Bearing Currents of Induction Machine – Fault Detection, Condition Monitoring, and Predictive Maintenance

Karolina Kudelina  
karolina.kudelina@taltech.ee

Hadi Ashraf Raja  
Tallinn University of Technology

Muhammad Usman Naseer  
Tallinn University of Technology

Siarhei Autsou  
Tallinn University of Technology

Bilal Asad  
Tallinn University of Technology

Toomas Vaimann  
Tallinn University of Technology

Ants Kallaste  
Tallinn University of Technology

Research Article

Keywords: induction motors, ball bearings, condition monitoring, machine learning, predictive maintenance

Posted Date: February 19th, 2024

DOI: https://doi.org/10.21203/rs.3.rs-3958875/v1

License: ☑️ This work is licensed under a Creative Commons Attribution 4.0 International License.  
Read Full License

Additional Declarations: No competing interests reported.
Version of Record: A version of this preprint was published at Electrical Engineering on May 6th, 2024. See the published version at https://doi.org/10.1007/s00202-024-02411-x.
Bearing Currents of Induction Machine – Fault Detection, Condition Monitoring, and Predictive Maintenance

Karolina Kudelina, Hadi Ashraf Raja, Muhammad Usman Naseer, Siarhei Autsou, Bilal Asad, Toomas Vaimann & Ants Kallaste

Department of Electrical Power Engineering and Mechatronics, Tallinn University of Technology, 19086 Tallinn, Estonia

* Correspondence: karolina.kudelina@taltech.ee

Abstract: Bearing failures in electrical machines present significant challenges, drawing attention in diagnostic research. The widespread use of variable-speed drives in various motor applications has intensified the impact of bearing currents, requiring comprehensive exploration in academic and industrial settings. This paper thoroughly investigates the issue, examining damage types and diagnostic methods specific to bearing currents in induction machines. Additionally, it offers insights from experiments conducted in controlled laboratory environments to simulate bearing current faults. By outlining the findings, the paper contributes valuable knowledge on identifying and mitigating bearing-related issues in electrical machines. With the shift towards Industry 4.0 standards, which integrate advanced technologies into manufacturing processes, there’s a growing emphasis on preventing production faults. Consequently, the paper extends its inquiry into signal pre-processing to enhance fault prediction accuracy by optimizing and refining machine signals. Given the dynamic nature of industrial standards and the rising demand for predictive maintenance strategies, this research holds significance. By striving for increased efficiency, reduced downtime, and enhanced reliability, the perspectives outlined aspire to make a meaningful contribution to the advancing 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. With their extensive utilization, the issue of maintenance is gaining significant prominence. Among electrical machines, three-phase induction motors stand out as the most frequently employed type, primarily because they meet key industrial demands, including low maintenance requirements, cost-effectiveness, compact design, and variable control capabilities [1]. Employing frequency converters for control purposes is not only the most cost-efficient method but also the simplest way to guarantee the optimal performance of electrical machines. However, these approaches often give rise to the occurrence of induced shaft currents.

There are numerous cases in the literature related to power electronics and bearing currents. Authors in [2] discuss a reduction of common-mode voltage and bearing currents in DC-link inverter. In [3], the influence of parameters on discharge bearing currents in inverter-fed induction motors is introduced. Authors in [4] present mitigation techniques and modelling for high-frequency bearing currents in inverter-fed AC drives. In [5], the authors discuss the experimental assessment of high-frequency bearing currents in the induction motor that is driven by a silicon carbide inverter.

Typically, visually identifying surface damage resulting from shaft currents on the bearing is a challenging task. Shaft currents do not consistently traverse through the bearing. Nevertheless, when they do, faults tend to manifest in regions where the lubricant coating is at its thinnest, primarily due to heightened stress in this particular area. Shaft currents are a challenging problem in the industry [6]. Some of the case studied and their solutions can be presented in wind turbines [7], marine applications [8], line production [9], or food production [10]. Each energy system constitutes a complex mechanism. Ensuring the device’s reliability necessitates the monitoring of numerous parameters, a task demanding substantial computational resources and modern technologies. Given the vast amount of data involved, it becomes logical to employ advanced diagnostic methodologies rooted in artificial intelligence [11]. These intelligent algorithms not only instruct the system in defect detection but also enable it to forecast potential faults in the future. Among the various methods available, machine learning-based algorithms stand out as the most prevalent tools employed in diagnosing rotating machines. Machine learning algorithms help create a complex weighted combination based on training data that can be used later to deduce results for the incoming data [12].

Regarding the bearing diagnosis in electrical machines, there are frequently used the following machine learning: decision trees [13], support vector machines [14], principal component analysis [15], and genetic algorithms [16]. Besides, there are used numerous variations of neural networks: convolutional neural networks [17], generative neural networks [18], and deep learning approaches [19]. This research prioritized approaches based on neural networks due to the ability for fast and effective learning.
This manuscript is organized as follows. Chapter II introduces the nature of bearing currents. In Chapter III, there are presented possibilities to detect bearing currents in the machine. Chapter IV describes the most typical damages inflicted by bearing currents. In Chapter V, the bearing faults caused by bearing currents are performed in the lab environment. Chapter VI presents a pre-processing of the datasets to get predictions presented in Chapter VII.

2. Bearing currents

Nowadays, the most cost-effective and easiest way to ensure the optimal operation of electrical machine is to implement the frequency converter control. This is the trending option observable throughout the world, which in turn means the usage of power electronics. Such solutions more frequently lead to shaft and bearing currents induced by frequency converter, which is a growing problem in the modern industry. Generally, bearing currents can be divided into two main categories: classical and inverter-induced bearing currents.

2.1. Classical bearing currents

As early as in 1927, it was stated that if it would be possible to design an ideally balanced and symmetrical motor, then both theoretical and practical indication of bearing current could not exist [20]. Usually, those reasons are referred to structural asymmetries of the machine, such as static or dynamic eccentricity, design asymmetries, unbalanced supply, broken connections of laminations, rotor faults, etc [21]. This phenomenon has been presented in [22] by the usage of simulations, where broken rotor bars induce eddy currents to the shaft leading to bearing damages. Due to the asymmetry of magnetic field, current is induced to the motor shaft. This in turn causes potential difference measurable between both ends of the shaft. According to standards, shaft voltage over 300 mV becomes harmful to bearings, although the lower level may also cause damage, when persisting for a longer period. In production, the design tolerances become more accurate and the quality of used materials has been increased significantly. Still, the monitoring of bearing currents remains important as they are potentially dangerous to the ball bearings. The emerging becomes extremely important for the motors starting from 100 kW. At the same time, classical bearing currents can be clearly measured in the motors from 7.5 kW [23]. Besides, it is reasonable to take preventive measures from bearing currents, such as insulated bearing or shafts, in the motors starting from 18.5 kW [24].

2.2. Inverter-induced bearing currents

Inverter-induced bearing currents can be further divided to subcategories: electrical discharge machining bearing currents, capacitive bearing currents, bearing currents caused by rotor ground currents, and high-frequency circulating bearing currents. The most spread reason for those currents is the common-mode voltage, which is caused by the inverter and the fast voltage rise and fall (high du/dt) at the motor terminals [25]. This phenomenon can be considered as the root cause for different types of bearing currents that harm potentially the bearings in motors running with variable speed drives. The categorization of those currents is presented in Fig. 1.

![Fig. 1 Categorization of bearing currents.](image-url)
Due to the coupling, the capacitance of the bearing and other parasitic capacitances is charged. As a result, there is a voltage rise on the motor shaft. If the breakdown voltage of the lubrication film is exceeded by the charged voltage at the shaft, the capacitive energy discharges through the bearings. This, in turn, causes the flow of the electrical discharge machining current. The current path is from the shaft to the frame, passing through the rings and rolling elements of the bearing. It is assumed in [26] that shaft voltages 3…30 V can be significant enough to cause discharges in the bearings. At the same time, as referred to in [27], the voltage level can be anywhere between 3 to 10% of the nominal voltage of the electrical machine.

The fast rises and falls of the common-mode cause high-frequency common-mode currents, which flow from the windings through the stator laminations, the air gap, the rotor, the shaft, and the bearings to the machine frame [26]. It happens due to the switching of transistors happening at every switching occurrence. If the motor is running at a higher speed, a thin dielectric layer of the lubricant occurs between the bearing races and rolling elements. This results in a capacitive bond between the frame of the machine and the shaft itself. Usually, these currents are relatively small in the 5…10 mA range. Hence, it is usually considered as harmless value to the bearings and the motor in general [28].

Bearing currents as rotor ground currents are caused by poor grounding of the motor frame [29]. More frequently, it happens since the rotor is grounded through the driven load. So, this is the case when the rotor itself is better grounded than the stator. This current flows through the motor bearings to the shaft, then to the load, and back to the converter used to control the initial machine.

Regarding the high frequency circulating bearing currents, the process goes as follows. High du/dt of the voltage in the machine terminals causes an additional high-frequency common-mode current and parasitic capacitances between the motor winding and the stator laminations. It can be with frequencies up to several megahertz. This current enters the rotating machine through the windings and leaves through the frame and lamination, exciting a high-frequency circular magnetic flux around the motor shaft. As a result, this flux induces a shaft voltage along the motor shaft. In case there is enough of this induced shaft voltage, it discharges through the bearings and generates a circulating current in the bearings, the shaft, and the motor frame. The voltage induced on the shaft has a potential difference between the ends of the shaft, which can exceed the breakdown voltage level of the lubricant leading to the circulating bearing current.

3. Diagnostic and reduction possibilities of bearing currents

Different methods exist to identify bearing currents in the electrical machine, such as Rogowski coil [30], currents transformer [31], common multimeter, etc. However, as the bearing faults primarily affect the vibration rather than the current spectrum, it is reasonable to consider vibration analysis [32]. The diagnostic possibilities for bearing currents can generally be divided into direct and indirect [33]. Table I compares different diagnostic approaches.

3.1. Direct methods

To detect shaft currents in a timely manner, direct diagnostic methods are preferred. Detection of bearing currents in the motor would allow timely fault prevention, which will inevitably lead to damage to the bearings of the electrical machine [34].

3.1.1. Multimeter

The presence of bearing currents can be detected in this way. However, these measurements only provide an indirect indication. A multimeter will generally indicate whether the bearings are at risk of sparking. An accurate measurement of shaft voltage requires a multimeter with a high input impedance. A multimeter with a higher input impedance will give better results.

3.1.2. Oscilloscope

A universal and practical measuring device, which provides an overview of the various currents in the motor, their shape, and parameters. In choosing the device, oscilloscopes with a bandwidth >100 MHz are preferred. It is advised to consider and record the ambient magnetic field level because the oscilloscope is substantially more susceptible to noise and interference than a multimeter. From the point of view of motor bearings, it is in principle sufficient to measure only the voltage and/or current of the shaft. During the measurement, the oscilloscope settings depend on many factors, such as motor size, speed, bearing type, temperature, etc. The time scale reduction could begin at ~500 s and the voltage increase at ~5 V The shaft voltage will often follow the phase voltage if there are no spark discharges in the bearings. The voltage during spark discharges is ±20…80 V, with increases in voltage occurring every 10 µs (during this time the bearing current is ~0 A). A few nanoseconds pass during the bearing spark discharge, when bearing current reaches a maximum.
All safety regulations must be followed during the measurement as oscilloscope must be placed in direct contact with
the motor shaft to measure the voltage.

3.1.3. Current transformer and non-inductive shunt

Shaft currents can also be measured with a current transformer and a high-frequency non-inductive (coaxial) shunt
(in the presence of oscilloscope). Non-inductive shunt typically consists of two conductive tubes that are electrically con-
ected to one another at one end, arranged inside of one another. The measured current flows in one direction from a
resistive material in the inner tube and a conductive material in the outer tube. There is no shunt saturation phenomenon
when compared to the current transformer. However, transient currents and the self-inductance phenomenon pose the
issues. Non-inductive shunts are used for this reason. The temperature coefficient of the material resistance affects the
shunts’ measuring accuracy as well. Therefore, the measurement results must either be adjusted, or measurements must
be taken at the specified temperature ranges.

3.1.4. Rogowski coil

A very common, simple, and safe method for measuring phase current and motor shaft current. During the measure-
ments of phase current, the Rogowski coil must be placed around the power cables (must not be placed around the
neutral cable). During the measurements of the shaft currents, coils be placed around motor shaft. In case if more than
one power cable is used, the Rogowski coil must be placed around all cables. To measure shaft currents, a Rogowski
measuring device must also be connected to a logger or oscilloscope (preferably with a bandwidth of 100 MHz or more).

Rogowski coil is a relatively inexpensive device for current measuring. Since magnetic materials are not used in the man-
ufacture of Rogowski coils, current transformers with this type of air core do not have saturation effects as well as they
also deal with overload. The sensitivity of the coil is also guaranteed over a wide operating frequency range (from hertz
to megahertz). The temperature compensation is easy due to the low temperature coefficient of the coil. The main dis-
advantages of the Rogowski belt are the fact that current measurement is not possible without the use of additional
electronics, which in turn requires the presence of a power supply. In addition, the Rogowski belt is noise sensitive, so
attention must also be paid to electromagnetic compatibility.

3.2. Indirect methods

Indirect diagnostic methods make it possible to detect bearing currents in electrical machines only when the surfaces
of bearings have already been damaged and rolling bodies move on the damaged surfaces generating vibration and noise.
Additionally, the detection of shaft currents by indirect methods requires an experience and good training, as there are
many different types of bearing damages.

3.2.1. Vibration analysis

This is one of the most common diagnostic techniques used in electrical machine diagnostics. Although vibration
analysis has proven to be a powerful tool for detecting bearing faults in electrical machines, segregating the bearing and
shaft currents inflicted faults from any other mechanical defect of the bearings is problematic. Hence, in the case where
such current inflicted failure modes are suspected, the vibration analysis must be complemented with other direct or
indirect diagnostic method, in order to validate the finding and prove the correctness of the diagnosis.

3.2.2. Ultrasound analysis

Ultrasonic detectors are also very suitable for indirect detecting of bearing currents. Similar to vibration analysis,
ultrasonic spectrum also shows the sound peaks caused by the passing shaft currents. In addition to data analysis, it is
possible to listen for bearing defects with an ultrasonic detector, like a stethoscope. Since the ultrasonic detector can
very clearly detect the corona and the sounds generated by the secondary solutions, it should theoretically be possible
to detect spark solutions generated by the shaft currents in the bearings with the ultrasonic detector. However, since
spark solutions in rolling bearings is very low in the ultrasonic region (with a maximum power of about 200 MHz), it is
very difficult to use such a method 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. For
instance, there are used insulated bearings or shafts [35], conductive greases [36], grounding contacts [37], frequency
converter regulation [38]. Table 1 summarizes the main options to decrease bearing currents [39].
Table 1 Possibilities to decrease bearing currents.

<table>
<thead>
<tr>
<th>Method</th>
<th>Effect</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>One insulated bearing</td>
<td>Ineffective</td>
<td>The circulating currents are reduced in the motor, but the lifespan of an uninsulated bearing is likely to be shortened.</td>
</tr>
<tr>
<td>One insulated bearing and grounding contact</td>
<td>Effective</td>
<td>The ground brush or ring must be on the non-insulated bearing side. Additionally, there can be used a common mode filter.</td>
</tr>
<tr>
<td>Two insulated bearing and grounding contact</td>
<td>Very effective</td>
<td>Very efficient solution with the usage of common mode filter.</td>
</tr>
<tr>
<td>Hybrid or ceramic bearings</td>
<td>No spark solutions</td>
<td>Very effective. Most likely the best solution for small motors.</td>
</tr>
<tr>
<td>Conductive grease</td>
<td>Effective if bearing currents are low</td>
<td>This is recommended as temporary solution only for smaller motors. Bearing currents increase and the lifespan of the bearing is reduced in several times due to the composition of the lubricant.</td>
</tr>
<tr>
<td>One grounding contact or ring</td>
<td>Effective</td>
<td>Regular maintenance is required for the grounding brush. The solution is suitable for smaller motors. There can be used a common mode filter.</td>
</tr>
<tr>
<td>Two grounding contacts or rings</td>
<td>Very effective</td>
<td>The solution is better suited for smaller motors. Regular maintenance is required for the ground brush. For larger motors, it is also recommended to install insulated bearings.</td>
</tr>
<tr>
<td>Correct groun and cabling</td>
<td>Longer cables can reduce currents</td>
<td>Proper grounding and cabling are a prerequisite for solving the problem. The main circulating leakage currents are reduced, as is the risk of motor insulation failures and disturbances.</td>
</tr>
<tr>
<td>Common mode filter (passive)</td>
<td>Relatively effective</td>
<td>The cheapest and most efficient of the filters. Reduces high frequency currents. In the case of large motors, additional measures are needed.</td>
</tr>
<tr>
<td>dU/dt filter (active)</td>
<td>Decreases a bit in case of larger motors</td>
<td>To be used for the highest output voltage (from 690 VAC).</td>
</tr>
<tr>
<td>Sine wave filter</td>
<td>Decreases</td>
<td>The reduction depends on the filter, but in any case, only the circulating shaft currents are reduced. The most expensive of the filters. Significant heat losses must also be considered.</td>
</tr>
</tbody>
</table>

The effectiveness of those methods depends mainly on the motor parameters and ambient environment. However, there is always a risk of shaft current leakage.

4. Damages of bearing currents

During the initial phase, it is not feasible to identify current damages in the bearing without dismantling the electrical machine. In such instances, one can observe microscopic deviations from the standard specifications on the bearing races. Visually, faults inflicted by bearing currents significantly differ from other mechanical defects [40].

It can be crucial to visually inspect replaced bearings 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. Typically, current-induced damages are only detectable in the advanced stages when the bearing surface is already compromised. Faults resulting from bearing currents tend to manifest in areas where the lubrication is thinnest due to heightened stress in those regions. Frequently, such damage results in the formation of fluting on the bearing surface, as shown in Fig. 2a. In cases of fluting, multiple lines become apparent across the bearing raceways. This condition is often associated with constant rotational speeds and low voltage. Another category of bearing current-related faults, typically observed when a motor operates at variable speeds, is referred to as frosting. An illustration depicting the occurrence of frosting in practical situations is presented in Fig. 2b. When a motor operates at low speed and receives power from a high-voltage source, a phenomenon known as “pitting” can occur in the bearing. Pitting is typically observed in motors designed for DC applications, such as railway motors. In such instances, one can notice the presence of small craters on the bearing surface, as illustrated in Fig. 2c. In addition to the previously mentioned instances of bearing current faults, another type of damage known as "dull-finish" may be encountered. The primary distinction between dull-finish and pitting lies in the size of the craters present 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. More frequently, the lubricant condition can point to the possible problem of the motor. The lubricant undergoes a darkening process because of bearing currents. When sparking occurs, the lubricant oxidizes and darkens due to electrical discharges.
5. Implementation of bearing current fault in the lab environment

To prevent severe consequences and economic losses in production, it is prudent to adopt strategies associated with predictive maintenance. In this scenario, the system can be trained to anticipate potential failures using artificial intelligence algorithms. The primary hurdle in implementing such approaches lies in acquiring the necessary training datasets. To achieve precise results and enable accurate forecasting, the initial step involves amassing a large quantity of high-quality datasets. For this reason, various faults were intentionally induced in laboratory settings on the bearings. As previously discussed, fluting typically arises under conditions of low voltage and constant rotational speed, frosting becomes apparent when the motor operates at variable speeds, and pitting is commonly observed in situations involving low speed and a high-voltage power source. To investigate and study these various scenarios, an experimental test bench was constructed, as shown in Fig. 3. Through experimentation, diverse instances of failures induced by bearing currents were successfully reproduced. The radial load was applied to the bearings through the tension of the belt.

![Fig. 3 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.](image)

- **Case 1** – 100 rpm and 10 A
  Lubricant darkening can be observed. In this case, DE-bearing as well as NDE-bearing have slightly darkened inner and outer raceways. Also, insignificant darkening of rolling elements occurred.

- **Case 2** – 100 rpm and 20 A
  This case revealed more serious case of lubricant darkening. Experiment was stopped due to the impossibility of the bearing to operate. Besides, DE-bearing has slight fluting in the inner raceway and darkened outer raceway. NDE-bearing has darkened inner as well as outer raceways. Both have darkened rolling elements.

- **Case 3** – 500 rpm and 10 A
  This case presents a slight darkening of the lubricant. Increase in rotational speed revealed an obvious case of fluting on inner raceway and darkened outer raceway in case of DE-bearing, as shown in Fig. 4. NDE-bearing has darkened inner
and outer raceways with slight fluting trails. Both bearing of inner raceway and fluting on outer raceway in case of DE-bearing.

Fig. 4 DE-bearing at 500 rpm and 10 A.

- Case 4 – 800 rpm and 10 A
  - Lubricant changed color. DE-bearing has fluting phenomenon on inner raceway and darkened outer raceway with slight fluting. In case of NDE-bearing, darkening of raceways was observed.

- Case 5 – 800 rpm and 20 A
  - This case revealed a serious case of lubricant darkening. Experiment was urgently stopped due to the impossibility of the bearing to operate. As seen in Figure 5, increase in rotational speed and current revealed an obvious case of pitting in combination with slight fluting of inner raceway and fluting on outer raceway in case of DE-bearing.

Fig. 5 DE-bearing at 800 rpm and 20 A.

At the same time, as shown in Fig. 6, NDE-bearing presented a case of frosting on inner and outer raceways. Both have darkened rolling elements with pitting or frosting phenomena.
In Table 2, a comparative analysis of all studied cases analysis with shaft current faults is presented.

Table 2 Bearing current faults under different conditions.

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Results</th>
<th>DE-bearing</th>
<th>NDE-bearing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Speed, rpm</td>
<td>Current, A</td>
</tr>
<tr>
<td>100</td>
<td>10</td>
<td>Darkened race</td>
<td>Darkened race</td>
</tr>
<tr>
<td>100</td>
<td>20</td>
<td>Slight fluting</td>
<td>Darkened race</td>
</tr>
<tr>
<td>500</td>
<td>10</td>
<td>Fluting</td>
<td>Darkened race</td>
</tr>
<tr>
<td>800</td>
<td>10</td>
<td>Fluting/pitting</td>
<td>Darkened race / slight fluting</td>
</tr>
<tr>
<td>800</td>
<td>20</td>
<td>Frosting</td>
<td>Frosting</td>
</tr>
</tbody>
</table>

6. Data analysis

Induction machines are the most spread among other motor types in production due to the easy maintenance, low cost, and high efficiency [41]. 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. 7.
As a result, there are numerous datasets, containing precise information about both healthy and faulty conditions. When it comes to bearing faults, their primary impact is on vibration rather than the current spectrum. Vibration signals have the capability to detect faults at a very early stage. For this reason, prioritizing vibration signals is common practice in cases of defective bearings. These bearing faults can be mathematically described in terms of four natural frequencies that influence the bearing’s behavior. They can be defined as outer race frequency (1), inner race frequency (2), rolling elements’ frequency (3) and cage frequency (4). These equations are as follows:

\[ f_o = \frac{N_b}{2} n \left( 1 - \frac{D_b}{D_c} \cos \beta \right) \]  
\[ f_i = \frac{N_b}{2} n \left( 1 + \frac{D_b}{D_c} \cos \beta \right) \]  
\[ f_{re} = \frac{D_c}{2D_b} n \left( 1 - \left( \frac{D_b}{D_c} \cos \beta \right)^2 \right) \]  
\[ f_c = n \left( 1 - \frac{D_b}{D_c} \cos \beta \right) \]  

where \( N_b \) – number of balls or rollers, \( D_b \) – ball or roller diameter (mm), \( D_c \) – bearing pitch diameter (mm), \( \beta \) – contact angle (degrees), \( n \) – mechanical rotor speed (Hz). Each defect present in a bearing assembly produces vibration at a natural frequency or a combination of several natural frequencies and its multiples (\( k = 1, 2, 3, ... \)), depending on the damage location [42].

In this study, the 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 across a range of loads (from 0% to 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 revolved around identifying these crucial signal segments for training and extracting significant patterns from them.

To detect early-stage damage, it is important to focus on identifying the small frequency components associated with faults. One way to pinpoint faults is by utilizing the fast Fourier transform (FFT) to reveal the presence of these faulty frequencies. Fig. 8 displays the vibration spectra of both healthy and faulty bearings with fluting. Notably, the amplitude of the faulty bearing is significantly higher than that of the healthy one. This disparity arises from the bearing’s difficulty in rotating due to surface damage. The fault exerts its most significant influence on the spectrum within the 0-500 Hz range, particularly in 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 is also worth examining for potential patterns during training. The range after 1000 Hz does not have a significant impact.

When conducting training, it's essential to consider the control environment. The amplitude and characteristics of fundamental harmonics vary depending on the type of control mode when a faulty bearing is involved. Notably, DTC exhibits a distinct shift in harmonics. Like in the previous case, the fault’s most significant effect on the spectrum occurs within the 0-500 Hz range, particularly in even harmonics. Conversely, there are no prominent harmonics in the 500-1000 Hz range except for the even harmonic at 700 Hz. Besides, the load factor was also considered during the training process. As seen from Figure 20, the fault exhibits varying characteristics depending on the load magnitude. These distinctive patterns offer significant value for training the system effectively. To enhance the accuracy of predictions, it is advisable to consider various parameters of motor operation.

7. Fault Prediction

In this research, two distinct approaches are employed in machine learning for fault detection and prediction. The initial approach entails the training of diverse machine learning models to detect faults in both inner and outer bearings. The second approach is centered on fault prediction, employing a machine learning method based on signal spectra to train data and evaluate the likelihood of specific faults occurring.

Upon the collection of data samples from the electrical machine, encompassing instances of bearing faults and healthy states, machine learning models were employed to pinpoint faults. Prior to training, the collected data underwent preprocessing, including denoising and normalization. Denoising involved the use of low-pass filters and median filtering. The denoised signal was then segmented into datasets, further 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 both healthy and faulty signals, including inner and outer faults.

For this study, eight distinct machine learning models were selected to compare result accuracies. 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. Fig. 9 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, a total of eight different machine learning models were utilized for training and validating the model.
Table 3 provides a comprehensive comparison of the validation accuracies of these models for bearing fault detection, encompassing all three cases of healthy states, inner faults, and outer faults. It is worth noting that these results hold the potential for further enhancement through the inclusion of higher-quality data and ongoing efforts to optimize the training of machine learning models.

<table>
<thead>
<tr>
<th>Machine Learning Model</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coarse Tree</td>
<td>83.30%</td>
</tr>
<tr>
<td>Coarse Gaussian SVM</td>
<td>91.70%</td>
</tr>
<tr>
<td>Fine Gaussian SVM</td>
<td>84.70%</td>
</tr>
<tr>
<td>Fine KNN</td>
<td>91.50%</td>
</tr>
<tr>
<td>Narrow Neural Network</td>
<td>85.40%</td>
</tr>
<tr>
<td>Medium Neural Network</td>
<td>85.40%</td>
</tr>
<tr>
<td>Bilayered Neural Network</td>
<td>85.40%</td>
</tr>
<tr>
<td>Trilayered Neural Network</td>
<td>85.90%</td>
</tr>
</tbody>
</table>

As evident from the results, the Coarse Gaussian SVM exhibits the highest validation accuracy among the trained models, closely followed by the Fine KNN model, which achieves nearly equivalent accuracy. Although Neural Network trained models show 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, but 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 is now utilized to identify unique frequency components within inner and outer bearing faults, aiding in the identification of fault occurrences within the incoming signal. This strategic use of denoised data holds promise for improving the precision of fault predictions. The gathered data is 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 training of the algorithm. An illustrative example of these components, along with their normalized amplitudes ranging from 0 to 1, is depicted in Fig. 10.
Through meticulous analysis of multiple samples, distinctive frequency components are pinpointed for each occurrence of faults. These frequency components serve to delineate the range for the transition state, representing the point at which a motor shifts from a healthy state to a faulty one. This information is instrumental in preparing data for the training of machine learning models geared towards predicting bearing faults. Every conceivable combination of frequency component value during the transition state is employed in data preparation. Subsequently, the faults are categorized into five labels, and the specific details are outlined in Table 4.

The trained models underwent blind validation, a subset of the accuracy validation results is depicted in Fig. 11.
Table 5 presents a comparison of the same models along with 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 provides a reliable identification of two faults with heightened accuracy. While these tests and models were evaluated using real-time data acquired from electrical machines, it’s noteworthy that certain models claim up to 95% accuracy for fault detection based on analytical equations or simulations. However, such high accuracy claims might not necessarily hold true in real-time scenarios. As evident from Table V, when the training data becomes more complex, models trained using neural networks demonstrate superior results compared to other methods.

Table 5. Bearing current faults accuracy comparison.

<table>
<thead>
<tr>
<th>Machine Learning Model</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coarse Tree</td>
<td>68.50%</td>
</tr>
<tr>
<td>Coarse Gaussian SVM</td>
<td>82.20%</td>
</tr>
<tr>
<td>Fine Gaussian SVM</td>
<td>81.70%</td>
</tr>
<tr>
<td>Fine KNN</td>
<td>53.80%</td>
</tr>
<tr>
<td>Narrow Neural Network</td>
<td>90.00%</td>
</tr>
<tr>
<td>Medium Neural Network</td>
<td>88.90%</td>
</tr>
<tr>
<td>Bilayered Neural Network</td>
<td>90.20%</td>
</tr>
<tr>
<td>Trilayered Neural Network</td>
<td>89.60%</td>
</tr>
</tbody>
</table>

The accuracy of these neural network models has notably increased in comparison 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. Among the models, 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 the utilization of superior quality data samples.

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 towards predictive maintenance, timely fault diagnosis has become paramount to prevent catastrophic failures. Consequently, academic research is increasingly focused on predictive maintenance for electrical machines, including induction motors.

This paper presents an analysis of the causes of bearing faults, diagnostic possibilities, and a technique for predicting such faults. The results indicate that the technique 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 the occurrence of faults in the electrical machine. These combinations were utilized to train additional models aimed at determining the probability of fault occurrence within the machine.

Therefore, this technique is effective for monitoring and diagnosing bearing faults in induction motors. However, it is advisable to validate the algorithm across various use cases and a broader range of faults. The algorithms trained using this approach can be deployed for real-time monitoring and detection of 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: Karolina Kudelina; Methodology: Karolina Kudelina, Hadi Ashraf Raja; Formal analysis and investigation: Muhammad Usman Naseer, Siarhei Autsou; Writing - original draft preparation: Karolina Kudelina; Writing - review and editing: Bilal Asad, Ants Kallaste; Funding acquisition: Toomas Vaiman; Supervision: Ants Kallaste.

Data Availability: Not applicable

References


7. AEGIS, Wind energy with no downtime - Study Case I. 2020.


9. AEGIS, Protecting VFD - Driven Motors in Distribution Centers - Case Study III. 2017.

10. AEGIS, Protecting VFD - Driven Motors in Dairy Production - Case Study IV. 2017.


