

Predictive Maintenance of Electrical Machines using Machine Learning and Condition Monitoring Data

S D Prabu Ragavendiran¹, Deepak Shahakar², D. Suvarna Kumari³, Ajay Singh Yadav⁴, P.M. Arthi⁵, N Rajesha⁶

¹Department of Computer Science and Engineering, Builders Engineering College, Tirupur, Tamil Nadu 638108, India.

²Department of Electrical Engineering, P.R. Pote Patil College of Engineering & Management, Amravati, Maharashtra 444602,

³Department of Electronics and Communication Engineering, Vignan Institute of Engineering for Women's, Visakhapatnam, Andhra Pradesh 530049, India.

⁴Department of Mathematics, SRM Institute of Science and Technology, Delhi-NCR Campus, Ghaziabad, Uttar Pradesh 201204,

⁵Department of AIDS, Vel Tech Multi Tech Dr. Rangarajan Dr. Sakunthala Engineering College(Autonomous), Chennai, Tamil Nadu 600062, India.

⁶Department of Electronics and Communication Engineering, Sri Eshwar College of Engineering, Coimbatore, Tamil Nadu 641202,

E-mail : sdpgobi@gmail.com, deepakshahakar@gmail.com, suvarnamtech515@gmail.com, ajaysiny@srmist.edu.in, arthicse1507@gmail.com, rajeshmurthy44@gmail.com

Abstract- Predictive maintenance improves electrical machinery performance and reliability across industries. Machine learning algorithms combined with real-time condition monitoring data reduce unscheduled delays, enable proactive maintenance planning, and predict future faults. This research describes predictive electrical equipment maintenance using machine learning and condition monitoring data. The suggested method involves data acquisition and preparation, feature extraction and selection, and model construction and deployment. Data preparation and gathering involve real-time measurement from electrical equipment sensors and processing to remove noise and outliers. Numerous methods are used to gain insights from raw sensor data. Include time-series analysis, signal processing, and feature engineering. In the feature extraction and selection phase, meaningful features are extracted from the preprocessed data to capture latent patterns that signal machine health. Feature selection methods like RFE, PCA, and correlation analysis can find predictive features. Before building and deploying predictive maintenance models, SVMs, neural networks, and random forests are trained on the chosen features. This research shows that predictive maintenance solutions that incorporate machine learning and condition monitoring data can benefit electrical equipment. Advanced analytics and real-time monitoring can boost efficiency, reliability, and cost savings in sectors.

Keywords:- Predictive Maintenance, Electrical Machines, Machine Learning, Condition Monitoring, Data Analytics, Fault Detection, Anomaly Detection

I. INTRODUCTION

The internet of things (IoT) has facilitated the digital exchange of data and instructions among commonplace objects. Industry Revolution or Industrial Standard 4.0 was initiated by the implementation of intelligent devices in manufacturing. Cyberphysical systems consist of

interconnected devices capable of remote management, decision-making, and interaction. Now that this is resolved, data collection sites that monitor the conditions of electrical devices can commence. It is possible to monitor certain electrical devices using the gathered data. The diagnosis and forecasting of device malfunctions can be facilitated by data analysis. Predictive maintenance and electrical machine condition monitoring are widely implemented in accordance with Industrial Standard 4.0. The latest developments in the technology and applications of electric machines are the focus of the efforts of numerous businesses[1].

Reduce expenses associated with routine maintenance by employing two predictive maintenance algorithms. The electrical machinery of the industry will operate with greater efficiency as a result of this research, which will also aid in the prevention of unanticipated errors and failures. To determine the optimal configuration, organizations typically assess the durability of equipment through an examination of both internal and external factors. To optimize the performance of various categories of electrical apparatus, such as offshore wind turbines, scientists have implemented condition monitoring systems. Conversely, a significant portion of this equipment is cumbersome and costly[2].

The industry intends to implement proactive and predictive maintenance to address issues and defects prior to their exacerbation, with the aim of cost reduction. Four distinct phases comprise electrical machine maintenance, as illustrated in Figure 1: reactive, periodic, proactive, and periodic. Predictive maintenance is gaining traction in the industry as it provides more cost-effective and comprehensive reporting on defect detection compared to planned maintenance. Researchers are currently exploring

alternative technologies in an effort to enhance outcomes, given the growing prevalence of predictive maintenance. Among the current research areas are solar-powered monitoring systems, air and noise pollution monitoring systems, and wearable devices for patient status monitoring[3].

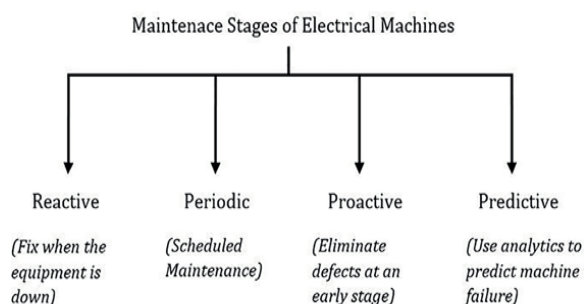


Figure.1. Denotes Maintenance of electrical machines.

Developments in microcontroller board technology have created novel research opportunities. An increasing number of scientists are dependent on these platforms for scalability. Efforts to develop condition monitoring systems have been the focus of prior research on wind turbines, weather sensors, electrical apparatus, autonomous vehicles, and robots. Many of these condition monitoring systems are still in development and may require significant refinement prior to being implemented on a large scale. The rate at which these devices can collect and transmit data without losing any of it is a frequent source of concern.

Converting existing SCADA/PLC systems is a challenging, expensive, and convoluted process. Significantly deficient in analysis capabilities are these systems. As a consequence, it is not utilised for the purposes of problem diagnosis or result generation. For the purpose of analysing acquired data and deriving conclusions, peripheral computing and cloud computing are utilised. Machine learning algorithms employ data gathered by machines during the process of analysis in order to train models[4].

II. RELATED WORKS

Cloud computing uses these learned models to sort and guess the data that comes in from electronic devices. Because these models needed a lot of storage space and computing power, they were mostly put into use on separate computers or in the cloud. Edge processing, on the other hand, is slowly becoming better than cloud computing. So, these models will not be stored in the cloud; instead, they will be run at the data collection interface node. This will make it easier to find errors and make decisions more quickly. Another benefit is that this will lower the amount of energy needed to send data across the network[5].

This chapter starts with a short overview of a condition tracking system based on microcontroller cards. It then moves on to talk about how the data was prepared and analysed. It also gives an overview of the training process, which uses datasets that are tailored to different situations and machine learning methods. A short look is given to predictive maintenance, covering both its current state and its possible uses. The following is a short summary.

A method for keeping an eye on the condition.

This part will go into more detail about a certain way to set up monitoring systems using microcontroller modules and cloud services. The peripheral node, the data collection system, and the cloud are the three technical parts that make up the condition tracking system[6]. Researchers often don't pay attention to the system of peripheral links. It is always best to have local analysis tools and enough computer power. A microcontroller board will receive the data, and the edge node will help with any network problems that come up.

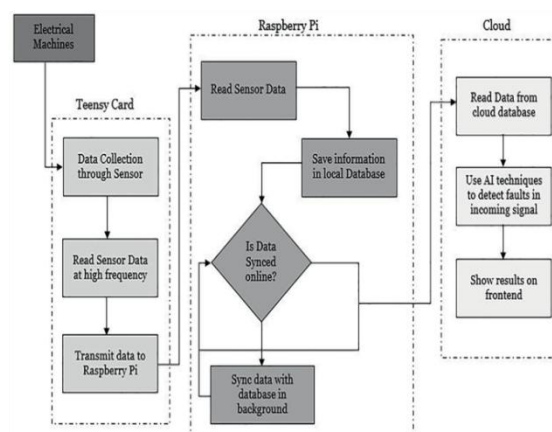


Figure.2 Denotes Flowchart of a condition monitoring system.

Sensors will be used by the data-gathering part to get information from the electrical machine. The inbound data goes through a calibration process before it is sent to the edge node through the microcontroller board. An analog-to-digital converter is what this part does most of the time because analogue sensors are so common in the business. After the data is collected, the information is sent to the edge point. In this case, the edge node does its job as a backup. The database that is used to store all new data is MySQL[7]. The databases in both the real world and the cloud are always up to date. Along the edges, some preprocessing tasks are possible, like digital screening. The third part of the system, which is housed in the cloud, is in charge of developing the user interface that the end user sees. In the process, diagnostics are also run to find any mistakes in the most recent synchronised data. People sometimes call this setup a "real-time condition monitoring system" because the data is shown on the front end of the app so quickly after it is gathered.

from the electrical unit. Figure 2 shows a simplified flowchart of how a condition tracking section is put together.

III. RESEARCH METODOLOGY

Preventative maintenance in accordance with the schedule.

Because businesses are shifting from performing planned maintenance to performing predictive maintenance, there is a need for additional research in this area. Although there are certain firms who are making investments in this subject, the majority of research is focused on fault detection rather than defect prediction. In order to accurately forecast the onset of defects at an early stage, it is necessary to possess the capacity to recognize troublesome frequency components. In addition to this, you need to have an understanding of the behavior of the signal and the frequency components that it possesses when the signal goes from being healthy to being defective. Locating these components is the first step in the process of training a model to forecast the occurrence of the problem and the length of time it will last[8].

The compilation of the data and the classification of the components will be the determining factors in this outcome. An investment of time and effort is going to be necessary, and this is not a little undertaking.

Scholars are actively studying more effective approaches in order to accomplish the development of a predictive model for flaws that can assist in the early detection of problems. Even while some companies may already be incorporating these algorithms into their systems, the necessary hardware is still unaffordable. The next natural evolution is predictive maintenance, which is the next logical progression[9]. It should be constructed in a way that is not only cost-effective but also independent of the hardware configuration; this offers an additional severe challenge in this field.

The application of algorithms for predictive maintenance encompasses a wide range of applications. It is possible to get findings with a higher degree of precision by mixing several methods. In a manner that is analogous to the methods of machine learning, the combination of fuzzy logic systems with signal processing has the potential to enhance the precision of predictive maintenance. When conducting research in this area, researchers frequently face the difficulty of insufficient data as well. It is difficult to train and validate a model using high-quality data in an industrial setting because there is a limited amount of data accessible[10].

This is especially true in the event that the model experience failures. Furthermore, in order for the models to be successfully trained, it is necessary to ensure that a considerable number of high-quality data is utilized. A

number of researchers are concentrating their efforts on fault patterns in order to establish a statistical equation for faults. This equation will make it possible to generate synthetic signals and offers the possibility of a solution to this problem. In the event that an electrical machine experiences a problem, the major role of this component is to precisely determine the frequency component range of amplitude. Despite the fact that this is a challenging task because it calls for considerable testing and data analysis, a significant amount of research is now being carried out in this field[11].

There are a few important steps that need to be taken in order to do research on the predictive maintenance of electrical equipment using condition monitoring data and machine learning. The following is one possible method that could be used in the research.

1. Figuring out what the problem is and how big it is:

List the machines or electrical parts that will be the focus of the research and explain what you hope to find.

- Clearly define the time range for prediction and the types of errors or failures that will make up the research's scope.

2. Collecting Data and Preprocessing It: Find out where the operational data, records of earlier maintenance, and sensor readings that are needed for condition monitoring can be found. Collect important information, making sure it includes a range of operating configurations and failure scenarios. Take care of any necessary data preprocessing tasks, such as getting rid of noise, handling lost values, and normalizing or standardizing features[12].

3. Feature Engineering and Selection: Take raw data and pull out the important features that machine learning models need. Use techniques like correlation analysis or domain knowledge to give priority to important features for predictive maintenance work.

4. When choosing and building a model, it's important to think about things like how fast the computer can handle the problem, how complicated the problem is, the type of data it has, and how it will be maintained in the future. This will help you figure out which machine learning methods are best. It is important to separate the data into three separate sets: testing, validation, and training[13].

- Make the chosen models work better by changing their hyperparameters while they are being trained with the training data.

5. Validation and evaluation: - Set up the right factors for judging how well predictive maintenance models work, like the area under the receiver operating characteristic curve (AUC-ROC), precision, accuracy, recall, or F1-score. Make sure that your learned models can handle new data by using the validation set.

Based on the test results, make any changes to the models that are needed. Keep doing this until the models work better.

6. Model Deployment and Integration: Add trained models to structures and systems that are already in place. To make maintenance work better, add the predictive maintenance system to the general workflow, which includes tools for making decisions and sending out alerts.

IV. RESULTS AND DISCUSSION

On the Raspberry Pi, the info is sent from the board to the edge node. The analog pin is being read for a large amount of data. Setting up a serial peripheral interface (SPI) link between the microcontroller board and the Raspberry Pi lets data flow at a steady rate with no loss. There is a clear difference in voltage between the Raspberry Pi and the microcontroller board. For example, some of these boards only produce 5 volts when they are turned on high. Pi, on the other hand, works at 3.3 volts when it's turned on, which is also needed to keep transmitted numbers from going over that limit. It is best to use a high sample rate when UART transmission is not needed. Table 1 shows sample rates and short descriptions of different types of contact channels over time.

Table.1. Comparison of sample rate for different communication methods

Communication method	Sample rate per second
UART	1800
I2C	2600
SPI	3600

It's enough to compare the speeds of several communication systems built into a single microcontroller PCB to get the sample rate per second stated above. The microprocessor board in this case is called an Arduino Mega. In all three cases, Arduino Mega and Raspberry Pi are the same when it comes to communication devices and other things, like the logger device's memory size. The results for the highest sampling rates an Arduino Mega reached after a few days of use in the specified connection mode, with no data loss seen while sending from the Mega to the Raspberry Pi are shown in Table 1. For example, the Teensy microcontroller board has a different range than the others. Because of this, the exact results may be different depending on the hardware.

These sampling rates are based on the idea that data can be sent continuously for hours or even days at a time without any loss. The results are better when you use newer boards with more processing power, but the microcontroller board you choose may change the sample rate for transfer. To lower the chance of losing data, the

data is synced with the cloud and saved in a local database at the same time as it is sent to Pi. Should the need appear in the future, Pi can also be used as a node for analysis, which includes digital filtering. Once the information has been sent, it is looked at in the cloud by many learned models to see if there are any problems. Because it's hard to understand numerical input data, the computed results are shown through an interface housed in the cloud. Along with being easy to use, the graphical user interface (GUI) gives clear results that don't overwhelm the user with unnecessary system information.

This is the case, as shown in Figure 5. uses resources in the cloud that can be expanded. Its two main parts are the graphical user interface and the background diagnosis analysis. A MySQL database holds the results of the diagnostic analysis, which is mostly written in Python. The PHP language is used for the user interface. The saved results are immediately shown on the graphical user interface after the database is updated. In this case, the cloud tools can be expanded as needed. A machine with a 16GB hard drive, 4vCPU cores, and 4GB of RAM is enough for basic data processing, such as running one or two background diagnostic tests. More diagnostic tests and gadgets on the edges of the network that connect to the cloud bring in more data, which can be increased as needed.

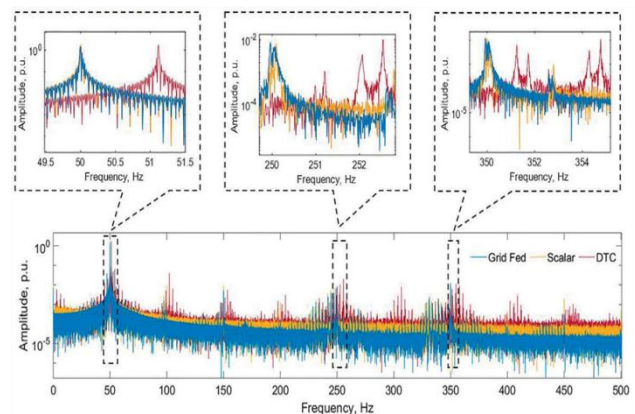


Figure.3. Current frequency spectra of a faulty motor under different control modes

The incoming data needs to be processed first before it can be used for research. The main focus of this research is on stochastic operations. Due to its unprocessed and temporal nature, the data must be checked to see if it can be used for its original purpose. By getting the Fourier transform of the input data, low-frequency components can be looked at, which can help find problems early on. A lot of operational factors, like load, control environment, and ambient environment, need to be taken into account in order for defect recognition to work well. Figure 6 shows the current frequency spectra of a motor with broken rotorbars when it is controlled in different ways,

such as grid fed, scalar, and direct torque. It is clear that the frequency parts of the signals are very different between the control modes. It is very important to keep this important thing in mind when teaching models.

The graphical user interface shows the results of the analysis, such as how likely it is that something will go wrong in each step and how to control the electrical machine from afar using the microcontroller board. As a result, there are many possible ways that this method could be improved. The addition of this function may help users get a better idea of what's going on with the electrical equipment. This may not only make it easier to find the cause of the problem, but it may also show which part of the electrical equipment is broken. The repair staff can use it to figure out if the problem needs to be fixed right away or if it can wait. That makes it faster for them to fix.

V. CONCLUSION AND FUTURE DIRECTION

The Internet of Things (IoT) is becoming more common in many areas and can be used for many things, such as remote control, finding problems, and keeping an eye on conditions. Predictive maintenance is becoming more important to stop losses as the industry moves away from planned maintenance. This is why predicted maintenance and problem diagnosis have become the most important things to think about. There is a detailed description of a condition tracking system, along with worries about the machine learning algorithm and the usefulness of predictive maintenance. Increasing processing power makes both the stability and speed of data transfer better. Unfortunately, inadequate data is still the main reason why intrained models don't work very well. On the other hand, researchers are now using reengineering methods to make statistical models. Researchers are working on making statistical models that can simulate the signals that electrical gadgets send out when they aren't working right. Scientists are making progress toward the day when it might be possible to use statistical models to send false signs, even though it takes a lot of work and focus. Along with machine learning techniques and maintenance methods, this chapter talks about some problems that come up in the field. It also describes a certain type of condition tracking system.

REFERENCES

- [1] Wang, J.; Hao, Y. Yield modeling for arbitrary defect outline. In Proceedings of the 8th International Conference on Solid-State and Integrated Circuit Technology, Shanghai, China, October 23-26, 2006.
- [2] Asami, T.; Nasu, H.; Takase, H. Oyamatsu. In Proceedings of the IEEE/SEMI Advanced Semiconductor Manufacturing Conference and Workshop, Boston, MA, USA, May 4-6, 2004; pp. 448-452.
- [3] R, G. et al. (2021). "Simulation Process of Injection Molding and Optimization for Automobile Instrument Parameter in Embedded System" *Advances in Materials Science and Engineering* vol. 2021, Article ID 9720297, 10 pages, 2021. <https://doi.org/10.1155/2021/9720297>
- [4] Ferris-Prabhu, V. Estimating the crucial area in yield forecasts. *IEEE J. Solid-State Circuits* 1985, 20, 874-878.
- [5] Venkatesan, K., Chandrasekar, A. & Ramesh, P.G.V. On-demand DWDM design using machine learning. *Soft Comput* 26, 6577-6589 (2022). <https://doi.org/10.1007/s00500-022-07181-x>.
- [6] M. T et al, "WPT: A Smart Magnetic Resonance Technology based Wireless Power Transfer System Design for Charging Mobile Phones," (IITCEE), Bangalore, India, 2024, pp. 1-6, doi: 10.1109/IITCEE59897.2024.10467828.
- [7] R, G. et al. (2022). "Optimization of Solar Hybrid Power Generation Using Conductance-Fuzzy Dual-Mode Control Method" *International Journal of Photoenergy*, Volume 2022, Article ID 7756261, 10 Pages, 2022 <https://doi.org/10.1155/2022/7756261>
- [8] R. Nuthakki, A. S. Murthy and D. Naik, "Single channel speech enhancement using a new binary mask in power spectral domain," 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA), 2018, pp. 1361-1366, doi: 10.1109/ICECA.2018.8474842.
- [9] De Vries, D.K., & Simon, P.L.C. Calibration of open interconnect yield models. In the Proceedings of the 18th IEEE International Symposium on Defect and Fault Tolerance in VLSI Systems, held on November 5, 2003, in Boston, Massachusetts.
- [10] Ahmed Z, Zeeshan S, Mendhe D, Dong X. Human gene and disease associations for clinical-genomics and precision medicine research. *Clin Transl Med*. 2020; 10: 297-318. <https://doi.org/10.1002/ctm.2.28>
- [11] Allan, G., & Walton, A. Efficient additional material critical area algorithms. *IEEE Trans. Computer Aided Design, Integr. Circ. Syst.* 1999, 18, 1480-1486.
- [12] G. A et al "Efficient Internet of Things Enabled Smart Healthcare Monitoring System Using RFID Security Scheme" *Intelligent Technologies for Sensors*, 1st Edition, 2023, Apple Academic Press, ISBN: 9781003314851.
- [13] Venkatesan, K., Chandrasekar, A. & Ramesh, P.G.V. On-demand DWDM design using machine learning. *Soft Comput* 26, 6577-6589 (2022). <https://doi.org/10.1007/s00500-022-07181-x>.