Predictive Maintenance of Ball Bearing Systems

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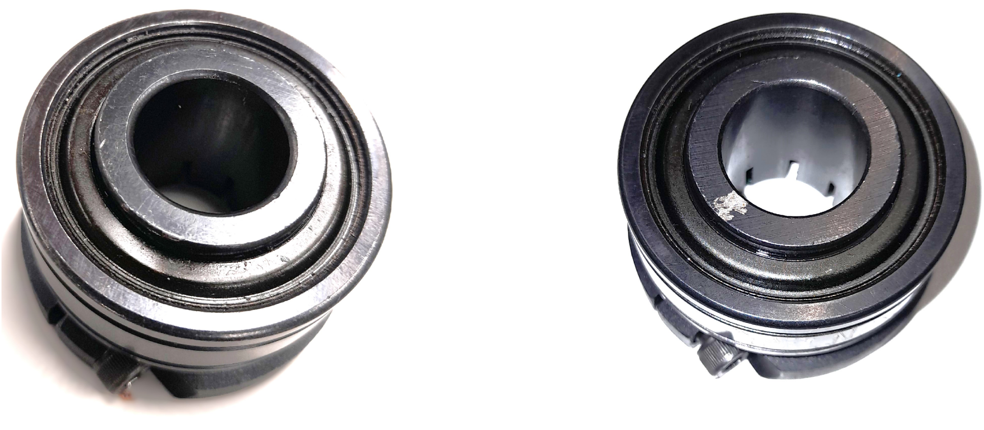
In the era of Industry 4.0 and beyond, ball bearings remain an important part of industrial systems. The failure of ball bearings can lead to plant downtime, inefficient operations, and significant maintenance expenses.

machine learning   deep learning   predictive maintenance

1. Introduction

The study of ball bearings in rotating machines has evolved over time due to technological advancements. Ancient civilisations developed early rotational devices such as waterwheels and windmills [1]. The rise of industrialisation further prompted innovation in rotating machines. These advancements led to the development of more efficient and sophisticated rotating machines with novel applications in various fields, including transportation, manufacturing equipment, domestic equipment, and power production. Ball bearings, consisting of outer and inner rings, a set of balls, and a cage, reduce friction and improve smooth rotation. They are an integral part of any rotating machinery and are responsible for 40 percent of machinery breakdowns [2][3][4]. These breakdowns are associated with their installation, poor maintenance strategy, fatigue, and regular wear.

The performance and efficiency of rotating machinery are greatly affected by bearings. Unexpected bearing faults often develop from their installation, maintenance strategy, fatigue, and regular wear, posing diagnostic challenges. These faults can be classified into two categories: distributed defects that affect a wide area, and localised defects that start as single-point defects (ref **Figure 1**). Inspection techniques like visual checks, ultrasound, and vibration analysis [5] help identify these faults, which is vital for machinery reliability.



(a) (b)

Figure 1. Example of two ball bearings with distributed and localised defects. (**a**) A ball bearing with distributed defects; (**b**) A ball bearing with a localised defect.

Distributed Defects: These defects impact bearings significantly and are challenging to identify based on specific frequency. They occur due to various reasons such as heat, vibrations, noise during operation, production errors, and excessive loads [6]. These faults can cause early rotor system failure or severe damage, making their detection challenging [7]. However, several inspection techniques such as visual observations and non-destructive methods can be employed [5].

Localised Defects: These faults are single-point issues caused by flaws in the manufacturing process, quality of raw material, or fitting errors [8]. Over time, as the bearings age, these localised defects progress and expand, leading to distributed fault patterns. These manifest as distinct vibrations, minimal changes in the load torque, and the emergence of multiple frequencies [9][10]. The distributed and localised defects pose a big problem to the throughput and efficiency of modern rotating machines. A timely identification of these faults can greatly improve the efficiency of rotating machines, and machine learning has a huge role to play in this regard.

By investigating failures, industries can identify weaknesses and refine their designs and manufacturing processes, leading to better quality. When products have defects or fail to meet standards, it results in unhappy customers, a decrease in market share, and increased costs due to quality-related problems such as recalls or repairs [11]. Even brief failures can impact continuous operations, leading to missed deadlines, financial losses, and delayed deliveries. To keep the production line running smoothly and safely, it is essential to have a well-organised system in place that effectively manages all aspects of the equipment, including machines and components. This requires a system that can diagnose potential breakdowns and taking proactive measures to prevent any impending faults or downtime. Implementing preventive measures through condition monitoring systems uncover cost-effective solutions, enhance safety by identifying and minimising hazards, and contribute to product development and innovation by providing valuable insights for iterative improvements. In the past, preventive maintenance techniques like time- and usage-based maintenance, fixed replacement intervals, and manual data analysis have been used. While these traditional methods provided some level of preventive capability, they were often reactive, time-consuming, and imprecise. In future industrial systems, the usage of advanced technologies like Internet of Things (IoT) [12], digital twin [13], and data-driven approaches like big data analytics, machine learning, and cloud computing [14][15][16] are being explored and employed.

Compared to existing manual data analysis techniques, the utilisation of Machine Learning (ML) has the potential to perform the function of forecasting and anticipating malfunctions [17] through the creation of algorithms that can detect patterns from data and use that understanding to make accurate predictions or choices. In particular, machine learning algorithms are very good at recognising anomalies in data, learning from patterns, data analysis, and optimisation of maintenance schedules. In recent years, machine learning [18] has become widely accepted and is being employed in a broad range of applications. There is hardly an area of everyday life where machine learning or deep learning algorithms are not finding their applications. Today, researchers see their application in fields such as self-driven cars [19], smart management of energy consumption in renewable energy communities [20]

[21], healthcare, transportation, supply chain and operations, image classification, and fault detection [16][22][23], to name a few. The integration of machine learning into fault detection for predictive maintenance is crucial as it facilitates the examination of vast quantities of information to recognise patterns and produce precise forecasts. Machine learning supplements maintenance planning in industries by analysing extensive datasets pertaining to a production process [22], detecting malfunctions and anomalies, and enabling proactive preventive maintenance strategies. Machine learning as a branch of artificial intelligence has proven to be a potent instrument for creating intelligent predictive algorithms across numerous applications. However, the effectiveness of these applications is contingent upon the suitable selection of the machine learning technique [22].

2. Predictive Maintenance of Ball Bearing Systems

In recent years, machine learning, which is a sub-field of artificial intelligence [18], has become widely accepted and has been employed in a broad range of applications such as self-driven cars [19], forecasting and anticipating malfunctions [17], smart management of waste water treatment [24][25][26], smart building in healthcare [27][28], transportation, supply chain and operations, image classification, and fault detection [16][22][23]. The integration of machine learning into fault detection for predictive maintenance is crucial as it facilitates the examination of vast quantities of information to recognise patterns and produce precise forecasts. Prognostic and diagnostic maintenance models are two basic approaches to ML-enabled predictive maintenance that are used to identify and address equipment issues before they lead to failure. Diagnostics maintenance involves using various tools and techniques to inspect equipment and identify any issues after they have occurred [29]. Vibration analysis is utilised to detect faults in rotating machinery or perform regular inspections to identify wear or damage in components. Once these faults have been identified, maintenance personnel can take action to repair or replace the affected parts. Prognostic maintenance, on the other hand, uses data analytics and machine learning algorithms to analyse data from sensors and other sources to identify patterns and trends that may indicate future issues [29]. This approach monitors the performance of a machine and uses data analysis to predict when it may fail based on changes in performance metrics. Prognostic maintenance allows maintenance personnel to take proactive steps to address potential issues before they lead to unplanned downtime or equipment failure.

In the research work of [22], the authors explored Support Vector Machine (SVM), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Deep Generative Systems (DGN) to identify mechanical part failure by using low-cost sensors for preventive fault detection. The study highlights their effectiveness in fault detection with CNN and RNN resulting in higher accuracy. However, this comes with higher computational costs, the need for reliable data and labelling, and the potential for treating fault diagnosis as a clustering problem. The authors in [2] presented a time-frequency procedure for fault diagnosis of ball bearings in rotating equipment using an Adaptive Neuro-Fuzzy Inference System (ANFIS) technique for fault classification. It combines a wavelet packet decomposition energy distribution with a new method that selects spontaneous frequency bands utilising a combination of Fast Fourier Transform (FFT) and Short Frequency Energy (SFE) algorithms. This method is potentially effective and efficient for bearing fault detection and classification in various conditions, making it appropriate for online applications. In [30], the researchers performed experimental findings involving a comprehensive analysis of the roller bearing's inner ring and cylindrical rollers. Several conventional techniques such as visual observation, Vickers Hardness (HV) testing, 3D Stereo-microscopy, Scanning Electron Microscopy (SEM), and lubricant inspection were employed. The study attributes severe wear to three-body abrasive wear and the introduction of metallic debris from broken gear teeth outside the roller bearing. Lubricant inspection was performed incorporating Fourier transform infrared spectroscopy, which concludes that the lubricant had not deteriorated significantly.

In [31], the authors employed frequency domain vibration analysis and envelope analysis, in combination with Kernel Naive Bayes (KNB), Decision Tree (DT), and k-nearest neighbors (KNN), to detect bearing failures. The authors in [32] incorporated a Random Forest (RF) classifier and Principal Component Analysis (PCA) to detect bearing failures in induction motors utilising a time-varying dataset while similar work of [33] considered using Linear Discriminant Analysis (LDA), Naive Bayes (NB), and SVM to evaluate waveform length, slope sign changes, simple sign integral, and Wilson amplitude for bearing faults detection in induction motors.

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