A Literature Review: Bearing Fault in BLDC Motor Based on Vibration and Thermal Signals

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Received: March 06, 2025; **Accepted:** April 21, 2025

***Abstract*—This review of the literature looks into the use of vibration and thermal signals for the diagnosis and detection of bearing problems in brushless DC (BLDC) motors. The study highlights the efficacy of current developments in diagnostic algorithms and signal processing approaches in detecting bearing irregularities. The comparative study of vibration and heat monitoring techniques is highlighted, along with a discussion of each method's benefits and drawbacks. The integration of various methods for improved fault detection accuracy is also examined in the paper. The results indicate that a hybrid strategy that combines temperature analysis and vibration provides a reliable way to identify BLDC motor problems early on, which could enhance maintenance plans and operational dependability.**

Keywords*— *Bearing Fault Detection, BLDC Motor, Vibration Analysis, Thermal Monitoring, Signal Processing Techniques

I. Introduction

Composed of inner and outer rings with rolling balls in between, bearings are essential parts of electric machinery. They are essential for maintaining a constant air gap between the rotor and the stator, which guarantees the best possible machine performance and efficiency. Bearings also transmit loads and support the stability and dependability of the machine. In order to avoid problems that might seriously affect machine performance and lifespan, resulting in unplanned failures and downtime, bearings must be properly monitored and maintained [1].

Bearings account for about 40% of induction motor damage, making them extremely prone to failure. Improper installation techniques that result in misalignment and inadequate support, as well as magnetic imbalances that cause unequal loads, are factors that contribute to bearing degradation. Temperature increases brought on by inadequate cooling and extended use of severe loads can deteriorate lubricants and bearing materials. Reduced lubricant amount or quality and imbalanced loading circumstances can further hasten wear and cause early bearing failure. Resolving these problems is essential to improving the longevity and dependability of electric machines. Bearing failures may be considerably decreased and their dependability increased by following the correct installation methods, correcting magnetic imbalances, managing temperatures, guaranteeing load balance, and keeping lubricated [1].

In the ever-changing world of industrial machinery, motors' efficient performance is essential to many processes across several sectors. Motors, the workhorses of many industrial applications, rely on intricate components to function perfectly. Two of these components that are necessary to get optimal performance are bearings and rotors. However, the degradation of these parts over time may lead to operational inefficiencies and, in certain cases, catastrophic failures. The field of motor bearing and rotor defect diagnosis has advanced significantly over time, adjusting to new problems and enhancing detection precision. This development is a result of continuous attempts to use cutting-edge technologies and procedures to improve the operational efficiency and dependability of machines. Traditional methods of motor bearing and rotor monitoring often involved manual assessments and periodic inspections and depended on the knowledge of maintenance personnel. These methods have limitations with regard to proactive intervention and real-time detection, albeit offering initial protection. Due to the extensive use of automation and cutting-edge technology by businesses, modern methods have replaced traditional ones in the monitoring landscape. This change highlights a move toward more accurate and efficient monitoring techniques, which are in line with the changing needs of industries for improved dependability and performance [2].

Researchers have been quantitatively evaluating dynamic reactions for decades using a range of sensors. A machine's condition can be ascertained using a variety of condition monitoring techniques, including vibration analysis, noise analysis, acoustic emission analysis, oil analysis, current and voltage analysis, and thermography [3].

A lot of spinning machinery, including motors and airplane engines, is essential to modern industrial civilization. Extreme working conditions can cause rolling bearings, which are essential and essential parts of machines, to fail. When bearing failures occur, rotating machinery's stability and dependability are compromised, resulting in financial loss and sometimes even fatalities. Designing precise and effective bearing failure diagnostic systems is therefore essential [4].

Electrical machines are widely used in commercial, residential, and industrial settings and are regarded as the foundation of the industry. These electric devices must operate in a variety of environments, including high wetness, fluctuating voltages and currents, severe ambient temperatures, regularly changing load conditions, and overloads that result in malfunctions and failures. Thirty to forty percent of rotating electric machine failures are attributed to bearing defects, which are thought to be the most common sort. According to earlier research, improper lubrication is the cause of 80% of bearing failures. The mechanical stress experienced during rotational movement and bearing currents is the primary source of the rotation that bearings undergo. The major causes of bearing failures include incorrect use, inappropriate maintenance, bad assembly, and poor installation. Current flow in the bearing is dependent on shaft voltages as well as capacitive currents generated by power supply control inverters and frequency. Another reason for bearing failures is contamination, which is mostly brought on by foreign materials in the bearing fluid. The foreign materials include sand and water that seeps past the seal and leads to bearing failures. Machine mechanical and electrical breakdowns have distinct characteristics that make them difficult to diagnose, and the majority of methods use motor current signature analysis (MCSA). The ball bearing in Figure 1 has a damaged cage, material fatigue, and corrosion from moisture [5].

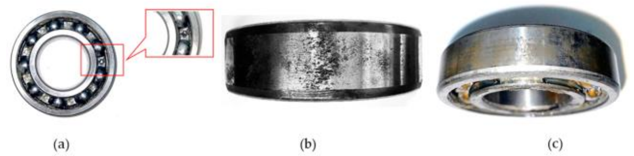

Fig. 1. (a) Structure for ball bearings. (b) A flaw in the outer raceway. (c) A flaw in the inner raceway. [5]

The structure of this document is as follows. The identification of bearing faults is covered in Section 2. The BLDC motor is covered in Section 3. Vibration analysis is then explained in Section 4. Thermal monitoring is also explained in Section 5. Techniques for signal processing are covered in Section 6. Lastly, this paper's conclusion.

II. METHODS

Several crucial phases are often included in the literature review method:

1. Finding pertinent sources, including books, journals, articles, and research papers, is known as source identification.

2. Gathering information from recognized sources is known as data collection.

3. Source evaluation is the process of determining each source's reliability and applicability.

4. Analysis and Synthesis: Examining the data gathered and putting together a summary of the conclusions.

5. Writing a well-organized review that includes an introduction, methods, findings, and commentary is known as review writing.

III. RESULT AND DISCUSSION

A. Bearing Fault Detection

Artificial intelligence (AI) has been widely used in motor defect detection technologies in recent years. Several model architectures and signal processing approaches have been introduced one after the other, all of which have demonstrated great diagnostic performance. The deep belief network was used by Shao et al. to identify induction motor problems. Hoang and Kang et al. created a deep learning and information fusion approach for diagnosing motor-bearing faults. Moreover, Shao et al. used a deep convolutional neural network (CNN) to interpret two-dimensional time-frequency pictures from one-dimensional vibration data in order to identify induction motor problems. In order to distinguish between bearing fault, demagnetization fault, and healthy states, Wang et al. presented a one-dimensional CNN model with many convolutional feature extraction modules. Furthermore, Shifat and Hur used vibration and current signals as inputs to the artificial neural network in order to identify brushless DC (BLDC) motor problems. Even though these techniques are capable of diagnosing motor faults effectively, they need a balanced dataset and a significant quantity of training data to get appropriate diagnostic results. However, motors often run in healthy states in real-world industrial settings, and data collecting systems typically get data from motors that are in good condition. As a result, there are very little motor failure data under different operating settings, which causes significant imbalances in the training data. Overfitting occurs during the model training process due to the imbalance of training data, and the minority class with little data has a poorer accuracy. Because of this, trained deep learning models frequently lack generality and usefulness. Furthermore, identifying defect data under various operating situations is expensive and requires a large number of human resources. The effectiveness of intelligent motor problem diagnostic systems is significantly reduced by these difficulties [6].

Bearing signal fault feature extraction and fault detection under variable speed operations can benefit from the precise local frequency spectrum information of vibration signals that time-frequency analysis can provide. suggested a novel time-frequency analysis technique to eliminate the impact of noise and significantly improve the weak nonlinear frequency modulated signal. suggested a classification approach for bearing faults using several time-frequency curves under situations of time-varying speed. suggested a low-rank, sparse decomposition of time-frequency representation for signals that are very non-stationary. suggested a time-frequency ridge estimation technique for diagnosing bearing faults. Feature extraction may be accomplished automatically using this approach without the need for further parameter changes or modifications [7].

The topic of synchronous motor defect detection has seen a revolution in recent years due to the ongoing advancements in deep learning. By identifying complex patterns and characteristics in the dataset, these deep learning-based models have the amazing capacity to learn how to classify data on their own, providing a revolutionary improvement in the precision and effectiveness of synchronous motor defect detection. For instance, a deep belief network and a sparse auto-encoder were created for defect diagnostics. They suggested a mechanism for fusing features from many sensors. Furthermore, a convolutional neural network for

Journal of Electrical, Electronic, Information, and Communication Technology (JEEICT)
Vol. 07 No. 1, April-2025, Pages 10-15 DOI: https://doi.org/10.20961/jeeict.7.1.100165

detecting permanent magnet synchronous motor problems was demonstrated. suggested a two-feature extraction technique to identify demagnetization and bearing faults. developed a new recurrent neural network based on attention to identify short-circuit problems [8].

Neural networks have been utilized extensively in recent years to analyze motor vibration signals and identify induction motor problems using extension neural networks (ENNs). Because of its exceptional qualities and potent capacity to extract features from complicated data, such as time-frequency analysis, target tracking, target diagnostics, and face recognition, convolutional neural networks, or CNNs, have found widespread use. suggested a multi-head 1D CNN that uses two accelerometers measuring in different directions to identify and diagnose six distinct sorts of electric motor faults as well as a normal motor. The findings demonstrated the accuracy of the suggested architecture for vibration time series-based multi-sensor fault detection. presented a 1D CNN architecture designed to improve the identification of rotor system faults. Similarly, a method for online bearing defect diagnostics based on 1D CNN and multi-sensor fusion was presented. The analysis of low-speed bearings, the study of multiple-fault diagnosis of marine turbine bearings, and the investigation of bearing fault diagnosis by combining 1D CNN with transfer learning techniques are noteworthy contributions to fault diagnosis using 1D CNN architecture [9].

The effectiveness of bearing failure detectors that employed several shallow neural network topologies—such as self-organizing Kohonen maps (SOMs), networks with radial basis function (RBFs), and multi-layer perceptrons (MLPs)—in detecting and classifying the failures was assessed. The X-axis had the greatest fluctuation after bearing failure and was employed as a defect indicator in this investigation, which monitored the vibration signal for different voltage frequencies and load torque in three axes. In order to leverage vibration harmonic components for signal processing, FFT and HTT were used. The MPL approach reached 100% accuracy in 15 training sessions, but the other approaches required more intricate frameworks to validate the performance of conventional NNs. For automotive applications, a multiscale shared learning network (MSSLN) was suggested for vibration-based bearing defect diagnosis. For five different forms of rotor failure identification in non-stationary situations, a multiscale kernel-based residual CNN (MK-ResCNN) was developed utilizing vibration signals. A deep enough network is unavoidable because to the requirement to extract deep and relevant information from vibration signals, which leads to a degradation issue. To get over this restriction, residual learning is used with MK-CNN in this work. However, the cost and complexity of the system are increased when vibration sensors are used to gather the vibration information [10].

Another bearing defect detection method for different operating situations is based on 2D CNN and Motor current signature analysis (MCSA). This technique avoided the signal-processing step of CNN by using the Garmian angular field (GAF) to translate time-domain current data into 2D pictures. A basic two-layer CNN is trained using the photos to identify bearing problems with a high accuracy of over 99% and a shorter calculation time. In order to get greater accuracy and improved performance during non-stationary operations and changing circumstances, multiscale learning is essential [10].

Numerous convolutional neural network-based techniques are available for system training, including one for defect diagnostics. A diagnosis approach that combines fuzzy entropy and empirical wavelet transform for bearing fault detection has been proposed, along with an intelligent diagnosis method for bearing faults using deep learning and compressed data acquisition. Additionally, a method for classifying transformer winding faults that combines frequency response analysis and support vector machines, a fault diagnosis method for rotating machines based on feature learning of thermal images, and a gear diagnosis method based on particle swarm optimization and probabilistic neural networks have been presented [11].

Applying empirical wavelet transform (EWT) to analyze the Fourier spectrum segments of motor vibration signals extracted by Fast Fourier Transform (FFT) revealed that empirical mode decomposition (EMD) can only extract one temporal frequency of the fault feature frequencies and cannot detect faults under strong noise interference. When comparing and analyzing the efficacy of EWT and EMD using simulated and real data, it was discovered that EWT performs better in weak feature detection and composite fault detection. In order to detect motor bearing faults, the root mean square value of the time domain signal was computed after the inverse Fourier transform was used to determine the time domain contribution of the respective spectral bands [12].

The status of both healthy and defective roller bearings was checked using EMD of acoustic signals derived from kurtosis and crest factors of the time domain. A step-varying vibrational resonance (SVVR) algorithm was proposed to examine the faulty status of a bearing by controlling the various parameters. Results from SVVR showed remarkable accuracy in extracting and improving the weak information status of bearing defect detection in the time domain. Extraction characteristics were evaluated with simulated and real-world signals [13].

B. BLDC Motor

Brushless direct current (BLDC) motors because of their benefits. Because they don't have brushes, BLDC motors are more reliable and have a high power density. A BLDC motor is a synchronous electric motor with a number of permanent magnets on the rotor and windings on the stator. By altering the direction of the magnetic fields produced by the stator coils, the rotor rotates [14].

All EVs are currently powered by permanent magnet (PM) motors, and vibration in PM motor components can reduce ride comfort, produce a lot of noise, and—most importantly—degrade vehicle performance. BLDC motors are widely utilized in modern industries such industrial automation, household appliances, and transportation because of their high power density and durability [15].

Either a Brushless Direct Current (BLDC) motor or an Alternating Current (AC) induction motor. There are benefits and drawbacks to each kind of engine. A revolving magnetic field on the stator is used by both BLDC and induction motors to produce torque on the rotor. The way AC induction motors operate is by using the stator's revolving magnetic field to induce current on the rotor. Torque is produced when the rotor's induced current creates its own magnetic field and combines with the stator's magnetic field. The permanent magnet rotor of the BLDC motor attempts to align itself with the magnetic field produced by the stator coils. By alternating the excitation of the stator windings, the stator magnetic field is rotated, producing motion. The BLDC rotor's usage of permanent magnets is another way that it differs from an induction motor. Because of their better power density and lighter wiring, high voltage (270 VDC) BLDC motors are becoming more popular in airplanes than their low voltage (115 VAC) AC equivalents. Instead of utilizing three large wires for each phase of a low voltage AC motor, two smaller wires can be used for the positive and negative motor terminations when using high voltage DC [16].

In 2020, the global market for electric motor production was valued at USD 163 billion. Brushless DC motors, or BLDC motors, are available on the market and are utilized in a variety of devices, including computers, fans, clippers, vehicles, and cordless power tools. They are employed in the computer, automotive, and mining industries [17].

Over the past ten years, permanent magnet electric motors—more specifically, brushless direct current (BLDC) and permanent magnet synchronous (PMSM) motors—have become more and more common. It may be seen in home appliances, traction applications, and industrial solutions like servo drives and actuators. This is caused, among other things, by the fact that permanent magnets enable devices to be smaller (since motors have a far higher power density), which also improves the devices' dependability and energy efficiency. By removing the mechanical commutator and brushes, two of the DC electric motors' most prone to damage components, BLDC motors may now be used in applications that need greater durability [18].

C. Vibration Analysis

Over many years, vibration analysis has been thoroughly researched and improved for the identification of bearing faults. Vibration data may easily be processed using well-established signal processing techniques including wavelet analysis, frequency analysis (e.g., Fast Fourier Transform), and time-domain analysis. There are several rules and regulations for deciphering vibration signals and locating certain fault signs [1].

Because the required vibration level rises when a breakdown occurs, vibration analysis is a highly helpful diagnostic approach, particularly in mechanical systems with drive heads linked to heavy loads. Another method to identify shifts in system behavior is to look for sideband spikes in signatures. Diagnosing and identifying rotating equipment faults in real time with a high success rate remains extremely challenging [2].

Three accelerometers are placed in relation to the universal coordinate system (X-, Y-, and Z-axes) in order to analyze vibration. The three accelerometers have typical sensitivity values of 95.5, 102.7, and 95.7 mV/g, respectively. Additionally, the two microphones' typical sensitivity is 45.2 and 49.7 mV/g. These three accelerometers are then placed at three prominent locations on the test bed: two at the motor casing and dynamometer flange, and one next to the motor base, which is the vibration's source [15]. A shallow neural network and vibration analysis were used to identify bearing failure in a PMSM. Moreover, these vibration evaluations of bearings primarily employ the typical fault frequency [19].

Mechanical engineering departments have embraced vibration analysis in addition to FEA when building test rigs for simulating faults in large equipment gearboxes. Numerous studies have emphasized the use of vibration analysis as an additional method for assessing the performance and dynamic behavior of mechanically geared systems. For example, the helical gears' observed helix angle is 30.5 degrees. A mesh stiffness calculation technique is developed. The dynamic behavior of a two-stage helical gear transmission system in an electric car running at a constant speed is shown mathematically. To validate the model, a bench test is carried out. It makes use of a friction model. After the friction and axial stiffness components have been carefully considered, the dynamic properties are analyzed. Similarly, in order to properly illustrate the special qualities of gear transmissions in this context, a proposal is made to create a novel virtual prototype model of a gear pair for a vibrating screen exciter. Among many other research, they show how crucial it is to combine vibration analysis with other analytical techniques, including finite element analysis, to improve the precision and efficacy of failure simulations in helical gear transmissions [20].

Researchers have used a range of data sources, including vibration, pressure, current, temperature, and acoustic measures, to diagnose these defects. Vibration analysis is now the primary technique for predictive maintenance of shaft problems within this range of diagnostic data. It may be used to direct routine maintenance and diagnose immediate faults. Usually, vibration measurements are taken online. They provide real-time diagnostic information about the condition of the equipment. When combined with other factors, vibrational data improves machine performance interpretation and diagnostics [21].

D. Thermal Monitoring

Problems with induction motors that are brought on by high-frequency inverter transients and the behavior that causes them. Both business and academia are making significant investments in research and development (R&D) pertaining to diagnostics and condition monitoring. An intelligent diagnostics system that combines the motor's real-time parameters—such as electrical, mechanical, flux, optical, acoustic, chemical, partial discharges, and others—with an electric machine is depicted in Figure 2 [22].

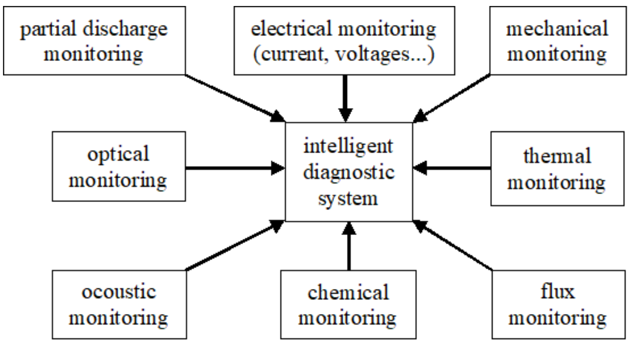

Fig. 2. Current advancements in intelligent diagnostics [22]

The system requires a more potent tool for feature extraction in order to forecast and train it to identify errors in the future. Furthermore, with the amount of data growing globally and computer science advancing at a rapid pace, it

Journal of Electrical, Electronic, Information, and Communication Technology (JEEICT)
Vol. 07 No. 1, April-2025, Pages 10-15 DOI: https://doi.org/10.20961/jeeict.7.1.100165

makes sense to re-create manufacturing using sophisticated techniques and artificial intelligence (AI). In the industry, thermal imaging is frequently used to track faults in their early stages of development. As an illustration, many machine learning (ML) algorithm variations may be applied in this situation to identify faults [23].

The development of thermographic fault diagnosis is motivated by the lack of scientific research on fault detection based on thermal imaging. Thermographic defect diagnostics of the ventilation in BLDC motors is described in this study. The Common Part of Arithmetic Mean of Thermographic Images (CPoAMoTI), a feature extraction technique, is suggested [17].

Many academics have devised methods for diagnosing motor faults. Different diagnostic signals, including as thermal, acoustic, vibration, and electric current signals, are used to diagnose electrical defects. Feature extraction and categorization are the foundation of several suggested defect diagnostic techniques. Deep learning, such as recursive, recurrent, and convolutional neural networks, is an additional strategy. Deep learning, feature extraction, and classification are frequently applied to defect detection. Thermal imaging, pyrometric analysis with an infrared laser pyrometer, vibration analysis, acoustic analysis, and chemical and oil analysis are some of the novel defect detection techniques that have recently been created [17].

Numerous applications, including fault identification, medical diagnosis, security, automobile and aircraft monitoring, astronomy, and rescue operations, frequently make use of thermal imaging. Thermal imaging-based fault diagnostics is non-invasive and non-contact. It is a very successful defect diagnostic technique. However, one drawback of thermal imaging cameras for defect diagnosis applications is their high cost [17].

The method is effective when the thermal imaging camera shivers between 0 and 1.5 [m/s2]. BLDC motors in the following states were examined: HB, 1FSB, 2FSB, and 3FSB. To analyze thermal pictures of the BLDC motor's defective shaft, PNID (power of normalized image difference), GoogLeNet, ResNet50, and EfficientNet-b0 were employed. Both the MeanE and the achieved efficiency E were 100%. For the analysis of thermal pictures, PNID, GoogLeNet, ResNet50, and EfficientNet-b0 perform well. EfficientNet-b0, ResNet50, and GoogLeNet were used for verification. PNID (power of normalized image difference), a novel feature extraction technique, was introduced. Thermal photos of the BLDC motor's malfunctioning shaft were analyzed using deep neural networks, namely GoogLeNet, ResNet50, and EfficientNet-b0 [24].

E. Signal Processing Techniques

One of the most important components of rotating machines is the bearing, and diagnosing problems with it is crucial to increasing the machines' availability and dependability. Regardless of speed circumstances, this research proposes an intelligent vibration signal-based fault diagnosis method for early bearing problem identification. A frequency shift-based hybrid signal processing strategy that combines the Hilbert Transform (HT) and Discrete Wavelet Transform (DWT) is part of the suggested methodology. Sliding window-based feature extraction comes next. The pertinent properties are then chosen using a recently created Henry Gas Solubility Optimization (HGSO). Finally, the Artificial Neural Network (ANN) model is trained using the best features in order to classify the various bearing defects. The speed independent model's efficacy was evaluated through experimental validation under both constant and fluctuating speed settings. The findings show that the suggested approach has a great deal of promise for removing unscheduled bearing failures in rotating machinery [25].

Rolling bearings are an essential component of rotating equipment, and their life prediction and problem diagnostics have been hot topics in engineering and research. Researchers are paying more attention to sliding, which may easily result in early bearing failure, as fault diagnostic technology advances. It is challenging to assess the degree of skidding in an in-service rolling bearing because of its intricate construction and motion mechanism. Furthermore, skidding will further modify the fault impulse signal, making it more challenging to extract fault features. The coupled modulation of speed and skidding makes it challenging to accurately assess skidding rate using vibration data, particularly when the crucial phase information is unavailable. This paper suggests a skidding evaluation and fault feature augmentation approach for rolling bearings without a key-phasor in order to address the aforementioned issues. By incorporating iterative Gaussian process regression and a phase recalculation method of the impact envelope signal, this research provides a two-step speed estimation approach based on the short-time Fourier transform. In addition to more precisely estimating the reference shaft speed, this technique computes the cage speed delay in relation to the theoretical value brought on by skidding [26].

IV. Conclusion

The literature study shows that bearing problems in BLDC motors may be effectively diagnosed and detected by utilizing both vibration and heat data. The effectiveness of recent developments in signal processing and diagnostic algorithms in detecting bearing abnormalities is highlighted. According to the study, which weighs the advantages and disadvantages of vibration and heat monitoring systems, a hybrid strategy that combines the two approaches provides a dependable early detection system. Operational dependability and maintenance schedules can both be enhanced by this hybrid approach.

Acknowledgment

The authors would like to thank RKAT PTNBH Universitas Sebelas Maret (UNS) for the Fiscal Year 2024 for providing facilities and support for this research. They acknowledge the grant received under the PENELITIAN HIBAH GRUP RISET (PENELITIAN HGR-UNS) A scheme with Research Assignment Letter Number: 194.2/UN27.22/PT.01.03/2024. The authors are grateful for the opportunity and resources provided by LPPM UNS, which have contributed to the successful completion of this research.

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