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Failure Analysis Of Centrifugal Pump By Using Computational Approach

Sharad Rajaram Bhadane[1], Kasi Raja Rao[2], Sanjay Tapiram Purkar[3]
[1]Department of Mechanical Engineering, Mandsaur University, Mandsaur, Madhya Pradesh, India, bhadanesharad01@gmail.com
[2]Department of Mechanical Engineering, Mandsaur University, Mandsaur, Madhya Pradesh, India, krajarao218@gmail.com
[3]Department of Mechanical Engineering, Shivajirao Kadam Institute of Technology, Indore, India, sanjaypurkar@skitm.in

Abstract
Centrifugal pumps play a crucial role in numerous industrial processes and are extensively utilized. The water supply system encompasses wastewater management, heating, and cooling. To date, there have been several criticisms regarding vehicles. Fault diagnosis based on induction engines is utilized in conjunction with the centrifugal pumps that have been received. There has been relatively little focus on this area. This paper aims to summarize and evaluate recent research and advancements. It monitors pump status through automated learning and defect diagnosis. The paper begins with a brief explanation of pump operation, including common pump malfunctions and fundamental engine principles. Current Signature Analysis Methods are then discussed in detail, followed by a comprehensive description of various vehicles. A training-based approach is presented, detailing the types of defects identified, experimental specifics, and the accuracy of transmission. The performance of different methodologies is systematically displayed in a single table. In conclusion, the author addresses practical considerations and challenges associated with data collection, storage, and real-world implementation.

Keywords: *Centrifugal pumps, fault diagnosis, induction motors, motor current signature analysis, signal processing*

1. INTRODUCTION

Centrifugal pumps (CPs) account for 70% of all pump types [1] and are widely used across various industries [2]. While modern pumps can have a lifespan of several years, they are still susceptible to failure. Such failures can result in undesirable malfunctions and, in severe cases, can lead to critical issues such as water supply disruptions in hospitals. This has prompted the swift advancement of intelligent monitoring techniques that utilize signal processing and machine learning methods to identify, diagnose, and forecast potential defects. These techniques may include monitoring schemes based on vibration, pressure, or current signatures from sensors. Motor current signature analysis (MCSA) is extensively utilized Predictive service technique that identifies malfunctions and monitors conditions through the analysis of stator currents. Key elements of centrifuges in induction motors [3]. The assistant editor oversees the review of this manuscript and His endorsement for publication was provided by R.K. Sackett. pump. This approach is founded on the concept of creating distinct models capable of identifying various faults. Signal processing and statistical techniques [4]. Acoustic emissions, vibration, and pressure concerns. If interference is detected, the system also functions effectively. In the comprehensive literature [5], MCSA is extensively employed for predictive Maintenance, meaning that maintenance is conducted solely based on requirements. It is more cost-effective than other maintenance types. MCSA monitoring systems can be implemented by adjusting the current of the pliers utilized as a power converter. Wire without requiring direct physical access to the pump. The great ease of deployment, non-invasive installation, and Coupled with relatively low costs and high detection precision This constitutes the primary benefit of MCSA. In certain applications, For instance, MCSA monitoring of flood pumps has proven to be the only feasible and practical method. When applying to a centrifugal pump, one can identify the MCSA. Only defects related to induction do not pertain to pump faults such as cavitation, workwheel failures, or other types of functional dysfunction, which can be addressed using suitable automated learning methods. In other words, MCSA employs the engine as a monitoring sensor for pump conditions [6]. For instance, [7] outlines the determination of dysfunction in pumps through deep learning, while [1] utilizes neural networks to predict growth in several stages of pumps. [8] explores cavitation defects through autolearning. Nevertheless, despite the extensive research on MCSA related to the induction engine [9], a systematic review reveals that MCSA-based techniques for detecting central malfunctions in pumps are not adequately documented in the literature. In this article, the author provides a systematic analysis. MCSA method based on automated learning of centrifugally Detection of pump dysfunction. Our objective is to present the ideal The analysis of recent studies in this domain encompasses a collection of techniques Issues, related methods of autolearning, and the structure of key findings. We also engage in a discussion Regarding sound-related challenges, data transmission, and collection specific to MCSA systems. In this context, when Contrasting preliminary work as thoroughly as possible, the author consolidates Sampling speed data, data collection apparatus, Other related aspects that offer additional practical insights to readers. To the best of our knowledge, this work is the first systematic Investigation of automated learning techniques for defect detection In centrifugal pumps. The remaining sections are structured as follows: Sections II and III-A1 highlight significant elements of the Centrifugal pump's design, including its components. Section III types elucidate the functions of keys and signal signals Treatment methods employed to extract critical features from faulty signals. A comparison of MCSA with other error Detection alternatives, such as vibration signal analysis, Is presented in Section III-A. As an induction engine, The primary components of centrifugal pumps are examined, Covering the relevant MCSA methods associated with the induction engine. Ultimately, the author presents mechanical training and partially Non-disruptive solutions based on training to aid researchers In comparing implementations.

2. Pump centrifugation operation

As illustrated in Figure 1, the centrifugal pump is composed of two primary components. Parts: The rotating components include the wood and work wheels, while the stationary component consists of a casing, the body boxes, rides, and electric motors, typically of the induction type Engine [8]. The fluid within the pump moves axially through the body's eyes, interacting with the blade of the work wheel. The rotation is radial, which facilitates the generation of speed and output pressure from the housing diffuser of the work wheels. This area of documentation, as noted by the authors, generally addresses disorders under investigation and compares the accuracy of detection of related documents. In the subsequent section, the author will first present the MCSA method, followed by a comprehensive explanation of each type. This will include detection based on the type of failure and MCSA.

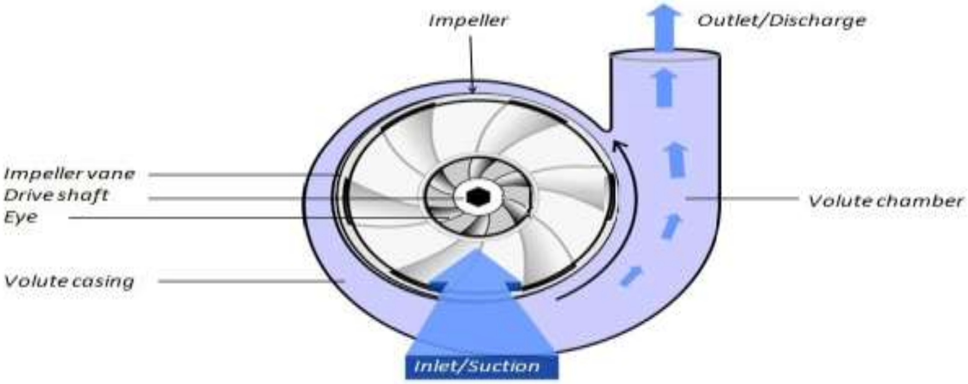

Figure 1. Centrifugal pump diagram with its main part marked

3. Analysis of engine current *signatures* and failure type

MCSA is founded on the principle that specific electrical and mechanical faults generate harmonics in electric current, which can be identified through a combination of signal processing and machine learning techniques. Healthy motors operate at a fundamental frequency of 50 Hz (60 Hz in the United States). However, as faults develop within the machine, various harmonics beyond 50 Hz begin to emerge [12]. The pump load influences the fundamental frequency component. Conversely, fluctuations in load lead to the generation of noise and harmonics [13]. Consequently, detection can be achieved by examining the lateral bands surrounding the fundamental frequency of the fault. The current is measured by attaching current probes to the power supply wires, making installation and maintenance relatively straightforward and cost-effective. The range of faults that MCSA can detect includes stator winding breakdown, broken rotor bars, or issues with electric bearings [15]. The types of faults identifiable by MCSA encompass:

- Bearing fault: Outer Race Fault [12], Inner Race Fault, ball defect [4], [16].
- Cavitation: [2], [8].
- Impeller: Inlet tip, exit tip fault [17], [18].
- Blockage [19]–[21]

A. Analysis of Vibration Signature for comparison

Vibration signature analysis (VSA) involves the examination of signals obtained from vibration sensors that are directly affixed to the pump [15]. This analysis can be performed by observing the spectral content of the signal, which allows for the identification of the specific part of the machine where a fault is present [22], [23]. It is assumed that the frequencies associated with the vibrations indicate the location of the fault within the machine [22], [23]. Vibration measurements can be taken using accelerometers, which must be positioned in close proximity to the rig of the centrifugal pump [23], [24]. Despite the benefits of VSA, the cost-effectiveness of MCSA, its capability to identify electrical faults [15], and its heightened sensitivity compared to alternative methods [6] render MCSA more practical. In the context of motor faults, MCSA is employed to detect both mechanical and electrical issues, while VSA requires acceleration measurements for displacement to identify faults. In terms of fault detection efficacy, Corne et al. [15] assert that MCSA is unable to differentiate between bearings at the drive-end and non-drive end if they share identical dimensions. Nevertheless, they recommend that the magnitudes of the frequency components be assessed [15], noting that unstable current samples will disperse the magnitudes of these components across the spectrum. Zhang et al. [25] further assert that MCSA is straightforward to implement and offers economic advantages. However, similar to the assertions made in the previous study, the fluctuating stator currents during bearing faults can complicate the establishment of a universal threshold for detection.

1. Failure Types

In this section, we will thoroughly examine some of the most prevalent faults associated with motors and pumps. Given that the induction motor serves as a crucial element of a centrifugal pump, we will begin by introducing the faults of induction motors that can be detected through Motor Current Signature Analysis (MCSA). Subsequently, Section III-A1. b will address faults specific to centrifugal pumps and the various methods available for their detection.

a. Induction Motor-Related Faults

i) DAMAGED ROTOR BARS

Broken rotor bars (BRB) primarily represent a mechanical fault in induction motors, exhibiting various degrees of severity: partial-BRB and one or more complete BRBs. The issue begins with a bar that is partially cracked, which impacts the physical parameters and complicates prediction efforts [26]. This fault can be physically replicated by drilling a hole through its entire depth [27]. Detection of BRBs can be accomplished through multiple methods, including MCSA, VSA, and even temperature monitoring. An illustration of a broken rotor bar fault is presented in Figure 2 [28].

FIGURE 2. Faults in broken rotor bars result in speed oscillations within the rotor, leading to accelerated wear of the bearings.

ii) BEARING

The bearing fault represents a significant mechanical issue in motors. [12] indicates that these faults account for 44% of failures in induction motors. This fault arises from insufficient lubrication, mechanical stresses on the bearing balls, misalignment, corrosion, and damage to the inner or outer race, among other factors [12]. These issues lead to irregular load distributions in the magnetic field, thereby altering both mutual and self-inductance [29]. An illustration of bearing damage is shown in Fig 3. Bearing faults can be identified using Vibration Signature Analysis (VSA) and Motor Current Signature Analysis (MCSA) [12], and they can be categorized into at least three distinct types: Outer-race fault (ORF) [12], inner-race fault, and ball defect [4]. The continuous wavelet transforms and 2D wavelet scalogram, in conjunction with relative wavelet energy, can also be employed alongside MCSA to detect ORF in ball bearings [29].

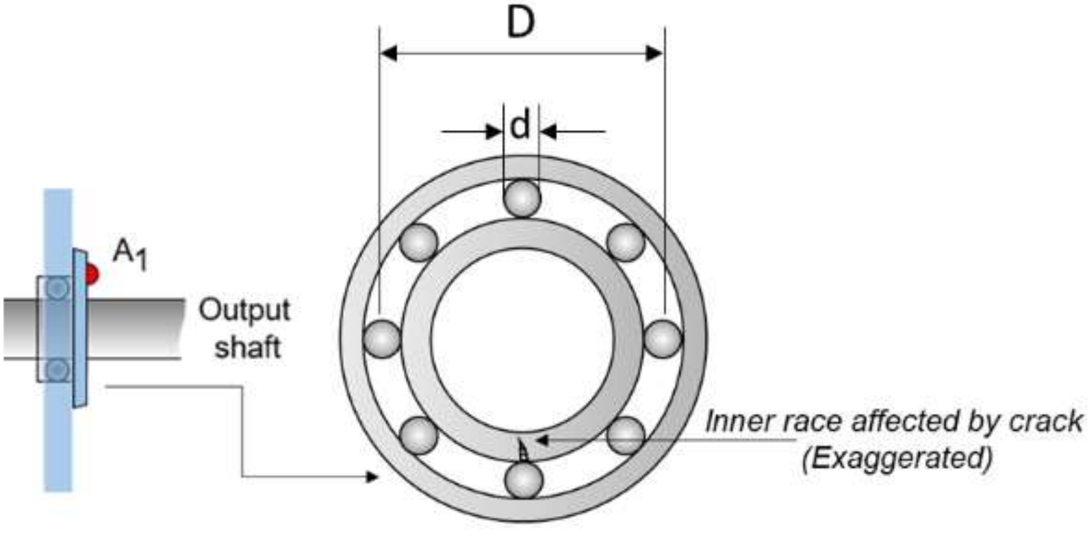

FIGURE 3. When a bearing fault is present, the rolling elements (balls) periodically traverse the defective area, generating impulses at a specific frequency that can be detected.

iii) STATOR WINDING

The stator winding (SW) fault represents a specific mechanical issue in induction motors (IM), accounting for 38% of IM failures [30]. The primary cause of stator faults is the deterioration of insulation, which subsequently leads to inter-turn short circuits [31]. Furthermore, if the developing fault is not addressed promptly, it can result in the destruction of the motor. The impact of the SW fault on motor current signature analysis (MCSA) signals is that an asymmetric SW generates spatial harmonics that fluctuate at a single frequency [30]. This phenomenon is clearly illustrated in Figure 4. There are various methods available for detecting SW faults, including the application of fuzzy logic utilizing motor current signature data to identify specific components [30].

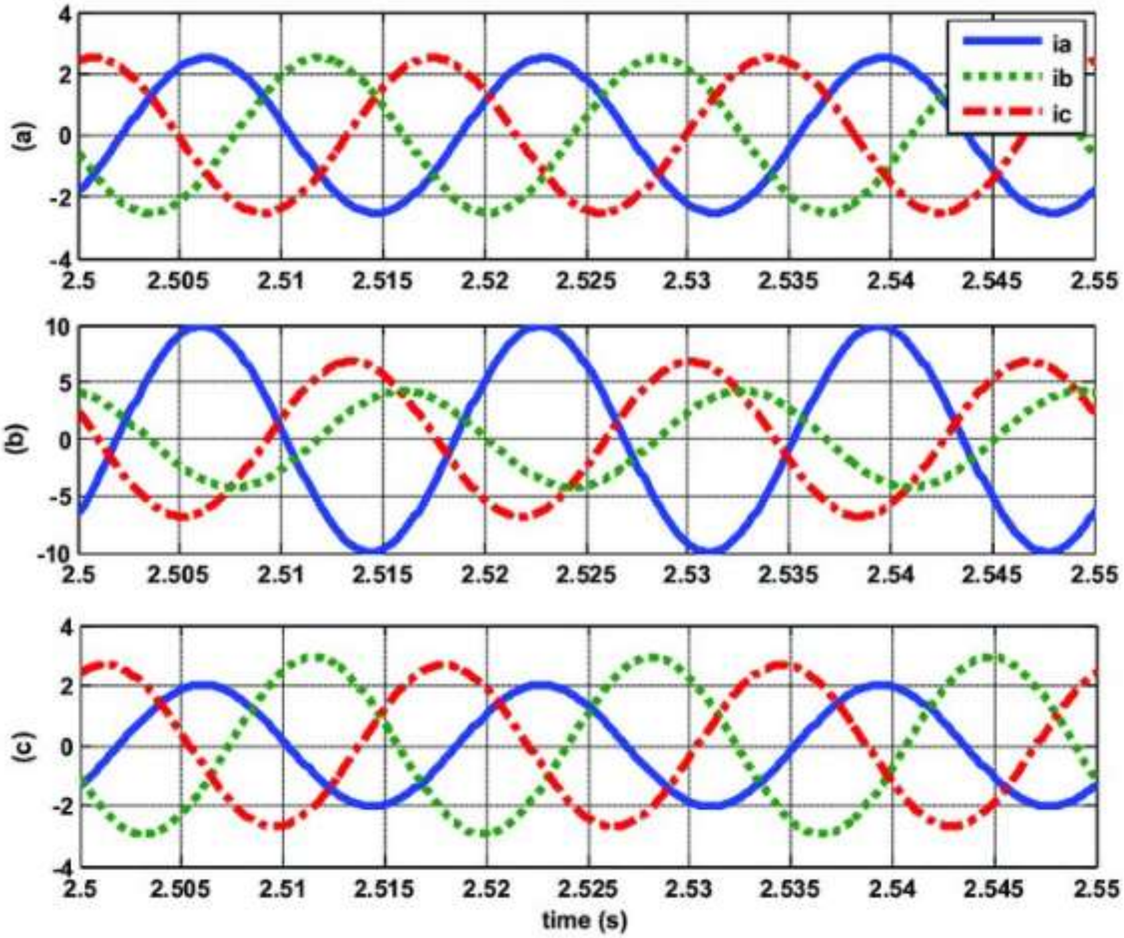

FIGURE 4. The phase currents of a functioning motor (top). A fault in the stator winding results in an imbalance in the motor currents (bottom)

b: FAULTS ASSOCIATED WITH CENTRIFUGAL PUMPS

Centrifugal pump failures can arise independently or may be interdependent in their development. These failures can be classified into two categories: Mechanical faults or fluid-flow induced faults [32].

i) Impeller

The impeller fault is a specific issue associated with centrifugal pumps that arises at the impeller blades. According to Tian et al. [17], defects on the impeller caused by inevitable cavitation and erosion lead to alterations in both static and dynamic torque, which can be detected through the current. This fault can be artificially induced by removing a section of metal [18] from the impeller. Figure 5 illustrates both healthy and faulty impellers [17]. Additionally, there are various sub-faults within the domain of the impeller fault, including the inlet tip and exit tip [17]. These sub-faults may result in a reduction in amplitude at the blade pass frequency in MCSA [33]. Moreover, an imbalance in the impeller can also lead to mechanical faults or hydraulic fluid flow faults [18], in addition to the sub-faults. These faults can be identified using several well-known methods such as VSA and MCSA [17], as well as intriguing techniques like DQ patterns [19] and discriminant feature extraction [18].

FIGURE 5. A clogged impeller diminishes the efficiency of the pump. This condition can be artificially induced by utilizing polystyrene to obstruct the impellers.

ii) CLOGGED IMPELLER

Another category of fault that manifests in the impeller region, and is effectively identified through MCSA, is a clogged impeller fault. This issue arises when pump impellers become obstructed by external materials such as polystyrene (refer to Figure 5), resulting in a diminished flow rate. This specific fault. A clogged impeller leads to a reduction in the effective value of motor current and a decrease in efficiency. When a clogged impeller fault occurs within the pump, its efficiency can decline by 9 to 15% [34]. The impact of this fault on the frequency domain is most significant when three or four out of seven channels are obstructed (essentially, half-sided clogging). The amplitude of the fault frequency notably increases at the 5th harmonics (791.9 Hz and 875.3 Hz) when sampled at a rate of 10 kHz over a duration of 30 seconds. This effect is more pronounced at elevated speeds such as 1800 rpm and 2500 rpm [34]. The equipment utilized by [34] comprises pressure sensors (IFM PU5413), data acquisition devices (NI USB-6363), and additional instruments in each pipe to assess differential pressure and the signal from the pressure sensor. An electronic pressure switch (WIKA PSD-30) and a temperature switch (WIKA TSD-30) are employed for life-accelerated testing.

iii) BLOCKAGE

A blockage fault refers to a situation where a pipe is obstructed, and it is a primary cause of pump failure. This fault arises from the closure or modulation of the pump's hand valve [19], [20]. In the case of hydraulic pumps, when the outlet is blocked, it leads to a decrease in hydraulic load, resulting in the pumping of a reduced volume of liquid and ultimately requiring less current [21]. If a pump becomes blocked and the motor ceases operation, it will not draw any current. Consequently, no MCSA data will be available for analysis. However, if the blockage occurs outside the pump's vicinity, MCSA signals can still be gathered, allowing for the identification of the fault. There are various methods to detect a blockage fault beyond merely employing MCSA in conjunction with deep learning or VSA. Since the blockage can exert pressure on the pump, deep learning techniques that utilize pressure signals can effectively identify the fault [20]. Furthermore, a detection system based on fuzzy logic or DQ pattern plotting through Park transformation, aided by MCSA, can also serve as a means to detect this fault [19], [21].

iv) CAVITATION

Cavitation faults arise when the absolute static pressure of the pump drops below the saturated vapor pressure of the fluid, leading to vaporization [2]. This pressure variation causes the fault detection methods based on blockages to intersect with this fault as well [20]. The primary five causes of cavitation faults include: pump housing failure, impeller destruction, excessive vibration, unnecessary power consumption, and reduced flow and pressure. There are five distinct types of cavitation: vaporization, turbulence, vane syndrome, internal recirculation, and air aspiration cavitation [8]. As noted in [35], prolonged operation under cavitation conditions can result in unsteady flow, which subsequently leads to failures in internal surfaces such as the volute, bearing, shaft, and seal, among others. Given that most centrifugal pumps utilize induction motors, which transmit all dynamic information through the stator current signal or transient power signal, Motor Current Signature Analysis (MCSA) can be employed to identify this fault [2]. Furthermore, Luo et al. [13] indicate that the stator current spectrum comprises fundamental frequency, harmonics, and noise. Thus, it can be deduced that these elements can be detected during MCSA for centrifugal pump fault identification.

4. METHODS

In this section, the literature concerning MCSA related to fault detection will be discussed. The authors will now provide a brief explanation of the criteria used for selecting papers and the rationale behind the choice of IM papers. The primary research criterion was based on a prioritized keyword search, which was conducted using the keyword 'MCSA' followed by 'fault detection', 'ML', and subsequently 'CP'. Among the papers the authors reviewed from sources such as IEEE, ScienceDirect, and others, the aim was to select the most pertinent and up-to-date publications. During the research, the authors noted that there were significantly more vibration, non-ML, IM based papers than those they were specifically seeking. To enhance the comprehensiveness of the ML survey paper and to increase the count of detectable faults using MCSA and ML, the authors also incorporated papers addressing IM faults, provided they met the essential MCSA and ML inclusion criteria. Considering that IM is a component of CP, a fault in one will ultimately impact the performance of the other, affecting the overall output.

A. FAULT DEVELOPMENT MODELS

Prior to engaging in discussions regarding any ML or non-ML based solutions for fault detection, the authors wish to highlight the significant mathematical modeling conducted by Ofuchi et al. [37] concerning the degradation of centrifugal pump head over time. The authors employed electric submersible pumps (ESPs) to examine their degradation under conditions of highly viscous flows. They hypothesize that ESPs will experience greater degradation due to their design being tailored for water-based operations. The objective of the authors is to propose a model that estimates the degradation of head and flow rate in a centrifugal pump operating across a wide range of Reynolds numbers. The data utilized is derived from two mixed flow type electric submersible pumps and one radial type pump. The authors apply polynomial models to estimate the degradation curve of the pumps' head under viscous operations. Ultimately, they compare their methodology with established engineering standards such as the Hydraulic Institute. Their findings from the three pumps are analyzed at varying rotating speeds and fluid viscosities. While industrial standards like HI and KSB yield similar curves, they tend to underestimate performance degradation, whereas the authors' model demonstrates superior accuracy in estimating head versus flow rate curves under conditions of moderate to high viscosity.

B. TRANSFORMATIONS

Transformations play a vital role in the detection of faults in pumps and motors, as they assist in extracting the pertinent features necessary for the primary technique. Notable examples include the Fourier transform, wavelet transform, and Park transform, which are utilized for feature extraction in Motor Current Signature Analysis (MCSA).

C. NON-MACHINE LEARNING METHODS

There are multiple solutions that completely avoid the use of machine learning, even while employing MCSA. One notable solution involves a centrifugal pump with specifications of three-phase, 1.5 hp, 3450 rpm, and 60 Hz, which suggests an electric diagnostic method for fault analysis without the need for additional sensors [19]. Irfan et al. [19] utilize motor line current and voltage to assess the three-phase line current, converting it into two-phase DQ patterns. A total of 1000 samples were gathered at a sampling rate of 4000 Hz from three-phase stator current sensors using the PXIe-1082 data acquisition module [19]. Fault detection is performed through pattern classification based on statistical indices following the generation of the DQ pattern plot. The effectiveness of this method is attributed to the shape of the figure. When the pump is functioning properly, it exhibits a hexagonal shape, whereas pumps with impeller faults or blockages display a distorted (fan-shaped circular) appearance. Their previous studies also addressed issues such as bearing damage, winding damage, and eccentricity [19]. They discovered that power consumption diminishes while amplitude increases with greater clogging and blockages, although amplitude decreases as the number of clogged channels rises. They noted that a higher number of clogged channels more accurately represent the characteristics. Additionally, increased speed levels help distinguish between minor faults and healthy conditions. Although the study did not develop an automated fault detection system, its emphasis on MCSA validated the hypotheses presented in other research and clarified the characteristics of faults' impacts on MCSA [34]. The authors of the paper also examined the constraints related to the frequency of fault detection, which they refer to as the blade pass frequency. They propose that the amplitude of the blade pass frequency is influenced by the faults present in the clogged impeller. However, this frequency remains unaffected when the pump operates as a circulation pump.

5. Centrifugal Motor Faults Oriented Solutions

The authors of [32] integrate MCSA and VSA in their research. They employ line-current probes and accelerometers to gather time domain-based data, which they subsequently convert into the power spectrum. They evaluate and select the most appropriate features: Mean, standard deviation, and the reciprocal of standard deviation [32]. Following this, they train and test a multi-support vector machine (MSVM). The authors utilize a 30 Hz centrifugal pump and examine 33 faults. They discover that each fault modifies the flow patterns, resulting in a distinct impact on the signatures. Consequently, with the MSVM approach, they intend to classify isolated and/or combined faults (for instance, the interdependence of mechanical and hydraulic CP faults), identify faults with varying severities (such as suction and discharge blockages), compare high and low-frequency resolutions, and categorize 33 critical centrifugal pump faults [32]. They gather 2000 samples at both 20 kHz and 5 kHz sampling rates, adjusting the ratio of test to training samples. The authors also experimented with different pairs of pump speeds (30-40, 40-50 Hz, etc.) to assess intermediate speeds as an alternative option in the absence of specific fault data. Ultimately, the achieved test classification accuracy for training/testing at the same speed is 83.2%, which declines if based on a different speed or improves with increased resolution [32].

6. Induction-motor Faults Oriented Solutions

In contrast to earlier MLP studies, the authors of [51] have developed a genuine test rig comprising three phases and a 1 hp (0.75 kW) AC induction motor. The data is collected at a frequency of 100 Hz, resulting in 4000 samples. The MLP model features a single hidden layer containing 46 neurons and three output parameters: healthy, inner race, and outer race faults. The loss is determined using MSE, along with the correlation factor [51]. The paper notes that the current spectrum rises with an increase in applied load, and the RMS and kurtosis features offer a reliable indication of the bearing's condition. In the presence of ORF, the amplitude exhibits a significant increase. The test dataset includes previously unseen data, amounting to a total of 360 sets, with 120 sets allocated for each condition [51].

7. SUMMARY AND PERFORMANCE COMPARISON

In this section, the research findings will be compared for induction motors (IM) and condition monitoring (CP). Although the authors undertook comprehensive research to identify CP faults based on machine learning studies that employ MCSA data, they noted a greater number of research papers addressing IM-related faults. Furthermore, the scarcity of recent journal articles from the past three years (2020-2022) posed challenges in locating MCSA-based publications on CP (or even IM) that utilize machine learning for fault detection. Additionally, it was observed that there is a significant volume of VSA-based research papers concerning CP. The authors also found that the most effective methods for classifying CP/IM faults were Convolutional Neural Networks (CNN), Random Forest (RF), and Multi-Layer Perceptron (MLP), all achieving success rates exceeding 95%. Consequently, by appropriately utilizing the features, it is possible to achieve near-perfect accuracy through the implementation of these studies. Another observation made was regarding the faults that are frequently investigated in the research papers reviewed by the authors. These commonly studied faults included Bearing Rotor Block (BRB), Insulation Resistance Fault (IRF), and Open Rotor Fault (ORF), as well as unbalanced power/voltage sources and stator windings, which are predominantly associated with IM faults.

8. CONCLUSION AND FUTURE WORK

The survey presented aims to deliver a systematic analysis of fault detection based on machine learning for centrifugal pumps. The primary goal was to elucidate the pertinent approaches and to critically assess the performance of different methods. Specifically, the survey discusses the advantages of MCSA and contrasts them with other alternatives such as VSA. After detailing the relevant machine learning techniques, data acquisition methods, and metadata, the authors have concluded that solutions based on CNN and MLP neural networks outperform SVM and other alternatives. Consequently, the authors are of the opinion that future developments in machine learning hold significant promise regarding both prediction accuracy and resource efficiency. Additionally, the survey underscores several practical challenges associated with fault detection in centrifugal pumps. This encompasses the scarcity of publicly available annotated datasets, which could be utilized to develop and evaluate the performance of various diagnostic algorithms. The authors aspire that this research will prove beneficial to other researchers and engineers in creating non-invasive and cost-effective predictive maintenance solutions for centrifugal pumps.

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