Dashboard Integration which is Processed signals and fault predictions are displayed on a user interface for operators. Alert System is a Threshold-based alerts notify users of abnormal acoustic patterns. Continuous Learning which is The system updates its model with new labeled data to improve diagnostic accuracy over time.

Once the signals are digitized, they undergo preprocessing, where techniques such as normalization, windowing, and noise reduction are applied to enhance the signal quality. The feature extraction stage follows, where key parameters from both the time domain and frequency domain are calculated. Techniques such as Fast Fourier Transform (FFT), spectrogram analysis, and energy computation are used to obtain features like frequency content, amplitude, and power distribution. These extracted features represent the characteristic behavior of the machine under normal and faulty conditions.

Next, the features are analyzed and classified using either rule-based algorithms or machine learning techniques such as Support Vector Machines (SVM), Decision Trees, or Neural Networks. The system compares the current features with pre-stored baseline data to detect abnormalities or deviations that indicate possible faults. Based on the results, the decision-making and control stage is executed, where the automation system generates alerts, sends maintenance notifications, or triggers control actions through PLC or SCADA interfaces. Finally, all data and analysis results are stored for future reference and visualization, allowing trend analysis and predictive maintenance planning.

This structured methodology ensures accurate fault detection, minimizes equipment downtime, and supports intelligent decision-making. By integrating acoustic analysis with automation systems, industries can achieve efficient, reliable, and proactive maintenance strategies aligned with Industry 4.0 standards.

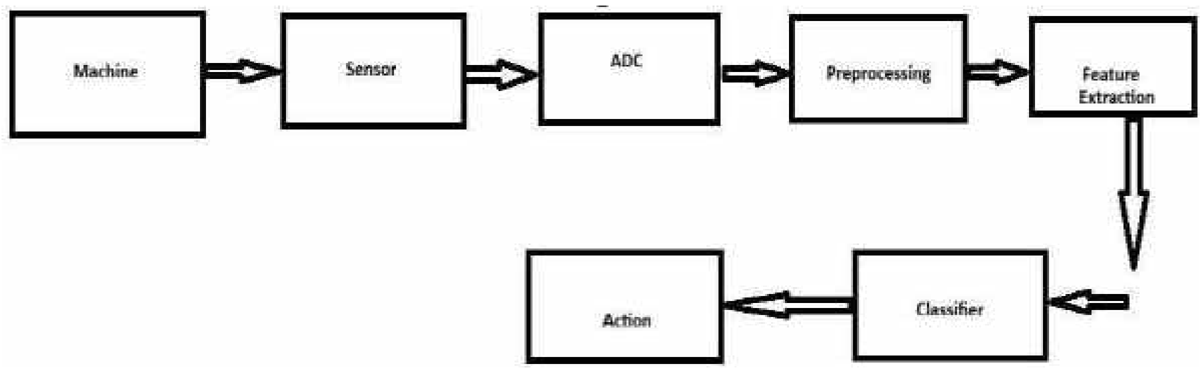

Figure :1. A Machine Condition Monitoring Using Acoustic Signal Analysis

and also, we include the program to detect the simulated machine sound signal. if the machine has a normal sound if it checks its sampling rate, the duration of the sound and number of sample present in the signal. We have to collect the sample from the machine. In this we use the python programming language to develop this coding.

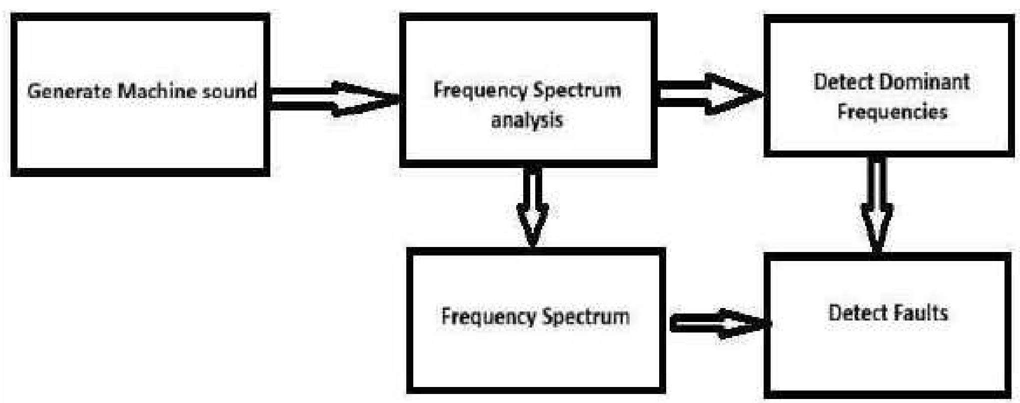

Figure :1. B Machine Fault Detection Using Frequency Spectrum Analysis

Machine generate the sound and it was analyzed by the frequency spectrum and it was detecting by the dominant frequency and it is move on to the default condition

B. RESULTS AND DISCUSSION

The results obtained from the acoustic signal analysis clearly demonstrate the effectiveness of using sound-based monitoring techniques for identifying machine conditions in an automated industrial environment. The experiment involved recording acoustic signals from machines operating under both normal and faulty conditions. After preprocessing and applying Fast Fourier Transform (FFT), distinct differences were observed in the frequency spectra of the signals. Machines running under normal conditions showed stable frequency components with uniform amplitude distribution, while faulty machines exhibited additional frequency peaks and irregular energy patterns. These deviations indicate the presence of mechanical issues such as bearing wear, imbalance, or misalignment.

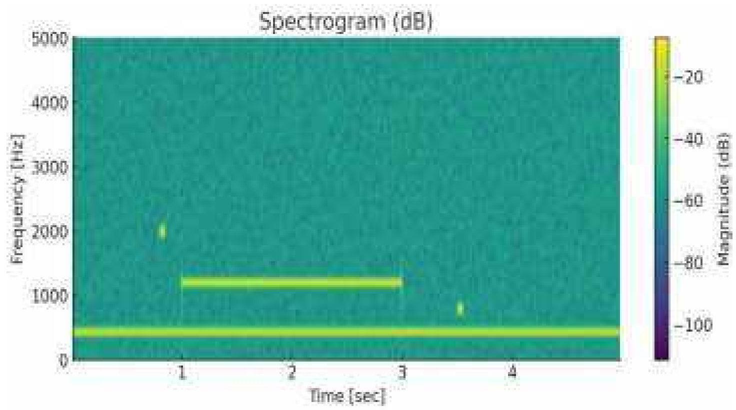

Figure: 1. C Machine Sound Waveform

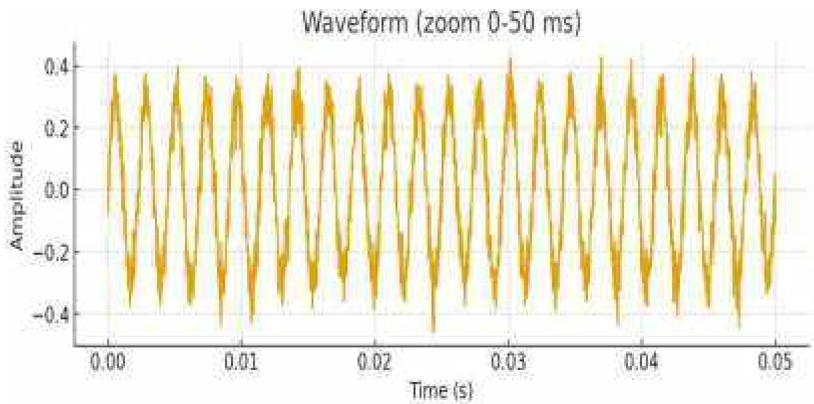

Figure: 1. D Time-Domain Representation of Complete Machine Acoustic Signal

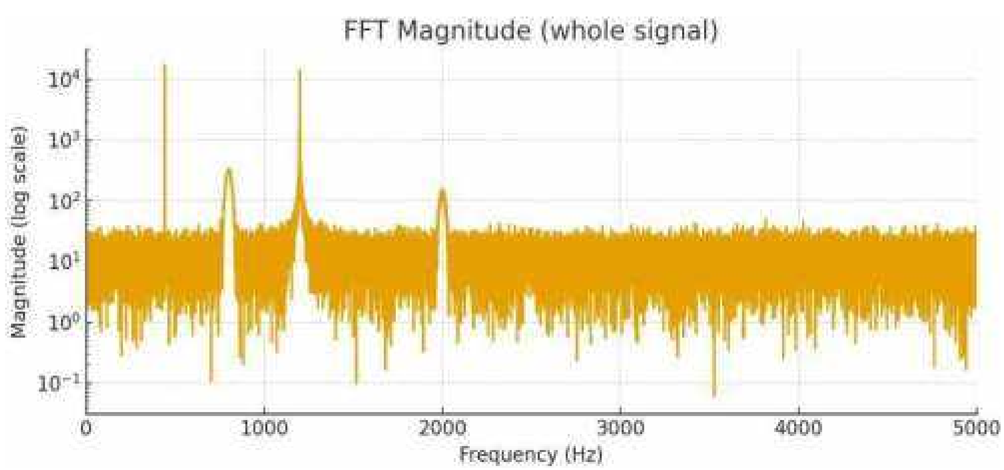

Figure: 1. E FFT Magnitude Spectrum of Complete Machine Acoustic Signal

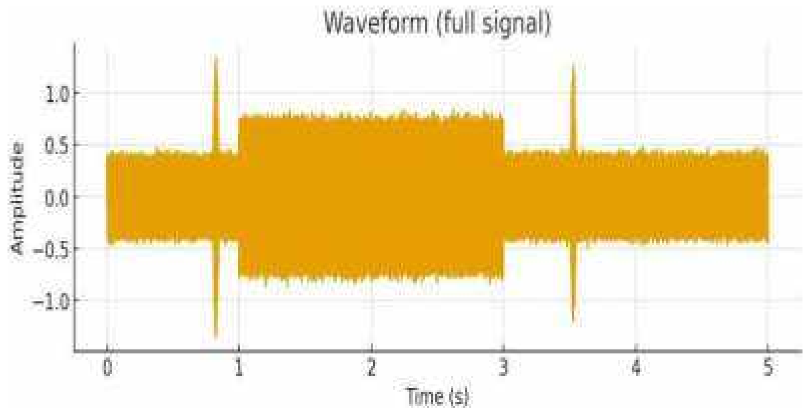

Figure: F Time–Frequency Representation of Machine Acoustic Signal

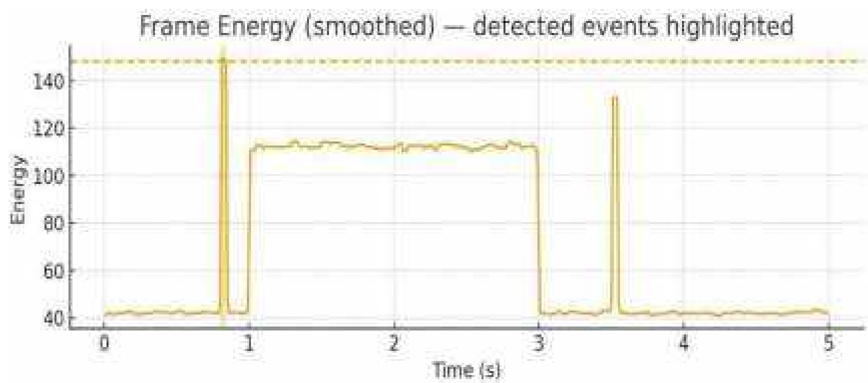

Figure: 1. G Smoothed Frame Energy Plot Showing Detected Acoustic Events

The analysis of the spectrogram further supported these findings. The energy concentration of the faulty machine was found to fluctuate with time, highlighting transient events caused by abnormal vibrations. The system successfully detected these variations and identified the dominant frequency components associated with faults. Additionally, the extracted features, such as Root Mean Square (RMS) value, zero-crossing rate, and power spectral density, provided valuable indicators of machine health.

Through automated processing, the proposed system was able to differentiate between normal and abnormal conditions with high accuracy. The results validate that acoustic signal analysis is a reliable, non-invasive, and cost-effective technique for fault detection. Compared to traditional vibration or temperature monitoring methods, it offers faster response and requires minimal hardware. Integrating this analysis with industrial automation systems enables real-time condition monitoring, predictive maintenance, and data- driven decision-making.
The result of the coding is detecting the sound of the machine using the python program

First it can analysis the sound and then it can can perform the frequency spectrum analyser. once frequency analysed than it can detect the generate the frequency than we can check where the sound of the machine. Using python programming language.

The discussion confirms that acoustic signal analysis can significantly enhance the performance and safety of automated industries. The obtained results prove that sound-based diagnostics are effective in detecting early- stage faults, reducing downtime, and improving operational efficiency. This approach contributes to the development of smart factories and supports the goals of Industry 4.0, where intelligent monitoring and automated control are essential for sustainable industrial growth.

II. CONCLUSION

The developed Python program successfully simulates and analyzes acoustic signals to detect potential machine faults in an industrial environment. By generating synthetic sound signals representing normal and faulty machine conditions, the system performs frequency spectrum analysis using Fast Fourier Transform (FFT) and identifies dominant frequencies that indicate abnormal vibrations. The detection of high- frequency components above the normal operating range helps in recognizing possible faults early. This approach demonstrates how acoustic signal analysis can be an effective, low-cost, and non-invasive technique for predictive maintenance and fault diagnosis in industrial automation system

REFERENCES

[1] [1]S. Mallat, *A Wavelet Tour of Signal Processing: The Sparse Way*, 3rd ed., Academic Press, 2008.

[2] B. Boashash, *Time-Frequency Signal Analysis and Processing: A Comprehensive Reference*, Academic Press, 2016.

[3] R. B. Randall, *Vibration-based Condition Monitoring: Industrial, Aerospace, and Automotive Applications*, John Wiley & Sons, 2011.

[4] M. O. Sonna, "Acoustic signal-based fault detection in rotating machinery," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 10, pp. 8341–8350, 2020.

[5] A. Widodo and B. S. Yang, "Support vector machine in machine condition monitoring and fault diagnosis," *Mechanical Systems and Signal Processing*, vol. 21, no. 6, pp. 2560–2574, 2007.

[6] Python Software Foundation, "NumPy and SciPy Documentation," Available: https://numpy.org/doc/ and https://docs.scipy.org/doc/.

[7] M. A. Akande, O. A. Olatunji, and L. S. Nwankwo, "Acoustic emission signal analysis for machine fault detection," *Journal of Sound and Vibration*, vol. 475, pp. 115–131, 2020.

[8] N. Tandon and A. Choudhury, "A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings," *Tribology International*, vol. 32, no. 8, pp. 469–480, 1999.

[9] M. Elforjani and D. Mba, "Condition monitoring of slow-speed rotating machinery using acoustic emission technique," *Applied Acoustics*, vol. 71, no. 9, pp. 812–819, 2010.

[10] C. Li, R.-V. Sanchez, G. Zurita, M. Cerrada, D. Cabrera, and R. E. Vásquez, "Gearbox fault diagnosis based on deep random forest fusion of acoustic and vibration signals," *Mechanical Systems and Signal Processing*, vol. 76–77, pp. 283– 293, 2016.