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A REVIEW ON Machinery Fault Diagnosis in Electric Motors Through Mechanical Vibration Monitoring Using Fiber Bragg Grating-Based Accelerometers

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Abstract - This paper presents a fault diagnosis system for electric motors using mechanical vibration monitoring with Fiber Bragg Grating (FBG)-based accelerometers. The system analyzes vibration signals under one healthy and nine faulty conditions, including bearing defects, rotor bar faults, misalignment, and imbalance. By extracting frequency-domain features from vibration spectra, the study identifies characteristic patterns such as high-order harmonics and slip frequencies associated with different faults. Machine learning techniques are applied, where the k-Nearest Neighbors (kNN) algorithm achieves 100% accuracy in classifying fault conditions, while k-means clustering validates fault grouping without labeled data. The results demonstrate that FBG-based sensors combined with intelligent algorithms provide an effective, reliable, and non-invasive solution for real-time motor condition monitoring and predictive maintenance in industrial applications

Context and Motivation: With the rise of Industry 4.0, reliable fault detection in electric motors is crucial to reduce downtime and maintenance costs. Mechanical vibration monitoring using advanced sensors like Fiber Bragg Grating (FBG) accelerometers offers accurate and real-time diagnostics.

Problem Statement / Objective: The objective is to detect and classify faults in electric motors such as bearing defects, rotor bar failures, misalignment, and imbalance.

Proposed Solution Overview: The approach uses Fiber Bragg Grating (FBG)-based accelerometers to capture vibration signals and applies machine learning techniques like k-Nearest Neighbors (kNN) and k-means clustering for fault identification.

Design Summary: A system with two FBG accelerometers, vibration data acquisition, FFT-based signal analysis, and ML models have been designed and tested on multiple fault conditions.

Expected Outcome: The system enables accurate fault detection (up to 100% classification accuracy) and supports predictive maintenance, improving efficiency and reducing industrial losses.

Keywords— FBG sensors, vibration analysis, fault diagnosis, FFT, machine learning

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OVERVIEW

The paper "Machinery Fault Diagnosis in Electric Motors Through Mechanical Vibration Monitoring Using Fiber Bragg Grating-Based Accelerometers" focuses on improving fault detection in electric motors using advanced sensing and data analysis techniques. With increasing industrial automation and the need for reliable machinery, early fault detection has become essential to reduce downtime, maintenance costs, and system failures. The study introduces the use of Fiber Bragg Grating (FBG)-based accelerometers for monitoring mechanical vibrations in electric motors. Unlike conventional sensors, FBG sensors offer advantages such as immunity to electromagnetic interference, high sensitivity, and suitability for harsh industrial environments. These sensors detect vibration by measuring wavelength shifts in optical fibers, which correspond to changes in acceleration. To evaluate the system, experiments were conducted using a machinery fault simulator under ten different conditions, one healthy and nine faulty cases. The faults considered include bearing defects, broken rotor bars, misalignment, and imbalance. For each condition, vibration signals were collected and analyzed to identify distinct patterns associated with specific faults. The methodology involves processing vibration data using Fast Fourier Transform (FFT) to convert signals into the frequency domain. This helps in identifying key features such as high order harmonics (for bearing faults) and slip frequencies (for rotor faults). These features form the basis for intelligent fault diagnosis. To enhance analysis, the paper integrates machine learning techniques. A supervised learning method, k-Nearest Neighbors (kNN), is used for classification of fault conditions, achieving very high accuracy. Additionally, an unsupervised approach using k-means clustering is applied to group similar fault patterns without labeled data. Dimensionality reduction using PCA is also used for better visualization and analysis of data patterns. The system design includes FBG sensors, an optical interrogator for data acquisition, signal processing techniques, and machine learning models for classification and clustering. The experimental results demonstrate that the proposed approach can accurately detect and distinguish between different fault conditions.

PROBLEM STATEMENT

Electric motors play a vital role in industrial applications, and their unexpected failures such as bearing defects, broken rotor bars, misalignment, and imbalance can lead to significant downtime, increased maintenance costs, and reduced system reliability. Conventional fault diagnosis techniques, including current, temperature, and acoustic analysis, often have limitations such as lower sensitivity, complex implementation, and vulnerability to electromagnetic interference. Mechanical vibration analysis is a promising non-invasive approach, but accurately identifying and classifying faults from vibration signals remains a challenge due to complex signal patterns and the need for precise sensing and analysis. Hence, there is a need to develop an advanced fault diagnosis system that utilizes high sensitivity sensors and intelligent algorithms to reliably detect, analyze, and classify different motor faults in real time, improving predictive maintenance and overall industrial efficiency.

OBJECTIVES

- To develop an effective system for detecting faults in electric motors using mechanical vibration monitoring.
- To utilize Fiber Bragg Grating (FBG)-based accelerometers for accurate and interference-free vibration sensing.
- To identify different motor faults such as bearing defects, rotor faults, misalignment, and imbalance.
- To analyses vibration signals using signal processing techniques like FFT to extract fault-related features.
- To implement machine learning algorithms (kNN and k-means) for fault classification and clustering.
- To evaluate the performance and accuracy of the proposed system under various fault conditions.
- To support predictive maintenance by enabling early and reliable fault detection in industrial applications

MOTIVATION

With the rapid growth of industrial automation, electric motors are widely used in critical applications where reliability is essential. Unexpected failures due to faults such as bearing damage, rotor issues, or misalignment can lead to significant downtime, increased maintenance costs, and loss of productivity. Traditional fault detection methods often lack accuracy and may be affected by electromagnetic interference. Therefore, there is a strong need for a reliable, non-invasive, and real-time monitoring system. Fiber Bragg Grating (FBG) sensors offer high sensitivity and robustness in harsh environments, while machine learning techniques enable intelligent fault identification. This motivates the development of an advanced system for efficient and accurate motor fault diagnosis.

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CORE OF THE PAPER

1. L. Macedo et al., "Machinery fault diagnosis in electric motors through mechanical vibration monitoring using fiber Bragg grating-based accelerometers," IEEE Sensors Journal, vol. 24, no. 13, July 2024.

Paper presents a novel approach for fault diagnosis in electric motors using mechanical vibration monitoring with Fiber Bragg Grating (FBG)-based accelerometers. The core contribution lies in integrating optical sensing technology with intelligent data analysis to improve fault detection accuracy and reliability. The system uses two FBG accelerometers mounted on motor bearings to capture vibration signals under different operating conditions. These sensors measure wavelength shifts caused by mechanical vibrations, which are then processed to obtain vibration spectra using FFT. Distinct fault signatures are identified, such as high-order frequency components for bearing faults and slip frequency sidebands for broken rotor bars. A key aspect of the paper is the application of machine learning techniques for fault analysis. A supervised learning model (k-Nearest Neighbors) is used for classification, achieving very high accuracy, while an unsupervised method (k-means clustering) is applied to group similar fault patterns without labeled data. Feature extraction includes parameters like wavelength shift, skewness, kurtosis, and frequency variance. The experimental validation is performed using a machinery fault simulator with multiple fault conditions, demonstrating the effectiveness of the proposed system. The results confirm that FBG-based sensing combined with machine learning provides a reliable solution for accurate fault diagnosis and supports predictive maintenance in industrial systems.

METHODS USED

The paper adopts a systematic methodology combining sensing, signal processing, and machine learning for fault diagnosis in electric motors. First, Fiber Bragg Grating (FBG)-based accelerometers are used to measure mechanical vibrations from the motor. These sensors detect changes in wavelength corresponding to vibration-induced strain. The accelerometers are mounted on motor bearings and tested under one healthy and multiple fault conditions. Next, the acquired vibration signals are processed using Fast Fourier Transform (FFT) to convert time-domain data into frequency-domain spectra. This helps in identifying characteristic fault features such as high-frequency harmonics (bearing faults) and slip frequencies (rotor faults). After feature extraction, statistical parameters like wavelength shift, skewness, kurtosis, and frequency variance are used as input features. Finally, machine learning techniques are applied:

- k-Nearest Neighbours (kNN) for supervised fault classification
- k-means clustering for unsupervised grouping of fault conditions

This approach enables accurate detection and classification of different motor faults.

KEY FINDINGS

- FBG-based accelerometers effectively detect mechanical vibrations and identify different motor faults with high sensitivity.
- Distinct vibration patterns were observed for each fault type:
- High-order frequency components for bearing faults.
- Slip frequency sidebands for broken rotor bars.
- The system successfully distinguished between healthy and faulty conditions using vibration spectrum analysis.
- The k-Nearest Neighbours (kNN) algorithm achieved 100% accuracy in fault classification.
- k-means clustering showed effective grouping of fault conditions, even without labelled data.
- The combination of optical sensing and machine learning proved reliable for fault diagnosis. The approach supports real-time monitoring and predictive maintenance, reducing downtime and maintenance costs

LIMITATIONS

- The study is conducted using a controlled laboratory setup, which may not fully represent real industrial environments.
- The system requires specialized FBG sensors and optical interrogators, which can increase initial cost.
- Accurate fault detection depends on proper sensor placement and calibration.

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- The machine learning model (kNN) relies on labelled data, which may not always be available in real applications.
- Limited number of fault types and conditions were tested, so generalization to all real-world faults is uncertain.
- Data processing and analysis may require skilled personnel and computational resources.

WORKING

DATA ACQUISITION

- Two flexible hinged Fiber Bragg Grating (FBG) accelerometers are mounted on the motor bearings.
- When the motor operates, faults like bearing damage or rotor issues create mechanical vibrations.
- These vibrations cause strain in the optical fiber, leading to a shift in Bragg wavelength.
- This wavelength shift represents the vibration signal of the motor.

SIGNAL PROCESSING

- The optical signal is captured using an optical interrogator.
- The collected data is converted from time-domain to frequency domain using Fast Fourier Transform (FFT).
- This generates a vibration spectrum, which helps identify fault specific frequency patterns.

FAULT IDENTIFICATION USING MACHINE LEARNING

From the vibration spectrum, important features are extracted.

Supervised Learning (kNN)

- The extracted features are fed into a k-Nearest Neighbours (kNN) model.
- oThe model compares new data with trained data and classifies the type of fault.

Unsupervised Learning (k-means Clustering)

- oData is grouped into clusters without labels.
- Helps identify whether the motor is healthy or faulty even without prior training data.

FAULT DETECTION OUTPUT

•The system identifies:

- bearing faults → High-frequency harmonics
- rotor faults → Slip frequency sidebands

•The output indicates the type and severity of the fault.

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COMPARISION OF TECHNIQUES

Year	Technique	Paper Name	Methods Used	Key Findings	Limitations
2011	Machine Learning-Based Methods	Artificial Neural Network-Based Fault Diagnostics of an Electric Motor Using Vibration Monitoring – Rad et al.	ANN, feature extraction	High accuracy in fault classification	Requires labelled data
2014	Wavelet Transform-Based Methods	Vibration Analysis for Bearing Fault Detection and Classification Using an Intelligent Filter Zarei et al.	CWT, time frequency analysis	Better detection of transient faults	High computational complexity
2022	FBG Sensor Based Monitoring	A Fiber Bragg Grating Based Accelerometer for Monitoring the Vibration of an Industrial Engine Prototype: A Preliminary Study Silveira et al.	Optical sensing + vibration analysis	High sensitivity, EMI immunity	High cost, complex setup
2024	FBG Sensor Based + AI/ML System	Machinery Fault Diagnosis in Electric Motors Through Mechanical FBG	FBG + FFT + kNN + k means	100% accuracy, reliable fault detection	Controlled environment, high cost

TABLE 1 TECHNIQUE COMPARISION

RESEARCH GAPS

- The proposed system is validated only using a machinery fault simulator, not in real industrial environments, limiting practical applicability.
- The approach relies on controlled experimental conditions (e.g., constant temperature), while real-world environments involve varying temperature and noise, which may affect sensor performance.
- The study uses offline data analysis, indicating a lack of fully implemented real-time fault detection systems.
- The machine learning model (kNN) depends on labelled datasets, which may not always be available in practical scenarios.
- Only a limited number of fault conditions are considered, so the system may not generalize well to all types of industrial faults.
- The system uses only vibration data, without integrating other parameters like temperature or current for improve accuracy.
- High dependency on FBG-based sensors, which are costly and complex compared to conventional sensors, may limit large-scale deployment.
- The paper suggests the need to optimize data processing (number of data points), indicating scope for improving computational efficiency.

TRENDS

- Shift from traditional monitoring methods (current, temperature analysis) to vibration-based fault diagnosis due to its non-invasive and effective nature.
- Integration of signal processing techniques (FFT) to extract meaningful frequency-domain features from vibration data.
- Growing use of machine learning algorithms for automatic fault classification and pattern recognition.
- Increasing focus on predictive maintenance instead of reactive maintenance to reduce downtime and costs.

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- Development of multi-functional sensing systems capable of detecting multiple fault types simultaneously aligned with Industry 4.0 concepts.

ADVANTAGES

- High sensitivity and accuracy: FBG-based accelerometers can detect small vibration changes, enabling precise fault identification.
- Immunity to electromagnetic interference (EMI): Optical sensing ensures reliable performance in electrically noisy industrial environments.
- Non-invasive monitoring: Fault detection is done without disturbing motor operation.
- Early fault detection: Capable of identifying faults at initial stages through vibration patterns.
- High classification accuracy: Machine learning (kNN) achieved up to 100% accuracy in fault detection.
- Multi-fault detection capability: Can detect various faults like bearing defects, rotor faults, misalignment, and imbalance.
- Supports predictive maintenance: Helps reduce downtime and maintenance costs.
- Suitable for harsh environments: Optical sensors are corrosion-resistant and safe.

DISADVANTAGES

- High cost of implementation: FBG sensors and optical interrogators are expensive.
- Complex system setup: Requires careful installation, calibration, and expertise.
- Limited real-world validation: Tested mainly in controlled laboratory conditions.
- Dependence on labelled data: Supervised learning (kNN) requires training data.
- Temperature sensitivity issues: Temperature effects are neglected in experiments but may impact real applications.
- Computational requirements: Signal processing and ML increase processing complexity.
- Limited fault coverage: Only selected fault conditions were analysed.

REAL WORLD USAGE

- **Industrial Motor Condition Monitoring**
  - FBG sensors are used to monitor vibration in electric motors, gearboxes, and rotating machinery.
  - Helps detect faults like bearing failure, rotor defects, and imbalance in early stages.
  - Used in industries such as manufacturing, power plants, and automation systems.
- **Railway and Transportation Systems**
  - FBG sensors are used to measure rail vibration and train movement.
  - Helps in detecting track faults and improving safety.
- **Oil and Gas Industry**
  - Used in pumps, compressors, and drilling equipment for fault detection.
  - Helps monitor components operating in harsh and submerged environments.
- **Automotive and Mechanical Systems**
  - Used for monitoring engine vibration, noise, and performance (NVH analysis).
  - Helps in improving vehicle safety and efficiency.
- **Research and Smart Monitoring Systems (Industry 4.0)**
  - Integrated with IoT and AI-based systems for real-time monitoring.
  - Used in smart factories and automated diagnostics systems.

CASE STUDIEs

Case 1: Industrial Motor Fault Diagnosis System

- The simulator ran between 17-35 RPS. This was done to separate motor‘s nominal frequency harmonics from grid frequency harmonics.
- The system was implemented on a machinery fault simulator with an electric motor.
- Two FBG-based accelerometers were mounted on motor bearings to capture vibration signals.

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- The setup tested 10 conditions (1 healthy + 9 faulty cases) including:
  - Bearing defects
  - Broken rotor bars
  - Misalignment
  - Imbalance
- Vibration data was processed using FFT and ML algorithms.

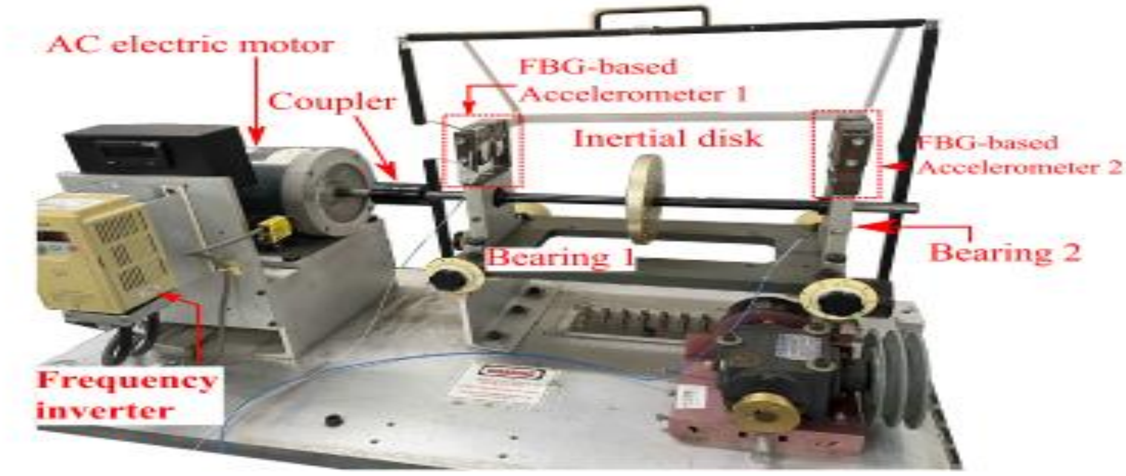

FIG 1 Fault Simulator

Case Study 2: Bearing Fault Detection using Frequency Analysis

- The system analysed vibration signals to detect bearing faults.
- Due to faulted bearing defects caused impacts which led to appearance of High-order Harmonics
- Using FFT, high-order harmonics were identified as fault signatures.
- Statistical features like kurtosis and skewness were used for classification.

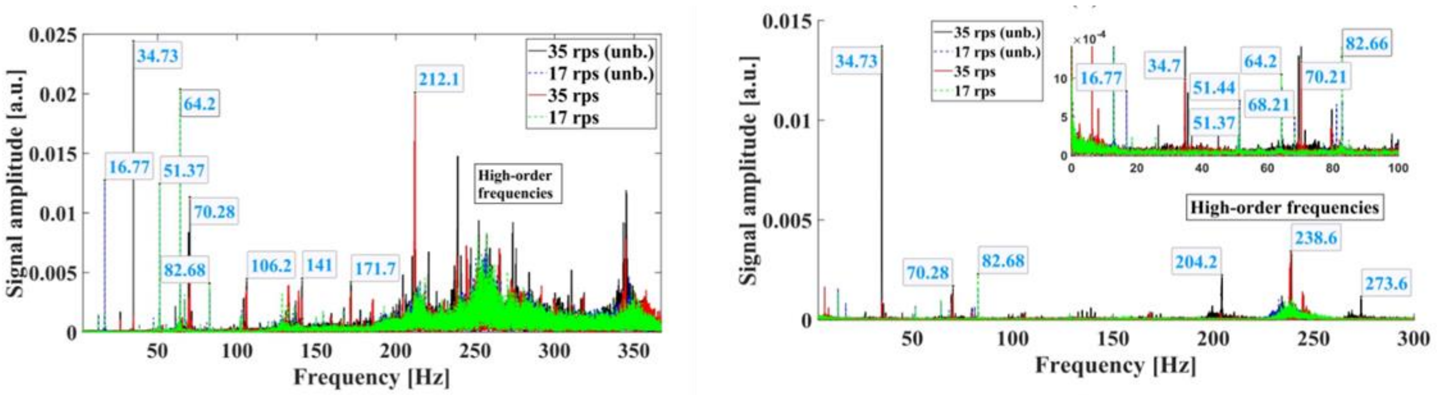

FIG 2 Vibration Spectra for Bearing Fault

Case Study 3: Broken Rotor Fault Detection using Frequency Analysis

- The system identified rotor faults by analysing vibration spectra.

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- Broken Rotor's created Magnetic Field Imbalance this led to production of Slip frequency side bands around the Main frequency.
- Faults were detected using slip frequency sidebands in the frequency domain.
- Machine learning helped classify rotor faults accurately.

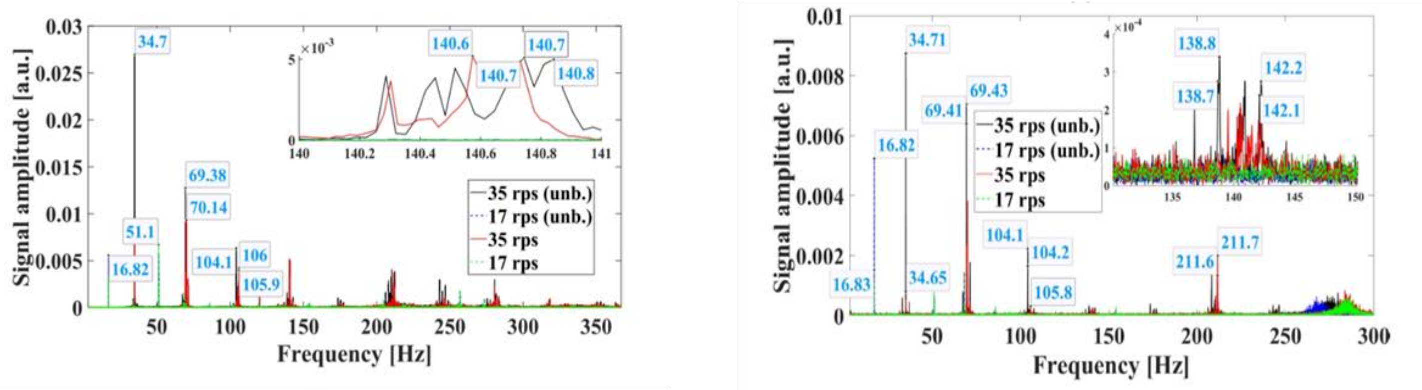

FIG 3 Vibration Spectra for Internal Bearing Fault

Case Study 4: Internal Bearing Fault Detection using Frequency Analysis

- This fault causes air-gap eccentricity (uneven gap between rotor and stator).
- Due to this Magnetic flux becomes non-uniform, Machine inductance varies and Vibration signal becomes distorted
- This results in Multiple Harmonics with High Order frequencies being introduced.

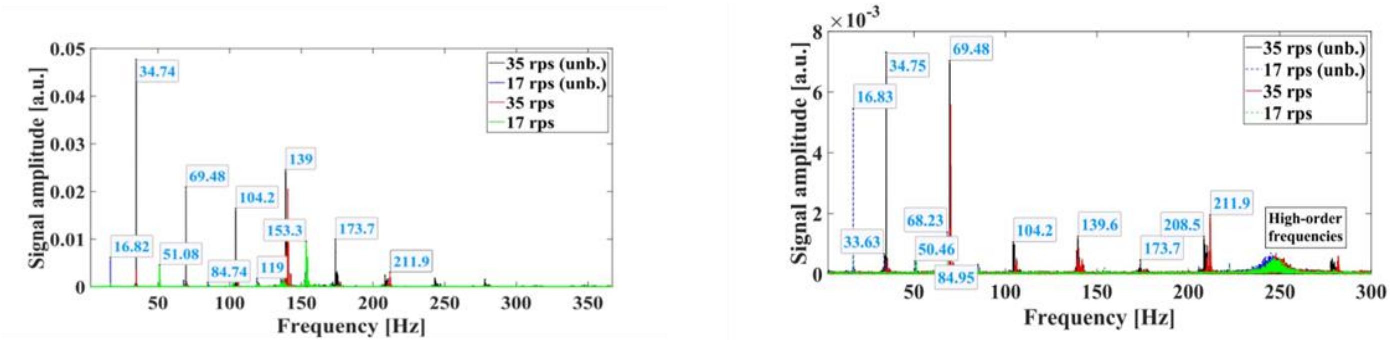

FIG 4 Vibration Spectra for Broken Rotor Fault

Case Study 5: Intelligent Fault Classification using Machine Learning

- Features were extracted from the Data from accelerometers placed on the Fault Simulator.
- These features were fed into kNN (Supervised Learning) and k-means clustering (Unsupervised Learning) ML algorithms.
- Supervised learning is a machine learning method where the model is trained using labeled data.
- Unsupervised learning is a machine learning method where the model is trained using unlabeled data.

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LIMITATIONS

- **High cost of FBG systems:** Optical sensors and interrogators are expensive, limiting large-scale deployment.
- **Complex installation and calibration:** Requires precise mounting and skilled personnel.
- **Controlled environment validation:** The system is mainly tested in laboratory conditions, not real industrial setups.
- **Dependence on labelled data:** Supervised methods like kNN require prior training datasets.
- **Limited fault coverage:** Only a specific set of faults (bearing, rotor, misalignment, imbalance) are analysed.
- **Temperature effects ignored:** Sensor performance may vary in real environments due to temperature changes.
- **Single-parameter analysis:** Focuses mainly on vibration without combining other current, temperature signals.

TECHNICAL CHALLENGES

- **Real-time implementation:** Converting offline analysis into real-time monitoring systems is challenging.
- **Noise and signal interference:** Industrial environments introduce noise affecting accuracy.
- **Data processing complexity:** FFT and machine learning increase computational requirements.
- **Sensor placement optimization:** Incorrect placement can reduce fault detection accuracy.
- **Scalability issues:** Difficult to implement across large industrial setups.

FUTURE SCOPE

- Develop real-time fault diagnosis systems instead of offline analysis for continuous monitoring.
- Design low-cost FBG or hybrid sensor systems to improve affordability and scalability.
- Extend the system to detect additional fault types and complex multi-fault conditions.
- Improve early fault detection (incipient faults) using high-resolution sensing and advanced analytics.
- Implement Edge computing or Cloud system solutions to enable faster decision-making.
- Enhance robustness by considering temperature variations and environmental effects.

EMERGING TRENDS

- Integration of Artificial Intelligence (AI) and Deep Learning for improved accuracy and automation.
- Use of IoT-enabled smart monitoring systems for remote diagnostics and control.
- Development of digital twins for real-time simulation and predictive maintenance.
- Adoption of multi-sensor fusion (vibration + current + temperature) for better fault analysis.
- Advancement in optical sensing technologies with higher sensitivity and compact designs.

CONCLUSION

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