A Review on Condition Monitoring of Wind Turbines Using Machine Learning Techniques

Dr. P. Muralidharan[1], Gaurav thakur[2], Shalini M[3], Vikalp Sharma [4], Abootharmahmoodshakir[5], and Anishkumar Dhablia[6]**,**

[*] *Assistant Professor, School of Business and Management, Christ university yeshwanthpur campus Bangalore, India.*
[†]*Department of Civil Engineering, Uttaranchal Institute of Technology, Uttaranchal University, Dehradun-248007, India.*
[‡]*Assistant Professor, Department of ECE,Prince Shri Venkateshwara Padmavathy Engineering College, Chennai – 127, India.*
[§]*Department of Computer Science & Engineering, IES College of Technology, Bhopal, Madhya Pradesh 462044 India.*
[**]*The Islamic university, Najaf, Iraq.*
[6]*Engineering Manager, Altimetrik India Pvt Ltd, Pune, Maharashtra, India*
anishdhablia@gmail.com.

Abstract. This document examines the most up-to-date research on the application of machine learning (ML) techniques in monitoring the conditions of wind turbines. The focus is on classification methods, which are used to identify different types of faults. The analysis revealed that the majority of the research utilizes Supervisory Control and Data Acquisition (SCADA) information, with neural networks, support vector machines, and decision trees being the most prevalent machine learning algorithms. The review also identifies several areas for future research, such as the development of more robust ML models that can handle noisy data and the use of ML methods for prognosis (predicting future faults).
Keywords: Wind turbine, Renewable energy, Condition Monitoring, Machine learning,

[*]Corresponding Authour *:muralidharan.p@christuniversity.in*

1. Introduction

Due in part to increased public investments and a growing awareness of climate change, we have observed swift technological progress in the field of renewable energy. As a result, the proportion of renewable energy sources, such as wind power, has been steadily on the rise when compared to conventional sources like fossil fuels. Wind energy, harnessed through turbines located either onshore (land-based) or offshore (at sea), has become a pivotal player in this transition. Offshore wind farms have gained prominence for several compelling reasons. Offshore wind farms can take advantage of the stronger and steadier winds at sea, which can lead to more reliable energy production [2]. Secondlyoffshore wind farms are less visible than onshore wind farms, which can mitigate potential conflicts of interest with residents [2].It is important to note that the maintenance costs of offshore wind turbines are significant. The cost of ensuring that these turbines operate optimally throughout their lifespan, which is typically 20 to 25 years, accounts for approximately 25% of the total cost of offshore wind farm installation. [3].In this context, the crucial importance of condition monitoring (CM) becomes apparent, as it entails closely monitoring the various components of wind turbines to identify any deviations from normal operation that could indicate potential faults in the future. It is clear that the capacity to anticipate and rectify these faults proactively, through effective CM procedures, has the potential to substantially decrease the costs associated with Operation and Maintenance (O&M). [4]. Traditionally, condition monitoring (CM) has been done by analyzing specific measurements and operational parameters, such as vibration, strain, temperature, and acoustic emissions. However, recent advances in sensor technology, signal processing, big data management, and machine learning (ML) have made it possible to use more integrated and comprehensive approaches to CM. These new approaches can use a variety of data sources to make more informed, reliable, cost-effective, and robust decisions about the condition of wind turbines.This paper reviews the latest developments in ML-based approaches to wind turbine CM. The review focuses on papers published since 2011, but also includes some important papers from before that date. The papers were selected using targeted search terms on Google Scholar, and were filtered based on their publication year, accessibility, citations, and overall relevance.

2. Widely deployed methods for condition monitoring of wind turbines

Condition monitoring (CM) within the context of wind turbines plays an essential role in the broader realm of Operations and Maintenance (O&M). O&M encompasses the management, monitoring, and overarching onshore control of wind farm operations. Simultaneously, it involves the maintenance aspect, which entails necessary interventions to sustain the installation's functionality. Maintenance strategies typically fall into three categories:

1. **Reactive Maintenance (or Corrective Maintenance)**: This approach is the costliest and least efficient, as it does not employ CM. Components are replaced only when defects become apparent or accumulate, resulting in potentially significant downtime.In this study, the authors focus on optimizing maintenance

strategies within complex production systems, particularly in the context of Industry 4.0. They emphasize the importance of predictive maintenance and introduce the concept of opportunistic maintenance, which considers not only the timing of maintenance but also the associated opportunity costs. To address this, reinforcement learning algorithms are employed to determine optimal maintenance schedules in stochastic production environments. The key findings highlight the agent's ability to learn and initiate maintenance actions just before machine breakdowns, thus reducing downtime and maintenance costs. The study also demonstrates the agent's capacity to optimize maintenance by considering factors like buffer volume, ultimately providing valuable insights into the application of reinforcement learning in manufacturing processes [5][16].This research underscores the significance of leveraging intelligent systems, particularly reinforcement learning, to enhance maintenance practices in Industry 4.0. By incorporating condition monitoring and proactive maintenance strategies, the study showcases the potential for substantial improvements in production efficiency and cost reduction. The agent's learning performance, as illustrated by its ability to predict breakdowns and optimize maintenance timing, is a promising step towards more efficient and adaptive maintenance strategies in complex production systems. These findings support the broader adoption of machine learning techniques in manufacturing, ultimately contributing to increased productivity and reduced operational costs in the evolving landscape of modern industry.

2. **Preventive Maintenance (Scheduled)**: In this method, components are replaced during scheduled maintenance interventions, ideally before any related faults manifest. It aims to proactively prevent failures. The current study [6] introduced a machine learning approach that focuses on data analysis for the purpose of predictive maintenance in wind turbines. The methodology iteratively evaluates different data preprocessing and feature selection strategies to improve the performance of machine learning models. The authors found that the methodology was able to improve the performance of machine learning models for predictive maintenance of wind turbines by handling missing values, outliers, and noise; selecting the most relevant features; and training the model on a holdout dataset.

Table 1. Predictive Maintenance of Wind Turbines using various machine learning algorithms [7]

Fault Label	*k-NN Accuracy*	*SVM Accuracy*	*CRA Accuracy*
Inner	92.10%	94.10%	95.20%
Ball7	95.80%	97.10%	97.60%
Ball14	94.90%	96.80%	97.20%
Outer14	93.50%	95.60%	96.00%
Outer7	92.30%	94.50%	95.10%
Normal	95.20%	96.60%	97.30%

3. **Predictive Maintenance (Informed by CM)**: This strategy leverages CM to predict the likelihood of component failures and schedules replacements in a timely manner, optimizing maintenance efforts [7].

CM can be approached from several perspectives:

1. **Granularity Levels**: CM can be applied at varying levels of granularity, ranging from monitoring individual sub-components of wind turbines (e.g., drivetrain) to assessing the entire wind farm as a cohesive unit. Different models can provide signals that, when combined, offer higher-level warnings for the entire turbine [8,9].

2. **Monitoring Types**: CM methods can be broadly categorized into two main types:

    - **Intrusive Monitoring**: This approach includes techniques like Vibration Analysis, shock pulse methods and oil debris monitoring. However, it imposes wear on the component being monitored [10][17].

    - **Non-intrusive Monitoring**: This category encompasses methods such as ultrasonic testing techniques, acoustic emission analysis, visual inspection, thermo graphy, and power signal analysis [10]. These methods do not physically impact the component during monitoring.

3. **CM for Diagnosis and Prognosis**:

    - **CM for Diagnosis (Fault Detection)**: This aspect involves identifying a fault when it occurs in real-time. Establishing the capability of CM to detect failures is a fundamental prerequisite for constructing a machine learning model for prognosis.

    - **CM for Prognosis (Fault Prediction)**: Here, the CM model identifies patterns in signal data that are predictive of future failures.

It is crucial to take into account factors like failure rates and downtime when deciding which components to monitor. Priority is often given to components with a higher likelihood of failure or those that can result in extended downtime, given their potential impact. Studies have provided insights into annual failure rates and downtime for different sub-systems of wind turbines, highlighting components like the rotor (especially the pitch system), transmission, and power system as having elevated failure rates [8] [9].

Moreover, offshore wind turbines typically experience increased failure rates with generators and converters in comparison to onshore wind turbines. Common failures in gearboxes include issues with slip rings, grease pipes, rotors, planetary gears, bearings, and lubrication systems [9] [10].

While various commercial CM systems are in use, there is no consensus on the future direction of research in this field. Current wind turbine CM relies heavily on established methodologies that have been borrowed from traditional industries that deal with rotating machines. Various techniques used for CM encompass acoustic measurements, monitoring of electrical effects, power quality and temperature monitoring, analysis of oil debris, and vibration analysis. Additionally, physics-based data analytics methods are applied [11]. Crabtree et al. observed a diversity of CM approaches and highlighted the need for further research to define a unified direction [12].

3. Trends and Future challenges

The cutting-edge maintenance approach utilized in the wind turbine sector involves the integration of real-time continuous condition monitoring systems (CMS). The researchers carried out a pair of surveys: one focused on commercially accessible CMSs designed for wind turbines (WTs), while the other concentrated on commercially accessible SCADA data analysis tools for monitoring the health of WTs. The study conducted in [13] examined the techniques employed by 20 suppliers and discovered that nearly all of them prioritize the identical subassemblies, namely blades, gearbox internals and bearings, main bearings, and generator bearings. In addition, vibration monitoring (VM), oil monitoring (OM), and fiber optic monitoring are the most commonly used monitoring techniques. In [14], a comprehensive analysis was conducted on 17 SCADA data analysis tools specifically designed for wind turbine condition monitoring (WTCM). Out of the 17 products, three were created by wind turbine manufacturers, two by renewable energy consultancies, two by an electrical equipment provider, nine by industrial software companies, and just one by a wind turbine operating company.

The wind power sector is presently moving towards the utilization of bigger wind turbines (WTs) in distant areas, with a growing preference for offshore locations due to their superior wind conditions. The dimensions and placement of these wind turbines present distinctive maintenance obstacles in contrast to conventional power generation systems. In order to tackle these obstacles, manufacturers of WTCMS need to enhance current monitoring methods or create innovative ones. The ultimate objective of CMS is to reduce the burden on operators through the utilization of intelligent software algorithms and automated analysis[15].

The wind turbine industry is transitioning towards intelligent machine health management (IMHM), representing a fourth-generation approach to maintenance. The primary objective is to create wind energy conversion systems (WECSs) capable of comprehending and autonomously making decisions. Achieving this objective necessitates the implementation of sophisticated condition-based maintenance systems founded on the principles of reliability-centered maintenance (RCM). Here are some of the new trends in the WTCM industry[15]:

- Remote monitoring: This involves collecting and analyzing data from WTs remotely, which can help to reduce the need for on-site visits by technicians.

- Big data analytics: This involves using advanced data analysis techniques to extract insights from large datasets, which can help to identify potential problems early on.

- Artificial intelligence (AI): This involves using AI algorithms to automate tasks such as data analysis and decision-making, which can free up technicians to focus on other tasks.

- Cybersecurity: This involves protecting WTCMS systems from cyberattacks, which are becoming increasingly common.

These are just some of the new trends in the WTCM industry. As the sector progresses, we can anticipate the emergence of additional inventive and efficient maintenance approaches[15].

- Toward Smart Monitoring: Wind turbine monitoring systems are becoming increasingly sophisticated, with the goal of developing systems that can automatically detect and diagnose problems. This would free up technicians to focus on other tasks and would also help to avoid false alarms.

- Necessity of Remote and E-Monitoring: Remote and e-monitoring systems are becoming increasingly important for wind turbines, as they are often located in remote areas. These systems allow technicians to monitor the condition of the turbines from a distance, which can save time and money.

- In-Service SHM: The significance of structural health monitoring (SHM) for wind turbines is on the rise, as it enables the early detection of potential damage. This can help to prevent catastrophic failures.

- Integration and Interaction of Monitoring and Control Systems: Monitoring and control systems are increasingly being integrated for wind turbines. This can improve the efficiency and reliability of the turbines.

- Estimation of the Remaining Component Life Service: Estimating the remaining service life of components in wind turbines is a challenge. However, there are a number of methods being developed to address this challenge.

- Future Research Challenges in WTCMTs: There are a number of future research challenges in wind turbine condition monitoring and testing. These challenges include developing more reliable and accurate prognostic techniques, improving the use of SCADA data, and developing smart, wireless, and energy-efficient sensors.

4. Conclusions

- Machine learning (ML) methods have been shown to be effective for condition monitoring of wind turbines. They can be used to detect faults, diagnose their causes, and predict their occurrence. This can contribute to enhancing the efficiency and efficacy of maintenance procedures, diminishing the maintenance expenses, enhancing the dependability of wind turbines, and prolonging their lifespan.
- The most common ML algorithms used for CM of wind turbines are neural networks, support vector machines, and decision trees. These algorithms can be used to learn the patterns in data that are associated with different types of faults. Once these patterns have been learned, the algorithms can be used to identify new faults or to predict the occurrence of future faults.

- The future challenges in ML-based CM of wind turbines include the development of more robust models that can handle noisy data and the use of ML methods for prognosis (predicting future faults). Noisy data is data that contains errors or inconsistencies. Robust models are less likely to be affected by noisy data. Prognosis is the ability to predict the occurrence of future faults. ML methods can be used to develop prognostic models that can predict the occurrence of faults before they happen.
- The application of machine learning in the condition monitoring of wind turbines is still in its infancy, yet it holds great promise in enhancing the efficiency and efficacy of maintenance procedures. The exploration of more resilient ML models and the utilization of ML for forecasting are two auspicious fields of study that have the potential to enhance the widespread acceptance of ML-based CM systems.

References

1. Y. Wolde-Rufael, "Energy consumption and economic growth: the experience of African countries revisited." Energy Economics, 31(2), 217-224, 2009. https://doi.org/10.1016/j.eneco.2008.11.005
2. M. Deveci, E. Özcan, R. John, D. Pamucar, H. Karaman, Offshore wind farm site selection using interval rough numbers based Best-Worst Method and MARCOS, Applied Soft Computing, Vol. 109,107532, 2021. https://doi.org/10.1016/j.asoc.2021.107532
3. P. Zhou, P.T. Yin,"An opportunistic condition-based maintenance strategy for offshore wind farm based on predictive analytics", Renewable and Sustainable Energy Reviews, Vol.109, 1-9, 2019, https://doi.org/10.1016/j.rser.2019.03.049
4. . M. Wilkinson et al. “Comparison of methods for wind turbine condition monitoring with SCADA data”, IET Renewable Power Generation,vol.8, no. 4, pp- 390-397 2014. https://doi.org/10.1049/iet-rpg.2013.0318
5. A.Kuhnle, J., Jakubik,&G. Lanza, “Reinforcement learning for opportunistic maintenance optimization”, Prod. Eng. Res. Devel. 13, 33–41 (2019). https://doi.org/10.1007/s11740-018-0855-7
6. M. Garan, K. Tidriri, and I. Kovalenko, “A Data-Centric Machine Learning Methodology: Application on Predictive Maintenance of Wind Turbines,” Energies, vol. 15, no. 3, p. 826, Jan. 2022, doi: 10.3390/en15030826.
7. G. K. Durbhaka and B. Selvaraj, "Predictive maintenance for wind turbine diagnostics using vibration signal analysis based on collaborative recommendation approach," 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Jaipur, India, 2016, pp. 1839-1842, doi: 10.1109/ICACCI.2016.7732316.
8. Schlechtingen, M.; Santos, I.F. Condition Monitoring with Ordinary Wind Turbine SCADA Data—A Neuro-Fuzzy Approach. Proceedings of the European Wind Energy Association (EWEA) Offshore 2011, Amsterdam, The Netherlands
9. Shafiee, M. (2016). Modelling and analysis of availability for critical interdependent infrastructures. International Journal of Risk Assessment and Management, 19(4), 299-314.

10. Davies, A. (Ed.). (2012). Handbook of condition monitoring: techniques and methodology. Springer Science & Business Media.
11. Sunder Selwyn T., Hemalatha S.,(2020),"Experimental analysis of mechanical vibration in 225kW wind turbine gear box",Materials Today: Proceedings,Vol.46,no.,pp.3292-3296.doi:10.1016/j.matpr.2020.11.461
12. H.D.M..de Azevedo, A.M., Araújo, A. M., &Bouchonneau, N. (2016). A review of wind turbine bearing condition monitoring: State of the art and challenges. Renewable and Sustainable Energy Reviews, 56, 368-379.
13. C.J. Crabtree, Y. Feng, &P.j.Tavner, " Detecting incipient wind turbine gearbox failure: a signal analysis method for on-line condition monitoring". In Proceedings of European Wind Energy Conference (EWEC 2010), Warsaw, Poland (Vol. 2023, p. 154156).
14. C.J. Crabtree, " Survey of Commercially Available Condition Monitoring Systems for Wind Turbines", Durham University: Durham, UK, 2010.
15. Chen, B. Survey of Commercially Available SCADA Data Analysis Tools for Wind Turbine Health Monitoring; School of Engineering and Computing Sciences, Durham University: Durham, UK, 2010.
16. P. Tchakoua, R. Wamkeue, M. Ouhrouche, F. Slaoui-Hasnaoui, T. Tameghe, and G. Ekemb, "Wind Turbine Condition Monitoring: State-of-the-Art Review, New Trends, and Future Challenges," Energies, vol. 7, no. 4, pp. 2595–2630, Apr. 2014, doi: 10.3390/en7042595.
17. Sunder Selwyn T., Hemalatha S.,(2020),"Condition monitoring and vibration analysis of asynchronous generator of the wind turbine at high uncertain windy regions in India",Materials Today: Proceedings,Vol.46,no.,pp.3639-3643.doi:10.1016/j.matpr.2021.01.656.