DOCTORAL THESIS

Artificial Intelligence Driven Approaches for Fault Prognostics of Electrical Machines Using Vibration Spectrum Analysis

Karolina Kudelina

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

Karolina Kudelina

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Tehisintellektil põhinevad lähenemisviisid elektrimasinate rikete prognoosimiseks vibratsioonispektri analüüsi abil

KAROLINA KUDELINA

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Contents

List of Publications

The list of author's publications, on the basis of which the thesis has been prepared:

I **Kudelina, K.**; Baraškova, T.; Shirokova, V.; Vaimann, T.; Rassõlkin, A. Fault Detecting Accuracy of Mechanical Damages in Rolling Bearings. Machines 2022, 10, 86. https://doi.org/10.3390/machines10020086.

II **Kudelina, K.**; Asad, B.; Vaimann, T.; Rassõlkin, A.; Kallaste, A.; "Production Quality Related Propagating Faults of Induction Machines," 2020 XI International Conference on Electrical Power Drive Systems (ICEPDS), St. Petersburg, Russia, 2020, pp. 1-5, doi: 10.1109/ICEPDS47235.2020.9249355.

III **Kudelina, K.**; Asad, B.; Vaimann, T.; Rassõlkin, A.; Kallaste, A.; Khang, H.V. Methods of Condition Monitoring and Fault Detection for Electrical Machines. Energies 2021, 14, 7459. https://doi.org/10.3390/en14227459.

IV **Kudelina, K.**; Asad, B.; Vaimann, T.; Belahcen, A.; Rassõlkin, A.; Kallaste, A.; Lukichev, D.V. Bearing Fault Analysis of BLDC Motor for Electric Scooter Application. Designs 2020, *4*, 42. https://doi.org/10.3390/designs4040042.

V **Kudelina, K.**; Vaimann, T.; Asad, B.; Rassõlkin, A.; Kallaste, A.; Demidova, G. Trends and Challenges in Intelligent Condition Monitoring of Electrical Machines Using Machine Learning. Appl. Sci. 2021, *11*, 2761. https://doi.org/10.3390/app11062761.

VI **Kudelina, K.;** Raja, H.A.; Naseer, M.U.; Autsou, S.; Vaimann, T.; Kallaste, Study of Bearing Currents in Induction Machine – Diagnostic Possibilities, Fault Detection, and Prediction. Electrical Engineering (2024). https://doi.org/10.1007/s00202-024-02411-x.

VII **Kudelina, K.**; Raja, H.A.; Rjabtšikov, V.; Naseer, M.U.; Vaimann, T.; Kallaste, A.; "Signal Processing and Machine Learning Techniques for Predictive Maintenance of Rotor Bars in Induction Machine," 2023 International Conference on Electrical Drives and Power Electronics (EDPE), The High Tatras, Slovakia, 2023, pp. 1-7, doi: 10.1109/EDPE58625.2023.10274030.

VIII **Kudelina, K.**; Raja, H.A.; Autsou, S.; Naseer, M.U.; Vaimann, T.; Kallaste, A.; Pomarnacki, R.; Hyunh, V.K.; "Preliminary Analysis of Mechanical Bearing Faults for Predictive Maintenance of Electrical Machines," 2023 IEEE 14th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED), Chania, Greece, 2023, pp. 430-435, doi: 10.1109/SDEMPED54949.2023.10271451.

IX **Kudelina, K.**; Raja, H.A.; Vaimann, T.; Kallaste, A.; Pomarnacki, R.; Hyunh, V.K.; "Preliminary Analysis of Bearing Current Faults for Predictive Maintenance," 2023 IEEE International Electric Machines & Drives Conference (IEMDC), San Francisco, CA, USA, 2023, pp. 1-5, doi: 10.1109/IEMDC55163.2023.10238934.

Author's Contribution to the Publications

Contribution to the papers in this thesis are:

I Karolina Kudelina is the primary author of this article. She wrote the initial draft of the paper. She prepared the theoretical part about bearing faults and implemented fault to healthy bearing for experiments.

II Karolina Kudelina is the primary author of this article. She highlights the significance of addressing manufacturing faults, often overlooked but prone to evolving during motor operation and resulting in undesirable consequences. She authored the initial draft of the paper. She presented this paper at the conference.

III Karolina Kudelina is the primary author of this article. She has written a comprehensive overview of advanced fault diagnostic and condition monitoring methods applicable to predictive maintenance. She wrote the initial draft of the paper.

IV Karolina Kudelina is the primary author of this article. She discussed the bearing faults and their primary causes. Additionally, she conducted experiments by inducing faults into healthy bearings, constructed a test bench for data collection, and performed analysis to detect damage within frequency spectra. She authored the initial draft of the paper.

V Karolina Kudelina is the primary author of this article. She conducted a study on promising machine learning-based diagnostic techniques, examining their attributes and application to predictive maintenance. She wrote the initial draft of the paper.

VI Karolina Kudelina is the primary author of this article. She conducted an analysis of the bearing current faults, explored diagnostic possibilities, and investigated a technique for predicting such faults. She authored the initial draft of the paper.

VII Karolina Kudelina is the primary author of this article. She presented an analysis of damages related to broken rotor bars and explored the potential of predicting them using various intelligent algorithms. Additionally, she investigated the impact of these faults on global electrical parameters. She wrote the initial draft of the paper. She presented this paper at the conference.

VIII Karolina Kudelina is the primary author of this article. She discussed the most common mechanical damages in bearings and their potential for prediction. Additionally, she investigated the impact of various control environments and loads on the global parameters of electrical machines. She authored the initial draft of the paper. She presented this paper at the conference.

IX Karolina Kudelina is the primary author of this article. She described the data pre-processing techniques used for training to predict potential bearing faults. She wrote the initial draft of the paper. She presented this paper at the conference.

Publications as a Co-Author

I Asad, B.; Vaimann, T.; Belahcen, A.; Kallaste, A.; Rassõlkin, A.; Ghafarokhi, P.S.; **Kudelina, K.** Transient Modelling and Recovery of Non-Stationary Fault Signature for Condition Monitoring of Induction Motors. Appl. Sci. 2021, 11, 2806. https://doi.org/10.

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VI Raja, H.A.; **Kudelina, K.**; Asad, B.; Vaimann, T.; Perspective Chapter: Fault Detection and Predictive Maintenance of Electrical Machines [Internet]. New Trends in Electric Machines - Technology and Applications. IntechOpen; 2023. Available from: http://dx.doi.org/10.5772/intechopen.107167.

VII Sardar, M.U.; Vaimann, T.; Kütt, L.; Kallaste, A.; Asad, B.; Akbar, S.; **Kudelina, K.** Inverter-Fed Motor Drive System: A Systematic Analysis of Condition Monitoring and Practical Diagnostic Techniques. Energies 2023, 16, 5628. https://doi.org/10.3390/en16155628.

VIII Billah, M.M.; Saberi, A.N.; Hemeida, A.; Martin, F.; **Kudelina, K.;** Asad, B.; Naseer, M.U.; Mukherjee, V.; Belahcen, A., “Generation of Unmeasured Loading Levels Data for Condition Monitoring of Induction Machine Using Machine Learning,” in IEEE Transactions on Magnetics, vol. 60, no. 3, pp. 1-4, March 2024, Art no. 8201104, doi: 10.1109/TMAG.2023.3312267.

IX Hemeida, A.; Billah, M.M.; **Kudelina, K.;** Asad, B.; Naseer, M.U.; Guo, B.; Martin, F.; Rasilo, P.; Belahcen, A., “Magnetic Equivalent Circuit and Lagrange Interpolation Function Modeling of Induction Machines Under Broken Bar Faults,” in IEEE Transactions on Magnetics, vol. 60, no. 3, pp. 1-4, March 2024, Art no. 8200704, doi: 10.1109/TMAG.2023.3306207.

1 Introduction

1.1 Electrical Machines

Nowadays, electrical machines and drive systems are crucial across various applications and industries, playing a significant role in enhancing efficiency and productivity. Given their widespread use in diverse applications, ensuring proper maintenance is essential. Electrical machines are indispensable elements of daily life, powering a wide range of applications starting from small appliances like fans and refrigerators to large-scale industrial machinery such as pumps, compressors, and turbines. Moreover, many systems and devices, which are crucial for both industrial and residential applications, heavily rely on electrical machines.

Their significance extends across various industrial sectors, including power generation, transportation, manufacturing, automation, and more. This widespread usage is attributed to their exceptional efficiency and reliability, making them indispensable in numerous industrial branches and applications. These systems serve in simplifying, securing, and enhancing convenience in daily life. Over the years, their importance has further escalated, owing to their reliability, speed range, efficiency, power density, and cost-effectiveness. Furthermore, electrical machines are indispensable components of renewable energy resources, such as wind turbines.

Industrial motors are expected to possess specific characteristics to meet operational demands effectively. These include low maintenance requirements, cost-effectiveness, compact size, durability, variable speed control capability, and resilience to varying operational conditions. Among them, the induction motor is the most prevalent machine type in industrial settings today. Induction motors are well-suited to fulfill all these requirements [1]. Three-phase induction motors, known for their high efficiency and cost-effectiveness, are widely applied in domestic fields and industrial applications [2].

1.2 Faults in Electrical Machine

Despite their advantages, different damages in combination with environmental conditions can impact induction machines during operation. It can significantly impact induction motors' effectiveness, maintenance, and longevity. Given the pivotal role of these motors across various industrial sectors, such failures are undesired and must be diligently prevented.

In general, stresses affecting the operation of electrical machines can be categorized into four main groups, commonly referred to as thermal, electric, ambient, and mechanical stresses [3]. These stresses often lead to the emergence of faults within the machine. The distribution of these faults is primarily influenced by the motor's parameters, including machine type, size, and rated voltage. However, mechanical faults represent a significant proportion of overall faults, manifesting in various forms such as eccentricity, broken rotor bars, cracked end rings, damaged bearings, and more [4]. At the same time, bearing faults are the most prevalent type of fault, accounting for around 40% of all machine failures [5].

Detecting and diagnosing bearing faults in induction motors is crucial due to their prevalence and impact on motor performance. These faults can lead to severe operational issues and compromise the motor's lifespan. Bearings, crucial components of rotating machinery, are susceptible to damage from various sources, including contamination, corrosion, and improper lubrication. Contaminants such as dust and moisture can infiltrate the bearing, causing structural damage and corrosion, ultimately leading to premature wear and failure.

Proper lubrication reduces friction, shields against corrosion, and prevents contamination, which is essential for preventing bearing faults. However, improper lubrication practices, such as insufficient or excessive grease application, can accelerate bearing wear and shorten its service life. Material fatigue, resulting from continuous loads that create cracks on the bearing's surface, is another common cause of bearing failure. Mechanical damages, such as manufacturing defects or misalignment, can significantly impact bearing performance.

In addition to bearing faults, other types of motor failures can occur, including rotor and stator faults. Rotor faults may involve broken rotor bars, end ring damage, or eccentricity, leading to uneven air gaps between the rotor and stator and motor instability. Stator faults, on the other hand, often stem from winding issues, such as short circuits or insulation degradation, which can result from thermal, electrical, ambient, or mechanical stresses. Monitoring and diagnosing these faults are essential for maintaining motor reliability and performance.

1.3 Condition Monitoring

Preventing induction motor failures is crucial, given their pivotal role in various industries. As presented in Figure 1, three main types of machine maintenance can be classified: corrective, preventive, and predictive maintenance [6].

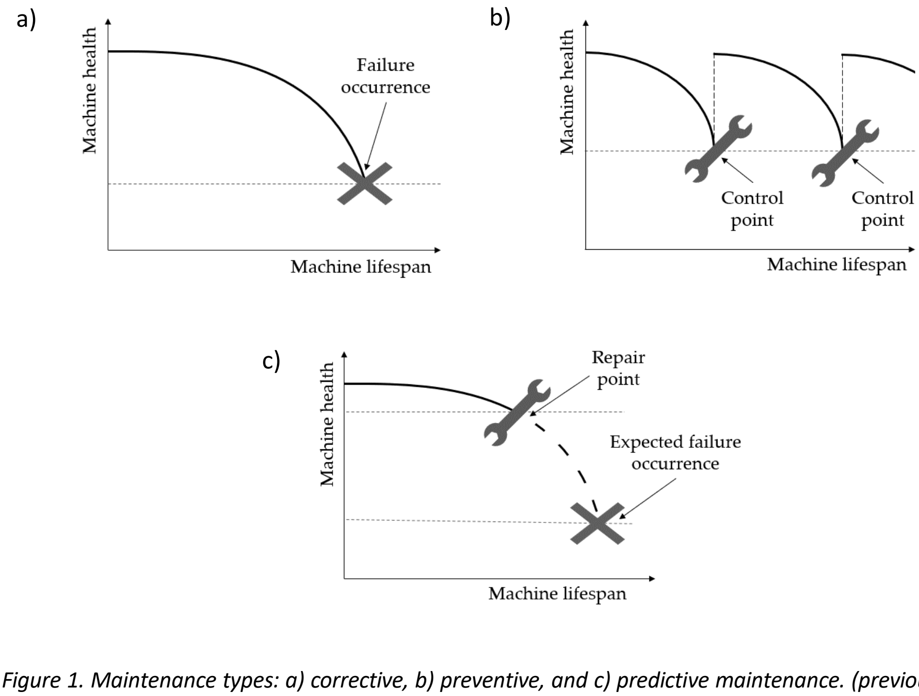


Figure 1. Maintenance types: a) corrective, b) preventive, and c) predictive maintenance. (previously published in article V)

As presented in Figure 1a, corrective maintenance, also known as reactive maintenance, involves repairing equipment after a failure has occurred [7]. This approach is suitable for small and less critical workstations where unexpected failures do not result in significant economic or catastrophic consequences. On the other hand, as shown in Figure 1b, preventive maintenance aims to prevent failures by regularly inspecting and servicing the equipment according to a predetermined schedule [8]. While this approach can extend the lifespan of machines, it provides limited information on the remaining useful lifetime and lacks prognostic capabilities. Additionally, scheduled inspections often require partial or total shutdowns of production processes, leading to inefficiencies and increased operating costs. To mitigate these issues, manufacturers increasingly use predictive maintenance, which relies on condition monitoring to anticipate failures based on the equipment's operational data [9]. This proactive approach helps reduce shutdown costs, minimize downtime, and optimize resource utilization. The predictive strategy is presented in Figure 1c.

Various parameters, such as current, vibration, temperature, and magnetic flux, need to be continuously monitored to ensure electrical machines' reliable and efficient operation. Moreover, specific fault patterns in the signals can indicate impending failure. Consequently, adopting condition-based monitoring becomes imperative for staying informed and making well-informed decisions regarding machine maintenance.

1.4 Predictive Maintenance

The possibilities arising from Industry 4.0, particularly cloud computing and the Internet of Things, result in more efficient diagnostics – predictive maintenance, thereby attracting big data and numerical models of the systems. As illustrated in Figure 2, this concept utilizes remote condition-based monitoring instead of scheduled maintenance routines, consequently reducing the utilization of logistic, energy, human, and material resources [10].

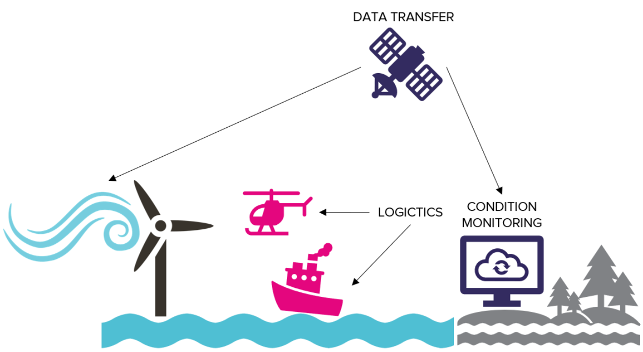


Figure 2. The concept of remote condition monitoring. (previously published in article VIII)

Every energy system embodies a complex mechanism that needs monitoring of numerous parameters, demanding substantial computational resources. Given the vast amount of data involved, employing advanced diagnostic approaches based on artificial intelligence is a reasonable choice. These intelligent algorithms will not only facilitate fault detection but also enable the system to predict potential faults. The primary challenge lies in the quantity and quality of training data. To ensure effective training, it is crucial to thoroughly examine the nature of machine faults, including their causes and impacts on global parameters.

1.5 Aim, Hypotheses, and Research Questions

The thesis hypothesizes that integrating fault representation, experimental data, and predictive models can significantly advance fault detection and prediction. This integrated approach is suggested to improve accuracy and optimize resources in identifying and forecasting potential faults within complex systems. Through these methodologies, the thesis aims to demonstrate how leveraging models alongside empirical data and machine learning algorithms can enhance fault detection capabilities and streamline maintenance processes.

The research question of this thesis revolves around investigating fault patterns across various fault types, focusing on developing comprehensive methods for fault detection, segregation, and prediction. This study encompasses several key components:

1. Development of a sophisticated test bench for implementing faults in a controlled environment.
2. Testing of faults to replicate real-world scenarios and gather data essential for analysis and training.
3. Exploration of faults representations to provide a deeper understanding of their characteristics and patterns.
4. Devising methods for effectively segregating different fault types to enhance the accuracy of fault detection algorithms.
5. Investigation of the utilization of machine learning and fuzzy logic algorithms for detecting, segregating, and predicting faults, thereby offering invaluable insights into optimizing maintenance strategies and improving system reliability.

1.6 Contribution and Dissemination

During the doctoral studies, the author contributed to 49 publications. The findings of this research have been disseminated through scientific publications, conferences, symposiums, doctoral schools, and other presentations. The dissertation is based on 10 primary scientific publications, comprising 6 journal papers and 4 conference papers presented at international conferences.

Scientific novelties:

1. Methodology for data collection using the test bench with faults inside the induction motor under different operational conditions.
2. Methodology for manual implementation of bearing current faults to healthy bearings for data collection.
3. A comparative analysis of the fault patterns under different operational conditions based on input line current and frame vibration.
4. Improvement in the definition of the transition state and data generation for effective fault prediction.
5. Improvement on signal spectrum-based fault predictive algorithm for electrical machines.
6. Development of a combination of machine learning algorithm and fuzzy logic for fault prediction.
7. Development of a neuro-fuzzy logic algorithm for fault prediction.

Practical novelties:

1. Development of the monitoring system to assess induction motor performance under different conditions, facilitating early fault detection.
2. Development of the test bench for inducing various bearing faults manually, enabling efficient data collection for analysis.
3. Development of the methodology for analysis of fault patterns based on current and vibration signals.
4. Validation of improved signal spectrum-based fault predictive algorithm for electrical machines.
5. Implementation of the combination of machine learning algorithm and fuzzy logic for fault prediction.
6. Implementation of the neuro-fuzzy logic algorithm for fault prediction.

1.7 Thesis Outline

The thesis is structured into six chapters, each addressing crucial aspects of fault detection and prediction in electrical machines.

Chapter 2 delves into the main faults of electrical machines, categorizing induction motor failures into three primary groups: stator, rotor, and bearing-related failures. Motor parameters such as type, size, and rated voltage influence the distribution of these faults. However, statistical analysis reveals that bearing faults account for most of the failures.

In Chapter 3, the focus shifts to condition monitoring for electrical machines. Understanding that fault occurrence is determined by various motor parameters; the chapter emphasizes the importance of monitoring multiple parameters such as vibration, current, temperature, magnetic flux, and torque to enhance machine reliability. A comprehensive overview of the main faults and their corresponding signatures is provided. Besides, this chapter delves into intelligent algorithms, underscoring their significance in ensuring proper maintenance of electrical machines and drive systems across different applications. The chapter emphasizes the critical role of diagnostic methods in this context.

Chapter 4 tackles data analysis and preprocessing, crucial for effectively training intelligent algorithms. It describes an experimental test bench setup, including components such as the testing machine, loading machine, and acquisition system. Various operational conditions and control environments are considered to gather accurate data for training purposes.

Lastly, Chapter 5 focuses on classification and prediction techniques, including machine learning and fuzzy logic approaches. This chapter explores methodologies for leveraging collected data to classify and predict faults in electrical machines, aiming to enhance fault detection capabilities and streamline maintenance processes.

2 Faults in Electrical Machines

Induction motor failures are classified into three main groups: stator, rotor, and bearing-related failures. The distribution of these faults is contingent upon motor parameters such as type, size, and rated voltage. Low-voltage machines primarily experience bearing-related faults, while high-voltage machines exhibit a higher portion of stator winding faults [11]. The general fault distribution in induction machines is presented in Figure 3, where, statistically, most of failures is related to bearing faults [12].

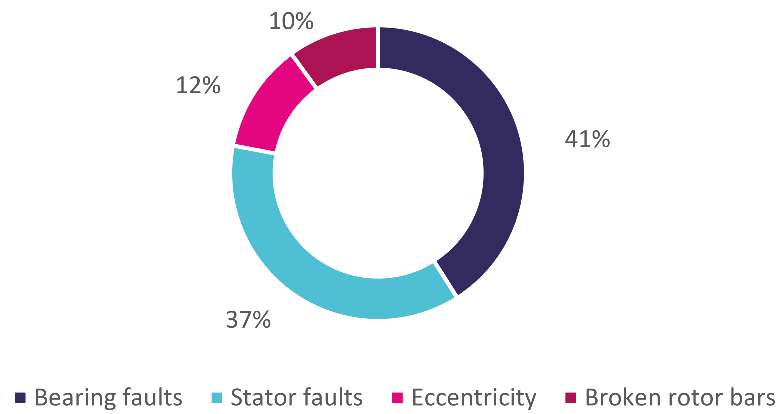


Figure 3. Distribution of faults in induction machines.

2.1 Bearing faults

Bearings are crucial parts of a rotating machine, yet they also account for the highest proportion of different damages. The production of bearings must follow strict standards. However, the actual lifespan of a bearing is often shorter than expected due to various stresses during operation, like unexpected overload, not enough lubrication, or incorrect installation [13]. Because electrical machines work in different conditions, bearings can be susceptible to many issues and damage. The causes of these problems are various environmental or manufacturing factors.

2.1.1 Contamination and Corrosion

When humid air enters the bearing, it compromises the lubricant properties at specific points of heightened load on the rings. Bearings are susceptible to pollution from dust, sand, and other abrasive particles, resulting in structural damage such as scratches and cracks. These pollutants can create significant dents when rolling elements push the debris into the rings.

Additionally, lubricants can become contaminated by water or other chemical substances, leading to the onset of bearing corrosion. Corrosion is a process involving the interaction between materials and the environment, resulting in material dissolution. Proper lubrication is a crucial operational factor determining the durability of a bearing. A well-chosen lubricant forms a thin oil layer, mitigating the impact of rolling elements against bearing rings and cages. Figure 4 illustrates an example of bearing corrosion.

Figure 4. An example of corroded bearing. (previously published in article I)

Lubrication serves to prevent premature wear and corrosion in bearings. Improper lubrication can manifest as either insufficient or excessive grease application. Insufficient lubrication induces friction and promotes crack progression, while excessive greasing may cause shaft slipping, leading to structural damage. Inappropriate bearing cage selection is a primary cause of such damages, as it fails to prevent the entry of particles into the bearing. To prevent these issues, corrosion-resistant lubricants can be employed. Additionally, maintaining a clean mounting process and refraining from using contaminated greases are vital preventive measures.

2.1.2 Lubricant Issues

Correct lubrication is a crucial operational aspect for bearings. The lubricant establishes an essential oil layer between working surfaces, simultaneously cushioning the impact of rolling elements on the rings and separator [14]. Lubrication is pivotal for ensuring the longevity of the bearing. Grease plays a key role in reducing friction, shielding the bearing from corrosion and wear, and preventing the entry of solid and liquid contaminants. Changes in the lubricant's condition can also indicate motor issues, with darkening occurring due to electrical discharges, as shown in Figure 5.

Figure 5. Improper lubrication of bearing. (previously published in article I)

Improper lubrication can manifest as either insufficient or excessive lubrication, both of which inevitably lead to premature bearing wear and a shortened service life [15]. Insufficient lubrication may result from the use of low-viscosity grease or an insufficient quantity of grease. Conversely, excessive lubrication can induce shaft slipping, leading to crack formation and development.

Furthermore, the improper selection of lubricants contributes to bearing contamination. Types of lubricants encompass plastic greases and various oil-based greases. Each lubrication method possesses unique characteristics, necessitating the selection of the method that best aligns with lubrication requirements. The choice of lubricant depends on the operating conditions of the bearing, particularly the temperature range, speed, and working environment. Bearings are mainly lubricated with plastic grease, which, in contrast to oils, offers prolonged efficacy at friction points, thereby reducing economic costs. While oils excel in enhanced heat dissipation, they come with the drawbacks of higher cost and the risk of leakage compared to plastic grease.

2.1.3 Wear and Material Fatigue

Material fatigue typically arises from continuous loads that create cracks on the bearing's surface [16]. The application of external forces to the bearing rings weakens the material, leading to cracking. With time, these cracks progress, rendering the bearing unsuitable for continued use. The durability of a bearing is measured by the number of revolutions it completes before the initial signs of material fatigue become evident on its rings and rolling bodies. Figure 6 presents an example of bearing material fatigue.

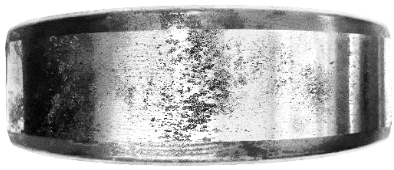


Figure 6. An example of material fatigue on bearing ring. (previously published in article I)

Continuous overloading, inadequate maintenance, and contaminated surfaces always contribute to material fatigue. Development and progression of this phenomenon are significantly influenced by the magnitude of the machine's applied load and rotational speed. Initially, microcracks appear in the subsurface, evolving over time to larger surface cracks, resulting in a roughened bearing surface. This phase may be accompanied by additional noise and vibration, coupled with an increase in the operating temperature of the bearing. Regular inspections and proper lubrication are essential preventive measures to reduce the risk of material fatigue in bearings.

2.1.4 Mechanical Damages

The majority of bearing faults stem from mechanical damage, which may result from manufacturing defects or unforeseen conditions during motor operation. Typically, these mechanical damages affect components such as inner and outer rings, cages, and rolling elements.

These mechanical damages may also arise from incorrect manufacturing or mounting processes, inadequate design, misalignment of bearing rings, or unequal proportions of rolling elements. Before installing the bearing, it is essential to inspect for manufacturing faults, including overall appearance, ease of rotation, and compliance with technical documentation requirements. In the case of open-type bearings, checks are necessary for contamination, corrosion, and the condition of the cage. For sealed-type bearings, an additional check on cages is crucial to prevent potential damage.

2.1.5 Shaft Currents

The extensive utilization of variable-speed drives in various motor applications has significantly heightened the impact of bearing currents [17]. Visually, damages caused by bearing currents exhibit distinct characteristics compared to other mechanical defects. It is crucial to visually inspect replaced bearings, especially if they have been changed during maintenance, and there are suspicions of shaft currents being present. The impact of these currents on the bearing is influenced by various factors, including the type of lubricant, rotational speed, applied current, operating duration, and the condition of the material [18].

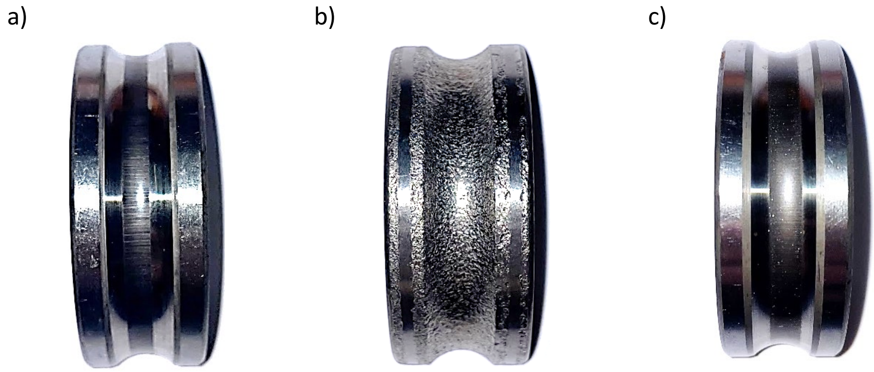


Figure 7. Common damages caused by bearing currents: a) fluting, b) frosting, and c) pitting. (previously published in article VI)

Typically, damages induced by current are only noticeable in advanced stages when the bearing surface is already compromised. Faults resulting from bearing currents tend to appear in areas with the thinnest lubrication due to heightened stress in those regions [19]. This frequently leads to the formation of fluting on the bearing surface, as shown in Figure 7a, where multiple lines become apparent across the bearing raceways. Such damage is often associated with constant rotational speeds and low voltage. Another category of bearing current-related faults, observed when a motor operates at variable speeds, is known as frosting. Figure 7b illustrates the occurrence of frosting in practical situations. When a motor operates at low speed and receives power from a high-voltage source, a phenomenon of pitting can occur in the bearing. Pitting is typically observed in motors designed for DC applications, such as railway motors. In these instances, small craters appear on the bearing surface, as shown in Figure 7c.

In addition to the previously mentioned bearing current faults, another type of damage known as dull-finish may occur. The primary distinction between dull-finish and pitting lies in the size of the craters on the bearing surface. In the case of dull-finish, these craters are significantly smaller, often requiring the use of a high-magnification microscope for proper examination.

2.2 Rotor Faults

Additionally, rotor faults can develop during the machine's operation. A prevalent form of rotor damage involves broken rotor bars and end rings, typically stemming from natural degradation leading to rotor wear. Thermal expansion can exacerbate this issue by causing cracks in the rotor bars. The differential expansion rates of copper bars and steel laminates, with copper expanding faster at higher temperatures, contribute to these cracks.

2.2.1 Eccentricity

Rotor damage induced by centrifugal force is often associated with eccentricity, defined as an uneven air gap between the rotor and stator. The air gap is defective if it exceeds 10% of the nominal value [20]. Factors such as improper installation, missing bolts, shaft misalignment, and rotor imbalance contribute to eccentricity. An example of rotor wear is presented in Figure 8.

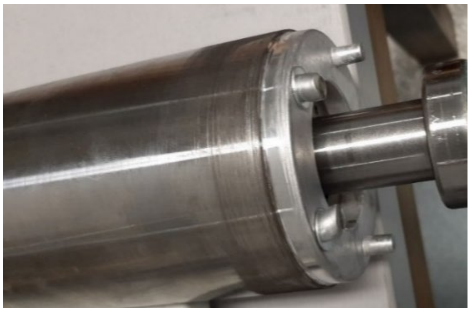


Figure 8. Rotor wear caused by centrifugal forces.

Motor eccentricity manifests in three main types: static, dynamic, and elliptical. Mixed eccentricity can also occur when the centers of the rotor and stator, along with the axis of rotation, are misaligned. In Figure 9, three main types of eccentricity are presented.

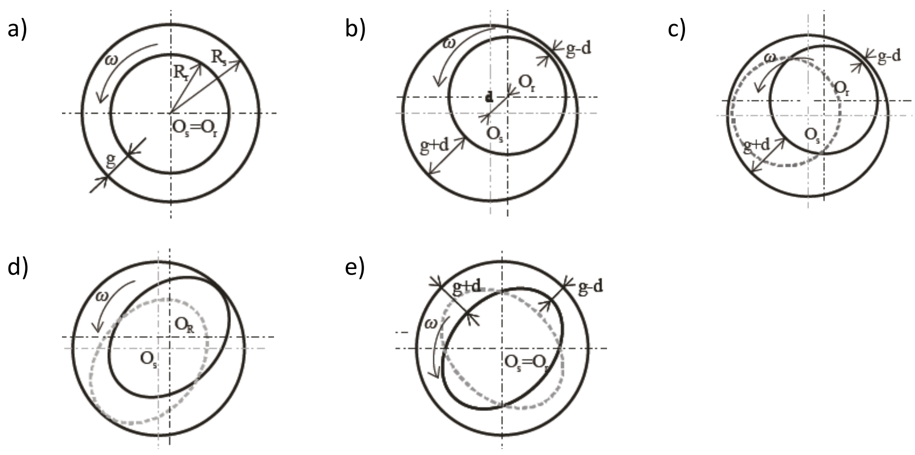


Figure 9. Rotor eccentricities: a) healthy, b) static, c) and d) dynamic, e) elliptic eccentricities. [21]

Static eccentricity (SE) stands out as the most prevalent type of eccentricity in motors, characterized by a fixed rotation axis of the rotor parallel to the stator axis over time. Dynamic eccentricity (DE), on the other hand, involves a variation in air-gap length over time. Elliptic eccentricity (EE) occurs when the center points of the stator and rotor align, yet a non-uniform air gap persists due to the elliptical shape of the rotor and changes in angles over time. The air-gap width for various eccentricities can be determined using the following equations:

$$g_{SE} = R_s - R_r + \sqrt{R_r^2 - (d \cdot \sin\beta)^2} \tag{1}$$

$$\delta_{DE} = \frac{|O_W \cdot O_r|}{g} \tag{2}$$

$$g_{EE}(t) = R_s - \sqrt{\left[(R_r + d) \cdot \cos\left(\frac{\omega t}{p} - \beta\right)\right]^2 + \left[(R_r - d) \cdot \cos\left(\frac{\omega t}{p} - \beta\right)\right]^2} \tag{3}$$

where g – air gap, R_S – radius of the stator, R_r – rotor radius, d –deviation, β – initial eccentricity angle, O_w – rotational center, O_s – stator symmetry center, p – number of poles [21].

2.2.2 Demagnetization of permanent magnets

Permanent magnets commonly fail due to demagnetization, which involves a partial or complete loss of magnetization [22]. Overloading and thermal expansion, particularly in machines operating at high temperatures without proper cooling, significantly elevate the risk of demagnetization. Electrical stress, such as short circuits, is another contributing factor. It is advisable to monitor magnet manufacturing for defects and signs of corrosion to prevent demagnetization. Partial demagnetization that produces additional harmonics in the stator currents can be found at the following frequencies:

$$f_{pdem} = f_f\left(1 \pm \frac{k}{p}\right) \tag{4}$$

where f_{pdem} – faulty frequency, f_f – fundamental frequency, k – integer, and p – number of poles [23].

Demagnetization of permanent magnets is often attributed to machine overload and thermal expansion [24]. Operating in high-temperature ranges without a proper cooling system significantly elevates the risk of demagnetization. Electrical stresses, including short circuits, are another factor that can impact magnet properties [25]. It is also advisable to monitor magnets during manufacturing for defects and signs of corrosion.

2.3 Stator Faults

Issues with the stator typically stem from problems with the windings, which are not only crucial but also highly sensitive in any motor. This percentage underscores the importance of prioritizing the protection of the windings in motor design and operation. Before a motor is commissioned, thorough checks are imperative to ensure that the windings are undamaged, correctly connected, and adequately insulated.

2.3.1 Winding failures

Among the most prevalent winding failures is a short circuit, typically starting from turn-to-turn short circuit [26]. Without prompt intervention, this issue can escalate into phase-to-phase or even phase-to-ground short circuits. Detecting inter-turn faults in their early stages is particularly challenging in the electrical machine industry. Even in the initial phase, an inter-turn short circuit can cause substantial damage, ultimately leading to machine breakdown. Different modes of short circuit are shown in Figure 10.

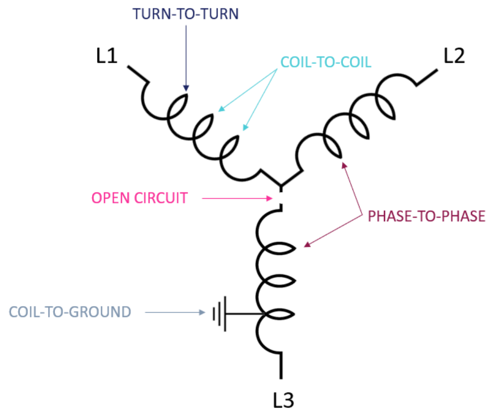


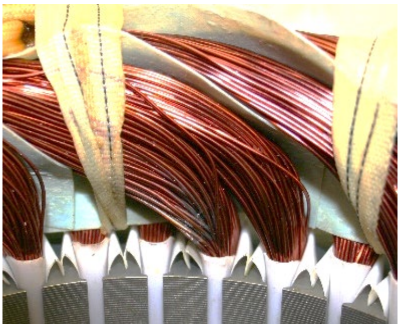
Figure 10. Common modes of short circuit in wye-connected stator.

The degradation of winding insulation can be attributed to various factors, with four primary stresses, collectively known as TEAM stresses, significantly influencing the degradation rate: thermal, electrical, ambient, and mechanical stresses [27].

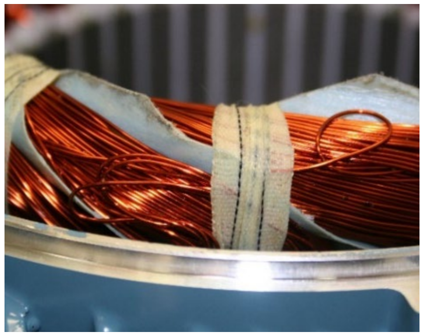
- Thermal stresses: Among the most prevalent stresses affecting machines are thermal stresses. Induction motors experience high starting currents, causing the temperature to surpass threshold values and leading to a decline in the insulation system.
- Electrical stresses: Insulation susceptibility arises from unstable supply voltage, transient voltages, unstable grounding, and incorrect rated values of the machine. Electric motors, especially those exposed to fast-switching inverters, are vulnerable to these stresses.
- Ambient stresses: This encompasses environmental factors impacting the motor, such as moisture, humidity, aggressive chemicals, dirt, and other particles. Each element can affect the machine and its insulation system differently, either individually or in conjunction with other stress types.
- Mechanical stresses: Various forces, including centrifugal and magnetic forces, influence machine operation. While numerous studies focus on monitoring and reducing these forces, limited research addresses quality control monitoring during production and the damage incurred on electrical machines during installation.

Special attention has been directed towards manufacturing faults, often overlooked but with the potential to evolve during motor operation, resulting in undesirable consequences. Ideally, machines should exhibit symmetry in all aspects, featuring sinusoidally distributed windings on both the stator and rotor sides, a smooth and consistent air gap, and uniformly distributed current in the stator and rotor windings to mitigate skinning and proximity effects. These ideal characteristics aim to achieve ripple-free speed and torque production without vibrations.

However, practical machines face limitations that prevent the realization of these ideals. Despite testing measurements falling within defined limits, visual inspections frequently reveal various damages in the motors. An example of some manufacturing damages is presented in Figure 11.



a)



b)

Figure 11. Manufacturing damages on induction motors: a) overheated winding insulation, b) improper winding placement. (previously published in article II)

Manufacturing faults, typically neglected during the design phase, tend to manifest during machine exploitation. These asymmetries can lead to heightened vibrations, causing friction among copper conductors and resulting in insulation damage. Asymmetrical faults, such as winding faults, induce additional sideband harmonic components at the fundamental frequency and can be defined by the following frequencies:

$$f_h = f_s(1 + 2sk);\ k = 1, 2, 3,\ldots;\ k \in N \tag{5}$$

where f_h – harmonic frequency, f_s – supply frequency, s – slip [28].

Additionally, the thermal profile of the machine becomes uneven, giving rise to hot spots at specific locations. Consequently, monitoring and predicting potential fault occurrences can markedly mitigate the adverse impact of damage on motor maintenance.

2.4 Summary

The chapter provides a comprehensive overview of the classification and causes of failures in induction motors, categorizing them into three main groups: stator, rotor, and bearing-related failures. Bearing faults, being the most common, are attributed to various factors such as contamination, lubrication issues, wear, and material fatigue. Contamination and corrosion, inadequate lubrication, and improper lubrication selection contribute significantly to bearing failures. Furthermore, material fatigue and mechanical damages are prevalent issues affecting bearing longevity. Additionally, the text discusses rotor faults, including broken rotor bars, end ring damage, and eccentricity, which can result from thermal expansion and improper installation. Stator faults, primarily related to winding issues such as short circuits and insulation degradation, are also highlighted, with emphasis on the importance of detecting and addressing these faults early. To sum up, to improve the machine's reliability, it's crucial to oversee numerous parameters.

3 Condition Monitoring using Artificial Intelligence

3.1 Global Parameters' Monitoring

As previously stated, the occurrence of faults is primarily determined by the motor's parameters, including machine type, size, rated voltage, and so forth. To enhance the machine's reliability, it is essential to monitor multiple parameters.

3.1.1 Vibration Monitoring

Vibrations within an electrical machine can originate from various sources, including magnetic fields, fluid flow, imbalances, and particularly from rotating elements like bearings, gearboxes, or rotors [29]. Currently, there is a diverse range of sensor types available for measurement technology, such as piezoelectric [30], capacitive [31], inductive [32], piezoresistive [33], and strain gauge [34] sensors.

Vibration analysis is a valuable tool for assessing the condition of electrical equipment and is extensively employed for diagnostic purposes [35]. It involves tracking changes through defined vibration signatures and identifying deviations within the system. These deviations manifest in alterations to acceleration amplitude, frequency values, and intensity. Detecting failures in a timely manner requires careful attention to specific frequency components within the harmonic spectrum [36]. These components can be identified in the frequency domain by performing Fourier transforms on the signals coming from the machine.

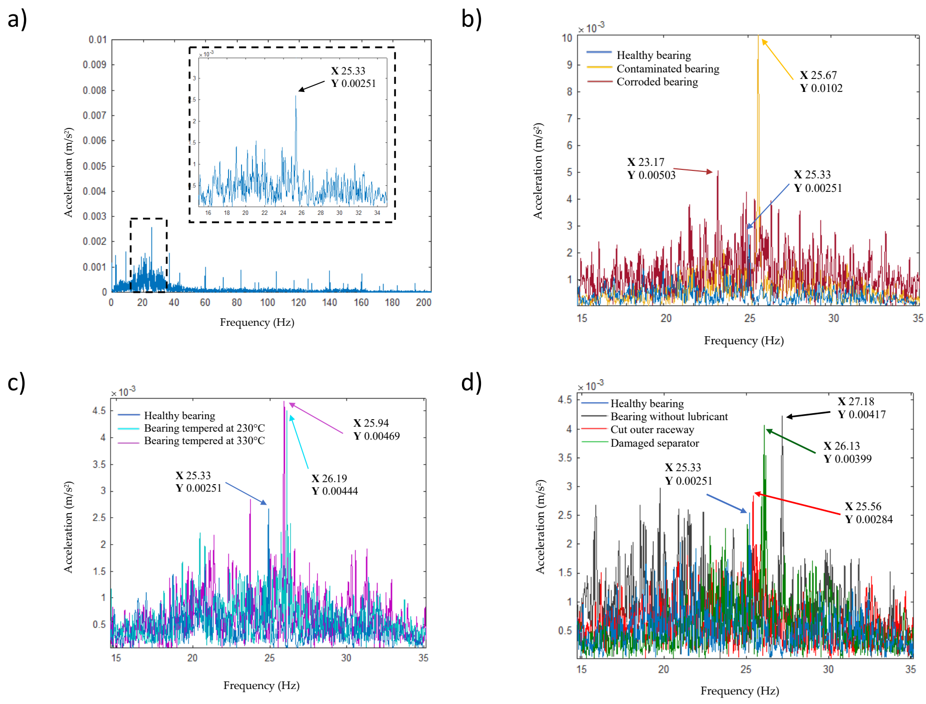


Figure 12. Fourier spectra of healthy and faulty bearings. (previously published in article IV)

As presented in Figure 12, in traditional diagnostic methodologies, vibration signals from both healthy and faulty bearings are utilized to compare them and detect a faulty pattern. The identification of specific frequencies on the FFT spectrum enables the observation of frequency variations in harmonic amplitudes, especially within fundamental components. This variation serves as a fault indicator.

3.1.2 Wear Monitoring

Wear condition monitoring in electrical machines plays a pivotal role in ensuring their optimal performance and longevity [37]. As these machines operate over time, various components, such as bearings and gears, are subjected to wear and tear. An example of stator wear is shown in Figure 13. Monitoring the wear condition involves assessing factors like vibration, temperature, and lubrication [38]. Vibration analysis helps detect irregularities in rotating elements, while temperature monitoring identifies potential overheating, which can accelerate wear.

Figure 13. Wear of stator.

The bearing is a crucial component of a rotating machine and is subject to various loads and forces, leading to a decrease in the motor's intended lifespan. In general, most friction losses in rotating machines are attributed to bearings. Consequently, monitoring the wear of bearings can greatly impact the proper functioning and overall reliability of the machine. The most frequent causes of bearing wear are high friction loads and insufficient lubrication. Bearing faults typically arise in areas where the lubricant coating is at its thinnest.

Additionally, monitoring lubrication levels is crucial as insufficient lubrication can lead to increased friction and wear [39]. By employing advanced sensing technologies and data analysis techniques, engineers can gather valuable insights into the wear patterns of critical components. Timely detection of wear allows for proactive maintenance, reducing the risk of unexpected breakdowns and enhancing the overall reliability and efficiency of electrical machines.

3.1.3 Electrical and Electromagnetic Monitoring

Monitoring the magnetic flux has become a widely used and effective method for detecting faults in electrical machines, given that many early failures result in a detectable magnetic asymmetry [40]. Electromagnetic measurement serves as an efficient means to monitor the electrical machine, either as an additional or alternative tool to stator current monitoring. In essence, an electric machine generates electromagnetic flux, and any minor imbalance in the magnetic or electric circuit is reflected in some of the transmitted fluxes [41]. Numerous studies have explored the monitoring of bearing damages [42], rotor faults [43], short circuits [44], and magnet problems [45] through the analysis of stray magnetic flux.

In most rotating electrical machines, which are typically symmetrical, magnetic flux is uniformly distributed. Any fault in the machine leads to an asymmetrical flux distribution, resulting in more localized magnetic stresses. The flux density across the broken bar increases, magnifying the peak induced current in subsequent rotor bars. This heightened current, along with increased magnetic forces, renders the affected components susceptible to faults, initiating a chain reaction. An example of flux distribution in the case of healthy and faulty rotor bars is presented in Figure 14.

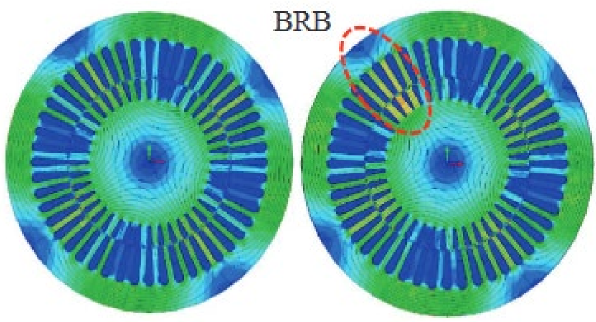


Figure 14. Flux distribution of healthy and faulty rotor bars in an induction motor. [46]

Crucially, the performance parameters of machines, such as torque, speed, voltage, and currents, are influenced by flux distribution. Analyzing these performance parameters enables the detection of any alterations in flux distribution due to a fault. These characteristics render diagnostic algorithms non-invasive and open a wide array of signal processing techniques for the condition monitoring of electrical machines.

3.1.4 Temperature Monitoring

Thermal monitoring is a crucial aspect of ensuring proper functionality. Elevated temperatures can significantly reduce the lifespan of electrical machines, causing damage to winding insulation, short circuits, accelerated aging of bearings, and degradation of rotor permanent magnets [47]. Common factors contributing to temperature increase include cooling system malfunctions and excessive currents flowing through windings [48].

In general, temperature-based monitoring can be categorized into two approaches: thermal image analysis and local spot measurement. An alternative method for thermal monitoring in rotating machinery is thermal imaging, which is presented in Figure 15.

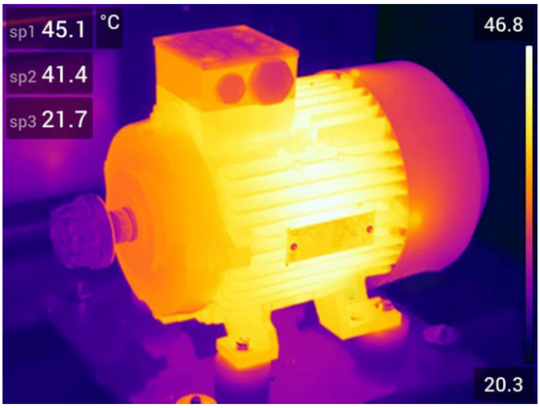


Figure 15. Thermal image of working induction motor.

For local thermal measurement, resistance thermometer detectors and thermocouples are commonly employed. However, using thermocouples or resistance temperature detectors for local monitoring may have limitations in safety applications, primarily due to the use of electrically conductive materials in the sensor structure [49]. Consequently, they may not be positioned in the hottest spots.

Table 1. Signatures of main faults in electrical machines. (previously published in article V)

Fault signatures	**Winding short circuit** [50], [51]	**Rotor broken bars** [52]	**Eccentricity** [53], [54]	**Bearing faults** [55]
Vibration	○	○	○	★
Current	★	★	○	★
Temperature	○	○	○	x
Magnetic flux changes	★	★	★	○
Chemical analysis	○	x	x	x
Torque changes	★	★	○	x

★- the most preferable parameter for condition monitoring; ○ - parameter can be used for condition monitoring; x- parameter cannot be used for condition monitoring.

3.2 Artificial Intelligence in Condition Monitoring

Nowadays, electrical machines and drive systems are extensively used across various applications and hold a significant role in industries. Given their diverse usage, ensuring proper maintenance is crucial. For this reason, the clever choice of diagnostic method is extremely important.

3.2.1 Machine Learning

A wide range of condition monitoring methods are available today to detect failures in electrical equipment. Many literature resources on intelligent health monitoring refer to machine learning. It is a field of study in computer science and artificial intelligence that does not directly solve problems but learns from applying solutions to similar problems [56]. Typical machine learning tasks include classification, regression, learning associations, clustering, and other machine learning tasks like reinforcement learning, learning to rank, and structure prediction [57]. Machine learning is closely related to data mining, which can discover new data patterns in large datasets. The main difference is that machine learning focuses on adaptive behavior and practical usage, while data mining concentrates on processing extensive amounts of data and discovering unknown patterns. Based on the dataset, known as training data, machine learning algorithms can build a model to predict and make decisions. There are many types of those algorithms, including supervised, unsupervised, semi-supervised, and reinforcement learning [58]. Figure 16 illustrates the most common methods used in machine learning.

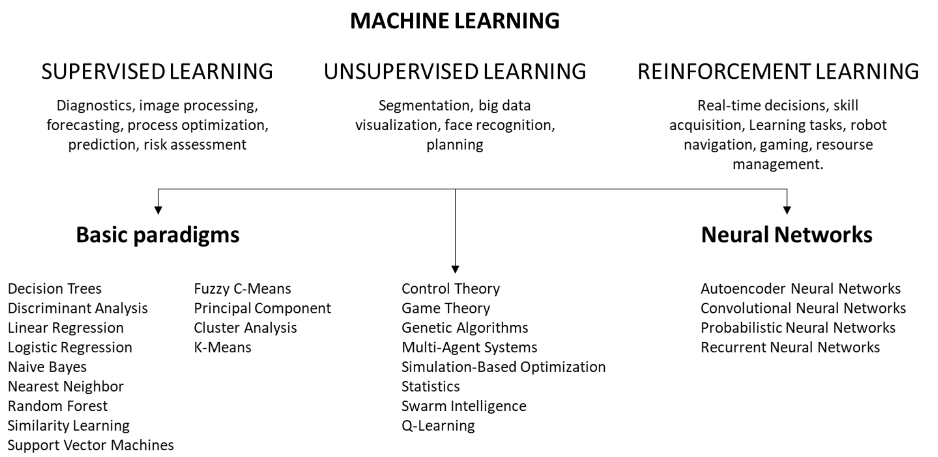


Figure 16. Common algorithms of machine learning.[59]

The basic paradigms of machine learning comprise supervised and unsupervised algorithms. Supervised machine learning, also referred to as “learning with a teacher,” involves learning from examples where both a training set (situations) and a test set (required solutions) are provided [60]. Obtaining these training sets poses challenges, particularly in industry and laboratories. Due to scheduled maintenance in industries and limited destructive testing in laboratories, acquiring enough faulty machines for training purposes is restricted. Additionally, collecting data with multiple faults (composite faults) in the same machine is non-trivial in both scenarios. At the same time, unsupervised machine learning, also known as “learning without a teacher,” involves discovering patterns from unknown data [61]. Here, only training data is available, and the objective is to cluster objects and/or reduce the volume of the given data. Some industrial systems utilize semi-supervised algorithms to achieve more precise outcomes. In such cases, some instances have both training and test sets, while others only have training data. In contrast to basic methods, reinforcement machine learning focuses on recognizing patterns in repetitive scenarios and generalizing from them [62]. The objective is to minimize errors and enhance accuracy by analyzing information before each step. Furthermore, the algorithm aims to maximize rewards (benefits) set in advance, such as minimizing resource expenditure, achieving desired values, or reducing analysis time. One widely used group of intelligent condition monitoring methods applicable to various machine parameters is artificial neural networks. Neural networks can be supervised, unsupervised, or reinforced. Many studies incorrectly categorize neural networks as distinct from machine learning. However, neural networks and deep learning are directly interconnected with computer science, artificial intelligence, and machine learning.

Supervised machine learning encompasses a wide range of functional algorithms capable of mapping inputs to desired outputs. Figure 17 illustrates the general algorithm of supervised learning.

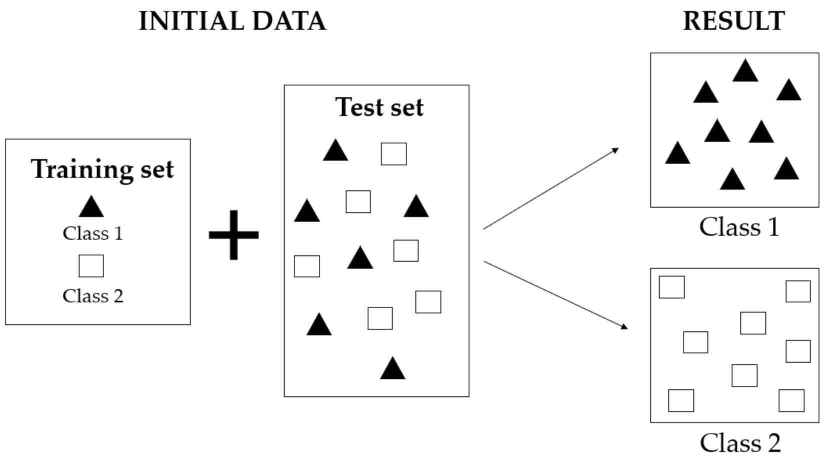


Figure 17. Concept of supervised learning. (previously published in article III)

Typically, supervised learning is used in classification and regression tasks: classifiers map inputs to predefined classes, whereas regression algorithms map inputs to a real-value domain. In essence, classification predicts the input category, while regression predicts a numerical value based on collected data. Supervised learning aims to identify features from labeled examples, thereby allowing for the analysis of unlabeled examples with potentially high accuracy. Essentially, the program establishes rules according to which the data is processed and classified. For the condition monitoring and diagnostics of electrical machines, decision trees [63] and support vector machines [64] are recognized the most suitable supervised algorithms.

Decision Trees: A decision tree is a decision support tool widely utilized in data analysis and statistics, with particular emphasis in artificial data mining. The objective of a decision tree is to construct a model that predicts the value of a target variable based on multiple inputs. The structure of a decision tree can be illustrated through branches and leaves. Branches contain attributes upon which the function relies, while leaves hold the values of the function. The remaining nodes encompass attributes that differentiate decision cases. An example of the decision tree algorithm is illustrated in Figure 18.

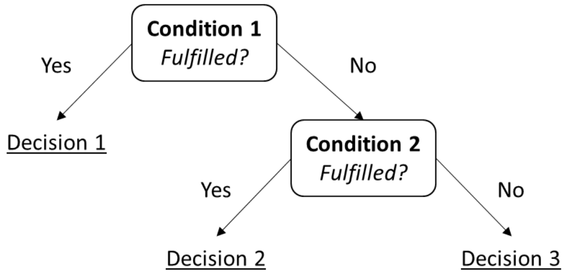


Figure 18. Diagram of decision tree. (previously published in article III)

Among other decision models, decision trees are the simplest and require minimal data to achieve success. Additionally, this algorithm can be combined with another decision model as a hybrid approach to achieve more accurate outcomes. However, these models are inherently unstable. A small amount of input data can lead to substantial changes in the decision tree structure, resulting in inaccurate results. Furthermore, regression algorithms may fail in the case of decision trees.

Support Vector Machines: Another widely used machine learning algorithm in condition monitoring is the support vector machines. In classification tasks, support vector machines are preferred as they can handle both linear and non-linear cases. For linear classification, each dataset is represented as a vector in an n-dimensional space, belonging to two classes. The algorithm's focus is on separating these data points to create a maximum gap between them. In non-linear classification, the kernel machine operates similarly to linear algorithms but applies to different datasets. The process of support vector machines is outlined in Figure 19.

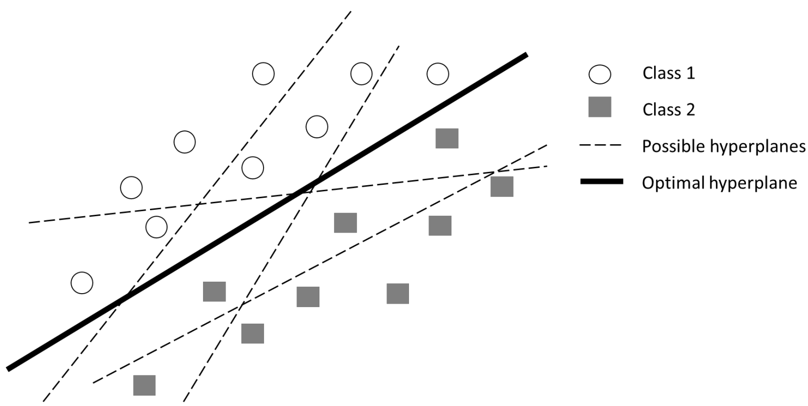


Figure 19. Concept of support vector machines. (previously published in article III)

Generally, support vector machines are an optimal tool when there is limited initial information about datasets. Like decision trees, they require less computational power to provide accurate results. However, processing particularly large datasets can be time-consuming. Additionally, managing the kernel machine for non-linear processes can pose a challenging task.

Unsupervised machine learning comprises algorithms capable of autonomously learning to perform a given task without the intervention of a teacher. It is commonly confronted with supervised learning, where the outcome is known, and the goal is to uncover relationships between system responses. In unsupervised learning, shown in Figure 20, the program endeavors to identify similarities between objects and categorize them into groups if similar patterns are detected. These groups are referred to as clusters.

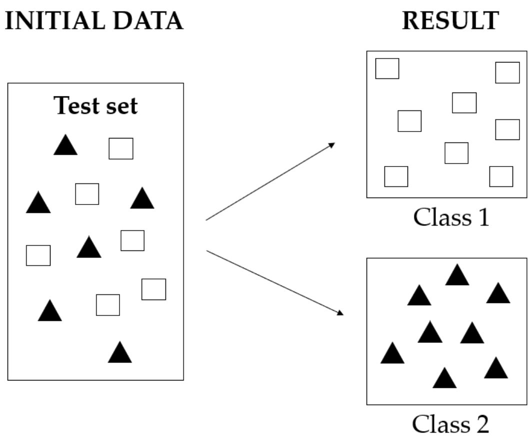


Figure 20. Concept of unsupervised learning. (previously published in article III)

In the diagnosis of electrical machines, principal component analysis is the most used algorithm [65].

Principal Component Analysis: More frequently, datasets are so vast that interpreting and discerning essential information becomes challenging. Principal component analysis stands out as one of the most prevalent algorithms for reducing the dimensions of data while retaining the least amount of information. Geometrically, principal component analysis can be interpreted, as demonstrated in Figure 21. The algorithm of principal component analysis unfolds as follows:

a) Points with specific coordinates are designated on the plane.
b) The direction of maximum data change is identified, and a new axis of principal component analysis is drawn through the experimental points.
c) Experimental points are projected onto the axis of principal component analysis.
d) It is assumed that all the points were initially projected on the axis of principal component analysis, and any deviations from this axis can be regarded as noise.

One of its key advantages is the independence of its components, with no correlation between them. This independence can notably expedite training time. However, these independent values may become less interpretable. There is still some degree of information loss, resulting in relatively less precise data analysis compared to the original values.

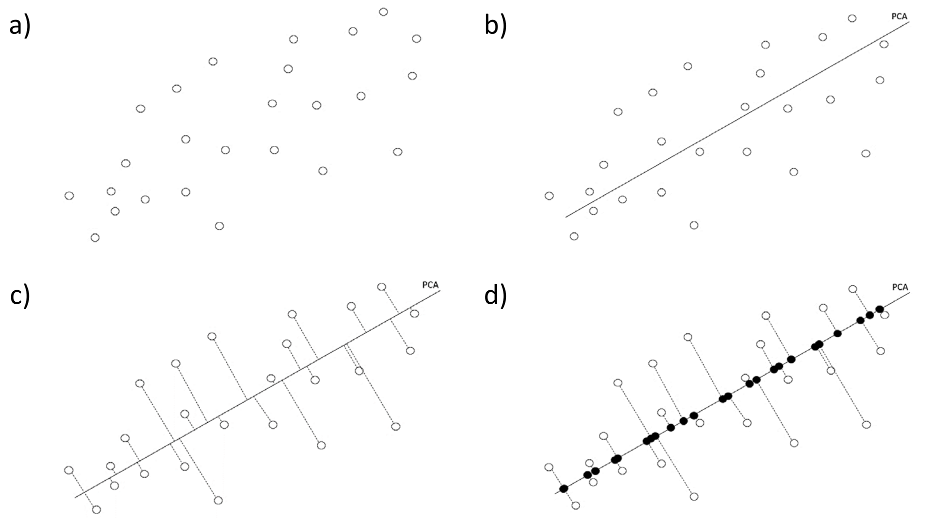


Figure 21. Support vectors and optimal hyperplane in non-linear classification: a) initial dataset, b) optimal vector determination, c) projection of initial dataset on the vector, d) new data parameters definition. (previously published in article III)

Reinforcement learning is a machine learning method in which the system (agent) learns through interaction with an environment. The general algorithm of reinforcement learning is depicted in Figure 22.

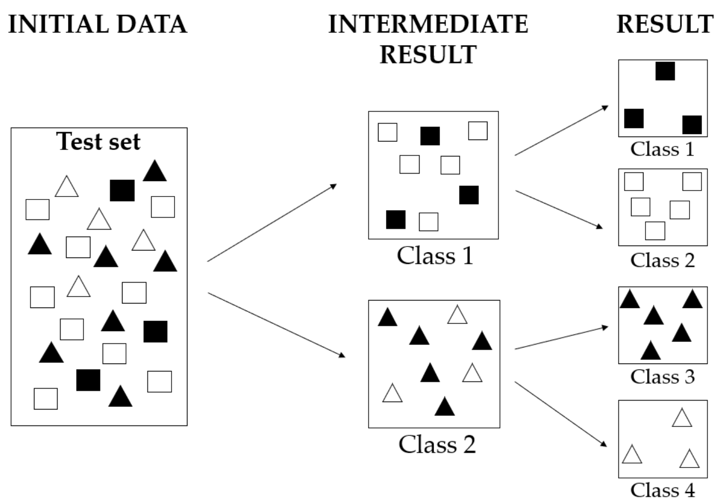


Figure 22. Concept of reinforcement learning. (previously published in article III)

Unlike supervised algorithms, reinforcement learning does not require labeled data pairs. Its primary focus is on striking a balance between navigating an unknown environment and leveraging existing knowledge. The genetic algorithm stands out as the most frequently used reinforcement algorithm in condition monitoring [66].

Genetic Algorithm: This algorithm serves as a tool for solving optimization problems and emulates natural selection mechanisms in the environment through random selection modeling. A distinctive aspect of genetic algorithm is its reliance on the "crossing" operator, inspired by its instrumental role in wildlife. In genetic algorithm, the problem is typically formalized so that its solution can be encoded as a vector of genes (genotype), with each gene possessing a certain value. In classical implementations, the genotype is assumed to have a fixed length. However, there are variations of genetic algorithm that are free from this limitation. The general diagram of genetic algorithm is illustrated in Figure 23. The optimization process employing genetic algorithm is as follows:

a) A task is defined, and numerous genotypes of the initial population are created.
b) This initial dataset is evaluated using the "fitness function," which assesses how effectively each genotype in the initial population addresses the task.
c) The best matches in the population are selected for the subsequent generations.
d) The top matches generate new solutions, and this process iterates until the task is accomplished, yielding a resultant population.

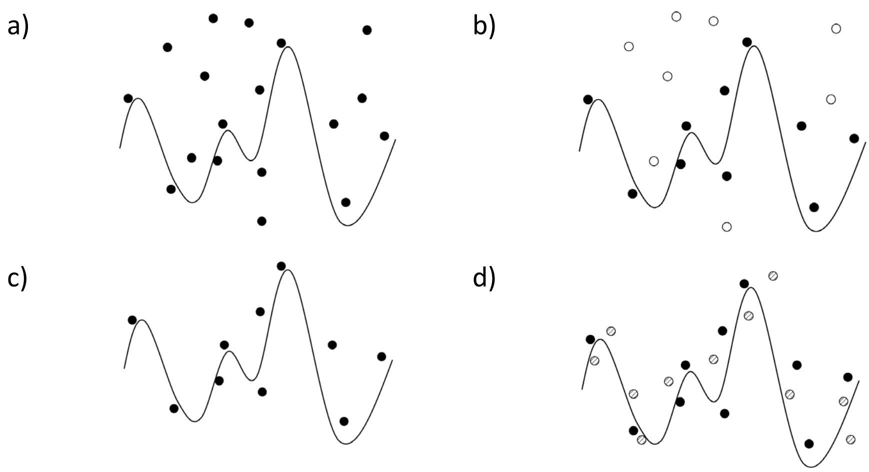


Figure 23. Genetic algorithm diagram: a) creation of initial population, b) application of fitness function, c) selection of the best coincidences, d) creation of resultant population. (previously published in article III)

One of the primary advantages of genetic algorithm is its independence from specific domain knowledge. The algorithm generates solutions through genetic operators, and multiple suitable solutions can be obtained. However, genetic algorithm may encounter degeneracy issues, where multiple chromosomes represent the same solution, leading to repeated occurrences of similar chromosome shapes. In such cases, the optimal solution is not guaranteed.

Neural Networks: Artificial neural networks have been proved as highly effective tools for condition monitoring and predicting remaining useful life due to their adaptability, nonlinearity, and ability to approximate functions [67]. One of the primary advantages of neural networks is their capability to outperform nearly every other machine learning algorithm. These algorithms are used to analyze and model processes of damage propagation and predict further failures based on collected data. The main tasks tackled by neural networks include classification, prediction, and recognition [68].

As shown in Figure 24, artificial neural networks are inspired by the biological nervous system's ability to learn and correct errors, aiming to replicate the brain's low-level structure. Neural networks are composed of machine learning algorithms that mimic the human brain, consisting of interconnected signals known as neurons. Both biological and artificial neurons comprise the cell body, dendrite (input), synapse (connection), and axon (output). The simplest model of an artificial neural network typically includes three layers of neurons: the input layer connected to a middle (hidden) layer, which is further connected to the final (output) layer.

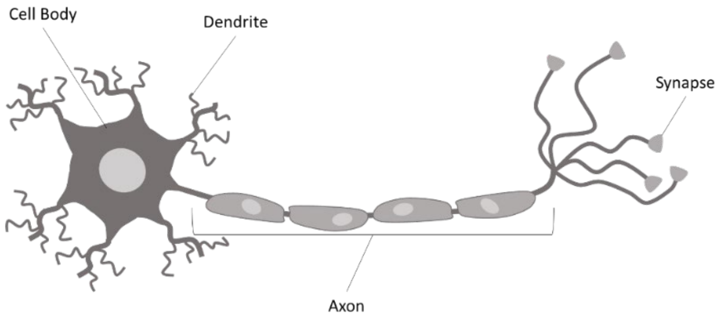


Figure 24. Neuron structure.

To achieve artificial intelligence, a system with a similar architecture needs to be constructed. The architecture of artificial neural networks is presented in Figure 15. Solving problems using neural networks necessitates collecting training data, which comprises observations with defined input and output variables. Neurons transmit signals from the input layer to the output, receiving data from the external environment (e.g., measuring systems, sensors), processing it, and transmitting signals through synapses to the hidden layer. The hidden layer processes these signals and forwards them to the output layer. Neurons act as computing units, receiving information, performing simple calculations, and transferring them further.

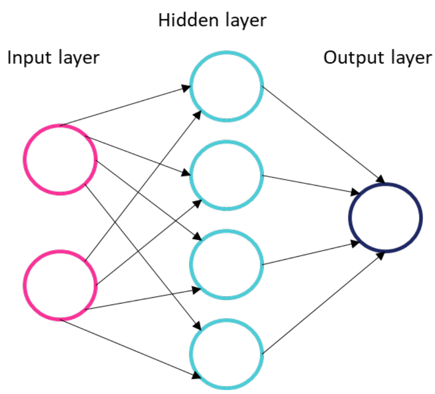


Figure 25. Architecture of artificial neural network.

Fast learning is one of the main advantages of neural networks over traditional algorithms. Training involves determining the coefficients of connections between neurons. Through training, neural networks can identify complex dependencies between input and output data and generalize it. Successful training enables the network to return correct results based on data absent in the training sample or incomplete or partially distorted data. When a neural network comprises more than three layers, a phenomenon known as deep learning or deep neural network arises. Deep learning, a subset of machine learning techniques within neural networks, analyzes large-scale machinery data, yielding more precise results. Overall, neural networks are considered a versatile tool for solving a wide range of problems.

However, each method has its limitations. Firstly, achieving precise results and making accurate predictions heavily depends on the quantity and quality of data – the challenge lies in striking a balance between underfitting and overfitting. Another common limitation for neural networks is the black box phenomenon. As previously mentioned, deep learning effectively learns the hidden layers of the architecture, mapping inputs to outputs. However, this process of approximating the function renders it difficult to gain insights into the structure and understand the cause of errors.

3.2.2 Fuzzy Logic

Fuzzy logic is another algorithm that finds successful application in various control systems of energy systems, closely resembling human perception processes and cognition [69]. Both fuzzy logic and machine learning are sub-fields of artificial intelligence. The primary distinction between fuzzy logic and traditional logic lies in their representations: traditional logic is limited to true or false values (1 or 0), while fuzzy logic can accommodate values ranging between 1 and 0 (including true, false, partially true, etc.). The primary configuration of the fuzzy logic block is depicted in Figure 25.

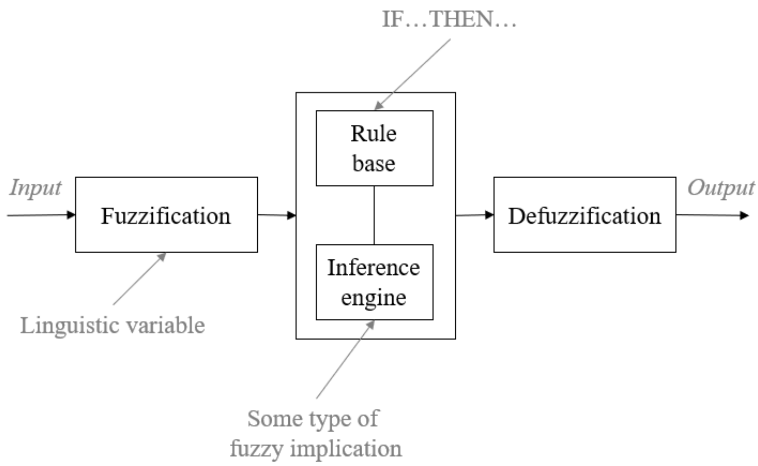


Figure 26. The structure of the fuzzy logic block. (previously published in article VIII)

It consists of fuzzification, where linguistic variables undergo transformation into fuzzy sets using membership functions. Fuzzy linguistic variables are used to express qualities across a specific spectrum. The rule base utilizes linguistic sentences to perform logic operations within the fuzzy block. The inference engine executes fuzzy implications to arrive at solutions. Defuzzification then converts variables from fuzzy sets into tangible, real values. The central component of the fuzzy logic block consists of fuzzy rules or sentences, constructed in the form of IF-THEN rules:

$$\textbf{\textit{IF}}\ x \text{ is } A,\ \textbf{\textit{THEN}}\ y \text{ is } B \tag{6}$$

Fuzzy logic offers distinct advantages in decision-making. Firstly, fuzzy logic employs rule-based sentences, making them readable and accessible for process operators. These rules can be constructed using everyday vocabulary, enabling operators to apply their practical experience directly. Its interface with natural language sets it apart from other methods, enhancing accessibility and user-friendliness. Furthermore, fuzzy logic allows decision-makers to incorporate multiple inputs, leveraging the advantage of including expert knowledge in the decision-making process. Operating as a nonlinear system, the fuzzy logic block can handle multiple inputs and outputs, providing recommended actions even in case of conflicts. However, there are several disadvantages. Fuzzy logic decisions involve more tuning parameters than classical approaches, potentially increasing complexity. Tracing data flow during execution can be challenging, complicating error correction. Fuzzy logic lacks a straightforward equation and mathematical apparatus due to its structure, making system analysis challenging and system stability assurance complex.

3.3 Summary

Besides, this chapter highlights the critical role of proper maintenance for electrical machines and drive systems due to their extensive usage across industries. It delves into the importance of selecting appropriate diagnostic method. The text provides a comprehensive overview of advanced diagnostic methodologies for ensuring the reliability and optimal performance of electrical machines. Table 2 provides a concise overview of the benefits and drawbacks of each diagnostic technique discussed above.

Table 2. Benefits and drawbacks of intelligent diagnostic techniques.

Diagnostic technique	Advantages	Disadvantages
Decision Trees	Small computational power, simple structure, data pre-processing is not needed, easy interpretation	Prone to overfitting, not suitable for regression tasks
Support Vector Machines	High dimensionality, operated with non-linear processes, small computational power, no needed in data specification	No ability to filter unnecessary information, complicated managing of kernel machine, overlapping risk
Principal Component Analysis	No overlapping, good visualization	Possible loss of information, reduced accuracy
Genetic Algorithm	Adaptive algorithm, rapid processing, multiple solutions	Can suffer from degeneracy, overlapping risk, may require significant computation

Artificial Neural Networks	Versatile, learns complex dependencies, fast learning	Need of qualitative data, black box phenomenon, overtraining risk
Fuzzy Logic	Flexible algorithm, no needed in specific hardware, easily reprogramming	Requires tuning parameters, inaccurate data lead to poor results

This chapter discussed various monitoring techniques for ensuring the reliability of electrical machines. Employing advanced sensing technologies and data analysis techniques enables proactive maintenance, reducing the risk of unexpected breakdowns and enhancing the efficiency of electrical machines. To ensure effective training of the intelligent algorithm, it is crucial to thoroughly investigate the nature of machine faults, their causes, and their impacts on global parameters. The primary challenge lies in the quantity and quality of training data.

4 Data Acquisition and Pre-Analysis

To gather qualitative and accurate data, an experimental test bench was constructed, as presented in Figure 27. As shown, the setup comprises a testing machine, loading machine, acquisition system (Dewetron). The tests were conducted at the rated speed. The parameters of the testing motor are presented in Table 3.

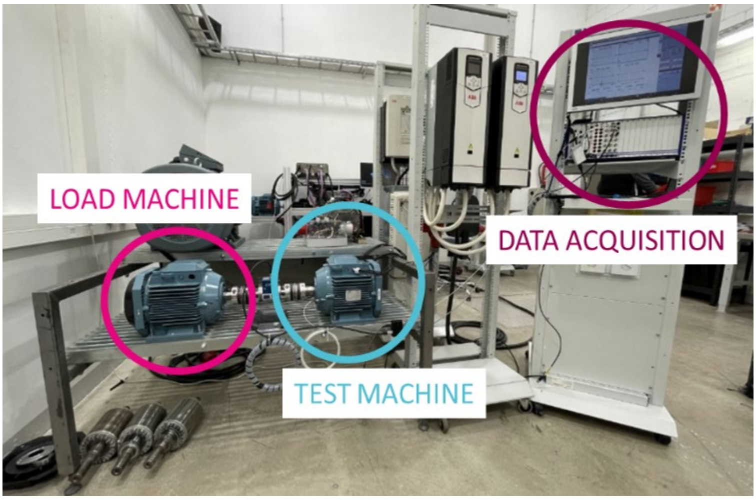


Figure 27. Experimental test bench. (previously published in article VII)

Table 3. Parameters of testing and loading motor.

Parameter	Value		
Voltage, V	Y 690	D 400	D 460
Frequency, Hz	50	50	60
Speed, r/min	1460	1460	1760
Power, kW	7.5	7.5	7.5
Current, A	8.8	15.3	12.9
Power factor	0.79	0.79	0.81

To ensure the accuracy of fault patterns for training purposes, various operational conditions of the rotating machine were considered. Signals were extracted from parameters such as current, voltage, torque, speed, and vibration to analyze the impact of faults. Testing was conducted under different motor loads, ranging from 0% to 100%. Additionally, data collection took place in diverse control environments, including grid-fed, scalar control, and direct torque control systems.

In the industrial sector, electrical machines are expected to exhibit high efficiency, manageable control, and cost-effectiveness. Consequently, three-phase induction motors are the predominant choice [70]. There are primarily two algorithms for controlling induction machines: scalar-based and vector-based. Scalar control adjusts the motor's speed by varying stator voltages and frequency while maintaining a constant air gap flux [71]. However, this method is most suitable for applications with static dynamics and uniform loads. An alternative to conventional pulse width modulation (PWM) motors is direct torque control (DTC) [72]. DTC enables direct regulation of motor parameters such as torque and flux, eliminating the need for additional hardware like modulators. This technique is widely adopted in manufacturing due to its ability to meet industrial requirements effectively.

For early fault detection, it is reasonable to consider small frequency components in the spectrum. This can be achieved by taking Fourier transforms of the incoming signal. For the ideal Fast Fourier Transform (FFT) with an infinite signal, the following equation holds:

$$f(t)= \sum_{n=-\infty}^{\infty} C_n e^{in\omega t} \cong \sum_{n=1}^{N} C_n e^{in\omega t};\ \omega = 2\pi \frac{f}{f_s}; \tag{7}$$

$$C_n = \frac{1}{2\pi}\int_{-\infty}^{\infty} f(x)\, e^{-inx} dx,\ n = 0, \pm 1, \pm 2, \dots \tag{8}$$

where f(x) is the signal under investigation, Cn is the complex Fourier, and fs is the sampling frequency (100 kHz). Evaluating the entire signal is not necessary, as it cannot save training time and simplify the training process. Instead, algorithm training will focus on areas where the fault's impact is most significant.

4.1 Broken rotor bars

The current spectrum is essential in this analysis since damaged rotor bars initially affect the current. Faults cause ripples in speed and torque on the frequency spectrum. Due to the dispersed layout of the rotor and stator windings, the frequency spectrum of the stator and rotor current contains several harmonics even under optimal supply and in healthy motor cases. The stator current undergoes modification at specific frequencies when a fault occurs. For this reason, emphasis was placed on analyzing the current spectrum in detecting rotor faults. In this study, various conditions of rotor bars in induction machines were examined, including both healthy and faulty states, with faults ranging from one to three broken rotor bars. For current measurements, Fluke current clamps were used. The rotor with three broken rotor bars is shown in Figure 28.

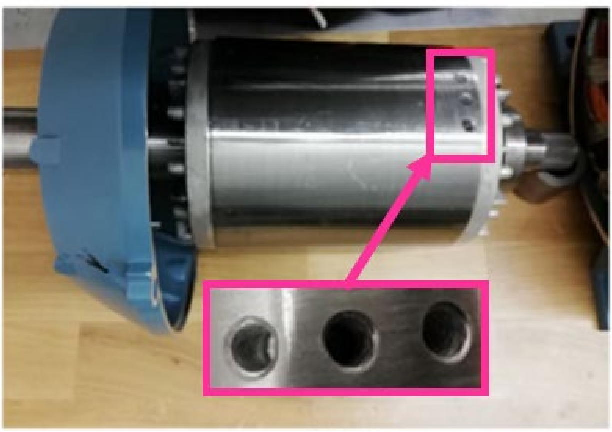


Figure 28. Rotor with three broken bars. [74]

The harmonics of a broken rotor bar can be quantitatively represented using the following equations in the frequency spectrum:

$$f_{BR} = f_S \pm 2ksf_S \tag{9}$$

$$f_{BR} = \left[\left(\frac{k}{p}\right)(1\text{-}s) \pm s\right] f_S \tag{10}$$

where k = 1, 2, 3, ..., fs is the supply frequency, p is the number of pole pairs, and s is the slip of the machine [73].

In Figure 29, the spectra of healthy and faulty rotor bars are presented, where 0BRB means heathy rotor, 1BRB – one broken rotor bar, 2BRB – two broken rotor bars, and 3BRB – three broken rotor bars. The fault notably influences the range of 0 to 1000 Hz most prominently. At the same time, the most significant range, particularly for algorithm training, lies within 0 to 500 Hz. For the training, the most significant values are 50 Hz, 250 Hz, and 350 Hz.

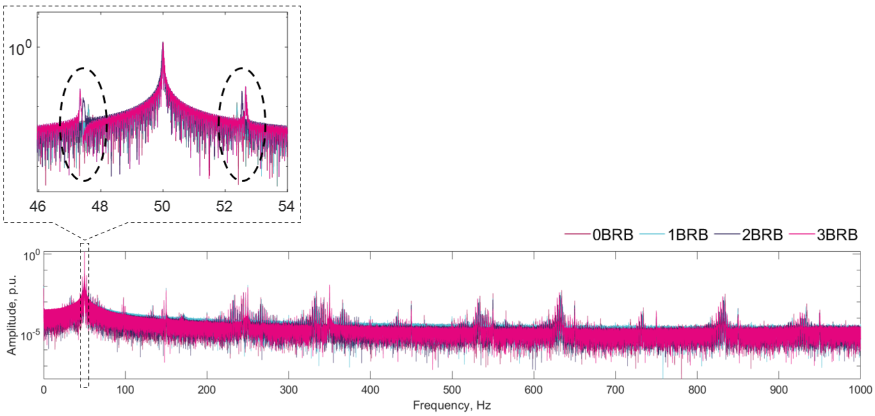


Figure 29. Frequency current spectra of healthy and faulty rotor bars.

From the spectra, it is evident that the fault development has a considerable impact on side harmonics. As the level of damage escalates, there is a corresponding rise in the amplitude of the side harmonics. Consequently, the spectrum of a rotor with three broken bars exhibits the highest side harmonics at the fundamental frequency. The performance of current signals at the frequency of 50 Hz is presented in Table 4.

Table 4. Current signals at frequency 50 Hz in different fault states.

State	**Axis**	**Value**
0BRB	Frequency (Hz)	50
	Amplitude (p.u.)	1.513
1BRB	Frequency (Hz)	49.99
	Amplitude (p.u.)	1.496
2BRB	Frequency (Hz)	49.99
	Amplitude (p.u.)	1.297
3BRB	Frequency (Hz)	49.99
	Amplitude (p.u.)	1.425

To ensure effective training, it is important to consider various conditions [75]. Comparison of spectra shows that grid-fed and scalar modes exhibit similar behavior, as presented in Figure 30. The primary distinction becomes evident in the behavior of side frequencies. However, the main observation centers on the frequency spectrum in the case of DTC, where a significant shifting in frequency components becomes apparent. Specifically, when a fault arises during operation under DTC, a discernible shift in the fundamental component within the frequency domain is evident. This phenomenon remains absent in both grid and scalar control modes.

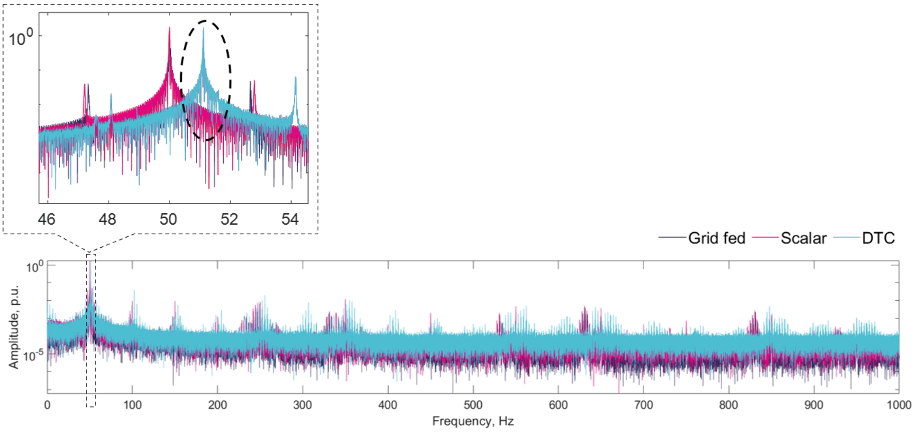


Figure 30. Frequency current spectra of rotor with three broken bars in different control modes.

The reason behind this phenomenon is that the net generated torque diminishes as the number of broken bars increases. In contrast, within the DTC environment, the controller endeavors to sustain a constant torque output by reducing the speed. This reduction in speed is achieved by decreasing the frequency of the fundamental component. In the case of different control modes, the performance of current signals at the frequency of 50 Hz is presented in Table 5.

Table 5. Current signals at frequency 50 Hz in different control modes.

Control	Axis	Value
Grid Fed	Frequency (Hz)	49.99
	Amplitude (p.u.)	1.425
Scalar control	Frequency (Hz)	50
	Amplitude (p.u.)	1.8
DTC	Frequency (Hz)	51.12
	Amplitude (p.u.)	1.71

For algorithm training, it is crucial to incorporate all operational conditions. This study specifically addresses the impact of loads, which is essential for comprehensive analysis [76].

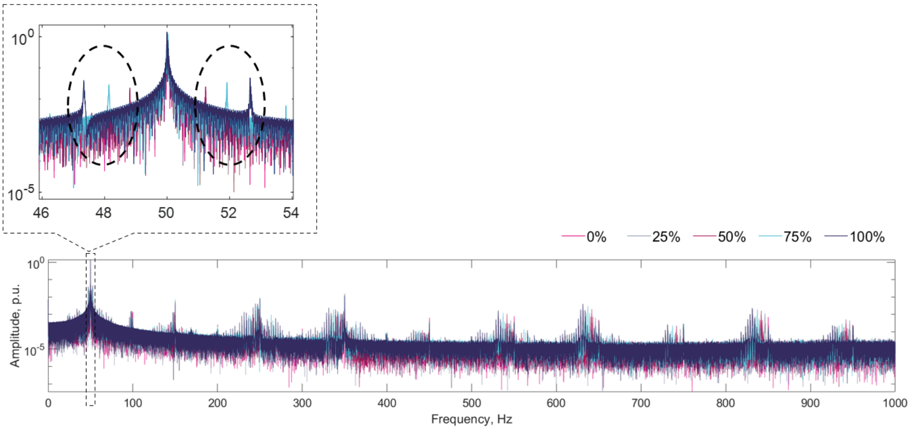


Figure 31. Frequency current spectra of rotor with three broken bars under different loads.

Load variations sometimes result in frequency shifts. Moreover, higher loads cause a greater influence on side harmonics. Like previous instances, the fault demonstrates its greatest impact within the frequency range of 0 to 500 Hz. All these aspects will be considered during algorithm training. In the case of different loads, the performance of current signals at the frequency of 50 Hz is presented in Table 6.

Table 6. Current signals at frequency 50 Hz under different loads.

Load	Axis	Value
0%	Frequency (Hz)	50.02
	Amplitude (p.u.)	0.77
25%	Frequency (Hz)	50.03
	Amplitude (p.u.)	0.7992
50%	Frequency (Hz)	50.02
	Amplitude (p.u.)	1.068
75%	Frequency (Hz)	50.03
	Amplitude (p.u.)	1.219
100%	Frequency (Hz)	49.99
	Amplitude (p.u.)	1.425

4.2 Bearing faults

This study investigated various mechanical damages of bearings, including damage to the inner or outer raceway, as well as faults in the cage. Additionally, the study examined damages caused by bearing currents. The vibration spectrum plays a pivotal role in the analysis of damaged bearings. For the experiments, vibration measurements were conducted using a triaxial accelerometer with a range of +/-100 g, positioned over the shaft. Bearing damages can be mathematically described using the following equations, which pertain to the natural frequencies of faulty bearings. Fault frequencies can be defined for the outer ring (11), inner ring (12), rolling elements (13), and cage (14).

$$f_{or} = \frac{N_b}{2} n \left(1 - \frac{D_b}{D_c} \cos\beta\right) \tag{11}$$

$$f_{ir} = \frac{N_b}{2} n \left(1 + \frac{D_b}{D_c} \cos\beta\right) \tag{12}$$

$$f_b = \frac{D_c}{2D_b} n \left(1 - \left(\frac{D_b}{D_c} \cos\beta\right)^2\right) \tag{13}$$

$$f_c = \frac{n}{2} \left(1 - \frac{D_b}{D_c} \cos\beta\right) \tag{14}$$

where Nb – number of rolling elements, Db – diameter of rolling element (mm), Dc – bearing pitch diameter (mm), β – contact angle (degrees), n – mechanical rotor speed (Hz) [77].

4.2.1 Mechanical damages

As shown in Figure 32, the study focused on the most common mechanical bearing faults, including faulty inner ring, faulty outer ring, and damaged cage. In this case, both healthy and faulty bearings were installed and tested in the test motor.

a) b) c)

Figure 32. Mechanical bearing faults: a) fault in the outer ring, b) fault in the inner ring, and c) damaged cage. (previously published in article VIII)

Figure 33 presents a comparison of various mechanical faults on the vibration spectrum, indicative of potential bearing issues. Noticeably, certain regions exhibit the most significant impact of faults. It is reasonable to investigate how these damages affect side harmonics. By comparing the fault patterns extracted from each signal with those of a healthy signal, it becomes feasible to discern specific fault signatures.

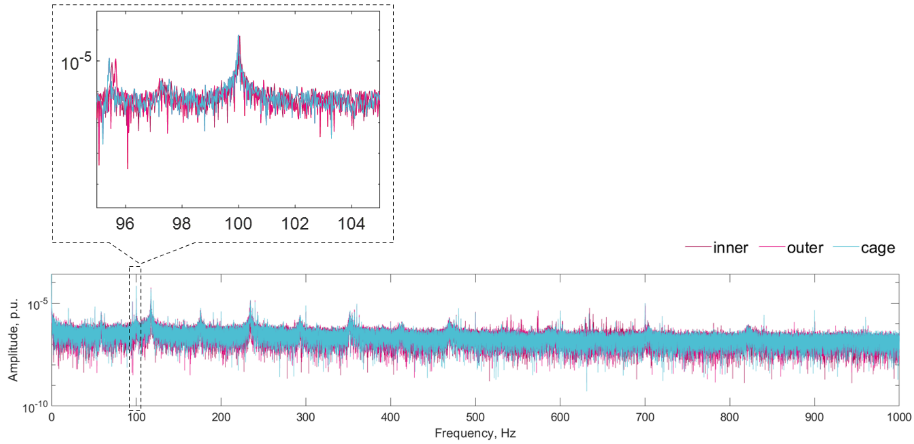


Figure 33. Frequency vibration spectra of damaged bearings.

These patterns will then be utilized for system training. The performance of signals at the frequency of 100 Hz in the case of damaged bearings is presented in Table 7.

Table 7. Vibration signals at frequency of 100 Hz in different fault states.

State	**Axis**	**Value**
Inner raceway	Frequency (Hz)	100
	Amplitude (p.u.)	6.436e-05
Outer raceway	Frequency (Hz)	100
	Amplitude (p.u.)	5.795e-05
Damaged cage	Frequency (Hz)	100
	Amplitude (p.u.)	6.922e-05

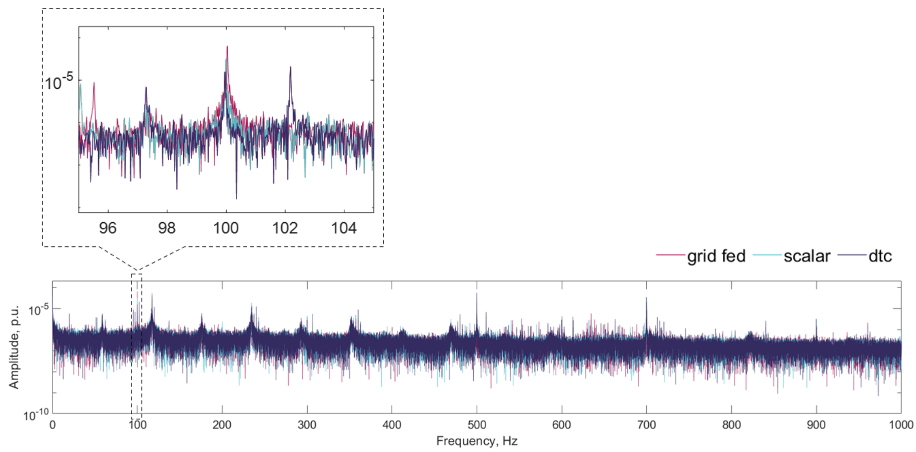


Figure 34. Frequency vibration spectra of bearing with fault in inner raceway in different control environments.

As shown in Figure 34, various control environments of the motor were compared, highlighting their influence on the vibration spectrum. It is crucial to take this into account during system training, as evident from the distinct behaviors observed in the signals. Particularly noteworthy is the substantial impact of DTC on side harmonics, as indicated by the graph. The comparison of spectra for different control environments in the case of a bearing fault in the inner raceways is presented in Table 8.

Table 8. Vibration signals at frequency of 100 Hz in different control environments.

Control	**Axis**	**Value**
Grid Fed	Frequency (Hz)	100
	Amplitude (p.u.)	6.436e-05
Scalar control	Frequency (Hz)	100
	Amplitude (p.u.)	3.229e-05
DTC	Frequency (Hz)	99.95
	Amplitude (p.u.)	1.559e-05

Furthermore, the impact of the load on machine performance was investigated. Tests were conducted across various load levels ranging from 0% to 100%. As illustrated in Figure 35, slight frequency shifts were observed depending on the load level.

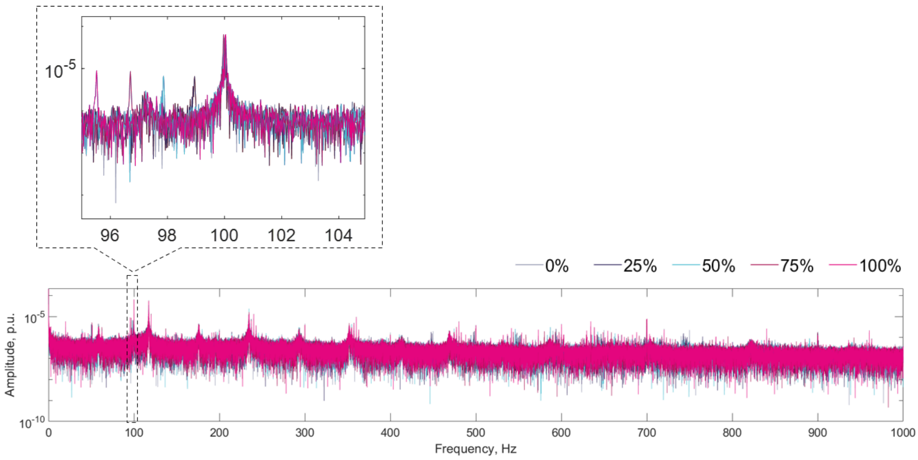


Figure 35. Frequency vibration spectra of bearing with fault in inner raceway under different loads.

Additionally, notable differences inside harmonics were evident under different load conditions. This disparity will also be taken into consideration for the implementation of predictive maintenance strategies. In the case of different loads, the performance of vibration signals at the frequency of 100 Hz is presented in Table 9.

Table 9. Vibration signals at frequency of 100 Hz under different loads.

Load	Axis	Value
0%	Frequency (Hz)	100
	Amplitude (p.u.)	5.402e-05
25%	Frequency (Hz)	100
	Amplitude (p.u.)	5.004e-05
50%	Frequency (Hz)	100
	Amplitude (p.u.)	5.307e-05
75%	Frequency (Hz)	99.96
	Amplitude (p.u.)	6.442e-05
100%	Frequency (Hz)	100
	Amplitude (p.u.)	6.436e-05

4.2.2 Bearing currents

Currently, the most economical and straightforward approach to ensuring the optimal performance of electrical machines involves employing frequency converter control. This method has been widely embraced worldwide, leading to increased adoption of power electronics. However, such solutions often result in shaft currents induced by the frequency converter, presenting a growing challenge in modern industry. Despite the longstanding recognition of bearing currents in electrical machines, which spans almost a century, it remains a significant area of research [78]. Failures arising from bearing currents cause substantial mechanical damage to electrical machines. In modern drive systems, the utilization of converters contributes to a phenomenon where current flows through the circuit comprising the bearings, the frame, and the machine shaft [79]. While mitigation solutions are increasingly being implemented to address bearing currents, it is important to acknowledge that they may inadvertently lead to reliability issues and require additional maintenance [80].

Typically, damages caused by electrical currents only become apparent in later stages, after the bearing surface has already been compromised. Faults resulting from these currents tend to emerge in areas with the thinnest lubrication layer, which experience heightened stress. Usually, as presented in Figure 36, these damages are classified into three categories: fluting, frosting, and pitting.

a) b) c)

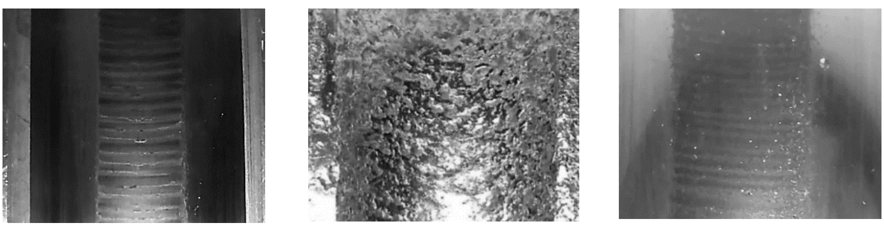


Figure 36. Common faults caused by bearing currents: a) fluting, b) frosting, c) pitting. (previously published in article IX)

One common manifestation is “fluting,” shown in Figure 36a, where multiple lines form across the bearing raceways. Fluting is often associated with constant rotational speeds and low voltage. Another type of fault, known as “frosting,” occurs when a motor operates at variable speeds, as illustrated in Figure 36b. In situations where the motor operates at low speeds with high-voltage power, “pitting” can arise in the bearing, as seen in Figure 36c. Pitting is commonly observed in DC motors, such as those used in railways, and manifests as craters on the bearing surface. Changes in the lubricant's condition can also indicate motor issues, with darkening occurring due to bearing currents. Sparking can lead to lubricant oxidation and darkening due to electrical discharges, as observed during the experiments shown in Figure 37.

Figure 37. Lubricant darkening due to discharges.

An experimental test bench for fault implementation was meticulously constructed to facilitate this investigation. Faults were induced in healthy bearings to obtain faulty bearings for experimentation, as shown in Figure 38.

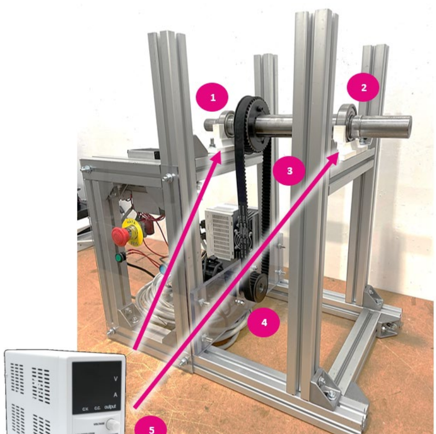


Figure 38. Experimental test bench for implementation of bearing current faults: 1) non-drive end bearing, 2) drive end bearing, 3) belt, 4) servo drive, 5) power supply. (previously published in article VI)

A diverse range of failures caused by bearing currents were successfully replicated through experimentation. Each fault type including fluting, frosting, and pitting was intentionally induced under controlled conditions. Table 10 provides an analysis of all studied cases involving shaft current faults.

Table 10 Faults implemented under different current levels and rotational speeds.

Conditions		Results		
Drive end bearing				
Speed, r/min	Current, A	Inner ring	Outer ring	Balls
100	10	Darkened race	Darkened race	No changes
100	20	Slight fluting	Darkened race	Darkened balls
500	10	Fluting	Darkened race	Darkened balls
800	10	Fluting	Darkened race / slight fluting	Darkened balls
800	20	Fluting/pitting	Slight fluting	Darkened balls/pitting
Non-drive end bearing				
Speed, r/min	Currents, A	Inner ring	Outer ring	Balls
100	10	Darkened race	Darkened race	Slightly darkened balls
100	20	Slightly darkened race	Darkened race	Darkened balls
500	10	Darkened race	Darkened race / slight fluting	Darkened balls
800	10	Slightly darkened race	Darkened race / slight fluting	Darkened balls
800	20	Frosting	Frosting	Darkened balls/frosting

As an example, the case of fluting is studied, which is presented in Figure 39.

Figure 39. Bearing with fluting used in experiments. (previously published in article VI)

The vibration spectra of healthy and faulty bearings with fluting shown in Figure 40. Remarkably, the amplitude of the faulty bearing significantly exceeds that of the healthy one. This difference arises because the damaged bearing encounters difficulties in rotation due to surface damage.

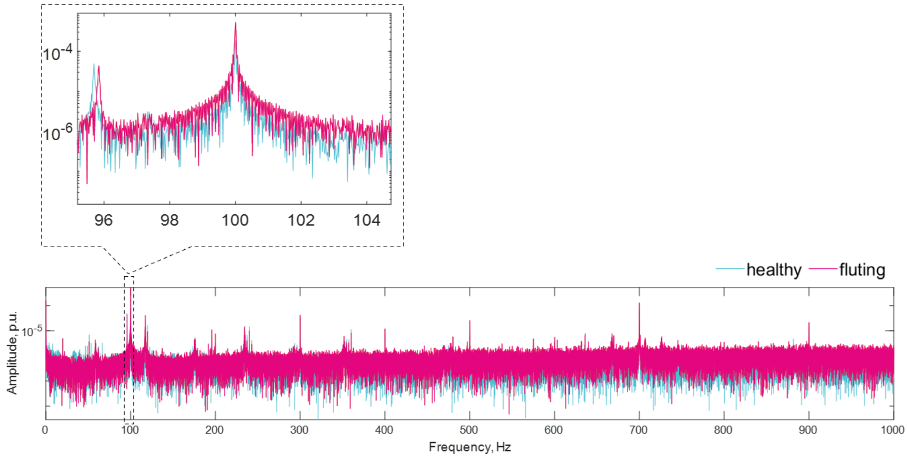


Figure 40. Frequency spectra of healthy bearing and bearing with fluting.

The fault exerts its most notable influence on the spectrum within the 0-500 Hz range, affecting even harmonics, particularly at 100 and 300 Hz. In the 500-1000 Hz range, there are no prominent harmonics except for the 700 Hz frequency, which warrants examination for potential patterns during training. Frequencies beyond 1000 Hz do not significantly impact the analysis. The spectra comparison of healthy bearing and bearing with fluting is presented in Table 11.

Table 11. Vibration signals at frequency of 100 Hz in case of healthy bearing and bearing with fluting.

State	Axis	Value
Healthy	Frequency (Hz)	100
	Amplitude (p.u.)	0.0001902
Fluting	Frequency (Hz)	100
	Amplitude (p.u.)	0.0005269

4.3 Summary

To mitigate severe consequences and economic losses in production, it is advisable to implement strategies related to predictive maintenance. The provided information outlines a comprehensive experimental study on detecting various faults in electrical machines, focusing on both rotor bars and bearings. Acquiring the necessary training datasets poses a significant challenge in implementing. Accurate forecasting requires gathering a large quantity of high-quality datasets. Therefore, various faults were intentionally induced in laboratory settings to facilitate this process. The study provides valuable insights into fault detection methodologies for electrical machines, highlighting the importance of considering operational conditions, control modes, and load variations for effective training of intelligent algorithms aimed at predictive maintenance. Fault patterns extracted from experimental data are utilized for system training purposes. However, when it comes to analysing vibration spectra, visually discerning differences in amplitudes can be challenging. To address this issue, artificial intelligence techniques were employed to accurately identify and define these variations.

5 Fault Classification and Prediction

Implementing trained models is a pivotal aspect of predictive maintenance and condition monitoring. The accuracy of these models is primarily contingent upon the quality and diversity of the training data employed. Therefore, it is imperative to utilize high-quality data samples encompassing various scenarios and an optimal number of features to achieve enhanced results.

The focus of this chapter is on predictive approaches, specifically targeting bearing faults. Three distinct methodologies are presented. This study evaluates three approaches to examine the accuracy of machine learning models and explore the potential improvement by incorporating fuzzy logic alongside machine learning. The initial phase, which involves the acquisition and pre-processing of the collected data to prepare it for training, is described in Chapter 4. Data acquired via the acquisition system is initially in the time domain, necessitating conversion into the frequency domain using the Fast Fourier Transform (FFT).

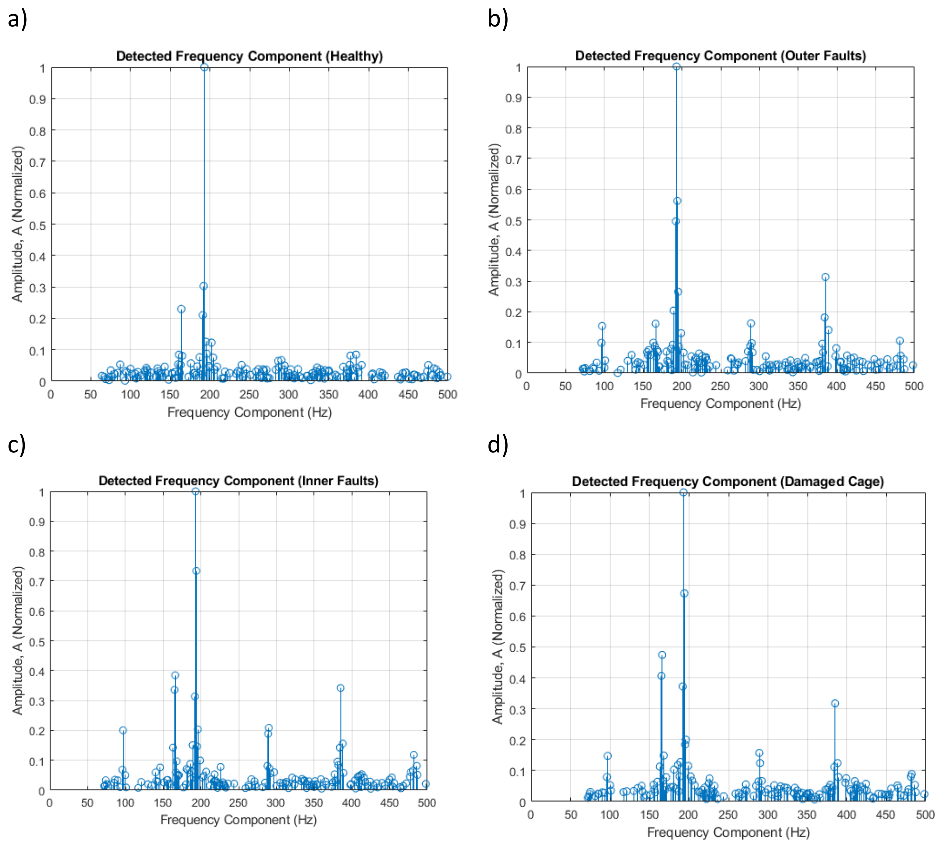


Figure 41. Selected frequency components for healthy and faulty bearings: a) healthy bearing, b) bearing with the damaged outer raceway, c) bearing with the damaged inner raceway, d) bearing with a damaged cage.

This approach prioritizes analyzing the vibration signatures of electrical machines and the impact of faults on them. Given the broad spectrum of frequency components, the primary objective is to pinpoint the most prominent ones and eliminate insignificant ones. By doing this, the resulting frequency components are reduced, facilitating the identification of distinct features. In this instance, the frequency range was capped at 500 Hz, as beyond this threshold, the amplitudes of frequency components become negligible and do not significantly contribute to the analysis.

Following this, the data undergoes further processing to evaluate the amplitude of these frequency components under both healthy and faulty conditions. This step is carried out across multiple samples collected from different induction machines to verify that the identified components are universally applicable to this specific fault. To ensure consistent results, all amplitudes are normalized to range between 0 and 1. Figure 41 illustrates an example of a frequency spectrum displaying both healthy and faulty scenarios, presenting frequency components alongside their corresponding amplitudes.

After analyzing numerous samples, the variations in the amplitude of frequency components for both healthy and faulty conditions are characterized. By conducting a thorough analysis, the range of amplitudes for the significant frequency components that indicate fault occurrence is established, as presented in Table 12.

Table 12. Frequency amplitude range for fault occurrence.

Frequency (Hz)	Amplitudes							
	Healthy Signal		Inner		Outer		Damaged Cage	
	Min	Max	Min	Max	Min	Max	Min	Max
36.01	1.77e-07	8.66e-06	1.27e-07	6.31e-06	5.69e-06	1.27e-07	6.25e-06	5.69e-07
42.11	4.51e-08	9.65e-06	2.85 e-06	8.12e-05	1.34e-07	7.59e-06	1.32e-07	5.14e-06
90.94	1.72e-07	7.68e-06	1.94e-07	7.36e-06	6.43e-08	1.94e-07	1.60e-07	7.74e-06
151.97	1.34e-07	9.37e-06	8.19e-09	6.13e-06	1.63e-07	5.01e-06	1.63e-07	5.01e-06
213.01	7.84e-08	5.23e-06	6.71e-08	4.85e-06	4.82e-08	5.39e-06	1.73e-07	5.67e-06
304.56	5.85e-08	1.46e-05	1.47e-07	1.04e-05	8.54e-08	5.71e-06	4.27e-08	1.07e-05
426.63	7.48e-08	4.27e-06	6.28e-08	4.23e-06	5.02e-08	3.45e-06	8.15e-08	4.15e-06

After pinpointing the ranges for specific components, it is possible to create various potential combinations of these transition layers. The transition layer represents the condition of the electrical machine as it moves from a healthy state to a faulty one. Figure 42 provides a visual representation of the distinctions between each stage. Every conceivable combination of frequency component values within the identified range for each fault is considered during the training of the machine learning model.

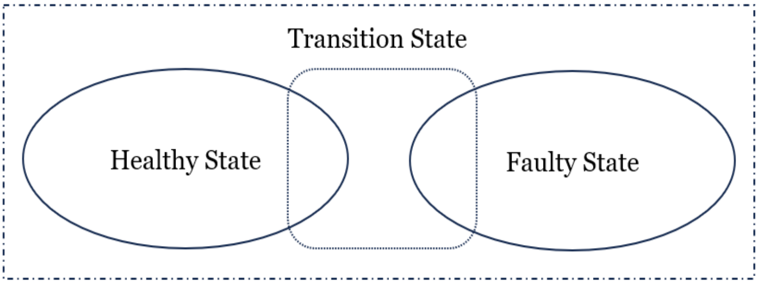


Figure 42. Illustrative diagram of states.

To define the transition state, three scenarios are considered. In the first scenario, the healthy and faulty cases share the same frequency component but differ in amplitudes. Here, the transition region is defined between the maximum healthy and minimum faulty amplitudes, with 10% added to each side. In the second scenario, the amplitudes of healthy and faulty cases overlap. In this scenario, the transition region is defined between the minimum faulty and maximum healthy amplitudes, again with 10% added to each side. In the third scenario, the healthy frequency component is absent in the faulty case. Therefore, the transition state is considered between the minimum and maximum amplitudes, with 10% added in each direction. Additionally, 10% above zero indicates a healthy component in case this component is present in other samples.

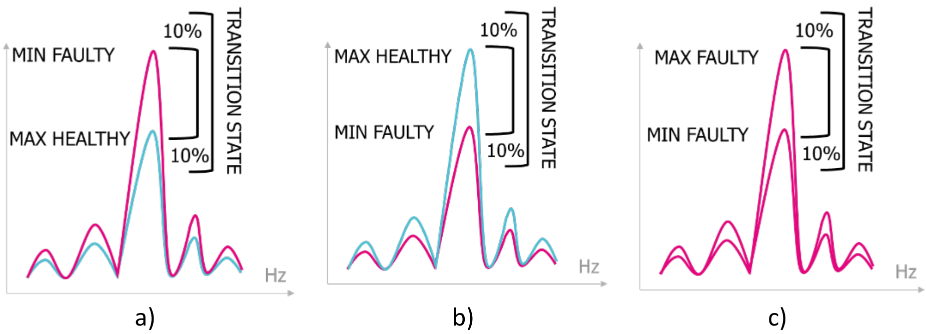


Figure 43. Three scenarios of transition state: a) healthy and faulty components have different amplitudes, b) healthy and faulty frequency components overlap, c) healthy component is not presented in the faulty case.

Once the frequency components and their amplitude ranges for both healthy and faulty cases are identified, the trend of amplitude change is documented. This documentation aids in generating data and forming combinations necessary for training machine learning models for fault prediction.

5.1 Machine Learning Trained Model

The first method describes the training of the purely machine learning model. Artificial neural networks stand out as the prevailing models for fault detection classification. Typically, these models are trained using high processing power systems or cloud systems to minimize training time. The general overview of the proposed method is presented in Figure 44.

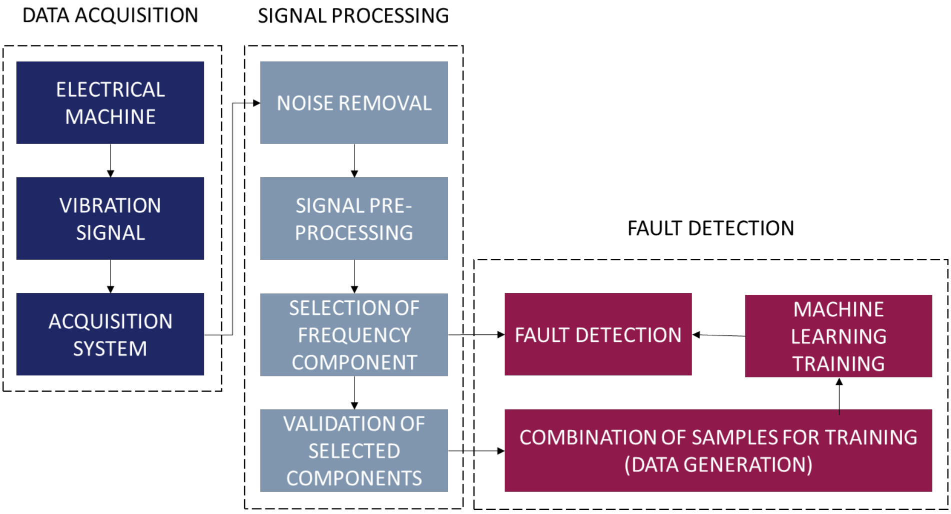


Figure 44. Overview of the proposed method with trained machine learning model.

Following the preparation of the data samples, they are classified into seven distinct states, encompassing healthy conditions, various faults, and the likelihood of these faults occurring. The fault classification is detailed in Table 13. Once the data is appropriately classified and labeled, it is primed for the training of machine learning models to predict faults.

Table 13. Assigned classification.

State of Data	**Assigned Label**
Healthy State	0
Chance for Inner Bearing Fault to occur	1
Chance for Outer Bearing Fault to occur	2
Chance for Damaged Cage Fault to occur	3
Inner Bearing Faulty State	4
Outer Bearing Faulty State	5
Damage Cage Fault State	6

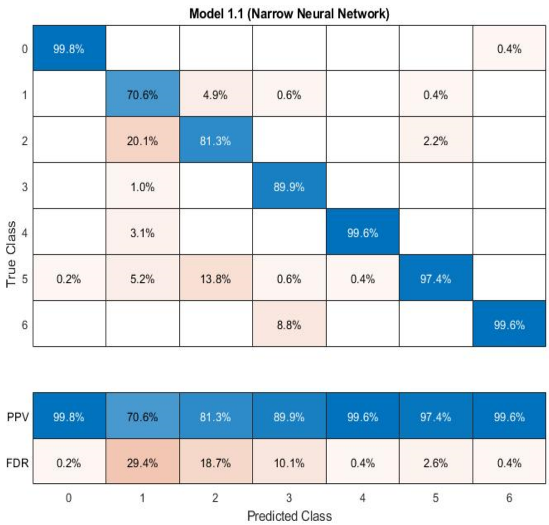
Table 14 displays the various numbers of layers and neurons considered for the neural network models.

Table 14. Neural network models.

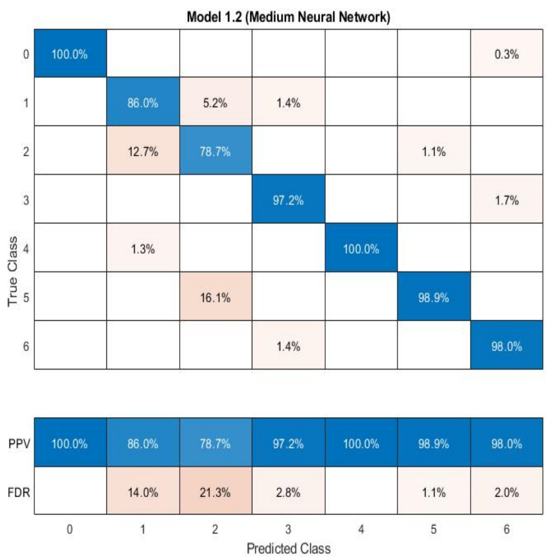
Machine Learning Model	Number of Neurons	Number of Layers
Narrow Neural Network	32	1
Medium Neural Network	64, 128	2
Wide Neural Network	128, 128	2
Bilayered Neural Network	256, 128	2
Trilayered Neural Network	128, 256, 128	3

Figure 45 illustrates a selection of accuracy validation results for the trained models.

a)



b)



c)

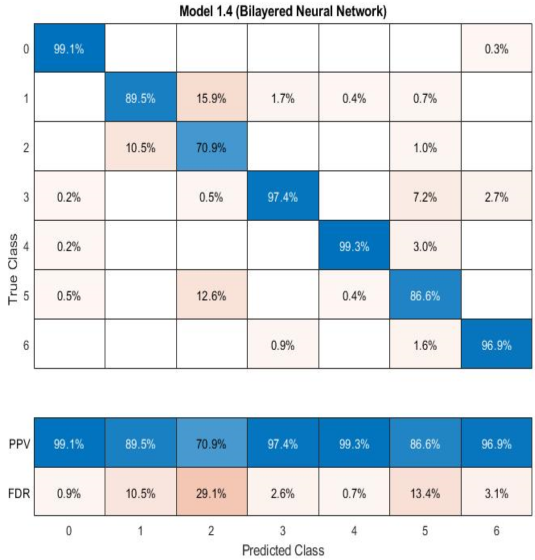


Figure 45. Machine learning results: a) Narrow Neural Network, b) Medium Neural Network, c) Bilayered Neural Network.

The figure above demonstrates that the accuracy of detection varies depending on the combination of states. A higher number of states typically results in a more complex model, where the accuracy for later stages may decrease. The results for predictions in case of vibration signals for different bearings states are shown in Table 15.

Table 15. Comparison results for vibration spectra.

Machine Learning Algorithm	**Accuracy (Validation)**
Narrow Neural Network	93.90%
Medium Neural Network	96.10%
Wide Neural Network	96.30%
Bilayered Neural Network	92.80%
Trilayered Neural Network	90.20%

The table above illustrates that among the combinations involving three faults, the Wide Neural Network model exhibits the highest accuracy. However, other neural network trained models also demonstrate close accuracies. Conversely, for scenarios involving two faults or a single fault, the accuracy surpasses that of the Wide Neural Network model. This trend suggests that as the complexity of the model increases, its accuracy tends to decrease. Besides, there exists a risk of over-training the model, underscoring the importance of determining the optimal number of samples required and fine-tuning the machine learning algorithm for optimal performance.

5.2 Machine Learning Trained Model with Fuzzy Control System

For this approach, the same configuration for different neural network models, as outlined in Table 14, is utilized. Each model is trained separately for every case, and the one exhibiting the best average accuracy is chosen for integration with fuzzy logic. While it's possible to employ different trained models for fuzzy logic combination, this study opts for using the same neural network trained model. The neural network models are trained for various combinations to encompass all potential scenarios of error detection. The fuzzy logic system functions as a control system, determining appropriate actions based on results and delivering a final decision for incoming signals. Figure 46 provides a general overview of this methodology.

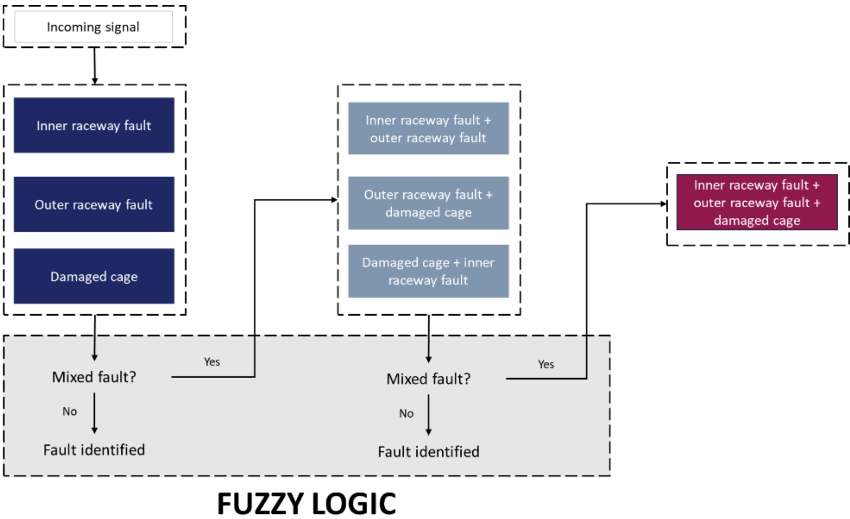


Figure 46. Overview of proposed method with trained machine learning model and fuzzy control system.

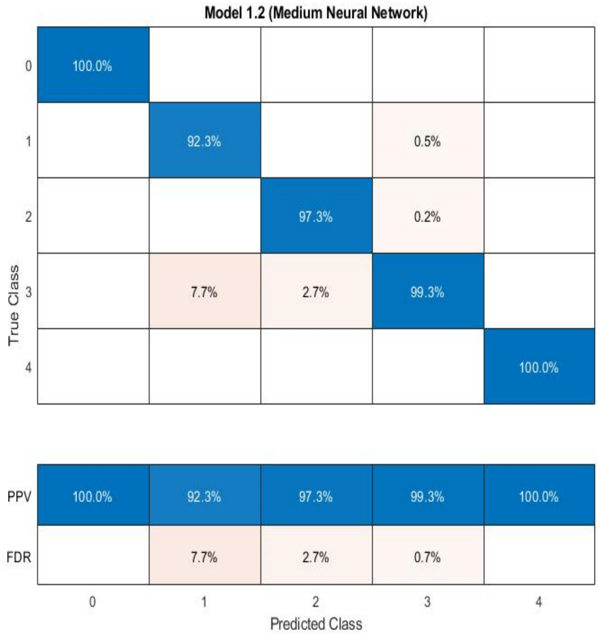
Table 16 presents different combinations of neural network cases considered for training and integration within the fuzzy logic control system.

Table 16. Neural network and fuzzy logic combination cases.

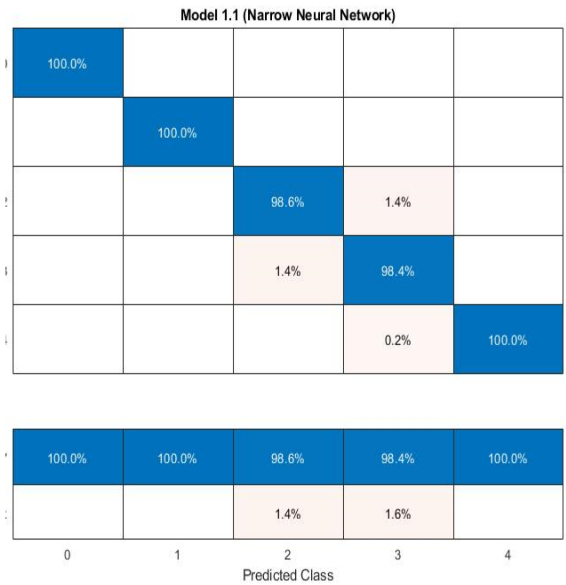
Combination Type	Combination
Case 1	Inner Raceway Fault
Case 2	Outer Raceway Fault
Case 3	Damage Cage Fault
Case 4	Inner and Outer raceway Fault
Case 5	Outer and Damaged Cage Fault
Case 6	Inner and Damaged Cage Fault
Case 7	All three faults

The results for the trained neural network model across different cases are depicted in Figure 47.

a)


Model 1.2 (Medium Neural Network)
True Class
0
1
2
3
4
100.0%
92.3%
0.5%
97.3%
0.2%
7.7%
2.7%
99.3%
100.0%
PPV
FDR
100.0%
92.3%
97.3%
99.3%
100.0%
7.7%
2.7%
0.7%
0
1
2
3
4
Predicted Class

b)


Model 1.1 (Narrow Neural Network)
100.0%
100.0%
98.6%
1.4%
1.4%
98.4%
0.2%
100.0%
100.0%
100.0%
98.6%
98.4%
100.0%
1.4%
1.6%
0
1
2
3
4
Predicted Class

c)

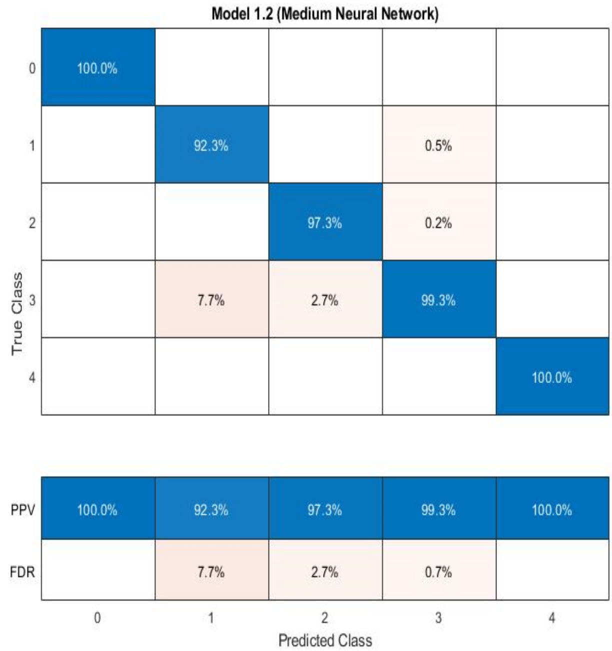


Figure 47. Machine learning results for different cases: a) Inner-Outer Combination, b) Inner-Damage Combination, c) Outer-Damage Combination.

Table 17 displays the accuracy results of various neural network trained models for each case, along with their average accuracy, providing a comprehensive understanding of the outcomes.

Table 17. Neural network trained models.

Machine Learning Model		Accuracy
Medium Neural Network	Case 1	99.80%
Wide Neural Network	Case 2	99.40%
Bilayered Neural Network	Case 3	99.90%
Bilayered Neural Network	Case 4	97.90%
Medium Neural Network	Case 5	98.50%
Narrow Neural Network	Case 6	99.30%
Wide Neural Network	Case 7	96.30%

Once the neural network trained model is selected, a straightforward fuzzy logic statement is devised for the incoming signal, integrating these trained models. This aids in determining the scenario with the best detected or predicted state, achieving higher accuracy than before. It's worth noting that during the training of each case, particular attention was paid to ensure that the conditions of each case were distinct from one another, minimizing overlap during separate detection attempts, albeit there may be some occurrences of false positives. Table 18 summarizes the results from neural network trained model accuracies compared to the outcomes from the combination of fuzzy logic with neural networks.

Table 18. Validation accuracy results for algorithms.

Algorithm	Accuracy
Neural Network	96.30%
Fully Logic and Neural Network Combination	100.00%

As it can be seen from the above results, combining different sets of neural network trained model can increase the overall accuracy of fault detection as compared to the training a single machine learning model for multiple faults. Although the execution time increases a little and it needs training of more models, the end schematics are more accurate and sustainable for longer period. This can help omit even a slight possibility of missing a fault that might result in being fatal for the system.

5.3 Neuro-Fuzzy Trained Models

In this approach, the methodology involves comparing a standard neural network algorithm with a fuzzy neural network algorithm. Here, a fuzzy logic layer is incorporated between the neural networks to refine the results and increase accuracy. Figure 48 provides a general outline of the training algorithm. The training and testing procedures are conducted using Python.

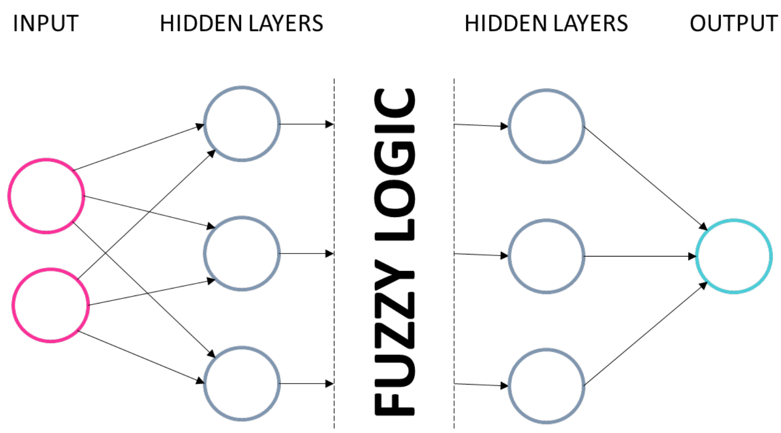


Figure 48. General overview of the approach with neuro-fuzzy trained model.

The training process for machine learning algorithms follows a similar structure, with the primary difference being the incorporation of the fuzzy layer as one of the hidden layers in the algorithm. In the initial study, the neural network training consists of 5 hidden layers, in addition to one input and one output layer. The number of neurons in each layer of the neural network is detailed in Table 19 for each case, enabling a comprehensive comparison. Moreover, fine-tuning the algorithms through adjustments in the number of neurons did not result in noticeably different outcomes. An early stop function is integrated to monitor for overtraining and ensure the achievement of the most optimized outcome for the trained algorithm.

Table 19. Number of neurons per layer for both neural network and fuzzy-neuro network training.

	Number of Neurons	
Layers	**Neural Network**	**Fuzzy-Neuro Network**
Hidden layer 1	128	128
Hidden layer 2	256	256
Hidden layer 3	512	512 (fuzzy layer)
Hidden layer 4	256	256
Hidden layer 5	64	64

Below is presented the pseudo code for the algorithm's implementation, outlining each step including the hidden layers. In the second case, a fuzzy layer is utilized instead of the conventional neural network layer. This approach provides additional flexibility for weight adjustment of the neural network hidden layers and introduces a control layer in between to enhance results.

1. Prepare the training dataset by filtering out noise from the collected data samples.
2. Partition the dataset into training and testing subsets, allocating 70% for training and 30% for testing.
3. Construct the neural network model utilizing TensorFlow's Keras API.
4. The model will consist of five hidden layers, each with varying numbers of neurons and employing a sigmoid activation function.
5. Introduce a hidden layer designated as a fuzzy layer in the case of the fuzzy-neuro algorithm.
6. Configure the output layer to contain a single neuron with a linear activation function.
7. Compile the model employing the Adam optimizer and mean squared error loss function.
8. Train the model on the training dataset, utilizing a batch size of 5 to 50 and conducting training for a maximum of 350 epochs.
9. Generate predictions on the testing dataset using the trained model.
10. Assess the predicted accuracy by comparing the predicted labels with the actual ones.
11. Visualize the results utilizing matplotlib, presenting two lines representing the actual and predicted values, respectively.

Once the model is trained, blind validation is performed using the test data samples that were initially separated during training. The validation accuracy is computed for both the trained neural and fuzzy neural networks. In this instance, Figure 49 displays the validation outcomes for both models.

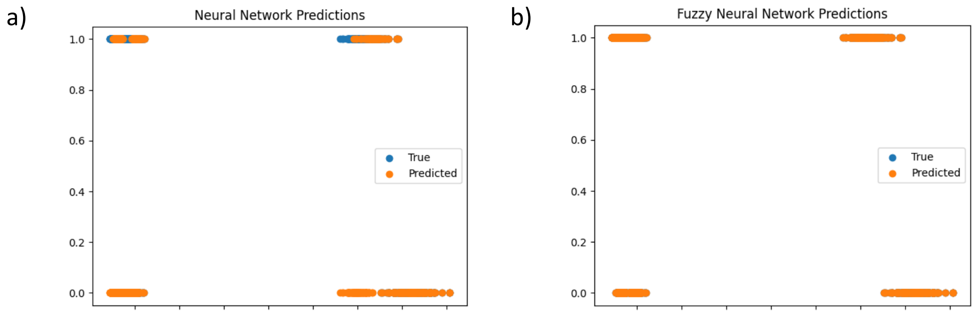


Figure 49. Validation results from a) machine learning algorithm, and b) neuro-fuzzy machine learning algorithm.

The results for the test data samples are shown in Table 20.

Table 20. Validation accuracy results for algorithms.

Algorithm	**Accuracy**
Neural Network	94.34%
Fuzzy-Neuro Network	99.40%

As shown in Table 20, the fuzzy-neuro network trained model outperforms the traditional neural network model for the same set of data samples. While this instance represents a relatively straightforward case, the 5% difference in accuracy suggests that the fuzzy-neuro network is poised to deliver superior accuracy for more complex combinations, encompassing various types of faults within the same trained model. Introducing multiple fuzzy logic layers into the combination can further refine weight adjustments, potentially leading to even better results.

5.4 Summary

The implementation of trained models is crucial for predictive maintenance and condition monitoring, with accuracy heavily reliant on high-quality and diverse training data. This study focuses on predictive approaches, particularly targeting bearing faults, evaluating three methodologies to examine the accuracy of machine learning models, and exploring the potential improvement by incorporating fuzzy logic alongside machine learning. Artificial neural networks are prominent for fault detection classification, but over-training risks underscore the necessity of optimal sample sizes and algorithm fine-tuning. Following data preparation, including conversion to the frequency domain and subsequent processing to identify significant frequency components, neural network models are trained for various fault combinations. Combining different sets of trained models can enhance fault detection accuracy compared to a single model. The inclusion of fuzzy logic further refines weight adjustments, potentially reducing false positives. This comprehensive approach minimizes the possibility of missing critical faults, ensuring system safety.

6 Conclusion and Future Work

This chapter concludes the results of the work. Besides, there are suggestions related to future work.

6.1 Conclusion

In the modern industrial landscape, electrical machines and drive systems play a pivotal role, powering various applications across industries and ensuring enhanced efficiency and productivity. From small household appliances to large-scale industrial machinery, electrical machines are indispensable elements of daily life. Their significance spans across sectors like power distribution, transportation, manufacturing, and automation, owing to their exceptional efficiency and reliability.

Despite their advantages, all electrical machines are prone to various faults, including bearing faults, rotor faults, and stator faults, which can significantly impact their performance and lifespan. Detecting and diagnosing these faults are crucial for ensuring operational reliability and preventing costly downtime. To address these challenges, the implementation of predictive maintenance strategies is crucial. Predictive maintenance, enabled by condition monitoring, allows for the prevention of failures based on the operational data of electrical machines. This proactive approach helps reduce shutdown costs, minimize downtime, and optimize resource utilization.

The main objective of this work was to develop the methodology for detection and prediction of the potential faults in electrical machines. First and foremost, the main faults of electrical machines, categorizing induction motor failures into primary groups, were discussed. A comprehensive overview of the main faults and their corresponding signatures was provided. It is important to monitor multiple parameters such as vibration, current, temperature, magnetic flux, and torque to enhance machine reliability. When it comes to data analysis, the role and choice of diagnostics method can be critical. An overview of advanced diagnostic methodologies and discussion of the benefits and drawbacks of each diagnostic technique were presented. However, success in implementing these approaches hinges on the careful curation of training data and a deep understanding of the underlying factors contributing to machine faults.

In the practical part of the study, data collection and pre-analysis, which is crucial for effective training of intelligent algorithms, was presented. A detailed description of an experimental test bench setup is provided, including components such as the testing machine, loading machine, and acquisition system. Various operational conditions and control environments are considered to gather accurate data for training purposes. Data acquisition was conducted under controlled conditions. Parameters including current, voltage, torque, speed, and vibration were meticulously monitored to capture the impact of faults on machine performance. Tests were conducted under different motor loads, ranging from 0% to 100%, and in diverse control environments including grid-fed, scalar control, and direct torque control systems.

Another crucial aspect of the experimental study was the investigation of bearing current faults. These faults, including fluting, frosting, and pitting, were induced under controlled conditions. Vibration spectra of healthy and faulty bearings were compared to identify significant differences, providing valuable insights into bearing fault detection methodologies.

The implementation of trained models is pivotal in predictive maintenance and condition monitoring, where accuracy is intricately linked to the quality and diversity of the training data. This study presented predictive approaches, specifically targeting bearing faults, and has evaluated different methodologies to assess the accuracy of machine learning models. Additionally, it explores the potential enhancement achieved by integrating fuzzy logic alongside machine learning.

As a result, artificial neural networks emerge as the predominant models for fault detection classification, leveraging high processing power systems or cloud systems to expedite training. However, the risk of over-training necessitates the consideration of optimal sample sizes and algorithm fine-tuning. Combining different sets of trained models proves to be advantageous, as it enhances fault detection accuracy compared to relying on a single model. Including fuzzy logic further refines weight adjustments, potentially mitigating false positives and increasing overall accuracy.

After thorough investigation and analysis, the findings of this research unequivocally support the main hypothesis proposed at the outset. It has been demonstrated that integrating fault representation, experimental data, and predictive models can make significant advancements in fault detection and prediction. Thus, this study substantiates the validity of the main hypothesis and contributes to the body of knowledge in diagnostics of electrical machines.

6.2 Future Work

In future work, a detailed comparative study between different fault detection and prediction models is essential to comprehensively understand each approach's strengths and weaknesses. By systematically analyzing various models, including machine learning algorithms and traditional methods, we can identify the most suitable techniques for specific applications, considering factors such as accuracy, computational efficiency, and ease of implementation.

Furthermore, neuro-fuzzy logic algorithms for fault detection and prediction need to be improved and validated. Enhancing the performance and reliability of these algorithms through validation processes will contribute to their wider adoption in real-world applications. Developing a web-based application for user-friendly use to train model results would enhance accessibility and usability for practitioners and end-users. Providing an intuitive interface for data input, model training, and result visualization can streamline the process of implementing fault detection and prediction systems in industrial settings.

Another important aspect of future work involves adding complex scenarios for fault detection and prediction in industrial environments in real time. Industrial systems often operate under dynamic and unpredictable conditions, necessitating the development of robust algorithms capable of effectively handling various fault scenarios.

List of Figures

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Abstract

Intelligent Condition Monitoring Methods for Electrical Machines and Drive Systems

Nowadays, electrical machines and drive systems are indispensable and used in numerous applications across industries. From household appliances to industrial machinery, these machines are vital for enhancing efficiency and productivity in sectors like power distribution, transportation, manufacturing, and more. However, despite their significance, electrical machines are prone to various faults, including bearing faults, rotor faults, and stator faults, all of which can significantly impact their performance and longevity. Detecting and diagnosing these faults are critical for ensuring operational reliability and minimizing costly downtime. To address these challenges, implementing predictive maintenance strategies is paramount.

This study aimed to develop a methodology for detecting and predicting potential faults in electrical machines. Initially, the main faults of electrical machines were discussed, categorizing induction motor failures into primary groups, and providing an overview of their corresponding signatures. Monitoring multiple parameters such as vibration, current, temperature, magnetic flux, and torque is crucial for enhancing machine reliability. Various advanced diagnostic methodologies were reviewed, considering their benefits and drawbacks.

In the practical part of the study, emphasis was placed on data collection and pre-analysis as crucial steps for effectively training intelligent algorithms. A detailed description of an experimental test bench setup, including the testing machine, loading machine, and acquisition system, was provided. Data acquisition was conducted under controlled conditions, considering various operational conditions and control environments to gather accurate data for training purposes. Additionally, bearing current faults, including fluting, frosting, and pitting, were induced under controlled conditions, and vibration spectra of healthy and faulty bearings were compared to identify significant differences.

The study also explored predictive approaches targeting bearing faults and evaluated different methodologies to assess the accuracy of machine learning models. Artificial neural networks emerged as predominant models for fault detection and classification, leveraging high processing power systems or cloud systems to expedite training. The inclusion of fuzzy logic further refined weight adjustments, potentially reducing false positives, and increasing overall accuracy.

In future work, a detailed comparative study among fault detection and prediction models is vital for a comprehensive understanding of their strengths and weaknesses. Additionally, improving and validating neuro-fuzzy logic algorithms for fault detection and prediction is crucial for wider adoption in real-world applications. Developing a user-friendly web-based application to train model results would enhance accessibility and usability for practitioners and end-users, streamlining the implementation process in industrial settings. Furthermore, future efforts should focus on incorporating complex scenarios for fault detection and prediction in real-time industrial environments. Industrial systems often face unpredictable conditions, necessitating the development of robust algorithms capable of handling various fault scenarios effectively.

Lühikokkuvõte

Elektrimasinate ja ajamisüsteemide intelligentsed seisundiseire meetodid

Tänapäeval kasutatakse elektrimasinaid ja ajamisüsteeme paljudes tööstusharudes. Kodumasinatest tööstusmasinateni on need masinad ülioluliseid tõhususe ja tootlikkuse suurendamiseks sellistes sektorites nagu elektrijaotus, transport, tootmine ja teised. Vaatamata nende olulisusele on elektrimasinad aga altid mitmesugustele riketele, sealhulgas laagri-, rootori- ja staatoririkketele, mis kõik võivad oluliselt mõjutada nende efektiivsust ja talitlust. Nende rikete tuvastamine ja diagnoosimine on töökindluse tagamiseks ja kulukate seisakuaegade minimeerimiseks ülioluline. Nende probleemide lahendamiseks on äärmiselt oluline rakendada ennustavaid hooldusstrateegiaid.

Antud uurimistöö eesmärk oli välja töötada metoodika elektrimasinate võimalike rikete tuvastamiseks ja prognoosimiseks. Kõigepealt käsitleti elektrimasinate peamisi rikkeid, kategoriseerides asünkroonmootori rikked põhirühmadesse ja andes ülevaate nende vastavatest signatuuridest. Mitme parameetri, nagu vibratsioon, vool, temperatuur, magnetvoog ja pöördemoment, jälgimine on masina töökindluse suurendamiseks ülioluline. Vaadati läbi erinevad täiustatud diagnostikameetodid, võttes arvesse nende eeliseid ja puudusi.

Uuringu praktilises osas pandi rõhku andmete kogumisele ja eelanalüüsile kui olulistele sammudele intelligentsete algoritmide tõhusaks treenimiseks. Esitati eksperimentaalse katsestendi seadistuse üksikasjalik kirjeldus, sealhulgas testimismasin, laadimismasin ja kogumissüsteem. Andmete kogumine viidi läbi kontrollitud tingimustes, võttes arvesse erinevaid töötingimusi ja juhtimiskeskkondi, et koguda treenimise jaoks täpseid andmeid. Lisaks indutseeriti kontrollitud tingimustes laagrivoolu rikked ning oluliste erinevuste tuvastamiseks võrreldi tervete ja vigaste laagrite vibratsioonispektreid.

Uuringus uuriti ka ennustavaid lähenemisviise, mis on suunatud laagrite riketele, ja hinnati erinevaid metoodikaid masinõppemudelite täpsuse hindamiseks. Tehisnärvivõrgud tõusid esile vigade tuvastamise ja klassifitseerimise valdavate mudelitena, kasutades suure töötlusvõimsusega süsteeme või pilvesüsteeme, et kiirendada treenimist. Hägusloogika kaasamine täiustas veelgi kaalu kohandamist, vähendades potentsiaalselt valepositiivseid tulemusi ja suurendades üldist täpsust.

Tulevases töös on rikete tuvastamise ja prognoosimise mudelite võrdlev uuring ülioluline, et mõista nende tugevaid ja nõrku külgi. Lisaks on tõrgete tuvastamise ja ennustamise närvi-hägusloogika algoritmide täiustamine ja valideerimine tähtis laiemaks kasutuselevõtuks reaalmaailmas. Mudelite tulemuste koolitamiseks kasutajasõbraliku veebipõhise rakenduse väljatöötamine parandaks praktikute ja lõppkasutajate juurdepääsetavust ja kasutatavust, lihtsustades rakendusprotsessi tööstuslikes tingimustes. Lisaks peab keskenduma keerukate stsenaariumide kaasamisele rikete tuvastamiseks ja prognoosimiseks reaalajas tööstuskeskkondades. Tööstussüsteemid seisavad sageli silmitsi ootamatu tingimustega, mistõttu on vaja välja töötada tugevad algoritmid, mis suudavad tõhusalt toime tulla erinevate rikete stsenaariumitega.

Author’s Publications

Publication I

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Article

Fault Detecting Accuracy of Mechanical Damages in Rolling Bearings

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Abstract: Electrical machines are to face different challenging factors during operation, such as high unexpected or excessive loads, unusual properties of the working environment, or intense fluctuations in rotation speed. Therefore, maintenance questions and predicting the accuracy of an equipment's condition have great importance. This study is based on the theory of vibration reliability. This article introduces the most common faults of bearings in electrical machines and discusses their diagnostic possibilities. Experimental setup, as well as studied bearing failures, are described. The accuracy of conducted experiments is introduced.

Keywords: ball bearings; fault diagnosis; vibration measurement; condition monitoring; failure detection; reliability

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1. Introduction

Condition monitoring and failure prediction of the equipment are crucial due to their wide usage in different applications. Considering options for servicing critical technical systems, creating the possibility of periodic measurements for all machines seems inevitable. However, proper assembly and careful maintenance of the equipment makes it possible to reduce the number of scheduled checks of the devices, including measurement of the vibration level up to two or three times a year. It is also related to security issues and resource savings. Therefore, the creation of an effective condition monitoring system would ensure the reliability of technical resources and the quality of service.

If the vibration frequency is not constant, fractional derivatives are used. These derivatives demonstrate effectively use of vibration acceleration changes and vibration intensity. The derivative order can be any actual number. The intensity of the vibration acceleration change is estimated by the frequency spectrum of the vibration power [1]. During the processing of signals, which inform on the level and balance of vibration, accuracy becomes critical, and, therefore, the ISO 16063 series of standards are used [2]. In case of the absence of a tachometer (conditions for performing repeated multiple measurements and with a rapidly changing speed of rotation of the drive shaft), the diagnostic method is described in [3].

Many studies in literature are related to the described problems. Authors in [4] present an analysis of feature extraction methods in vibration-based condition monitoring for low-speed slew bearing. In [5], authors introduce a study of fault diagnosis of a low-speed bearing based on acoustic emission signal and multi-class relevance vector machine. In [6], an optimization method was applied to diagnose rolling bearing malfunctions, such as an optimization-based improved kernel novel method based on machine learning. At the same time, reducing the dimension of output values makes sense when assessing signs of machine part malfunctions, although it is difficult to determine the main influencing factors. Impressive findings on the diagnostic analysis of acceleration signals from rolling element bearings are presented in [7]. Analyzing the envelope makes it possible to strongly estimate masking signals from gear elements in non-stationary conditions. Authors in [8] apply the basic calculations of the uncertainty of measurement results during vibration transmission, but do not estimate the standard uncertainty. Attention is paid to the assessment accuracy of the rolling bearings state in [9]. One of the approaches of real-time monitoring mode is proposed, but it is not proven that all the requirements for the accuracy of the assessment are met. The application of numerical modeling for applied studies of the state of mechanical systems is presented in [10]. Good results were obtained in the interference suppression mode. An assessment of the accuracy of monitoring the technical condition of objects is given in [11]. The industry has experimentally confirmed that vibration sensors increase the accuracy of measurements. The article [12] presents an interesting algorithm for predicting the state of machining tools during the processing of parts. The mathematical modeling problems are solved in [13] by constructing multifactorial mathematical models for turbine units. The article presents modern methods for wear monitoring of turning tools and the possibility of using the phase chronometer diagnostic method to assess tool wear [14]. Authors in [15] discuss challenges and perspectives of data-driven fault diagnosis for traction systems in high-speed trains.

The reliability of equipment that operates in heavy conditions is based mainly on the analysis of spontaneous emissions of oscillatory processes and on the study of damage accumulation. The initial distribution of defects, operating conditions, and the mechanical system's interaction with the environment leads to accidental failures. It is necessary to describe the behavior of a mechanical system with a high degree of accuracy. A dynamic model of a closed electric drive with a measuring system configured for a monitoring mode is considered as a mechanical system. The measuring system must meet the Certificate in Investment Performance Measurement of Mutual Recognition Arrangement (CIPM MRA) conditions. Thus, the measurement system must be intelligent and time-bound. The SI-based data exchange system standard introduced metrology into digital format. All data are collected and processed according to this unit system.

This article is organized as follows. In Section 2, the most common faults of bearings in electrical machines are introduced and their diagnostic possibilities are discussed. Section 3 presents experiments done in the framework of the given study describing the test bench and studied bearing failures. In Section 4, the results of the conducted experiments are presented and their accuracy is discussed.

2. Bearing Faults

According to statistics, 50% of all failures in electrical machines are referred to as mechanical faults causing additional noise and vibrations and leading to the total breakdown of the device [16]. Bearings are the critical elements of a rotating machine. At the same time, bearing faults carry the highest portion of mechanical damages. The manufacturing of bearings is to be carried out under stringently defined requirements. However, the actual lifespan of the bearing is much lower than it is supposed to be due to different forces affecting it during operation, such as unexpected overload, insufficient lubrication, and improper bearing installation [17]. As electrical machines operate in other conditions, bearings can be prone to many faults and damages. The reasons for these failures are different environmental or manufacturing factors.

2.1. Mechanical Damages

Most bearing faults are related to mechanical damages, which can occur due to manufacturing failures or unexpected conditions during motor operation. Usually, these mechanical damages are referred to as inner and outer rings, cages, or rolling elements. An example of a faulty bearing cage is shown in Figure 1.

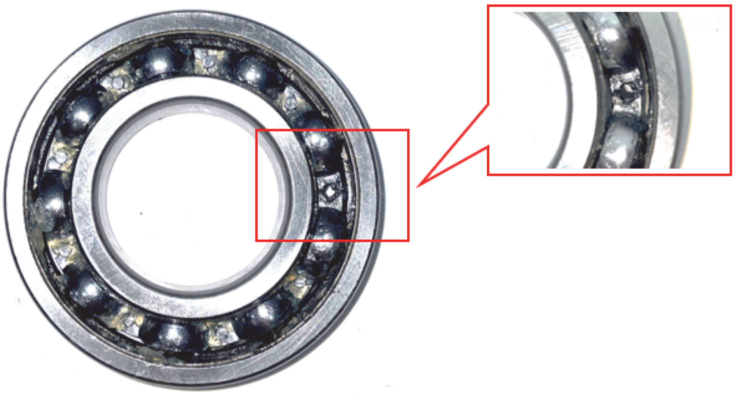


Figure 1. Damaged cage in rolling bearing.

These mechanical damages can also be caused by an incorrect manufacturing or mounting process, improper design, misalignment of bearing rings, or unequal proportions of rolling elements. Before placing the bearing, it is mandatory to check for manufacturing faults: general appearance, rotational ease, and clearances of technical documentation requirements. Usually, open-type approaches are to be checked for contamination, corrosion, and cage condition. For sealed-type bearings, cages should also be checked to prevent possible damages.

2.2. Material Fatigue

Material fatigue is usually caused by continuous loads that crack the bearing's surface. If external forces are applied to the bearing rings, the strength of the material decreases, causing it to crack. Over time, cracking progresses, and, eventually, the bearing becomes unsuitable for further exploitation. The bearing's durability is measured by the number of revolutions that the bearing makes before the first signs of material fatigue become noticeable on rings and rolling bodies [18]. An example of bearing material fatigue is shown in Figure 2.

Figure 2. Material fatigue of a rolling bearing.

Continuous overload, poorly maintained, and contaminated surfaces—all these factors inevitably lead to material fatigue. This phenomenon, its time occurrence, and developing process largely depend on the magnitude of the machine's applicable load and rotational speed. Initially, microcracks appear in the subsurface. By process development, the surface of the bearing begins to crack on a larger surface and becomes rough. In this case, additional noise and vibration can be detected. In addition, the operating temperature of the bearing increases. The bearing should be regularly checked and well lubricated to prevent this failure.

2.3. Ambient Contamination

When humid air enters the bearing, it tears lubricant properties at certain points of an increased load on rings. In addition, lubricants can become polluted by water or other chemical substances. As lubricant properties are deteriorated, bearing corrosion appears. Corrosion is a process between material and environment that results in material dissolution. Proper lubrication is one of the bearing operating conditions that determines its durability. Rightly selected lubricant provides a thin oil layer, which helps to soften the impact of rolling elements against bearing rings and cages.

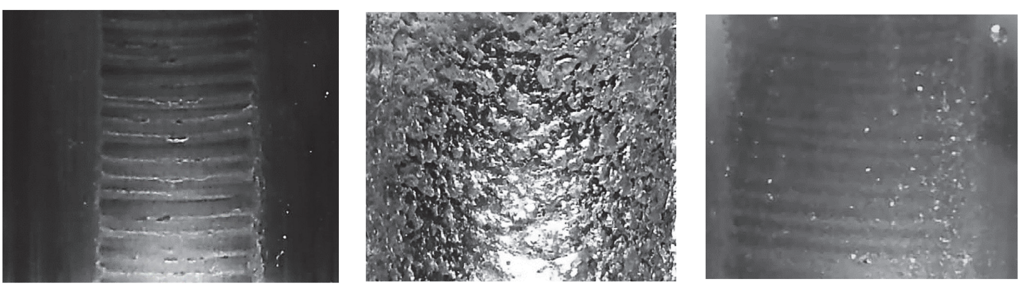
Moreover, the lubricant prevents the bearing from premature wear and corrosion. Improper lubrication can be referred to as an insufficiently as well as excessively greased bearing. Insufficient lubrication causes friction and crack progression, while an overly greased bearing results in the shaft slipping and leads to structural damage. An example of bearing corrosion is shown in Figure 3.

Figure 3. Corroded surface of a rolling bearing.

Bearings can also be polluted by dust, sand, and other abrasive particles. This pollution leads to structural damages of the bearing (e.g., scratches, cracks) and produces significant dents when the rolling element rolls the shaving into the rings. The main reason for these damages is the wrongly selected bearing cage, preventing such particles from entering the bearing. As a preventative factor, corrosion-resistant lubricants can be used. Moreover, it is vital to keep the mounting process clean and not to use contaminated greases.

2.4. Bearing Currents

Bearings are often affected by shaft currents. If current passes through the bearing, damages will appear on the bearing surfaces. Usually, these failures occur in bearing areas, where the lubricant layer is the thinnest due to the increased load at these points. The most common damages caused by shaft currents are shown in Figure 4. Fluting usually occurs with low voltage and constant rotational speed, where multiple lines occur across bearing rings. At the same time, frosting occurs if the motor operates at varying speeds. Pitting is usually caused by low speed and supplied high-voltage sources. Practically, dull-finish can also be observed, which resembles pitting, but the size of the craters are much smaller.



(**a**) (**b**) (**c**)

Figure 4. Faults caused by shaft currents: (**a**) fluting, (**b**) frosting, and (**c**) pitting.

The first indicator of a possible problem related to shaft currents is lubricant darkening, which oxidizes during sparking caused by electrical discharges, as shown in Figure 5.

Figure 5. Darkened lubricant.

At the initial stages, these damages are not visible and cannot be detected without disassembling the bearing and searching for microscopic deviations on the bearing rings and rolling elements [19]. By fault development, the damage inflicted on the bearings due to currents differs visually from other bearing damages. For this reason, it is crucial to inspect changes in bearings in all cases during service if there is a reason to suspect the presence of bearing or shaft currents, especially in those cases where bearings are used in larger power class frequency converter-fed electrical machines.

3. Experiments

The dynamic model of the electric drive was studied in the torque control mode. Drive composition: a three-phase asynchronous motor C71B-2 with cage rotor, rotary optical encoder with IR-LED, precision ball bearings, grooved ball bearing 6004-2ZR, and belt drive with eccentric belt pulley with a pretension V-belt. The test bench is presented in Figure 6.

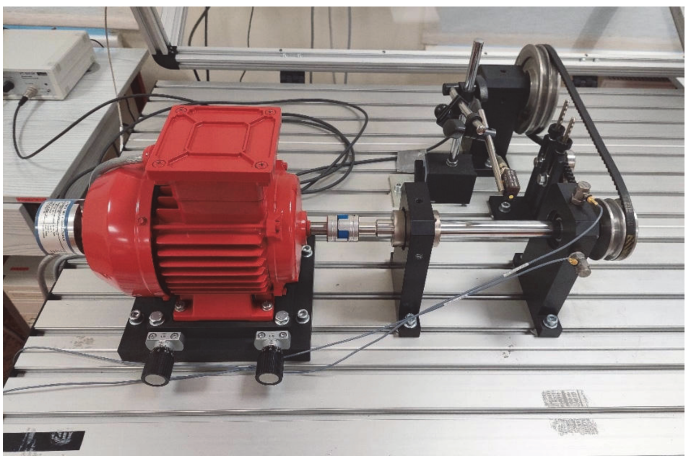


Figure 6. Bearing testing.

The highest speed and the shorter interval between signals made it possible to obtain more accurate metrological support for monitoring the technical condition of a ball radial single-row rolling bearing. As shown in Figure 7, the accelerometer output signal's root mean square (RMS) value was measured. The frequency range and measurement uncertainty allow you to accurately evaluate the results of comparing different bearing fault signature extractions.

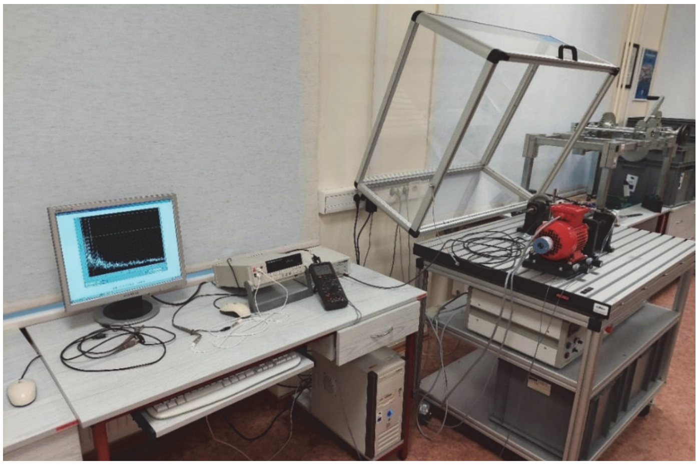


Figure 7. Experimental test bench.

Before the experiment, the belt was pre-tensioned, thereby maintaining the speed of the rotation of the shaft. In the experiment, a vibration stand with the following characteristics was used: a non-linearity of ±1%, measuring range of ±490 m/s^2 or ±50 g; broadband resolution of 3434 μm/s^2. Small transverse and angular vibrations of the vibration stand table do not significantly affect the measurement results. The deviation of the acceleration amplitude during the measurement process is not more than 0.05% of the displayed value. The test unit's electronic noise is below the maximum value of the output signal.

Deep groove ball bearings (type 6004 2RS) were used in these experiments. Healthy bearings were studied as well as bearings with additional damages. As shown in Figure 8, the following cases were studied: the healthy bearing, bearing with damaged inner ring, bearing with damaged outer rings, bearing with broken cage, complex bearing damage (damaged outer ring, inner ring, and cage), and bearing with material fatigue.

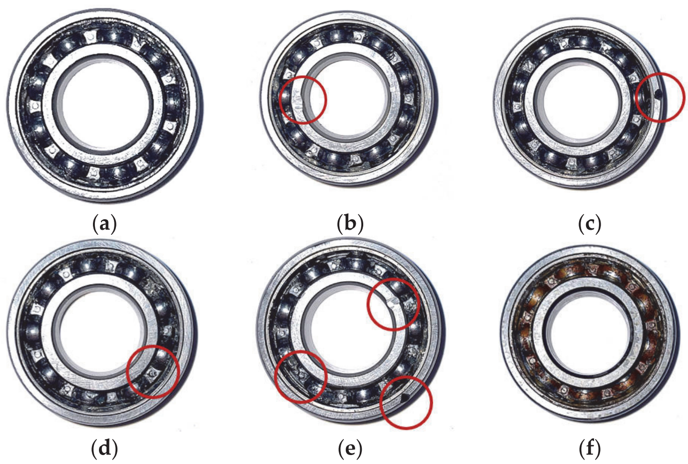


Figure 8. Studied bearings with different damages: (**a**) healthy bearing, (**b**) bearing with damaged inner ring, (**c**) damaged outer ring, (**d**) damaged cage, (**e**) complex damage, and (**f**) material fatigue.

4. Results

The data exchange should be carried out very quickly. Synchronization of the measurement system was carried out programmatically. The created software was effectively used to detect malfunctions in the drive parts at a low speed. A program was developed for more accurate recording of shock loads at low shaft rotation frequencies that allow recording shock loads in milliseconds. With such a sampling rate of vibration signals, it is challenging to diagnose malfunctions in bearings in belt drives. The shaft rotation frequency was 300 rpm in the experiment, thus the sampling frequency was 5 Hz. Low frequency and accessing a digital voltmeter at every millisecond made it possible to assess the condition of the bearing with great accuracy.

The algorithm is suitable for processing vibration spectra, which will allow continuous instant monitoring in the future. To implement the theoretical foundations of diagnostics, a custom program Lucia was created and written in C++ using the MFC (Microsoft Foundation Classes) library for synchronous monitoring of the state of the drive. MATLAB 2021b without Toolbox application was used only for process visualization. Lucia is aligned with MATLAB 2021b software. There are two options for synchronizing the measurement system's operation: the program makes a measurement request and reads data from the port, setting the print-only mode.

In this way, you can change the data transfer rate and the intervals between data. All parameters can be monitored, and the results of diagnostics of the condition of the drive parts can be evaluated more accurately. The diagnosis of bearings with known malfunctions was carried out. Further, diagnostics of similar bearings with unknown malfunctions were carried out. The measurements are synchronized, as the timestamp of each measure is displayed in milliseconds and ticks. Based on these data, it is possible to estimate the interval between measurements and the data transfer rate. Theoretical values of data transfer rates do not correspond to actual values due to the asynchronous data exchange mode via COM port. The condition-monitoring scheme of using the custom Lucia program is shown in Figure 9.

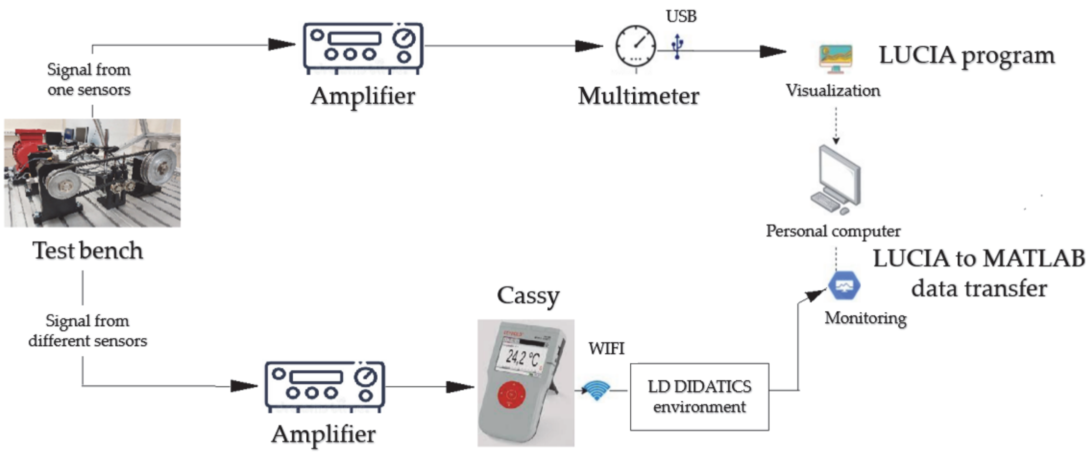


Figure 9. Condition-monitoring scheme of using custom Lucia program.

An alternative approach to the metrological control of the technical condition of rolling bearings is based on a single measurement information format. As an etalon, we use a bearing with a known character of the damage. At the first stage, we establish the ratio between the values of frequencies occurring due to damage in the etalon bearing depending on the speed, considering the measurement uncertainties. At the second stage; we use this information to establish the ratio necessary to assess the condition of a bearing with an unknown nature of damage based on the readings of the measurement system.

Conducting comparative measurements [20], the value of F_s, which is the response of a malfunction of the etalon bearing, is compared with the value of F_c, which is the response of a malfunction of a bearing with unknown damage. As a rule, during the implementation of such measurements, the difference between these values $\Delta = F_c - F_s$ is determined. This difference is used to make corrections to the measurement result in the future. In this case, the estimation of measurement uncertainty consists of estimating this difference's uncertainty Δ. The model equation in the case of comparing the results has the form:

$$\Delta = (F_C + \Delta_C) - (F_S + \Delta_S + \theta_S) \tag{1}$$

where $F_C$the value associated with the response of a bearing malfunction with unknown damage; $F_S$the value associated with the failure response of the etalon bearing; $\Delta_S$quantization error of the measuring instrument at the first stage of measurements; $\theta_S$non-excluded systematic error of the measuring instrument; Δ_C—error of quantization of the measuring instrument at the second stage of measurements. The following uncertainties correspond to the listed input values:

- u (F_S)—Uncertainty associated with the scattering of readings related to the etalon bearing, and determined statistically when performing multiple measurements;
- u (Δ_S)—Uncertainty of quantization of the measuring instrument at the first stage of measurements;
- u (θ_S)—The uncertainty of the measuring instrument obtained from the value of its non-excluded systematic error;
- u (F_C)—Uncertainty associated with the scattering of readings related to a bearing with an unknown nature of the damage, and determined statistically when performing multiple measurements;
- u (Δ_C)—Uncertainty of quantization of the measuring instrument at the second stage of measurements.

As the quantization error of the measuring instrument is the same at the two stages of measurement, it can be ignored. In this case, when processing the measurement results, it is advisable to use the method of reduction [ISO/IEC]. Then, the total standard uncertainty of comparative measurements will be determined by the expression:

$$u(\Delta) = \sqrt{u^2(F_C - F_S) + u^2(\theta_S)} \tag{2}$$

where u ($F_C - F_S$)—is the uncertainty associated with the scattering of the difference in readings at the first and second measurement stages statistically determined. The extended uncertainty of comparative measurements will be equal to:

$$U = t_{0.95}\{(n-1)\left[\frac{u(\Delta)}{u(F_C - F_S)}\right]^4\} \cdot u(\Delta) \tag{3}$$

As mentioned, created software is coordinated with the MATLAB r2021b program. The most common envelope analysis method in non-stationary conditions was carried out for a bearing with an expected defect on the inner ring at a shaft rotation speed of 300 revolutions per minute. The envelope method was specifically used to demonstrate monitoring effectiveness with the created Lucia software. By synchronizing the monitoring process, it is possible, with an accuracy of less than 0.1%, to identify increasing failures in the parts of the electric drive. The experimental process can be shown in the example of the bearing with the damaged inner ring. The estimated frequencies arising from damage, depending on the rotational speed for a roller bearing type 6006 at a given shaft rotation speed, is 27.1 Hz. As the laboratory has an etalon (specifically designed according to standards) bearing with damaged inner rings, this particular prototype with damage on the inner ring was chosen to calculate the accuracy of diagnostics of the rolling bearing condition. The inner ring failure response frequency at a shaft speed of 300 rpm is 27.1 Hz.

The original raw data containing the failure responses in the inner ring of the studied bearing can be visualized in the spectrum. This bearing has not been operated, and, therefore, it has been selected as the initial working standard with a known failure pattern. The raw data are presented in the time domain, as shown in Figure 10.

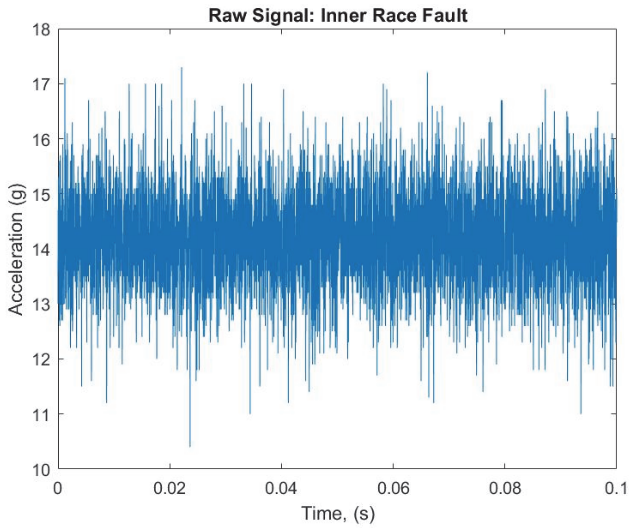


Figure 10. Raw signal of broken inner ring in time domain.

The motor shaft speed is 300 rpm. At this frequency, it is difficult to detect failures of the rolling bearing. In Figure 11, a visualization of the same original raw data in the frequency domain is presented.

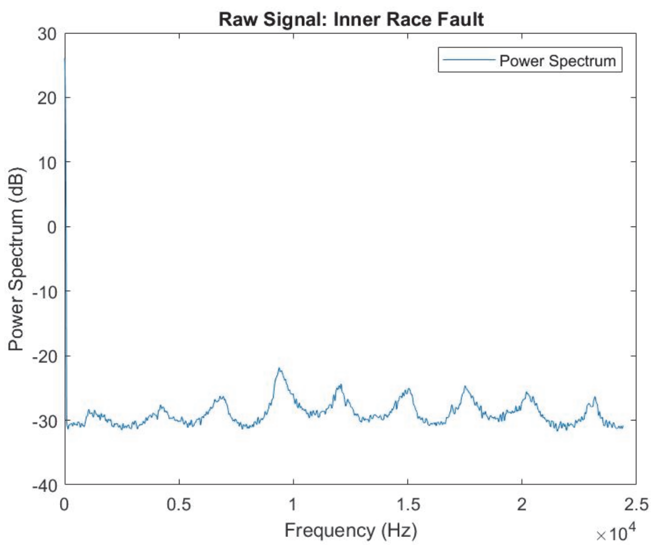


Figure 11. Raw signal of the damaged inner ring in frequency domain.

Figure 12 presents the power spectrum of the unprocessed signal in the low-frequency region. On an enlarged scale, it is possible to study the amplitude-frequency vibration spectrum of the acceleration envelope in the rolling bearing with defects on the inner ring.

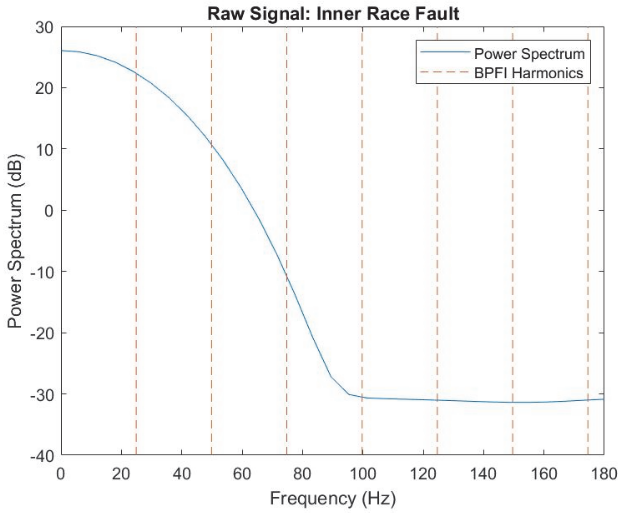


Figure 12. Power spectrum of raw signal.

Time-frequency analysis of the raw signal does not accurately distribute the energy over frequency intervals for any partitioning of the frequency domain. At the frequency response, the modulation frequency can be observed at about $1/(0.055 - 0.0046) = 111$ Hz. It indicates that the bearing has a potential problem in the inner ring, as shown in Figure 13. In the graph, the horizontal arrow shows the time interval in order to determine the likelihood of detecting a potential damage in the inner ring of the bearing.

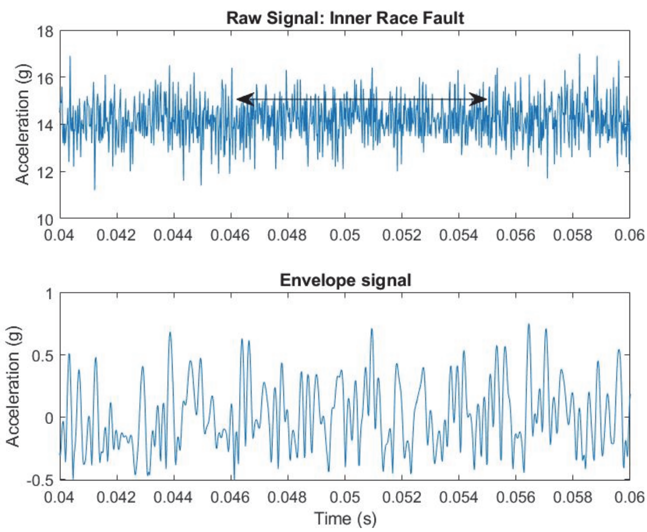
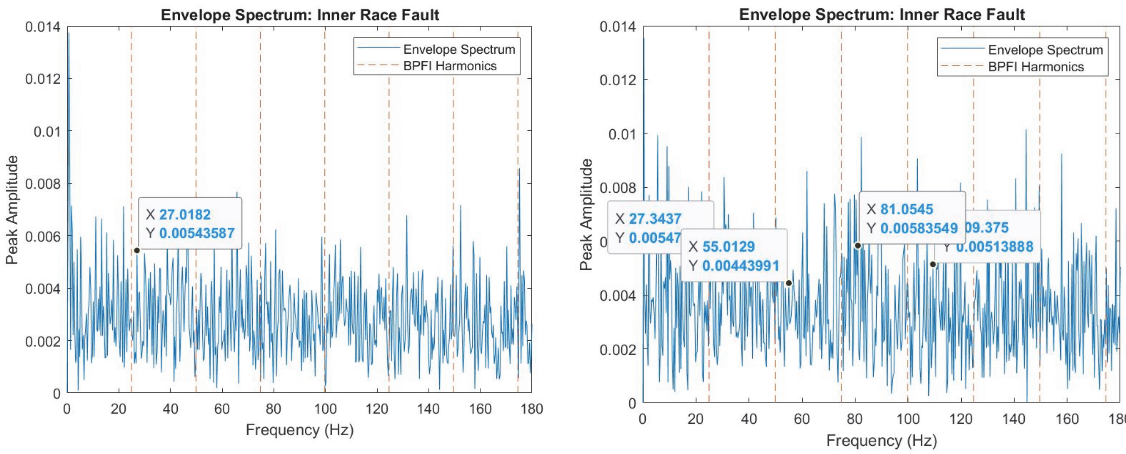


Figure 13. Power spectrum of raw signal.

A similar method and vibration diagnostics with different signal transmission rates and intervals between signals were carried out for the etalon bearing with known damage on the inner ring and the bearing with expected damage on the inner ring. The information transfer rate was correlated with the intervals between the signals and varied from five measurements per second to 20 measurements per second. The intervals between the signals ranged from 70 milliseconds to 400 milliseconds. The results are shown in Figure 14, where the spectrum of the acceleration envelope of a rolling bearing with defects in the inner rings presents a failure response frequency at 27.0182 Hz.



(**a**) (**b**)

Figure 14. Acceleration envelop of a rolling bearing with damaged inner ring: (**a**) etalon bearing and (**b**) experimental bearing.

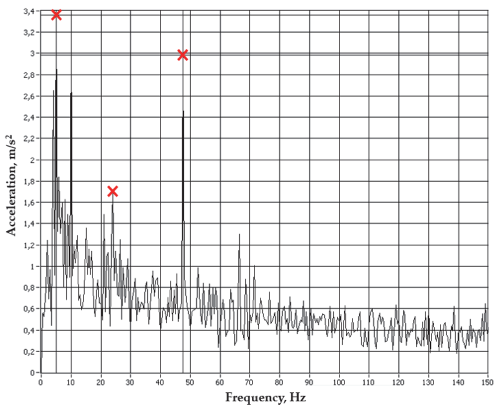
The accuracy of conducted experiments is presented in Table 1. According to the calculations of the metrological characteristics of the measurement system, the error in transmitting signal information over communication lines is ±1 ms.

Table 1. Measurement uncertainty and comparison of diagnostic results of an etalon bearing and experimental bearing with damaged inner ring.

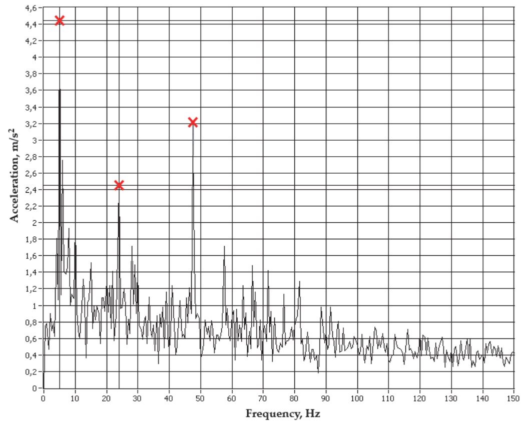
Input Value	**Estimation of the Input Value, Hz**	**Standard Uncertainty, Hz**	**Number of Degrees of Freedom**	**Sensitivity Coefficient**	**The Contribution of Uncertainty**
F_S	27.0182	0.83 1.4	4 ∞	-1 -1	$-u_A(\overline{F}_S)$ $-u_B(\overline{F}_S)$
F_C	27.3437	0.83	4	1	$u(F_C)$
θ_S	0	0.3125	∞	-1	$-u(\theta_S)$
Output Value	**Evaluation of the Output Value**	**Total Standard Uncertainty**	**Effective Number of Degrees of Freedom**	**Coverage Coefficient**	**Extended Uncertainty**
Δ	0.3255	1.8	4	$t_{0.95}(\nu_{eff})$	-

Figure 15 presents the vibration spectra of a healthy bearing and the bearing with the damaged inner ring. The speed of the motor shaft is presented at the frequency of 5 Hz, while the speed of the damaged V-belt measured at the bearing block for the small belt pulley in the vertical direction is presented at the frequency of 47.5 Hz. The faulty frequency of the bearing can be presented at the frequency of 23.5 ± 5.7 Hz. Noise pulses are identified here at the rotation frequency of 2 Hz in both cases. Comparing the frequency spectrum of the healthy bearing to the faulty bearing, the amplitude of the faulty one is significantly higher. The inner ring failure response frequency at a shaft speed of 300 rpm is 27.1 Hz.

Figure 16 present vibration spectra of faulty bearings. In these cases, the speed of the motor shaft is also presented at the frequency of 5 Hz, while the speed of the damaged V-belt is measured at 47.5 Hz. Faulty frequencies of the bearing are presented at the frequency of 23.5 ± 5.7 Hz.

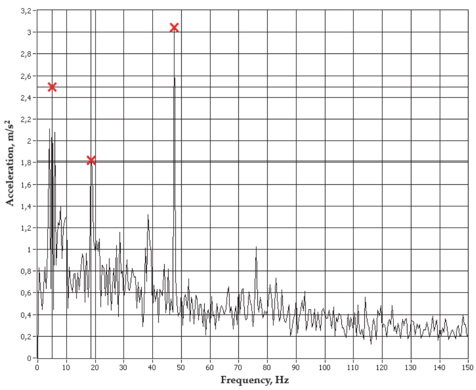


(**a**)

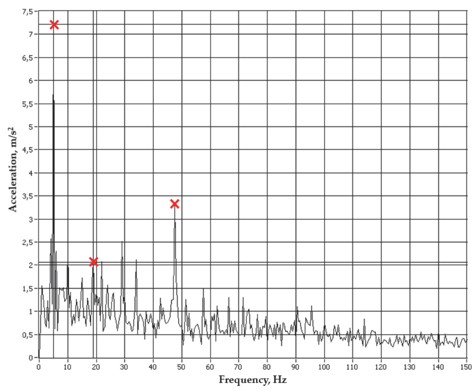


(**b**)

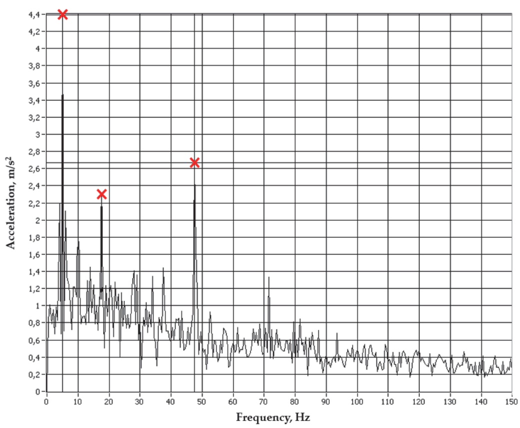
Figure 15. Comparison of vibration spectra of (**a**) healthy bearing and (**b**) bearing with damaged inner ring.



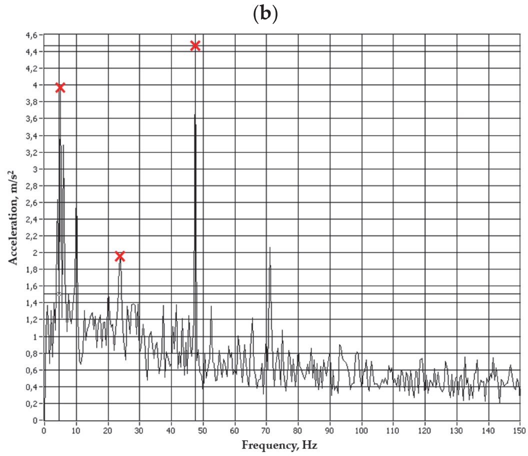
(**a**)



(**b**)



(**c**)



(**d**)

Figure 16. Vibration spectra of faulty bearings: (**a**) damaged outer ring, (**b**) damaged cage, (**c**) complex damage, and (**d**) material fatigue.

The damage frequency of the outer ring is located at 23.5 Hz, which is the fundamental frequency. A higher harmonic component is presented in the case of a damaged cage due to the higher operating asymmetry. In the case of complex fault, harmonic features of the damage are visible but also depend on the fault development stage. The bearing with material fatigue demonstrates higher noise compared to the healthy bearing. The sidebands at the distance of the cage rotation frequency of 2 Hz are visible.

5. Conclusions

The diagnostics of rolling bearings using the proposed method allows us to evaluate the accuracy of the classification of bearing faults. This method is suitable not only for the identification of single defects. The time-frequency method with an accurate data transmission system will also identify multiple bearing failures. The experiments conducted demonstrate that increasing the data transfer rate and reducing the interval between pulses in a real situation increase the accuracy of diagnostics. The effectiveness of the proposed diagnostic program is proven by the example of fault monitoring of both the etalon bearing and the bearing with the expected malfunction on the inner ring, for experimental testing of the program using bearings with multiple defects. This method will cover the entire frequency range of vibration diagnostics, identify defects early, and track their appearance in real-time. The results obtained have a high degree of reliability, at 95%. Thus, the high accuracy of determining time intervals makes it possible to further improve this method's information capacity. Faulty patterns of the experimental bearing can be used for predictive maintenance approaches, which will be considered for future work.

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Production Quality Related Propagating Faults of Induction Machines

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***Abstract*—This paper presents a study of ten identical induction motor. Due to the wide usage of induction machines in different industries, the maintenance and reliability of such devices is getting a great importance. The main failures of induction motors are listed, as well as the reasons for these failures have been pointed out. A special attention has been paid to manufacturing faults, which usually are not taken into consideration, but can evolve during the motor operation and lead to undesirable consequences.**

Keywords—induction motors, manufacturing, stators, testing, production control.

I. Introduction

Three-phase induction motors are the most widely used electrical machines type [1]. High efficiency and relatively low cost make these motors attractive in a variety of applications. Despite the given advantages, electrical and mechanical faults in combination with environmental conditions can influence the maintenance of the motor and its lifespan. Due to the fact that induction motors play a key role in the different fields of industry, these failures are undesired and are to be avoided.

Induction motors faults can be classified into three main groups: stator, rotor, and bearings related faults. The distribution of these faults depends on the motor's parameters, such as machine type, size, rated voltage, etc. In the case of low-voltage machines, there is a majority of bearings related faults, while the high-voltage machines receive a higher proportion of stator winding faults [2]. According to the statistics, 36% out of all the faults are related to the stator winding failures [3]. The stator winding faults usually develop from a turn-to-turn short circuit. Without timely intervention, this fault can grow to phase-to-phase or phase-to-ground short circuits. Due to the fact that this inter-turn fault is hardly detectable in the early stages of its development, this topic is largely challenging in the electrical machine industry. Even in the initial stage, an inter-turn short circuit can result in serious damage and lead to the breakdown of the machine. Therefore, the monitoring and prediction of possible fault appearance can significantly reduce the negative effect of damage on motor maintenance [4], [5].

Many studies have been conducted in the last decades related to diagnostics methods of turn-to-turn short circuit and their detecting possibilities. Thus, researchers in [6] analyze the possible effects of an inter-turn short circuit on the electromagnetic field of the induction machine. Authors in [7] show, based on finite element method (FEM) analysis, pulsation torque in the machine under turn-to-turn short circuit condition. In [8], the authors propose a motor square current signature analysis (MSCSA) to detect the inter-turn fault in the induction machine.

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Degradation of the winding insulation can be caused by many factors. Generally, four main stresses can be distinguished, which can affect the degradation rate of the winding insulation, also known as TEAM stresses: thermal, electrical, ambient, and mechanical stresses [9].

a) Thermal stresses: The most common stresses that can affect the machine are the thermal stresses. Particularly, in the case of induction motors, the starting current is high. During the starting of the motor, the temperature can exceed the threshold value and cause a decrease in the insulation system.

b) Electrical stresses: Insulation can be affected by unstable supply voltage, transient voltages, unstable ground, incorrect rated values of the machine. Particularly, electric motors can be affected by fast switching inverters.

c) Ambient stresses: This is a combination of the factors, which come from the environment surrounding the motor [10], such as moisture, humidity, aggressive chemicals, dirt, and other particles. Each of them can affect the machine and its insulation system differently – directly or in combination with other stress types.

d) Mechanical stresses: During the machine operation, many forces influence it: centrifugal, magnetic, etc. There are many studies related to the monitoring and reduction of these forces. However, there are a few types of research done about quality control monitoring in production and damages inflicted on the electrical machine during the motor installation.

This paper shows the study of newly manufactured induction motors. The measurements were carried out and the results are presented. However, despite the test results, significant damages were found, which can lead to the breakdown of the machine in the future.

II. Measurements

In the given research, ten identical three-phase induction motors were tested. The technical data of the motors is given in Table I.

TABLE I. Technical Data of the Tested Motors

Parameters	Value			Unit
Connection	Y	D	D	
Frequency	50	50	60	Hz
Voltage	690	400	460	V
Power	7.5	7.5	7.5	kW
Speed	1460	1460	1760	r/min
Current	8.8	15.3	12.9	A
Torque	49	49	40.6	Nm

Firstly, the low frequency (120 Hz) inductance measurement was carried out. Tests were performed with digital LCR meter with an accuracy of 0.5, 0.7, and 1.2% to resistance, capacitance, and inductance respectively. The results are shown in Table II.

TABLE II. INDUCTANCE MEASUREMENT

Motor nr.	Value			Unit
	U	V	W	
Motor 1	57.14	66.66	76.50	mH
Motor 2	71.39	75.01	54.44	mH
Motor 3	62.93	78.35	60.87	mH
Motor 4	59.14	78.68	60.23	mH
Motor 5	64.69	60.41	82.63	mH
Motor 6	65.68	76.99	59.49	mH
Motor 7	59.74	75.84	62.58	mH
Motor 8	62.67	66.14	82.02	mH
Motor 9	58.69	70.76	84.74	mH
Motor 10	77.95	69.84	55.38	mH

Additionally, resistance measurement was performed the. Resistance was measured with a digital multimeter, which has 0.003% DC voltage accuracy and 0.005% resistance accuracy. The resistance results are shown in Table III. Inductance and resistance measurements have not identified any deviation in parameters and all the values meet the defined limits.

TABLE III. RESISTANCE MEASUREMENT

Motor nr.	Value			Unit
	U	V	W	
Motor 1	1.77	1.70	1.74	Ω
Motor 2	1.72	1.67	1.67	Ω
Motor 3	1.67	1.69	1.71	Ω
Motor 4	1.67	1.70	1.89	Ω
Motor 5	1.67	1.67	1.66	Ω
Motor 6	1.67	1.69	1.69	Ω
Motor 7	1.68	1.70	2.19	Ω
Motor 8	1.70	1.68	1.66	Ω
Motor 9	1.69	1.70	1.68	Ω
Motor 10	1.71	1.66	1.68	Ω

In addition, the insulation resistance measurement of stator windings was carried out. These results also have met the limits.

III. VISUAL INSPECTION

Even though the measurement results are within the defined limits, the visual inspection indicates a variety of damages in the motors. Due to the fact tested motors were non-used, thus, described in given chapter damages were inflicted to the motors are caused manufacturing factors in production. Manufacturing faults are not usually taken into account during the design process and they tend to occur during the exploitation of the machines [11].

a) Motor 1: In the case of Motor 1, after a visual inspection, insulation damages on the winding of the motor were found, as shown in Fig. 1.

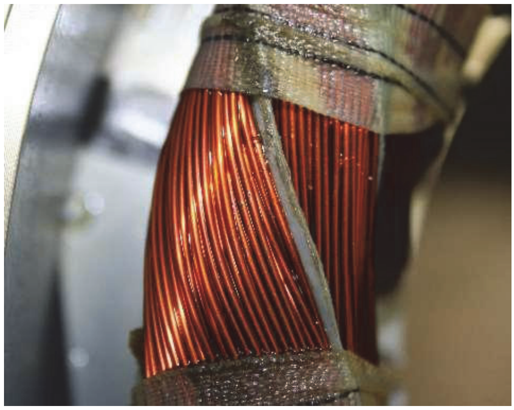

Fig. 1. Insulation damage in Motor 1.

b) Motor 2: Identically to the previous example, the visual inspection of Motor 2 revealed winding insulation damages, which are shown in Fig. 2. In addition, an improper placement of winding wire was found.

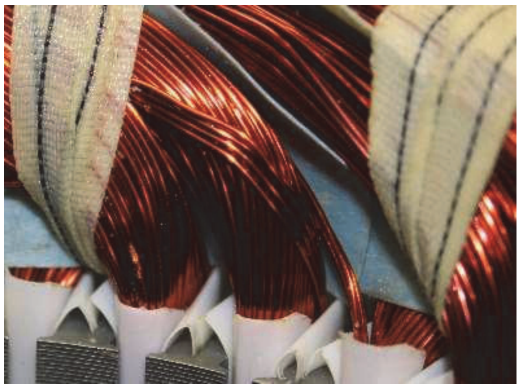

Fig. 2. Insulation damage and improper winding placement in Motor 2.

c) Motor 3: In the case of Motor 3, as shown in Fig. 3, it is possible to detect the overheating tracks of the winding insulation.

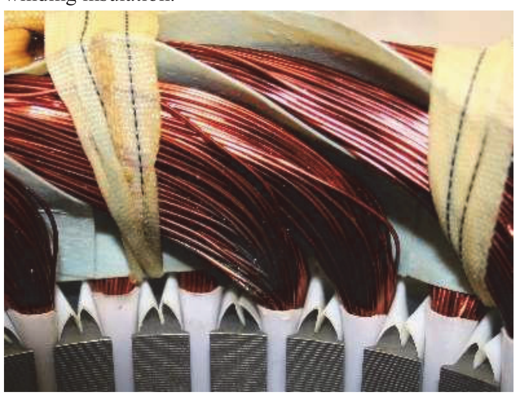

Fig. 3. Overheated winding insulation in Motor 3.

Similarly, to previous examples, improper placement of the winding wire was also found, as shown in Fig. 4.

Fig. 4. Improper winding placement in Motor 3.

d) Motor 4: The visual inspection of Motor 4 has revealed the fault of stator lamination. As shown in Fig. 5, the lamination stacks of the stator are curved.

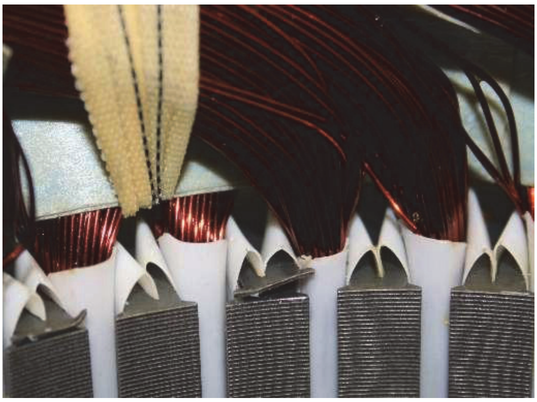

Fig. 5. The curvature of the lamination stacks in Motor 4.

e) Motor 5: Improper wire concentration as shown in Fig. 6 was found in case of Motor 5.

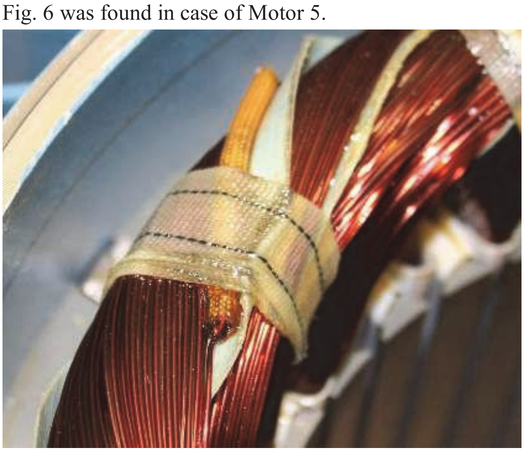

Fig. 6. Wire concatenation in the motor's winding in Motor 5.

f) Motor 6: In the case of Motor 6, winding insulation damages were detected, as shown in Fig. 7.

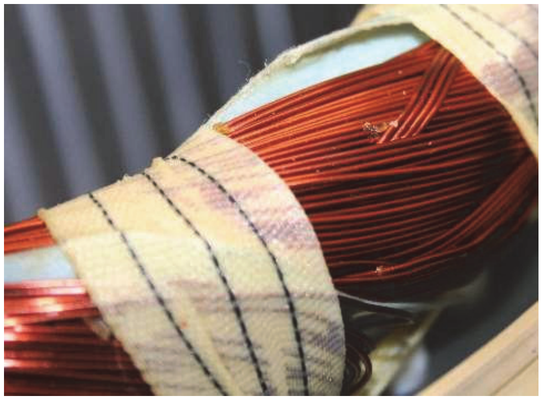

Fig. 7. Insulation damage in Motor 6.

g) Motor 7: Visual inspection of Motor 7 indicated an improper placement of winding wire, shown in Figs. 8 and 9.

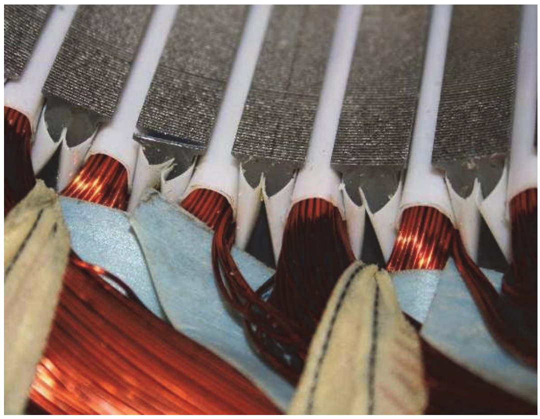

Fig. 8. Improper winding placement in Motor 7.

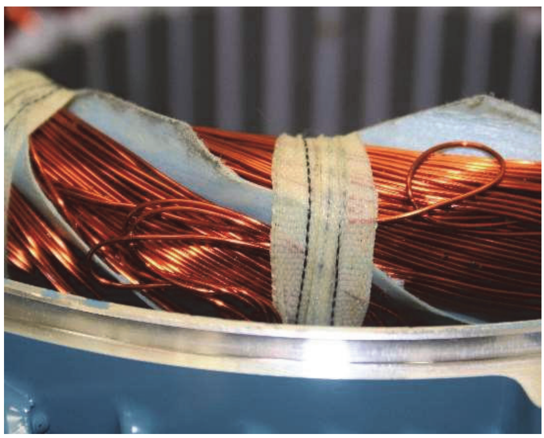

Fig. 9. Improper winding placement in Motor 7.

h) Motor 8: As shown in Fig. 10, the winding of Motor 8 was bruised. Moreover, the improper winding placement was also detected, shown in Fig. 11.

Fig. 10. Bruised winding in Motor 8.

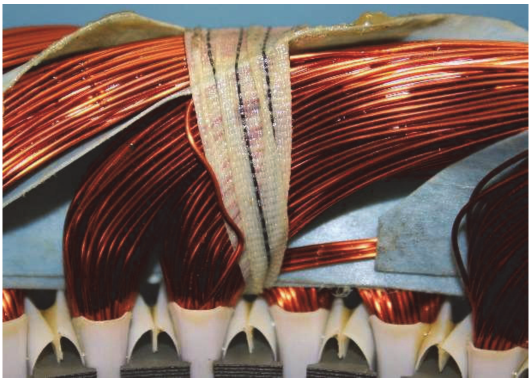

Fig. 11. Improper winding placement in Motor 8.

IV. Discussion

The ideal machines should be symmetrical in all aspects. Their windings should be sinusoidally distributed in the stator and on the rotor side. They should have a smooth and constant air gap [12]. The current in the stator and rotor windings should be uniformly distributed to avoid the skinning and proximity effects. All these ideal features can lead to the ripple-free speed and torque production and no vibrations.

But in the case of practical machines, all these ideal scenarios cannot be implemented due to various kinds of limitations. The stepped distributed windings on the stator side, the cage structure on the rotor side, the non-uniform air gap due to inherent eccentricities, the stator and rotor slot openings, the non-linear nature of the magnetic material, the skinning and proximity effects generate various kind of current harmonics and the air gap flux density do not remain pure sinusoidally distributed.

The most prominent harmonics are the winding and slotting harmonics which spread across the entire frequency spectrum of the stator current and induced voltages [13]. These harmonics produce rotating fluxes having different angular velocities with resulting in oscillating speed and torque profiles. These oscillations produce vibrations in the machine and the stator windings become their first victim with a result is the insulation damages [14].

Although the ideal structure is not possible, the effect of the harmonics can be reduced by making the three-phase windings symmetrical. By doing so, most of the harmonics can be canceled out at the star common node and the negative sequence currents in the delta connection.

The case study of ten machines from the same manufacturer having the same rated values reveals significant impairments. The differences are more prominent on the stator side related to the winding problems. The difference in the measured inductance and resistance profile is significant, which is because of the problems in the windings as shown in the figures.

Since the inductance is the function of the effective number of stator and rotor turns per slot and the air gap, hence form Table II and Table III it can be concluded that although the number of turns per slot is the same their effective value is different. This difference is visible in the end winding region in the form of bad conductor placements. The resistances are also different due to the same reason. The resistance difference is small because they are representing DC resistances. This difference will increase under AC conditions because of the skinning and proximity effects.

These asymmetries may lead to increased vibrations with resultant scratch among the copper conductors leading to their insulation damage. Also, the thermal profile of the machine will not remain uniform leading to the hot spots at specific locations.

These asymmetries can reduce the life of the machine and cause the starting point of the stator failures. Since the faults are degenerative, these problems can cause a catastrophic situation in the form of total burn over. Moreover, once the inter turn short circuit starts, the following frequency components start appearing in the current spectrum.

$$f_t = f_s\left[\frac{n}{p}(1-s) \pm \nu\right], \quad \nu = 0, 1, 3, 5, \ldots \qquad (1)$$

where f_t is the short circuit representing frequencies in the stator current, n is the number of phases, s is the slip, p is the number of poles, and ν is the harmonic order.

V. Conclusion

In this paper, ten motors from the same manufacturer with the same rated parameters are taken as a case study. Their phase inductances and resistance are measured to check their symmetry. The possible causes of the difference in inductance and resistance profiles are investigated by visual inspection of their stator windings. In the light of the results and discussion it can be concluded that A special attention should be paid to possible manufacturing faults and taken them in account during the design process. Particularly, the reliability, safety, and extended lifetime of the machine, special care towards the windings should be taken into consideration. All three phases should have symmetrical inductance and resistance profiles to limit the asymmetry-based harmonics. The end winding portions should be handled carefully to avoid any minor damage which can become the starting point of the fault.

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Publication III

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Review

Methods of Condition Monitoring and Fault Detection for Electrical Machines

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Abstract: Nowadays, electrical machines and drive systems are playing an essential role in different applications. Eventually, various failures occur in long-term continuous operation. Due to the increased influence of such devices on industry, industrial branches, as well as ordinary human life, condition monitoring and timely fault diagnostics have gained a reasonable importance. In this review article, there are studied different diagnostic techniques that can be used for algorithms' training and realization of predictive maintenance. Benefits and drawbacks of intelligent diagnostic techniques are highlighted. The most widespread faults of electrical machines are discussed as well as techniques for parameters' monitoring are introduced.

Keywords: artificial intelligence; condition monitoring; failure detection; fault diagnosis; fuzzy logic; machine learning; neural networks; reliability

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1. Introduction

Condition monitoring and fault diagnostics of electrical machines are gaining heightened popularity. It is because the vital role that electrical machines play in industry and domestic life is increasing day by day. Electrical machines always remain prone to faults because of the mechanically moving parts associated with them, the harsh industrial environment, and no doubt the increasing probability of failure with life. Conventional maintenance techniques can be broadly classified into two categories: reactive maintenance and preventive maintenance. Preventive maintenance is mainly related to the scheduled overhauling of a system and whether or not it requires maintenance, while reactive maintenance comes into play when the failure has already occurred. Unfortunately, both methods are not suitable in industry, as they have a substantial economic impact. In the case of reactive maintenance, the machine is already broken, disrupting the process.

In contrast, overhauling all machines, whether healthy or faulty, is not a good solution in preventive maintenance. In comparison, predictive maintenance is a better choice, one in which the machine's health can be continuously monitored, and only faulty machines can be selected for maintenance. Moreover, since the fault can be detected at an early stage, the machine can be repaired before any catastrophic situation. However, predictive techniques are rather complicated depending upon the type of the machine, the drive control mechanism, and the load behavior. This is why a great many research fields are involved in the predictive maintenance of electrical machines. Those fields may include signal processing, statistical data analysis, artificial intelligence, mathematical modelling, and the design and optimization of sensors and processing boards. This paper presents a glimpse of the state of the art of condition monitoring of electrical machines so that the reader can know the trends and challenges in this field. A wide range of diagnostic fields, with many citations, is summarized, along with corresponding attributes.

2. Intelligent Diagnostic Techniques

Due to increasing computational power and cloud computation, different mathematical models of motors' faults can be trained in artificial intelligence algorithms. Machine learning is an optimal tool in machine health monitoring for dealing with extensive amounts of data [1]. Machine learning is compared frequently to data mining as both attempt to discover new data patterns in numerous datasets. The principal difference is that machine learning deals mostly with adaptive behavior and operative utilization, while data mining processes large amounts of data [2]. By the usage of training data, machine learning algorithms can create a forecasting and decision-making model. There are many algorithms for machine learning. As shown in Figure 1, these algorithms can be generally divided into three groups: supervised, unsupervised, and reinforcement learning [3–5].

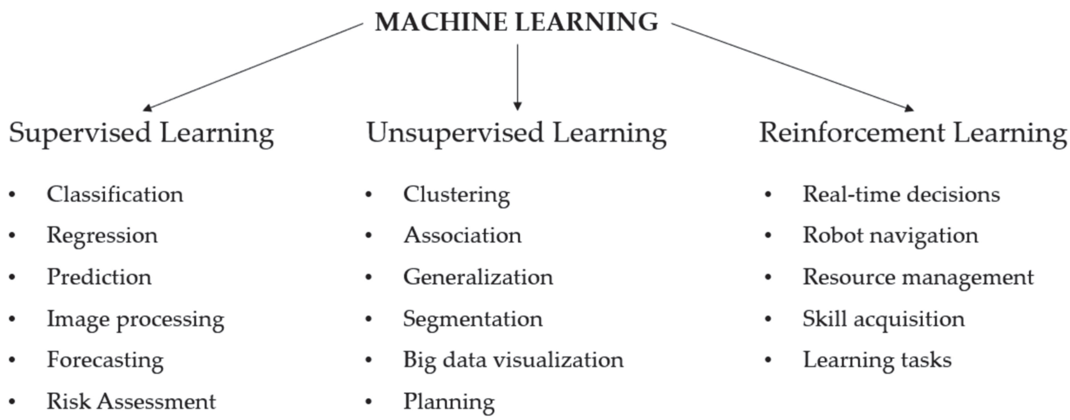


Figure 1. Machine learning algorithms.

In the case of supervised machine learning ("learning with a teacher"), the training dataset and test dataset are set so that the algorithm can map inputs to the desired outputs by the labelled examples. These algorithms are suitable for classification and regression tasks [6,7]. Unlike supervised learning, unsupervised machine learning ("learning without a teacher") is dedicated to understanding and discovering patterns from an unknown dataset. Unsupervised algorithms are primarily used for the generalization and association of datasets [8,9]. In this case, the primary function is to group objects into clusters and reduce the amount of data. Reinforcement learning is used to decrease errors and increase accuracy by analyzing the data after each iteration. These algorithms are spread in robot navigation, resource management, and real-time decisions [10–12]. In diagnostics of electrical machines, the following algorithms are used: decision trees [13], support vector machines [14], principal component analysis [15], and genetic algorithm [16].

2.1. Decision Trees

Decision trees represent supervised machine learning that is widely used for data prediction and analysis [17]. In this case, the algorithm is focused on creating a model that can forecast the desired output based on multiple inputs. The general algorithm of decision trees is shown in Figure 2.

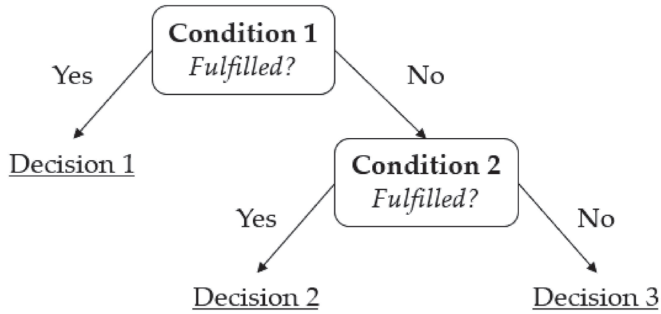


Figure 2. The general algorithm of decision trees.

Decision trees are the simplest among decision-making algorithms and require a very small amount of data to achieve a result. To obtain more accurate results, decision trees are frequently used in parallel with other algorithms. However, decision trees are considered unstable algorithms; insignificant changes in input data can lead to serious changes in decision trees' structure, leading to inaccurate results. Additionally, regression algorithms usually fail.

2.2. Support Vector Machines

Another widely used supervised machine learning algorithm is support vector machines, which are suitable for regression tasks, feature extraction, and classification [18,19]. In the case of classification tasks, where support vector machines are preferable, algorithms can deal with linear and non-linear cases [20]. For linear classification, each dataset represents a vector in n-dimensional space and belongs to two classes. Therefore, the algorithm focuses on separating these data points so that there would be a maximum gap between them. In the case of non-linear classification, the kernel machine acts the same way as for linear algorithms but replaces the datasets [21]. The method of support vector machines is described in Figure 3.

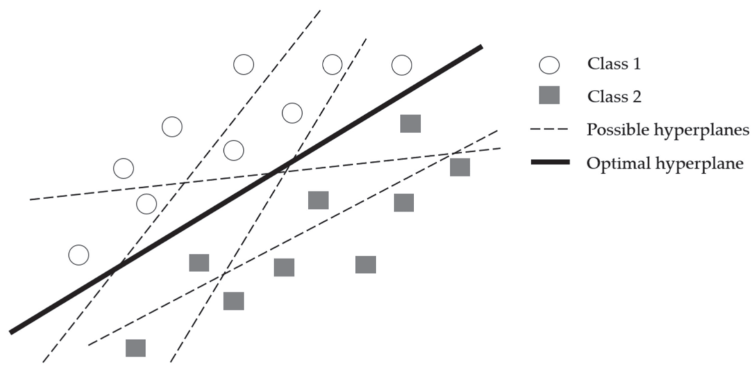


Figure 3. Finding an optimal hyperplane.

Generally, support vector machines are an optimal tool if there is no initial information about datasets. Similar to decision trees, less computation power is needed to provide accurate results. However, it can take a lot of time to process the information in datasets that are especially large. Moreover, managing a kernel machine for non-linear processes can be a complicated task.

2.3. Principal Component Analysis

Unsupervised algorithms can learn spontaneously and perform a given task by finding connections between system responses [22]. However, if datasets are extremely large, it can be challenging to extract important information. For this reason, algorithms find similarities between objects and divide objects into groups (clusters) [23]. The principal component analysis is a good solution for reducing data dimensionality, while losing a minimal amount of information at the same time. A general algorithm of principal component analysis is shown in Figure 4. The algorithm can be described as follows [24].

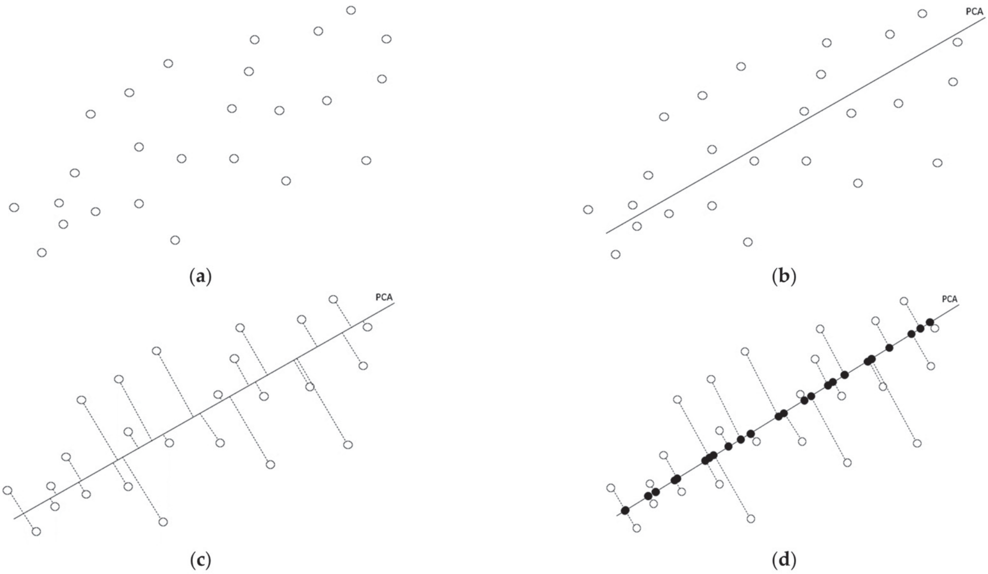


Figure 4. Principal component analysis: (**a**) initial data points, (**b**) creation of optimal vector PCA, (**c**) projection of initial data points on the vector PCA, (**d**) definition of new datasets [24].

Firstly, experimental data points with the specific coordinates are set on a plane. Then, the vector of maximum data change is set on the plane. Next, experimental points are projected on the vector. Finally, these projections create new datasets on the vector, and any deviations from the vector are considered to be noise. The main benefit of principal component analysis is that the algorithm considers each data point as an independent component and does not correlate between them. Thus, this method can significantly reduce training as well as processing time. Nonetheless, considering each datapoint as an independent component can lead to a loss of information and reduced accuracy of the results.

2.4. Genetic Algorithm

Reinforcement algorithms of machine learning differ clearly from basic approaches. In this case, the system learning process is performing by interaction with the environment [25]. These algorithms are mostly focused on solving optimization problems. One of them is a genetic algorithm, the principle of which is shown in Figure 5.

The algorithm can be described as follows. Each data point is represented in genes. A vector of genes creates the genotype of the population. Initially, the so-called fitness function is created, which describes how well the genotype performs the task. Then, the most accurate coincidences are selected, which will be used to create the next generation. The given process continues until the task is fulfilled and the resultant population is formed.

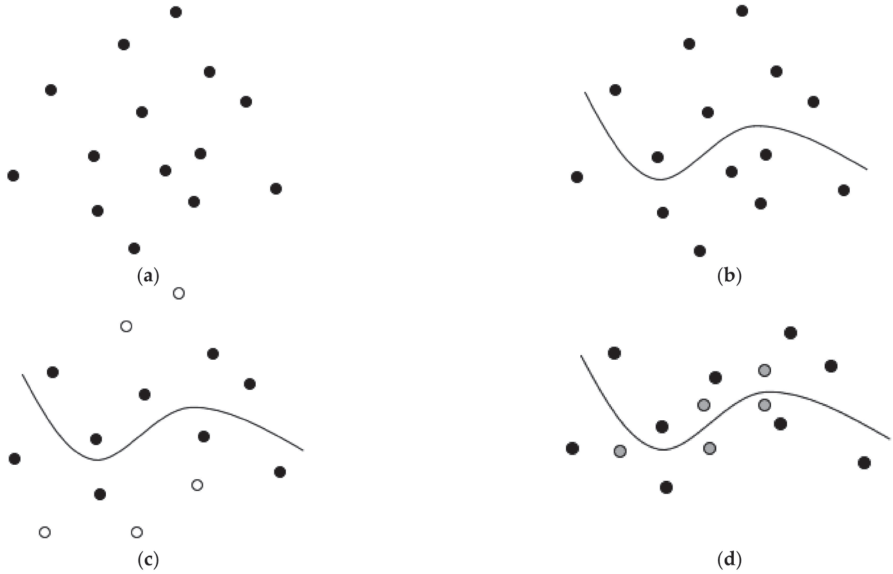


Figure 5. Genetic algorithm: (**a**) definition of initial population, (**b**) fitness function application, (**c**) selection of coincidences, (**d**) definition of resultant population.

A genetic algorithm is considered as an optimal solution if there is no clarified knowledge about the data domain. In this case, the result is generated through genetic operators. The main drawback is that this genetic population can suffer from degeneracy (different chromosomes represent the same solution). In this case, an accurate result is not possible.

2.5. Artificial Neural Networks

Another machine learning method, which is often considered a separate field, is the artificial neural network approach. This technique is widely applicable to condition monitoring of machine parameters [26]. Network algorithms can cover classification [27], prediction [28], and feature extraction [29]. In addition, artificial neural networks can be a part of supervised, unsupervised, or reinforcement learning [30]. In simple models, as shown in Figure 6, an artificial neural network consists of three layers: input, hidden, and output layer.

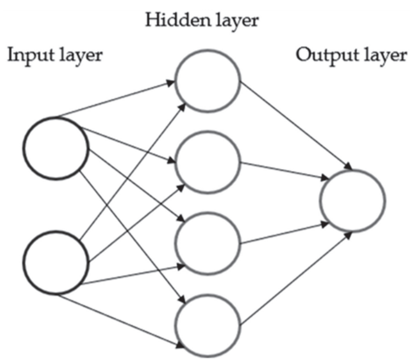


Figure 6. The architecture of artificial neural networks.

To solve a problem, neurons transfer signals between the input and output layer through connections. These algorithms are not to be programmed; they are supposed to be learned. Searching for the connection coefficients between neurons is meant to occur by learning. The easy and fast learning process is one of the main benefits of neural networks. Algorithms are also able to restore incomplete or even destroyed data when training has been successful.

Neural networks also have several limitations. For accurate results, a balance must be found between overfitted and underfitted data; an overly approximated model will not give precise results, while an extremely detailed algorithm will be too flexible but too complicated for further implementation. Additionally, the "black box" phenomenon is quite widespread in the case of neural networks, where approximating a hidden layer can lead to mistakes in artificial structure [31,32].

2.6. Fuzzy Logic

Fuzzy logic is another algorithm successfully applied in various control applications of energy systems, which resembles human perception processes and cognition [33]. Fuzzy logic, as well as machine learning, are sub-fields of artificial intelligence. The main difference between fuzzy logic and traditional logic is that in traditional logic, an outcome can be represented only by true or false values (1 or 0), while an outcome in fuzzy logic can be represented in any value between 1 and 0 (true, false, partially true, etc.). As shown in Figure 7, the classical model of fuzzy logic consists of the following stages: fuzzification, rule base, and defuzzification [34]. Fuzzification converts input data into fuzzy sets. The rule-based stage is a block of the decision-making system. Finally, defuzzification converts fuzzy sets back into real values.

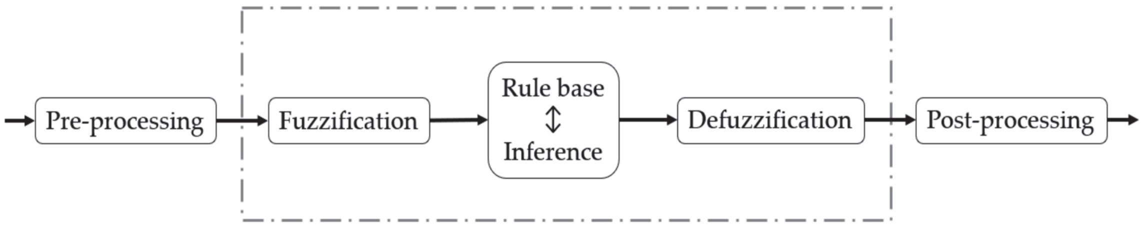


Figure 7. Control principle of fuzzy logic.

In fuzzy fault diagnosis, there are many approaches available, such as the Mamdani approach [35], fuzzy neural network [36], Takagi–Sugeno approach [37], etc. Therefore, it is essential to select the best-suited algorithm to be applied to the system. Each of them has certain benefits and drawbacks. Generally, fuzzy logic is considered a simple solution in decision-making tasks. Fuzzy logic can also perform approximate reasoning by a combination of membership functions through a set of rules [38]. However, to develop a fuzzy system, a large amount of data is needed. Moreover, the development of fuzzy rules can complicate data analysis.

2.7. Summary

In Table 1, the benefits and drawbacks of all of the aforementioned diagnostic techniques are summarized.

Under industry conditions, data collection can be a complicated task. Due to the regular controls in production, only a limited number of faulty rotating machines are possible, which means a limited number of tests to be performed for training purposes. Additionally, data collected in cases of composite faults in the same machine are not straightforward in another scenario. Therefore, for effective AI training, mathematical models with different faulty conditions must make diagnostic algorithms more reliable. Therefore, it is important to understand the nature of machine failures, causes, and impacts.

Table 1. Benefits and drawbacks of intelligent diagnostic techniques.

Diagnostic Technique	Advantages	Disadvantages
Decision Trees	Small computational power is required Simple structure No need for data pre-processing	High possibility of overtraining Not suitable for regression tasks Increased training time
Support Vector Machines	Operation in high dimensionality Work with non-linear processes Small computational power is required No need for data specification	No ability to filter unnecessary information Complicated managing of kernel machine Overlapping risk
Principal Component Analysis	No overlapping Reduced training time Good visualization	Possible loss of information Reduced accuracy
Genetic Algorithm	Adaptive algorithm Rapid processing	Overlapping risk
Artificial Neural Networks	Perform any ML algorithm Fast learning Not sensitive to data noise	Must be balance between under- and overfitted data "Black box" phenomenon Overtraining risk
Fuzzy Logic	Simple structure Flexible algorithm No need for specific hardware Easy reprogramming	A lot of data is needed Inaccurate data lead to poor results

3. Faults of Rotating Electrical Machine

As electrical machines operate under different industrial conditions, various failures eventually occur after long-term continuous operation. The failures' distribution depends mainly on the machine parameters; in low-voltage motors, bearing-related faults are the majority, while high-voltage motors receive mostly stator winding-related failures [39]. In general, the biggest portion of overall failures in electrical machines results in mechanical faults, such as bearing faults, eccentricities, broken rotor bars, broken end rings [40]. In addition, electrical stresses and demagnetization problems can contribute to the shortening of motor lifespan. All of the faults will be discussed in detail in the following sub-chapters.

3.1. Bearing Faults

One of the key parts of a rotating electrical machine is its bearings. The design and production of the bearing are to be conducted according to stringent quality requirements. Nonetheless, during motor running, different internal and external loads affect the bearings. This, in turn, reduces the duration of the actual life of the bearing. Different defects and mechanical damage are frequently met due to the wrong placement, manufacturing mistakes, or misalignment of bearing details [41]. For this reason, it is important to control possible manufacturing damage before bearing mounting and motor running launch.

To avoid disastrous consequences, different parameters of bearing must be monitored. Bearing failures can be described through mathematical equations that refer to the natural frequencies of a faulty bearing. Based on bearing geometry, which is shown in Figure 8, faulty frequencies can be defined for the outer raceway (1), inner raceway (2), rolling elements (3), and cage (4).

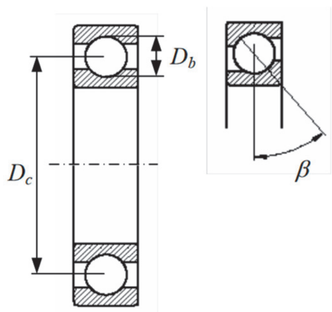


Figure 8. Bearing geometry [42].

Faulty frequencies for these cases can be defined as follows:

$$f_{or} = \frac{N_b}{2} n \left(1 - \frac{D_b}{D_c} \cos\beta\right) \quad (1)$$

$$f_{ir} = \frac{N_b}{2} n \left(1 + \frac{D_b}{D_c} \cos\beta\right) \quad (2)$$

$$f_s = \frac{D_c}{2D_b} n \left(1 - \left(\frac{D_b}{D_c} \cos\beta\right)^2\right) \quad (3)$$

$$f_c = \frac{n}{2} \left(1 - \frac{D_b}{D_c} \cos\beta\right) \quad (4)$$

where N_b—number of rolling elements, D_b—diameter of rolling element (mm), D_c—bearing pitch diameter (mm), β—contact angle (degrees), n—mechanical rotor speed (Hz) [42].

Bearings are affected by different environmental factors, such as moisture, increased ambient temperature, dust, etc. Lubricant coating at the contact points between surfaces can be torn if humid air enters the bearing. Additionally, without a proper seal, different substances can pollute the lubricant and spoil its properties. Environmental processes resulting in material resolution cause bearing corrosion. An example of a corroded bearing is shown in Figure 9. However, increasing a bearing's cleanliness does not always improve its fatigue properties [43]. Cyclic and continuous loads have a remarkable effect on the running performance of the bearing, including material fatigue, wear, and stiffness [44]. These stresses cause micro-cracks in the structure of the bearing. Without timely maintenance, cracking eventually expands, and the bearing becomes incompatible for further operation. Bearing durability can be referred to as the number of revolutions made before the first fatigue signs appear on bearing surfaces [45]. This phenomenon can be avoided or remarkably recessed by timely analysis of the bearing lubricant.

The proper lubrication of a bearing is one of the critical points determining its motor's durability and reliability in general. When the lubricant is selected correctly, it forms the needed coating between elements and softens the impact of the rolling bodies against the bearing rings and cage. Additionally, lubricant is used to reduce the risk of corrosion and wear [46]. To increase the bearing lifetime, a fully flooded bearing and the corresponding base oil viscosity should be considered [47].

Additionally, the bearing lubricant directly affects the strength of shaft currents and influence on the bearing, which in the long term can lead to serious damage and destroy the bearing [48]. Due to the development of energy systems and power electronics, electrical machines, and particularly the bearing, can be injured by electrical corrosion, causing danger to the whole motor system [49]. The effect of shaft currents on a bearing depends mostly on several parameters, such as rotational speed, lubricant properties, current value, operation time, and bearing material. Bearing current-related damage can be revealed by increased noise and vibration, but in the late stages when the surface of the bearing is already damaged [50]. The damage is visible on the bearing surfaces at places where the load is the largest. Practically, the following bearing current-related damage can be classified as fluting, frosting, pitting, and dull-finish. Fluting occurs in a combination with low voltage and constant rotational speed, which does not appear for a longer period of time [51]. In Figure 9, an example of bearing fluting is shown in magnification.

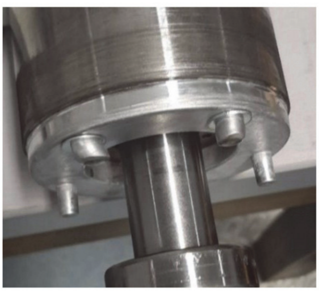
Figure 9. Bearing fluting.

At the same time, frosting can appear in cases of varying rotational speeds. Pitting usually appears in applications with a high-voltage source, causing a multiplicity of small craters on the bearing surface [52]. In the case of dull-finish, this phenomenon resembles pitting but with much smaller craters that can be studied in detail only by a microscope with a particularly high magnification [53].

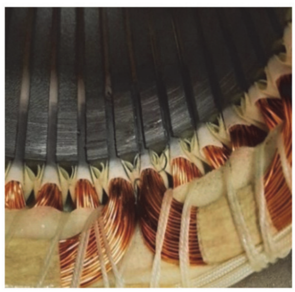
Bearings, as a critical part of rotating machinery, are prone to damage and failure. For this reason, it is extremely important to monitor the condition of the bearing operation. Temperature measurement, noise, and vibration analysis, as well as periodical control of the lubricant quality can significantly reduce the risk of bearing damage.

3.2. Rotor Faults

Eccentricity can be described as an inconsistent air gap between the rotor and stator of the motor, which is mainly caused by improper installation, lack of or missing bolts, misalignment of the shaft, and rotor imbalance [54]. Centrifugal forces contribute as well to rotor wear, as shown in Figure 10.



(**a**)



(**b**)

Figure 10. Damages caused by centrifugal force: (**a**) rotor wear and (**b**) stator wear.

An air gap is considered to be faulty if it exceeds 10% of the nominal value [55]. As shown in Figure 11, there are the following types of rotor eccentricity: static [56], dynamic [57], and elliptic [58]. Authors in [59] have discussed these cases.

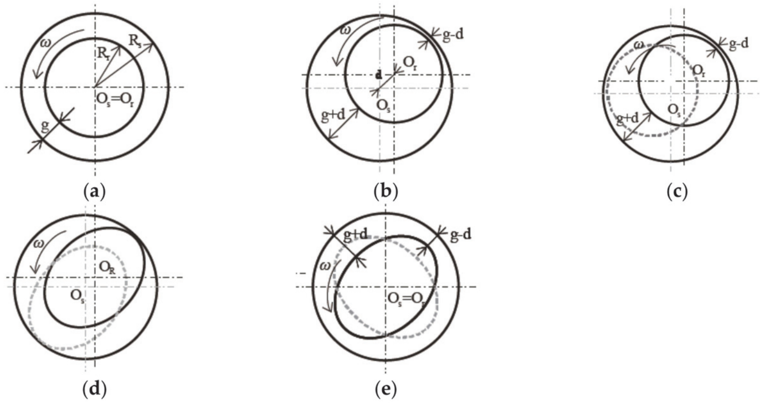


Figure 11. Types of rotor eccentricity: (**a**) healthy; (**b**) static; (**c**) and (**d**) dynamic; and (**e**) elliptic eccentricities [59].

Static eccentricity (SE) is the most widespread type of eccentricity in the motor, where the rotation axis of the rotor is parallel to the stator axis and fixed in time. In the case of dynamic eccentricity (DE), the air-gap length changes in time. Elliptic eccentricity (EE) occurs when stator and rotor center points match; however, a non-uniform air gap still exists because the elliptical shape of the rotor and angles change over time. The width of the air-gap in cases of different eccentricities can be found with the following equations [59]:

$$g_{SE}= R_s - R_r + \sqrt{R_r^2 - (d \cdot \sin \beta)^2} \tag{5}$$

$$\delta_{DE} = \frac{|O_W \cdot O_r|}{g} \tag{6}$$

$$g_{EE}(t) = R_s - \sqrt{\left[(R_r + d) \cdot \cos\left(\frac{\omega t}{p} - \beta\right)\right]^2 + \left[(R_r - d) \cdot \cos\left(\frac{\omega t}{p} - \beta\right)\right]^2} \tag{7}$$

where g—air-gap, R_S—radius of the stator, R_r—rotor radius, d—deviation, β—initial eccentricity angle, O_w—rotational center, O_s—stator symmetry center, p—number of poles.

Practically, mixed eccentricity can also be found when rotor and stator center points and rotational axis are shifted from each other.

The most frequent permanent magnet fault is demagnetization, which means partial or complete magnetization loss [60]. Partial demagnetization that produces additional harmonics in the stator currents can be found at the following frequencies [61]:

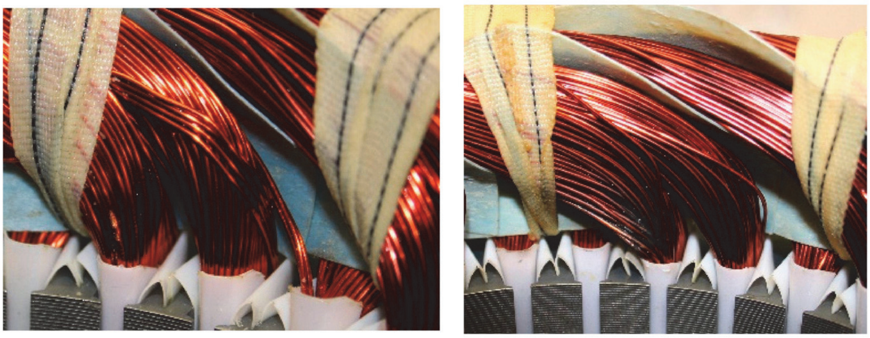
$$f_{pdem}= f_f\left(1 \pm \frac{k}{p}\right) \tag{8}$$

where f_{pdem} is a faulty frequency, f_f is a fundamental frequency, k is an integer, and p is the number of poles.

Demagnetization of permanent magnets can be frequently caused by machine overload and thermal expansion [62]. Machines operate in high-temperature ranges, and the absence of a proper cooling system significantly increases a demagnetization risk. Another factor that can impact magnet properties is electrical stress, including short circuits [63]. It is also reasonable to control magnet manufacturing defects and signs of corrosion. Another widespread form of rotor damage is related to rotor bars and broken end rings [64]. One of the most common reasons for such a failure is natural degradation, which causes rotor wear [65]. Additionally, thermal expansion can lead to cracked rotor bars [66]. As rotor bars are made of copper, while laminations are made of steel, bars will expand more quickly in cases of increased operating temperature.

3.3. Stator Faults

Insulation is one of the most prone-to-fault parts among the components of an electrical machine [67]. In overall statistics, stator winding failures are 36% of all the faults [68]. Winding failures usually start from a turn-to-turn short circuit. Subsequently, without timely maintenance, the failure can grow to a phase-to-phase or phase-to-ground short circuit [69]. Since this inter-turn fault is hardly detectable in the early stages of development, this topic is immensely challenging in the electrical machine industry [70]. Even if control test results meet defined values, each insignificant damage of stator winding can lead to the future breakdown of the machine [71]. Spread winding failures are shown in Figure 12.



(**a**) (**b**)

Figure 12. Stator winding faults: (**a**) improper winding placement, (**b**) insulation damage.

Asymmetrical faults, such as winding faults, induce additional sideband harmonic components at the fundamental frequency and can be defined by the following frequencies:

$$f_h = f_s(1 + 2sk);\ k = 1,\ 2,\ 3, \ldots;\ k \in N \quad (9)$$

where f_h—harmonic frequency, f_s—supply frequency, s—slip [72].

Many factors can influence the degradation of the winding insulation. More frequently, the degradation rate of winding insulation is affected by four main stresses, also known as TEAM (thermal, electrical, ambient, and mechanical) stresses [73]. In addition, damage can also be inflicted on motors due to the manufacturing process and production. During the designing process, manufacturing damage is not usually considered, but it tends to occur during the exploitation of a machine [74].

4. Overview of Diagnostic Methods Used in Condition Monitoring

To provide reliable and effective exploitation of an electrical machine, many parameters, such as current, vibration, temperature, magnetic flux, are to be monitored. In addition, different faults have certain signatures that give a signal about upcoming failure. For this reason, condition-based monitoring is a solution that allows one to be informed and make decisions regarding the maintenance of the machine.

4.1. Vibration Analysis

Vibrations can come from many different sources in an electrical machine, including magnetic fields, fluid flow, imbalances, and, especially, rotating elements, such as bearings, gearboxes, or rotors [75]. Vibration analysis can be defined as change monitoring from defined vibration signatures and extracting deviations in the system. Deviations are to be found in acceleration amplitude, frequency value, and intensity. Nowadays, many sensor types can be used. By measuring technology, sensors can be piezoelectric [76], capacitive [77], inductive [78], piezoresistive [79], and strain gauge [80].

Vibration analysis can provide useful information about the health of electrical equipment; thus, it is widely used for diagnostics. Regarding classical diagnostic approaches, authors in [81] used vibration signals of healthy as well as faulty bearings to identify specific frequencies on the FFT spectrum, where frequency variation of harmonic amplitudes, particularly in fundamental components, is presented as a fault indicator, which is shown in Figure 13.

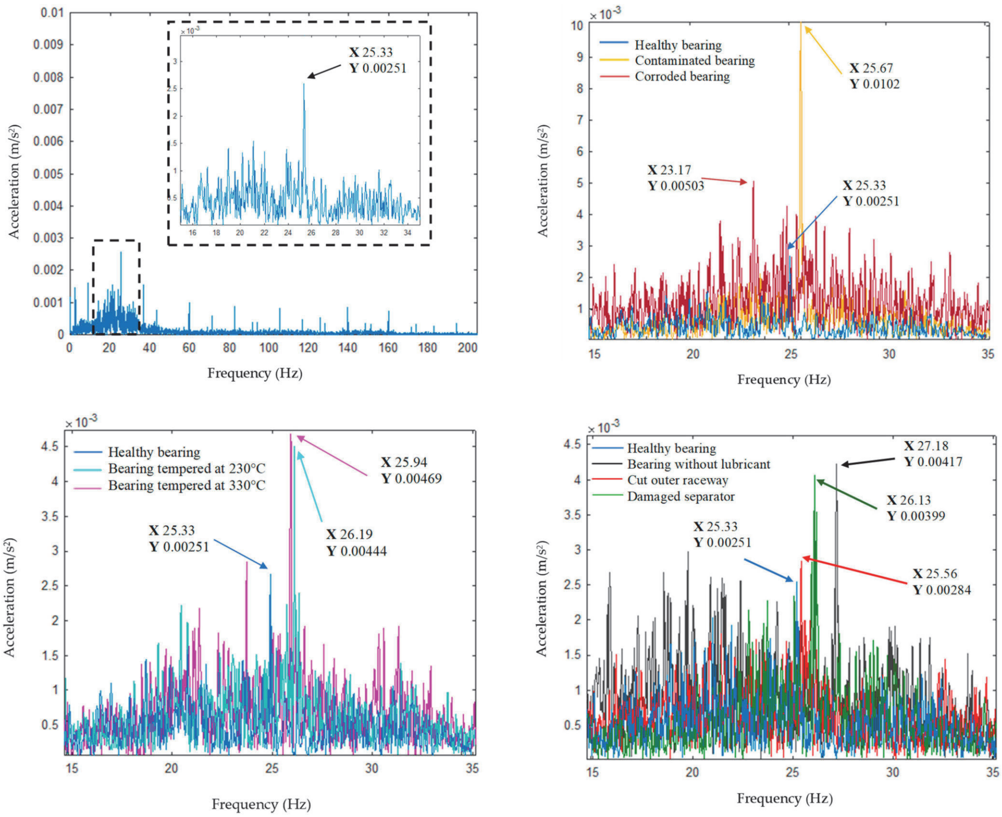


Figure 13. FFT spectra of healthy as well as faulty bearings [81].

Classical and intelligent approaches are frequently used in combination. In [82], authors propose a novel method for predicting the remaining useful lifetime of bearings based on continuous wavelet transform and convolutional neural networks, where image features improve result accuracy. At the same time, in [83], the authors propose a novel hybrid method of convolutional neural network and support vector machine to effectively identify an incipient fault in rotating machinery. The proposed solution does not need manual feature extraction or data processing. Authors in [84] also propose a condition-monitoring method of bearing fault based on deep convolutional neural network and random forest ensemble learning to achieve high accuracy in failure diagnosis under complex operating conditions. However, there are several limitations: computational time and quality of raw data. Authors in [85] use a genetic algorithm for diagnostics of gearboxes based on vibration signals to improve the process of data exploration and exploitation.

4.2. Electrical and Electromagnetic Monitoring

Monitoring magnetic flux has become a widespread and effective method for fault detection in electrical machines, as many early failures create a magnetic asymmetry that can be detected [86]. Electromagnetic measurement can be efficiently used to monitor the electrical machine as an additional or alternative tool to stator current monitoring. By definition, an electric machine produces electromagnetic flux, where any small unbalance in the magnetic or electric circuit is reflected in some of the transmitted fluxes [87]. There are many research studies on the monitoring of bearings damage [88], rotor faults [89], short circuits [90], and magnet problems [91] through the stray magnetic flux. Authors in [92] provide an example of flux distribution in the case of healthy and faulty rotor bars, as shown in Figure 14.

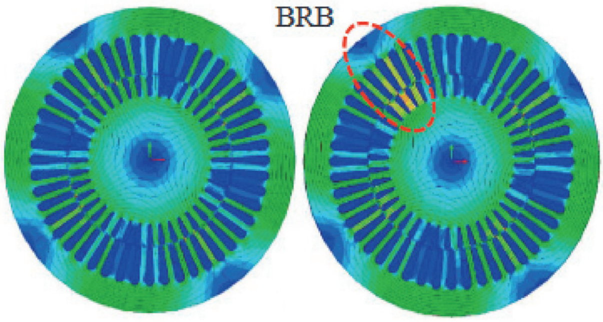


Figure 14. Flux distribution of healthy and faulty rotor bars in an induction motor [92].

Most of the rotating electrical machines are symmetrical, generating uniformly distributed magnetic flux. Any fault in the machine results in asymmetrical flux distribution, resulting in more local magnetic stresses. An example of flux distribution in the case of healthy and faulty rotor bars is shown in Figure 14. It is clear from the figure that the flux density across the broken bar increases in magnitude, which increases the peak induced current in subsequent rotor bars. These increased current and magnetic forces make them vulnerable to a fault, leading to a kind of chain reaction. A machine's performance parameters such as torque, speed, voltage, and currents function to distribute flux. The analysis of those performance parameters can detect any change in flux distribution due to any fault. These facts make the diagnostic algorithms non-invasive and open a broad field of signal processing techniques that can be used for condition monitoring of electrical machines.

In harmonic spectrum and data analysis-based techniques, the frequency components of any global signal are evaluated according to cause of production. The discovered frequency components can be further used for the health monitoring of electrical machines, either by visual inspection or with the help of advanced statistical data analysis techniques. A variety of research articles dealing with spectrum analysis for various machines can be found in the literature. The stator winding insulation degradation fault analysis of permanent magnet synchronous motor (PMSM) using the harmonic analysis of fault current is presented in [93]. The authors of [94] used matching pursuit and wavelet transformation for current features extraction and machine learning-based fault diagnostic algorithms for induction motor analysis. The detection of bearing faults by statistical analysis of a motor's stray flux is presented in [95]. The inter-turn short circuit fault analysis in permanent magnet multiphase machines using spectrum analysis of combined voltage space vector is presented in [96]. The fault diagnosis of induction machines using harmonic order tracking analysis of a stator's current is presented in [97]. The use of wavelet transform for stator current analysis during motor startup is presented in [98,99]. The utilization of non-stationary stray flux harmonics for training feed-forward neural networks for monitoring wound rotor induction motors is presented in [100]. The use of transient stray fluxes and the currents for the fault diagnosis of damper winding in synchronous motors is presented in [101], while a similar work for fault detection of circular pumps is reported in [102]. Based on the type of the signal, the harmonic spectrum and data analysis-based techniques can be broadly classified into two categories: transient analysis and steady-state analysis. Although both types are very diverse fields, a good glimpse of induction machines fault diagnosis can be seen in: transient [103–105], steady-state [106,107].

The harmonic spectrum analysis-based techniques are very old and well established because most of those techniques are based on non-invasive signals. Various signal processing techniques can be easily deployed, computationally less intense, and no kind of sophisticated apparatus is required. The measured signals can be analyzed at any remote location. However, with the increasing trend of drive utilization, special purpose machines and different working environments make the conventional current and flux monitoring techniques very challenging. The reliability of diagnostic algorithms will no doubt increase if the algorithm mathematically knows the machine under inspection. Moreover, if the mathematical models in the drive are compatible with the diagnostic algorithm, the drive can continuously monitor the machine's health.

Due to these factors, researchers are moving towards modelling- and parameters estimation-based diagnostic techniques. For this purpose, the development of mathematical models with reduced simulation time and that are compatible with faults simulation is the first milestone to be achieved. Various modelling techniques are available in the literature, e.g., modified winding function-based models [108–111], circular convolution theory-based [112], the hybrid FEM-analytical [113,114]. These models can be used in parallel with the real working machine to estimate design parameters. For example, authors in [114] proposed utilizing an induction motor's FEM model for parameters estimation using hardware in the loop environment. In [115], the induction motor's inversion model was used to estimate different performance parameters for health monitoring.

4.3. Wear Monitoring

As mentioned, the bearing is one of the essential parts of a rotating machine that is to be affected by various loads and forces, which reduce the motor's intended lifespan. Generally, most friction losses in rotating machines are referred to as bearings. Therefore, wear monitoring of bearings can significantly affect a machine's proper operation and reliability in general. The most common causes for bearing wear are high friction load and lack of proper lubrication. Bearing faults tend to occur in areas where lubricant coating is the thinnest. Authors in [116] discuss a method for bearing state monitoring by simulating lubricant state under different pressure conditions.

Regarding lubricant conditions, which directly impact the bearing's durability, authors in [117] use ultrasonic sensors that were instrumented on the inner and outer bearing raceways to detect lubricant conditions. In [118], the authors propose an improved grey k-means clustering model for monitoring bearing wear conditions. Finally, authors in [119] propose a fault tree analysis for wear monitoring in wind turbine bearings.

4.4. Temperature Measurement

Thermal monitoring is an important component of proper functioning. Excessive temperature increases shorten the lifespan of an electrical machine, destroy winding insulation, cause short circuits, lead to aging of bearings, and degrade the rotor permanent magnets [120]. The most common reasons for temperature increase are cooling-system failures and excessive currents through windings [121].

Generally, temperature-based monitoring can be divided into two approaches: thermal image analysis and local spot measurement. For local thermal measurement, there resistance thermometer detectors and thermocouples are mostly used. At the same time, local monitoring using thermocouples or resistance temperature detectors can be limited by safety applications, especially due to the usage of electrically conductive material in the sensor structure [122]. Therefore, they cannot be placed in the hottest spot.

Thermal imaging is another potential option for thermal monitoring in rotating machinery. In [123], as shown in Figure 15, the authors present a method of feature extraction using thermal images. For classification, the nearest neighbor classifier, k-means, and back-propagation neural network were used.

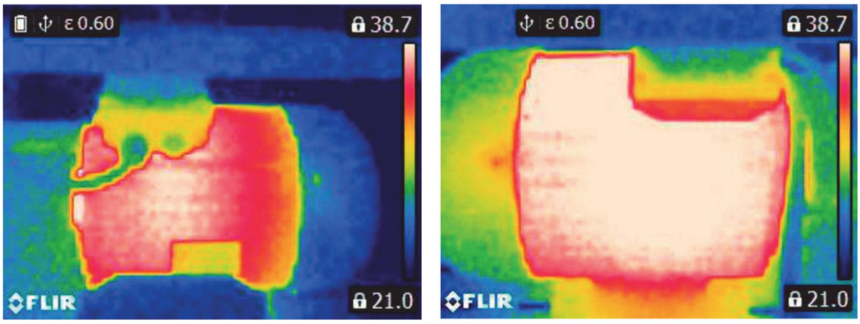


Figure 15. Thermal image of healthy as well as a faulty motor with damaged ring of squirrel-cage [123].

Authors in [124] discuss a study to determine thermal conditions using thermal imaging, which allowed effective and accurate measurement results. In [125], the authors propose a fault diagnosis method based on thermal images, where several intelligent algorithms were used for model training. Finally, authors in [126] discuss a novel image classification method—cloud detection using a random forest classifier.

5. Discussion and Conclusions

Electrical machines fault diagnostics and predictive maintenance have gained increasing popularity. This is because of the increasing influence of electrical machines and drives in industry and everyday human life. Condition monitoring and predictive maintenance are essential for a system's reliability and have a direct influence on economic aspects. Because of the different types of machines, the various control mechanisms, and the wide range of different working environments, no one condition-monitoring algorithm can be considered uniquely suitable.

These algorithms vary for different systems depending upon several parameters. This is the reason why the field of fault diagnostics and condition monitoring depends upon various technical matters. The associated research areas may include signal processing, sensors design and optimization, statistical data analysis, artificial intelligence, numerical methods, calculus, mathematical modelling, etc. The dependency of the fault diagnostic algorithm on single or multiple topics makes this field very diverse and makes it challenging to summarize easily and quickly.

In order to give the reader a glimpse of the state of the art of this field, a variety of advanced fault diagnostic and condition monitoring techniques are summarized in this paper. Different diagnostic techniques that can be used for algorithms' training and predictive maintenance are presented. The benefits and drawbacks of each intelligent diagnostic technique are highlighted. The most widespread faults of electrical machines are discussed, and techniques for parameters' monitoring are introduced.

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Publication IV

Kudelina, K.; Asad, B.; Vaimann, T.; Belahcen, A.; Rassõlkin, A.; Kallaste, A.; Lukichev, D.V. Bearing Fault Analysis of BLDC Motor for Electric Scooter Application. Designs 2020, 4, 42. https://doi.org/10.3390/designs4040042.

designs

Article

Bearing Fault Analysis of BLDC Motor for Electric Scooter Application

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Abstract: In this paper, the bearing faults analysis of the brushless DC motor is presented. The research method is based on the analysis of the vibration signal of healthy as well as faulty bearings by the identification of specific frequencies on the vibration spectrum. For the experiment, the most common faults were inflicted on the bearings. As the used motor is intended for electric scooter applications, seven different damages were chosen, which are highly likely to occur during the scooter operation. The main bearing faults and the possibility of fault monitoring are addressed. The vibration data are gathered by the acceleration sensors placed on the motor at different locations and the spectrum analysis is performed using the fast Fourier transform. The variation in the amplitude of the frequency harmonics particularly the fundamental component is presented as a fault indicator.

Keywords: ball bearings; DC motors; brushless machine; fault diagnosis; vibration measurement

1. Introduction

In recent years, brushless DC (BLDC) motors have gained wide attention in the electrical machine industry. The main feature of BLDC motors lies in their construction. The absence of brushes makes the machines more reliable and efficient. Moreover, brushless construction reduces the overall dimensions and weight of the motor. Because of these benefits, BLDC motors have attracted the interest of many researchers.

Brushless construction makes BLDC motors valuable in different industries. Because of the fact that BLDC motors are controlled electronically, these motors play an important role in applications, where sparks can be a critical factor [1]. In addition, brushless machines have gained a wide attention in different domestic applications [2–4]. Besides, BLDC motors have the potential of contributing to renewable energy [5–7].

During the last years, BLDC motors have contributed to the development of environmentally friendly and innovative electric vehicles. Many studies have been done with the purpose of comparing different motor types and their suitability for automotive applications [8]. BLDC motors are more preferable for electric vehicle applications because of the wide speed and power ranges [9–11]. Another noticeable trend in the automotive industry is the integration of BLDC motors into electric scooter applications, where the main requirements from the motor are high power density and starting torque [12]. BLDC motors meet those requirements for most of the special applications quite easily as compared to the other type of machines.

As discussed, BLDC motors have found usage in a variety of applications; therefore, unexpected failures of such machines are undesirable and are to be avoided. Studies related to the faults of BLDC motors focus generally on the stator windings or rotor related faults, also problems related to Hall-effect sensors are studied in detail [13–15]. However, there are only a few researches dedicated to the study of bearing-related faults [16]. Nonetheless, taking into account the growth in usage of BLDC motors, the sudden failure of such a basic and important component as a bearing can have significant economic and dangerous consequences. Therefore, condition monitoring and ensuring the reliability of the bearing is extremely important.

The fields of condition monitoring and signal processing are directly related to each other. The selection of the appropriate signal along with the suitable signal processing technique is the most important step for predictive maintenance [17,18]. Almost all advanced signal processing algorithms rely on the basic signal processing techniques such as Fourier transform, short time Fourier transform, and wavelet transform, etc. The fundamental objective of these techniques is to detect the fault-based frequency components from the signal under investigation. Several research articles related with these techniques can be found in the literature. In [19,20] fast Fourier transform (FFT) was used to investigate the stator current of squirrel cage induction motor for the segregation of supply, spatial, and fault-based harmonics. In [21] FFT was used along with a band stop filter to improve the legibility of current spectrum for fault diagnostics of induction motor. In [22] FFT was used for the validation of the simulation results with that obtained from the practical setup. In [23], evaluation based on wavelet transforms new processing method to detect stator related faults in the induction motors was presented. In [24], authors use wavelet transform for bearing fault diagnostics.

In general, the vibration analysis has been widely used for electrical machines fault analysis in the past decades. This technique offers more precise fault analysis and results compared to other techniques, especially, in the case of BLDC motors. In this work, vibration signal analysis was used for the study of the bearing faults of BLDC machine. The vibration analysis has several advantages over traditional diagnostic techniques, such as motor current signature analysis (MCSA), leakage flux analysis, etc. The MCSA-based fault definition frequencies are well-defined in the case of high power induction and synchronous machines. However, in the case of special purpose machines, like BLDC, the impact of drives and complex structure makes conventional MCSA techniques hazier. In contrary, the vibration signal does not need any specific definition equations. The diagnostic algorithm can be made reliable and the fault can be detected only by comparing the faulty vibration signal with the healthy one. The amplitude of the fundamental vibration frequency component can be used as a threshold and a reliable indicator of fault rather than the detection of certain harmonics from a wide range of frequencies.

The main core of this paper is related to the bearing faults of BLDC motors. The aim is to present a study where typical bearing damages are implemented on healthy bearings, in order to explore the impact of these faults on machine performance. This paper is arranged as follows. Section 2 presents possible bearing faults of BLDC motors. In Section 3, fault diagnostic possibilities are described. In Section 4, experimental setup and research methods are pointed out. Section 5 shows the results analysis and discussion of performed research, and finally, Section 6 presents the conclusion.

2. Bearing Faults

Bearing is a basic element of an electrical machine. The production of bearings is carried out under stringent requirements for the quality. However, the actual lifespan of the bearing can be lower than it was intended to be. This can occur because of many reasons, such as unexpected overload, insufficient lubrication or improper lubricant, improper bearing installation, etc. Because of the fact that the operating conditions of electrical machines can be different, the bearing can be affected by many fault types. The reasons for bearing failures can be different environmental or manufacturing factors, such as [25]:

(1) Bad lubrication;
(2) Wrong emplacement;
(3) Contamination;
(4) Shaft currents.

By monitoring the operation of bearings, measuring temperature, noise, vibration, and periodically analyzing the quality of the lubricant, the risk of bearing damage can be significantly reduced.

2.1. Material Fatigue

This phenomenon is usually caused by cyclic and continuous loads, which crack the surface of the bearing. When cyclic stresses are applied to a material, failure of the material occurs at stresses much below the ultimate tensile strength of the material, because of the accumulation of damage [26]. If fatigue cracking progressively expands to a larger surface, the bearing eventually becomes unsuitable for further operation.

The durability of a bearing is counted in the number of revolutions that the bearing makes before the first signs of fatigue failure become noticeable on raceways and rolling bodies. Progressive stages of material fatigue on the bearing surface are shown in Figure 1.

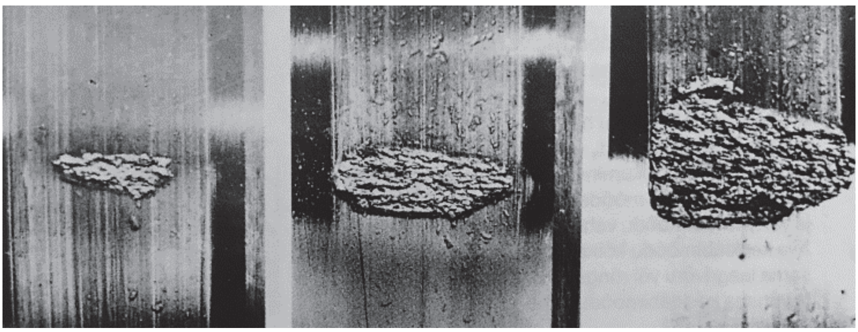


Figure 1. Progressive stages of material fatigue on the bearing surface [27].

The time when the first signs of material fatigue appear on the bearing surface depends on the rotational speed of the bearing and the magnitude of the load. In the initial stage of fault development, some microcracks remain on the subsurface. By further damage development, the surface of the bearing begins to exfoliate and crack on a larger surface. As a result, the surface of the bearing becomes rough. At this stage, the first symptoms are additional noise and vibration. Moreover, the operating temperature of the bearing increases. Constant overload, poorly treated, and contaminated surfaces inevitably lead to fatigue phenomena. This can be avoided or significantly slowed down if the bearing is clean (not contaminated) and well lubricated.

2.2. Improper Lubrication

One of the most important operating conditions for a bearing, which determines the durability of a bearing, is its proper lubrication. Correctly selected lubricant forms a thin oil coating, which softens the impact of the rolling bodies against the bearing cage and rings. Additionally, the lubricant protects the bearing from corrosion and wear.

The fact of improper lubrication can occur in the case of either insufficiently or excessively greased bearing. Insufficient lubrication, which can occur because of low viscosity of the lubricant or its small amount, causes friction and crack progression. Over-greasing results in undesirable shaft slipping and leads to structural damage of the bearing.

Additionally, improper selection of the lubricant can have a negative impact on bearing operation. Grease lubrication as well as different oil-based lubricants (oil-mist, air-oil, or jet lubricants) are used in bearings. Each lubrication method has its unique advantages. The main criterion for selecting between grease and oil-based lubrication is to minimize the total life-cycle cost of the motor, including such parameters as cost of service, repair, maintenance of the motor, and the number of years the motor remains in service [28,29]. The life-cycle analysis implies important procedures in order to reduce impact of electric machines on the environment [30]. To meet this requirement, the lubricant method should be selected respectively to the operating conditions of the bearing. The choice of lubricant depends on the operating conditions of the bearing, in particular the temperature range, speed, and operating environment. Lubrication of bearings is mainly carried out using greases. The main advantage of grease over oils is that it operates in friction places for a longer time and thus reduces spending. However, oil-based lubricants are also widely used. A significant advantage of oils over greases is improved heat dissipation. However, compared to greases, the disadvantages of oils are high price and risk of leakage.

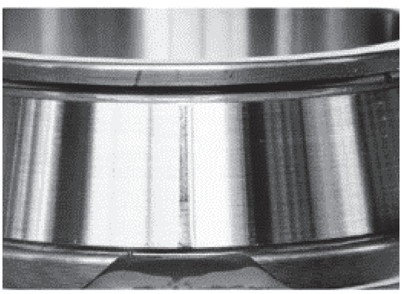
2.3. Wrong Emplacement

The defects in the bearings may also come up due to improper design of the bearing or improper manufacturing or mounting, misalignment of bearing races, the unequal diameter of rolling elements [31]. Before mounting, the bearing should be checked for manufacturing faults: compliance with the appearance, ease of rotation, and clearances to the requirements of technical documentation. Visually, bearings of open-type must be checked for nicks, traces of contamination, corrosion. For sealed-type bearings, the gaskets should be checked to detect possible damages.

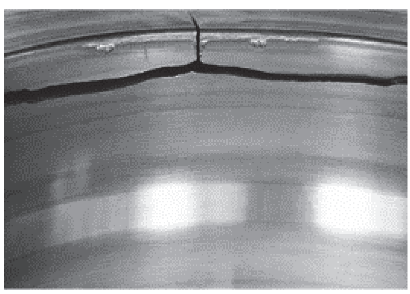
Before the installation, the mounting surfaces of the shells and shafts have to be checked. The surfaces of shafts and shells mating with bearings must be thoroughly washed, wiped, dried, and greased with a thin layer of lubricant. Additionally, the alignment of the shaft must be controlled. It is necessary to check the deviation from the alignment of all landing surfaces located on the same axis for compliance with the standards specified in the technical documentation.

The application of mounting forces to the separator or hit directly on the ring is inappropriate. It is allowed to apply light blows to the ring only through a sleeve of non-hardened structural steel. The most appropriate are the mounting methods in which simultaneous and uniform pressure is applied around the entire circumference of the mounted ring.

In Figure 2a, a chip on a large rib of the inner ring of a tapered bearing is shown. This occurs when an incorrect axial or heavy striking load is applied to the bearing. In addition, it can occur if inappropriate force was applied to the rib during installation or dismantlement of the bearing. Cracks, as shown in Figure 2b, appear as a result of the application of heavy striking load or excessive tightness. This phenomenon is observed in those cases when the outer ring is weakly established on the shaft, and slip occurs.



(**a**)

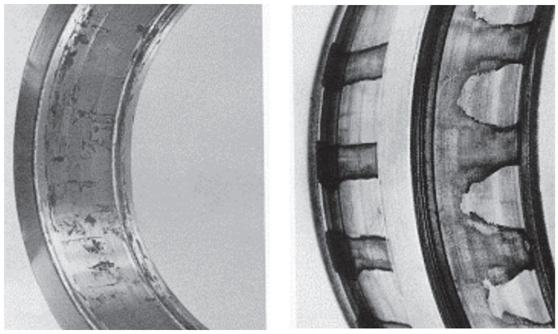


(**b**)

Figure 2. Chips (**a**) and cracks (**b**) due to the wrong emplacement of the bearing [32].

2.4. Contamination

Corrosion is a process between material and environment, which results in material dissolution. Corrosion can be caused by moisture that enters the bearing from the atmosphere. Humid air enters the bearing and tears the lubricating coating at the contact points of surfaces and raceways. In addition, the grease can become contaminated when water or other chemically active substances pollute the lubricant. As the lubricant properties are deteriorated, bearing corrosion is caused. To prevent this failure, the corrosion-resistant greases can be used. The possible impact of the environment on the bearing is shown in Figure 3.



(**a**) (**b**)

Figure 3. Traces of corrosion on the bearing surface: (**a**) Traces of corrosion on the outer ring of the bearing; (**b**) traces of corrosion due to the water impact on the inner ring of the bearing [33].

Bearings can be polluted by sand, dust, or other abrasive particles, which in turn interferes with bearing operation and leads to scratches, cracks, or other structural damage [34]. Mainly, it can occur in hand with wrong bearing gasket selection. This can cause an entering of various particles (dust or dirt) into the bearing. Foreign particles, such as metal shavings that penetrate the bearing, produce dents when the rolling body rolls the shaving into the raceway. In order to prevent this, the right gasket should be selected. Also, it is important to keep clean during assembly and not to use contaminated lubricants.

2.5. Shaft Currents

Bearings can be affected by shaft currents. This fault occurs when electric current passes the bearing from one ring to another through the rolling elements. The size of the damage depends on the level of the current, exposure time, load, rotational speed, lubricant selection. More frequently, the damages related to shaft current can be indicated by increased noise and vibration. In addition, shaft currents cause the heating of the bearing material. Sometimes it can lead to the fusion of the material. As a result, a variety of colored areas are formed on the surface of the bearings, as well as the rolling elements.

This fault is clearly detectable on the bearing surface. Shaft current damages usually appear in the areas of the bearing, which were loaded the most. The reason for this is that the lubricant coating in the area is the thinnest, which contributes to the damage development. The appearance of damaged surfaces is related to three major types of current faults in the bearing: “fluting,” “frosting,” and “pitting.” The visual appearance of these damages is shown in Figure 4.

The first shaft current fault, called fluting, occurs in the combination of low voltage and constant rotational speed. Fluting is characterized by multiple lines across the inner and outer rings, as shown in Figure 4a. Another shaft current fault, shown in Figure 4b, is called frosting. This damage occurs when the motor runs at varying speeds. Pitting is caused by the low rotational speed in combination with the high voltage source. It is mostly related to single crater damage and typically seen in DC applications such as railway traction motors [35]. The size of the crater is small, as shown in Figure 4c but visible to the naked eye. Practically, yet another current fault can be detected, which is called dull-finish. This damage resembles pitting, but the craters on the bearing surface are much smaller. The appearance of these craters can only be detected under a microscope using very high magnification. To limit the negative impact of shaft currents, electric current should not be passed through the bearing. In this case, bearings with electrical insulation can be used. Additionally, during electrical welding operations, the motor shaft should be grounded to prevent the passage of electric current.

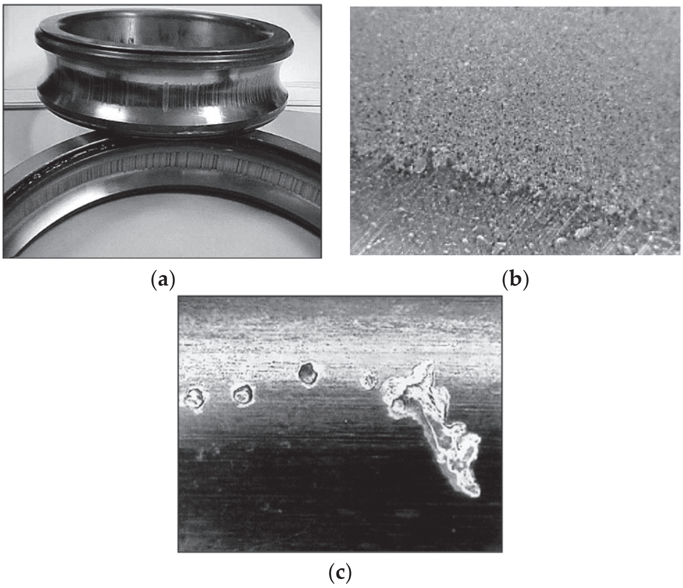


Figure 4. The visual appearance of shaft currents on the surfaces of the bearings: (**a**) fluting, (**b**) frosting, (**c**) pitting [29,30].

3. Diagnostic Possibilities

Almost all advanced condition monitoring and fault diagnostics methods depend on signal processing techniques. Among a variety of signal processing techniques, the Fourier transform has been widely used for the conversion of a signal from the time domain to the frequency domain. Although the Fourier transform is a very strong tool for the analysis of a signal, it possesses several limitations. The algorithm, which can solve the complex Fourier formulas for a signal in a quicker way, is called the fast Fourier transform (FFT). The ideal FFT formula is designed for a signal of infinite length, as shown in Equation (1), which is practically not possible:

$$f(t) = \sum_{n=-\infty}^{\infty} C_n e^{in\omega t} \cong \sum_{n=1}^{N} C_n e^{in\omega t} \tag{1}$$

where;

$$\omega = 2\pi \frac{f}{f_s}$$

$$C_n = \frac{1}{2\pi} \int_{-\infty}^{\infty} f(x) e^{-inx} dx, \;\; n = 0, \pm 1, \; \pm 2, \; \ldots\ldots$$

where C_n is the complex Fourier and $f(x)$ is the signal under investigation and fs is the sampling frequency (100 kHz).

The length of the signal can be reduced by truncating the signal to a finite length. This truncation can be done using various windowing functions such as rectangular, Hamming, Chebyshev, Hann, etc. These windows start leaking their energy in the frequency bins of the spectrum, which is called the spectral leakage. Moreover, if the signal is the same in all other similar intervals, it means that the signal is stationary and in the steady-state regime. Similarly, the discontinuities in the signal can be fatal for the frequency analysis using FFT.

The field of fault diagnostics is very broad containing a huge number of industrial and domestic applications. All applications are different in design, structure, working environment, and the types of signals which can be used for its condition monitoring. The signals can be broadly classified into two types, stationary and non-stationary. Although, the majority of applications work in a steady-state regime where the signals are supposed to be stationary and without discontinuities, in some applications, the transient analysis can give more concrete information about their health. In the transient interval, most of the signals are non-stationary, which makes their time-frequency analysis inevitable.

The FFT fails to do time-frequency analysis of a non-stationary signal while taking it as a single truncated piece. However, this problem can be solved by moving the window across the signal and doing the Fourier analysis of the signal in that particular window while considering the signal in the window as stationary. This approach is called a short-time Fourier transform (STFT). Although, this technique can give the time-frequency analysis of the signal that the spectrum resolution is the problem. This resolution problem is because of the inherited drawbacks of the FFT algorithms upon which STFT depends. If someone increases the length of the moving window, he can get good frequency resolution but poor time resolution. Similarly, by decreasing the length of the truncation window, the time resolution can be improved but frequency resolution will be poor. Therefore, there is a trade-off between time and frequency resolution of the spectrum according to Heisenberg's uncertainty principle.

These FFT-related problems can be avoided to a great extent by using the wavelet transform. Unlike STFT where the signal is divided into the small chunks and FFT is the performer for each, in wavelet transform, a window of known amplitude and frequency is swiped across the complete signal to check the location where it fits the most with the signal. This moving window is called the mother wavelet which is swiped across the signal n times with varying amplitude and frequency. It can give a much better resolution as compared to the corresponding STFT but at the cost of increased complexity. A comparison of the common diagnostic techniques is presented in Table 1.

Table 1. Comparison of diagnostic techniques [36].

Diagnostic Technique	**Benefits**	**Drawbacks**
FFT	Small losses of information.	Works only with stationary signals Aliasing
	Less computational power	Bad resolution Spectral leakage
STFT	Analysis of non-stationary signals	Bad time-frequency resolution, spectral leakage, aliasing
	3-D (time-frequency-amplitude) plots can be more informative.	Compromise between time and frequency More computational power is required as compared to FFT
Wavelet transform	Very precise technique, Better time-frequency resolution	More memory and computational power are required as compared to STFT
	More efficient and flexible for analysis, analysis of non-stationary signals.	Precision requires more iterations.
Advanced techniques	More efficient analysis More precise results	Sophisticated technology is required, Requires a lot of computational power.

With the growing power of the computers and onboard processors, cloud computations, and the Industry 4.0 standards, the world is moving toward advanced predictive maintenance techniques. Unlike protective and reactive maintenance techniques, predictive maintenance techniques are becoming increasingly popular because of their positive financial impact. The advanced diagnostic techniques may include pattern recognition, machine learning, parameters estimation, neural networks, Fuzzy logic, and inverse problem theory, etc., [35,37–39]. However, all those techniques somehow depend on the fundamental signal processing techniques, described in Table 1.

4. Experimental Setup and Methods

In the framework of the given research, the typical bearing faults were inflicted on the bearings with the purpose of investigating the failure effect on the vibration spectrum of the motor. There were used identical ball bearings made from chrome steel with the same material standard. For the experiments, a three-phase BLDC intended for electric scooter application was used. All the measurements were performed at rated rotating speed 600 rpm. As the signal measuring tool, there were used three acceleration sensors ±4 g type QG40N, which were screwed to the test bench. The sensitivity error of used acceleration sensors is <±1%.

In the experiments, as shown in Figure 5, there were used three identical acceleration sensors, which were screwed into the test bench at different distances. Sensor 1 was mounted over the shaft of the motor, where the vibrations are supposed to be higher and more tangible on the vibration spectrum. Sensor 2 was placed beyond the shaft. Sensor 3 was mounted on the most distant edge from the motor. It was done in order to find an optimal place for the data acquisition. This paper focuses on the data taken from Sensor 1 which was placed over the shaft of the machine. Because of the proximity to the motor shaft, the vibrations in Sensor 1 are more tangible, which in turn provides more accurate results.

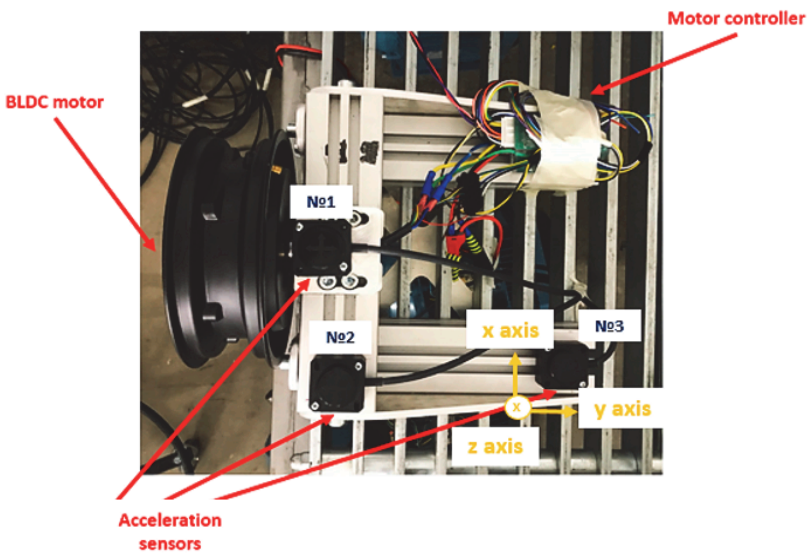


Figure 5. Placement of acceleration sensors on the test bench.

Data acquisition was performed at sampling rate 100 kHz using Dewetron OXYGEN software. In the framework of the given experiment, only fast Fourier transform (FFT) is used to detect and compare the amplitude of the fundamental frequency component in case of healthy and faulty bearings. The FFT algorithms are well mature and are very easy to be implemented in Matlab.

As the given motor is used in a certain application, specifically in electric scooter application, seven typical bearing failures, which can occur during the scooter operation, were chosen and inflicted on bearings, as shown in Figure 6. Eventually, eight bearings were tested.

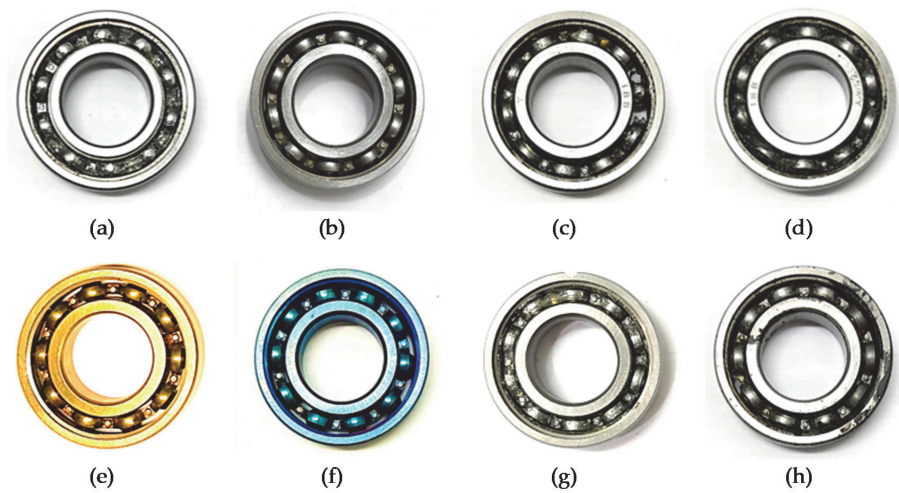


Figure 6. Tested bearings: (**a**) healthy bearing, (**b**) bearing without lubricant, (**c**) bearing with damaged separator, (**d**) contaminated bearing, (**e**) bearing tempered at 230 °C, (**f**) bearing tempered at 330 °C, (**g**) bearing with the cut outer raceway, (**h**) corroded bearing.

Faulty bearings present a specific vibration spectrum, which differs from the spectrum occurring in the case of a healthy bearing. In theory, it is possible to differentiate four fundamental frequencies (harmonics) in a loaded rolling bearing, which are used for diagnostics. Specific processes on different parts of the bearing cause these harmonics. In the literature, these processes (parameters) are designated as follows: rotation frequency on the outer raceway (F_H), rotation frequency on the inner raceway (F_B), operation of the bearing cage (F_C), and rotation frequency of the bearing balls (F_{TK}). The numerical values of the frequencies of these harmonics depend on the ratio of the geometric dimensions of the bearing elements, and, of course, are uniquely related to the rotation frequency of the rotor (F_1).

Practically, three most frequently encountered types of signals spectra, which correspond to various stages of defect development can be identified. On the first stages of defect development, as shown in Figure 7a, a presentable harmonic F_H appears on the FFT spectrum. The presence of the frequency peak on the spectrum allows to suppose and identify explicitly an existence of the defective element.

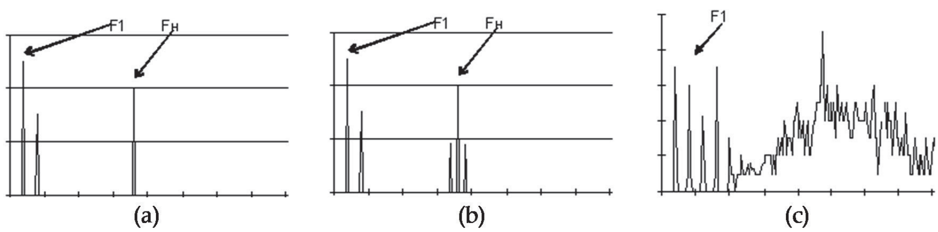


Figure 7. Stages of damage development: (**a**) early fault stage; (**b**) progressive fault stage; (**c**) final fault stage [40].

As the defect develops, the first pair of side harmonics on the left and right side near the main frequency peak, as shown in Figure 7b, can be observed on the spectrum. With further degradation, other frequency pairs appear near the main frequency peak. In the given research, a good example of this phenomenon was observed in relation to contaminated bearing. The reason for this phenomenon is that the failed rolling body shifts so much that the adjacent rolling bodies already bear the main load to support the shaft of the mechanism [40].

At this stage, the bearing fulfills its intended functions. However, because of the added stresses, further operation of the bearing leads to definite breakdown of the device. In the last stages, the failure develops to such an extent, that the bearing degrades and does not fulfill its functions. This stage can be identified by appearing of additional harmonics, which have a random character, as shown in Figure 7c. This occurrence was not detected in this experiment.

As discussed, for data analysis different diagnostic techniques can be used. In the given research, as the signal is stationary and the motor rotates with constant speed, FFT was chosen to analyze the results. For the clearer data presentation, signals FFT spectra were also studied and presented on the logarithmic scale.

5. Result Analysis and Discussion

Figure 8 presents the vibration signals of the healthy bearing. As it can be seen, the most noticeable vibration signal (y-axis) comes from sensor 1, which was placed above the motor shaft.

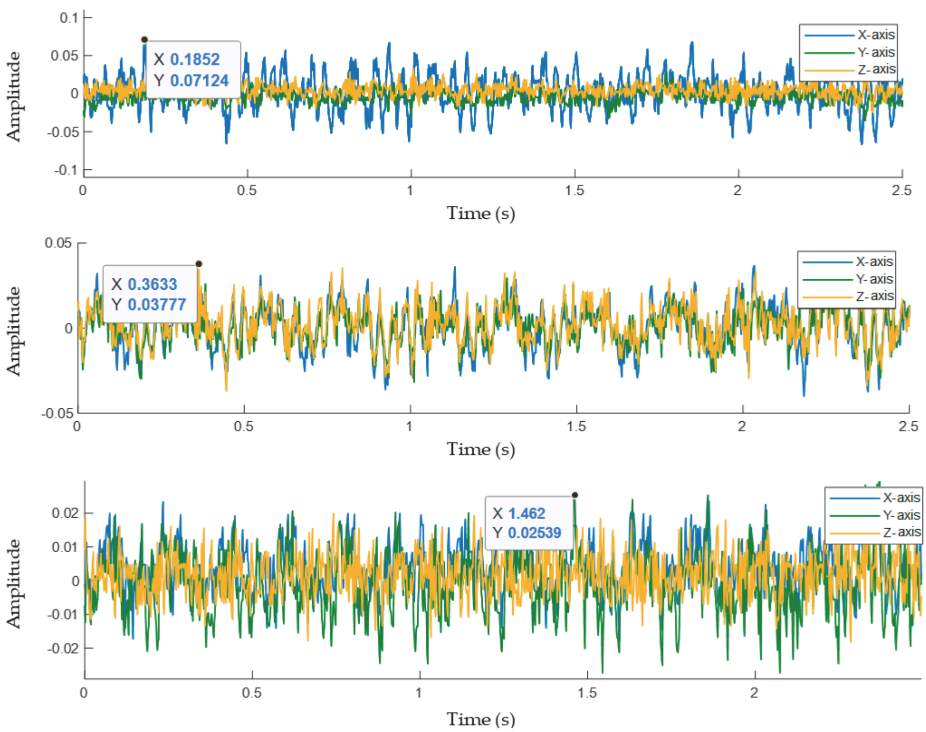


Figure 8. Vibration signals of healthy bearing: (**top**) signal taken from sensor 1, (**middle**) signal taken from sensor 2, (**bottom**) signal taken from sensor 3.

By moving away from the shaft, the vibrations decrease. Therefore, the signal taken from sensor 1 would be more informative in the further result analysis. Mainly, the vibrations occur in x-axis, while the signal in y- and z-axes does not change much.

Every system has a bandwidth of vibrational frequencies, which depends upon its natural frequency bandwidth and a variety of parameters, such as ambient factors, foundation of the motor, etc. In the given research, the most prominent frequencies appear in a frequency range of about 15Hz—35Hz. In the framework of given research, the amplitude of the most powerful vibrational frequency component of faulty bearing was compared with the one obtained from the healthy bearing.

The FFT spectrum of healthy bearing is shown in Figure 9. The window length in this case, as well as in the following graphs, is 31,0195 samples. In the case of healthy bearing, the acceleration amplitude of the fundamental harmonic reaches the value of 0.00251 m/s^2 at the frequency 25.33 Hz. Comparing it with the spectra of the faulty bearings, which are shown and discussed below, it can be seen that the acceleration amplitudes of the faulty bearings are much higher.

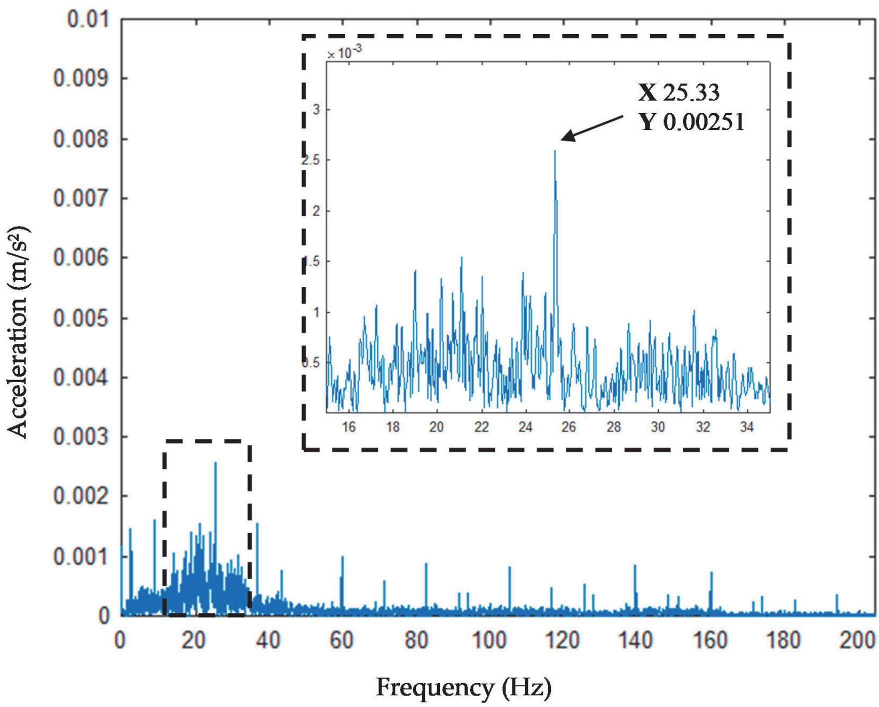


Figure 9. Fast Fourier transform (FFT) spectra of healthy bearing in the range of 0–200 Hz.

For better representation of the signals of faulty bearings, all of the inflicted damages were grouped and presented separately as the FFT spectra. The first group of the faults (contaminated and corroded bearings) can be referred to as damages caused by ambient factors. The most noticeable acceleration amplitude was observed in the case of contaminated bearing, which is 0.0102 m/s^2. Another fault, where FFT spectrum differs compared to healthy bearing, is corrosion. From Figure 10, a wide spectrum of harmonics in the range of 0–40 Hz and frequency peaks in the range of 120–170 Hz can be observed, which in turn indicates the presence of a fault in the bearing.

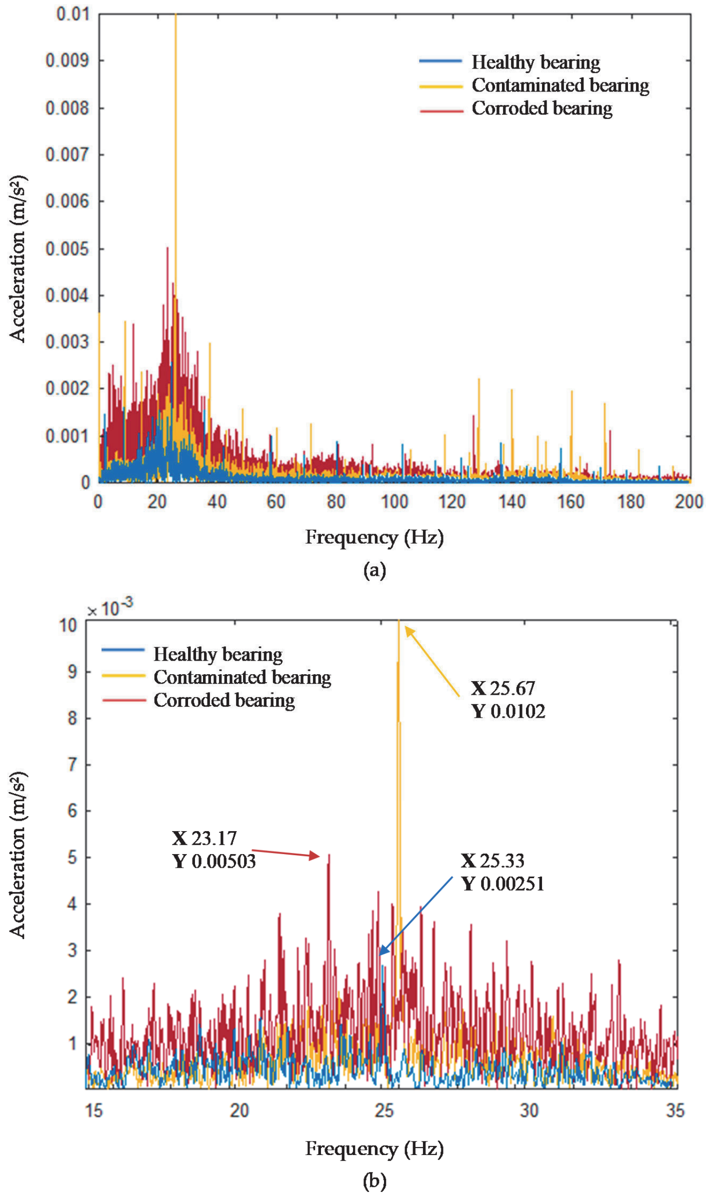


Figure 10. FFT spectra of contaminated and corroded bearings in comparison with healthy bearing: (**a**) FFT spectrum, (**b**) FFT spectrum in the range of 15–35 Hz.

In the following experiment, bearings tempered at different temperatures were investigated. Comparing these spectra with each other, there is no significant difference. As seen from Figure 11, in both cases the side harmonics appear in the spectrum on the left and right side of the main frequency peak. In addition, a frequency spectrum in the range of 120–170 Hz was observed. All these aspects notify of the presence of damage and mechanical weakening in the bearing.

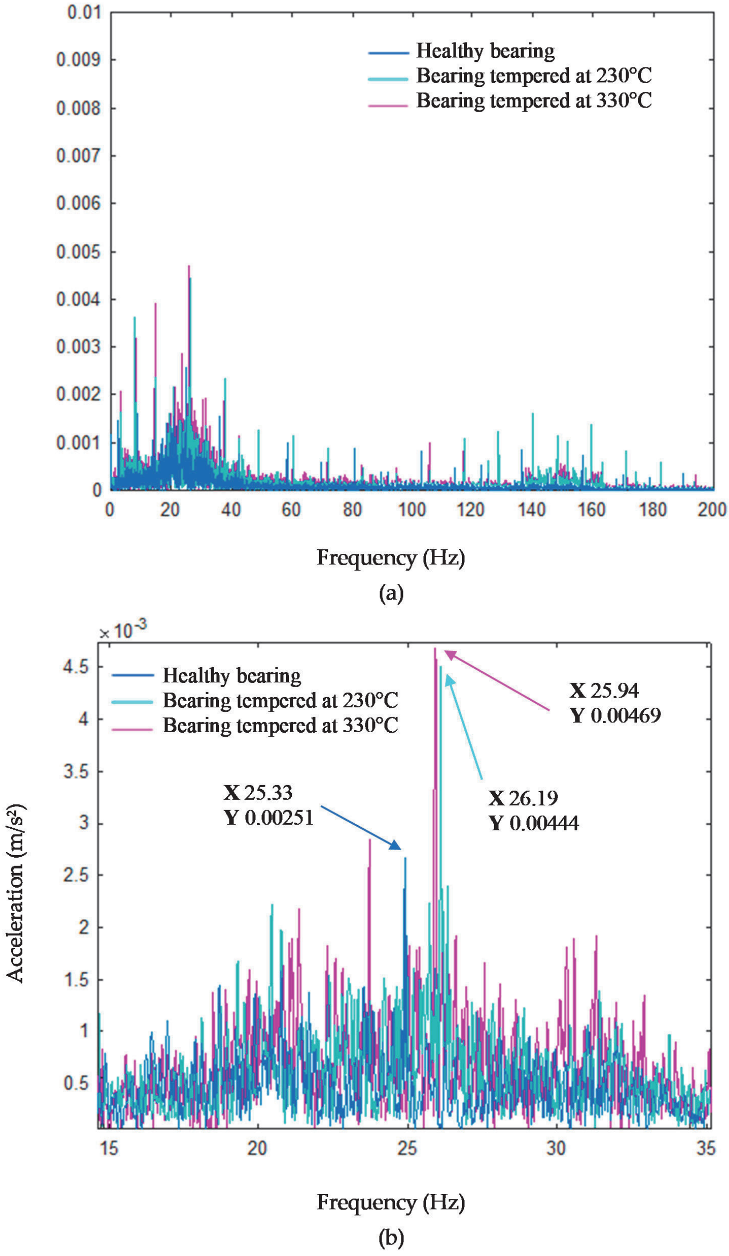
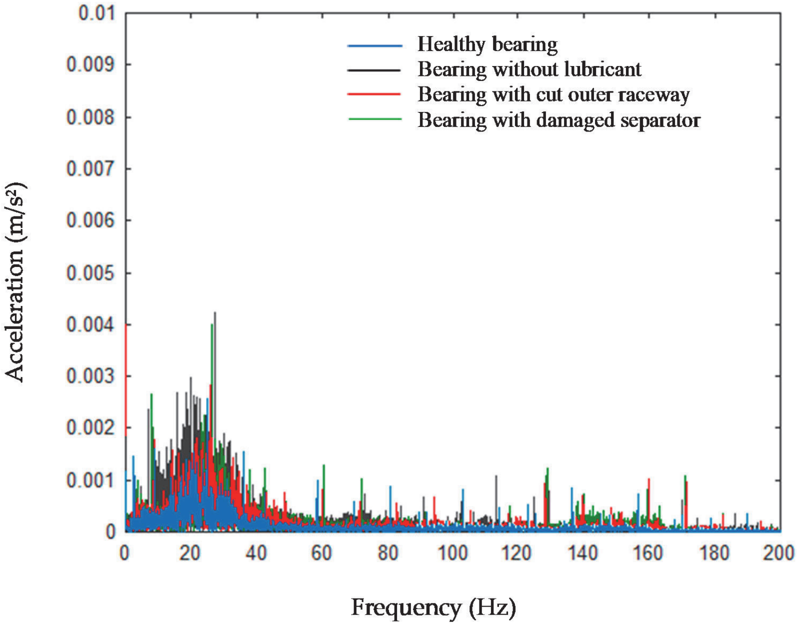
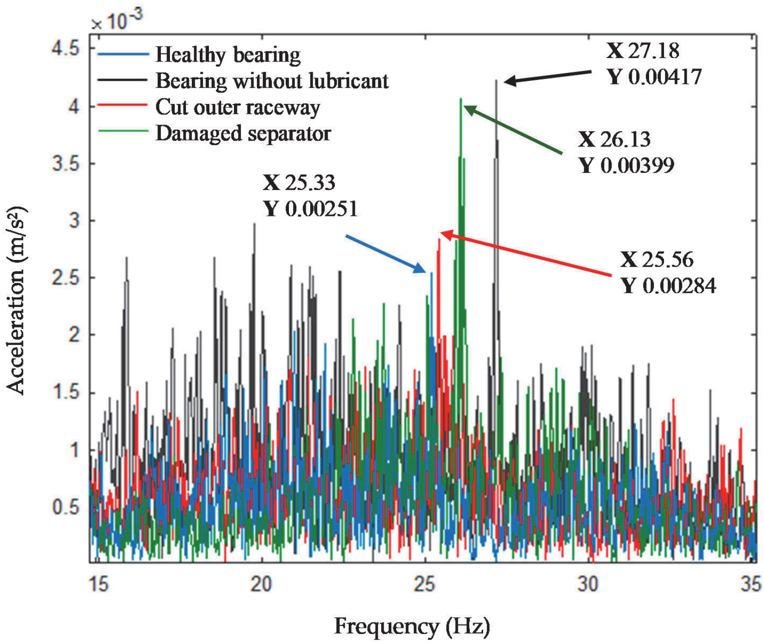


Figure 11. FFT spectra of tempered bearings in comparison with healthy bearing: (**a**) FFT spectrum, (**b**) FFT spectrum in the range of 15–35 Hz.

In the case of the last fault group (bearing with cut outer raceway, bearing with damaged separator, and bearing with removed lubricant), the faults spectra appear similarly to the ones of tempered bearings, as seen from Figure 12. Presentable frequency peaks can be observed in each of the cases. Similarly to the faults discussed previously, frequency spectra in the range of 120–170 Hz can be also observed.



(a)



(b)

Figure 12. FFT spectra of faulty bearings in comparison with healthy bearing: (**a**) FFT spectrum, (**b**) FFT spectrum in the range of 15–35 Hz.

A comparison analysis of the results is shown in Table 2. Out of the several harmonics the most powerful component (fundamental) is chosen as the benchmark signal in the healthy case. The difference in the amplitude of that component defines the severity of the fault.

Table 2. Comparing table of the results.

Bearing	Faulty Frequency (Hz)	Acceleration Amplitude (m/s^2)	Difference in Acceleration Compared to Heathy Bearing (m/s^2)
Healthy bearing	25.33	0.00251	-
Contaminated bearing	25.67	0.0102	0.00769
Corroded bearing	23.17	0.00503	0.00252
Bearing tempered at 230 °C	26.19	0.00444	0.00193
Bearing tempered at 330 °C	25.94	0.00469	0.00218
Without lubricant	25.56	0.00284	0.00033
Cut bearing	26.13	0.00399	0.00148
Damaged separator	27.18	0.00417	0.00166

As presented, the most noticeable difference in acceleration compared to healthy bearing was found in the case of contaminated bearing, which is 0.00769 m/s^2. The smallest difference in acceleration (0.00148 m/s^2) occurred in the case of bearing, in which the outer raceway was cut. In the light of the above results, it is evident that with the inclusion of fault the fundamental vibration component goes stronger. The more developed the damage is, the stronger is the vibration component. The amplitude of this component can be considered as fault indicator. Moreover, each fault gives its specific frequency pattern. Therefore, based on the spectrum, it is possible to detect and segregate the fault type.

6. Conclusions

Over the past years, BLDC motors have gained wide attention in different domestic and industrial branches because of their characteristics. Because of popularity gain, the unexpected faults of such motors can be fatal and lead to negative consequences. In reference to motor failures, many studies have been done with regard to stator or rotor faults. Although the topic of bearing related faults has not been particularly revealed and discussed in the literature. Nevertheless, the bearing is the basic component of the electrical machine and unforeseen faults are unfavorable.

This paper proposes a study of bearing faults and their diagnostics possibilities. In the framework of the given research, the most common bearing failures were discussed and the reasons for these failures were explained. In this experiment, seven typical bearing faults were inflicted on the healthy bearing. In the experiments, BLDC motor intended for electric scooter application was used. Therefore, the most spread faults that can occur during the electric scooter exploitation were applied to the bearings. This study presents a possible method for bearing fault detection in BLDC motor using acceleration sensors.

Different bearing faults were compared and analyzed. The experimental results in Section 3 address that each damage gives a specific vibration spectrum. According to the spectrum, the type and the development stage of the damage can be detected. The amplitude of the fundamental vibration frequency component can be used for defining a threshold level. It also can be a reliable indicator of fault rather than the detection of certain harmonics from a wide range of frequencies. The integration of other sophisticated diagnostic techniques into research and improvement of the given analysis method will be considered as future work.

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Review

Trends and Challenges in Intelligent Condition Monitoring of Electrical Machines Using Machine Learning

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Abstract: A review of the fault diagnostic techniques based on machine is presented in this paper. As the world is moving towards industry 4.0 standards, the problems of limited computational power and available memory are decreasing day by day. A significant amount of data with a variety of faulty conditions of electrical machines working under different environments can be handled remotely using cloud computation. Moreover, the mathematical models of electrical machines can be utilized for the training of AI algorithms. This is true because the collection of big data is a challenging task for the industry and laboratory because of related limited resources. In this paper, some promising machine learning-based diagnostic techniques are presented in the perspective of their attributes.

Keywords: fault diagnostics; machine learning; artificial intelligence; pattern recognition; neural networks

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1. Introduction

Nowadays, electrical machines and drive systems are being used in many applications and play a significant role in industries. As electrical machines are used in different applications, the maintenance question is of great importance. Today, there are plenty of condition monitoring methods to detect failures in electrical equipment. In general, diagnostic techniques can be divided into the following groups [1–5]:

- Noise and vibration monitoring,
- Motor-current signature analysis (MCSA),
- Temperature measurement,
- Electromagnetic field monitoring,
- Chemical analysis,
- Radio-frequency emissions monitoring,
- Acoustic noise measurement,
- Model and artificial intelligence-based techniques.

Generally, stresses that impact electrical machines' operation can be classified into four main categories, also known as TEAM (Thermal, Electric, Ambient, and Mechanical) stresses. Because of these stresses, faults tend to appear in the machine.

Statistically, 36% of all motor failures are related to the stator winding faults [6]. Usually, winding failures develop from a turn-to-turn short circuit [7]. Without timely maintenance, this fault can grow to phase-to-phase or phase-to-ground short circuits [8]. Due to the fact that this inter-turn fault is hardly detectable in the early stages of its development, this topic is mainly challenging in the electrical machine industry [9]. From the point of view of reliability, in this case, one of the most critical points is electrical machines' insulation [10]. Insulation plays a significant role during the design processes [11]. The insulation condition can be defined by chemical, mechanical, or electrical analysis of the insulating materials [12].

Mechanical faults make a significant proportion of overall faults in the form of eccentricity, broken rotor bars, cracked end rings, damaged bearings, etc. [13]. A broken rotor bar is a widespread and frequently occurring fault. In the machine, this fault can be caused by high operating temperature, cracks in the bar, or natural degradation [14]. Some effects can indicate a broken rotor bar: torque oscillations, high radial speed, sparking, rotor asymmetry [15]. This fault is difficult to be exposed at the early stages, but it is equally essential for avoiding negative and catastrophic consequences in production.

Another mechanical fault that occurs in an electrical machine is eccentricity. Eccentricity faults refer to the inconsistent air gap between the rotor and the stator. The air gap eccentricity exceeding 10% is considered a fault [16]. There is a variety of eccentricity types: static eccentricity (SE), dynamic eccentricity (DE), and elliptic eccentricity [17]. Additionally, there are cases when mixed eccentricity occurs in electrical machines. Eccentricity is mainly caused by improper installation, bolts lack or missing, shaft misalignment, or rotor imbalance [18]. Eccentricity faults can cause additional noise and vibration [19]. When the eccentric fault becomes severe, it will cause friction between the stator and the rotor and, as a result, affect the regular operation of the motor.

At the same time, another widely spread mechanical failure is bearing faults. The production of bearings is carried out under stringent requirements for quality. However, the bearing's real lifespan can be significantly decreased due to different ambient and manufacturing factors, such as material fatigue, improper placement, contamination, improper lubrication, and bearing currents [20]. Constant monitoring of the bearing parameters, such as temperature measurement, timely lubricant analysis, noise, and vibration measurement, could significantly decrease the risk of bearing damage [21].

The distribution of all the faults mentioned above depends mainly on the motor's parameters, such as machine type, size, rated voltage, etc. To increase the reliability of the machine, many parameters must be monitored [22]. The main faults and their signatures are shown in Table 1.

Table 1. Signatures of the main faults in electrical machines.

Fault Signatures	**Winding Short Circuit** [23,24]	**Rotor Broken Bar(s)** [25]	**Eccentricity** [26,27]	**Bearing Faults** [28]
vibration	✔	✔	✔	★
current	★	★	✔	★
temperature	✔	✔	✔	✕
magnetic flux changes	★	★	★	✔
chemical analysis	✔	✕	✕	✕
torque changes	★	★	✔	✕

★—the most preferable parameter for condition monitoring; ✔—parameter can be used for condition monitoring; ✕—parameter cannot be used for condition monitoring.

As shown in Figure 1, three main types of machine maintenance can be expressed to be applied in practice: corrective, preventive, and predictive maintenance [29].

In the case of corrective maintenance, also known as reactive maintenance, all needed repairs are assumed to be done after the failure has already occurred. However, this solution is appropriate only for small and insignificant workstations, where unexpected failure does not lead to economic or catastrophic consequences. Alternatively, many manufacturers assume preventive maintenance to the machine to avoid fatal outcomes. In this case, the electrical equipment needs to be regularly checked by the manufacturers through scheduled and specified inspections.

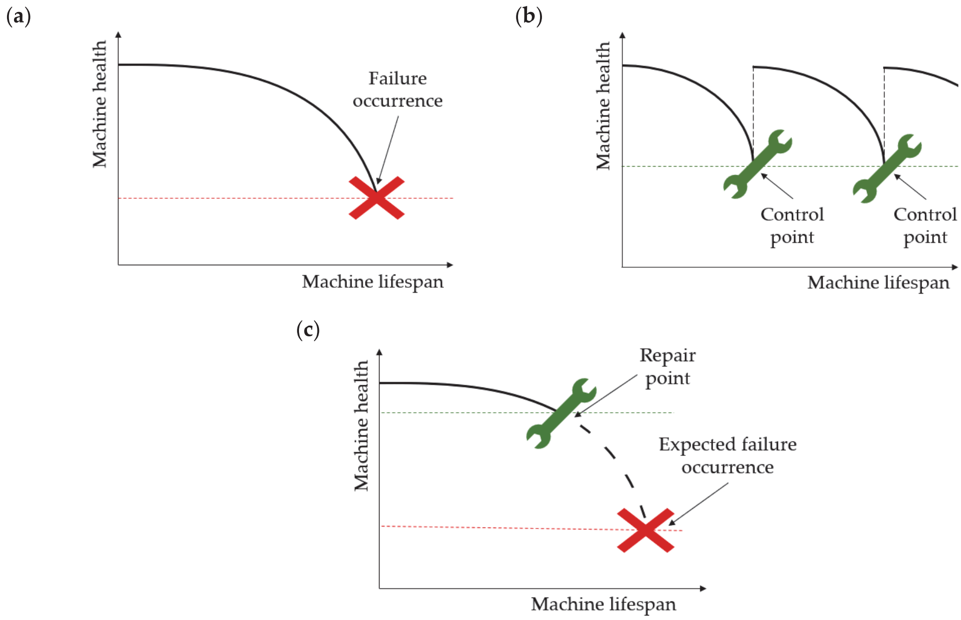


Figure 1. Maintenance types: (**a**) corrective maintenance, (**b**) preventive maintenance, (**c**) predictive maintenance.

Although this solution can prolong machine lifespan, this schedule-based condition monitoring approach provides very little information on the remaining useful lifetime (RUL) of the devices and does not allow for their prognostic and full exploitation [30]. Moreover, because of the scheduled controls in production, it usually means a partial or total shutdown of the manufacturing process, leading to inefficient resource usage and extra operating costs.

To decrease shutdown costs and minimize downtime, manufacturers switch their production over predictive maintenance [31,32]. Condition monitoring is an essential component of predictive maintenance that allows forecasting a further failure based on electrical equipment's working conditions. A schematic illustration of the condition monitoring is shown in Figure 2. As can be seen, condition monitoring consists of several stages. The accuracy of measuring systems largely depends on the sensors used for data acquisition. Signal processing is one of the essential stages in condition monitoring.

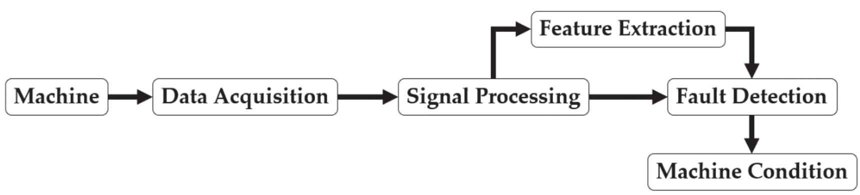


Figure 2. General diagram of decision models.

For feature extraction, to predict and teach the system to detect faults in the future, the system needs a more powerful tool. Moreover, as the data amount is increasing worldwide and computer science is rapidly developing, it is reasonable to remake production under advanced approaches using artificial intelligence (AI). There are widely used thermal imaging in industry to monitor the fault at the early stages of development [33]. In this case, as an example, different variants of machine learning (ML) algorithms can be used for fault detection. These algorithms, as well as their comparison, are described in the following chapters.

2. Diagnostic Possibilities with Machine Learning

Many types of research about intelligent health monitoring refer to machine learning (ML) [34–36]. ML is a study of computer science and artificial intelligence that is not oriented directly to problem solution but rather learning in the process by applying solutions to many similar problems [37]. Typical tasks of ML are classification and regression, learning associations, clustering, and other machine learning tasks, such as reinforcement learning, learning to rank, and structure prediction [38]. ML is closely related to data mining, which can discover new data patterns in large datasets. The main difference is that ML is concentrated on adaptive behavior and operative usage, while data mining focuses on processing extensive amounts of data and discovering unknown patterns. Based on the dataset, so-called training data, ML algorithms can build a model that predicts and makes decisions. There are many types as well as algorithms of ML. These algorithms can be supervised, unsupervised, semi-supervised, and reinforcement [39]. Figure 3 shows the most common methods used in machine learning.

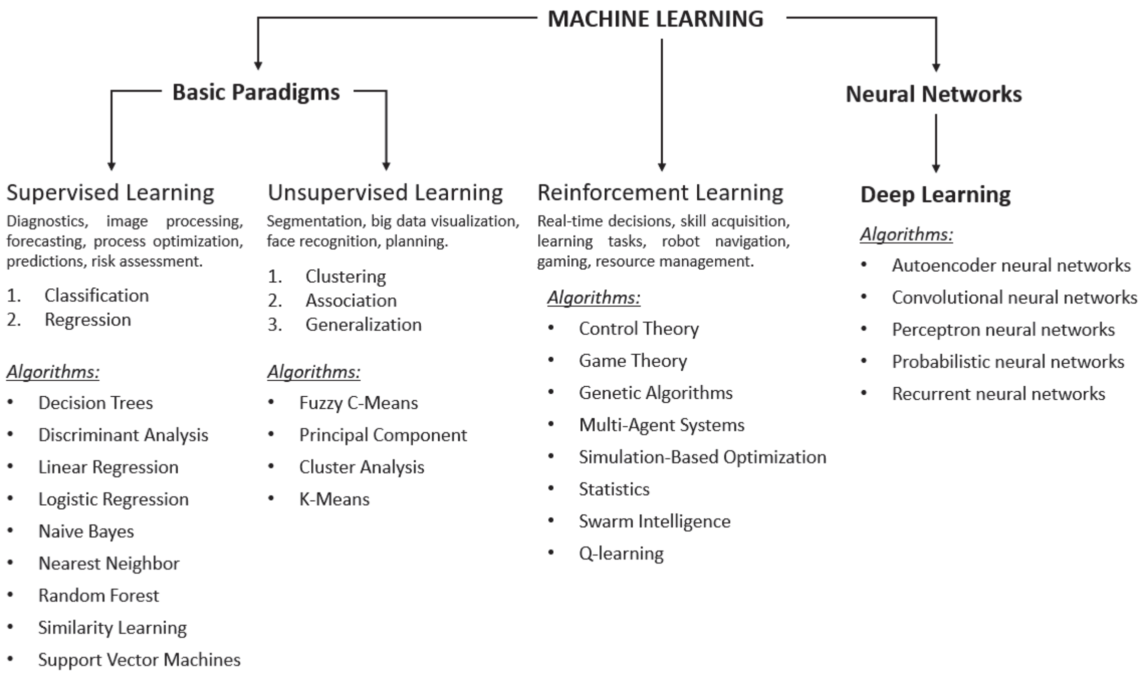


Figure 3. Algorithms of machine learning.

The basic paradigms of ML are supervised and unsupervised algorithms. Supervised ML, also known as "learning with a teacher," is a type of learning from examples, where the training set (situation) and test set (required solution) are set [40,41]. Those training sets are challenging to obtain from industry and laboratories. Because of the limited number of faulty machines working in the industry due to scheduled maintenance (preventive) and in laboratories, a limited number of destructive tests can be performed for training purposes. Moreover, data collection with more than one fault (composite faults) in the same machine is not straightforward in both scenarios. Thanks to the increasing computational power of computers and cloud computation, the mathematical models of electrical machines can train AI algorithms. A comparison of different types of mathematical models of induction motors and their attributes can be found in [42,43].

At the same time, unsupervised ML, also known as "learning without a teacher", is a type of learning where patterns are to be discovered from unknown data [44,45]. In this case, there is only training data, and the aim is to group objects into clusters and/or reduce a large amount of the given data. Sometimes, industrial systems use semi-supervised algorithms in order to get a more precise outcome. In this case, some cases have both training set and test set, while some have only training data.

Differently from basic approaches, reinforcement ML focuses on understanding patterns in repetitive situations and their generalization [46]. The purpose is to minimize errors and increase accuracy; the machine learns to analyze the information before each step. Moreover, the machine aims to get the maximum reward (benefit) from the learning, which is set in advance, such as minimum resource spending, reaching the desired value, minimum analyzing time, etc.

One group of widely used intelligent condition monitoring methods, which can be successfully applied to condition monitoring of many machine parameters, is artificial neural networks (ANNs). ANNs can be supervised, unsupervised, and reinforced. Many studies mistakenly consider NNs as a separate field from machine learning groups. However, NNs and deep learning are related to computer science, artificial intelligence, and machine learning. A diagram of NNs related fields is shown in Figure 4.

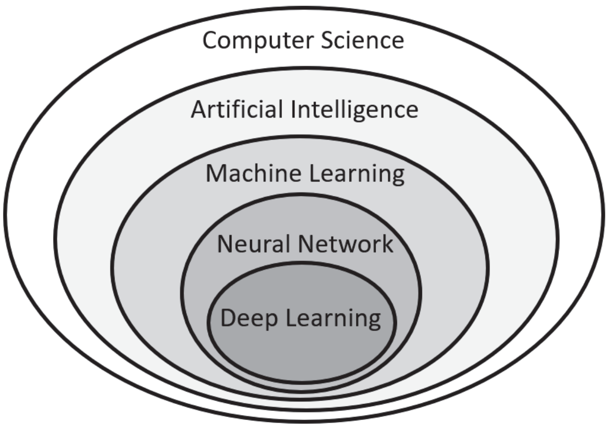


Figure 4. Neural network-related fields.

Machine learning is a powerful tool with a broad set of different algorithms that can be applied for solving many problems. These algorithms, as well as other applications, are described in more detail in the following chapters.

3. Supervised Machine Learning

Supervised ML includes a variety of function algorithms that can map inputs to desired outputs. Usually, supervised learning is used in the classification and regression problems: classifiers map inputs into pre-defined classes, while regression algorithms map inputs into a real-value domain. In other words, classification allows predicting the input category, while regression allows predicting a numerical value based on collected data. The general algorithm of supervised learning is shown in Figure 5.

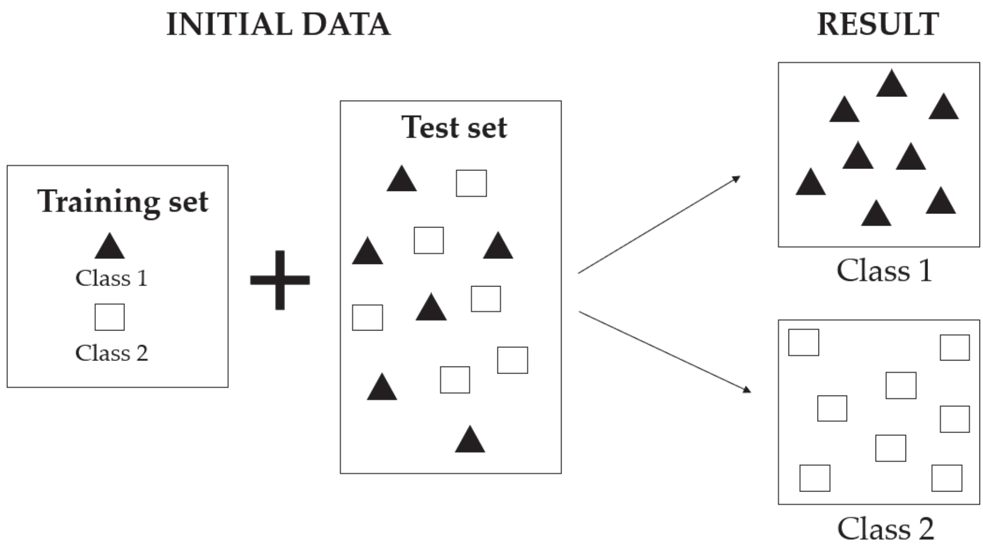


Figure 5. Supervised learning algorithm.

Unsupervised learning aims to discover features from labeled examples so it is possible to analyze unlabeled examples with possibly high accuracy. Basically, the program creates a rule according to what the data are to be processed and classified.

Among supervised algorithms, the most widely used are the following algorithms: linear and logistic regression [47,48], Naive Bayes [49,50], nearest neighbor [51,52], and random forest [53–56]. In condition monitoring and diagnostics of electrical machines, the most suitable supervised algorithms are decision trees [57–59] and support vector machines [60–62].

3.1. Decision Trees

A decision tree (DT) is a decision support tool extensively used in data analysis and statistics. Special attention has been paid to DTs in artificial data mining. DTs' goal is to create a model that predicts the target's value based on multiple inputs. The structure of DTs can be represented by branches and leaves. The branches contain attributes on which the function depends, while leaves contain the values of the function. The other nodes contain attributes by which the decision cases are different. An example of the DT algorithm is shown in Figure 6.

Among other decision models, DTs are the simplest and need a little amount of data to succeed. Moreover, this algorithm can be a hybrid model with another decision model in achieving a more accurate outcome. However, these models are unstable. A little amount of input data can lead to a significant change in the decision tree structure, leading to inaccurate results. Additionally, regression algorithms can fail in the case of decision trees.

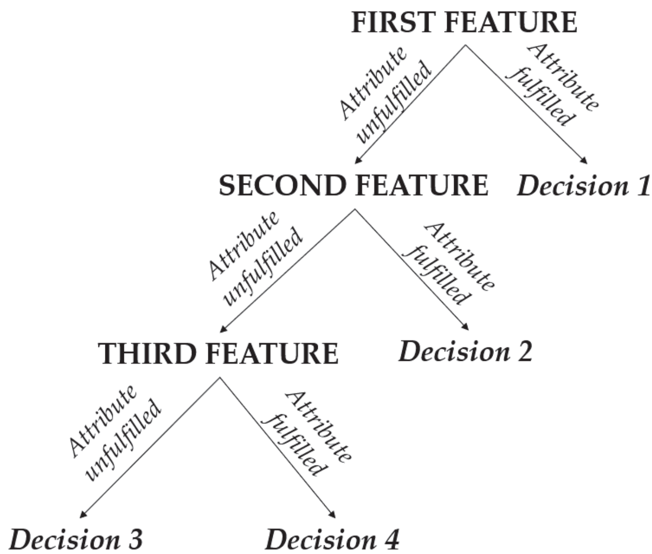


Figure 6. Decision tree diagram.

3.2. Support Vector Machines

Another widely used condition monitoring set of ML algorithms are the support vector machines (SVM). This is a set of supervised models used for regression, novelty detection tasks, feature reduction, and SVM, which is preferable in classification objectives [63]. In linear classification, each datapoint is represented as a vector in n-dimensional space (n—the number of features). Each of these points belongs to only one of two classes. Figure 7 shows an example of data classification.

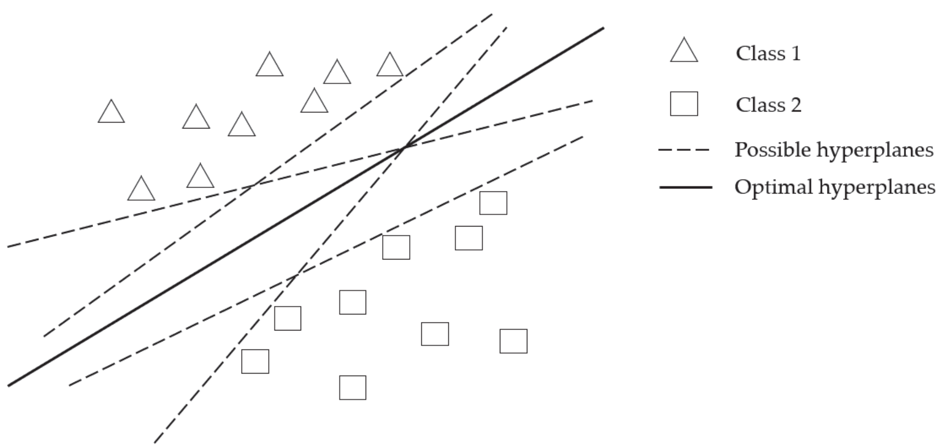


Figure 7. Possibilities in the finding of the optimal hyperplane.

In the picture, two data classes are represented: Class 1 (triangles) and Class 2 (squares). The aim is to separate these points by a hyperplane of dimension ($n-1$), ensuring a maximum gap between them. There are many possible hyperplanes. Maximizing the gap between classes contributes to a more confident classification and helps to find an optimal hyperplane. As shown in Figure 8, to detect the optimal hyperplane, it is essential to find support vectors that can be defined in as closer position to the hyperplane as possible.

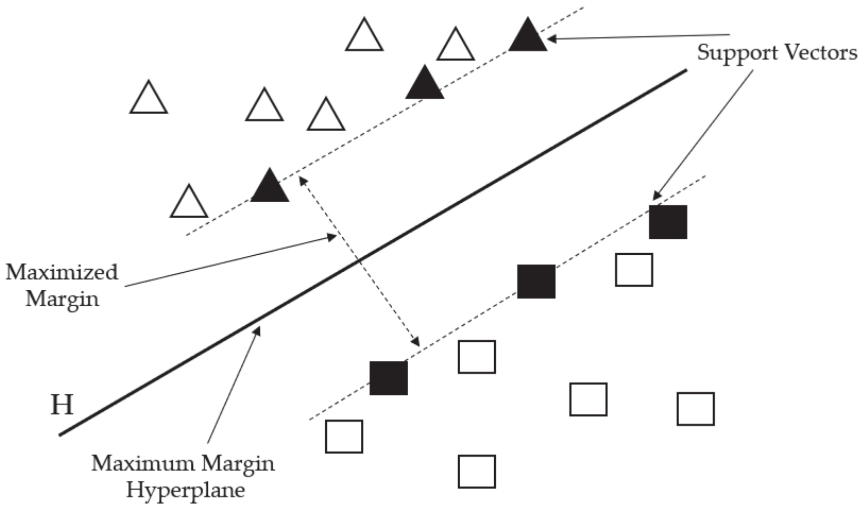


Figure 8. Support vectors and optimal hyperplane in linear classification.

In addition to linear classification, SVMs can deal with non-linear classification using the kernel trick, also known as the kernel machine. As shown in Figure 9, the processing algorithm is similar to the linear one, but the kernel function replaces the datapoints.

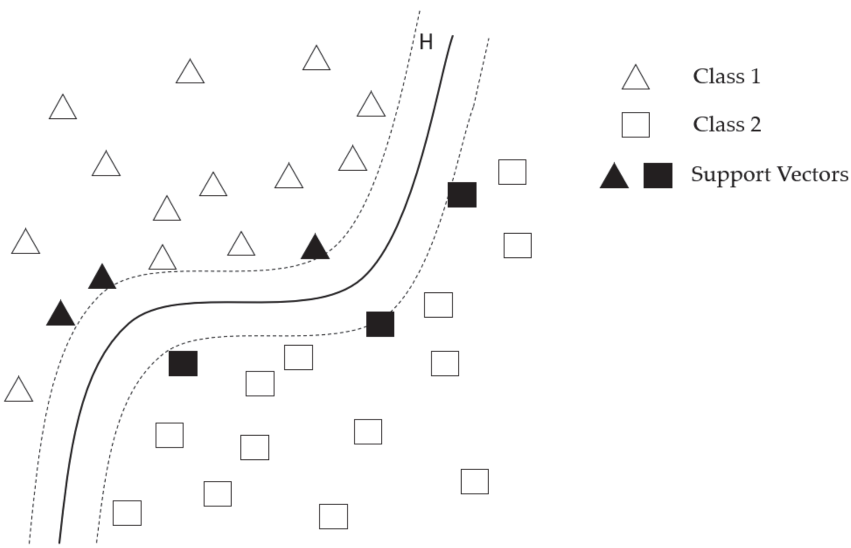


Figure 9. Support vectors and optimal hyperplane in non-linear classification.

SVM is a good solution when there is no initial information about the data. This method is highly preferred because of the little computation power needed to produce results with significant accuracy. Although kernel machine is a great advantage of SVM, its managing is a complicated task. Moreover, it can take a long time to make large amounts of data processed, so SVM is not preferable in large datasets.

Supervised ML approaches are widely applicable for condition monitoring of electrical machines. Many relevant kinds of research can be found in the literature. The authors in [64] proposed a new signal processing method for fault diagnosis of low-speed machinery based on DT approaches. In [65], the authors applied statistical process control and supervised ML techniques to diagnose wind turbine faults and predict maintenance needs. The researchers in [66] presented a semi-supervised ML method that uses the DT algorithm's co-training to handle unlabeled data and applied to fault classification in electric power systems. In [67], the authors proposed a RUL prediction method of lithium-ion batteries using particle filter and support vector regression.

4. Unsupervised Machine Learning

Unsupervised ML includes algorithms that can learn spontaneously to perform a proposed task without intervention from a teacher. Unsupervised learning is often contrasted with supervised learning when an outcome is known, and it is required to find a relationship between system responses. In unsupervised learning, as shown in Figure 10, the program tries to find similarities between objects and divide them into groups if there are similar patterns. These groups are called clusters. Among supervised algorithms, the most widely used are the following algorithms: cluster analysis, fuzzy c-means [68,69], and k-means [70]. In the diagnosis of electrical machines, principal component analysis is the most frequently used algorithm [71–73].

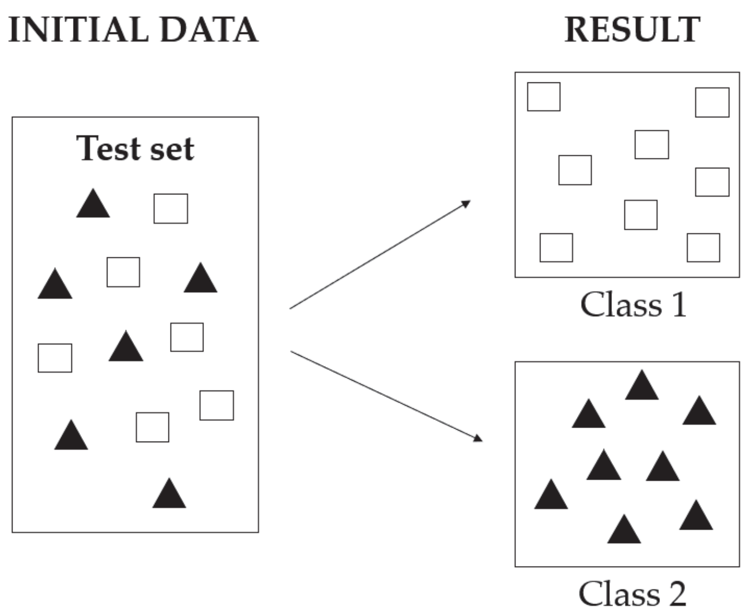


Figure 10. Unsupervised learning algorithm.

More frequently, the dataset is so large that it is difficult to interpret and distinguish the necessary information. Principal component analysis (PCA) is one of the most spread algorithms to reduce the data's dimensions while losing the least amount of information. PCA can be interpreted geometrically, as shown in Figure 11.

The algorithm of SVM is as follows:

(a) Points with specific coordinates are designated on the plane.
(b) The direction of the maximum data change is selected, and a new axis PCA is drawn through the experimental points.
(c) Experimental points are to be projected on the axis PCA.
(d) It is assumed that all the points were initially projected on the axis PCA, and all deviations from this axis can be considered as noise.

If noise is considerable, another axis can be added perpendicular to the first one to describe the data's remaining change. As a result, there is a new representation, which has a smaller number of variables, where all variables are considered, and none of them are deleted. An insignificant part of the data is separated and turns into noise. The main components give the initially hidden variables that control the data device.

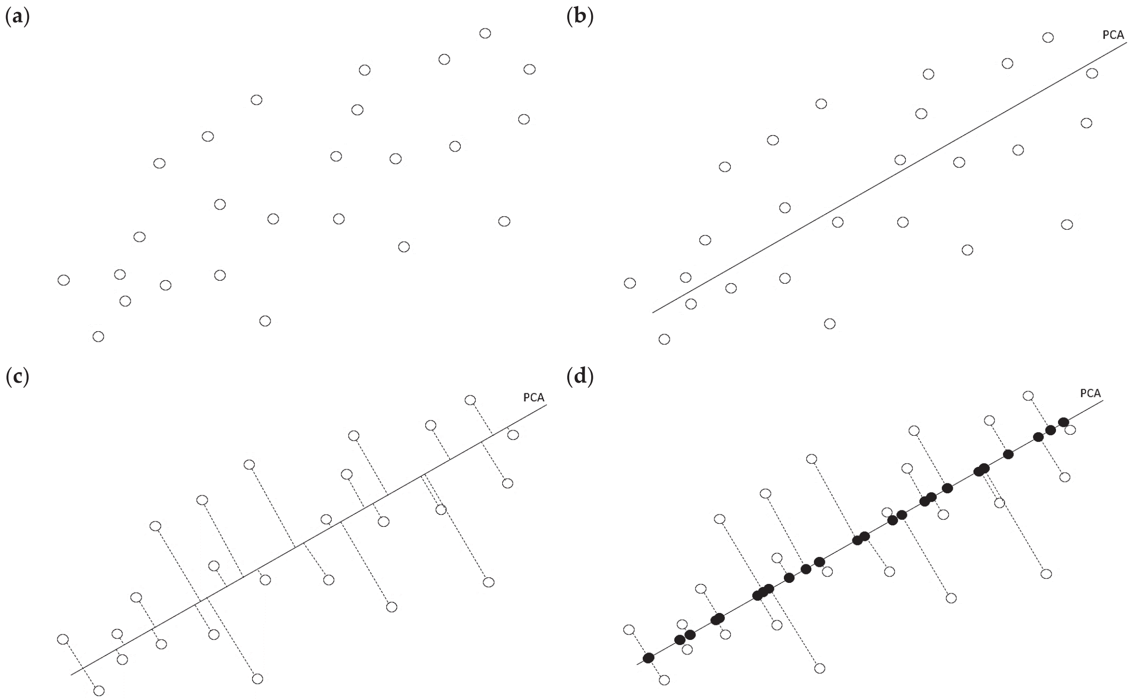


Figure 11. Support vectors and optimal hyperplane in non-linear classification: (**a**) initial dataset, (**b**) optimal vector determination, (**c**) projection of initial dataset on the vector, (**d**) new data parameters definition.

PCA is the most common approach to dimensionality reduction. It is a useful tool for the visualization of large datasets. One of PCA's main advantages is that components are independent of each other, and there is no correlation between them. It can significantly reduce the training time. At the same time, these independent values can become less interpretable. Besides applying PCA, there is still information loss, and the data analysis is relatively less precise than the original values.

Many studies are available in the literature where unsupervised algorithms are used for the analysis of high-dimensional datasets. In [74], the authors applied a new method to the fault diagnosis of rolling bearings in the field of high-dimensional unbalanced fault diagnosis data based on PCA for better classification performance. In [75], researchers used a PCA-based method to monitor non-linear processes. The researchers in [76] proposed a PCA-based hybrid method for monitoring linear and non-linear industrial processes.

5. Reinforcement Learning

Reinforcement learning (RL) is one of the ML methods, where the system (agent) learns by interacting with some environment. Different from supervised algorithms, there is no need for labeled data pairs. RL is mainly focused on finding a balance between an unknown environment and existing knowledge. The general algorithm of reinforcement learning is shown in Figure 12.

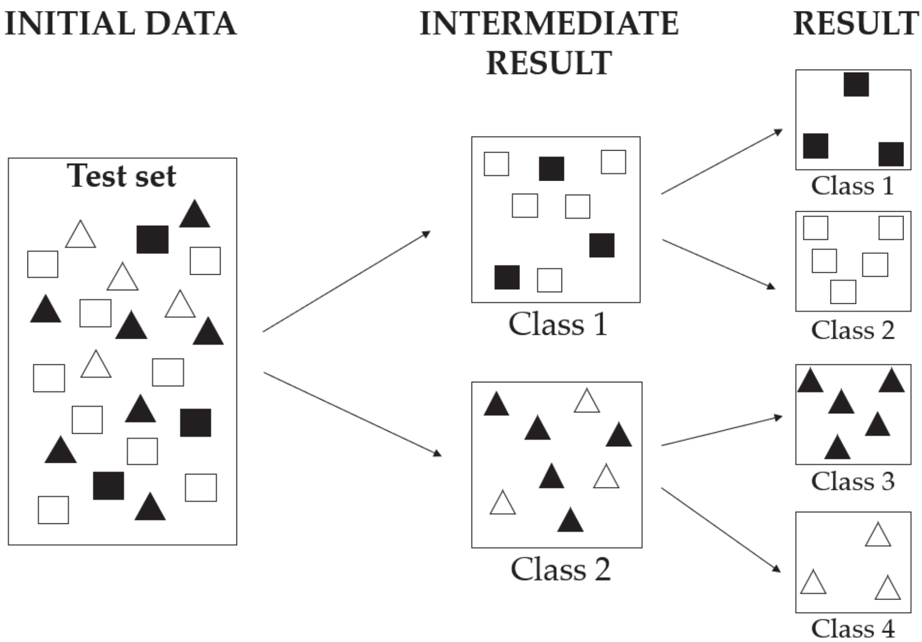


Figure 12. Reinforcement learning algorithm.

One of the algorithms, which can be used in data mining and cluster analysis, is swarm intelligence [77–79]. Swarm intelligence (SI) describes a decentralized and self-organized system's collective behavior, which is considered an optimization method. SI system consists of agents (boids) that interact with each other and the environment. SI should be a multi-agent system with self-organized behavior, which could exhibit a reasonable behavior. This algorithm can adapt to changes and converge fast at some optima. Simultaneously, solutions are dependent sequences of random decisions and can be trapped in local minimum in complex tasks.

At the same time, the more frequently used reinforcement algorithm in condition monitoring is the genetic algorithm [80–82]. A genetic algorithm (GA) is a tool for solving optimization problems and modeling random selection using natural selection mechanisms in the environment. A distinctive feature of the GA is the emphasis on using the "crossing" operator, which uses the instrumental role of crossing in wildlife.

In the case of GA, the problem is formalized so that its solution can be encoded in the form of a vector of genes (genotype), where each gene has some value. In classical implementations of GA, it is assumed that the genotype has a fixed length. However, there are GA variations that are free from this limitation. The general diagram of GA is shown in Figure 13.

Basically, the optimization algorithm with the usage of GA is as follows:

(a) There is a task, and many genotypes of the initial population are to be created.
(b) This initial set of data is to be assessed using the "fitness function," which determines how well each initial population's genotype solves the task.
(c) After this, the best coincidences are to be selected in the population for the next generations.
(d) The best coincidences obtain new solutions. This process repeats until the task is fulfilled and a resultant population is created.

The main benefit of GA is that specified knowledge about the domain is not needed. GA generates a solution through genetic operators. Moreover, a result can contain more than one appropriate solution. However, GA sometimes suffers from degeneracy. The degeneracy can occur if multiple chromosomes represent the same solution. The same shapes of chromosomes occur repeatedly. In this case, the optimal solution is not guaranteed.

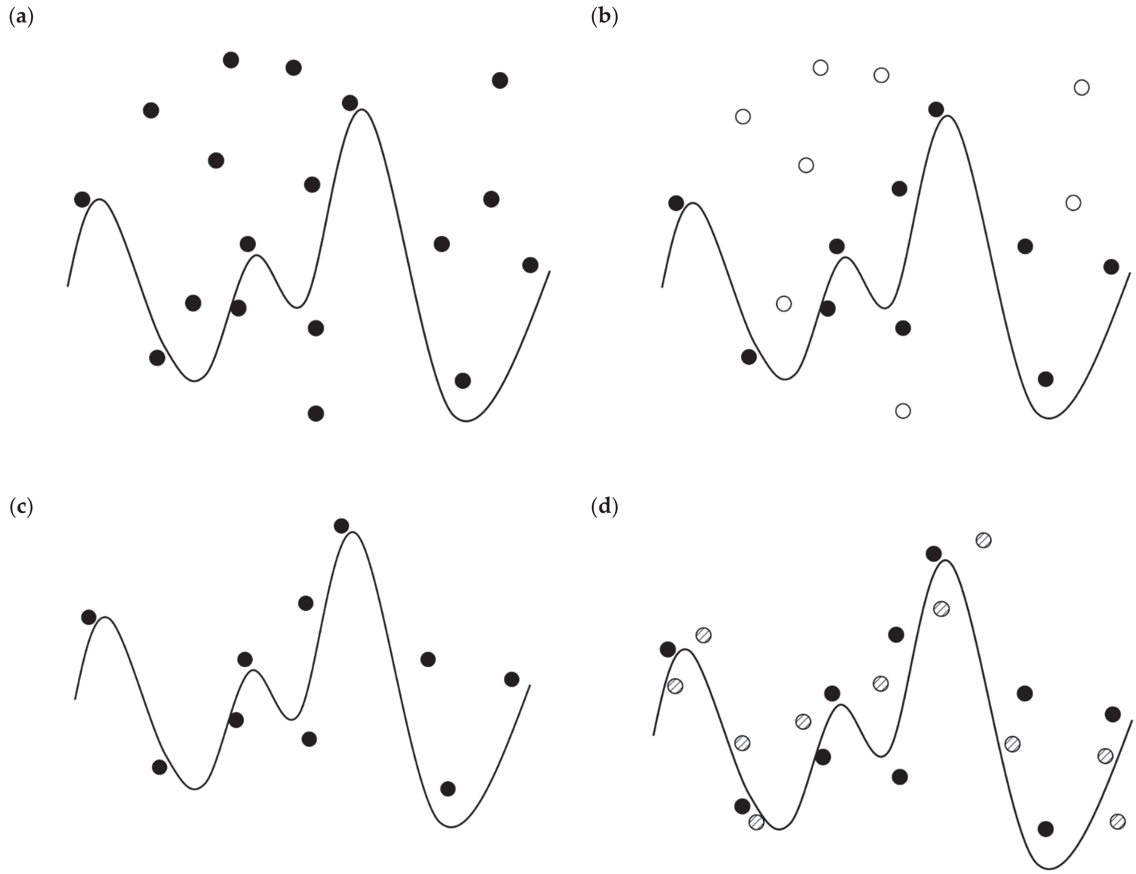


Figure 13. Genetic algorithm diagram: (**a**) creation of initial population, (**b**) application of fitness function, (**c**) selection of the best coincidences, (**d**) creation of resultant population.

Nonetheless, GA is an efficient tool for industrial processes optimization. In [83], researchers proposed a new method based on GAs that can be used for both fault-type classification and RUL prediction. The authors in [84] proposed a method based on genetic mutation particle swarm optimization for gear faults diagnosis. In [85], researchers proposed a GA-based method to optimize and improve the photovoltaic array accuracy.

6. Neural Networks

ANNs have been proved as quite approving tools for condition monitoring and prediction of RUL due to their adaptability, nonlinearity, and arbitrary function approximation ability [86,87]. The main advantage of NNs is that they can outperform nearly every other ML algorithm. This method is supposed to analyze and model processes of damage propagating and predict further failures based on collected data. The main tasks that neuron networks deal with are [88,89]:

1. Classification,
2. Prediction,
3. Recognition.

Artificial neural networks originate from attempts to reproduce biological nervous systems' ability to learn and correct errors by modeling the brain's low-level structure. To create artificial intelligence, you need to build a system with a similar architecture. The architecture of an ANN is shown in Figure 14.

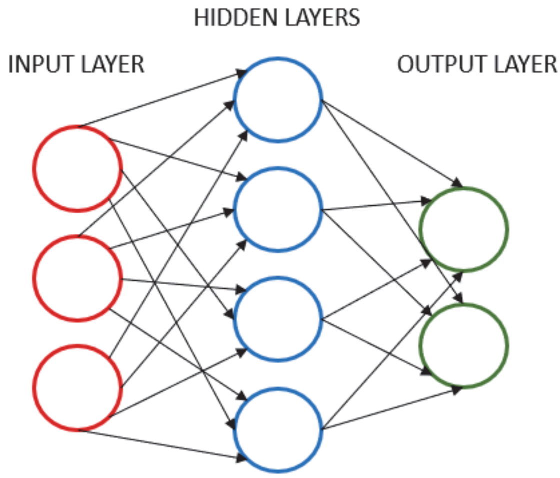


Figure 14. Neural network architecture.

ANNs consist of machine learning algorithms that constitute the human brain with connected signals called neurons. Neurons, both biological as well as artificial, consist of the cell body, dendrite (input), synapse (connection), and axon (output). As seen from the picture, the simplest model of an artificial neural network has three layers of neurons. The first (input) layer is connected to a middle (hidden) layer. The hidden layer is connected to the final (output) layer. In case of the neural networks, to solve a given problem, it is necessary to collect training data. A training dataset is a collection of observations, of which the values of the input and output variables are defined and specified. The neurons transfer a signal from the input layer to the output. The input layer neurons receive data from the outside environment (measuring system, sensors) and, after processing them, transmit signals through the synapses to the neurons of the hidden layer. The neurons of the hidden process receive signals and transmit them to the neurons of the output layer. Basically, the neuron is a computing unit that receives information, performs simple calculations on it, and transfers it further.

Neural networks are not being programmed; they are learning. Learning is one of the main advantages of neural networks over traditional algorithms. Technically, training consists of finding the coefficients of connections between neurons. In the process of training, the neural network can identify complex dependencies between input and output data and perform generalizations. This means that in case of successful training, the network will be able to return the correct result based on data absent in the training sample and incomplete or partially distorted data.

If a neural network consists of more than three layers, which is an increasing tendency nowadays, the algorithm can be considered a deep learning or deep neural network (DNN). Generally, deep learning is one of the ML techniques in ANNs which analyzes big machinery data with more precise results.

NNs have been considered as a universal tool in solving many problems. However, each method has its own limitations, and NNs are no exception. Usually, NNs are used as a hybrid with some other condition monitoring techniques. All the limitations of ANNs and other mentioned ML techniques are given in the following section.

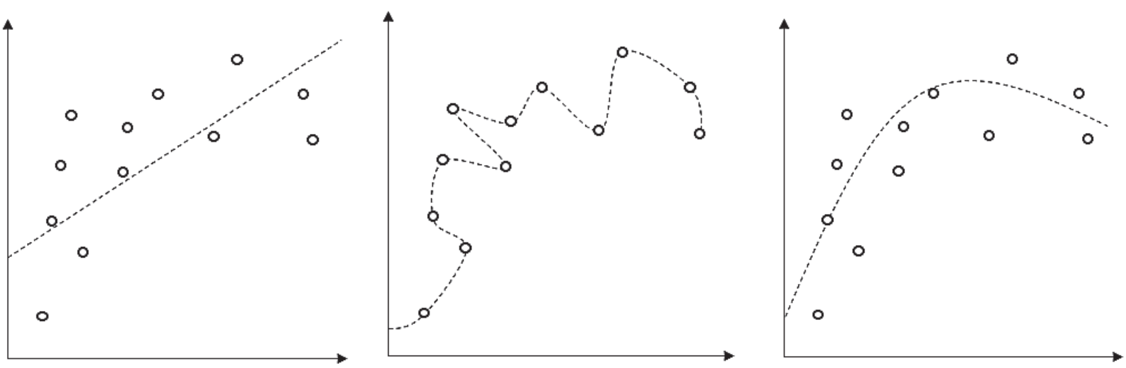
Different types of NN are used for different parameters monitoring. In the literature, a variety of applications can be found. The authors in [90] proposed a novel intelligent fault diagnosis method based on multiscale convolutional NN to identify different failures of wind turbine gearbox. In [91], the authors proposed an intelligent bearing fault diagnosis method combining compressed data acquisition and deep learning, which provides a new strategy to handle the massive data more effectively. The authors in [92] proposed a deep transfer learning (DTL)-based method to predict the remaining useful life in manufacturing. In [93], the author suggested a novel deep convolutional NN cascading architecture for performing localization and detecting defects in power line insulators. Many algorithms have been developed over the years for the automated identification of partial discharges. In [94], an application of a neural network to partial discharge images is presented, which is based on the convolutional neural network architecture, to recognize the aging of high-voltage electrical insulation.

7. Trends in Condition Monitoring and Discussion

The maintenance of the electrical equipment is a very challenging topic at present. Proper, reliable, and efficient fault diagnostic techniques are becoming more and more essential as the world moves towards Industry 4.0 standards [9]. A major issue related to the prediction and condition monitoring is the reliability of the used methods [95,96]. ML algorithms have given a potent tool for classifications. ML methods are not a novelty; thus, researchers meet different limitations. Nowadays, intelligent condition monitoring methods mentioned in previous chapters are mainly used together as a hybrid to get more precise and robust results of fault diagnostics in industrial systems [97].

The main problem of machine learning and neural networks is the training datasets required for system training. To meet precise results and make accurate predictions, the amount and the quality of data play a significant role. Mostly, the dataset shows irrelevant features, requiring a function to build a model. This function will represent how flexible the model is. The main problem with the data is either overfitting or underfitting.

Big data is a trending challenge nowadays. At the same time, high dimensionality and the limited number of training samples lead to overfitting [98]. Frequently, this problem occurs with neural networks [99]. Overfitting means that there is a very qualified training dataset but a very poor test dataset. Simultaneously, the system cannot perform well if the training set is too small or if the data is too noisy and corrupted with irrelevant features. There can be an underfitting phenomenon where the test dataset is good enough, but training data are inferior. All the examples are shown in Figure 15.



(**a**) (**b**) (**c**)

Figure 15. Data generalization: (**a**) test data is underfitted, (**b**) test data is overfitted, (**c**) test data is balanced.

As shown in Figure 15, both underfitted and overfitted models describe the same dataset. Although the too generalized model does not give the priciest results, at the same time, the overfitted model has a definite idea and is not flexible enough for upcoming new datasets. The challenge is to find a balance between underfitting and overfitting by the usage of different models.

ML is a widespread trend in load forecasting. Many operating decisions, such as reliability analysis or maintenance planning, are based on load forecasts [100]. In this case, artificial neural networks have paid significant attention to proper performance. The main problem overfitted sub-optimization system of ANN that can lead to uncertain forecast results [101]. Working in dynamically changing environments can be a complicated task for NNs. Even if the network has been successfully trained, there is no guarantee that it will work in the future. The market is continually transforming, so today's model can be obsolete tomorrow. In this case, various network architectures must be tested to choose the best one that could follow changes in the environment. Moreover, in the case of NNs, a phenomenon can occur known as catastrophic forgetting. This means that NNs cannot be sequentially trained in several tasks. Each new training set will cause rewriting of all neuron weights, and, as a result, the previously trained data will be forgotten.

Another spread limitation for NNs is the so-called "black box" phenomenon. As was already mentioned, deep learning successfully learns hidden layers of NN architecture mapping inputs and outputs. Approximating the function makes it impossible to study insights into the structure and, as a result, study a cause of a mistake. For this reason, in particular, it is reasonable to choose some other technique or to use NNs in combination with another algorithm.

8. Conclusions

A review of the state of the art, machine learning-based fault diagnostic techniques in the field of electrical machines is presented in this paper. The artificial intelligence-based condition monitoring techniques are becoming more popular as computer power is increasing day by day. Unlike conventional on-board processors responsible for data collection and analysis, the utilization of powerful remote resources using cloud computation gives the freedom of unlimited memory and processing power to handle big data vital for intelligent techniques. Moreover, by effective training of AI algorithms using mathematical models with various faulty conditions, the diagnostic algorithms can be made more reliable.

The collection of these big data is neither possible from industry nor the lab environment. It is not possible from the industry because of the limited number of faulty machines under service. In the lab, a limited number of machines can be broken due to economic constraints. Due to the trend of mounting sensors on the remotely located machines and collecting their data over the cloud, the processing power-related constraints are resolved. Machine learning makes a considerably significant portion of AI techniques. For future work, the studied techniques will be implemented in practice on real industrial objects. Those techniques can use statistical or convention signal processing techniques to detect fault-related patterns and estimate electrical machines' life estimation. Moreover, they give the flexibility to train algorithms under a variety of working conditions. Those conditions may include grid fed, scalar control, low load, and changing load in case of induction machines in particular and for the rest of other machines in general.

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Publication VI

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ORIGINAL PAPER

Study of bearing currents in induction machine: diagnostic possibilities, fault detection, and prediction

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Abstract
Bearing failures in electrical machines pose significant challenges, attracting attention in diagnostic research. The widespread adoption of variable-speed drives across various motor applications has increased the effects of bearing currents, necessitating thorough exploration in both academic and industrial contexts. The paper contributes valuable insights into identifying and addressing bearing-related issues in electrical machines. It comprehensively investigates the matter, investigating damage types and diagnostic techniques specific to bearing currents in induction machines. Moreover, it provides insights from experiments conducted in controlled laboratory settings to replicate bearing current faults. As the industry integrates advanced technologies into manufacturing processes and gains traction, preventive maintenance is increasingly emphasized. Consequently, the paper expands its investigation into signal pre-processing to enhance fault prediction accuracy by optimizing machine signals. Given the dynamic nature of industrial standards and the growing demand for predictive maintenance strategies, this research presents a predictive method for early fault detection. Aiming for heightened efficiency, reduced downtime, and enhanced reliability, the perspectives outlined in this paper make a meaningful contribution to the evolving field of predictive maintenance.

Keywords Induction motors · Ball bearings · Condition monitoring · Machine learning · Predictive maintenance

1 Introduction

Nowadays, electrical machines and drive systems play a pivotal role in various domestic and industrial sectors. Their widespread use has brought maintenance concerns to the forefront. Among these machines, three-phase induction motors are particularly prominent due to their ability to meet various industrial needs, such as low maintenance, cost-effectiveness, compact design, and variable control capabilities. Using frequency converters for control is the most cost-effective method and ensures optimal performance [1]. However, this approach can lead to the generation of induced shaft currents. Numerous cases in the literature are related to power electronics and bearing currents. Authors in [2] discuss a reduction in common mode voltage and bearing currents in the DC-link inverters. In Plazenet et al. [3], the influence of parameters on discharge bearing currents in inverter-fed induction motors is introduced. Authors in [4] present mitigation techniques and modeling for high-frequency bearing currents in inverter-fed AC drives. In Xu et al. [5], the authors discuss the experimental assessment of high-frequency bearing currents in the induction motor driven by a silicon carbide inverter.

Identifying surface damage resulting from shaft currents on bearings is typically challenging, especially visually. Shaft currents don't consistently pass through the bearing. However, when they do, faults often appear in areas where the lubricant coating is thinnest due to heightened stress. Shaft currents pose a significant challenge in various industries [6]. Case studies and their solutions can be found in wind turbines [7], marine applications [8], assembly lines [9], and food production [10]. Each energy system is complex, and ensuring device reliability requires monitoring numerous parameters, which demands substantial computational resources and modern technologies. Given the vast amount of data, employing advanced diagnostic methodologies rooted in artificial intelligence becomes logical [11]. These intelligent

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algorithms not only detect defects but also forecast potential faults in the future. Among various methods available, machine learning-based algorithms are the most prevalent tools for diagnosing rotating machines. They create a complex weighted combination based on training data, which can later be used to deduce results for incoming data [12]. When it comes to diagnosing bearing issues in electrical machines, commonly employed machine learning techniques include decision trees [13], support vector machines [14], principal component analysis [15], and genetic algorithms [16]. Additionally, various neural network variations are utilized, such as convolutional neural networks [17], generative neural networks [18], and deep learning approaches [19]. This research has prioritized neural network-based approaches for their ability to learn quickly and effectively.

This study makes significant contributions to the field of predictive maintenance by addressing the critical challenge of acquiring training datasets for implementing artificial intelligence algorithms. This systematic approach enriches the available datasets and provides valuable insights into the early detection and diagnosis of bearing faults. Consequently, it advances the development and implementation of predictive maintenance strategies.

The paper thoroughly investigates bearing currents in induction machines, covering damage types and diagnostic techniques, particularly emphasizing preventive maintenance strategies. Various faults were deliberately induced in laboratory settings to overcome the challenge of acquiring training datasets for artificial intelligence algorithms in predictive maintenance. The study underscores the significance of vibration signals in the early detection of bearing faults, mathematically describing them in four natural frequencies. Datasets encompass data from current, voltage, torque, speed, and vibration collected under different control settings and loads. Additionally, the paper explores machine learning approaches for fault detection and prediction, enriching available datasets and offering insights into early fault detection and diagnosis, thus advancing the development and implementation of predictive maintenance strategies in industrial settings.

This manuscript is organized as follows. Chapter 2 introduces the nature of bearing currents. Chapter 3 presents the possibility of detecting bearing currents in the machine. Chapter 4 describes the most typical damages inflicted by bearing currents. In Chapter 5, the bearing faults caused by bearing currents are performed in the lab environment. Chapter 6 presents a pre-processing of the datasets to get predictions in Chapter 7.

2 Bearing currents

At present, the most cost-effective and straightforward means of ensuring optimal performance of electrical machines involves the application of frequency converter control. This strategy is widely embraced globally, resulting in a heightened adoption of power electronics. However, these solutions often give rise to shaft currents induced by the frequency converter, presenting an escalating challenge in modern industry.

Despite the longstanding acknowledgment of bearing currents in electrical machines, which has persisted for nearly a century, it remains a prominent area of investigation [20]. Failures arising from bearing currents inflict significant mechanical damage on electrical machines. In contemporary drive systems, deploying converters contributes to a phenomenon wherein current traverses the circuit, encompassing the bearings, frame, and machine shaft [21]. Although mitigation measures are increasingly employed to tackle bearing currents, it is noteworthy that they may inadvertently engender reliability concerns and necessitate additional maintenance [22].

In general, bearing currents can be classified into two primary types: classical bearing currents and inverter-induced bearing currents.

2.1 Classical bearing currents

In 1927, it was observed that the presence of theoretical and practical indications of bearing current could be eliminated if an ideally balanced and symmetrical motor design was achievable [23]. Typically, these issues stem from structural irregularities within the machine, including static or dynamic eccentricity, design inconsistencies, unbalanced power supply, laminations with broken connections, and faults in the rotor [24]. This phenomenon was demonstrated in [25] through simulations, wherein broken rotor bars produced eddy currents in the shaft, leading to bearing damage. The asymmetry of the magnetic field induces a current in the motor shaft, resulting in a measurable potential difference between both ends of the shaft. According to standards, a shaft voltage exceeding 300 mV is considered detrimental to bearings, although lower levels may also cause damage if persisting for prolonged periods. Despite enhancements in design tolerances and the quality of production materials, the monitoring of bearing currents remains essential due to their potential risk to ball bearings. This concern becomes particularly critical for motors starting from 100 kW. Additionally, classical bearing currents can be readily detected in motors from 7.5 kW [26]. Furthermore, it is advisable to implement preventive measures against bearing currents, such as insulated bearings or shafts, in motors starting from 18.5 kW [27].

2.2 Inverter-induced bearing currents

Inverter-induced bearing currents encompass several categories: electrical discharge machining bearing currents, capacitive bearing currents, bearing currents caused by rotor ground currents, and high-frequency circulating bearing currents. The classification of these currents is illustrated in Fig. 1. The primary source of these currents is the common mode voltage generated by the inverter and the rapid voltage fluctuations (high du/dt) at the motor terminals [28]. This phenomenon is the root cause of various types of bearing currents capable of causing damage to bearings in motors operating with variable-speed drives. As a result of coupling, the bearing capacitance and other parasitic capacitances become charged, leading to a voltage buildup on the motor shaft. If this accumulated voltage surpasses the breakdown voltage of the lubrication film, capacitive energy discharges occur through the bearings, resulting in electrical discharge machining current flow. The path of current travels from the shaft to the frame, passing through the rings and rolling elements of the bearing. Shaft voltages ranging from 3 to 30 V are significant enough to induce discharges in the bearings [29], with voltage levels typically between 3 and 10% of the electrical machine's nominal voltage [30].

The rapid fluctuations in the common mode voltage trigger high-frequency common mode currents to traverse various components of the motor, including the windings, stator laminations, air gap, rotor, shaft, and bearings [29]. These currents emerge from transistor switching during each switching event. At higher speeds, a thin dielectric layer forms between the bearing races and rolling elements, establishing a capacitive connection between the machine frame and the shaft. Typically, these currents range from 5 to 10 mA and are generally considered non-detrimental to the bearings and motor [31].

Bearing currents arising as rotor ground currents stem from inadequate grounding of the motor frame [32]. This situation often arises when the rotor is grounded through the driven load, resulting in a more robust grounding than the stator. This current traverses through the motor bearings to the shaft, the load, and the controlling converter.

Regarding high-frequency circulating bearing currents, the process involves the rapid du/dt of the voltage at the machine terminals, generating additional high-frequency common mode currents and parasitic capacitances between the motor winding and stator laminations. With frequencies reaching several megahertz, these currents ingress the rotating machine through the windings and exit through the frame and laminations, creating a high-frequency circular magnetic flux around the motor shaft. This flux induces a shaft voltage that, if adequate, discharges through the bearings, generating a circulating current in the bearings, shaft, and motor frame, potentially surpassing the lubricant's breakdown voltage.

3 Diagnostic and reduction possibilities of bearing currents

Several techniques exist for detecting bearing currents in electrical machines, such as the Rogowski coil [33], current transformer [34], and a conventional multimeter. However, given that bearing faults predominantly affect vibration rather than the current spectrum, vibration analysis emerges as a viable option [35]. Diagnostic approaches for bearing currents generally fall into direct and indirect methods [36].

3.1 Direct methods

Direct diagnostic methods are favored for promptly detecting shaft currents. Detecting bearing currents in the motor enables timely intervention to prevent faults, ultimately safeguarding the bearings of the electrical machine [37]. While this approach identifies bearing currents, it provides only an indirect indication. A multimeter can indicate if bearings are prone to sparking, but precise measurement of shaft voltage requires a multimeter with high input impedance for optimal accuracy.

A universal and practical measuring device is recommended for a comprehensive assessment of various motor currents, shapes, and parameters. Oscilloscopes with a bandwidth exceeding 100 MHz are preferred for this purpose. Considering and recording ambient magnetic field levels are crucial, as oscilloscopes are more susceptible to noise and interference than multimeters. When focusing on motor bearings, measuring only shaft voltage and current is typically sufficient.

When measuring shaft currents, the oscilloscope's settings depend on factors such as motor size, speed, bearing type, and temperature. Time scale reduction could start at approximately 500 microseconds, while voltage increase could begin at around 5 V. Shaft voltage usually mirrors phase voltage unless spark discharges occur in the bearings, leading to voltage fluctuations of $\pm$ 20…80 V every 10 microseconds.

Alternatively, shaft currents can be measured using a current transformer and a high-frequency non-inductive (coaxial) shunt, preferably alongside an oscilloscope. Non-inductive shunts, comprising two conductive tubes, mitigate shunt saturation compared to current transformers but may face challenges with transient currents and self-inductance. Due to the temperature coefficient of the shunt material resistance, adjustment of measurement results or adherence to specified temperature ranges may be necessary.

Using a Rogowski coil is a common, straightforward, and safe method for measuring phase and motor shaft currents. During phase current measurements, the coil should encircle power cables (excluding the neutral cable), while for shaft current measurements, it should encircle the motor shaft. If multiple power cables are present, the coil should encompass

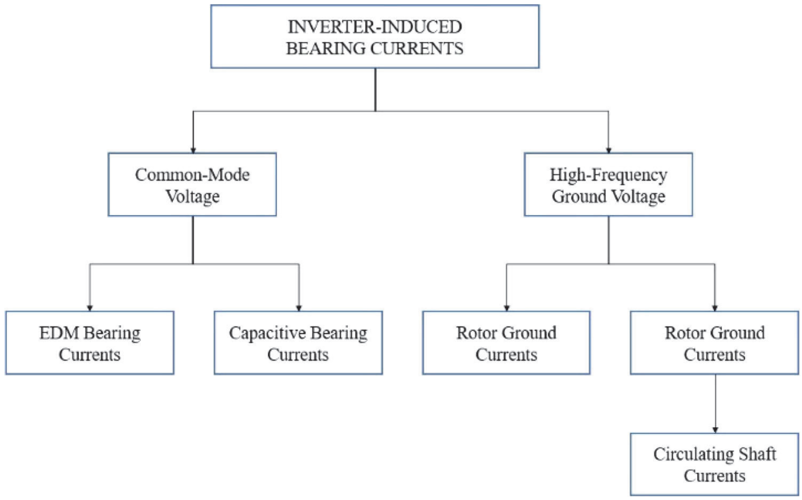

Fig. 1 Categorization of bearing currents

all cables. A Rogowski measuring device connected to a logger or oscilloscope, preferably with a bandwidth exceeding 100 MHz, facilitates shaft current measurements. However, the Rogowski coil requires additional electronics and power supply and is susceptible to noise, necessitating attention to electromagnetic compatibility.

3.2 Indirect methods

Indirect diagnostic methods for detecting bearing currents in electrical machines are used only after the bearing surfaces have suffered damage, prompting the rolling bodies to produce vibration and noise. Moreover, identifying shaft currents indirectly demands expertise and thorough training due to the diverse bearing damage types.

Vibration analysis stands as a commonly utilized tool in electrical machine diagnostics. While vibration analysis effectively pinpoints bearing faults, discerning faults arising from bearing and shaft currents amid other mechanical defects in the bearings can pose a challenge. Thus, when such current-induced failure modes are suspected, vibration analysis must complement other direct or indirect diagnostic techniques to validate findings and ensure diagnostic accuracy.

Ultrasonic detectors are also suitable tools for indirectly detecting bearing currents. Similar to vibration analysis, the ultrasonic spectrum exhibits sound peaks resulting from passing shaft currents. Beyond data analysis, ultrasonic detectors allow for listening to bearing defects like a stethoscope. While theoretically capable of detecting spark discharges generated by shaft currents in bearings, the low level of spark discharges within the ultrasonic range (with a maximum power of about 200 MHz) renders this method challenging to implement in practice.

3.3 Limitation possibilities

In the case of motors with a power of more than 100 kW, there are some solutions to decrease bearing currents. Table 1 summarizes the main options for reducing bearing currents.

The effectiveness of these methods primarily depends on motor parameters and the surrounding environment. However, shaft current leakage remains a risk.

4 Damages of bearing currents

During the initial phases, detecting damages caused by electrical currents in the bearings often necessitates dismantling the electrical machine, which isn't practical. Instead, subtle deviations from standard specifications on the bearing races may be observed at a microscopic level. Visually, faults resulting from bearing currents stand out from other mechanical defects [46]. It is crucial to visually inspect replaced bearings, especially if changes occur during maintenance and there are concerns about shaft currents. The impact of these currents on the bearing is influenced by factors such as lubricant type, rotational speed, applied current, operating duration, and material condition.

Typically, damages induced by electrical currents become apparent only in later stages when the bearing surface has already been compromised. Faults resulting from these currents often manifest in areas with the thinnest lubrication layer, experiencing heightened stress. One common manifestation is "fluting," as depicted in Fig. 2a, where multiple

Table 1 Possibilities to decrease bearing currents

Method	Effect	Comment
One insulated bearing [38]	Ineffective	Circulating currents within the motor may be mitigated, but an uninsulated bearing's lifespan is prone to shortening
Conductive grease [39]	Effective if bearing currents are low	This is advised as a temporary measure solely for smaller motors. As bearing currents escalate, changes in the lubricant's composition significantly reduce the bearing's lifespan
One insulated bearing and grounding contact [40]	Effective	The ground brush or ring should be positioned on the non-insulated bearing side. For further mitigation, a common mode filter can be employed
Two insulated bearings and grounding contact	Very effective	An exceptionally effective solution is the utilization of a common mode filter
Common mode filter (passive) [41]	Relatively effective	The most economical and effective among filters, it diminishes high-frequency currents. However, for large motors, supplementary measures are necessary
Hybrid or ceramic bearings [42]	No spark solutions	Highly effective, it is arguably the optimal solution for small motors
One grounding contact or ring [43]	Effective	Regular maintenance is required for the grounding brush. The solution is suitable for smaller motors. A common mode filter can be used
Two grounding contacts or rings	Very effective	The grounding brush must be regularly maintained. This solution is well-suited for smaller motors and can be complemented with a common mode filter
dU/dt filter (active) [44]	It decreases a bit in the case of larger motors	This will be utilized for the highest output voltage, reaching up to 690 VAC
Sine wave filter [45]	Decreases	The extent of reduction varies depending on the filter, but it primarily targets the circulating shaft currents. This filter type is the costliest among options and entails considerable heat losses that need to be considered
Correct ground and cabling	Longer cables can reduce currents	Proper grounding and cabling are fundamental prerequisites for addressing the issue. This approach effectively reduces the main circulating leakage currents, thereby lowering the risk of motor insulation failures and disturbances

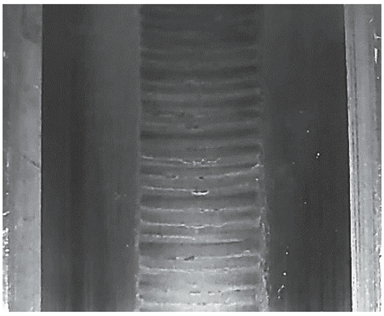

Fig. 2 Common fault caused by bearing currents (fluting)

Fig. 3 Lubricant darkening due to discharges

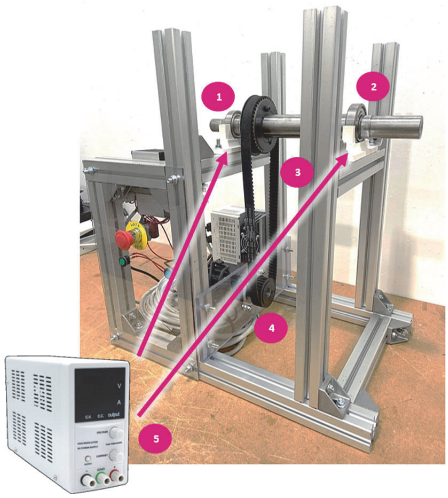

Fig. 4 Experimental test bench for implementation of bearing current faults: (1) non-drive end bearing, (2) drive end bearing, (3) belt, (4) servo drive, (5) power supply

lines form across the bearing raceways. Fluting is frequently associated with constant rotational speeds and low voltage. Additionally, frosting and pitting can occur due to bearing currents. However, the focus of this paper is primarily on the fluting fault.

Changes in the lubricant's condition can also serve as indicators of motor issues, with darkening often attributed to bearing currents. Sparking can result in lubricant oxidation and darkening due to electrical discharges, as observed in experiments depicted in Fig. 3.

5 Implementation of bearing current fault in the laboratory environment

To mitigate severe consequences and economic losses in production, it is advisable to implement strategies related to predictive maintenance. The system can be trained to predict potential failures using artificial intelligence algorithms in this context. However, acquiring the necessary training datasets is a significant challenge in implementing such approaches. To achieve accurate forecasting, gathering a large quantity of high-quality datasets is crucial. Hence, various faults were intentionally induced on the bearings in laboratory settings.

Faults were induced in healthy bearings to obtain faulty bearings for experimentation. An experimental test bench for fault implementation was meticulously constructed to facilitate this investigation. As previously mentioned, fluting typically occurs under conditions of low voltage and constant rotational speed, frosting manifests when the motor operates at variable speeds, and pitting is commonly observed in situations involving low speed and a high-voltage power source. The radial load was applied to the bearings through the belt's tension. An experimental test bench was constructed to investigate and analyze these different scenarios, as illustrated in Fig. 4.

Faults were intentionally induced under controlled conditions to mimic real-world scenarios. A diverse range of failures induced by bearing currents were successfully replicated through rigorous experimentation. Table 2 presents an analysis of all studied cases with shaft current faults.

In this paper, there were studied the fluting failure that appeared in case of 500 r/min and 10 A. In this scenario, the lubricant exhibited a slight darkening. With an increase in rotational speed, a clear case of fluting was observed on the inner raceway and a darkening on the outer raceway in the case of the DE-bearing, as illustrated in Fig. 5. Meanwhile, the NDE bearing displayed darkened inner and outer raceways with subtle fluting trails. Additionally, both bearings showed darkening of the rolling elements.

Table 2 Bearing current faults under different conditions

Conditions		Results		
Speed, r/min	Current, A	Inner ring	Outer ring	Balls
Drive end bearing				
100	10	Darkened race	Darkened race	No changes
100	20	Slight fluting	Darkened race	Darkened balls
500	10	Fluting	Darkened race	Darkened balls
800	10	Fluting	Darkened race/slight fluting	Darkened balls
800	20	Fluting/pitting	Slight fluting	Darkened balls/pitting
Non-drive end bearing				
100	10	Darkened race	Darkened race	Slightly darkened balls
100	20	Slightly darkened race	Darkened race	Darkened balls
500	10	Darkened race	Darkened race/slight fluting	Darkened balls
800	10	Slightly darkened race	Darkened race/slight fluting	Darkened balls
800	20	Frosting	Frosting	Darkened balls/frosting

Fig. 5 DE bearing at 500 r/min and 10 A

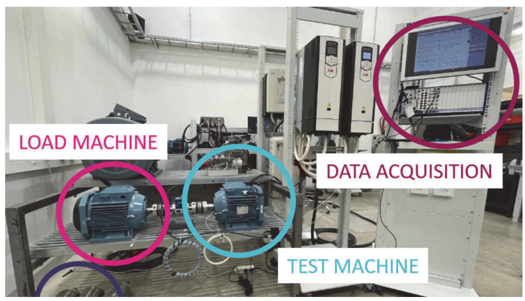

Fig. 6 Experimental test bench

6 Data analysis

Induction machines are the most spread among other motor types in production due to their easy maintenance, low cost, and high efficiency [47]. These machines are typically employed in variable-speed drives, which utilize power electronics for motor control, often using a frequency converter. Consequently, there is a rising incidence of inverter-induced shaft and bearing currents. This study focused on testing bearing faults in induction machines, and the experimental test bench is illustrated in Fig. 6. The setup comprises a testing machine, a loading machine, an accelerometer, and an acquisition system.

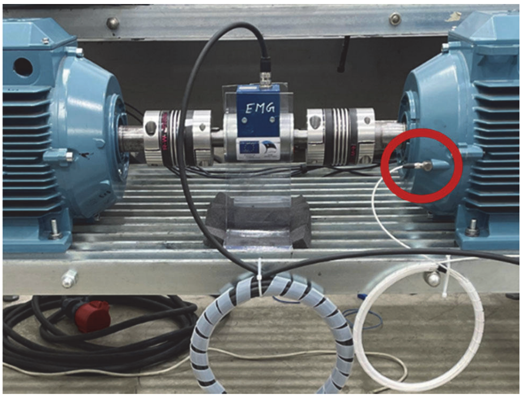

Fig. 7 Placement of triaxial accelerometer over the shaft

Dewetron DEWE2-M18 was used as an acquisition system for data gathering and processing. The parameters of the testing and loading motors are as follows:

Parameter on induction motor	Value		
Voltage, V	Y 690	D 400	D 460
Frequency, Hz	50	50	60
Speed, r/min	1460	1460	1760
Power, kW	7.5	7.5	7.5
Current, A	8.8	15.3	12.9
Power factor	0.79	0.79	0.81

Regarding bearing faults, their primary impact is on vibration rather than the current spectrum. The vibration spectrum is essential in this analysis of damaged bearings. In the experiments, a triaxial accelerometer K-Shear $\pm$ 100 g with a sensitivity of 50 mV/g placed over the shaft was used for vibration measurements. The rated values are related to acceleration and measured in g. The placement of the accelerometer is presented in Fig. 7.

This study's datasets encompassed information extracted from various parameters, including current, voltage, torque, speed, and vibration. Data collection occurred under diverse control settings (grid-fed, scalar, DTC) and various loads (0–100%). To streamline the process and optimize resource usage, it was unnecessary to analyze the entire signal. Focusing on one or two specific regions where the fault's influence is most pronounced sufficed. The primary objective involved identifying these crucial signal segments for training and extracting significant patterns.

As a result, numerous datasets contain precise information about healthy and faulty conditions. Vibration signals can detect faults at a very early stage. For this reason, prioritizing vibration signals is common practice in cases of defective bearings [48]. Identifying the frequency components associated with faults is crucial to detect early-stage damage. One effective method for pinpointing faults is employing the fast Fourier transform (FFT), which unveils the presence of these faulty frequencies. Figure 8 illustrates the vibration spectra of healthy and faulty bearings affected by fluting. Notably, the amplitude of the faulty bearing significantly surpasses that of the healthy one. This discrepancy arises because the damaged bearing encounters difficulties in the rotation due to surface damage. The fault exerts its most notable influence on the spectrum within the 0–500 Hz range, affecting even harmonics, especially at 100 and 300 Hz. In the 500–1000 Hz range, there are no prominent harmonics except for the 700 Hz frequency, which warrants examination for potential patterns during training. Frequencies beyond 1000 Hz do not significantly impact the analysis.

When conducting training, it is crucial to consider the control environment's characteristics. The amplitude and features of fundamental harmonics differ based on the type of control mode, especially when dealing with a faulty bearing. DTC exhibits a noticeable alteration in harmonics. In such cases, the fault's most pronounced impact on the spectrum is typically observed within the 0–500 Hz range, particularly affecting even harmonics. Conversely, the 500–1000 Hz range usually lacks prominent harmonics, except for the even harmonic at 700 Hz.

Furthermore, the load factor plays a significant role in shaping the fault's characteristics, as presented in Fig. 9. Load variations result in frequency shifts. Higher loads also have a greater influence on side harmonics. Like previous instances, the fault demonstrates its greatest impact within the 0–500 Hz frequency range.

These distinctive patterns offer valuable insights for effectively training the system. To improve prediction accuracy, it is advisable to consider various parameters of motor operation.

7 Fault prediction

In the case of predictions, the fluting case was studied. The data collected from the test bench are based on the impact of fluting on different areas of bearings, including inner and outer raceways. The same data were then utilized for training machine learning models to detect and predict fluting faults on different bearing parts. This research employs two distinct approaches in machine learning for fault detection and prediction of fluting faults. The initial approach involves training diverse machine learning models to detect damages on inner and outer raceways due to the fluting. The second approach centers on fault prediction, employing a machine

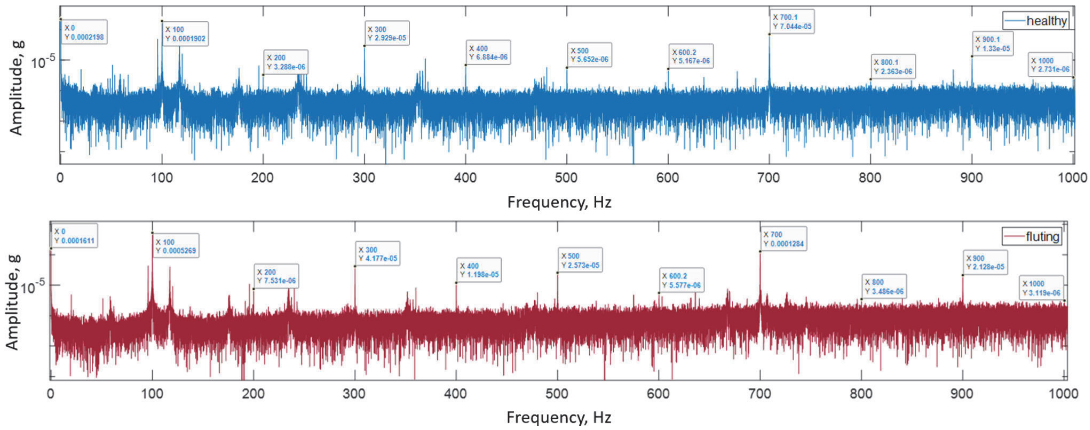

Fig. 8 Vibration spectrum of healthy bearing and bearing with fluting

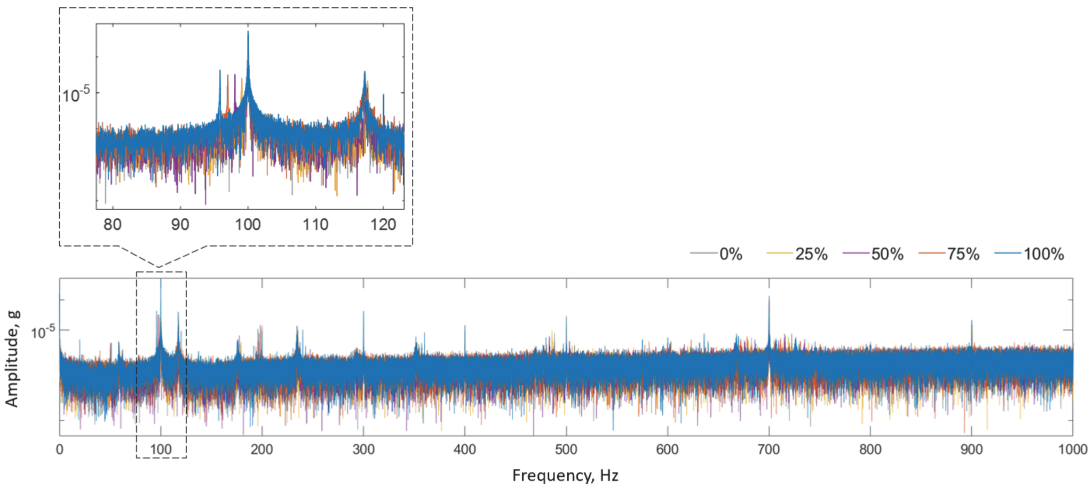

Fig. 9 Vibration spectrum of bearing with fluting under different loads

learning method based on signal spectra to train data and evaluate the likelihood of specific faults occurring. The technique implemented in this study is described in Fig. 10.

Machine learning models were employed to pinpoint faults upon collecting data samples from the electrical machine, encompassing instances of bearing faults and healthy states. Before training, the collected data underwent preprocessing, including denoising and normalization [49]. Denoising involved the use of low-pass filters and median filtering. The denoised signal was then segmented into datasets and divided into training and testing sets, with 20% of the data reserved for model validation. The electrical machine's sampling frequency was set at 20 kHz. The training dataset comprises 23 million data points with a sampling frequency of 20 kHz, covering various manifestations of healthy and faulty signals, including inner and outer faults. For this study, eight distinct machine learning models were selected to compare result accuracies. Table 3 thoroughly compares the validation accuracies of these models for bearing fault detection, covering all three scenarios of healthy states, inner faults, and outer faults. It is essential to highlight that these results have the potential for further improvement by incorporating higher-quality data and continuous endeavors to optimize the training of machine learning models. The results show that the Coarse Gaussian SVM demonstrates the highest validation accuracy among the trained models, closely followed by the Fine KNN model, which achieves equivalent accuracy.

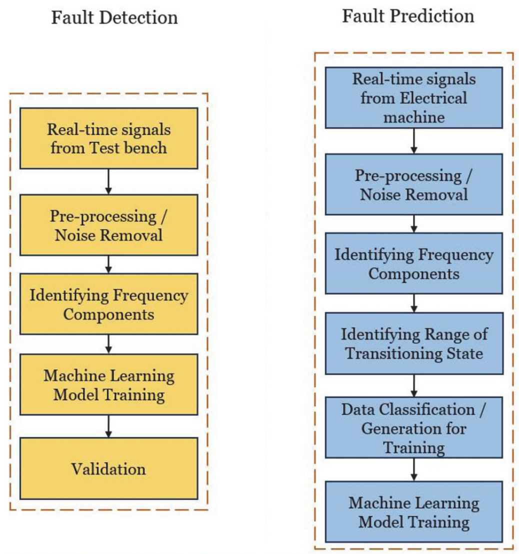

Fig. 10 Flowchart of the implemented method

Table 3 Bearing current faults accuracy comparison

Machine learning model	Accuracy (%)
Coarse tree	83.30
Coarse Gaussian SVM	91.70
Fine Gaussian SVM	84.70
Fine KNN	91.50
Narrow neural network	85.40
Medium neural network	85.40
Bilayered neural network	85.40
Trilayered neural network	85.90

The configurations for each model were set to be general and were not extensively optimized for improved results in this specific study. Careful consideration was given to the settings for each model to prevent overfitting on the training datasets. These same settings were considered when approaching the second part of the methodology to ensure a fair comparison between the trained models. Further enhancements can be explored by optimizing parameters for each machine learning model. In the case of neural network models, consideration was given to models with up to 16 hidden layers featuring a variable number of neurons, reaching up to 1000 per layer. Figure 11 illustrates the validation accuracy achieved by some of these trained models. It also displays the validation results for three of the trained models. In this study, eight different machine learning models were utilized for training and validating the model.

Although the neural network-trained models exhibit a slight lag in performance, there is optimism that with the inclusion of higher-quality data, it may be possible to refine and enhance the accuracy of these machine learning models. In the realm of fault prediction, the same models will be scrutinized. Still, the data will be prepared using a signal spectrum-based approach to assess whether the models can maintain high accuracy for predictions or if any notable changes occur.

The denoised data are now utilized to identify unique frequency components within inner and outer bearing faults, aiding in identifying fault occurrences within the incoming signal. This strategic use of denoised data holds promise for improving the precision of fault predictions. The gathered data are employed to identify frequency components crucial for training the machine learning algorithm for predictive purposes. This process is carried out independently for each case, with the frequency components identified based on disparities in their amplitudes between healthy and faulty scenarios. The chosen components are subsequently utilized in the algorithm training. An illustrative example of these components, along with their normalized amplitudes ranging from 0 to 1, is depicted in Fig. 12.

Through meticulous analysis of multiple samples, distinctive frequency components are identified for each occurrence of faults. These frequency components play a crucial role in delineating the range for the transition state, which represents the point at which a motor transitions from a healthy state to a faulty one. This information is vital in preparing data for training machine learning models to predict bearing faults. Every possible combination of frequency component values during the transition state is utilized in data preparation. Subsequently, the faults are categorized into five labels, with specific details outlined in Table 4.

The trained models underwent blind validation; a subset of the accuracy validation results is depicted in Fig. 13.

Table 5 compares the same models and their validation accuracies in the context of the fault prediction model. The accuracy of the models varies based on the complexity of each model. Nevertheless, the second approach proves valuable in predicting fault occurrences in the machine by issuing a warning in advance, signaling the likelihood of a specific fault. This early warning capability holds significant potential for mitigating economic losses. The accuracy of fault prediction hovers around 90%, a commendable result as it reliably identifies two faults with heightened accuracy. While these tests and models were evaluated using real-time data acquired from electrical machines, it is noteworthy that specific models claim up to 95% accuracy for fault detection based on analytical equations or simulations. However, such high-accuracy claims might not necessarily hold in real-time scenarios, as evident from Table 5; when the training data

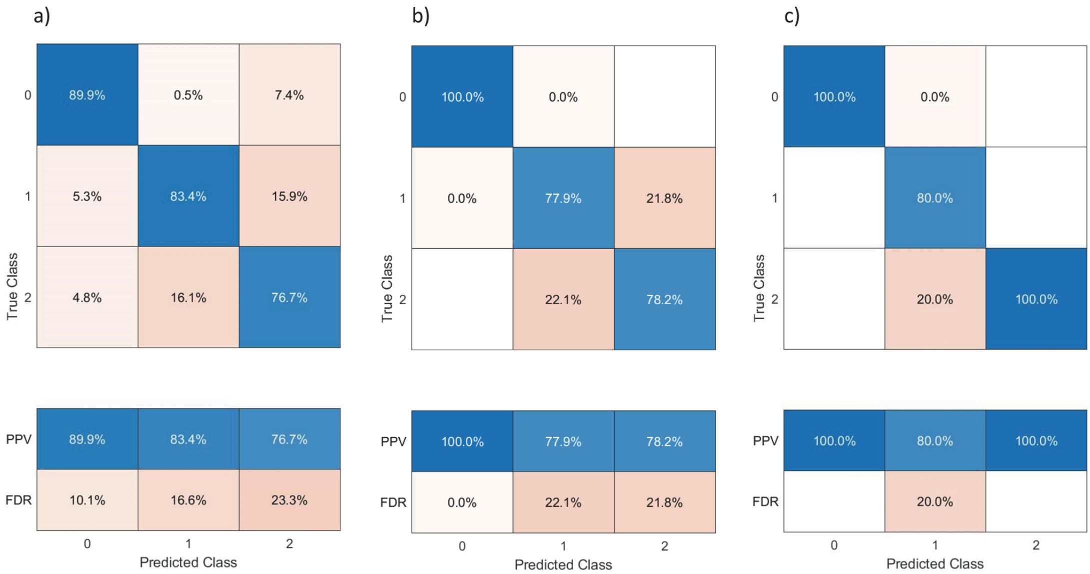

Fig. 11 Machine learning results **a** coarse tree, **b** trilayered neural network, **c** coarse Gaussian SVM

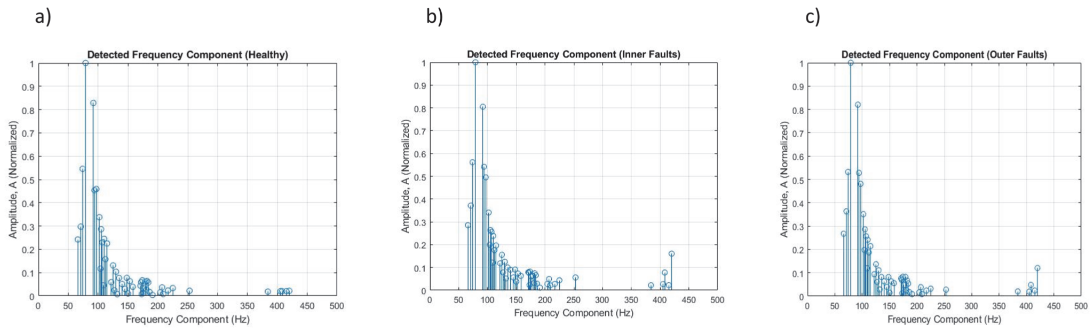

Fig. 12 Frequency spectrum with normalized amplitude of identified frequency components (0–1)

Table 4 Assigned classification

State of data	Assigned label
Healthy State	1
Chance for inner bearing fault to occur	2
Chance for outer bearing fault to occur	3
Inner bearing faulty state	4
Outer bearing faulty state	5

become more complex, models trained using neural networks demonstrate superior results compared to other methods.

The accuracy of these neural network models has notably increased compared to other models. Further improvements in accuracy can be achieved by training with higher-quality data and by combining multiple models trained in a singular fault detection model. The coarse tree stands out as the best performing model for fault detection, while its accuracy in fault prediction is comparatively lower. However, neural network models maintain a commendable level of accuracy, with the bilayered neural network yielding the best results in fault prediction. This underscores the potential for neural network models to achieve even better results with increased complexity and utilizing superior quality data samples.

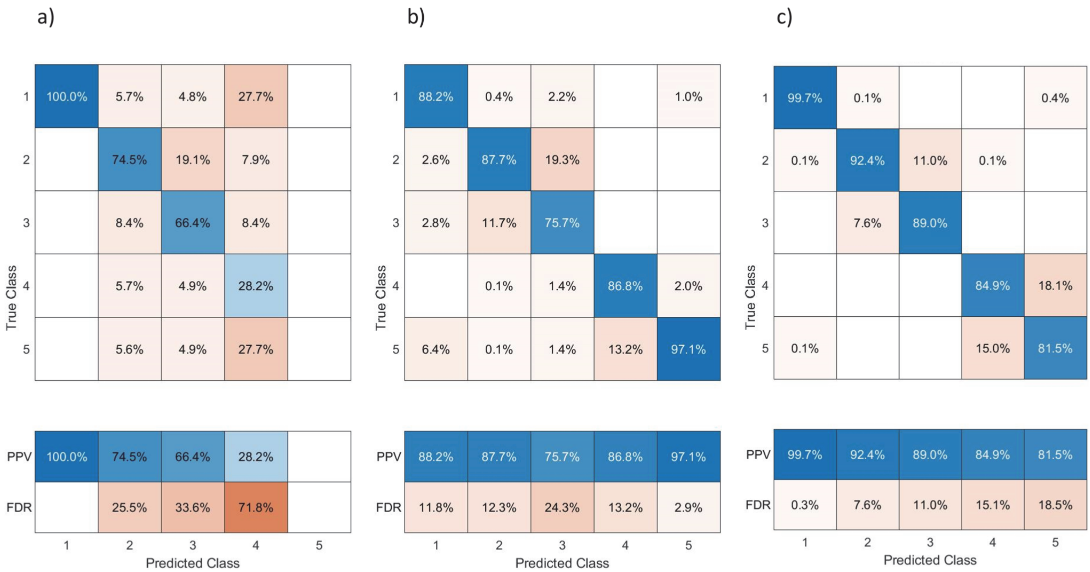

Fig. 13 Machine learning results **a** coarse tree, **b** coarse Gaussian SVM, **c** bilayered neural network

Table 5 Bearing current faults accuracy comparison

Machine learning model	Accuracy (%)
Coarse tree	68.50
Coarse Gaussian SVM	82.20
Fine Gaussian SVM	81.70
Fine KNN	53.80
Narrow neural network	90.00
Medium neural network	88.90
Bilayered neural network	90.20
Trilayered neural network	89.60

8 Discussion and conclusion

Induction motors play a critical role in various industrial applications, and failures in electrical machines, particularly in bearings, can have severe consequences. Monitoring the health of induction motors and their components has become standard practice in today's industry, thanks to the advent of the Internet of Things (IoT). As the industry shifts toward predictive maintenance, timely fault diagnosis has become paramount to prevent catastrophic failures. Consequently, academic research increasingly focuses on predictive maintenance for electrical machines, including induction motors.

This paper analyzes the causes of bearing faults, diagnostic possibilities, and a technique for predicting such faults. The results indicate that the method used for pre-fault detection in bearings achieves a high level of accuracy, approximately 90%, when employing neural networks. Frequency components were carefully chosen to pinpoint faults, aiding in model training. Subsequently, amplitudes of these selected frequency components were assessed for both faulty and healthy scenarios. Various combinations were then generated to detect faults in the electrical machine. These combinations were utilized to train additional models to determine the probability of fault occurrence within the machine.

Therefore, this technique effectively monitors and diagnoses faults in induction motors. However, validating the algorithm across various use cases and a broader range of faults is advisable. The algorithms trained using this approach can be deployed for real-time monitoring and detecting bearing faults in induction motors. Additionally, there is potential for further improvement by considering all potential faults exhibiting current fluctuations. In the future, it will be considered to train the algorithm for different fault types based on different spectra.

Author contributions Conceptualization was performed by KK; methodology by KK, HAR; formal analysis and investigation by MUN, SA; writing—original draft preparation—by KK; writing—review and editing—by BA, AK; funding acquisition by TV; supervision by AK.

Data availability Not applicable.

Declarations

Conflict of interest The authors declare no conflict of interest.

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Publication VII

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Signal Processing and Machine Learning Techniques for Predictive Maintenance of Rotor Bars in Induction Machine

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***Abstract*—New technological innovations, such as integrating information technology with physical devices, have emerged due to the industrial revolution 4.0. This has led to the development of intelligent machines, which fall under the Internet of Things (IoT) field. As a result of this integration, industrial processes have become more efficient and productive. In addition, it has reduced maintenance costs and downtime by applying condition monitoring and machine learning algorithms to electrical machines. Despite these advancements, there is still a lack of algorithms for predicting faults in electrical machines, which is an area of ongoing research. This paper presents a comparative analysis of different machine learning models with a combination of the signal spectrum-based machine learning approach for predicting broken rotor bars in induction machines as a potential solution for predictive maintenance. The method is validated by real collected data from a working induction machine. The preliminary comparison based on the training time and the results' accuracy is presented.**

Keywords—artificial intelligence, fault prediction, predictive maintenance, machine learning, neural network.

I. Introduction

Diagnostics and condition monitoring of electrical machines have gained practical importance due to their wide usage in different domestic and industrial branches [1], [2]. At the same time, every energy system is prone to failure. Unexpected faults eventually lead to inefficient resource usage and economic losses in production. While energy systems have many parameters that must be monitored to prevent unexpected failures, they are also complex mechanisms [3]. To avoid potential faults, the optimal solution is predictive maintenance [4].

Different intelligent approaches can be applied to accurately predict the electrical machine's operation [5], [6]. Authors in [7] introduce a new signal processing method based on decision tree algorithms for bearing diagnosis of low-speed machines. In [8], the authors propose a detection algorithm for line-to-line faults in photovoltaic arrays based on a support vector machine. In [9], a deep principal component analysis is applied to monitor non-linear processes. Authors in [10] propose a gear fault diagnosis method based on genetic mutation particle swarm optimization. In [11], an artificial neural network algorithm is used for condition monitoring and prediction of remaining useful life (RUL) in electrical equipment.

During the operation, the electrical machine is affected by different external forces and stresses, known as TEAM (thermal, electrical, ambient, and mechanical) stress [12]. Eventually, failures occur in the machine. As introduced in Fig. 1, broken rotor bars constitute, on average 10% of all faults in induction machines [13].

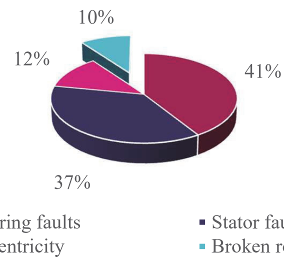

Fig. 1. Fault distribution in rotating machines.

This paper is focused on damages related to broken rotor bars and the possibility of predicting it by different intelligent algorithms. The impact of these faults on global electrical parameters was studied. These results were used to train the system to detect and forecast potential damages. For this, various machine learning algorithms were compared and validated.

II. The Fault Impact on Parameters of the Machine

In this study, the possibilities for predictive maintenance of broken rotor bars will be discussed. The stator current modifies a particular frequency when a fault occurs. The harmonics of a broken rotor bar can be quantitatively represented in the following equations in the frequency spectrum:

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$$f_{BR} = f_S \pm 2ksf_S \quad (1)$$

$$f_{BR} = \left[\left(\frac{k}{p}\right)(1\text{-}s) \pm s\right] f_S \quad (2)$$

where k = 1, 2, 3, ..., fs is the supply frequency, p is the number of pole pairs, and s is the slip of the machine [14].

The properties of electrical machines in the industry must be high efficiency, manageable control, and relatively low cost. Consequently, three-phase induction motors are the most widely used motor type [15, 16]. Generally, there are two types of algorithms for controlling induction machines: scalar-based and vector-based. When using scalar control, the motor's speed is managed by varying the stator voltages and frequency while maintaining a constant air gap flux [17]. However, this approach is appropriate without dynamics and variable loads. The alternative to conventional pulse width modulation (PWM) motors is direct torque control (DTC) [18]. The motor parameters (e.g., torque and flux) are regulated directly when using DTC. It denotes the absence of a modulator or other extra hardware. DTC technique is commonly used in manufacturing as it meets industrial demands.

In this study, different conditions of rotor bars in induction machines were tested – healthy and faulty (one, two, and three broken rotor bars). The parameters of the testing motor are as follows:

Parameter	Value		
Voltage, V	Y 690	D 400	D 460
Frequency, Hz	50	50	60
Speed, r/min	1460	1460	1760
Power, kW	7.5	7.5	7.5
Current, A	8.8	15.3	12.9
Power factor	0.79	0.79	0.81

The experimental test bench is shown in Fig. 2. As seen, the setup includes a testing machine, loading machine, acquisition system (Dewetron), and several rotors with different number of broken rotor bars. The tests were performed with rated speed.

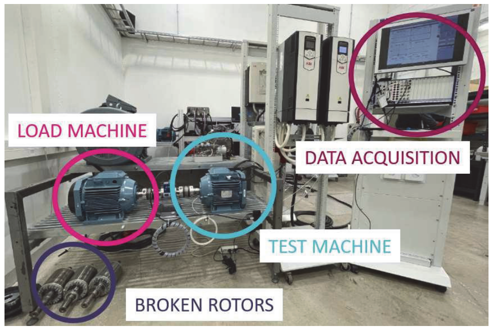


Fig. 2. Experimental test bench.

These datasets were received from vibration, torque, speed, currents, and voltage signals. Additionally, datasets were examined under various conditions, including loads (ranging from 0% to 100%) and control modes (grid-fed, scalar, and DTC) [19, 20]. Various datasets were consequently received.

The current spectrum is essential in this analysis since damaged rotor bars initially impact the current. On the frequency spectrum, faults cause ripples in speed and torque. Due to the scattered nature of the rotor and stator windings, the frequency spectrum of the stator and rotor current contains several harmonics even in optimal supply and healthy motor cases. For current measurements, Fluke current clamps were used.

For early fault detection, it is reasonable to consider tiny frequency components in the spectrum. It is possible by taking Fourier transforms of the incoming signal. For the ideal FFT with an infinite signal, there is the following equation:

$$f(t) = \sum_{n=-\infty}^{\infty} C_n e^{in\omega t} \cong \sum_{n=1}^{N} C_n e^{in\omega t};\ \omega = 2\pi \frac{f}{f_s}; \quad (3)$$

$$C_n = \frac{1}{2\pi}\int_{-\infty}^{\infty} f(x)\, e^{-inx} dx,\ n = 0, \pm 1, \pm 2, \dots \quad (4)$$

where f(x) is the signal under investigation, Cn is the complex Fourier, and fs is the sampling frequency (100 kHz).

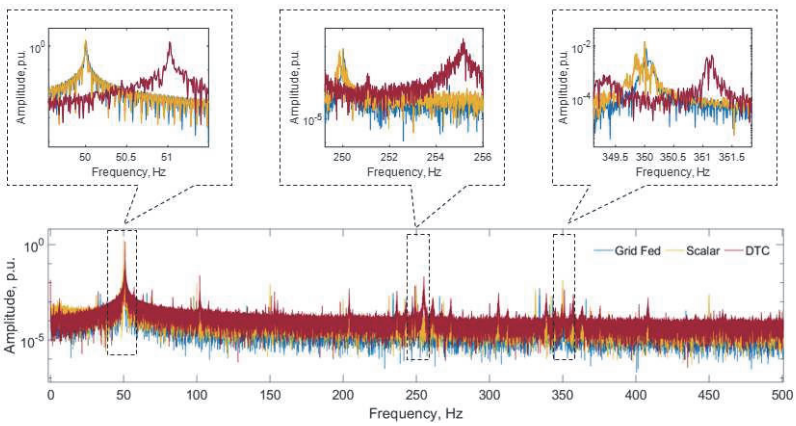


Fig. 3. Current spectrum of the healthy motor in different control modes.

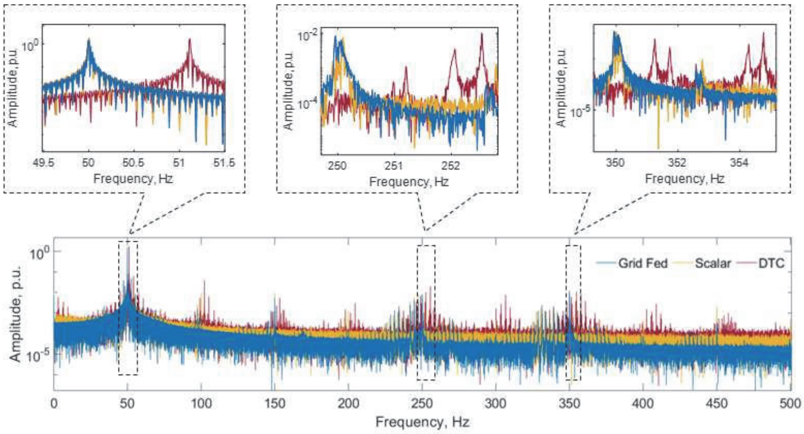


Fig. 4. Current spectrum of the motor with broken rotor bars in different control modes.

It is not necessary to evaluate the complete signal – it will save training time and simplify the training process. Instead, algorithm training will be done in areas where the fault's impact is the highest. The current spectrum of the healthy motor in different control modes is presented in Fig. 3. As seen, grid-fed and scalar modes behave similarly. At the same time, the main finding is related to DTC, where a significant shift in frequency components occurred.

It is observed that the fundamental component shifts in the frequency domain when a fault occurs while the machine is working in DTC control mode. This shift does not happen in the case of the grid and scalar control modes. The net generated torque decreases with the increased number of broken bars. While in the case of the DTC environment, the controller tries to maintain constant torque by dropping the speed. The speed drop is maintained by decreasing the frequency of the fundamental component.

As seen in Fig. 4, similar frequency shifting phenomena occurred in the case of damaged rotor bars. The problem caused the amplitude increase of the fundamental frequency components. By fault development, more noise emerges in the frequency spectrum.

Two presentable regions of the spectrum can be studied and trained on. The first one is the frequency range of 0-500 Hz when the fault significantly impacts even harmonics. For fault prediction, harmonics at 750 Hz should also be considered. Table I presents the fundamental frequency of healthy and faulty cases under different control environments.

TABLE I. CURRENT AT FUNDAMENTAL FREQUENCY (50 HZ) IN DIFFERENT CONTROL ENVIRONMENTS

		Healthy motor	***Motor with broken rotor bars***
Grid fed	X	50	49.99
	Y	1.513	1.425
Scalar	X	50	50
	Y	1.762	1.8
DTC	X	51.02	51.12
	Y	1.477	1.71

* X is the frequency (Hz), and Y is the amplitude (p.u.)

Fig. 5 shows the current spectrum of the healthy motor under various loads. It is evident that altering the load has a distinctive effect on the spectrum's behavior. At the same time, Fig. 6 presents the current spectrum of the faulty motor, which also shows that behavior is changing due to the load increase.

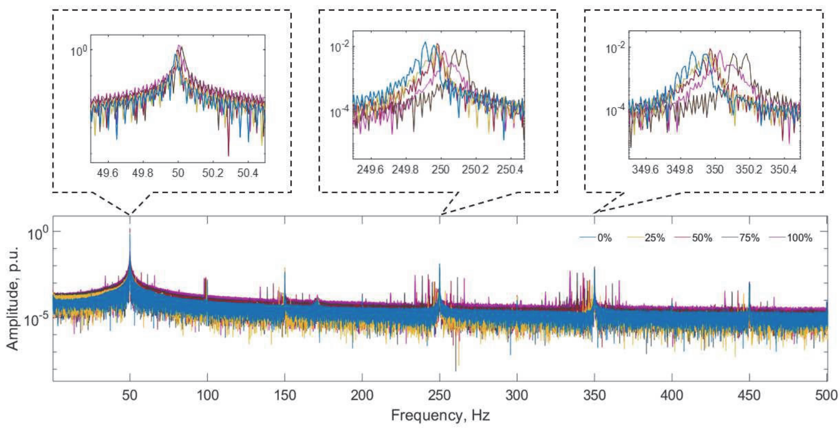


Fig. 5. Current spectrum of the healthy motor under different loads.

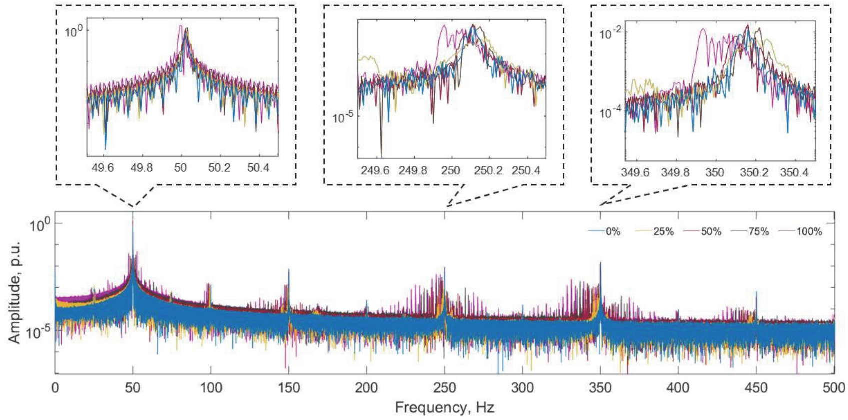


Fig. 6. Current spectrum of the motor with broken rotor bars under different loads.

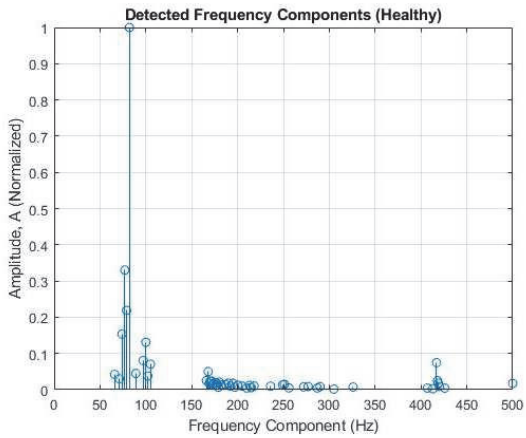
The frequency ranges of 0-500 Hz and 750 Hz, where the damage impacts even harmonics, are presentable regions for both the healthy and faulty spectra to be considered during the training. Table II presents the fundamental frequency of healthy and faulty cases under different loads.

TABLE II. CURRENT AT FUNDAMENTAL FREQUENCY (50 HZ) IN DIFFERENT LOADS

		Healthy motor	*Motor with broken rotor bars*
0%	X	49.98	50.02
	Y	0.6868	0.77
25%	X	49.99	50.03
	Y	0.8153	0.7992
50%	X	49.99	50.02
	Y	0.9466	1.068
75%	X	50.02	50.03
	Y	1.306	1.219
100%	X	50.01	49.99
	Y	1.364	1.425

III. METHODOLOGY AND RESULTS

Here, the signal spectrum-based machine learning approach [21] uses multiple faults, including one and two broken rotor bars in the electrical machine. After narrowing down the frequency components, the data is further processed to identify the frequency components which will be used for training machine learning algorithms for fault prediction. This is done separately for healthy, one broken rotor bar (1BRB) and two broken rotor bars (2BRB). This process is carried out on multiple samples from different machines, so the identified frequency components are universal for each case and not specific. After identification of the frequency components, their amplitudes are used to define the states in which the electrical machine is, whether it is healthy, faulty, or in a transition state between healthy and faulty. Such an example of detected frequency components with normalized amplitudes between 0 – 1 for each case is shown in Fig. 7.



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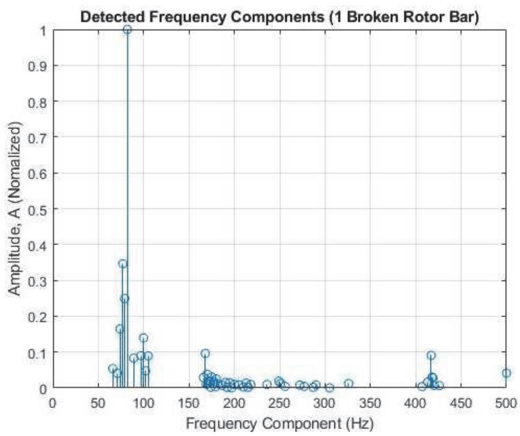

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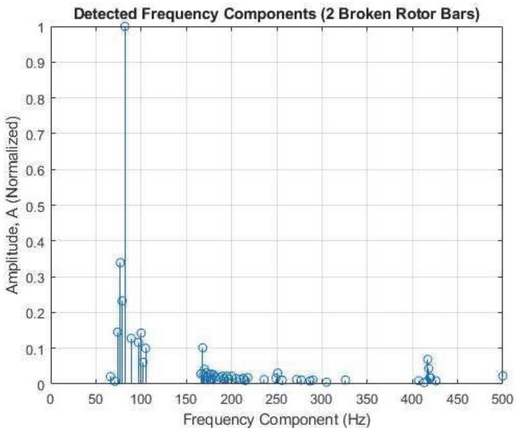


(c)

Fig. 7. Frequency spectrum with normalized amplitude (0 – 1) of detected frequency components: a) healthy case, b) one broken rotor bar (1BRB), and c) two broken rotor bars (2BRB).

After careful analysis of multiple samples from different machines, the amplitude ranges of these frequency components for each case are determined for fault occurrence. These determined values are then used to define the range of transition state, which is a state when a motor is transitioning from a healthy phase towards a faulty phase, which will then be used to prepare data for training of the machine learning models for prediction of faults of the electrical machine.

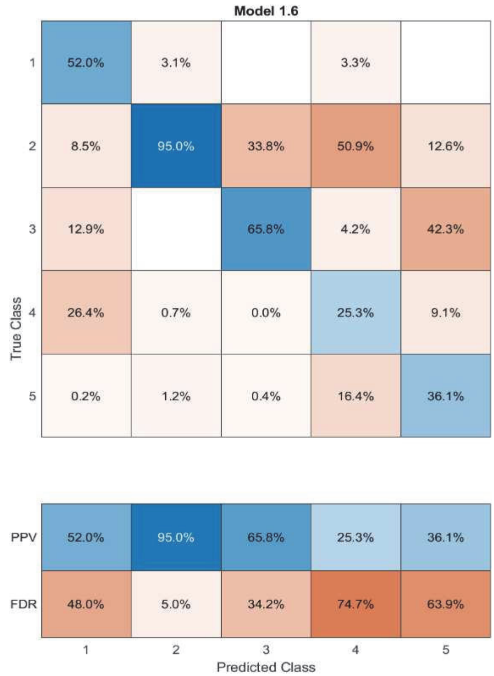
Once the range is defined, data is prepared for training the machine learning model with every possible combination of frequency component value in the transition state. In this case, the probability of the faults is not defined, whereas they will be classified into different labels for different faults along with their transition from a healthy state. This way, it will be easier to predict if there is a chance of a fault occurring in the electrical machine. Here, 1BRB and 2BRB faults are considered for training the machine learning algorithm.

After the data is generated for the transition state using interpolation between its defined range, the next step is to train the machine learning model and test it for validation. The data points for validation were randomly generated from the defined ranges for the transition state, whereas healthy and faulty cases were collected from an electrical machine. For the training, 150,000 data samples were used with a validation of 18,000 data samples which will be increased further. The data samples for training are classified into five labels, shown in Table III.

TABLE III. CLASSIFICATION ASSIGNED

State of data	Classification label
Healthy State	1
Transition to 1BRB Fault	2
Transition to 2BRB Fault	3
1BRB Faulty State	4
2BRB Faulty State	5

Machine learning models were trained using blind validation, i.e., the samples used to validate the models were not used for training. For this paper, eight models were considered, with the majority of the neural networks for training. Fig. 8 shows the confusion matrix for the best-trained and worst-trained models.



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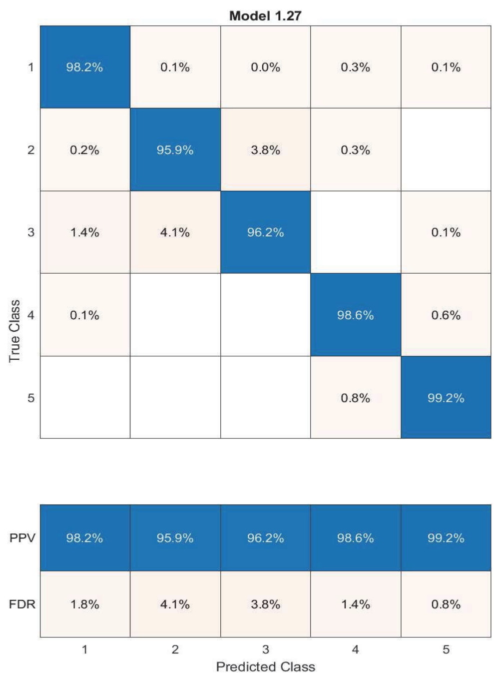

(b)

Fig. 8. Machine learning results: a) Gaussian Naive Bayes, b) Wide Neural Network.

Table IV presents the time taken for training different machine learning algorithms. It also gives the comparison analysis validation result for different machine learning trained models.

TABLE IV. MACHINE LEARNING MODELS COMPARISON RESULTS IN TERMS OF TIME AND ACCURACY

Machine learning algorithm	Accuracy (validation)	Time (s)
Fine Gaussian SVM	86.00 %	21.808
Fine KNN	85.80 %	9.48
Coarse Tree	75.60 %	0.85
Linear Discriminant	92.60 %	1.73
Gaussian Naive Bayes	60.60 %	2.22
Kernel Naïve Bayes	80.80 %	291.94
Narrow Neural Network	95.90 %	47.11
Medium Neural Network	96.20 %	40.36
Wide Neural Network	96.60 %	27.61
Bilayered Neural Network	96.40 %	47.82
Trilayered Neural Network	95.50 %	49.74

The idea was to compare and validate different variations of layers and number of neurons. Most of the neural network trained models have high accuracies and are lying in the same range. Compared with one fault presented here [17], the accuracies for the models have dropped with the introduction of multiple faults. The training time taken by wide settings of neural networks takes less time to train than other neural network models and has high accuracy. Whereas some different machine learning model takes less time, their accuracy is way lower. The worst-performing machine learning model among the compared models was the Gaussian Naïve Bayes model, with an accuracy of only 60.60 %. It can be further improved with more extensive data sets but must be validated further.

IV. CONCLUSION AND DISCUSSION

Although there has been significant research in predictive maintenance, a reliable predictive maintenance algorithm has yet to be fully developed. Currently, most algorithms focus on detecting faults rather than predicting them. While some commercial products are available, they are costly and specific to certain companies. Additionally, the technology used in these products is often proprietary and includes both hardware and software components. The algorithm discussed in this paper aims to provide a more stable and versatile solution for predicting faults in electrical machines, which can be applied to various types of defects.

This paper presents a comparative analysis between different machine learning algorithms regarding training time and accuracy for predictive analysis of electrical machines faults. The study further validates the signal spectrum-based machine learning approach algorithm for predicting faults in an electrical machine. The method involves including multiple defects of electrical machines for data preparation and training machine learning algorithm models for validation. Although it requires some pre-processing for the incoming signals, the time taken is short, and the models can be tested in real-time scenarios. The results are promising and endorse that the algorithm can be used for fault prediction of multiple fs with higher accuracy.

Despite progress in the field, there is still room for improvement in the method for predicting faults in electrical machines. This includes expanding the algorithm’s scope to cover a broader range of faults and accounting for various combinations of healthy, transition, and faulty states. This would make the algorithm more versatile and valuable for predictive maintenance. Additionally, incorporating more layers of transition states and combinations could improve the algorithm's ability to determine the urgency of maintenance. With further development and testing, this real-time approach may be possible to predict different electrical machines' faults.

The approach presented in this work is still in its early stages. It would be beneficial to test its general approach and assess how well it can predict faults in electrical machines by changing the faulty signal. Further research should focus on testing the algorithm for different faults and evaluating its accuracy to enhance its effectiveness. Additionally, future work should include testing the algorithm with larger data sets and more complex defects.

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Publication VIII

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Preliminary Analysis of Mechanical Bearing Faults for Predictive Maintenance of Electrical Machines

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***Abstract*—Nowadays, electrical machines are used in numerous applications, where unexpected faults are to be prevented. Sophisticated technologies are demanded to be able to manage big data of machines conditions and store these datasets remotely using cloud computation. This data is necessary for algorithms to be trained and predict further failures. This paper presents a study of bearing faults for predictive maintenance. The data collection in lab environment and its preliminary analysis is introduced. The impact of different control modes and loads on global parameters of rotating machines is discussed. The fault classification and prediction techniques are presented.**

Keywords—artificial intelligence, bearings, condition monitoring, electric motors, fault detection, Fourier transforms, predictive maintenance, rotating machines.

I. Introduction

Condition monitoring and timely fault detection in electrical machines have gained a reasonable importance. Nowadays, every energy system represents a complicated mechanism that is prone to damage [1]. In order to provide a reliable operation, it is needed to monitor many parameters to prevent unexpected failures. As information technologies are developing rapidly, there are used advanced diagnostic approaches to detect and predict faults. The possibilities emerging with Industry 4.0, especially cloud computing and Internet of Things, lead to more efficient diagnostics – predictive maintenance, which attracts big data and numerical models of the systems. This concept, as presented in Fig. 1, uses remote condition-based monitoring over scheduled maintenance routine, which in turn reduces the use of logistic, energy, human, and material resources.

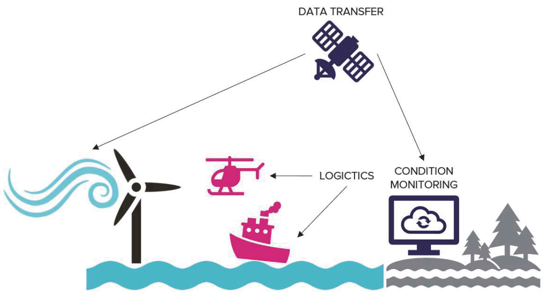


Fig. 1. The idea of remote condition monitoring.

There are many algorithms that can be used for system training. Authors in [2] present a fault diagnosis method based on convolutional neural networks. In [3], there is proposed an intelligent diagnosis method for bearing faults using compressed data acquisition and deep learning. In this research [4], authors present a diagnosis approach that combines empirical wavelet transform and fuzzy entropy for bearing fault detection. In [5], authors introduce a possibility of machine health monitoring based on recurrent unit networks. Authors in [6] introduce a method for classification of transformer winding faults combining frequency response analysis and support vector machines. In [7], authors propose a fault diagnosis method for rotating machines based on feature learning of thermal images. Authors in [8] introduce a gear diagnosis method based on particle swarm optimization and probabilistic neural networks.

The main challenge is the amount and quality of training data. For effective training, it is crucial to study the nature of machine faults, their causes and impacts on global parameters.

The research leading to these results received funding from the EEA/Norway Grants 2014–2021, Industrial Internet methods for electrical energy conversion systems monitoring and diagnostics. The "Industrial Internet methods for electrical energy conversion systems monitoring and diagnostics" benefits from a 993000 € grant from Iceland, Liechtenstein, and Norway through the EEA Grants. The project aims to provide research in the field of energy conversion systems and to develop artificial intelligence and virtual emulator-based prognostic and diagnostic methodologies for these systems. The project contract with the Research Council of Lithuania (LMTLT) No is S-BMT-21-5 (LT08-2-LMT-K-01-040).

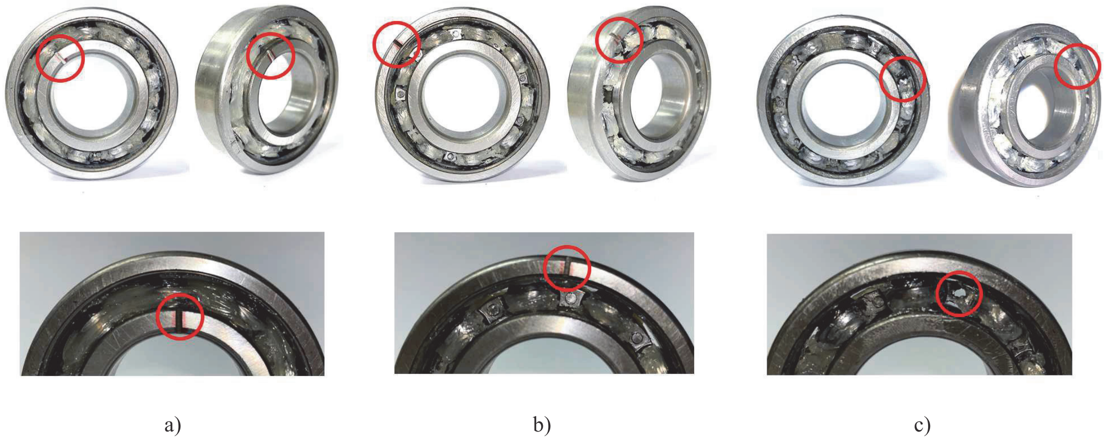


Fig. 2. Mechanical bearing faults: a) fault in outer ring, b) fault in inner ring, c) damaged cage.

II. Data Collection and Pre-Processing

Bearings are one of the most important parts of the rotating machine. The production and design of the bearings are conducted under strict quality conditions. At the same time, there are different internal and external loads that affect the bearings during the motor operation [9]–[11]:

- Mechanical damages,
- Contamination,
- Material fatigue,
- Improper lubrication,
- Shaft currents.

Any unexpected failure can lead to fatal consequences in production [12]. To avoid it, constant condition monitoring must be provided.

Bearing damages can be described mathematically by using the following equations, which refer to the natural frequencies of faulty bearings. Faulty frequencies can be defined for outer ring (1), inner ring (2), rolling elements (3), and cage (4).

$$f_{or} = \frac{N_b}{2} n \left(1 - \frac{D_b}{D_c} \cos\beta\right) \tag{1}$$

$$f_{ir} = \frac{N_b}{2} n \left(1 + \frac{D_b}{D_c} \cos\beta\right) \tag{2}$$

$$f_b = \frac{D_c}{2D_b} n \left(1 - \left(\frac{D_b}{D_c} \cos\beta\right)^2\right) \tag{3}$$

$$f_c = \frac{n}{2} \left(1 - \frac{D_b}{D_c} \cos\beta\right) \tag{4}$$

where Nb – number of rolling elements, Db – diameter of rolling element (mm), Dc – bearing pitch diameter (mm), β – contact angle (degrees), n – mechanical rotor speed (Hz) [13].

As presented in Fig. 2, the most frequent mechanical bearing faults were studied: faulty outer ring, faulty inner ring, and damaged cage. In order to teach the system to predict the potential failures in the machine, a proper amount of qualitative data is required. The experimental test bench for data collection is presented in Fig. 3.

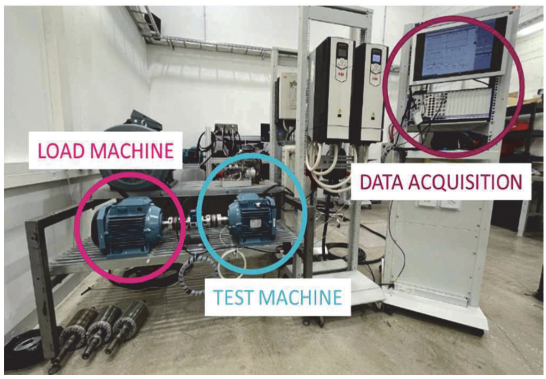


Fig. 3. Experimental test bench.

As seen, the setup includes testing machine, loading machine, acquisition system (Dewetron). The parameters of the testing motor are as follows:

Parameter	Value		
Voltage, V	Y 690	D 400	D 460
Frequency, Hz	50	50	60
Speed, r/min	1460	1460	1760
Power, kW	7.5	7.5	7.5
Current, A	8.8	15.3	12.9
Power factor	0.79	0.79	0.81

In this case, healthy as well as faulty bearings were placed into the test motor. The data was gathered and recorded thought acquisition system. As a result, numerous datasets of bearings' condition were collected.

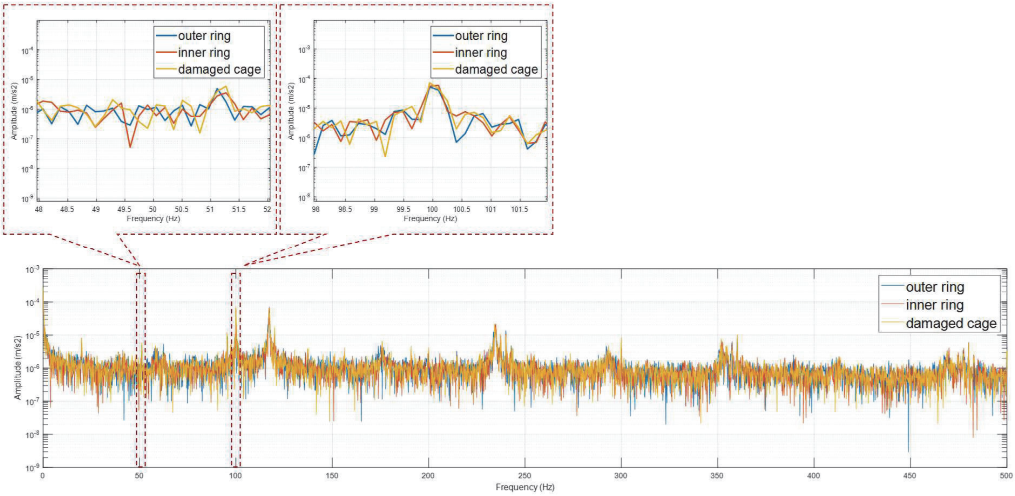


Fig. 4. Comparison of mechanical bearing faults on vibration spectrum.

In order to have accurate fault patterns for training purposes, there were considered different operation conditions of the rotating machine. First of all, to study an impact of the fault on machine parameters, the signals were taken from current, voltage, torque, speed, and vibration. The data was collected in different control environments: grid fed, scalar control, and direct torque control. Besides, there were considered different levels of motor load – the tests were conducted at 0%, 25%, 50%, 75%, and 100% loads.

For timely failure detection, it is important to consider specific frequency components in the harmonic spectrum [14]. These components can be detected in the frequency domain by taking Fourier transforms of the signal coming from the machine. As the bearing fault has the primary fault effect on the vibration spectrum, vibration patterns were prioritized in this case.

Fig. 4 introduces the preliminary comparison of different mechanical faults on vibration spectrum, which can appear in the bearings. As seen, there are some regions, where the impact of fault is the highest. However, it is important firstly to study the impact of fault on fundamental harmonics. Then, it is reasonable to explore, how the damages influence on side harmonics. As a result, it is possible to extract fault pattern from each signal comparing it with healthy signal. Those patterns will be used for system training.

In this research, the impact of machine operating conditions was studied. As presented at Fig. 5, there were compared several control environments of the motor and their impact on vibration spectrum. It is important to consider this fact during the system training. As seen from the graph, the signals have a different behavior on fundamental harmonics. In this case, the understanding of this difference will be important in detection of potential fault at early stage.

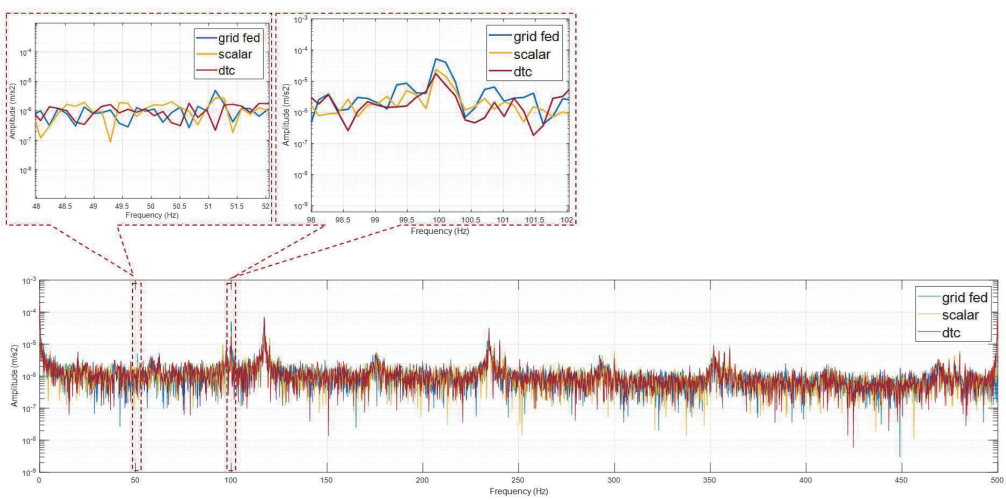


Fig. 5. Faulty bearing with damaged outer ring on vibration spectrum for different control enviroments of the motor.

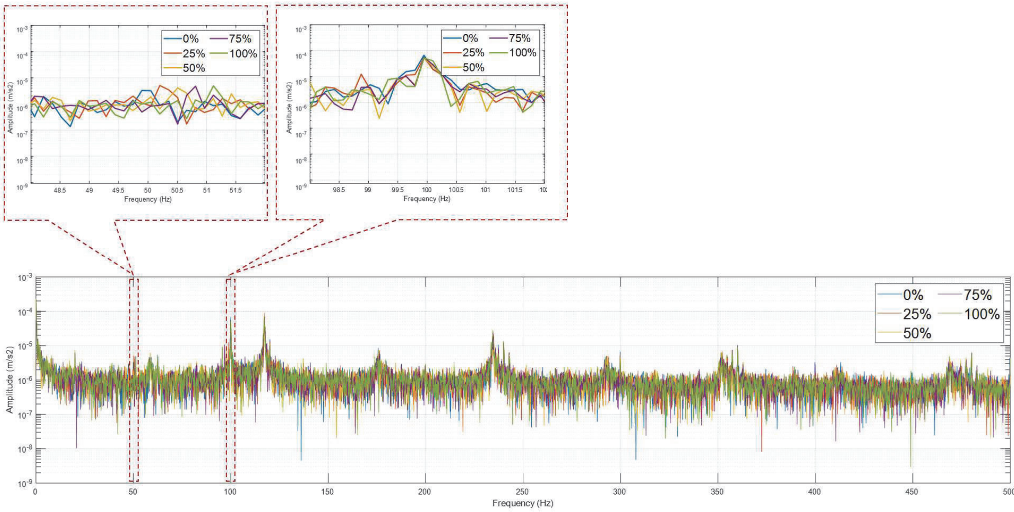


Fig. 6. Faulty bearing with damaged outer ring on vibration spectrum for different loads of the motor.

Besides, the impact of load on machine performance was studied. In this case, the tests were performed on several load levels from 0% to 100%. As seen from Fig. 6, there is a shifting in frequency depending on load level at the fundamental harmonics of 50 Hz. This difference will be also considered for implementation of predictive maintenance.

The vibration signals gathered through the system will also include some noise due to the effect of external parameters. It is also considered to denoise the signal using wavelet or a smoothening function focused on vibration signals. For the preliminary analysis, the denoising is not considered and the signal is taken as such to see the effect of denoising functions later on.

III. Fault Classification and Predictive Maintenance

The data is gathered using the acquisition system and then classified into healthy and faulty cases for machine learning model training. The data here consists of multiple faults on different loads including inner, outer and damaged cage of the bearing faults. Data samples are classified into two stages: healthy and faulty with each fault having its own label. The labeling and classification of data samples are shown in Table I.

TABLE I. CLASSIFICATION AND LABELING OF TRAINING DATASETS

Data Sample Type	Label Assigned
Healthy signal	0
Faulty state (inner faults)	1
Faulty state (outer faults)	2
Faulty state (damaged cage faults)	3

The data used for training is gathered at a sampling frequency of 20 kHz and consists of 3 million data points with 150k data points used for blind validation of the trained model.

The incoming signal is analyzed and the frequency components are identified which will be used to extract features for training of the models.

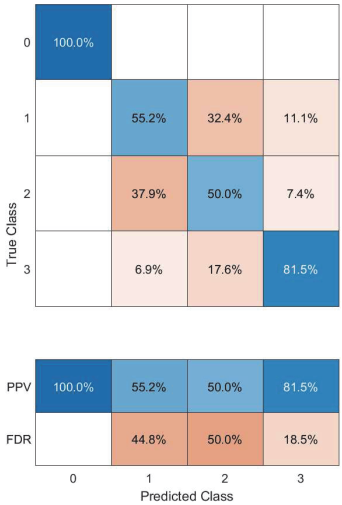
The classified data is then used to train models using different machine learning algorithms. The models were cross validated to avoid data leakage and overfitting of the models. The training data sample was evenly divided for each state. Multiple machine learning techniques were used to train the model among which top 5 are considered to be presented in this paper.

Fig. 7 shows the confusion matrix for two of the machine learning models with respect to their accuracies. Here, for the training of models, conventional machine learning techniques are used to keep the training simple and quick. As the combination of faults becomes more complex, the time of training increases, which is why deep learning techniques were not considered for this study. In future, deep learning techniques will also be considered to check on the comparison between machine learning and deep learning techniques with respect to time and accuracy.

For comparison purposes, current signature was also considered for the training of machine learning models for the same set of faults. It is to see which one gives a better result as compared with the other. As, the vibration signals for each case is too near each other and there might also be noise present it becomes difficult to differentiate them with ease. Whereas, in the case of current spectrum it is much easier to identify the frequency components, which are fluctuating because of faults.

The current spectrum was analyzed using signal spectrum-based approach [15] and spectrum analysis [16] was used to cover up missing data points.

a)



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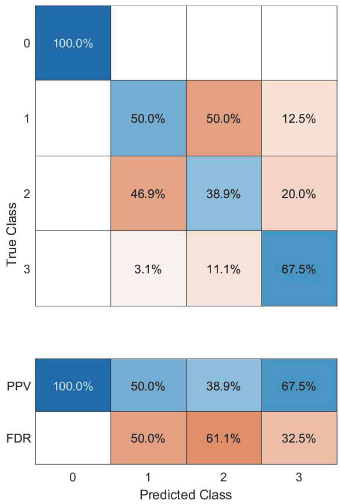

Fig. 7. Confusion matrix for machine learning algorithms: a) Linear Discriminant, b) Wide Neural Network.

Fig. 7 shows the accuracy for the validation of each case, which can also be improved by adding more quality data and denoising the signal. Increasing the data set for training might also help to increase the accuracy of the end result. This also solidifies that it might be possible to train models for prediction of faults occurrence of bearings but it will need more quality data set to train a good model. As the accuracy for healthy case is high, whereas for faulty cases as the vibration signals are too near, there is a need for more data samples to improve quality.

The above data shows that in each other case the accuracy is consistent although low but it can be improved further but needs more processing and samples. Positive predictive value (PPV) shows the percentage of data samples that were correctly predicted, whereas false detection ratio (FDR) is the percentage of the signals that were detected wrongly on validation by the trained model. Table II shows the comparison between different machine learning techniques with respect to accuracy.

TABLE II. COMPARISON RESULTS FOR VIBRATION SPECTRUM

Machine Learning Algorithm	Accuracy (Validation)
Linear Discriminant	70.80 %
Linear SVM	65.80 %
KNN	58.00 %
Wide Neural Network	66.70 %
Medium Neural Network	65.70 %

The accuracy of the different configurations of neural network is more consistent than the others except in the case of linear discriminant. Although the combination of faults is complex, it might still be possible to further improve the results by adding more quality data and pre-processing the signal to remove noise. As compared to the vibration signals, current spectrum gives better results and the faults can be distinguished more significantly. The results for current spectrum for same set of faults is shown in Table III.

TABLE III. COMPARISON RESULTS FOR CURRENT SPECTRUM

Machine Learning Algorithm	Accuracy (Validation)
Linear Discriminant	85.60 %
Linear SVM	82.80 %
KNN	78.00 %
Wide Neural Network	84.40 %
Medium Neural Network	85.50 %

The accuracy of current spectrum trained models [15] is higher from the vibration spectrum as the faults there are more visible and distinct, but the accuracy for vibration spectrum can be increased further by doing noise removal and smoothening of the signal further. Adding more data samples will also help in training a better model utilizing vibration spectrum.

IV. CONCLUSION

With the advancement in technology and the mind set to move towards cost-effective industrial applications, predictive maintenance has become one of the foremost essentials for the industry. With most of the industries moving towards predictive maintenance from scheduled maintenance to cut down costs of unforeseen shutdowns and resources, researchers are proposing new designs and algorithms utilizing machine learning and internet of things. The diagnostics of electrical machines is also more focused on online methods as compared to the offline ones so that the industrial processes can be made more efficient.

In this paper, prediction of electrical machines bearing faults based on vibration spectrum analysis using machine learning is analyzed. Preliminary analysis is done on the collected data using signal spectrum approach in addition to machine learning models. As, the vibration signals are volatile and there might be noise present in the signal, the results show an accuracy around 70.80 % for linear discriminant method. Whereas, the neural network result shows 66.70 % accuracy, which needs to be analyzed and improved further. Whereas, if current spectrums are considered this accuracy goes to around 85.00 % for similar case. Hence, it might be possible to predict when a healthy machine is transitioning towards faulty state for a complex combination of faults based on the trained model but further analysis is needed. The results can be further improved by denoising the signal and adding more quality data set for training of models.

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Publication IX

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Preliminary Analysis of Bearing Current Faults for Predictive Maintenance

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***Abstract*—Bearings faults, one of the most common mechanical failures in the electrical machine, have been the diagnostic interest for a long time. The questions related to bearing currents have become an important issue due to a growing number of motors running with variable-speed drives. This paper introduces a bearing current problem presenting the leading causes and damages of induction machine bearing currents. As the world is moving towards Industry 4.0 standards and fault prediction in production is becoming an extremely crucial topic, this paper presents a pre-processing of training datasets and possibilities for predictive maintenance. The experimental results of fault implementation in a laboratory environment to collect training datasets are discussed.**

Keywords*—*AC motors, artificial intelligence, ball bearings, condition monitoring, fault detection, machine learning, predictive maintenance

I. Introduction

Three-phase induction motors are the most commonly used type of electrical machine [1]. At the same time, implementing frequency converter control is the most cost-effective and easiest way to ensure the optimal operation of the electrical machine. However, such approaches frequently lead to shaft currents induced by frequency converters, which is a challenging problem in production and industry. In the case of motors with a power of more than 100 kW, there are some solutions to decrease bearing currents, such as insulated bearings or shafts [2], conductive greases [3], grounding contacts [4], frequency converter regulation [5]. The effectiveness of the aforementioned methods depends mainly on the motor parameters and ambient environment. However, there is always a risk of shaft current leakage.

Initially, the bearing damage caused by shaft currents is impossible to detect visually [6]. Shaft currents do not always flow through the bearing. However, if it flows, the fault occurs in those parts where the lubricant coating is the thinnest due to the overload in this area. There are many ways to identify bearing currents in the electrical machine using different methods, such as Rogowski coil [7], currents transformer [8], common multimeter, etc. However, as the bearing faults primarily affect the vibration rather than the current spectrum, it is reasonable to consider vibration analysis [9].

Every energy system represents a complicated mechanism that needs monitoring of numerous parameters, which in turn requires significant computational resources. Due to this big data, it is reasonable to use advanced diagnostic approaches based on artificial intelligence. These intelligent algorithms will teach the system not only to detect but also to predict potential faults. Regarding the bearing diagnosis in electrical machines, there are frequently used the following algorithms: decision trees [10], support vector machines [11], principal component analysis [12], and genetic algorithms [13]. This research prioritized approaches based on neural networks due to the ability for fast and effective learning.

II. Bearing Currents – Causes and Damages

There are several types of bearing current faults [14]. As presented in Fig. 1, bearing current faults differ from other mechanical damages. Fluting traces can often be found on the bearing raceways, as shown in Fig. 1a. This damage is clearly visible, as in this case, multiple lines occur across the bearing raceway. Fluting usually appears due to the constant rotational speed and low voltage. Frosting is another bearing current fault, which can be detected on the bearing raceways if the motor operates at varying speeds. The appearance of this fault is shown in Fig. 1b. Pitting appears when the motor is supplied by a high-voltage source and runs at low speed. Therefore, pitting is usually presented in DC motor applications, e.g., railway motors. In the case of pitting, small craters are observed on the bearing raceway, as shown in Fig. 1c.

More frequently, the visible condition of the lubricant can indicate a possible problem in the machine. One of the indicators, which can point to the presence of bearing currents, is the darkening of the bearing lubricant. In this case, the sparking caused by electrical discharges oxidizes the lubricant and changes its color. This is the first sign of a possible problem related to shaft currents.

The research leading to these results received funding from the EEA/Norway Grants 2014–2021, Industrial Internet methods for electrical energy conversion systems monitoring and diagnostics. The "Industrial Internet methods for electrical energy conversion systems monitoring and diagnostics" benefits from a 993000 € grant from Iceland, Liechtenstein, and Norway through the EEA Grants. The project aims to provide research in the field of energy conversion systems and to develop artificial intelligence and virtual emulator-based prognostic and diagnostic methodologies for these systems. The project contract with the Research Council of Lithuania (LMTLT) No is S-BMT-21-5 (LT08-2-LMT-K-01-040).

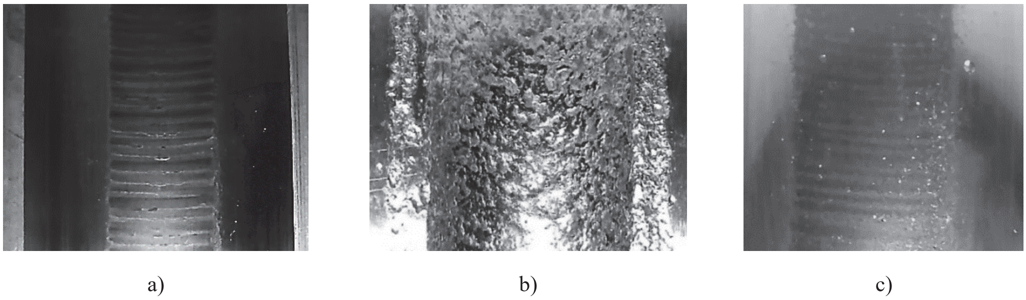

Fig. 1. Bearing current faults: a) fluting, b) frosting, c) pitting.

III. Data Collection and Pre-Processing

To avoid fatal and economic consequences in production, it is reasonable to implement advanced approaches related to predictive maintenance. In this case, the system can be taught to predict potential failures using intelligent algorithms. The most challenging aspect of such approaches is the training datasets required for training. Gathering a huge number of qualitative datasets is essential to reach an accurate forecast. For this reason, the different faults were implemented to the bearing in the lab environment by combining different current and rotating ranges. The experimental test bench was described in [15] and presented in Fig. 2.

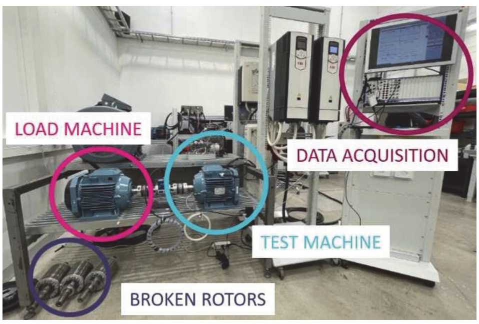

Fig. 2. Experimental testbench.

Various cases of failures caused by bearing currents have been achieved during experiments (fluting, frosting, pitting). The experimental results are presented in Table I. As a result, numerous datasets with healthy and faulty data were presented. For the training, there was used a fluting case of 500 rpm and 10 A, as presented in Fig. 3.

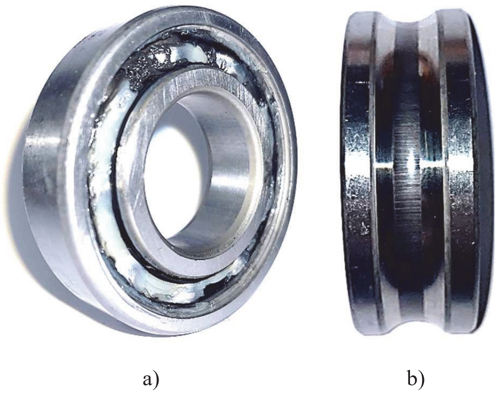

Fig. 3. Experimental bearing 500 rpm and 10 A: a) general view, b) bearing profile with fluting traces.

TABLE II. Bearing Current Faults under different Conditions for DE-Bearing

Conditions		**Results**		
DE-bearing				
Speed, rpm	***Current, A***	***Inner ring***	***Outer ring***	***Rolling elements***
100	10	Darkened race	Darkened race	No changes
100	20	Slight fluting	Darkened race	Darkened balls
500	10	Fluting	Darkened race	Darkened balls
800	10	Fluting	Darkened race, slight fluting	Darkened balls
800	20	Fluting/pitting	Slight fluting	Darkened balls, pitting
NDE-bearing				
Conditions		**Results**		
Speed, rpm	***Current, A***	***Inner ring***	***Outer ring***	***Rolling elements***
100	10	Darkened race	Darkened race	Slightly darkened balls
100	20	Slightly darkened race	Darkened race	Darkened balls
500	10	Darkened race	Darkened race, slight fluting	Darkened balls
800	10	Slightly darkened race	Darkened race, slight fluting	Darkened balls
800	20	Frosting	Frosting	Darkened balls, frosting

In this research, these datasets were taken from current, voltage, torque, speed, and vibration parameters. Besides, data was gathered under different operating conditions: control environments (grid fed, scalar, DTC) and loads (from 0% to 100%). To save training time, there is no need to analyze the whole signal. It is enough for one or two specific regions where the fault impact is the highest. To detect damage timely, the small fault-based frequency components should be considered using a fast Fourier transform (FFT).

In case of bearings, the vibration spectrum is the better way to detect a damage. At the same time, e.g. rotor bars fault, the current spectrum provides the better information [16]. For this reason, vibration spectrum was prioritized in this study. Fig. 4 presents the vibration spectrum of healthy and faulty bearings with fluting in direct-torque control and fully loaded. As seen from the graph, a faulty frequency's amplitude is much higher than a healthy one's amplitude, which is caused by the difficulty of the bearing rotating due to the damaged surface. Results show that the fault has the highest impact on the spectrum in the range of 0-500 Hz in even harmonics (especially 100 and 300 Hz). In the range of 500-1000 Hz, there are no noticeable harmonics expect of 700 Hz that can also be studied for the potential patterns for the training. For system training, signals under other control environments and loads were considered. As a result, the certain pattern of the particular fault can be distinguished from the spectrum.

IV. Predictive Maintenance

After gathering data samples for healthy and faulty cases, machine learning models were trained using a signal spectrum-based approach. The difference between its implementation in this article to the original is the definition of the transition state. Here, the transition state is not further divided into different parts. The datasets are divided into three stages: healthy, transition, and faulty. Data samples are gathered at a sampling frequency of 20k Hz. The incoming data is processed, i.e., denoised, determining frequency components, and normalized before the generation of the data samples used for training machine learning algorithms. The labeling and classification of data samples are shown in Table II.

TABLE II. Classification and Labeling of Training datasets

Data Sample Type	Label Assigned
Healthy Signal	1
Transition State (Inner Faults)	2
Transition State (Outer Faults)	3
Faulty State (Inner Faults)	4
Faulty State (Outer Faults)	5

The labeled data is then used to train models using different machine learning algorithms. To check their accuracy, blind validation is used, i.e., the data samples used to validate the results were not used in training. A total of 14 million data sets were used to train different machine learning models. Also, to avoid data leakage, trained models were cross-validated. The training data was divided evenly, with each state comprising 20% of the training data. Different machine learning techniques were utilized for training models, among which the top 5 results are presented in the paper. Fig. 5 shows the confusion matrix for two of the machine learning methods. Here, conventional machine learning techniques are used to train the models due to their speed and simplicity. As the pre-analysis of incoming current signals using signal-based spectrum analysis has already simplified the features used for model training, conventional techniques still give us higher accuracies with shorter training times. It is also possible to analyze the results easily rather than deep learning techniques. However, as the combination of faults becomes more complex, deep learning techniques will be used in the future for training and study will be considered to see which one is more beneficial in comparison of accuracies and time taken for training.

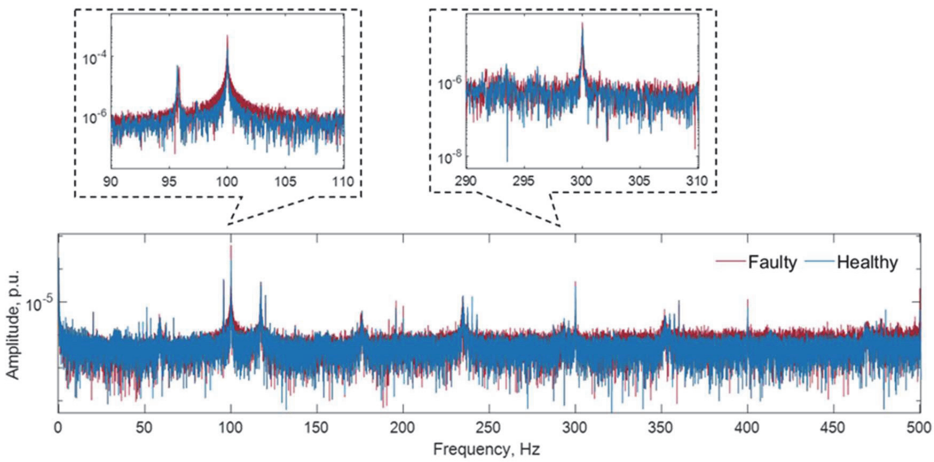

Fig. 4. Vibration spectrum of healthy bearing and bearing with fluting (DTC, full load).

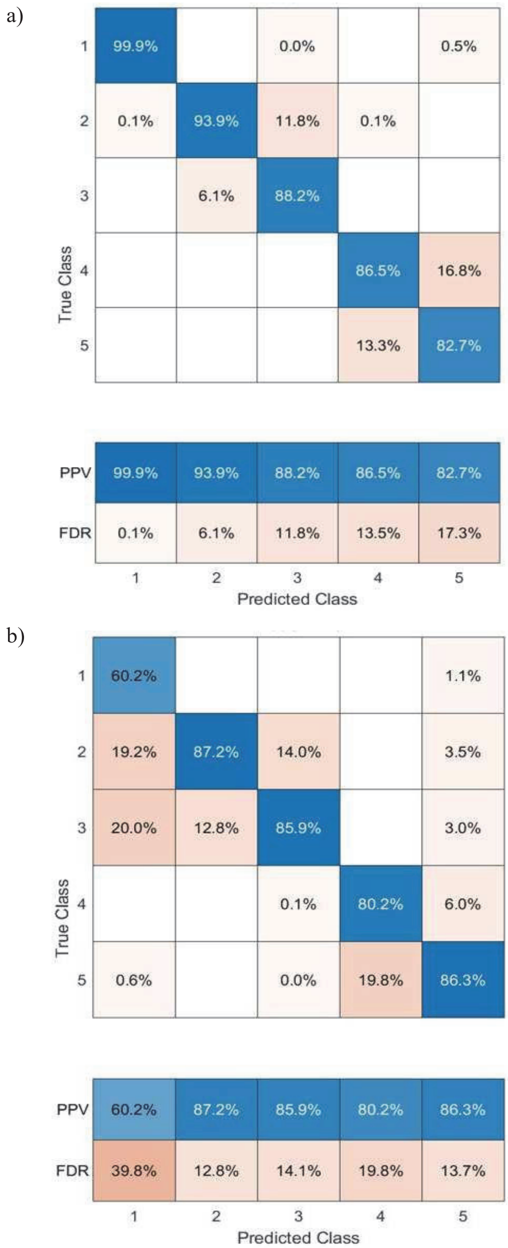

Fig 5. Confusion matrix for machine learning algorithms: a) Bilayered Neural Network, b) Cubic KNN.

As seen, Fig. 5 shows the validation accuracy for each case, which can also be improved by adding more quality data samples for training. This also solidifies that it is possible to predict the occurrence of inner and outer faults within an electrical machine with the help of a signal spectrum-based predictive maintenance approach. Table III shows that different machine learning algorithms are giving almost similar validation accuracies, with the Bilayered Neural Network performing best among them.

TABLE III. COMPARISON RESULTS

Machine Learning Algorithm	Accuracy (Validation)
Linear SVM	88.70 %
Cubic KNN	83.55 %
Narrow Neural Network	89.60 %
Bilayered Neural Network	90.60 %
Trilayered Neural Network	90.00 %

The accuracy of the neural networks can be further improved by adding more data samples for healthy and faulty cases and defining more scenarios.

CONCLUSION

Predictive maintenance has become one of the foremost essentials for the industry in the current era. It helps shorten losses and improve production costs. New algorithms and approaches are being proposed for predictive maintenance and fault diagnostics of electrical machines, primarily based on offline methods. The need is to implement an algorithm in real-time with higher accuracy, enabling the industry to make its process more efficient.

In this paper, predictions of electrical machines' bearing faults are considered using a signal spectrum-based machine learning approach for fault prediction. Preliminary analysis is done on the collected data, and the approach is used to train using different classified faults. The results show an accuracy of around 90% for machine learning based algorithms. Hence, predicting faults while the electrical machine is transitioning towards a faulty state is possible with higher accuracy. This can be further improved by adding more quality data sets to the training sample and further defining scenario combinations for fault occurrence so that every aspect of it is covered.

This approach is being tested on other spread faults of electrical machines and at the moment have been able to work with higher accuracy validation. For the future work, this will be tested out for different faults to valid the general approach of the method.

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RAIMONDAS POMARNACKI is an associated professor in Faculty of Electronics in Vilnius Gediminas Technical University. He focuses on the research of electromagnetic phenomena, microwave devices, numerical mathematics, and informatics. He has a significant experience in software development for embedded systems for controlling and monitoring electrical and electronic devices. For a few years, he created and implemented various signal processing and neural network methods algorithms to analyze, detect and control various behaviors for autonomous vehicles, motor control, and smart work of electromagnetic devices such as antennas. He was the leader of 2 R&D projects and a senior participant in 12 others. He participated in over 10 international conferences abroad and in Lithuania.

HUYNH VAN KHANG received the D.Sc. (Tech.) degree in electrical engineering from Aalto University, Espoo, Finland, in 2012. He was an Associate Professor in electrical power engineering with the University of Agder, Grimstad, Norway, from 2013 to 2019, where he is currently a Professor with the Department of Engineering Sciences. His research interests include electrical machines, condition-based maintenance, and applied power electronics.

Curriculum vitae

Personal data

Name:	Karolina Kudelina
Date of birth:	07.08.1997
Place of birth:	Narva, Estonia
Citizenship:	Estonian

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Education

2020–2024	Electrical Power Engineering and Mechatronics, Tallinn University of Technology, PhD
2018–2020	Energy Conversion and Control Systems, Tallinn University of Technology, MSc
2015–2018	Electrical Power Engineering, Tallinn University of Technology, BSc
2004–2015	Narva-Jõesuu Secondary school

Career

1.09.2020–…	Tallinn University of Technology, School of Engineering, Department of Electrical Power Engineering and Mechatronics, Junior Researcher (1.00)
13.01.2020–31.08.2020	Tallinn University of Technology, School of Engineering, Department of Electrical Power Engineering and Mechatronics, Engineer (0.50)
05.06.2018–27.07.2018	Enefit Energiatootmine AS, Engineer, traineeship (1.00)
19.06.2017–14.07.2017	Enefit Energiatootmine AS, Electrician, traineeship (1.00)

Honours and awards

2023	Winner of the “Science to Wikipedia 2023” competition in the fields of natural and real sciences and medicine (3rd place)
2022	L’Oréal-UNESCO For Women in Science Young Talents Program - Baltics
2022	Scholarship of Zonta Foundation, Estonian National Culture Foundation
2022	Rein Lind Doctoral Scholarship in the Field of Automation and Electronics
2021	Competition “3 Minute Science”, Estonian Academy of Science, finalist
2021	Dora Plus short-term study mobility scholarship
2021	IEEE IES Students and Young Professionals best paper competition (PEMC conference), 1st place
2021	The Best Ambassador of Power Electronics & Motion Control Competition, 1st place

2021	Doctoral Study Scholarship of Mati Jostov
2021	Technical Student of the Year, Estonian Association of Engineers
2020	Kristjan Jaak Scholarship
2020	Scholarship of Tamkivi Foundation for Natural Sciences, Estonian National Culture Foundation
2020	Estonian Research Council 1st Prize: National Award for Master's Students in Engineering and Technology Field for Master Thesis "Bearing Fault Analysis of Brushless DC Motors"
2019	Erasmus+ Scholarship

Language competence

English	Fluent
Estonian	Fluent
Russian	Native
French	Intermediate
Spanish	Beginner

Elulookirjeldus

Isikuandmed

Nimi:	Karolina Kudelina
Sünniaeg:	07.08.1997
Sünnikoht:	Narva, Eesti
Kodakondsus:	Eesti

Kontaktandmed

E-post:	karolina.kudelina@taltech.ee

Hariduskäik

2020–2024	Elektroenergeetika ja mehhatroonika, Tallinna Tehnikaülikool, doktoriõpe
2018–2020	Energiamuundus- ja juhtimissüsteemid, Tallinna Tehnikaülikool, magistriõpe
2015–2018	Elektroenergeetika, Tallinna Tehnikaülikool, bakalaureuseõpe
2004–2015	Narva-Jõesuu Keskkool

Teenistuskäik

1.09.2020–...	Tallinna Tehnikaülikool, Elektroenergeetika ja mehhatroonika instituut, Doktorant-nooremteadur (1,00)
13.01.2020–31.08.2020	Tallinna Tehnikaülikool, Elektroenergeetika ja mehhatroonika instituut, Insener (0,50)
05.06.2018–27.07.2018	Enefit Energiatootmine AS, Elektriinsener, praktika (1,00)
19.06.2017–14.07.2017	Enefit Energiatootmine AS, Elektrimontöör, praktika (1,00)

Teaduspreemiad ja tunnustused

2023	Konkursi “Teadus Vikipeediasse 2023” võitja loodus- ja täppisteaduste ning meditsiinivaldkonnas (3. koht)
2022	L’Oréal-UNESCO noorte talentide Baltikumi programmi “Naised teaduses” auhind
2022	Zonta fondi stipendium, SA Eesti Rahvuskultuuri Fond
2022	Rein Lind automaatika ja elektroonika valdkonna doktoriõppe stipendium
2021	Konkurss “Teadus 3 minutiga”, Eesti Teaduste Akadeemia, finalist
2021	Dora Plus lühiajalise õpirände stipendium
2021	IEEE IES Students and Young Professionals parima artikli konkurss, 1. preemia
2021	“The Best Ambassador of Power Electronics & Motion Control” konkurss, 1. preemia
2021	Mati Jostovi nimeline doktoriõppe stipendium
2021	Aasta Tehnikaüliõpilane, Eesti Inseneride Liit
2020	Kristjan Jaagu stipendium

2020	Tamkivi Reaalteaduste fondi stipendium, SA Eesti Rahvuskultuuri Fond
2020	Üliõpilaste teadustööde 2020. a riikliku konkursi tehnika ja tehnoloogia valdkonnas magistriõppe astmes I preemia konkursitöö “Harjavabade alalisvoolumootorite laagririkete analüüs” eest
2019	Erasmus+ stipendium

Keelteoskus

Inglise keel	Kõrgtase
Eesti keel	Kõrgtase
Vene keel	Emakeel
Prantsuse keel	Kesktase
Hispaania keel	Algtase

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