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PREDICTIVE-ADAPTIVE MAINTENANCE APPLIED FOR OPTIMIZING THE PERFORMANCE OF INDUSTRIAL ELECTRICAL SYSTEMS AND EQUIPMENT

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Abstract. ***In the Industry 4.0 era, predictive maintenance became a crucial element in ensuring the efficiency and reliability of intelligent industrial systems. This paper proposes a critical study on the role and benefits of predictive maintenance in the context of optimizing and enhancing the performance of industrial electrical systems, more specific the on the asynchronous machine, highlighting emerging perspectives and challenges associated with the implementation of this advanced technology. Additionally, it brings to the forefront the latest concepts and solutions in predictive maintenance to provide a more comprehensive and conclusive view at the time of conducting this case study.***

Keywords: predictive maintenance, power electricals system, inductor motors faults, electrical equipment malfunctions.

1. INTRODUCTION

Industry 4.0 represents a paradigm shift in the evolution of the industrial sector, characterized by the extensive use of digital technologies to transform, and improve production processes. This fourth industrial revolution integrates advanced technologies such as the Internet of Things (IoT), Data Analysis, Artificial Intelligence (AI), Cloud Computing, and others to create intelligent and interconnected systems within factories and production chains. This new industrial era envisions increasing efficiency, reducing costs, improving product quality, and rapidly adapting to market changes using advanced digital technologies [1, 2].
The main objectives proposed to be pursued in this study will be outlined in the following lines [3]:

- **Optimization of industrial systems' performance**: Analyzing how predictive maintenance can contribute to optimizing the performance of industrial systems, ensuring their operation at maximum capacity, and preventing possible failures.
- **Integration of advanced technologies**: Investigating the integration of advanced technologies, such as the Internet of Things (IoT), smart sensors, and data analysis, within the predictive maintenance process to obtain a comprehensive view of equipment condition.
- **Cost efficiency and downtime reduction**: Evaluating the impact of predictive maintenance on maintenance costs and reducing downtime, contributing to increased operational efficiency and maximizing profitability.
- **Machine Learning and predictive algorithms**: Exploring the application of machine learning technologies and predictive algorithms for developing precise failure prediction models and early identification of equipment degradation signs.
- **Data security and confidentiality**: Addressing data security and confidentiality aspects in the implementation of predictive maintenance within the context of smart industrial systems.

This paper highlights the importance of predictive maintenance in advancing industrial systems towards higher levels of intelligence and efficiency. By exploring both technological and practical aspects, it offers a comprehensive vision of the future of predictive maintenance within the landscape of smart industry.

2. GENERAL CONCEPTS

Throughout history, the maintenance of industrial systems and equipment has evolved in a continuous effort to manage and prevent defects that may occur in production chains [4].
The deterioration or incapacity of a system to fulfill its required function according to specified operating conditions is defined as a defect. This can result from wear and tear, production errors, or other issues affecting system functionality.
The period between the onset of deterioration and the point at which the system can no longer perform its required function is termed the defect development time. Monitoring this time is crucial for anticipating and intervening before the defect causes shutdowns or serious operational issues [5, 6].
To identify and remedy defects, it's necessary to access specific parameters or significant variables of the system that provide information about their condition. This process often involves the use of sensors and monitoring devices to collect data on system performance and is generally referred to as defect detection and diagnosis.
The monitoring and diagnosis system is a module comprising equipment responsible for capturing and analyzing signals from the system, as well as detecting and diagnosing defects. This is a critical aspect of predictive maintenance, as it enables problem identification before they escalate and affect system operations [7-9].

Maintenance of industrial systems involves a complex set of technical and organizational activities aimed at ensuring optimal functioning. These activities include regular equipment maintenance, repairing and replacing worn or defective components, efficiently planning, and managing resources, and implementing preventive maintenance practices to avoid failures and unplanned production shutdowns [10, 11].

In this process of improving equipment performance and reliability, various maintenance techniques and concepts have been developed and implemented, such as:

1. **Reactive Maintenance**: Involves addressing electrical equipment or industrial systems only when a defect or malfunction occurs. In this approach, maintenance activities are reactive to the obvious signs of failure and focus on remedying the symptoms without investigating or addressing the root cause of the issue.
2. **Corrective Maintenance:** Involves scheduling maintenance activities at predetermined time intervals to keep critical equipment or systems in optimal working condition. The effectiveness of this maintenance program is evaluated based on the total cost of the life cycle of the machines or critical systems, prioritizing optimal functionality over the speed of resuming operations.
3. **Preventive Maintenance:** In contrast to corrective maintenance, preventive maintenance involves the planning and regular implementation of maintenance activities to prevent anticipated failures and defects. This includes periodic inspections, component replacements at specific intervals, and other scheduled activities to keep equipment in optimal operating condition. Although it can reduce the risk of unforeseen failures, preventive maintenance can be costly and may require significant planning and coordination resources.
4. **Predictive Maintenance:** Predictive maintenance focuses on regular and detailed monitoring of system and process conditions in real-time, using various technologies and sensors. The main goal is to detect and correct issues before they become severe and cause unplanned disruptions in production.

This method involves continuously comparing measured data with the predefined technological limits of the equipment. When deviations from these limits are detected, investigations and analyses are initiated to identify possible causes of the problems [12-14].

The data obtained from monitoring are essential for planning maintenance interventions, which are scheduled in the early stages of issues. This allows the maintenance team to intervene before defects cause unplanned production shutdowns or other major problems.

By implementing predictive maintenance, companies can minimize costs associated with emergency repairs and unplanned production interruptions while simultaneously improving the efficiency and reliability of their operations [15-16].

Advantages:

- Reduced Maintenance Costs: By detecting and addressing issues in their early stages, predictive maintenance avoids the high costs associated with emergency repairs and unplanned production interruptions.
- Maximized Equipment Uptime: By scheduling maintenance interventions at optimal times based on data collected from monitoring, predictive maintenance contributes to extending equipment lifespan and maximizing their trouble-free operating time.
- Resource Planning Optimization: Predictive maintenance enables more efficient planning of human and material resources required for equipment maintenance.
- Reduced Risk of Unexpected Failures: By detecting potential issues in their early stages, predictive maintenance helps minimize the risk of unexpected failures and unplanned production shutdowns. This ensures a more stable and predictable operation of systems and processes.
- Improved Safety: By identifying and addressing safety issues before they become critical, predictive maintenance contributes to improving workplace safety and reducing the risk of accidents or incidents.

Main Techniques Used for Predictive Maintenance:

- ✓ Vibration Analysis
- ✓ Lubricant Analysis
- ✓ Ultrasonic Noise Detection
- ✓ Thermography

Specific Methods for Electrical Systems:

- ✓ Complex Impedance Measurement
- ✓ Insulation Resistance Measurement
- ✓ Analysis of Harmonic Spectrum of Phase Current.

3. MAINTENANCE AND TESTING OF ELECTRIC MACHINES

Motors represent the heart of most industrial production processes, which is why these machines deserve increased attention to ensure the reliability of the production process. In this regard, numerous techniques have been developed for real-time monitoring of the behavior and performance of motors [17-19].

Monitoring the condition of electric machines is a continuous process of evaluating equipment's health throughout its entire life cycle. The primary goal of a predictive monitoring system is to identify the early development of faults. For the maintenance department, it is crucial to detect each fault as early as possible to allow for planned machine downtime.

From a structural perspective, the components of an electric machine include:

Types of defects in the operation of electric machines:

Defects at the mechanical system level:

a) Bearing defects.
b) Coupling defects.
c) Shaft defects.

Defects at the magnetic system level:

a) Eccentricities of the rotor core.
b) Anisotropies.
c) Non-uniformities.

d) Core cracks.

Defects at the electrical system level:

a) Short circuits in the winding coils.
b) Defects in cage windings.
c) Defects in the brush-collector or brush-ring collector system.
d) Winding interruptions.
e) Bar or short-circuit ring cracks.
f) Issues with collector brushes or the brush-collector or brush-ring collector system [20].

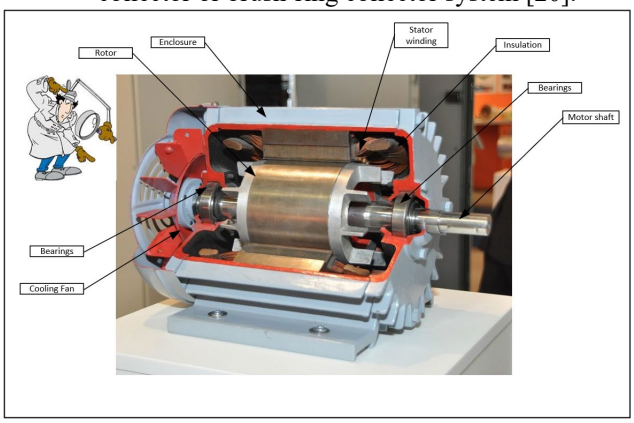


Figure 1: Structural elements of the electric machine.

Bearing defects represent approximately half of all issues encountered in electric machines. These defects can arise from various reasons, including:

1) Axial and radial overload caused by shaft deformation.
2) Corrosive action of water, acids, etc.
3) Lack or insufficient adequate lubrication.
4) Contamination with abrasive particles.
5) Improper mounting, lack of centering, or inadequate fixation.
6) Issues related to the electric circuit of the electric machine.
7) Slightly less prevalent than bearing defects are coil winding defects (30%-40%). Going into more detail, typical defects here include:
   a) Interruption of a phase winding.
   b) Reversal of phase winding ends.
   c) Short circuit between elementary conducting turns or between coils of the same phase.
   d) Short circuit between windings of two different phases.

Cage winding defects account for 5%-10% of all defects that may occur in the operation of electric machines [21, 22]. The types of defects to mention here are:

a) Cracks or interruptions in bars.
b) Destruction of bar junctions with short-circuited front rings.

All these enumerated defects can lead to negative effects on the proper functioning of the electric machine, namely:

a) Overheating of the induction machine.
b) Inability to start the machine.
c) Rotor speed lower than nominal.
d) Vibrations and noises.
e) Imbalance of rotating parts.

For all these defects, there are detection methods available:

1. Spectral analysis of stator/rotor currents.
2. Axial flux analysis.
3. Spectral analysis of vibrations.
4. Machine noise analysis.
5. Thermographic analysis.

Below are tables presenting various characteristics of the motor and operating conditions based on the number of motors, sample rate, number of defects, and defect rate:

Table 1. Power vs. defect rate [5].

Power [kW]	*100-500*	*501-5001*	*1001-2000*	*2001-4000*	*4001-6000*	*6001-8000*	*8001*
Motor no.	228	126	47	36	30	11	5
Sample rate	3208	1556	474	378	313	112	94
Defects no.	164	33	15	11	9	11	7
Defect rate [%]	5.11	2.12	3.16	2.91	2.88	9.82	7.45

Table 2. Maintenance intervention time vs. defects rate [5].

Maintenance intervention	**≤12 months**	**13-24 months**	**≥25 months**
Motor no.	435	47	1
Sample rate	5677	444	14
Defects no.	229	19	2
Defects rate [%]	4.03	4.28	14.29

Table 3. Voltage vs. defect rate [5].

Voltage [V]	**3000-5000**	**6000**	**6600-10500**	**11000-13800**
Motor no.	16	366	39	62
Sample rate	444	4761	445	485
Defects no.	5	211	13	21
Defects rate [%]	1.13	4.43	2.92	4.33

Tabel 1: Age vs. defect rate [5]

Age [years]	**0-5**	**5-10**	**10-15**	**15-20**	**20-25**	**>25**
Motor no.	40	224	124	7	33	55
Sample rate	127	1919	1546	124	725	1694
Defects no.	6	43	51	6	39	105
Defects rate [%]	4.72	2.24	3.30	4.84	5.38	6.20

Tabel 2: Environment vs. defect rate [5]

Environment	*Indoor*	*Outdoor*
Motor no.	105	378
Sample rate	1418	4717
Defects no.	28	222
Defects rate [%]	1.97	4.71

Based on the tables presented earlier, conclusions can be drawn regarding the probability of a defect occurring during the operation of an asynchronous motor,

considering the diversity of factors that can influence this aspect. The reported results were developed based on an investigation into cage motor failures in the petroleum, petrochemical, gas terminal, and refinery industries [5, 23].

4. SPECTRAL ANALYSIS OF STATOR/ROTOR CURRENTS

This detection method is essential because to obtain information that can accurately describe a signal (current/voltage/vibration, etc.), frequency analysis is performed. Spectral analysis is equivalent to transforming information from amplitude-time terms into amplitude-frequency terms, but in a more compact manner. It should be noted that graphically, this is represented in decibels (dB) as a function of the frequency spectrum [24, 25].

Events that overlap and may be confused in the time domain are clear and separated into individual components in the frequency domain. The waveform contains a lot of information, otherwise inaccessible to the naked eye. Some information is found in very low-level components whose magnitude may be smaller than the width of the waveform graph line. However, such very low-level components can be important if they indicate an evolving problem, such as a bearing defect.

Spectral analysis of stator/rotor currents involves detecting and separating current components based on which an electric motor defect can be identified, such as rotor bar deterioration, a short circuit between stator winding turns, or rotor eccentricity [26].

The specific method to make this spectral analysis of the currents, as presented in the specialized literature [1], contains the following equipment:

1. Current Transformer (CT) for signal measurement.
2. A shunt mounted at the output terminals of the CT.
3. Spectrum Analyzer.

The setup should be made as presented below:

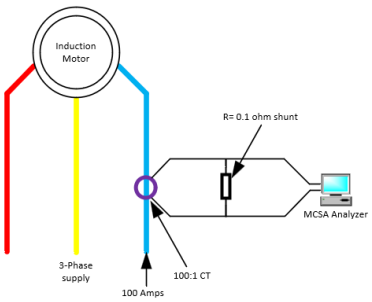


Figure 2: Measurement setup of the spectral analysis.

The stator windings are used as current transducers, collecting signals (induced currents) from the rotor (while also providing information about the operating condition of the stator) [6, 26]

Monitoring of the asynchronous machine's current is done using a current sensor (clamp ammeter, current transformer) with a resistive shunt at the output, which records the signal in real-time. This signal is then transmitted to the spectrum analyzer. In an ideal scenario, the current waveform is a pure sine wave, but this waveform contains numerous harmonics [6, 25].

The frequency range of interest in the spectral analysis of currents is typically between 0-5 kHz. According to Nyquist's theorem, this requires a sampling rate of at least 10,000 samples per second [6, 26]

The images below are the result of the study [1, 28] and depict the spectral analysis of the currents along with the accompanying physical defects observed:

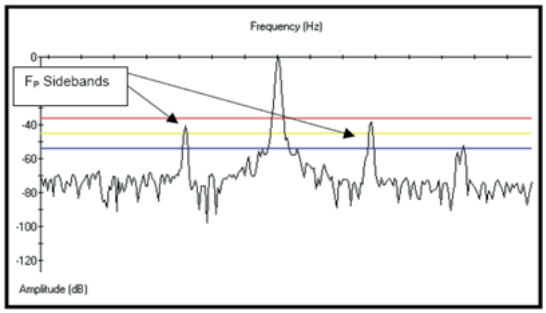


Figure 3: Spectral analysis of the stator currents - defect shown [1]

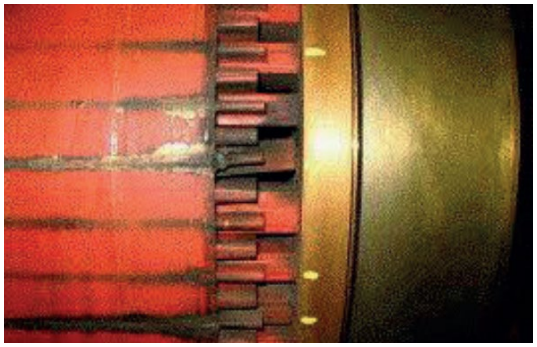


Figure 4: Rotor bars with defects [1].

Rotor bar defects are very common in asynchronous machines. These are caused by an excessive number of starts. It is therefore crucial to detect this type of defect before the bar detaches from the rotor, which inevitably leads to severe or even irreparable damage to the entire motor.

When there are broken bars in the rotor, the current components from the stator windings can be detected at certain frequencies given by the formula [6]:

$$f_{brb} = f_g \cdot \left[k \cdot \left(\frac{1-s}{p}\right) \pm s\right], \quad (1)$$

where:

f_{brb} - frequency of the broken rotor bar, f_g - grid frequency, p - number of pole pairs, s - slip, k= 1,2,3 … (constant).

In Figure 3, the upper and lower sidebands can be observed, separated by the double value of the slip frequency. This slip frequency is determined by the formula [6]:

$$f_{slip} = s \cdot f_g, \quad (2)$$

where f_{slip} is slip frequency.

Generally, if the difference between the main band and the sidebands is greater than 50 dB, the rotor has no defects. When the difference is in the range of 40 – 50 dB, then it is likely that a bar is damaged. If the difference is less than 40 dB, then there are multiple broken bars [6].

Stator current analysis is used to assess the condition of the stator winding and the connection circuit. A detailed analysis determines the condition of the winding and the connection circuit. The calculation of the following parameters is performed [2]:

- Voltage imbalance.
- Current imbalance.
- Impedance imbalance.
- Power factor imbalance.
- THD (Total Harmonic Distortion).
- Peak factor.

Through the analysis of the obtained results, it is possible to accurately assess the condition of the stator winding and the connection circuit. The quantitative and qualitative analysis of these parameters determines the location and level of damage. The current components influenced by short circuits occurring in the stator windings can be identified at frequencies calculated as follows:

$$f_{st} = f_g\left(\frac{n}{p}(1-s) \pm k\right), \quad (3)$$

where f_{st} is the frequency of the short-circuit component, n: 1, 2, 3, … (constant).

The relationship between current imbalance and impedance imbalance indicates whether the defect in the connection circuit is in the form of a high resistance point or if it is a fault in the stator windings. Additionally, an evaluation of the frequency regulator, if present, is conducted. The regularity of switching in the power supply block is checked. Moreover, the level of higher harmonics injected into the network by the regulator, which affects the operation of other devices, is determined [1, 20].

The application of the signal processing in the identification of the induction motor state and the application of *Machine Learning* could be challenging. The literature reveals numerous signal processing techniques for the interpretation of the output signals.

By simulating a few defects for the asynchronous machine in a specific tool, such as MATLAB-Simulink, it is possible to train the machine learning models with the input data.

In the following example, the Classification Learner application in MATLAB was used for training the machine learning models [4, 22].

The figure from below shows the plot matrix of the output data:

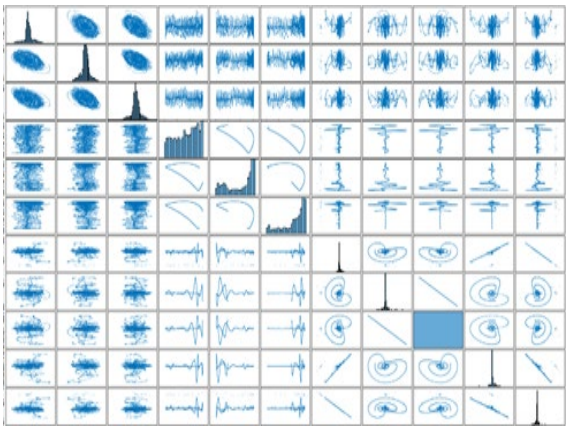


Figure 5: Plot Matrix [4].

Expanding on this insight, the next step involves selecting a machine learning (ML) model based on various algorithms, including Decision Trees, Support Vector Machines (SVM), Logistic Regression, K-Nearest Neighbors (KNN), and Naive Bayes. However, based on diverse study cases, Decision Trees emerged as the most accurate model, achieving an accuracy rate of 92.1% [4, 19].

Below is a picture of the confusion matrix of decision tree algorithm in MATLAB showing the accuracy of the model on specific fault such as: open circuit fault, short circuit fault, motor overload fault, broken rotor bar fault etc. [4, 18].

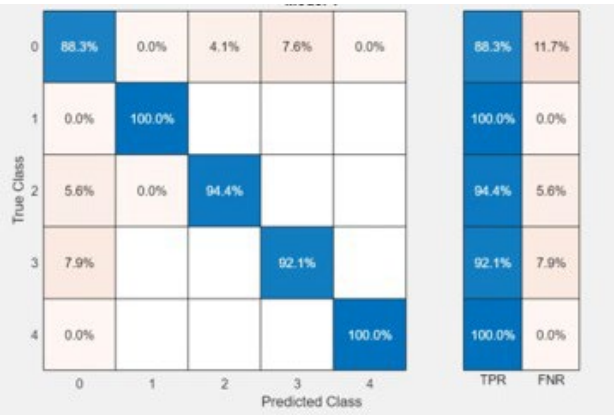


Figure 6: Confusion Matrix of Decision Trees Algorithm [4]

The main advantages of using the Decision Tree Algorithm are:

Prioritizing the faults: Decision Trees inherently assess the significance of features by ranking them based on their importance in classifying faults. This feature ranking mechanism facilitates the identification of critical factors contributing to fault detection [4].

Adaptability: Decision Trees exhibit a remarkable ability to adapt to complex and non-linear relationships present in the dataset. This adaptability is particularly beneficial when dealing with the intricate nature of fault patterns observed in induction motors [4].

5. CONCLUSIONS

Predictive maintenance represents an extremely vast field, offering numerous opportunities for exploration and study. In this paper, we specifically addressed the application of predictive maintenance in the context of electric machines, a particularly important aspect given the essential role they play in various industries.

By analyzing recent studies, we have identified the main defects and issues encountered in the operation of electric machines, as well as the proposed solutions for preventing and addressing them. It is essential to focus on preventing the occurrence of an entire chain of defects that could affect the entire industrial process, with predictive maintenance playing a crucial role in this regard.

To further research in this field, the set target is to use a set of experimental data to train an artificial intelligence (AI) system, utilizing the subset of AI known as Machine Learning (ML). This system will be capable of analyzing the collected data, processing it, and performing accurate diagnosis of the condition of electric machines. Additionally, it will be able to provide personalized maintenance solutions tailored to the specific needs of each individual piece of equipment.

The principle of collaboration between humans and AI enables more efficient data management, more precise analysis, and informed decision-making regarding electric machine maintenance. As a result, human operators will benefit from the support and assistance of AI in performing maintenance tasks, leading to increased efficiency and productivity in industrial maintenance activities.

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